International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Cardiovascular Disease Prediction from Retinal Images using Machine Learning

G.AnilKumar
Electronics and Communication Engineering
R.V.R & J.C College of Engineering,India anilkumargutta23@gmail.com

P.Pavani
Electronics and Communication Engineering
R.V.R &J.C College of Engineering ,India ppatibandla29@gmail.com

K.Venkata Ramgopal
Electronics and Communication Engineering
R.V.R &J.C College of Engineering,India ramgopal4537@gmail.com

G.NaveenKrishna
Electronics and Communication Engineering
R.V.R &J.C College of Engineering,India naveenkrishna12@gmail.com

***Abstract*— The structure and function of the microvascular are significantly influenced by the key cardiovascular disease risk factors of hypertension and heart attacks. Images taken with a fundus camera can be used to spot irregularities in the blood vessels of retina that indicate the extent injury on blood vessels by hypertension and heart attacks. Using machine learning and AI techniques, detecting the preclinical signs that fall below the threshold of an observer. The proposed methodology aimed to investigate the effects of hypertension and heart attacks on morphological characteristics of retinal blood vessels. With a diagnosis of hypertension and heart attack, data scientists collect retinal images. Interference data is removed— information about structures other than that retinal vasculature using the vessel segmentation method, leaving only morphological details about the blood vessel of retina.**

Keywords— Heart Disease, Retinal Image, Microvasculature, Hypertension

I. Introduction

Heart disease is one of the main reasons why the mortality rate has been increasing over time in the industrialized world. As a result, it is absolutely essential to predict heart diseases in order to lower the fatality rate [1]. The prevalence of heart diseases can be seen using a variety of approaches available today. However, it cost more money and take longer to diagnose the condition. Heart and eye have an extremely strong relationship. Each necessary option that supports direct microcirculation includes the membrane. When a heart issue occurs, the membrane offers a window for the identification of alterations in the microvasculature [2]. For the duration of this research work, a unit of measurement was used in a way of machine learning, classification algorithms. Nancy Masih, Huma Naz, Sachin Ahuja [3] stated that proposed study attempts to detect coronary heart disease at an early stage. Find the best region in fundus images that can increase the predictive power of models for retinopathy categorization, according to Qian Wu and Abbas Cheddad [4]. This study aims to determine whether there is a specific location that could aid in better predicting the retinal disease. According to Fatima Dilawar Mulla and Naveen Kumar Jayakumar [5], the study aims to comprehend and establish the reliability and application of these questions in identifying the risk factors for diagnosis. Jie Xu, Kanmin Xue, and Kang Zhang [6] described the fundamental steps involved in creating an AI model that can locate databases of ocular fundus photos that are accessible to the general public. An innovative method for assessing computer-aided diagnosis of typical, healthy, and abnormal photos of stroke patients have been described by Sukesh Kumar and K. Mahadevan [7]. A Umamageswari, J Shiny Duela, and K Raja [8] indicated the effective exudate and vessel detection from retinal pictures for the analysis of retinal vascular problem.

II. PROPOSED METHODOLOGY

The method aims to create a system for visual image-based heart disease detection, especially in young people, to identify heart disease. In the study, a dataset of retinal imaging is used, and retinal vessel segmentation is used to separate the vessels in the images. In a number of specialties, such as laryngology, neurosurgery, and ophthalmology, the analysis of blood vessels is crucial for diagnosis, therapy planning and execution, and assessment of clinical outcomes. Therefore, vessel segmentation is a crucial method for using the retinal image to detect heart disease. Changes in the eyes may be a sign of many conditions. Fuzzy C-Mean Clustering (FCM) is used to categories and contrast the results, and the output is contrasted with Convolutional Neural Network (CNN). The system model of the proposed methodology is shown in Fig.1.

