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Different Deep Learning Techniques in Heart Disease Classification: Survey

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ABSTRACT

Cardiovascular disease prediction is a serious challenge for clinical data analysis. This study examines deep learning-based categorization strategies for heart disease. Deep learning algorithms are employed with echocardiograms to categorize heart disease. This paper uses echocardiography to predict and identify heart abnormalities, with the help of decision-making and forecasting, based on the copious data the healthcare sector has provided. Medical experts can forecast clinical outcomes, which helps them choose the best course of action. In-depth longitudinal electronic health records are a rich source of historical data with complex patterns that have the potential to be leveraged by machine learning to improve physicians' prediction abilities (EHR) significantly. Most contemporary medical specialties rely on imaging as one of the most data-rich components of electronic health records when making treatment decisions (EHRs). Only a few tasks in medical image processing and reconstruction have seen success using machine and deep learning, including registration, segmentation, and feature extraction. Cardiac imaging sequence analysis must incorporate the extraction of spatial and temporal characteristics to forecast crucial information throughout time correctly.

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1. INTRODUCTION

For both male and female mortality, heart disease is the main contributing factor. With new diseases emerging daily, the medical industry is rapidly expanding, necessitating the development of an effective remedy strategy. Early detection of this condition helps save the lives of people. The heart's ability to beat well is essential to life [1]. That affects the heart in a negative way overall, as well as several problems that fall into this group, including coronary

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artery disease (CAD), cardiomyopathy, Cardio Vascular Disease (CVD), and other conditions resulting from poor blood flow in the body [2].

1.1. Some Types of Heart Disease

There are numerous illnesses, including cardiovascular disease, cardiomyopathy, and coronary artery disease (CAD)(CVD). Heart Valve Disease: A sort of discomfort brought on by a decline in blood flow is coronary artery disease. The decrease in arterial flow will hurt the vein and make regular heartbeats (systolic and diastolic) functions uncomfortable. CVD is the primary factor in fatal illnesses, serious disabilities, and disability [2]. Three conditions that increase the risk of CVD are CAD, rheumatic fever, and rheumatic heart disease. Coronary artery narrowing, which culminates in coronary heart disease (CHD), which eventually causes myocardial infarction, is the reduction in the heart's blood flow (MI). An artery may become blocked if plaque or fat deposits accumulate there, which causes blood clots to form. As a result, the heart muscle receives inadequate blood flow, which results in intense chest pain [2,3].

1.2. Echocardiogram

To detect heart disease early that can use an echocardiogram. As a result, it is believed that the most frequently used tool in the field of the circulatory system for detecting heart illness is an echocardiogram (also known as an echo). It is utilized primarily because it may diagnose and treat cardiac ailments early on. It is a quick, painless, reliable, practical, and inexpensive method for showing the pressure gradient of heart lesions. Echo is regarded as safe because it employs sound waves instead of radiation. To create images of the heart, Echo utilizes standard Doppler ultrasonography, two-dimensional (2D), and three-dimensional (3D) ultrasound. By adjusting the probe angle, echocardiography (echo) uses the ultrasonic principle to capture images of the heart muscle in various directions. The right ventricle left ventricle (LV), right atrium, and left atrium are the four chambers of the human heart. The echo devices can be used to examine the chambers and chamber walls [3]. A weakly supervised semantic segmentation model was trained using end-systole (ES), and end-diastole (ED) left ventricle tracings from human experts. Video frame, human expert tracings, and the model were all used to train it and are paired (top row), allowing the segmentation of video frames for which there have never been any human tracings (bottom row) [4].

