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Cardiovascular Imaging using Machine Learning: A Review

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Abstract*: *Cardiovascular diseases are a significant cause of death worldwide, making early detection and diagnosis critical for reducing mortality and morbidity. The interpretation of complex medical images can be made easier with the use of machine learning algorithms, which could result in more precise cardiovascular imaging diagnosis. In this review paper, we provide an overview of the state-of-the-art in machine learning-based cardiovascular imaging, including the datasets, imaging modalities, and algorithms currently available. We also discuss the significant challenges and opportunities in the field, highlighting recent advances in machine learning algorithms for automated cardiac image analysis. Specifically, we focus on the application of deep learning and convolutional neural networks for cardiac image segmentation and classification of cardiac conditions, including heart failure, myocardial infarction, and arrhythmias. We explore the potential of these algorithms to improve the accuracy and efficiency of cardiovascular imaging and discuss the need for standardized datasets and evaluation metrics to enable better comparison of different algorithms. We also discuss the importance of interpretability in machine learning algorithms to enhance trust and transparency in their predictions. Overall, this review provides a comprehensive overview of the current state and future potential of machine learning in cardiovascular imaging, highlighting its significant impact on improving the diagnosis and treatment of cardiovascular diseases.

Keywords*: *Machine Learning, Deep Learning, Cardiac Image Segmentation, Analysis, Diagnosis, Interpretation

I. INTRODUCTION

A. Overview of Cardiovascular Imaging Techniques

Cardiovascular diseases (CVDs) are a group of conditions that affect the heart and blood vessels, accounting for over 17 million deaths each year worldwide [1,2]. Early identification and diagnosis of CVDs are crucial in reducing mortality and morbidity. To aid in the diagnosis and management of these conditions, cardiac imaging has become an integral part of the clinical workflow, providing detailed images of the heart and its function. Commonly used modalities for cardiac imaging include echocardiography, computed tomography (CT), magnetic resonance imaging (MRI), and nuclear imaging. These techniques can provide vital information for the diagnosis and management of a range of cardiac conditions, such as coronary artery disease, myocardial infarction, heart failure, and valvular heart disease. However, each imaging modality has its advantages and limitations, and the choice of technique depends on various clinical factors. Interpreting cardiac images can be challenging, particularly for rare or complex cases, and requires specialized expertise and time. Inadequate availability of such resources can lead to delayed diagnosis and treatment, resulting in suboptimal patient outcomes.

B. Role of Machine Learning in Cardiovascular Imaging

Early detection and diagnosis of CVDs can significantly improve patient outcomes, as treatment is most effective when the disease is in its early stages. While traditional diagnostic techniques, such as physical examination and blood tests, can provide important information, they have limitations. Medical imaging techniques can provide a more comprehensive picture of a patient's cardiovascular system, enabling more accurate diagnoses. In recent years, there has been growing interest in applying machine learning techniques in the field of medical science. For example, radiology has demonstrated the usefulness of machine learning in confirming provisional diagnoses [3]. Machine learning algorithms can assist in the interpretation of complex medical images, enabling physicians to make more accurate diagnoses. Recent work has demonstrated that cardiovascular imaging has improved in accuracy and effectiveness due to the application of machine learning. To identify patterns in images that are difficult or impossible for clinicians to perceive, machine learning techniques are used [4]. Algorithms can also be employed to automate specific steps in the imaging process, such as segmenting the heart and blood vessels, thereby increasing productivity and reducing the time required for picture interpretation. Additionally, [5] explains how machine learning (ML) and deep learning (DL) algorithms can be used to forecast the probability of developing particular diseases, such as heart failure. For instance, machine learning algorithms can be used in conjunction with patient information, such as age and family history, to predict the likelihood of developing heart failure in cardiac imaging analysis. Early intervention, which can reduce the possibility of contracting the illness, helps clinicians identify individuals at risk. Last but not least, machine learning has the potential to transform cardiovascular imaging. It can enhance accuracy and efficiency, automate certain portions of the imaging process, identify patterns in the images, and even predict the likelihood of developing a particular disease.

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It is a fascinating new area of study that could completely change how heart and vascular diseases are identified and treated. In this paper, we review the current state of the art in the use of machine learning algorithms for the analysis of cardiac images, including a summary of available datasets, imaging types, and algorithms. We discuss the various modalities of cardiac imaging and the specific applications of machine learning in each modality. We also discuss the potential benefits and limitations of these techniques, as well as future research directions in this field.

II. IMAGING TYPES

A. Echocardiography

Ultrasound waves are used in the non-invasive imaging procedure known as echocardiography to take pictures of the heart. It is frequently used to identify and treat a variety of cardiac problems, including valvular heart disease, myocardial infarction, heart failure, and coronary artery disease. It provides crucial details on the dimensions and configuration of the heart's chambers, the thickness and motion of the heart walls, and the operation of the heart valves.

The automated segmentation of the left ventricle is an example of how machine learning is integrated into echocardiography. Assessing left ventricular function, a key predictor of cardiovascular morbidity and mortality, requires accurate segmentation of the left ventricle. Traditional manual segmentation techniques are time-consuming and prone to inter-observer variability. On the other hand, machine learning algorithms can accurately and consistently segment the left ventricle in a fraction of the time needed for manual segmentation.

B. Nuclear imaging

Nuclear imaging is a sort of medical imaging that creates images of the heart using radioactive tracers. These tracers are injected into patients, and when they accumulate in the heart, they enable the visualisation of how the organ functions and how blood flows through it. Positron emission tomography (PET) and single photon emission computed tomography (SPECT) are two standard nuclear imaging methods.

C. Computed Tomography (CT)

X-rays are used in the medical imaging technique known as computed tomography (CT) to provide detailed pictures of the human body. The heart and blood vessels can be seen in detail using CT scans, allowing for the detection of several cardiovascular diseases, including coronary artery disease, faulty heart valves, and aortic aneurysms.

D. Magnetic Resonance Imaging (MRI)

A non-invasive imaging technique called magnetic resonance imaging (MRI) creates precise images of the body by using magnetic fields and radio waves. It offers high-resolution pictures of the heart and blood vessels, enabling the identification of various cardiovascular disorders, including aortic aneurysms, heart muscle damage, and valve problems.

E. Ultrasound

High-frequency sound waves are used in the non-invasive procedure of ultrasound imaging to create images of the body. This imaging technique can produce finely detailed images of the heart and blood vessels, enabling the identification of various cardiovascular diseases, including aortic aneurysms, blood clots, and valve issues.

F. Positron Emission Tomography (PET)

Positron emission tomography (PET) is a non-invasive imaging method that produces images of the body using radioactive tracers. Using images of the heart and blood vessels provided by PET scans, a variety of cardiovascular diseases, such as coronary artery disease, heart muscle damage, and heart valve issues, can be identified.