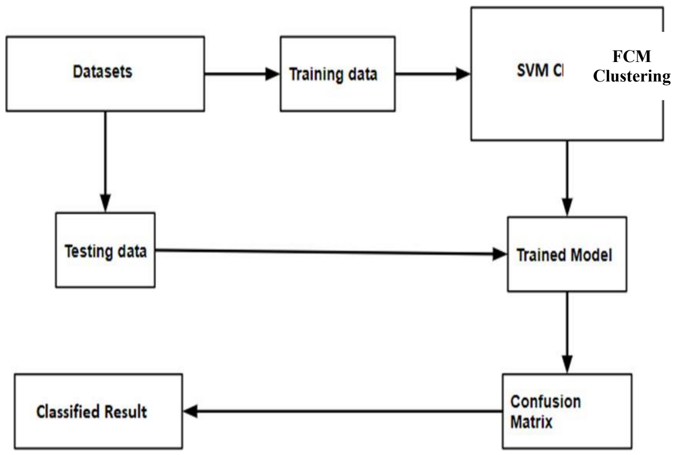


Fig. 1. System Model

A. Dataset

There is no need to flatten the input images to ID whenFCM is used instead of Nave Bayes because SVM can handle working with 2D image data.

This helps preserve the spatial characteristics of images. Several retina datasets are used, which may be divided into three groups. The dataset is comprised of images from the Kaggle data science website that fall into one of the three categories: images of hypertension, heart attacks and normal fundus. In Fig. 2. to Fig. 4.
are few examples of dataset image being used. Two classes independently classified every participant as having a heart attack or having hypertension twice [9]. On a communication system for archiving pictures, labelling was first evaluated using the original images, and then it was evaluated again using the shrunken utilised for the learning data itself. The test was evaluated using the temporal dataset, and the internal dataset and temporal dataset were the two types of datasets used. Subgroups for testing (15%), validating (15%), and training (70%) were created using the internal dataset.

Fig. 2. Sample Dataset of Retina for Heart Attack

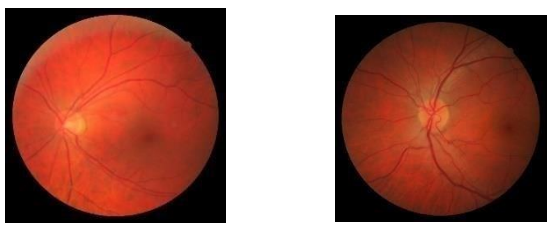


Fig. 3. Sample Dataset of Retina for Hypertension

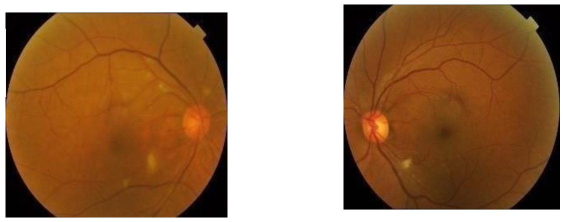


Fig. 4. Sample Dataset of Retina for Normal Fundus

III. *Vessel Segmentation*

As part of the analysis of Blood vessel segmentation is essential in the colour retinal fundus pictures used in ophthalmology to monitor and diagnose retinal illnesses like macular degeneration due to aging, arteriosclerosis, retinopathy caused by diabetes, and retinopathy due to hypertension. Accurately diagnosing retinal diseases can be done with the help of this procedure. This study employs Contrast Limited Adaptive Histogram Equalization (CLAHE), a technique that is efficient at removing noise and improving the visibility of blood vessels on images, to separate blood vessels on retinal images. The commonly used contrast enhancement method known as CLAHE has proven to be very successful for medical images. By reducing the maximum slope in the transformation function, this method adaptively improves contrast throughout the entire picture.

IV. *Feature Extraction*

Feature extraction is a useful technique when less computing power is required without losing important or relevant data. Feature extraction may help reduce the amount of duplicated data for a specific study. Phases of machine learning that focus on learning and generalization are sped up by data reduction and the computer's attempts to produce variable combinations [10]. The f following attributes were recovered using FCM: color, shape, texture, size, and ridges.

- Color- The most useful visual attribute of all is color, which has been extensively exploited in picture retrieval systems. Color spaces of three dimensions are typically used to define colors. They could be Hue, Saturation, and Brightness, Hue, Saturation, and Value, or Red, Green, and Blue [11].
- Shape- Shape characteristics should be reproducible, meaning that features derived from different retina datasets should be same. Shape features can be thought of as higher-level features than color or texture.
- Texture - Energy, entropy, homogeneity, correlation, contrast, dissimilarity, and maximum probability are the retrieved texture features for the texture [12].
- Size - When an image dataset needs to be rotated or corrected for lens distortion, remapping can be used; by contrast, image scaling is needed when the total number of pixels needs to be changed. When you zoom in on an image, you can see more detail because there are more pixels there. Actual size x magnification = image size.