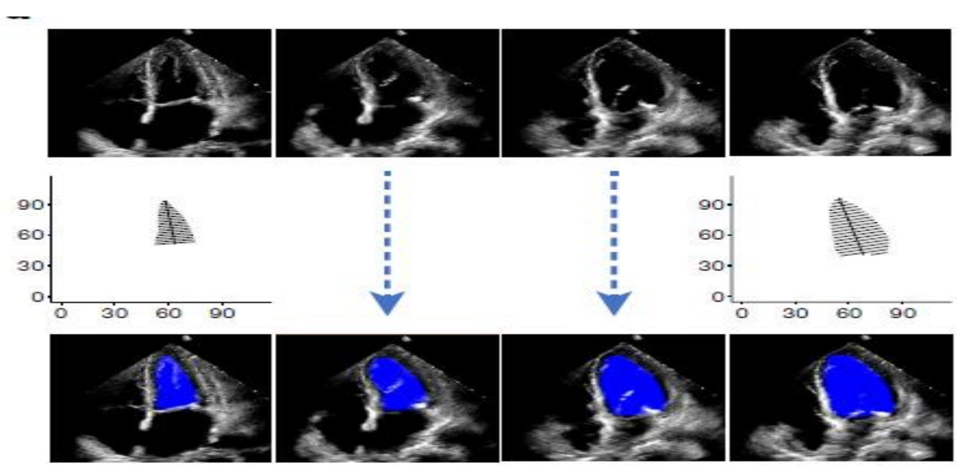

Figure 1. Image Of Echocardiograms Taking from Different Angles[4]

Lack of a cardiologist in most hospitals, particularly in rural locations, always results in incorrect diagnosis or early disease unpredictability, which all endanger lives. Using computers, medical imaging has developed into a diagnostic tool that provides details about anatomical structures using imaging techniques, including computed tomography (CT) and magnetic resonance imaging (MRI), angiography, and echocardiography [5]. During cardiac contraction, the LV wall deforms, Such as by radial thickening (positive strain) and longitudinal shortening (negative strain) (echo). No matter how experienced and skilled the practitioner is, the human eye is unable to discern or measure this [6].

Numerous studies on medical image analysis have used images that individuals previously properly identified. It is recommended to employ tens of thousands of photos with labels while developing new models in the field of echocardiography [7].

1.3. Machine learning

Machine learning is a different method of applying AI that classifies datasets on heart disease with fewer features and more excellent accuracy indicators. Machine learning has great promise for helping doctors make predictions based on the identification of intricate patterns in previously collected data [7]. Methods of machine learning are essential for both prediction and data analysis. The size and complexity of medical data make it difficult for traditional approaches to handle. The initial objective of the ML case study is to create a system of recommendations for the early detection and treatment of a cardiac condition or to showcase cutting-edge, extremely promising methods for doing so [6].

Four categories can be made out of it:

1- Supervised learning: A function that indicates the input the output should be based on the function determined from a set of labeled training samples, according to the labeled training data. Learning is accomplished by classifying practice data with the appropriate solutions.

2- Unsupervised learning: This part of teaching does not provide prior training due to the unlabeled dataset. The machine can only automatically group unsorted data based on data similarities, differences, and hidden patterns.

3- Semi-supervised learning: Semi-supervised education falls between supervised and unsupervised learning since the incoming data is only partially labeled [8].

4- Reinforcement learning: This sort of learning involves training a machine by trial and error. The algorithm builds on its prior experiences until it has investigated every conceivable situation and identified the best action to take to attain optimal performance. It is frequently used in robotics and video games [9].

1.4. Deep learning (DL):

Deep learning, a brand-new branch of machine learning (ML), was created to address the drawbacks of traditional machine learning techniques during the automation age. Because until the feature extraction stage, most classification systems utilizing traditional techniques are of low quality. Extraction of relevant information from data is typically time-consuming and challenging. A feature extractor structure needs to have extensive prior domain knowledge to gather knowledge from large amounts of data effectively. Instead of manually selecting features, deep networks automatically produce complex hierarchies of raw information to construct a data representation hierarchy [10].

1.4.1. Significance of (DL)

Over the past five years, it has been applied to a variety of systems with outstanding outcomes. The deep learning algorithm makes an effort to learn independently of any human supervision. Both supervised and unsupervised categorization is used in deep learning. The concealed layers are learned afterward, features are trained to create a model. Artificial neural networks construct numerous hidden layers from the input to provide accurate and helpful output [1].

1.4.2. CNN

“Convolutional neural networks” are a subset of deep feed-forward neural networks used for the segmentation and classification of images, among other image-processing tasks. In a typical CNN, there are three different types of layers: convolutional, pooling, and fully connected, which are used for spatial modeling. Deep learning algorithms (CNNs) are frequently employed for image processing and analysis with the use of weights and biases, CNNs can take photos as input data and reconstruct them to assess the significance, allowing it to discriminate between the attributes of one image in comparison to another. The capacity of CNN models to detect spatial and temporal relationships in pictures through the use of filters is one of their key strengths [7].

