Facilitating the Detection of ASD in Ultrasound Video using RHOOF and SVM

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***Abstract*—In the medical field various motion tracking techniques like block matching, optical flow, and histogram of oriented optical flow (HOOF) are being experimented for the abnormality detection. The information furnished by the existing techniques is inadequate for medical diagnosis. This technique has an inherent drawback, as the entire image is considered for motion vector calculation, increasing the time complexity. Also, the motion vectors of unwanted objects are getting accounted during abnormality detection, leading to misidentification / misdiagnosis. In this research, our main objective is to focus more on the region of abnormality by avoiding the unwanted motion vectors from the rest of the portion of the heart, allowing better time complexity. Proposed a region-based HOOF (RHOOF) for blood motion tracking and estimation; after experimentation, it is observed that RHOOF is four times faster than HOOF. The performance of supervised machine learning techniques was evaluated based on accuracy, precision, sensitivity, specificity, and area under the curve. In the medical field more importance is given to the sensitivity than accuracy. Support vector machine (SVM) has outperformed other technique on sensitivity and time complexity, hence chosen for abnormality classification in this work. An algorithm has been devised to use combination of RHOOF and SVM for the detection of atrial septal defect (ASD).**

***Keywords*—Two dimensional; apical four chamber; region-based histograms of oriented optical flow; machine learning; area under the curve; support vector machine; congenital**

I. Introduction

Cardiac diseases are mainly categorized into congenital and acquired. Congenital diseases are birth defects. Many of them can be treated or prevented by taking necessary corrective measures like surgeries. Acquired diseases have an impact on the overall functioning of the heart. Hence, more emphasize is given to the physical structure and overall functioning of the heart. Representation and evaluation of cardiovascular movements have become a significant step in the analysis. Heart-related disorders/diseases can be visualized and analyzed using an ultrasound, which is the easiest and most widely used real-time method. The ultrasound findings vary from patient to patient due to the differences in the structure of the heart. Hence, experts play a very vital role in capturing correct ultrasound images, accurate analysis and interpretation of results. As there is a difference in the results of a heart ultrasound, appearance-based methods are not recommended for the machine learning (ML) algorithm classification of cardiovascular disease.

The overall objective of this study is to devise an algorithm for facilitating automatic detection of atrial septal defect (ASD) using motion vector analysis of ultrasound videos in combination with ML algorithms.

ML is a next-generation technology used worldwide in various fields and applications. Medical field is no exception to this technology. Nowadays, ML technology is increasingly used worldwide. Several studies have been conducted in the medical field using ML as one of the enablers for early and accurate detection of diseases and because of the availability of data in the form of electronic media. A huge amount of data in the form of numbers, images, videos, pictures, and reports are generated and transmitted in the medical field on a daily basis. With the appropriate use of new technology, real-time data can be provided as and when required, regardless of the location. Because of the advantages over other diagnostics techniques, ultrasound is one of the most popular techniques used in the medical field.

There is an ongoing study evaluating the ultrasound method in terms of real-time analysis, quality of the output, and disease coverage, which provided a very good opportunity for researchers to use this next-generation technology; through this experimentation, ML and other computer vision techniques were used for the prediction of heart abnormalities. Recently, researchers have evaluated the utilization of several techniques like optical flow (OF), BPNN and SVM [9], in the detection of cardiovascular abnormalities.

The field of computer vision has described several OF estimation techniques. An OF measures the angle and magnitude of brightness patterns in an image or moving objects and plots them in the form of vectors called motion vectors (MVs). OF provides lot of information on the spatial patterns based on the rate of change.

This study used the image and video processing techniques in combination with ML for the classification of ASD. As this defect usually develops in the upper chambers of the heart, our study focused more on the detection of abnormality, that is, the hole in the septal wall. Using a computer vision technology to identify the location of defects, the blood movement from the left to right atrium (LA to RA) is studied. The MVs in this area were examined closely to establish the pattern; using the MV pattern and direction, the ML model has been trained. This trained model is then used for testing.

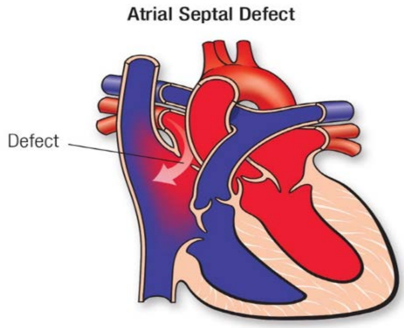


Fig. 1. Heart with Atrial Septal Defect (Source: Heart.Org).

As seen in the “Fig. 1”, hole in the septal wall allows the movement of blood from the LA to RA or vice versa. A dynamic analysis of the ultrasound findings assists in detection of ASD. The movement of blood can be tracked using motion estimation analysis methods.

The sections were arranged as below:

Section II: Related Work.

Section III: Methods.

Section IV: Experimental Results.

Section V: Conclusion.

Section VI: Future Work.