G. Single Photon Emission Computed Tomography (SPECT)

Single photon emission computed tomography (SPECT) is a non-invasive imaging technique that produces images of the body using radioactive tracers. SPECT scans can aid in the detection of various cardiovascular disorders, including coronary artery disease, valve issues, and heart muscle damage, by providing images of the heart and blood vessels.

H. Types of Cardiac Diseases

As noted in reference [6], it is essential to be aware of the various types of CVD diseases before examining the applications of machine learning in cardiology. According to Bernard et al. [7], due to the complex structure of the heart, cardiac diseases are classified based on irregularities or failures as follows:

Table- I: Types of Cardiac Diseases

Function	Diseases
Contractile Function	Heart Failure (HF)
Coronary Blood Supply	Coronary artery disease (CAD), Myocardial infarction (MI)
Circulatory Flow	Aortic or mitral stenosis/regurgitation (MR)
Heart Rhythm	Atrial fibrillation (AF), Ventricular tachycardia (VT)

III. AVAILABLE DATASETS

A. Cardiac Imaging Datasets

Collections of medical images, known as cardiac imaging datasets, are used to train machine learning algorithms for detecting heart disease. These datasets often include a substantial number of cardiac images gathered via CT or MRI scans, or other types of medical imaging. The images in the dataset are usually annotated with labels indicating the presence or absence of specific cardiac conditions. The use of these datasets enables machine learning models to learn from a large number of examples, thereby enhancing their ability to diagnose heart disease accurately. Cardiac imaging datasets are a crucial tool in the development of image-based machine learning for diagnosis.
of heart disease. Some examples of cardiac imaging datasets are shown in the

Table below.

Table- II: Types of Cardiac Diseases

Name	Type	Country	Year	Size
[8]	SPECT	USA	2009	20,400
[9]	MRI	Germany	2011	20,000
[10]	Echo/CT	Netherlands	2012	3,451
[11]	MRI	Canada	2013	9700
[12]	Echo	France	2014	45
[13]	MRI	Germany	2016	45,000
[14]	MRI	France	2017	150
[15]	Echo	France	2019	500

B. Publicly Available Datasets

In the context of cardiovascular imaging, several publicly accessible datasets can be utilised to train and test machine learning algorithms. The Cardiac MR Imaging Segmentation (ACDC) dataset [14], the Multi-Modality Whole Heart Segmentation (MM-WHS) dataset [16][17][18], and the Automated Cardiac Diagnosis Challenge (ACDC) dataset are some of the datasets that are most frequently utilised..

C. Challenges in Using Publicly Available Datasets

While publicly available datasets can be helpful for training and evaluating machine learning algorithms, several challenges are associated with their use. One of the main challenges is the limited number of annotated images, which can limit the generalizability of machine learning algorithms. Additionally, publicly available datasets may not always be representative of the patient population, leading to biased results.

D. Creating Custom Datasets

To address the limitations of publicly available datasets, researchers may choose to create custom datasets. This involves acquiring images from patients, annotating the photos to create ground truth labels, and using the pictures and labels to train and evaluate machine learning algorithms. Custom datasets can be more representative of the patient population, leading to more accurate results.

IV. LITERATURE SURVEY

Machine learning algorithms can be applied to various tasks in cardiovascular imaging, including image segmentation, classification, and analysis. Some of the commonly used algorithms include convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs) [19].

A. Image Segmentation

Image segmentation is a method of dividing an image into distinct regions that correspond to different objects or structures in the image. In cardiovascular imaging, segmentation is utilized to isolate the heart and blood vessels from images. To achieve accurate and efficient segmentation of cardiovascular images, machine learning algorithms such as CNNs have been utilized in several studies. For example, Taeouk Kim et al. [20] employed a CNN to segment the left ventricle of the heart in 2D echo images. In comparison to manual segmentation, the study showed that the CNN was able to achieve average Dice metrics of 0.90 and 0.91 for the U-Net and segAN, respectively.

B. Image Classification

In the field of cardiovascular imaging, image classification involves labelling an image based on its content to aid in the diagnosis of various cardiovascular diseases, including heart failure and coronary artery disease. As discussed in previous works [21], several studies have utilized machine learning algorithms, such as RNNs and DBNs, to achieve accurate and efficient classification of cardiovascular images.

C. Image Analysis

Image analysis refers to the process of extracting information from images to gain insights into the underlying structures and functions. In the field of cardiovascular imaging, image analysis is used to evaluate the anatomy and function of the heart and blood vessels. To achieve accurate and efficient analysis of cardiovascular images, several studies have employed machine learning algorithms, including CNNs and RNNs. For instance, to precisely segment the left ventricle, Bhan et al. [22] suggested a modified U-Net model with context-enabled segmentation (LV). With dice scores of 0.96 and 0.93, respectively, the model produced statistically significant findings for the endocardial and epicardial walls. With regard to clinical characteristics like ejection fraction, end-diastolic volume (EDV), and end-systolic volume, the model likewise demonstrated a strong positive correlation of 0.98(ESV).

D. Review of recent publications

Image segmentation aims to assign a label to a particular image or video, which can significantly benefit from supervised machine learning methods in the field of cardiology. According to Nick et al. [23], most of the initial breakthroughs in classifying medical images took place in situations where sizable datasets had already been labeled, such as chest X-rays or mammograms, which are images gathered as part of standard clinical care. Unfortunately, the scale of datasets is often constrained by increasing obstacles to data exporting or exchange in many other instances. Interest in picture classification has increased in recent years, particularly since 2018, despite researchers not having worked on it before the advent of Convolutional Neural Networks (CNNs).

In cardiovascular imaging, support vector machines have shown promising outcomes. The use of machine learning techniques to identify heart failure with preserved ejection fraction (HFPEF) utilising left ventricular (LV) strain and strain rate imaging is covered by Tabassian et al. [24]. The researchers investigated different machine learning algorithms to predict the presence of HFPEF and demonstrated that the most accurate predictor was a support vector machine (SVM) model based on LV peak strain and strain rate. A radiomics technique based on SVM is presented by Cetin et al. [25] for computer-aided diagnosis utilising cardiac cine-MRI. To train and test the model's accuracy, the study employed a database of 800 cine-MRI scans with known anomalies. The results showed an accuracy of 92.3%, highlighting the promise of this strategy for computer-aided diagnosis.