1.4.3. RNN

"Recurrent neural networks" are a type of neural network where the prior outputs of those layers determine the current inputs to hidden layers. They can now interact with a time sequence that contains temporal relations, for example, to do text categorization and audio recognition. In comparison to CNNs, the literature demonstrates that RNNs are more effective for sentiment analysis. Due to recurrent feedback connections, RNN models with internal state or short-term memory are appropriate for solving sequential problems, such as categorization, foretelling, and production of speech Due to vanishing gradient, Long-term dependencies in the input sequences (i.e., spanning more than 10 times steps) are complex for simple RNNs trained using stochastic gradient descent to comprehend [1].

1.4.4. LSTM

Hochreiter and Schmidhuber first presented the long short-term memory RNN architecture in 1997. This network's ability to manage long-term dependencies is its defining feature. The LSTM cell, which functions as a memory cell and can both recall and forget information, is the primary distinction between it and an RNN. The cell state, which represents the data flow in an LSTM, uses a set of gates to decide if an input is substantial enough to be remembered and whether previously recorded data should still be remembered or forgotten. Input, output, and forget gates are among these gates. Applied videos, as opposed to images, offer a more challenging input because they are composed of frames. The vanishing gradient problem can be solved and long-term dependency can be eliminated using LSTM [10].

1.5. Performance Metrics

The effectiveness of the performance of the algorithms is evaluated and verified using performance measures. One of the most commonly used performance criteria in classification is accuracy. The following list includes the many performance measurements used: It is a metric that figures out the proportion of the appropriate type to all samples [6].

1.5.1. Classification Accuracy

It is a metric that figures out the proportion of correctly classified samples to all samples. Accuracy alone suffices as a metric for a class with the same number of samples.

1.5.2. Logarithmic Loss

It functions by criticizing incorrect categorization. More accuracy will be achieved with a lesser loss. The multi-class classification works well with it.

1.5.3. Confusion Matrix

It is a matrix that details a model's overall performance. The confusion matrix can be used to calculate the following.

- Precision: The ratio of True Positives (TP) and False Positives is what matters (FP). two classes of classification.

- Recall: Percentage of the True Positives (TP) & False Negatives (FN) is what it stands for (FN). Recall for two-class categorization

- F1- Score: Its precision and recall are symmetrical, about two-class classification [1]. as shown in the table:

Accuracy =(TP+TN) /(TP+TN+FP+FN) [the overall effectiveness of the model]

Precision =TP / (TP+FP) [How precise are the optimistic predictions]

Recall sensitivity =TP / (TP+FN) [Actual positive sample coverage]

Specificity =TN / (TN+FN) [Actual negative sample coverage]

F1- score =2TP / (2TP+FP+FN) [Hybrid metrics are helpful for classes that aren't balanced]

2. Studies to Predict Heart Disease

You divided these studies into groups according to the technique they used:

2.1. LSTM

Vani [11] centered on diagnosing cardiovascular disease the author developed a more effective long-short-term memory (LSTM) model. The suggested model used the LSTM unit's adaptive threshold structure to learn the temporal properties connected to CVD progression at various time points. Additionally, to make the proposed model training process with various time series lengths simpler, the authors adopt the target repeat prediction approach for the output of the hidden layer at each time step. The patient's many diagnostic tags are forecasted as output thanks to the use of the Sigmoid function as the multi-activation output's function. Heart rate and cholesterol were chosen as the attributes when utilizing the classification algorithm because they have been established as the main causes of atherosclerosis. The proposed model achieved 89.6 accuracies. The surrogate dataset was used to test the suggested model.

KUMARI [1] focused on the offering of health diagnostic choices for heart disease that could be improved by enhancing these prediction structures. illnesses of the heart and CVDs.As a hybrid strategy, the author suggested Random Forest with Bi-LSTM. The suggested solution achieved 90 %. When applied to the Cleveland dataset.

Wahlang et al [6] focused on the echo's ability to spot heart problems early. The authors suggested two methods for classifying different types of regurgitation, classifying Long Short-Term Memory (LSTM) as normal or abnormal and using a Variational Autoencoder (VAE) based autoencoder methodology they apply SVM (Support Vector Machine) Due to the amount of data, VAE and SVM methods work better when classifying images as normal or pathological in 2D and 3D Doppler (still images), whereas LSTM performs better when classifying photos as video graphics. The proposed approach achieved 86%. When used with the scant information requested.

Manur et al [12] focused on improving the precision of heart disease prognosis. Bi-directional Long Short-Term Memory with Conditional Random Field was suggested by the authors (BiLSTM-CRF). When used on the dataset (UCI), the proposed approach produced a 90.04% success rate.