II. Related Work

Mrunal N. Annadate and Manoj S. Nagmode, in [1] proposed a motion vectors-based algorithm using block matching technique (Elongated Horizontal Large Diamond Search Pattern – EHLDSP) for tracking of Blood Movement in the heart for enabling the detection of Atrial Septal Defect. Mrunal N. Annadate and Manoj S. Nagmode, in [2], proposed an automatic detection of heart disorder (Hypertrophic Cardiomyopathy) using watershed segmentation technique. Achmad Solichin, Agfianto Eko and Agus Harjoko, in [3] proposed an OF feature-based method to detect the direction of an object movement. Author proved the usage of HOOF for the detection of object movement direction in the video. They also emphasized on the three main parameters affecting the success of results; number of frames, their interval and size of the grid. Results obtained for accuracy, precision, recall and direction detection error rate are 98.1%, 35.6%, 41.2% and 25.28%, respectively. The proposed approach is 22 times faster than other approaches which uses object detection and segmentation as pre-step. Mrunal N. Annadate and Manoj S. Nagmode, in their previous study [4] they have worked on the de-noising filters of seven different categories and proved that Three Ranking and Lee outperformed other de-noising filters. Rashmi, Nagaraja NS and Ashwin Kumar, in [5] presented HOFO- and support vector machine (SVM)-based techniques for detection of abnormal behavior. Here the research is accomplished in two parts, computing the histogram of optical flow orientation followed by a non-linear one-class Support Vector Machine. For optical flow Lucas Kanade method was used. Rensso Victor Hugo Mora Colque, Matheus Toledo Lustosa de Andrade, Carlos Caetano, and William Robson Schwartz, in [6] showcased the detection of anomalous events in videos. Here author proved that proposed descriptor is capable of extracting the information from cuboids. Unlike their previous work, in this research both magnitude and direction of the optical flow was used for the histogram generation. Also, showcased the improvements by comparing the results obtained with conventional HOOF. Database used by the author has various limitations like size, saliency of the anomalies and evaluation criteria.Achmad Solichin, Agfianto Eko Putra and Agus Harjoko, in [7] proposed a Histogram of Oriented OF (HOOF)-based method for determination of movement direction. The experiment results show False Positive Per Grid (FPPG) as 28.32%, and False Negative Per Grid (FNPG) as 4.08%. The role of grid size in faster identification of movements is proved in this research. Chetana D Patil and Bharathi V K, in [8] proposed Histogram of OF Orientation and Magnitude (HOFM) and K-nearest neighbor (KNN) classifiers for abnormal event detection and classification. Not only orientation measurement using temporal information but also velocity extraction using magnitude of flow vectors is done by the researcher to achieve the event detection. G.N.Balajia, N.Chidambaramc, and T.S.Subashinib, in [9] proposed method performs well for the automatic classification of echocardiogram in all the four standard views; parasternal short-axis, parasternal long-axis, apical 2 chamber and apical four chamber, using back propagation neural network (BPNN) and SVM with an 87.5% accuracy. Limitation of the existing study is non-inclusion of views such as subcostal view, Doppler view, etc. J.R.R. Uijlings, N. Rostamzadeh, I.C. Duta, and N. Sebe, in [10] presented various techniques to address the problems related to computational efficiency. The focus of this research is to evaluate the trade-off between computation time and accuracy for video classification. Authors have achieved this through fast Matlab implementation of HOG and HOF and made this publicly available.

Daniel Tenbrinck, Xiaoyi Jiang, Sönke Schmid, Jörg Stypmann, and Klaus Schäfers, in [11] described, how presence of speckle noise violates the Intensity Constancy Constraint’ (ICC) assumption of optical flow techniques. To overcome this issue, they have proposed use of local statistics and introduced an optical flow method using histograms as discrete representations for motion analysis. Tian Wang Hichem Snoussi, in [12] proposed a novel spatiotemporal feature descriptor, called histogram of optical flow orientation, magnitude and entropy (HOFME), which is an improvised version of HOFM. On the data set, proposed algorithm showed 100% and 83% of accuracy in recognizing anomalous events at two different locations. Alessandro Becciu, Luc Florack, Hans van Assen, Vivian Roode, Sebastian Kozerke, and Bart M, in [13] proposed a new three-dimensional (3D) multiscale OF-based method for analyzing a true 3D cardiac motion at voxel precision. Rizwan Chaudhry, Gregory Hager, Ren´e Vidal and Avinash Ravichandran, in [14] proposed usage of generalization of the Binet-Cauchy kernels to nonlinear dynamical systems (NLDS) and represented each frame of a video using a histogram of oriented optical flow (HOOF) to recognize human actions by classifying HOOF time-series. Balza Achmad, Aini Hussain, and Mohd. Marzuki Mustafa, in [15] extracted three successive frames from an ultrasound video and presented an OF-based enhancement technique. The focus of the research in this paper is to remove speckle. Author made use of optical flow technique in three consecutive frames and reconstructing the resultant image with reference to the preceding and succeeding image using fusion and Lukas-Kanade method for obtaining optical flow. F Wang, D Beymer, and T Syeda-Mahmood, in [16] presented a method of echocardiographic sequence registration. Aditi Roy, Arun K. Majumdar, Shamik Sural, and Jayanta Mukherjee, in [17] represented an echocardiogram video in the form of hierarchical state-based model. Author carried out experiments on 20 echo videos and compared the results with manual annotation done by two experts. View classification accuracy is 97.19% and misclassification error is in the acceptable range (less than 13%), and corresponds to the frames of state boundaries. Schlomo V Aschkenasy et al. in [18] presented an algorithm for the automatic classification of cardiac views like A4C, A2C, and PLAX. Navneet Dalal and Bill Triggs, in [19] experimentally proved that HOG descriptors outperform existing gradient and edge descriptors. Further optimization of algorithm and increase in the speed of detection are the areas of improvement. John L. Barron, Steven S. Beauchemin, and David J. Fleet, in [20] carried out the empirical comparison between different techniques to overcome the shortage of quantitative evaluation of optical flow in other researchers' studies. In this study, evaluation is done on the basis of density of velocity measurement, accuracy, and reliability.

Berthold KP Horn and Brian G Schunck in [21] presented a method to find optical flow patterns, based on the assumption of smooth variation of brightness pattern of the velocity across the image. This method is popularly used by the researchers till date. Bruce D. Lucas, and Takeo Kanade, in [22] presented a spatial intensity gradient-based innovative technique used for image registration. The differential method presented by the authors for optical flow estimation assumes constant flow in a local neighborhood of the pixel under consideration, and solves the basic optical flow equations for all the pixels in that neighborhood. Navneet Dalal, Bill Triggs and Cordelia Schmid, in [23] proved that a differential OF histogram provides the best performing motion-based descriptors. The combined detector reduces the false alarm rate by a factor of 10 relative to the best appearance-based detector. J. H. Park, C. Simopoulos, J. Otsuki, S. K. Zhou1, and D. Comaniciu, in [24] built a system for automatic classification of the heart views through use of machine learning which extracts the knowledge from an annotated database. This system automatically classifies four standard cardiac views: apical four chamber and apical two chamber, parasternal long axis and parasternal short axis. Author achieved a classification accuracy of 96%. Current system can handle pre-defined views only. SS Beauchemin and JL Barron, in [25] investigated the computations performed using the OF methods and further scrutinized the hypothesis and assumptions used by these methods. .Matthew Eric Otey et al., in [26] used Markov Random Fields (MRF) model for part-based representation and automatic recognition and grouping of the heart chambers in the different views. Current system can handle simple distributions for the properties of parts, complex distributions are not possible at this stage. Rensso Victor Hugo Mora Colque, William Robson Schwartz, and Carlos Antˆonio Caetano J´unior, in [27] proposed a feature descriptor called HOFM for detection of an anomalous event.