• Ridges - The attempt to utilize software to discover ridges in a photograph is known as ridge detection, and it is employed in image processing. Similar to topographical ridges, ridges are defined as curves whose points are local maxima of the function. The points of the curves that make up a function with N variables' ridges are local maxima in N 1 dimensions.

V.Fuzzy C-Means Clustring(FCM)

One of the most widely used supervised learning methods is the FCM because it can be applied to both categorization and regression problems. A form of machine learning algorithm known as a support vector machine modifies features by using kernel techniques. In order to make it simpler to distinguish between the classes after the transformation, kernel functions translate the data into a different, sometimes higher dimensional space. In machine learning, it is frequently used to address classification problems. There are several kernel functions used in FCM for categorization, including the linear kernel, gaussian radial basis formula (RBF), polynomial kernel, and sigmoid kernel kernels are among the most widely used kinds of kernelization due to their similarity to the 0 when the distance between the points is great, indicating that the points are dissimilar.

$$F1\ score = \frac{2(Precision+Recall)}{(Precision+n\ Recall)} \quad (4)$$

The FCM method seeks to identify the optimal decision boundary or line that can classify the n-dimensional space, enabling subsequent data points to be rapidly assigned to the appropriate category. We call this best-decision boundary a hyperplane. FCM selects the extreme points and vectors to build the hyperplane. The technique is known as a support vector machine because it makes use of support vectors, which are extreme examples. FCM classifier is utilized to identify heart disease [13]. In one, the dataset is trained and tested using a support vector machine classifier. The diagnosis is performed using a non- linear FCM class model. By creating a tree structure and assessing the input data by making a decision at random based on the attributes of the image, the algorithm aids in more accurate object identification.

VI. Preprocessing

Pre-processing is the method of improving image data as well as the process of enhancing image features for subsequent processing in the application. Here, the captured retinal image or the inputted retinal image has been pre-processed for the clear observation of the image data, and the identification of the data is used for finding the accuracy of disease. The pre-processing methods we used were histogram equalization, performance evaluation metrics like accuracy, F1-score sensitivity, precision, and Matthews Correlation Coefficient (MCC), and image resizing.

A. Histogram Equalization

To increase the contrast of images, histogram equalization, a technique for computer-aided image processing, is applied [14]. It accomplishes this by successfully spreading out the most prevalent intensity values by significantly widening the image's intensity range. Using the image histograms, the

Gaussian distribution. The degree to which two things are identical or close to one another. This kernel has the following mathematical representation:

$$K(X_1, X_2) = \exp\left(-\frac{\|X_1 - X_2\|^2}{2\sigma^2}\right) \quad (1)$$

where σ is variance and $\|X_1 - X_2\|$ is the Euclidean distance between the two points X_1 and X_2. The RBF kernel can have a maximum value of 1 when $\|X_1 - X_2\|$ is 0, which occurs when the points are the same, i.e., $X_1 = X_2$. When the points are identical, there is no space between them, making them incredibly similar. The kernel value is less than 1 and near to

$$TPR = \frac{TP}{(TP+FN)} \quad (3)$$

The F1 score, a machine learning evaluation metric, rates a model's precision. It incorporates a model's recall and precision ratings. The accuracy metric shows how many times a model properly predicted over the entire dataset. This measure can only be trusted if the dataset is class-balanced, meaning that each class contains an equal number of samples.

contrast is adjusted. This process is important for enhancing the image's quality and is useful for removing features.

B. Performance Evaluation Metrics

For each model, 5-fold cross validation (CV) is used to assess it. The models were assessed for precision, sensitivity, F1-score, accuracy, and correctness with respect to MCC. The following equations emphasize these metrics:

$$Precision = \frac{TP+TN}{(TP+FP+TN+FN)} \quad (2)$$

where TP stands for True Positive, FP for False Positive, TN for True Negative, and FN for False Negative. The TP rate (TPR) is calculated to know the percentage of positive data that was expected to be positive. The term sensitivity also refers to the true- positive rate. The degree to which repeated measurements under constant circumstances yield the same findings is what is meant by the term precision.

Following feature extraction testing, the set of photos is processed, the test image is classed, and the accuracy is plotted.

Utilizing accuracy, the model's performance is assessed. As used in other studies, it is defined as the proportion of correctly identified cases divided by the total number of instances in the dataset.