Chen et al [13] focused on sick individuals who are unsure of which outpatient department they should register with. The (Att-BiLSTM) attention-based bidirectional, long-short-term memory model, was introduced by the authors for use by service robots. The proposed solution achieved 96%. The Taiwan E Hospital dataset is being used.

2.2. CNN

Mehmood et al [14] focused on using real-world datasets in a way that can help with the early detection of a probable heart attack. The authors proposed developed a method called Cardio Help that estimates the possibility that a patient may have cardiovascular disease using a deep learning algorithm (CNN). The proposed solution achieved 97% when applying the dataset (UCI).

Ouyang et al [4] focused on the progress of cardiac function in the diagnosis of cardiovascular. The authors proposed a three-dimensional (3D) convolutional neural network (CNN) method that performs better than human specialists at the crucial tasks of left ventricle segmentation, ejection fraction estimation, and cardiomyopathy assessment.

This model successfully diagnoses heart failure as having a reduced ejection fraction, predicts ejection fraction with a mean absolute error of 4.1%, and precisely segments the left ventricle with a Dice similarity coefficient of 0.92. The proposed solution is applied to the Echo Net-Dynamic dataset.

ALI et al [8] focused on the improvement of features and removal of the underfitting and overfitting issues brought on by the predictive model by preventing these issues from occurring. When compared to traditional ANN and DNN models for the prediction of heart disease, the performance of the hybrid models the authors devised, known as 2-DNN, is assessed. The accuracy of the suggested solution was 93.33%. when applied to UCI dataset.

DEGERL et al [15] focused on detecting Myocardial infarction (MI) in early time. The authors proposed a convolutional neural network (CNN) encoder-decoder (E-D) model. The proposed solution achieved 86.85% for MI detection. When applied to the HMC-QU dataset.

Leclerc et al [16] focused on improving 2D echocardiographic images: heart structures to establish an efficient diagnosis. The authors proposed determining the extent to which the cutting-edge encoder-decoder deep convolutional neural network CNN's approaches can be to assess 2D echocardiographic images. The proposed solution achieves an accuracy superior to 92%to the segmentation network and all ten auto-encoders. An applied to the CAMUS dataset.

Chen et al [17] focused on segmenting echo images by independently analyzing video constituent frames and determining the ED and ES. The authors proposed temporally consistent video segmentation. The 3D U-Net was utilized as the shared feature extractor for the motion tracking and video segmentation tasks. A 1x1x1 convolution layer supervised with a combined cross-entropy and multi-class Dice loss was utilized as a segmentation head to acquire the 4-channel frame-level segmentation of the clip. A 3x3x3 convolution layer was utilized to obtain the input clip's bi-directional motion fields between the frames. Using local cross-correlation and smoothness loss, the motion field's outputs were observed. The weights were initially trained using the above segmentation and motion losses in a warm start. The proposed solution achieved high performance. Using the echo Net-Dynamic dataset.

Gao et al [18] focused on helping to improve and support professionals in the detection of heart illnesses. The authors proposed a concentrate on CNN architecture that combines both automatic and selective deep-learning networks. This CNN design with two-strand networks functions as a result. To classify the eight prospective classes of echocardiogram recordings. The proposed solution achieved the best classification results with up to 92.1% accuracy. After being applied to the hospital data from Tsinghua University in Beijing and Fuzhou University in Fuzhou, China.

Muhtaseb et al [19] focused on effective video interpretation, learning spatiotemporal elements is a crucial task, particularly in medical images like echocardiograms. The authors' proposed (EchoCoTr) method for calculating the left ventricular ejection fraction (LVEF) from ultrasound films makes use of the power of vision transformers and CNNs.The suggested remedy was successful by 82%. When used with the dataset from EchoNet-Dynamic.

Deng et al [20] focused on improving the early detection of heart disease by comparing the left ventricular volume at the end of each diastole and systole. The left ventricular region must be manually annotated, which takes time and relies on humans, leading to high inter-observer variance and low precision. On echocardiogram images, manually locate the left ventricle. For left ventricle segmentation in echocardiography, the authors presented the Trans Bridge, a compact hybrid model employing the transformer and CNN structure. The suggested solution has 78.7% fewer parameters overall, and the Dice coefficient has increased to 91.4%.