III. Methods

The dataset chosen for experimentation comprised 20 MPEG4 (MP4) videos because AVI does not support HEVC/H265 codecs. The length of each video is considered as 1 second because one heartbeat or cardiac cycle takes about 0.8 sec to complete. The images are cropped from these videos to the same size to avoid impact on the overall analysis. All our videos have a standard frame rate of 30fps.

A. *Proposed Methodology – Region-based HOOF (RHOOF)*

"Fig. 2", demonstrate the block schematic of the end-to-end process flow for abnormality detection; each step in this block diagram is covered in more detail in the subsequent sections of this study.

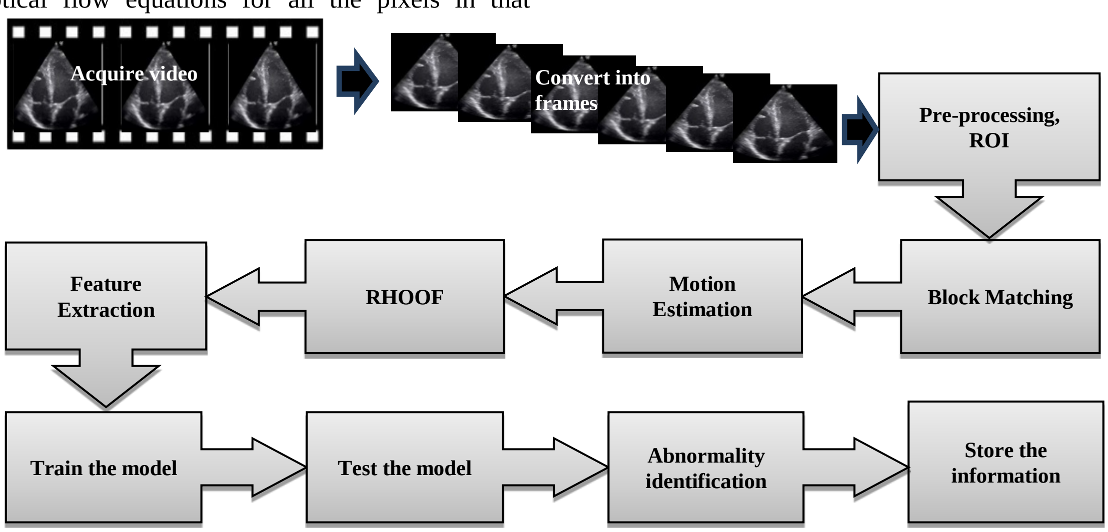


Fig. 2. Block Schematic of a Proposed Methodology.

B. *Pre-processing*[4]

Multiple noise models and de-noising filters were studied and evaluated based on various performance parameters, as part of a pre-processing combination of best performing Lee and the three ranking filters were used for de-noising, as reported in a previous study.

C. *ROI Identification*

During run time image cropping is done to focus on the septal wall area only, and the algorithm automatically marks the ROI in each frame. By doing this we are avoiding the unwanted motion vectors from other regions or rest of the portion of the heart, as a result ASD identification and diagnosis becomes easy and accurate.

D. *Motion Estimation*[1]

In the last decade, several studies regarding motion estimation have been conducted. Motion analysis is performed using two conventional methods: Block Matching and Optical Flow. These techniques were used to quantify the velocity pattern of moving objects. The distribution of velocity movement based on the brightness pattern is evaluated in the image sequence of the video. The three-dimensional arrangement of the object and rate of change-specific information can be derived from these image sequences.

1) Optical Flow (OF)[1:] The motion estimation in terms of image intensity gradient change can be evaluated based on OF. The vector that provides movement between pixels of each frame is called OF. The sequence of continuous frames makes a video, and its signal is a three-dimensional function (f) of m, n, and t (where m and n are spatial or plane coordinates and t is time) as shown in equation 1. The assumption of brightness consistency across successive frames can be stated using the following equation:

$$f(m,n,t) = f(m+dm, n+dn, t+dt) \tag{1}$$

Where, m+dm and n+dn are displacements and t+dt is new time.

Here, left-hand side of the “(1)” is the 1st frame and right-hand side is the subsequent frame; as mentioned above, brightness across the frame is constant, which means that brightness at m and n of the first frame is equivalent to m+dm and n+dn in the subsequent frame. Equation 1 can be represented as follows:

$$I_x m + I_y n + I_t = 0 \tag{2}$$

Where, spatiotemporal image brightness derivatives are defined by Ix, Iy, and It. And m is horizontal and “n” is vertical optical flow and “t” is time.

2) Block Matching[1:] Here current frame of a video is divided into macro blocks of equal sizes and comparison between macro blocks of adjacent frames is carried out. Location wise movement of macroblock is traced by drawing a vector called as motion vector (MV). Likewise, movement of all macro blocks in the frame is calculated to estimate the motion.

