2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC)

Machine Learning applied to support medical decision in Transthoracic echocardiogram exams: A Systematic Review

Vilson Soares de Siqueira*†, Diego de Castro Rodrigues*†, Colandy Nunes Dourado‡, Moisés Marcos Borges‡, Rogério Gomes Furtado‡, Higor Pereira Delfino, Diogo Stelle†, Rommel M. Barbosa†, Ronaldo Martins da Costa†
* *Federal Institute of Tocantins, IFTO, Colinas, Brazil*
{vilsonsoares, diego.castro}@ifto.edu.br
†*Federal University of Goias, UFG, Goiânia, Brazil*
delfino.higor@discente.ufg.br, {diogostelle, rommel, ronaldocosta}@inf.ufg.br
‡*Diagnostic Imaging Center, CDI, Goiânia, Brazil*
{rogerio.sbcgo, colandynunes1}@gmail.com

***Abstract*—The echocardiogram (ECHO) is an ultrasound of the heart used to diagnose heart diseases (DHC). The analysis and interpretation of ECHO are dependent on the doctor's experience. However, software that uses artificial intelligence to analyze ECHO images or videos is contributing to support the physician's decision. This paper aims to perform a Systematic Literature Review (SLR) on artificial intelligence (AI) techniques applied in the automation of Transthoracic Echocardiogram (TTE) processes, to support medical decisions. The study identified more than 800 articles on the topic in the leading scientific research platforms. To select the most relevant studies, inclusion and exclusion criteria were applied, where 45 articles were selected to compose the detailed study of the SRL. The results obtained with the extraction of information from the papers, identified 3 groups of primary studies, namely: identification of the cardiac vision plan, analysis of cardiac functions and detection of cardiac diseases. SRL identifies that the set of Machine learning (ML) techniques are being widely applied in the tasks of segmentation, detection and classification of images obtained from ECHO. The techniques based on Convolutional Neural Network (CNN), presented the best Accuracy rates. Research shows a strong interest in automating ECHO processes. However, it is still an open research field, with the potential to generate many publications for researchers.**

***Keywords*-Echocardiogram, Ecocardiography, Machine Learning, Deep Learning, Systematic Review**

I. Introduction

The Progress in the analysis of ultrasound images has always been fundamental to the advancement of research with image-oriented diagnosis, because ultrasound provides real-time image acquisitions [1]. The echocardiogram is not very invasive and does not expose the patient to radiation.

ECHO analysis depends on the physician's experience. However, artificial intelligence is efficient in the practical application of identification, quantification, and interpretation of TTE images. The use of ML models can reduce image analysis time, optimize clinical decision-making, and provide interactive feedback to train less experienced physicians [2].

Although similar works are found in the literature investigating ML [3] or Deep Learning (DL) techniques applied to medical images and cardiovascular images [4], [5]. They use survey methodology, while this article presents a SRL.

This article aims to conduct a secondary study on AI techniques applied to support medical decisions and process automation at TTE. The specific objectives are: Search in the leading scientific bases, studies of AI techniques applied to TTE; Read the articles and create a mini-abstract of each one; Group primary studies with similar objectives; Categorize the mini-abstracts; Identify the state-of-the-art when possible.

This paper is organized as follows. The SRL protocol methodologies are presented in section II. The data extraction and the grouped mini-abstracts are presented in section III; Finally, discussions and conclusions are presented in sections IV and V.

II. Materials and Methods

For Budgen et al. [6], the use of an SRL is mainly intended to provide an impartial, objective, and systematic approach to answering a research question by finding all relevant research results from primary empirical studies. An SRL is considered a secondary study. The SRL elaboration follows the guidelines described by Kitchenham et al. [7] being divided into three stages: Planning, Selection, and Critical Analysis of the results.

A. Planning

1) Initially, an exploratory analysis of the literature was performed to define the keywords and research sources. 2) A search in the main scientific base of the health field "Pubmed" using the terms: "*Echocardiogram OR Echocardiography*"; 3) A Filter with the term "*Artificial intelligence*" was added. Thus, the articles indicate a trend towards an AI sub-field "*Machine learning*"; 4) The complete search string was: ((*Echocardiogram OR Echocardiography*) AND ("*Machine learning" OR "Deep Learning*")); 5) Finally, the

978-1-7281-7303-0/20/$31.00 ©2020 IEEE
DOI 10.1109/COMPSAC48688.2020.0-215

articles were extracted from the main scientific bases: ACM (Association for Computing Machinery), IEEE (Institute of Electrical and Electronics Engineers), Science Direct, PubMed, and Web Of Science. The search was restricted to articles published in the last 5 years and written in English.

The following research questions guide SRL:

Q1) What are the best ML techniques applied to TTE to support the medical decision?
Q2) What are the GAPs for the TTE sub-problems?
Q3) What are the most used techniques?

B. Selection

For the selection of articles, the protocol was prepared according to the guidelines of Kitchenham et al. [8]. The following Inclusion (I) and Exclusion (E) criteria were defined:

I1) Articles that used AI techniques applied to TTE analysis.
I2) Articles that are complete and written in English.
E1) Articles that do not approach TTE.
E2) Articles that do not specify the AI technique used.
E3) Articles that do not perform experiments.