Dutta et al [21] Focused on the classification of clinical data with severe class imbalances and the prediction of coronary heart disease (CHD). The authors proposed an effective Convolutional neural network with feature weight estimation based on least absolute shrinkage and selection (LASSO). Before transferring the layer's output to successive convolutional layers, it is crucial to homogenize the key features using a fully connected layer. The authors' final recommendation was to perform training once every epoch to raise classification accuracy. When applied to the NHANES dataset, the generated CNN architecture from the recommended solution has a classification power of 77% to correctly classify the presence of CHD and classify the absence of CHD cases on testing data, which makes up 85.70% of the total dataset.

2.3. Different Techniques:

Soni et al [22] focused on creating a GUI-based interface to enter the patient's information and determine whether or not the patient has a heart illness. The authors proposed a weighted associative classifier (WAC), different weights are assigned to different attributes according to their predicting capability. The proposed solution achieved delivered more accuracy in comparison to other Associative Classifiers that are presently in use. When applied to the dataset (UCI).

Yazdani et al [23] focused on Cardiologists were approached to check the validity of the significant feature scores and criteria that were identified for diagnosing heart disease. The authors suggested an algorithm that assesses the strength of the key elements that indicate cardiac disease. The suggested fix worked 98% of the time. Applying it to the dataset (UCI).

Yang et al [24] focused on segmentation that is effective and precise during the operation. A patch-of-interest (POI) selector and a FuseNet are combined to form the POI-FuseNet that the authors proposed. While FuseNet may utilize 2D and 3D FCN characteristics to exploit contextual information hierarchically, the POI picker can effectively choose the interested regions that include the instrument. The proposed approach outperformed state-of-the-art solutions, which had a 100% success rate with the lowest axis error, with a Dice score of 70.5%.

Danu et al [25] focused on insufficient medical imaging data training deep learning models. The authors suggested Using transfer learning techniques by reusing learned layers from the first classification challenge to increase the learning performance for the second task. The proposed solution achieved for this first task 95.83% accuracy while the other achieved 92.38% operating. By reusing the learned layers from the first classification challenge, transfer learning techniques can be used to enhance learning performance for the second task. The accuracy increased to 95.43% when applied to the DICOM dataset as a result of the knowledge transfer process.

Kusunose [26] focused on automated diagnosis is required in the field of echocardiography. The author suggested creating algorithms that could monitor heart parameters to enhance human activities including picture segmentation, measurement of cardiac structural and functional characteristics, and finding clinically meaningful insights to provide a precise diagnosis in echocardiography. The proposed solution achieved 97%. When applied to the dataset unclear.

Esfeh et al [27] focused on It has been challenging to automate reliable EF estimates in echocardiograms (echo) due to poor and variable image quality and a lack of data to train data-driven algorithms. For automatic EF assessment in echo films, the authors suggested a Bayesian learning approach. The suggested solution demonstrated unequivocally the superior performance of the Bayesian model in the clinically important lower EF population. when utilized on the dynamic echo net dataset.

Hughes et al [28] focused on highlighting the relationship between imaging characteristics and the biomarkers of vascular and systemic illness. The authors said that they created a significant correlation between some biomarkers (BNP) and echo Net-Lab and that this relationship can be used to explain why echo Net-Labs perform so well for BNP. Echo Net-Labs was able to predict anemia with an area under the curve (AUC) of 0.80 and a high BNP with an AUC of 0.82 using the Echo Net-Labs dataset from the echo net.

Liu et al [29] focused on improving the early detection of heart disease and LVEF measurement. The authors proposed developing the biplane Simpson's approach and a DL algorithm built on U-Net (DPS-Net) was used to calculate LVEF. The proposed method displayed outstanding performance in LV segmentation and LVEF measurement across phenotypes and echo systems using DPS-Net and the EchoNet-dynamic dataset, CAMUS data sets, and one clinical data set acquired from our institutions.

Alaa et al [30] focused on enabling the adaptation of pre-trained models in setups where fewer annotated data might be available for supervised training. The authors proposed to provide a uniform evaluation technique, which we refer to as the Echocardiographic Task Adaptation Benchmark (ETAB), which assesses how well an echocardiogram is represented visually. Applying the suggested method to the Echo Net-Dynamic, EchoNet-LVH, Unity, CAMUS, and TMED datasets resulted in high performance.