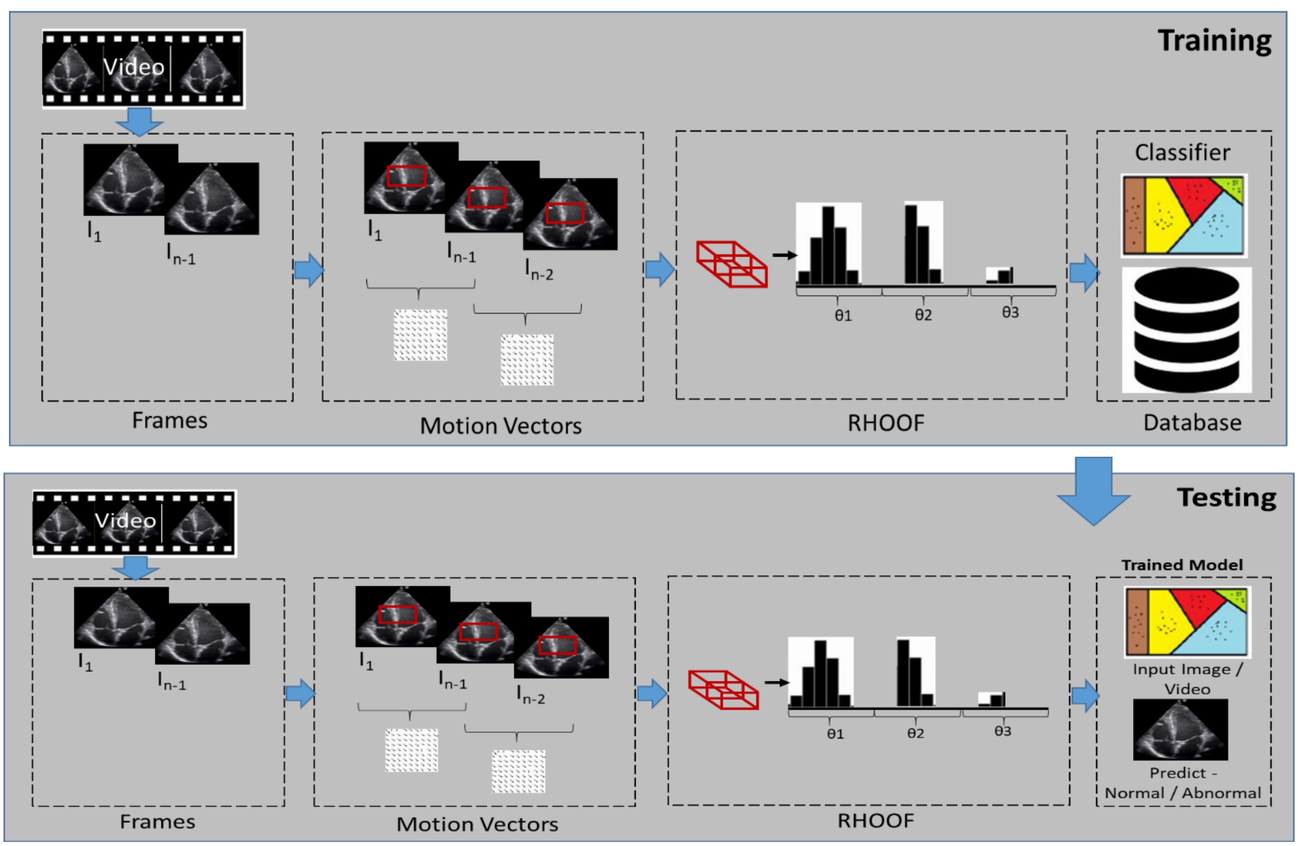


Fig. 3. Diagrammatic Illustration of a Proposed RHOOF based Approach to Classify Heart Abnormality.

"Fig. 3" shows the diagrammatic illustration of proposed RHOOF, wherein the acquired video was converted into frames using an algorithm; the region of interest was identified; the optical flow was extracted for each frame to calculate MV; and the features like magnitude and direction were provided as input to the algorithm to calculate region-based HOOF (RHOOF). These inputs were further fed into the ML algorithm for heart abnormality classification. For each block, a RHOOF feature was computed, and the vector was created and denoted as Fx for frame x as shown in the figure. Every frame in RHOOF was denoted as a vector of n x n. Equally spaced bins were spread over 0 degree to 360 degrees. As seen in the "Fig. 4", two neighboring blocks overlap 50% on each other during RHOOF calculation. The computation time depends on the size of the block.

The values extracted from motion vector has horizontal and vertical components: U and V at pixel(x,y), respectively. Angle θ denotes motion vector direction and whose value is between 0 degree and 360 degrees. It was derived based on U and V values. The direction and magnitude of the motion vector are calculated as follows:

$$\theta(x, y) = \tan^{-1}\frac{V(x,y)}{U(x,y)} \tag{3}$$

And magnitude as

$$magnitude = \sqrt{x^2 + y^2} \tag{4}$$

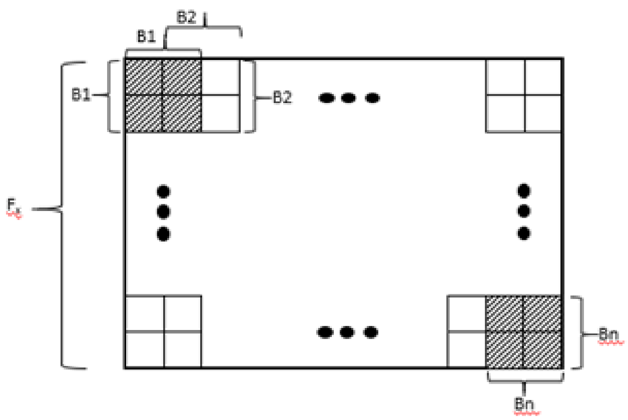


Fig. 4. Region-based Histogram of Optical Orientation of Frame k.

After obtaining the direction and magnitude of the motion vector at each point, it was normalized and the movement directions were clubbed into various Bins like Bin1, 2,..,9, as per θ value. No movement direction points were denoted as Nil. RHOOF features were analyzed to identify the movement direction, and histogram was obtained. Grid processing will not process the grid if there is no motion in it; this reduces the overall processing time. The RHOOF values were accumulated using the following equation:

$$Hoof_b(m, n) = \sum_{frame=1}^{P} Hoof_b(m, n) \tag{5}$$

Where, "b" stands for bin, P is the number of frames and (m,n) values corresponds to grid(m,n).

The representation of histograms is not dependent on motion directions.

"Fig. 5" explains how the histogram magnitude is distributed in nine bins.

E. Classification

ML is a subset of artificial intelligence and used for data analysis so that the system can learn from data and patterns, and decide on its own with/without human intervention. In the initial stage, started with pattern recognition, now various algorithms are developed to perform many tasks. Through an artificial intelligence, computer can identify whether the trained model is exposed to a new set of data and automatically re-train the model.