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Borkar et al. [26] discuss an SVM-based supervised machine learning system created for the diagnosis of heart diseases in their paper. The algorithm is based on a combination of two data sets: electrocardiogram (ECG) and heart rate variability (HRV). The authors compare its performance to that of existing algorithms and evaluate it on a sample dataset. The results demonstrate that the new algorithm outperforms traditional techniques in terms of accuracy, with a precision of 0.98. Moghaddasi et al. also employ the SVM approach in their paper [27], using a combination of textural features, such as color and texture, to classify MR severity into four groups: mild, moderate, severe, and very severe. The authors demonstrated the potential to accurately classify MR severity with an average accuracy of 92.6%. Furthermore, the authors discussed the potential for utilizing this automated technique for other medical applications, such as the detection of abnormalities in cardiac images.

Random forest and logistic regression have also shown promising results in cardiac imaging. The random forest can be used in combination with SVM and LR to achieve better results, as discussed in [28] and [29]. Moreno et al. [28] present a new method for predicting cardiac disease using a regional multiscale motion representation. The proposed approach utilises an array of motion descriptors to capture the motion of a region of interest within a patient's image, which is then employed to generate a predictive model for diagnosing cardiac diseases. The study's findings indicated that the proposed method may reliably predict the presence of cardiac disease. Baeßler et al. [29] focused on the application of machine learning and texture analysis in their research paper. The authors divided the images into two classes using a support vector machine algorithm: one for participants with hypertrophic cardiomyopathy and the other for controls. By comparing the accuracy and other metrics of this method with those of a manual analysis by an expert radiologist, the effectiveness of this method was assessed. The outcomes demonstrated that hypertrophic cardiomyopathy was correctly detected in the photos by the machine learning-based analysis. The capacity of texture analysis on non-enhanced cine Magnetic Resonance (MR) images to distinguish between subacute and chronic left ventricular myocardial scarring is the subject of another research investigation by Baeßler et al. [30]. The authors compared the outcomes of texture analysis performed on 45 patient MR images with histological results. According to the findings, texture analysis demonstrated 88% specificity and 91% sensitivity in detecting myocardial scars. In their paper, Wolterink et al. [31] used RF as well and obtained an accuracy of 86%. The study examines the automatic segmentation and classification of illness using cardiac cine Magnetic Resonance (MR) images.

As deep learning has evolved, the use of Convolutional Neural Networks (CNNs) for cardiac imaging has increased. The CNN model has shown very promising results, overcoming the limitations of previous models. Lu A et al. [32] used a multi-view regression of clinical measurements to develop their model. This model was then tested on a dataset of echocardiography tests from the University of Michigan and was found to identify anomalies accurately. The paper also discussed the importance of clinical measurements in detecting anomalies. The authors concluded that their approach could be used to reduce the cost of echocardiography testing and improve the accuracy of medical diagnoses. The topic of Wolterink et al. [33] research work is a deep learning-based technique for automatic coronary artery calcium scoring in cardiac computed tomography angiography (CTA). The authors used paired CNNs to recognize and segregate calcium deposits in CTA slices. They demonstrated that their method could precisely identify and measure the levels of coronary artery calcium by evaluating its effectiveness using a dataset of 50 individuals. The results of this work demonstrate that coronary artery calcification in CTA may be precisely detected and measured using deep learning. An end-to-end learning method for cardiac Magnetic Resonance Imaging (MRI) data segmentation and diagnosis is provided by Snaauw et al. in [34]. By demonstrating its efficacy using a publicly available cardiac MRI dataset and obtaining 78% accuracy, the authors describe the advantages of their methodology over currently used techniques.

In [35] [36] [37], the advantages of the CNN model in imaging cardiovascular disease (CVD) are also covered. The Automated Cardiac Diagnosis Challenge (ACDC) 2017 dataset is used in all three papers. The left ventricle is segmented in cardiac imaging by Khened et al. [35] using a multi-scale residual DenseNet architecture. The design combines a deep residual learning method with a fully convolutional neural network (FCNN) to increase accuracy and durability. After being evaluated on a sizable dataset of cardiac imaging, the model is tested on a different dataset. The results demonstrate that the model outperforms the most recent state-of-the-art models, with a total accuracy of 93.85%.

Ajay et al. [36] explore the use of the CNN model to classify heart diseases from MRI images. The authors applied a CNN with a three-layer architecture and compared the results with the traditional feature-based approaches. They then tested the model using a publicly available dataset of MRI images and analysed its performance, achieving 95% accuracy. The authors concluded that the CNN-based technique outperformed traditional feature-based strategies. In their publication [37], Jelmer et al. explain the creation and application of a deep learning-based segmentation system for the automatic segmentation and disease categorization of cardiac cine MR images. The system uses a supervised machine learning algorithm and a multi-task convolutional neural network (CNN) to segment the walls of the left ventricle (LV), left atrium (LA), and right ventricle (RV). The proposed system is evaluated using a dataset of 203 cardiac cine MRI images of healthy individuals and patients with coronary artery disease (CAD). It successfully segments the LV and RV with a Dice coefficient of 0.91, the LA with a Dice coefficient of 0.83, and the disease with an accuracy of 72.9%. The outcomes suggest that the proposed system is feasible for cardiac cine MRI image segmentation and disease categorisation. S.

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Brown et al. propose a Convolutional Neural Network (CNN) based algorithm for the automated segmentation of myocardial infarction (MI) in cardiac MRI scans in their paper [38]. The algorithm is tested on a different test set of 100 patients after being trained on a dataset of 400 instances. Dice Similarity Coefficient (DSC) results reveal an overall value of 0.92, proving the efficiency of the suggested algorithm.

Some other lesser-employed ML algorithms for CVD imaging include Artificial Neural Networks, Clustering, and GBRT. In [39], Cikes et al. classify patients into four phenogroups based on their response to CRT using a machine-learning technique called Phenogrouping. When compared to established clinical standards for judging patient response, the machine learning-based strategy shows higher accuracy. In [40], Kolossváry et al. demonstrate that radiomic characteristics are more accurate and specific than traditional quantitative computed tomographic measurements. The work offers proof that coronary plaques with the napkin-ring indication can be precisely identified using radiomic characteristics.

Zhang et al. develop an algorithm based on ANN and test it on a dataset of 250 cases in their paper [41]. The results show an improvement in accuracy of up to 10%. The algorithm is also evaluated on a separate test set of 50 patients, showing an accuracy of 86.4%. The findings imply that deep learning algorithms can be applied to increase the precision of chronic MI diagnosis on non-enhanced cardiac MRI scans. Lastly, in their paper [42], Han et al. study the use of resting myocardial computed tomography (CT) perfusion to identify physiologically relevant coronary artery disease (CAD). The authors employ an ML algorithm to assess the incremental role of resting myocardial CT perfusion in addition to traditional angiography for predicting CAD. The findings of their study demonstrate that resting myocardial CT perfusion, when used in conjunction with conventional angiography, has incremental value in the prediction of physiologically significant CAD, with a greater area under the curve than conventional angiography alone.

These are just a few examples of recent research papers in the field of cardiovascular imaging using machine learning. Deep learning techniques are showing promising results in the automatic diagnosis of heart diseases from different types of medical images and signals.