Hughes et al [31] focused on highlighting imaging phenotypes and systemic and cardiovascular disease biomarkers' connections. The authors suggested creating anemia elevated troponin I, blood urea nitrogen (BUN), and B-type natriuretic peptide can all be detected using the video-based deep learning system EchoNet-Labs (BNP), and values of 10 more lab tests from echocardiograms. The proposed method identified anemia (low hemoglobin) with an AUC of 80% (79%- 81%), raised BNP with 86% (85%–88%), elevated troponin I with 75% (73%-78%), and elevated BUN with 74% (72%-76%). By using the Cedars-Sinai external test dataset, EchoNet-Labs was able to detect elevated troponin levels at 75% (72%-78%) and BNP levels at 82% (0.79-0.84), as well as an AUC of 80% (77%-82%) for diagnosing anemia.

Reynaud et al [32] focused on improving the job of detecting End-Systolic (ES) and End-Diastolic (ED) frames and computing the ejection fraction of the left ventricle automatically. With the help of a transformer architecture built on a residual auto-encoder network and a BERT model modified for token classification, the authors proposed a unique method for ultrasound video interpretation. Permits the processing of videos of any duration. On movies of any duration, the suggested approach produced an average frame distance of 3.36 frames for the ES and 7.17m frames for the ED. when used on the dataset from Echonet-Dynamic.

Deepthi et al [33] focused on the prognosis of cardiac illness. The authors suggested an amalgamation of a Random Forest, Naive Bayes, and Support Vector Machine. Principle Component Analysis with firefly optimization algorithm was utilized as feature extraction. The proposed solution achieved a 99.73% accuracy rate. Applying it to the dataset (UCI).

2.4. Hybrid Techniques:

Baccouche et al [34] focused on increasing prediction performance accuracy for unbalanced datasets on heart disease. The authors proposed a new BiLSTM or BiGRU with CNN combined random and average under-sampling resampling approach. The accuracy and F1-score of the suggested model ranged from 91% to 96%. Data from the Medical Norte Hospital in Mexico, which was used to compile the dataset, contains 800 records and 141 indicators, including age, weight, blood sugar, blood pressure, and clinical complaints.

Chandra et al [35] focused on reducing the operator's reliance on screening environments and lowering subjectivity to enhance diagnosis. Signal amplification, dropout, speckles, and shadows all affect the quality of echocardiographic images. Additionally, machine settings and human operators determine the acquisition's quality. To locate leaflets in an apical four-chamber view, the authors suggested a customized Yolo3 with MobileNet as a backend. employed minimal settings for high-accuracy archiving. Papillary muscles are connected to mitral leaflets. With 30 patients and 1800 photos for training and 30 patients and 1800 images for testing, the suggested approach attained an accuracy of 98% for the tricuspid valve leaflet and 90% for the overall accuracy. when combined with information received from Ranchi's Cozy Care Hospital and the Indian state of Jharkhand. A total of 2400 images, 600 of which are used for testing and 1800 for training, are included.

Hwang et al [36] focused on centered on the differential diagnosis of left ventricular hypertrophy (LVH) on echocardiography is sometimes elusive and calls for a plethora of further tests. The authors suggest a combination of a convolutional neural network with short-term memory (CNN+LSTM) method was developed to independently categorize probabilities of HHD, HCM, and ALCA diagnoses on each image. Compared to echocardiography experts (accuracy of 80.0% and 80.6%, respectively), the suggested solution was more accurate (92.3%).

Dezaki et al [37] focused on creating and characterizing the echocardiography data's cardiac cycle phase is essential for automated systems that track numerous heart parameters. Individual variations in heart rate and the way the cardiac architecture appears make accurate classification challenging. The authors proposed integrating recurrent neural networks (RNNs) with deep residual neural networks (ResNets), which simulate the temporal connections between subsequent frames while recurrent neural networks (ResNets) extract the hierarchical characteristics from the individual echocardiogram frames In huge datasets of echocardiograms with varying degrees of pathological states, the authors offer evidence that such new architecture outperforms baseline architecture for the automatic characterization of the cardiac cycle phase. The average absolute frame detection errors for ED and ES are 3.7 and 4.1, respectively. The proposed technique had an R2 score of 0.66.

Patra [38] concentrated on fetal heart motion as a crucial diagnostic marker for the anatomical and congenital heart disease functional assessment. To evaluate movies of fetal echocardiography. The author put out a technique for combining deep convolutional and recurrent architectures that takes advantage of certain spatial and temporal characteristics of diverse anatomical substructures within a broad spatiotemporal framework. The suggested answer had a 94% accuracy rate.12 healthy individuals provided 91 routinely scheduled fetal echocardiography films. The gestational ages were between 20 and 35 weeks.