C. Image Resizing

Image resizing is the method or technique used to increase or decrease the pixel count of an image and shorten the resolution of the image input provided. Resizing without resampling means changing the physical size of the image but not the data on the image. The method helped us remove the unwanted data and focus on the mostly required information for the skin type analysis. The process helped us resize the images given as input to the required image pixel and data size.

VII. IMPLEMENTATION AND RESULT

The predicting cardiovascular disease by training on a Kaggle Dataset using FCM-machine learning in Python 3.7. The aim is to classify the retinal images of Kaggle dataset using machine learning, based only on the morphology of the individual retinal image. To get this done, various modules in Python were imported. Thonny IDE is used for execution [15]. In the paper, FCM is used to present a dependable and robust strategy for detecting hypertension and heart attacks in extremely cluttered photos. Using retinal pictures, the crowded images are produced. The candidate affected region proposals made by multilevel graph cut are also provided by the image sequences. The suggested region is categorized into classes for hypertension or heart attacks as part of the which suggests that the classifier is working reasonably effectively.

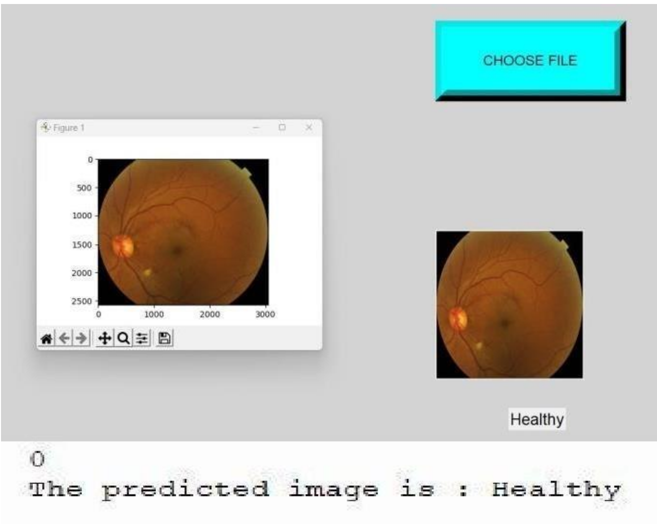


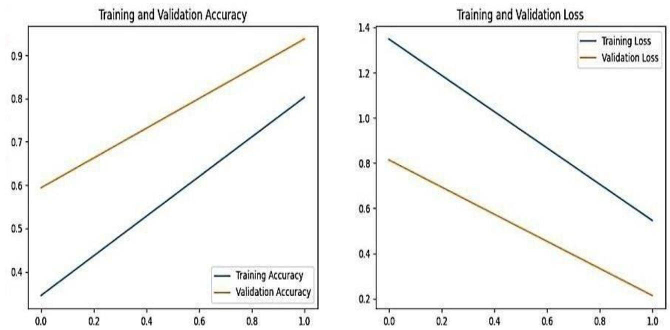
Fig. 8. Training and Validation curve

The classifier will overfit if gamma is set too high, producing a high training score but a low validation score. In essence, the TPR vs FPR at various threshold settings to distinguish the signal from noise is plotted in the Receiver Operator Characteristic (ROC) curve. It displays a classification model's performance across all categorization levels. The Fig.
9.shows the ROC for the FCM proposed in this paper to detect Fig. 5. Prediction of Healthy Class the Cardiovascular disease.

verification process, which identifies whether the planned region is actually afflicted or not. While the output is already known, predicting whether a person has cardiovascular disease or No Cardiovascular Disease is an example of supervised machine learning. A classification problem exists. Outcomes are classified into 3 classes:

- 0(Zero) as Healthy as shown in Fig. 5.
- 1(One) as having heart disease as shown in Fig. 6.
- 2(Two) as having Severe Hypertensive Retinopathy as shown in Fig. 7.