Table- III: List of Recently Published Literature

Publication	Methodology	Dataset	Performance
Zhang et al., [41]	Artificial Neural Network	212 MRI images of patients with chronic MI	AUC - 0.94
Cetin et al., [25]	Support Vector Machine	MICCAI 2017 dataset	ACC - 0.92
Wolterink et al., [31]	Random Forest	MICCAI 2017 dataset	ACC - 0.86
Lu A et al., [32]	Convolutional Neural Network	927 Echo in the form of DICOM	AUC - 0.84
Borkar et al., [26]	Support Vector Machine	439 Echo in DICOM	ACC - 0.98
Wolterink et al., [33]	Convolutional Neural Network	250 CT collected independently	ACC - 0.72
Moghaddasi et al., [27]	Support Vector Machine	102 Echo (Tehran Heart Centre dataset) [25]	ACC - 0.99
Tabassian et al., [24]	Clustering	100 Echo Images	ACC - 0.81
Cikes et al., [39]	Clustering	MADIT-CRT Dataset [28]	ACC - 0.95
Moreno et al., [28]	Support Vector Machine and Random Forest	45 MRI (MICCAI dataset)	Diagnosis of Myocardial Infarction
Baeßler et al., [29]	Logistic Regression and Random Forest	32 patients with HCM	AUC - 0.95
Snaauw et al., [34]	Convolutional Neural Network	100 MRI (ACDC dataset)	ACC - 0.78
Baeßler et al., [30]	Logistic Regression	MRI of 120 patients	ACC - 0.92
Kolossváry et al., [40]	Radiomics	60 CT collected independently	ACC - 0.91
Han D et al., [42]	Gradient Boosting Decision Tree	DeFACTO Dataset [35]	AUC - 0.75
Khened et al., [35]	Convolutional Neural Network	ACDC Dataset	ACC - 0.95
Ajay et al., [36]	Convolutional Neural Network	ACDC Dataset	ACC - 0.95
Jelmer et al.,[37]	Convolutional Neural Network	ACDC Dataset	Dice coefficient - 0.91
S. Brown et al., [38]	Convolutional Neural Network	Dataset of 100 patients having a Myocardial infarction (MI)	Dice Similarity Coefficient (DSC) of 0.92

V. PIPELINE FOR CARDIOVASCULAR IMAGING USING MACHINE LEARNING

The following section outlines the basic pipeline for building a machine learning algorithm for cardiovascular imaging. This pipeline involves several steps which are essential for the successful development of such an algorithm. These steps include preprocessing of medical images, feature extraction and selection, model training, and evaluation of the algorithm's performance. Each of these steps is crucial and requires careful consideration to ensure that the final algorithm is accurate and reliable in detecting and diagnosing cardiovascular diseases.

1. Data Collection: The first step in cardiovascular imaging using machine learning is the collection of data. This involves acquiring high-quality imaging data from different modalities such as Echocardiograms and MRI scans.
2. Data Pre-processing: The collected data then undergoes pre-processing to standardize it and eliminate any artifacts that may interfere with analysis. This can involve image enhancement, filtering, and noise reduction.
3. Image Segmentation: The pre-processed data is then segmented to isolate the area of interest. This is typically done through manual or automated processes, and can involve image thresholding, region growing, or active contour methods.
4. Feature Extraction: After segmentation, features are extracted from the segmented image. This step involves identifying and quantifying various image features such as texture, shape, and intensity, which can be used as inputs for the machine learning algorithms.

5. Machine Learning Model: The extracted features are then fed into the machine learning model for training. This can involve different types of models, such as convolutional neural networks, support vector machines, or decision trees, depending on the specific application.
6. Model Evaluation: Once the model is trained, it is evaluated on a separate dataset to determine its performance. This involves calculating various evaluation metrics, such as accuracy, sensitivity, and specificity, to assess the model's ability to classify images accurately.
7. Deployment: After the model is trained and validated, it can be deployed for use in clinical practice. This involves integrating the model into clinical workflows, such as electronic health records or imaging software, to facilitate the interpretation of cardiovascular images and support clinical decision-making.

The pipeline of image-based machine learning diagnosis typically involves several steps, as shown in Figure 1. First, the images of the subject are collected using medical imaging techniques, such as CT or MRI scans. After that, the images are pre-processed to reduce noise and improve image quality. Following that, the pre-processed images are sent into a machine learning model that has been trained on a large dataset of tagged images. The model utilises its learned knowledge to predict the subject's diagnosis. Finally, the prediction is reviewed by a medical expert to confirm its accuracy and to ensure the best possible treatment plan for the patient.