ML is not a new technique, has been used for a long time, and is applied in today's applications; its use has given a new face and momentum to it. ML is broadly classified into two classes, supervised and unsupervised. In the first category, the model is trained using labeled examples; the desired output is already known based on the input. In the second category, there is no historical labels available against the input data, the system or algorithm is trained to find some structure or pattern within, and works best on transactional data.

Various ML algorithms are applied to determine the best performing classifier; the following section describes the various ML algorithms that were used in the current study.

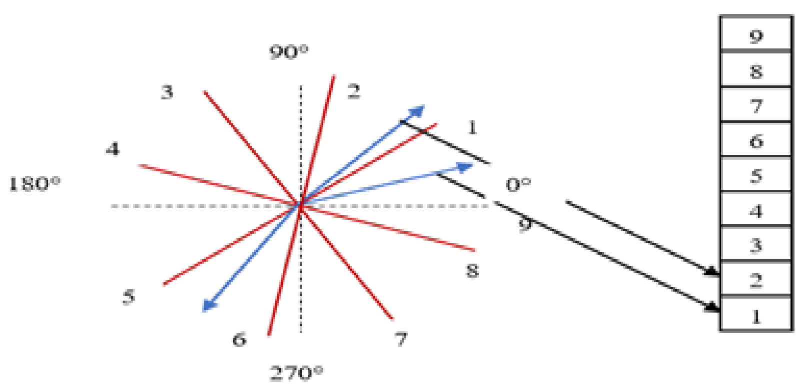


Fig. 5. Motion Vector Distribution in Nine Bins.

Decision tree analysis is a predictive modelling tool for supervised learning. It is constructed using an algorithmic approach by splitting the data set based on certain conditions, subsequently used for classification and regression tasks. The model is created based on the "if-then-else" principle or series of questions and conditions to predict the value of the target variable; if there are more validation conditions, the tree will be more complex.

Labelled training data is used to build a predictive model in discriminant analysis. It is further divided into two categories, linear and quadratic. In this technique, it is assumed that within a group there exists an equal covariance matrix and normally distributed variables. A hyper-plane is created based on the number of classifying variables to minimize the miscalculations constructed between two different groups.

Logistic regression is a predictive analysis used to define the data, because of its association with dependent binary variables and other independent variables like ordinal or nominal. In this technique, it is assumed that the dependent variable is binary, and there is no high correlation within predictors. The good example could be to calculate the probability of having a heart attack through analysis of influential parameters like body weight, calories/fat intake, and age.

SVM is another technique used for regression and classification. In this technique, every data element is plotted as a point in the feature dimension space. The hyper plane is drawn to best fit the two classes; based on that, classification is carried out. Identifying the right hyper plane is very crucial in SVM; usually, the plane that divides the two classes well is chosen as a hyper plane.

KNN is a supervised algorithm referred for classification and regression; this method is easy and simple to implement. The algorithm works on the principle that similar things are near or close to each other, or they are in close proximity by capturing the idea of similarity. Choosing the right value of K is of prime importance in this algorithm; the value that reduces the errors during iterations and has the ability to make accurate predictions is chosen as the best K value. If the value of K decreases, the predictions become less stable and vice versa.

An ensemble is ML algorithm that makes use of various base algorithms or a combination of algorithms to predict the optimal model. The use of a combination of algorithms provides better predictive models in certain situations. The purpose of combining various algorithms is to decrease bias (boosting), reduce variance (bagging), and increase predictions. This technique is further divided into two categories, sequential (e.g., AdaBoost) and parallel (e.g., Random Forest). Homogeneous base learners make use of a single base learning algorithm, whereas heterogeneous learners make use of a multiple learning algorithm.

Images of twenty videos were given as input to the ML algorithms/models. We have split the data into training and testing in the ratio of 80:20.

F. *Training the Model*

All of the models mentioned in previous sections were applied for analysis; the best performing model is chosen for further testing.

G. *Testing the Model*

Once the best performing model is selected for prediction, a test video is provided as an input to the trained model to check their performance and the output is recorded.

H. *Identification of Abnormalities*

Based on training, the selected model will predict whether input video is normal or abnormal.

I. *Storing the Information*

Once the abnormality is identified, the same gets stored against the video in the database; that is, the said video is marked as normal/abnormal in the database for future reference and training.

Is carried out on the acquired dataset in three phases as explained below. Various ML techniques performance is evaluated based on the following statistical parameters.

IV. Experimental Results

Performance parameters:

$$\text{Accuracy} = (TP+TN) / (TP+FP+TN+FN) \tag{6}$$

Where, TP= true positive, TN=true negative, FP=false positive, and FN=false negative.

$$\text{Precision} = TP/(TP+FP) \tag{7}$$

$$\text{Sensitivity} = TP/(TP+FN) \tag{8}$$

$$\text{Specificity} = TN/(TN+FP) \tag{9}$$

$$\text{Area under the curve (AUC)} \tag{10}$$

Phase 1: Process of calculating OF

1) The video is fed and converted into frames
2) The region for analysis is determined.
3) Pre-processing procedures are carried out like de-noising and region cropping.
4) Two consecutive frames are read.
5) $f_x d_x$, $f_y d_y$, $f_t d_t$, and MV are calculated.
6) The MV is plotted.
7) The next two consecutive frames are obtained.
8) Steps 5 to 7 are repeated.

Phase 2: Process of calculating RHOOF

1) The MVs are obtained from the OF.
2) The features like a magnitude and direction of the MVs using above "(3)" and "(4)", respectively.
3) The values obtained in step 2 are divided into nine different bins depending on the "Θ" value and spread over "0" degree to "360" degrees.

The bin values are fed into the algorithm to calculate the histogram.

The histograms of RHOOF are calculated.

The histogram is plotted.

Phase 3: Process of identifying the heart abnormality based on RHOOF

1) The RHOOF descriptor data are fetched.

2) ML algorithms like a decision tree, discriminant analysis, logistic regression, SVM, KNN, and Ensemble are applied.