In the Fig. 8. plot, at various values of the kernel parameter gamma, the training and validation scores of an FCM are shown. At very low gamma values, both the training and validation scores are poor. This is known as underfitting. High values for both scores are produced by medium gamma values,



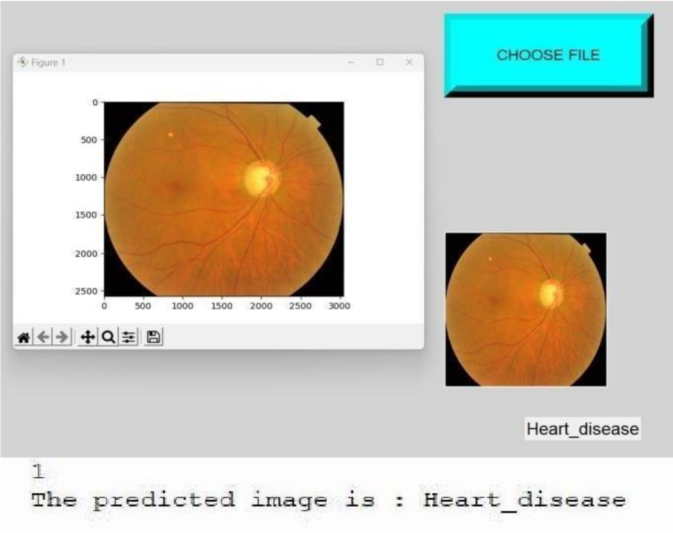


Fig. 9. ROC curve

Fig. 10 gives the confusion matrix, which used to assess how well the classification models work given a particular set of test data. Only when the real test data values are known can it be decided. The matrix itself is simple to understand, but the associated terms might be. Since it displays the mistakes in the model performance as a matrix, it is also referred to as an error matrix.

TABLE I. COMPARISON TABLE FOR SVM AND CNN PERFORMANCE

Table Head	Performance Metrics				Algorithm
	Precision	*Recall*	*F1 score*	*Accuracy*	
Class 1	0.98	0.96	0.97	97.46	FCM
Class 2	0.95	1	0.97		
Class 3	1	0.96	0.98		
Class 1	0.95	0.93	0.95	95.32	CNN
Class 2	0.97	0.92	0.92		
Class 3	0.96	0.91	0.92		

The classification performance of the FCM model was compared with CNN. The overall accuracies of the methods

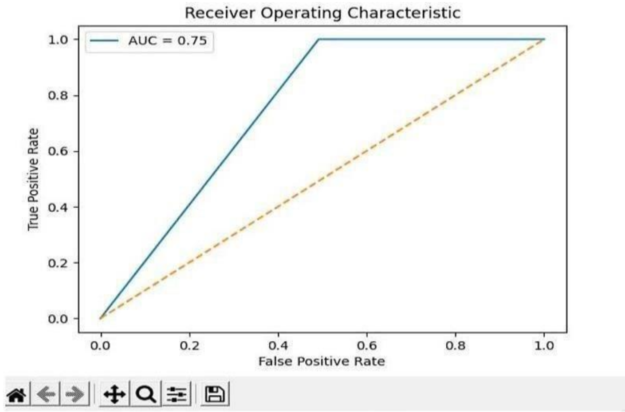


Fig. 6. Prediction of Heart Disease Class

Fig. 7. Prediction of Severe Hypertensive Retinopathy Class

indicated that the proposed model using FCM outperforms the CNN methods in the classification of Kaggle datasets of retinal images. The results shown in Table I demonstrated that FCM achieves the highest classification accuracy of 97.46%, which is nearly 2% higher than the accuracy obtained by CNN. The three classes comparison is also provided for both FCM and CNN in the Table I. The Precision, Recall and F1 score for all three classes is better in FCM compared to CNN.

VIII. CONCLUSION

Even though the size of the dataset for machine learning was minimal,FCM features were used to improve performance. As well as a number of methods were used to minimize the overfitting and increasing generalization, like shrinking the size of the model, utilizing dropout layers, and data augmentation, the model eventually began to exhibit overfitting after a predetermined number of iterations. The inputs of the model has highly linked because these strategies could only remix existing information rather than create new information. As the validation loss stopped getting better, the proposed system will stop the training process. When utilizing segmented dataset, the model's accuracy and precision on the test set are marginally higher than when using improved dataset, and the recall also ostensibly higher.

Using Kaggle datasets for retinal images, the effectiveness of the FCM and the CNN machine learning algorithms is contrasted. The results demonstrate that both models have respectable rates of precision, recall, and accuracy. Nonetheless, the FCM model's accuracy and recall are 1% greater than those of the CNN model.

REFERENCES

[1] Roth, G.A.; Mensah, G.A.; Johnson, C.O.; Addolorato, G.; Ammirati, E.; Baddour, L.M.; Barengo, N.C.; Beaton, A.Z.; Benjamin, E.J.; Benziger, C.P., "Global burden of cardiovascular diseases and risk factors", J. Am. Coll. Cardiol. Vol 76, pp.2982–3021, 2020.