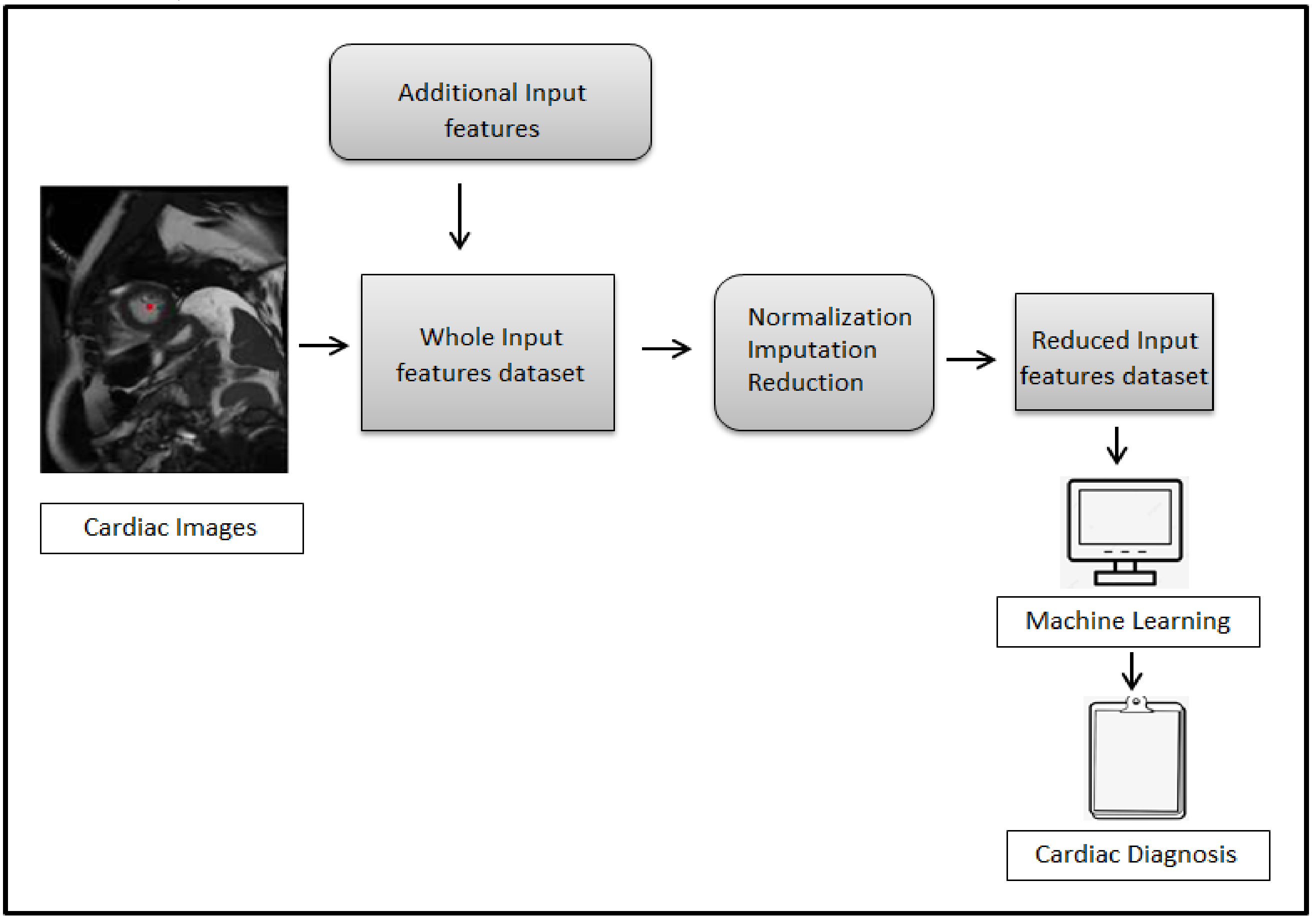

Figure I. Image-Based Machine Learning Diagnosis Pipeline

VI. ALGORITHMS

Several machine learning techniques can be used for CVD imaging. Some examples include deep learning, convolutional neural networks, and support vector machines. These techniques can be used to automatically analyze images of the heart and identify abnormalities, such as the presence of blockages in the coronary arteries. This can be useful for diagnosing CVD and guiding treatment decisions. Additionally, based on a person's medical background and imaging data, machine learning can be used to predict the likelihood of developing CVD. This can help with the early detection and prevention of the disease.

A. Logistic Regression

A statistical model called logistic regression is used to forecast binary outcomes (outcomes with only two possible values, such as yes/no or 0/1). It is a form of regression analysis that uses a set of independent variables to make predictions about a continuous result. The likelihood of an event occurring in the context of logistic regression is the expected outcome and is expressed as a number between 0 and 1. In medical research, logistic regression is frequently used to predict a patient's likelihood of developing a specific condition based on their medical history and other relevant variables.

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For instance, based on a patient's age, gender, family history, and other risk variables, a logistic regression model might be built to estimate the likelihood that the patient will develop CVD. The model would then produce a probability value indicating the possibility that the patient will develop CVD. This can help identify individuals at high risk and direct preventive interventions. The use of the Logistic Regression algorithm can be seen in [29][30].

B. Support Vector Machine

A supervised learning method used for classification and regression problems is called a support vector machine (SVM). It operates by identifying the optimal line or hyperplane in a dataset that can distinguish between various classes or goal values. The margin between the different classes is maximized by this line or hyperplane, which is known as the decision boundary. When attempting to forecast one of two classes in binary classification problems, SVMs are frequently used (such as "positive" or "negative"). They can also be applied to multi-class classification tasks, where the objective is to predict one of several classes.

In the context of CVD imaging, an SVM can be trained on a dataset of heart images, along with corresponding labels indicating whether CVD is present or not. The SVM would then learn to differentiate between healthy and abnormal images and could be used to predict the likelihood of CVD in new images. This may aid in the early detection and diagnosis of the disease. SVM has been widely popular, and its implementation can be seen in [25][26][27][28].

C. Random Forest

An ensemble learning approach used for both classification and regression tasks is called a random forest (RF). Because it is made up of numerous decision trees, each of which predicts something about the data, it is referred to as a "forest." Averaging or majority vote on the forecasts of the individual trees results in the final prediction. Random forests are popular because they are relatively easy to train, and they often produce highly accurate predictions. They are also resistant to overfitting, meaning they are less likely to make predictions that are overly specific to the training data and do not generalise well to new data.

In the context of CVD imaging, a random forest can be trained on a dataset of heart images, along with corresponding labels indicating the presence or absence of CVD. The random forest would then learn to differentiate between healthy and abnormal images and could be used to predict the likelihood of CVD in new images. This could be useful for the early detection and diagnosis of the disease. [31]

D. Artificial Neural Network

A form of machine learning technique called an artificial neural network (ANN) is modelled after the structure and operation of the human brain. The layers are composed of several interconnected nodes, sometimes referred to as "neurons." The input layer receives the input data, which is then processed and altered as it moves through the network's many layers. The output layer then delivers the anticipated outcome. ANNs are frequently utilized for a variety of applications, such as time series forecasting, natural language processing, and picture recognition. They excel in jobs that call for the understanding and processing of intricate, nonlinear relationships. In the context of CVD imaging, an ANN can be trained on a dataset of heart images, along with corresponding labels indicating the presence or absence of CVD. The ANN would then learn to recognize patterns in the images that are indicative of CVD and could be used to predict the likelihood of the disease in new images. This could be useful for the early detection and diagnosis of CVD. [41]

E. Convolutional Neural Network

An artificial neural network called a convolutional neural network (CNN) is specifically designed to analyse input with a grid-like structure, such as an image. The reason it employs the mathematical operation known as convolution, which aids the network in learning spatial hierarchies of features in the data, is why it is referred to as a "convolutional" neural network. CNNs are frequently employed for applications such as object identification, image classification, and facial recognition because they are highly effective at performing image recognition tasks. Convolutional layers, pooling layers, and fully connected layers are among the layers that make up a neural network. In the context of CVD imaging, a CNN can be trained on a dataset of heart images, along with corresponding labels indicating the presence or absence of CVD. The CNN would then learn to recognize patterns in the images that are indicative of CVD and could be used to predict the likelihood of the disease in new photos. This could be useful for the early detection and diagnosis of CVD. Among all the research papers surveyed for this review work, it can be observed that the CNN algorithm shows the most promising results, and its implementation can be seen in [32] [33] [34] [35] [36] [37] [38].

F. Recurrent Neural Networks (RNNs)

A class of deep learning methods known as recurrent neural networks (RNNs) has been extensively utilised in the field of natural language processing. Cardiovascular imaging has utilised RNNs to perform tasks such as image segmentation and lesion detection. RNNs' capacity to simulate sequential relationships in images is one of their primary advantages, which can be particularly helpful for identifying structures like blood vessels.