3) The TP, TN, FP, and FN values are obtained.

4) The statistical parameters like accuracy, precision, sensitivity, and specificity are derived using the algorithms.

5) The performance of the above ML algorithms is evaluated based on the statistical parameters.

6) The best performing algorithm is selected, and the model is trained.

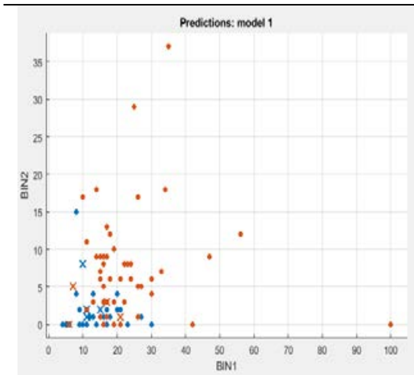
7) The sample is tested.

8) The abnormality is identified.

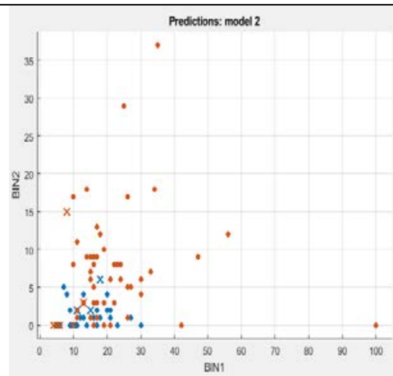
ASD is seen in the upper two chambers of the heart in the form of hole on the septal wall separating left atrium (LA) and right atrium (RA), as such septal wall is our focused area or ROI in this study. During run time image cropping is done to locate the septal wall, and the algorithm automatically marks the ROI in each frame. We focused more on the region where abnormalities can be detected correctly by avoiding the unwanted motion vectors from the rest of the portion of the heart, allowing better time complexity, also ASD identification or diagnosis becomes easy and accurate.

We used 2D echocardiography–apical four chamber view videos of 20 different patients, gathered from the hospital and the open source database, for experimentation.