Ulloa et al [7] centered on improving clinical occurrences to forecast cardiac disease and help physicians decide the best course of action. The authors proposed a fully 3D Convolutional Neural Network (CNN) design. It substantially reduces the number of parameters a fully linked network would need to learn by making use of an image's spatial coherence. The proposed solution increased accuracy even more (AUC 85%), demonstrating that the trained neural network outperformed two skilled cardiologists at predicting death. A sizable collection of 723,754 clinically acquired echocardiographic movies (around 45 million pictures) connected to 27,028 patients' longitudinal follow-up information.

AHMED et al [39] focused on improving diagnostic heart disease. in several clinical computer-aided diagnostic methods. The authors proposed (CNN&LSTM) to use pre-trained ResNet 101 model networks as a deep features extractor to combine spatial and neutrosophic temporal descriptors to extract both deep CNN features. combined both feature types after extracting deep spatial and temporal features. Finally, we divide each echo clip into eight cardio-views using an LSTM classifier. The proposed solution achieved 96.3 ٪ accuracies in DICOM-formatted echocardiogram clips.

Dezaki et al [40] focused on end-systolic (ES) and end-diastolic (ED) frame detection in an echocardiographic cine sequence is challenging. Convolution neural networks (CNNs)-based visual feature extraction and recurrent neural networks (RNNs)-modeling the temporal dependencies between each frame in a sequence were proposed by the authors. The authors examine the performance of two CNN architectures—DenseNet and ResNet—along with four RNN architectures—long short-term memory, bi-directional LSTM, gated recurrent unit (GRU), and bi-GRU—discussed. DenseNet and GRU trained are the components of the ideal deep learning model.3,087 patient trials make up the dataset. Each study is a DICOM-formatted 2D echo AP4 view cine sequence collected from a single patient. For the ED and ES frames, the proposed approach produced frame mismatch values of 0.20 and 1.43, respectively.

Feng et al [41] focused on improving as a result of intra- and inter-frame noise, categorizing echocardiograms at the video level is difficult. The authors suggested attention to temporal aspects in a bidirectional Long Short-Term Memory (LSTM) network and Convolutional Neural Networks (CNN) for spatial features. The proposed solution achieved an accuracy of 91.18%. When used on a dataset of 170 movies that have been carefully categorized by expert cardiologists (80 normal and 90 abnormal).

Wang et al [42] centered on due to solar energy's unpredictable and inconsistent nature, integrating it into conventional energy infrastructure is incredibly challenging. The authors constructed an LSTM-Convolutional Network (LSTM+ CNN) hybrid deep learning model and used it to forecast solar power. The long-short-term memory network extracts the temporal properties of the data first, and the convolutional neural network model the data's spatial features are extracted. after that. Findings demonstrate that the hybrid prediction outperforms the model the most accurate single prediction model in terms of accuracy.

Blaivas et al [43] focused on automating the determination of left ventricular ejection percent requires sophisticated algorithms and accurate visualization and tracing of endocardial borders. For sequential image (video) analysis, the authors suggested using a Long Short-Term Memory algorithm with the VGG-16 CNN. One method for analyzing video is the LSTM network, which uses a VGG-16 (CNN) to assess each frame successively. When used to estimate LVEF from brief real-time echo video clips visually, the suggested solution DL algorithm demonstrated promise and proved to be reassuringly accurate. For EF calculation, simpler methods are employed rather than intricate DL ones. Using the EchoNet-Dynamic database as a testbed.

Table 1: the schedule shows a summary of methods, datasets, and evaluation.

Title paper	Authors and years	The methods proposed	dataset	Type used	Evaluation%
[33]	Deepthi 2014	SVM, RF, and NB	UCI	image	99.73
[22]	Soni 2011	WAC	UCI	image	_
[23]	Yazdani 2021	measures the strength of the significant features	UCI	image	98
[24]	Yang 2021	POI-FuseNet	_	image	Dice score of 70.5
[25]	Danu 2022	transfer learning techniques	DICOM	video	95.43