[2] Schiffrin EL, Park JB, Intengan HD, Touyz RM, " Correction of arterial structure and endothelial dysfunction in humanessential hypertension by the angiotensin receptor antagonist losartan", Circulation, 101(14), pp.1653–9, April 2000.

[3] Xu, C.; Xu, L.; Gao, Z.; Zhao, S.; Zhang, H.; Zhang, Y.; Du, X.; Zhao, S.; Ghista, D.; Liu, H, "Direct delineation of myocardial infarction without contrast agents using a joint motion feature learning architecture", Med. Image Anal., vol 50, pp.82–94, 2018.

[4] Q. Wu and A. Cheddad, "Segmentation-based Deep Learning Fundus Image Analysis," *2019 Ninth International Conference on Image Processing Theory, Tools and Applications (IPTA),* Istanbul, Turkey, 2019, pp. 1-5, doi: 10.1109/IPTA.2019.8936078.

[5] F.D. Mulla and N. Jayakumar,"A Review of Data Mining & Machine Learning approaches for identifying Risk Factor contributing to likelihood of cardiovascular diseases," *2018 3rd International Conference on Inventive Computation Technologies (ICICT),* Coimbatore,India,2018,pp.631635,doi:10.1109/ICICT43934.2018.90 34257.

[6] Ghantous, C.M.; Kamareddine, L.; Farhat, R.; Zouein, F.A.; Mondello, S.; Kobeissy, F.; Zeidan, A, "Advances in cardiovascular biomarker discovery", Biomedicines, vol 8, pp.552, 2020

[7] Al-Absi, H.R.; Refaee, M.A.; Rehman, A.U.; Islam, M.T.; Belhaouari, S.B.; Alam, T, "Risk Factors and Comorbidities Associated to Cardiovascular Disease in Qatar: A Machine Learning Based CaseControl Study", IEEE Access, vol 9, pp.29929– 29941, 2021.

[8] A Umamageswari, J Shiny Duela, K Raja, "Identifying Diabetics Retinopathy using Deep Learning based Classification",2021 22nd International Arab Conference on Information Technology (ACIT), 1- 6, 2021.

[9] Wang Z, Chen Z, Zhang L, Wang X, Hao G, Zhang Z, "Status of Hypertension in China: Results from the China Hypertension Survey", Circulation.; 137(22), pp.2344–56. February 2018.

[10] Sudarshan, V.K.; Acharya, U.R.; Ng, E.; San Tan, R.; Chou, S.M.; Ghista, D.N. "An integrated index for automated detection of infarcted myocardium from cross-sectional echocardiograms using textonbased features (Part 1) ", Comput.Biol.Me,vol 71,pp.231-240,2016.

[11] R.S. Jeena, A. Sukesh Kumar and K. Mahadevan, "Stroke diagnosis from retinal fundus images using multi texture analysis" Journal of Intelligent & Fuzzy Systems, January 2019 DOI: 10.3233/JIFS- 169914,2019.

[12] Larroza, A.; López-Lereu, M.P.; Monmeneu, J.V.; Gavara, J.; Chorro, F.J.; Bodí, V.; Moratal, D, "Texture analysis of cardiac cine magnetic resonance imaging to detect nonviable segments in patients with chronic myocardial infarction", Med. Phys., vol 45, pp.1471–1480, 2018

[13] Vidya, K.S.; Ng, E.; Acharya, U.R.; Chou, S.M.; San Tan, R.; Ghista, D.N., "Computer-aided diagnosis of myocardial infarction using ultrasound images with DWT, GLCM and HOS methods: A comparative study", Comput. BioMed., vol 62, pp. 86–93. 2015.

[14] Madani, A.; Ong, J.R.; Tibrewal, A.; Mofrad, M.R., "Deep echocardiography: Data-efficient supervised and semi-supervised deep learning towards automated diagnosis of cardiac disease", NPJ Digit. Med., vol 1, pp.1–11, 2018.

[15] Xu, C.; Xu, L.; Gao, Z.; Zhao, S.; Zhang, H.; Zhang, Y.; Du, X.; Zhao, S.; Ghista, D.; Liu, H, "Direct delineation of myocardial infarction without contrast agents using a joint motion feature learning architecture", Med. Image Anal., vol 50, pp.82–94, 2018.