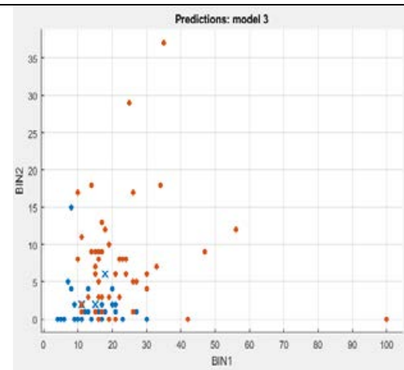
Scatter Plot



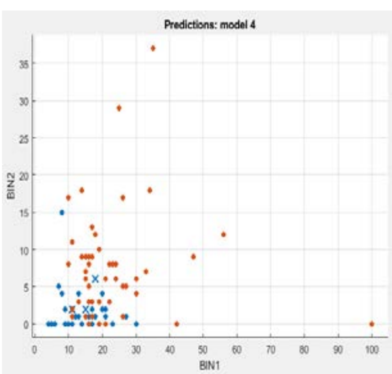
a. Decision tree



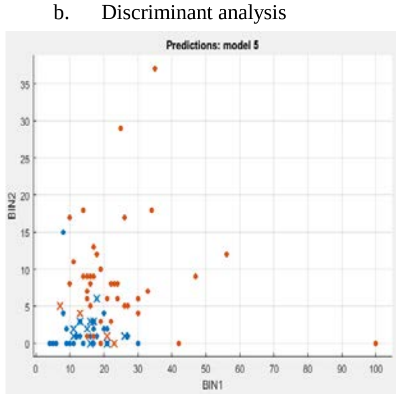
b. Discriminant analysis



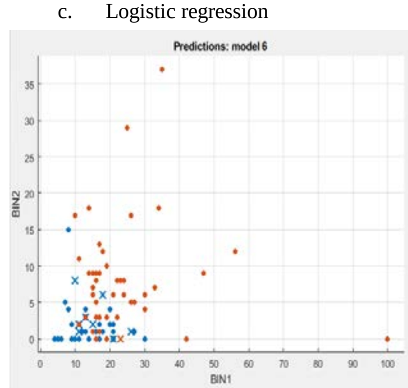
c. Logistic regression



d. SVM

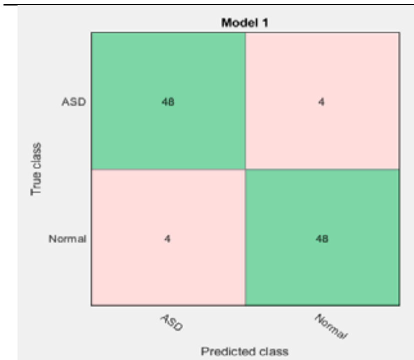


e. KNN

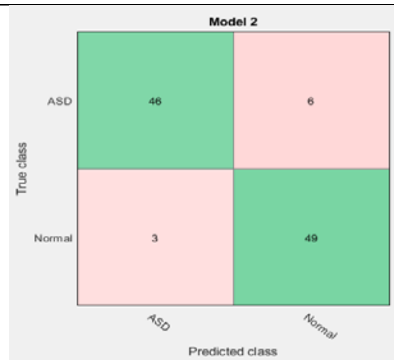


f. Ensemble

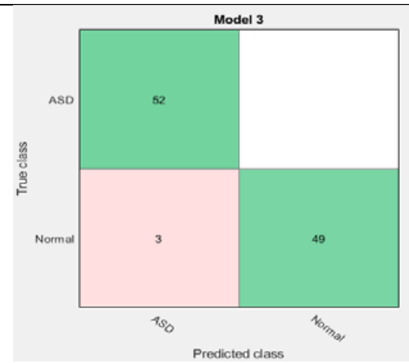
Confusion Matrix



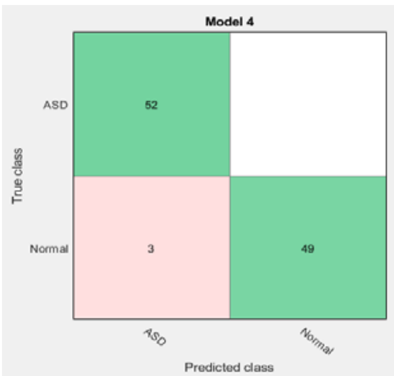
a. Decision tree



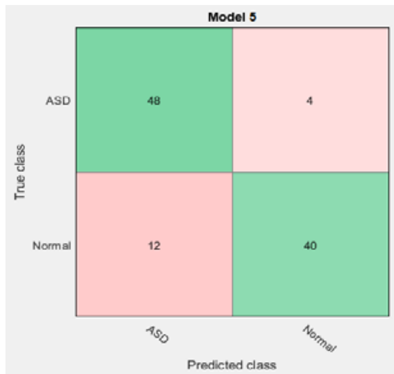
b. Discriminant analysis



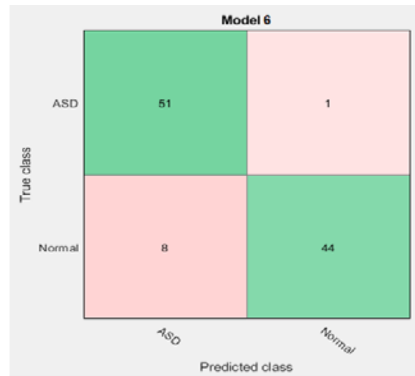
c. Logistic regression



d. SVM

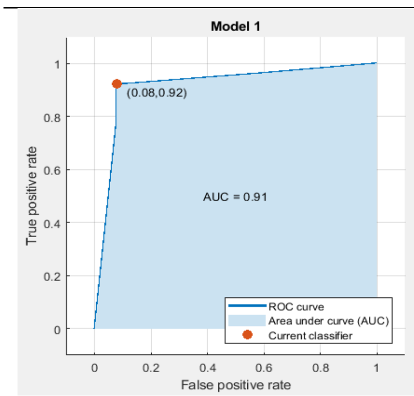


e. KNN

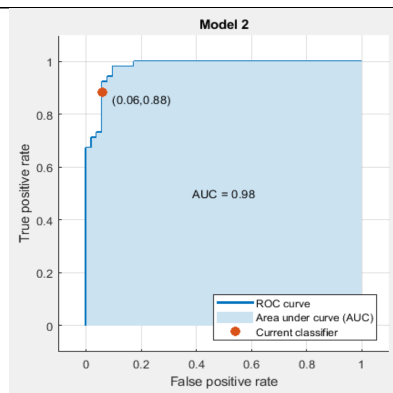


f. Ensemble

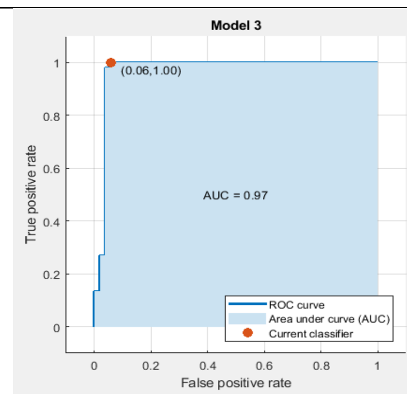
ROC and AUC



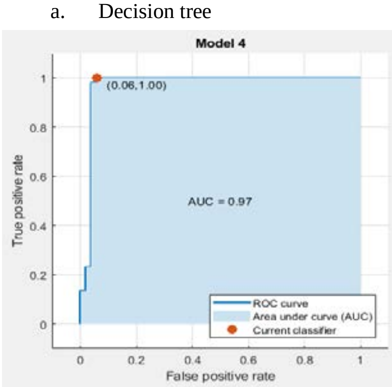
a. Decision tree



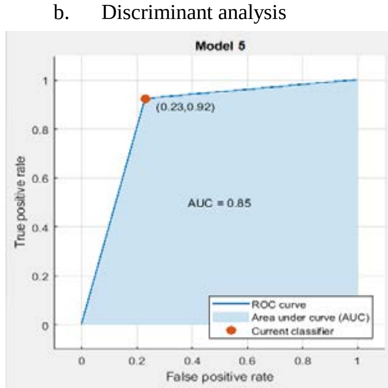
b. Discriminant analysis



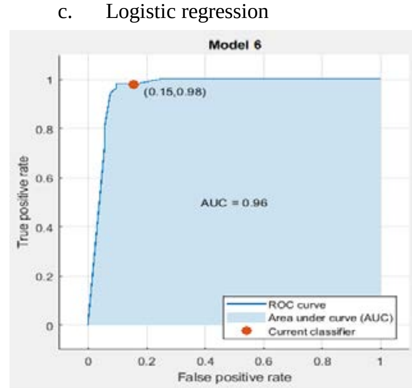
c. Logistic regression



d. SVM



e. KNN



f. Ensemble

Fig. 6. Machine Learning Algorithm(s) output. Scatter Plot of (a) Decision tree. (b) Discriminant analysis. (c) Logistic regression. (d) SVM. (e) KNN. (f) Ensemble. Confusion Matrix of (a) Decision tree. (b) Discriminant analysis. (c) Logistic regression. (d) SVM. (e) KNN. (f) Ensemble ROC and AUC of (a) Decision tree. (b) Discriminant analysis. (c) Logistic regression. (d) SVM. (e) KNN. (f) Ensemble.