G. Graph Convolutional Networks (GCNs):

Graph convolutional networks (GCNs) are a type of deep learning algorithm that has been widely used in the field of graph-based learning. GCNs have been applied to cardiovascular imaging to perform tasks such as image segmentation and lesion detection. One of the key strengths of GCNs is their ability to learn representations of graph-structured data, which can aid in detecting complex structures, such as blood vessels.

H. Clustering

Clustering is a type of unsupervised machine-learning technique that involves grouping a set of data points into clusters based on their similarities.

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In the context of CVD imaging, clustering could be used to group images of the heart based on the presence or absence of CVD. Clustering can be a valuable tool for CVD imaging, as it enables the automatic grouping of images based on their similarity, without the need for predefined labels. This can facilitate the identification of patterns and trends in the data, ultimately improving the accuracy of CVD diagnosis.

To achieve this, a clustering algorithm would be trained on a large dataset of unlabeled images. The algorithm would then use the features of each image (such as the shape and size of the heart, or the presence of specific abnormalities) to determine which images are similar to one another. These similar images would be grouped into clusters, with each cluster representing a different group of images. Once the clusters have been formed, they can be used to make predictions on new images. For example, if a new image is added to the dataset, the clustering algorithm can determine which cluster the image belongs to, and this can be used to predict the presence or absence of CVD in the image. [24][39]

I. Gradient Boosting Decision Tree

Gradient boosting is a technique for training a group of weak learners (like decision trees) such that they can build on one another and produce a robust final model. A particular type of machine learning algorithm, known as a decision tree, employs a structure like a tree to make predictions. They are frequently used for classification tasks and are efficient at identifying patterns in data. By employing gradient boosting to train a collection of decision trees, GBDT combines these two methods. Each tree in the ensemble is trained using the mistakes made by the earlier trees, allowing the trees to learn from one another and enhance the model's overall performance.

In the context of CVD imaging, GBDT can be used to train a model on a large dataset of labelled images, indicating the presence or absence of CVD. The model could then be used to make predictions on new images, enabling the identification of CVD in real-time. [42]

Table- IV: ML Algorithms Used in Various Publications

Algorithm	Research Paper
Logistic Regression	[29] [30]
Support Vector Machine	[25] [26] [27] [28]
Random Forest	[31]
Artificial Neural Network	[41]
Convolutional Neural Network	[32] [33] [34] [35] [36] [37] [38]
Clustering	[24] [39]
Gradient Boosting Decision Tree	[42]

VII. APPLICATIONS OF MACHINE LEARNING IN CARDIOVASCULAR IMAGING

A. Diagnosis of Cardiovascular Diseases

Machine learning algorithms have shown promise in aiding the diagnosis of cardiovascular diseases by leveraging medical imaging data. By extracting features and patterns from images and signals, these algorithms can analyse large volumes of data and provide accurate and efficient diagnoses. For instance, deep learning models have been created to automatically diagnose cardiac conditions using a variety of imaging modalities, such as electrocardiogram (ECG) data, echocardiograms, magnetic resonance imaging (MRI), and computed tomography (CT) scans. As shown in Section II of this work, these models have the potential to improve the detection of cardiovascular illnesses. They have shown high accuracy rates of up to 93.6%.

B. Segmentation and Quantification of Cardiovascular Structures

The segmentation and quantification of cardiovascular structures, which is essential for the diagnosis and treatment of cardiovascular illnesses, may be aided by machine learning algorithms. The left ventricle, right ventricle, and myocardium may all be identified and separated using these techniques in medical imaging. Important clinical parameters, including ejection fraction, myocardial mass, and wall thickness, can be obtained by segmenting these structures. Convolutional neural networks (CNNs) and U-Net are two deep learning techniques that have been widely used for segmentation tasks, demonstrating high accuracy and robustness across various cardiovascular imaging modalities.

C. Image-Based Risk Prediction

By examining both medical images and other clinical data, machine learning algorithms can help predict the likelihood of cardiovascular events, such as heart attacks and strokes. To produce more accurate risk assessments, these algorithms can combine imaging data with traditional risk factors, including age, gender, and medical history. For instance, models have been created to accurately and reliably estimate the risk of coronary artery disease based on coronary CT angiography pictures. By identifying high-risk patients who might benefit from early intervention and individualised treatment programmes, these algorithms have the potential to enhance patient outcomes.

D. Image-Guided Therapies

Machine learning algorithms have the potential to support image-guided therapies for cardiovascular diseases, such as catheter-based interventions and surgeries, by providing real-time guidance and feedback to clinicians. This can enhance the accuracy and safety of the procedure. For example, in the case of atrial fibrillation, machine learning algorithms have been developed to provide real-time guidance for catheter ablation procedures. These algorithms can achieve high accuracy while reducing radiation exposure to the patient and the clinician. This shows the potential of machine learning algorithms in improving the efficiency and outcomes of image-guided therapies in cardiovascular medicine.

VIII. EVALUATION AND COMPARISON OF MACHINE LEARNING ALGORITHMS

A. Metrics for Evaluation of Algorithms

It is necessary to assess the performance of these models to create cardiovascular imaging models that utilise machine learning algorithms effectively.

The model's ability to correctly identify positive and negative cases, as well as the degree of confidence in its predictions, is frequently evaluated using evaluation metrics such as accuracy, precision, recall, F1 score,

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area under the curve (AUC), and a confusion matrix. The type of cardiovascular imaging dataset and the specific research issue under investigation determine the relevant evaluation metrics to use.

B. Comparison of Different Algorithms on Different Datasets

For cardiovascular imaging, several machine learning techniques have been proposed, including deep learning, support vector machines, decision trees, and random forests. The effectiveness of various algorithms on various datasets can be compared to reveal the advantages and disadvantages of each strategy. The effectiveness of machine learning algorithms can be significantly impacted by factors such as dataset size, class imbalance, and feature selection. To assess the robustness and generalizability of alternative techniques, it is crucial to compare them across multiple datasets.

IX. LIMITATIONS OF CURRENT ALGORITHMS

Despite the promising results of machine learning algorithms in the field of cardiovascular imaging, several limitations remain that need to be addressed further to improve the accuracy and reliability of these algorithms. One of the main limitations is the need for extensive and diverse datasets to train the algorithms. The algorithms can only be as good as the data they are trained on, and the availability of high-quality imaging data with comprehensive annotations can be a limiting factor in the development of practical algorithms. Another limitation is the lack of standardization in the datasets used for training and validation, which can make it difficult to compare the results of different algorithms. Additionally, there is a need for more effective evaluation metrics that can provide a more comprehensive and accurate assessment of algorithm performance. Currently, the evaluation metrics used for machine learning algorithms in cardiovascular imaging tend to be limited in scope and do not necessarily reflect the real-world clinical performance of the algorithms. This can make it challenging to compare the results of different algorithms and determine which ones are best suited for specific applications.