[26]	Kusunose 2022	assessment of heart structural and functional characteristics, picture segmentation, and the identification of clinically meaningful insights	_	image	97
[27]	Esfeh 2020	Bayesian learning framework for automated EF assessment in echo videos	EchoNet-Dynamic	video	_
[31]	Hughes 2021	substantial correlation between various biomarkers and Net-results Lab's (BNP)	EchoNet-lab	video	AUC was 0.80 for anemia prediction, 0.82 for elevated BNP prediction, 0.75 for elevated troponin prediction, and 0.69 for elevated BUN prediction
[29]	Liu 2020	establishing a U-Net-based DL algorithm (DPS-Net)	EchoNet-Dynamic and CAMUS	video	_
[30]	Alaa 2022	ETAB	EchoNet-Dynamic, EchoNet-LVH, Unity, TMED and CAMUS	video	_
[28]	Hughes	built video-based deep learning system EchoNet-Labs.	EchoNet-lab	video	AUC = 0.80 for anemia, 0.8 for identifying raised BNP, 0.75 (0.73-0.78) for elevated troponin, 0.74 for elevated BUN, and up to 0.72 for anemia
[32]	Reynaud 2021	Residual Auto-Encoder Network and a BERT	EchoNet-Dynamic	image	_
[1]	KUMARI 2021	Bi-LSTM	UCI	image	90
[11]	Vani 2021	LSTM	surrogate dataset	image	89.6
[6]	Wahlang 2021	LSTM and VAE	limited data provided upon request	image	86
[12]	Manur 2020	BiLSTM-CRF	UCI	image	90.04
[13]	Chen 2020	Att-BiLSTM	Taiwan E Hospital	image	96
[15]	DEGERL 2021	E-D CNN	HMC-QU	video	86.85
[4]	Ouyang 2020	3D(CNN)	Echo Net-Dynamic	video	MAE of 4.05 and R2 of 0.81
[19]	Muhtaseb 2022	EchoCoTr	EchoNet-Dynamic	video	MAE of 3.95 and R2 of 0.82
[17]	Chen 2021	video segmentation 3D U-Net	EchoNet-Dynamic	video	MAE of 5.8%

[14]	Mehmood 2021	CNN	UCI	image	97
[35]	Chandra 2020	Yolo3 with MobileNet	Data collected from cozy care hospital	video	90
[16]	Leclerc 2021	the most recent encoder-decoder technology CNN's	CAMUS	video	92
[44]	Patila 2021	RCNN	EchoNet-Dynamic	video	-
[21]	Dutta 2020	CNN employs the least absolute shrinkage and selection (LASSO)	NHANES	image	85.70
[8]	ALI 2019	2-DNN	UCI	image	93.33
[7]	Ulloa 2018	3D_CNN	collection of 723,754 clinically acquired echocardiographic movies	video	85
[18]	Gao 2017	CNN	China's Tsinghua University Hospital in Beijing	video	92.1
[20]	Deng 2021	Trans-Bridge, a lightweight hybrid model using the transformer and the CNN	EchoNet-Dynamic	video	Dice score of 91.4%
[34]	Baccouche 2020	BiLSTM or BiGRU and CNN	Medical Norte Hospital in Mexico	image	91
[36]	Hwang 2022	hybrid CNN-LSTM	_	video	92.3
[37]	Dezaki 2017	RNN&CNN	_	video	R2 score of 0.66.
[38]	Patra	CNN&RNN	91 regularly scheduled fetal echocardiogram films from 12 healthy participants	video	94
[39]	AHMED 2020	CNN&LSTM	_	video	96.3
[40]	Dezaki 2020	CNN&RNN	_	video	Mismatched frames for the ED and ES frames at 0.20 and 1.43
[41]	Feng 2021	CNN&LSTM	_	video	91.18
[42]	Wang 2019	LSTM&CNN	_	video	_
[43]	Blaivas 2022	CNN&LSTM	EchoNet-Dynamic	video	RMSE was 11.98 and MAE was 8.08%.

3. Conclusion

The early detection of aberrant heart diseases will help save raw healthcare data processing is what defines lives. When analyzing the raw data, (ML) machine-learning techniques were employed to provide a fresh and creative understanding of cardiac disease. In the medical field, it is challenging and essential to predict cardiac disease. The death rate can be considerably decreased, though, if the sickness early detection and prevention measures put in place soon after are practical. It is strongly advised that this study be further improved to focus instead of only using theoretical frameworks and simulations and conduct research on actual datasets [45]. better forecasting techniques. Additionally, novel feature selection methods can be developed to gain a deeper comprehension of crucial elements and boost the precision for predicting heart disease. Using cardiac ultrasound information, deep learning can improve our understanding of heart disease subgroups and automate the workflow for echocardiography. To promote participation in research using cutting-edge representation learning methods on echocardiographic data, there is a need for uniform benchmarks due to the dearth and dispersion of publicly accessible echocardiogram data sets [30].

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