TABLE I. ANALYSIS OF RESULTS

Method	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Precision (%)**	**AUC**
Logistic regression	98.1	100	96.1	96.2	0.97
SVM	98.1	100	96.1	96.2	0.97
Discriminant analysis	95.2	96.1	94.2	94.3	0.98
Ensemble	95.2	96.1	94.2	94.3	0.96
Decision tree	91.3	94.2	88.4	89.0	0.91
KNN	89.4	94.2	84.6	85.9	0.85

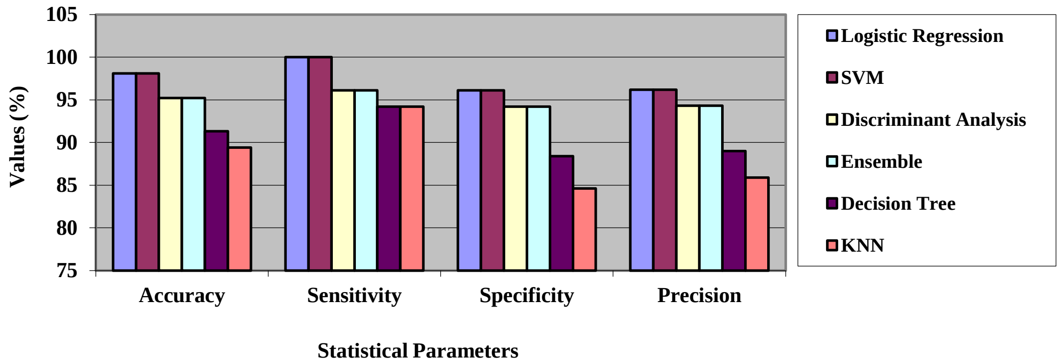


Fig. 7. Graphical Representation of Results.

Using block matching technique EHLDSP proposed in our previous work [1], the movement pattern and direction of vectors can be determined. Based on the values of RHOOF, MV direction and magnitude is obtained. MVs with the same direction/angle were grouped together and were put into nine different bins based on the magnitude and angle of the direction to form a histogram. The movement of pixels from each frame of the video is used to train various classifiers and treat them as descriptors.

During the training stage, the extracted features from RHOOF were used to train the model and is saved, which is used for testing the sample data and determine the abnormality. The model was trained using 20 ultrasound videos (comprising 520 frames), 10 each of Normal and Abnormal.

"Fig. 6" showcases the performance of various ML classifiers, in the form of scatter plot, confusion matrix, the ROC and AUC. The scatter plot displays the value of two variables or data points and their co-relation. As a sample representation, in this manuscript we have included the scatter plots of comparison between bin1 and bin2 using six different ML models/classifiers.

As seen in the scatter plot, there are very few outliers and wrongly identified points which are marked as "x". Confusion matrix is drawn between the predicted class (x-axis) and true class (y-axis). In our case comparison was done using two parameters; ASD and Normal.

Based on the model/classifier performance, data gets divided into four main categories; TP, TN, FP, and FN. This information is further used for calculating accuracy, precision, sensitivity, and specificity parameters using the "(6), "(7)", "(8)" and "(9)", respectively.

In the medical field, algorithms ability to correctly identify the disease (true positive rate) is known as sensitivity, while the ability to correctly identify the non-disease (true negative rate) is known as specificity. As a result, more importance is given to sensitivity over specificity in the medical field; in our study, the LR and SVM has the highest sensitivity (100%). Sensitivity and specificity have an inverse relation; an increase in the value of either parameter will decrease the value of the other and vice versa.

In the confusion matrix, values in the green boxes represent TP and TN, respectively, and those are in the red/white boxes represent FP and FN, respectively. The receiver operating characteristics (ROC) is a curve of probability, while area under curve (AUC) indicates the degree of separability. AUC and ROC are used in ML, particularly during classification to visualize the performance of algorithms.

AUC can have a value between 0 and 1; when the AUC is 0.7, this indicates that 70% of the time model will be able to accurately identify positive and negative classes. An AUC value is considered as acceptable if it is between 0.7 and 0.8, excellent in case it is between 0.8 and 0.9, and outstanding if more than 0.9 [28].

For drawing the ROC, false positive rate (FPR) and true positive rate (TPR) values are plotted on the x-axis and y-axis, respectively. The blue line in the graph indicates the ROC curve and shaded portion or the area under the blue line is called as AUC. The red point on each classifier graph, indicates the performance of that classifier. The AUC values are obtained based on the performance of various classifiers and are given in Table I. “Fig. 7” is the graphical representation of accuracy, sensitivity, specificity, precision values from Table I.

In our study, SVM algorithms had an AUC of 0.97, which was well above 0.9 and thus categorized as outstanding. Although the AUC of a discriminant analysis is slightly higher (0.01) than that of SVM, this will not have any major impact on our overall classifier selection.

The accuracy obtained by another researcher [9] for histogram plus SVM was 85% and that for histogram and BPNN was 87.5%, for ultrasound video. In this research, the RHOOF and SVM classifier had an accuracy of 98.1%.

The computer with INTEL Core i7 processor and 16 GB memory was used for experimentation on MATLAB R2017b.

V. Conclusion

In this study, experimentation was carried out using RHOOF for extraction of features and six different ML techniques to choose the best performing model, which can be further used for abnormality identification. Before applying RHOOF, de-noising was carried out to remove the speckle noise present in an ultrasound video. As mentioned in Table I, the performance of all six techniques was analyzed based on the accuracy, sensitivity, specificity, precision, and AUC to choose the best performing model for abnormality identification. More importance was given to the sensitivity over specificity in the medical field. The following models were evaluated on accuracy and sensitivity: decision tree (91.3%, 94.2%), discriminant analysis (95.2%, 96.1%), logistic regression (98.1%, 100%), SVM (98.1%, 100%), ensemble (95.2%, 96.1%), and KNN (89.4%, 94.2%). From Table I, we can conclude that logistic regression (LR) and SVM had outperformed the other ML algorithms with an accuracy of 98.1% and sensitivity of 100%, respectively. However, during experimentation it is observed that SVM takes 1/3rd of time than LR for training, as a result we have chosen SVM for abnormality identification. Also, LR has a tendency of considering more outliers, which might lead to in-correct diagnostics. As this study is performed to evaluate the technique used in diagnosing cardiovascular problems, more emphasis is given to the correct identification of the disease. Using combination of proposed RHOOF algorithm with SVM we could correctly identify the ASD.

VI. Future Work

In other research fields, open databases are easily accessible; today, as a researcher in the biomedical engineering field, we faced a lot of challenges in obtaining medical images, and videos of required diseases, due to ethical and legal constraints. In the future, we aim to create a publicly/freely available database for researchers, with the help of practitioners and medical institutions.

VII. Declaration of Conflicting Interests

The author(s) declare(s) that there is no conflict of interest.

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