Another limitation is the lack of generalizability of the algorithms to different imaging modalities, populations, and disease states. Algorithms developed for one imaging modality may not necessarily perform well on a different modality, and their performance may also vary depending on the specific population or disease state being studied. Despite these limitations, the potential benefits of machine learning in cardiovascular imaging are significant, and there is a need for continued research and development in this area. The future of cardiovascular imaging is likely to involve a combination of machine learning algorithms and traditional imaging techniques, enabling more accurate and efficient diagnosis and management of cardiovascular diseases.

X. DISCUSSION AND FUTURE PERSPECTIVES

Despite these limitations, the future of cardiovascular imaging using machine learning is bright. There is a need for further research to address the limitations mentioned above, including the limited size and diversity of datasets, as well as the lack of standardisation in algorithm evaluation. Additionally, there is a growing interest in using machine learning algorithms for image-based risk prediction and image-guided therapies, which have the potential to revolutionize the diagnosis and treatment of cardiovascular diseases. Furthermore, there is a need for more research to develop algorithms that are interpretable and can provide explanations for their predictions, thereby increasing transparency and trust in these models.

XI. CONCLUSION

In conclusion, machine learning has shown great promise in the field of cardiovascular imaging. Machine learning algorithms have the potential to enhance the detection and treatment of cardiovascular diseases by providing accurate and efficient analysis of cardiovascular images. However, several limitations still need to be addressed, including the limited size and diversity of datasets, the lack of standardisation in algorithm evaluation, and the lack of interpretability in machine learning models. Nevertheless, the future of cardiovascular imaging using machine learning is promising, and further research is needed to address these limitations and develop more advanced algorithms for this field.

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Authors Contributions	Ms. Rachana Pandey wrote the initial manuscript draft and contributed to the study conception and design. She performed the literature search and categorization, developed the ML pipeline model, and wrote the imaging-type literature section. Ms. Pandey also coordinated the remaining sections and wrote the dataset, application, and algorithm sections, as well as the abstract, introduction, limitations, future perspective, and conclusion sections.

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REFERENCES

1. World Health Organization. (2019). Cardiovascular diseases (CVDs). Retrieved from https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)
2. NHS website. (2022, June 24). Cardiovascular disease. Nhs.uk. Retrieved from https://www.nhs.uk/conditions/cardiovascular-disease/
3. Al'Aref SJ, Anchouche K, Singh G, Slomka PJ, Kolli KK, Kumar A, Pandey M, Maliakal G, van Rosendael AR, Beecy AN, Berman DS, Leipsic J, Nieman K, Andreini D, Pontone G, Schoepf UJ, Shaw LJ, Chang HJ, Narula J, Bax JJ, Guan Y, Min JK. Clinical applications of machine learning in cardiovascular disease and its relevance to cardiac imaging. Eur Heart J. 2019 Jun 21;40(24):1975-1986. doi: 10.1093/eurheartj/ehy404. PMID: 30060039. [CrossRef]
4. Aaron D. Aguirre, Kenneth T. Shelton."Remote monitoring in the use of extracorporeal membrane oxygenation and acute mechanical circulatory support", Current Opinion in Critical Care, 2022. Publication: Viswanathan Rajagopalan, Houwei Cao. [CrossRef]
5. T P Pushpavathi, Santhosh Kumari, N K Kubra. "Heart Failure Prediction by Feature Ranking Analysis in Machine Learning", 2021 6th International Conference on Inventive Computation Technologies (ICICT), 2021 [CrossRef]
6. Rahul Deo, Brigham and Women's Hospital, University of California, San Francisco, 2019. https://ocw.mit.edu/courses/6-s897-machine-learning-for-healthcare-spring-2019/pages/lecture-notes/
7. O. Bernard, A. Lalande, C. Zotti, F. Cervenansky, et al." Deep Learning Techniques for Automatic MRI Cardiac Multi-structures Segmentation and Diagnosis: Is the Problem Solved ?" in IEEE Transactions on Medical Imaging, vol. 37, no. 11, pp. 2514-2525, Nov. 2018 doi: 10.1109/TMI.2018.2837502 [CrossRef]
8. Slomka PJ, Betancur J, Liang JX, Otaki Y, Hu LH, Sharir T, Dorbala S, Di Carli M, Fish MB, Ruddy TD, Bateman TM, Einstein AJ, Kaufmann PA, Miller EJ, Sinusas AJ, Azadani PN, Gransar H, Tamarappoo BK, Dey D, Berman DS, Germano G. Rationale and design of the Registry of Fast Myocardial Perfusion Imaging with Next generation SPECT (REFINE SPECT). J Nucl Cardiol. 2020 Jun;27(3):1010-1021. doi: 10.1007/s12350-018-1326-4. Epub 2018 Jun 19. PMID: 29923104; PMCID: PMC6301135. [CrossRef]
9. The German National Cohort, Nako database, 2011. https://nako.de/
10. Onderzoekscentrum (2022, July 29). De Maastricht Studie. https://www.demaastrichtstudie.nl/ [CrossRef]
11. Canadian Alliance for Healthy Hearts and Minds, 2013, https://cahhm.mcmaster.ca/
12. Challenge on Endocardial Three-dimensional Ultrasound Segmentation, MICCAI challenge 2014. https://www.creatis.insa-lyon.fr/Challenge/CETUS/databases.html
13. Die Hamburg City Health Study (HCHS), Hamburg City, November 2021, Available at: https://hchs.hamburg/
14. Automated Cardiac Diagnosis Challenge (ACDC), 2017. https://www.creatis.insa-lyon.fr/Challenge/acdc/
15. CAMUS, Cardiac Acquisitions for Multi-structure Ultrasound Segmentation, University Hospital of St Etienne (France), Available at: https://www.creatis.insa-lyon.fr/Challenge/camus/databases.html
16. Xiahai Zhuang: Multivariate mixture model for myocardial segmentation combining multi-source images. IEEE Transactions on Pattern Analysis and Machine Intelligence 41(12): 2933-2946, 2019. [CrossRef]
17. Xiahai Zhuang and Juan Shen: Multi-scale patch and multi-modality atlases for whole heart segmentation of MRI, Medical Image Analysis 31: 77-87, 2016 [CrossRef]
18. X Luo & X Zhuang: X-Metric: An N-Dimensional Information-Theoretic Framework for Groupwise Registration and Deep Combined Computing. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2022-11 online published (IF: 24.314) [CrossRef]
19. Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436-444, 2015. [CrossRef]
20. Kim T, Hedayat M, Vaitkus VV, Belohlavek M, Krishnamurthy V, Borazjani I. Automatic segmentation of the left ventricle in echocardiographic images using convolutional neural networks. Quant Imaging Med Surg. 2021 May;11(5):1763-1781. doi: 10.21037/qims-20-745. PMID: 33936963; PMCID: PMC8047352. [CrossRef]
21. Puttagunta M, Ravi S. Medical image analysis based on a deep learning approach. Multimed Tools Appl. 2021;80(16):24365-24398. doi: 10.1007/s11042-021-10707-4. Epub 2021 Apr 6. PMID: 33841033; PMCID: PMC8023554.
22. Bhan, A.; Mangipudi, P.; Goyal, A. Deep Learning Approach for Automatic Segmentation and Functional Assessment of LV in Cardiac MRI. Electronics 2022, 11, 3594. https://doi.org/10.3390/electronics11213594 [CrossRef]
23. Nick James, Lianna Gerrish, Nikita Rokotyan, Patrick A. Gladding. "Machine Learning Applied to Routine Blood Tests and Clinical Metadata to Identify and Classify Heart failure", Cold Spring Harbor Laboratory, 2021 [CrossRef]
24. Tabassian M, Sunderji I, Erdei T, Sanchez-Martinez S, Degiovanni A, Marino P, et al. Diagnosis of heart failure with preserved ejection fraction: machine learning of spatiotemporal variations in left ventricular deformation. J Am Soc Echocardiogr. (2018) 31:1272–84. doi: 10.1016/j.echo.2018.07.013 [CrossRef]
25. Cetin I, Sanroma G, Petersen SE, Napel S, Camara O, Ballester MAG, et al. A radiomics approach to computer-aided diagnosis with cardiac cine-MRI. In: International Workshop on Statistical Atlases and Computational Models of the Heart. Quebec City, QC: Springer (2017). p. 82–90. [CrossRef]
26. Borkar S, Annadate M. Supervised machine learning algorithm for detection of cardiac disorders. In: 2018 Fourth International Conference on Computing, Communication, Control and Automation (ICCUBEA). Pune: IEEE (2018). p.1–4. [CrossRef]
27. Moghaddasi H, Nourian S, Nourian S. Automatic assessment of mitral regurgitation severity based on extensive textural features on 2D echocardiography videos. Comput Biol Med. (2016) 73:47–55. Doi: 10.1016/j.compbiomed.2016.03.026 [CrossRef]
28. Moreno A, Rodriguez J, Martínez F. Regional multiscale motion representation for cardiac disease prediction. In: 2019 XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA). Bucaramanga, CO: IEEE (2019). p. 1–5. [CrossRef]
29. Baeßler B, Mannil M, Maintz D, Alkadhi H, Manka R. Texture analysis and machine learning of non-contrast T1-weighted MR images in patients with hypertrophic cardiomyopathy–preliminary results. Eur J Radiol. (2018) 102:61–7. doi: 10.1016/j.ejrad.2018.03.013 [CrossRef]
30. Baeßler B, Mannil M, Oebel S, Maintz D, Alkadhi H, Manka R. Subacute and chronic left ventricular myocardial scar: accuracy of texture analysis on nonenhanced cine MR images. Radiology. (2017) 286:103–12. doi: 10.1148/radiol.2017170213 [CrossRef]
31. Wolterink JM, Leiner T, Viergever MA, Išgum I. Automatic segmentation and disease classification using cardiac cine MR images. In: International Workshop on Statistical Atlases and Computational Models of the Heart. Quebec City, QC: Springer (2017). p. 101–10. [CrossRef]
32. Lu A, Dehghan E, Veni G, Moradi M, Syeda-Mahmood T. Detecting anomalies from echocardiography using multi-view regression of clinical measurements. In: 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018). IEEE (2018). p. 1504–8. [CrossRef]

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Journal Website: www.ijrte.org

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33. Wolterink JM, Leiner T, de Vos BD, van Hamersvelt RW, Viergever MA, Išgum I. Automatic coronary artery calcium scoring in cardiac CT angiography using paired convolutional neural networks. Med Image Anal. (2016) 34:123–36. doi: 10.1016/j.media.2016.04.004 [CrossRef]
34. Snaauw G, Gong D, Maicas G, van den Hengel A, Niessen WJ, Verjans J, et al. End-to-end diagnosis and segmentation learning from cardiac magnetic resonance imaging. In: 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019). Venice: IEEE (2019). p. 802–5. [CrossRef]
35. Khened, Mahendra, Kollerathu, Varghese Alex, Krishnamurthi, Ganapathy, et al. Fully convolutional multi-scale residual DenseNets for cardiac segmentation and automated cardiac diagnosis using an ensemble of classifiers, Medical image analysis, 2019, Elsevier [CrossRef]
36. Ajay Sharma, Raj Kumar, Varun Jaiswal, et al. Classification of Heart Disease from MRI Images Using Convolutional Neural Network, IEEE International Conference on Signal Processing, Computing and Control 2021, JUIT, Solan, India [CrossRef]
37. Jelmer M. Wolterink(B), Tim Leiner, Max A. Viergever, Ivana I˘sgum1, et al. Automatic Segmentation and Disease Classification Using Cardiac Cine MR Images, Springer International Publishing AG, part of Springer Nature, 2018 [CrossRef]
38. S. Brown, J. Lee, and Y. Kim, "Automated Segmentation of Myocardial Infarction using Convolutional Neural Networks," Computerized Medical Imaging and Graphics, vol. 58, pp. 1-9, 2022.
39. Cikes M, Sanchez-Martinez S, Claggett B, Duchateau N, Piella G, Butakoff C, et al. Machine learning-based phenogrouping in heart failure to identify responders to cardiac resynchronization therapy. Eur J Heart Fail. (2019) 21:74 85. doi: 10.1002/ejhf.1333 [CrossRef]
40. Kolossváry M, Karády J, Szilveszter B, Kitslaar P, Hoffmann U, Merkely B, et al. Radiomic features are superior to conventional quantitative computed tomographic metrics to identify coronary plaques with napkin-ring sign. Circulation. (2017) 10:e0 06843. doi: 10.1161/CIRCIMAGING.117.006843 [CrossRef]
41. Zhang N, Yang G, Gao Z, Xu C, Zhang Y, Shi R, et al. Deep learning for diagnosis of chronic myocardial infarction on nonenhanced cardiac Cine MRI. Radiology. (2019) 291:606–17. doi: 10.1148/radiol.2019 182304 [CrossRef]
42. Han D, Lee JH, Rizvi A, Gransar H, Baskaran L, Schulman-Marcus J, et al. Incremental role of resting myocardial computed tomography perfusion for predicting physiologically significant coronary artery disease: a machine learning approach. J Nucl Cardiol. (2018) 25:223–33. doi: 10.1007/s12350-017-0834-y [CrossRef]

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