In figure 1, the SRL steps are presented with the results returned using the search string. With the search on the scientific bases, 854 articles were found, after reading the titles and abstracts, 675 were discarded. Then, 179 remained, and 61 repeated. Therefore, 118 were selected for complete reading and data extraction. After full-reading, 73 articles were excluded based on the exclusion criteria, and 45 articles included in the SRL. It is important to emphasize that the objective of the SRL is to analyze the articles that apply AI techniques in TTE for medical support.

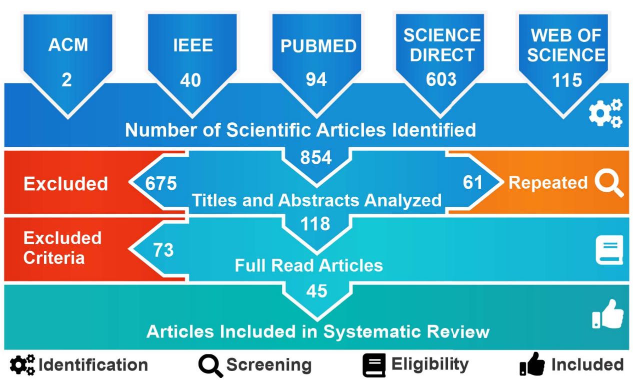

Figure 1. The Systematic Review Proces

In the III section, mini-abstracts of articles are presented, classified by type of problem. In tables I,II, and III, the types of problems are identified with a separator line.

III. Machine Learning Applied to TTE

During the initial search on the Pubmed platform, it was found that the most used AI techniques belong to the class of ML methods and algorithms. ML is a subfield of AI. Thus, we delimit the search to find articles that use ML and DL techniques. After the readings and extractions of the information, the works were categorized into groups and sub-groups, where the papers were grouped into 4 categories. Are the following: A) Cardiac vision image acquisition Plan; B) Analysis of cardiac functions; C) Detection of cardiac disease; Subgroups are presented when there is more than one different subcategory belonging to a group. The mini-abstracts are presented, ordered by techniques. Thus, providing the reader with a quick preview of each sub-problem.

A supplementary material with more information is available at: https://github.com/vilsonsoares/SRL-ML-TTE.

A. *Cardiac Vision Image acquisition plan*

For Balaji et al. [9], the automatic classification of cardiac vision is the first step to automate the analysis of the movement of the walls, the diagnosis of diseases aided by computer, the calculation of the measurement, and others.

Table I
Papers: Cardiac Vision Image acquisition plan

Id	Ref	Dim	Task	TL	Techniques	Metrics	Precision
1	[9]	2D	C	SP	SVM-BPNN	Acc	0.875
2	[10]	2D	C	SP	LC-KSVD	Acc	0.950
3	[11]	2D	C	SP	BoVW	Acc	0.900
4	[12]	2D	C	SP	CNN	Acc	0.921
5	[13]	2D	C	SP	CNN	Acc	0.917
6	[14]	2D	C	SP/SSP	GAN CNN	Acc	0.923 0.912
7	[15]	2D	C	SP/SSP	CNN	Acc	0.840
8	[16]	2D/3D	C	SP	CNN	Acc	0.983
9	[17]	3D	C	SP	HF	Acc	0.804

Legend: Reference (Ref), Dimension (Dim), Type learning (TL), two-dimensional (2D), three-dimensional (3D), Supervised (SP), Semi-Supervised (SSP), Classification Task (C), Accuracy (Acc).

Balaji et al. [9] proposed a fully automatic classification of cardiac vision on echocardiogram. The system is built based on a ML approach that featuring two resources 1) Histogram features and 2) Statistical features. Classifiers Suport Vector Machine (SVM) and Back Propagation Neural Network (BPNN) were used.

Khamis et al. [10] presented a classification algorithm that employs several stages in the spatio-temporal feature extraction approaches, with Cuboid Detector and supervised dictionary learning (LC-KSVD) to exclusively improve the automatic recognition and accuracy of Cardiac Vision Classification.

The representations proposed by Penatti et al. [11] depend on Bag-of-visual-words (BoVW), used successfully by the computer vision community in problems of visual recognition. An essential element of the proposed representations is the sampling of images with large regions, drastically reducing the execution time of the image characterization procedure. The experimental evaluation of the proposed approach compares different image descriptors to classify four cardiac vision plans.

Madani et al. [13] used CNN to create a classification model to identify the type of vision of the echocardiogram examination; in their experiment, 15 types of examination views were labeled. The accuracy of the correctness of the model was 97.3% for 12 of them, and 91.7% for 15. A specialist echocardiographer assessed the same inputs, and the accuracy was 70.2–84.0% of correct answers. In Madani et al. [14] General adversarial Network (GAN) and CNN were used for the same views, and using Ensemble managed to improve accuracy. Zhang et al [15] used CNN to automatically determine 23 types of echocardiographic image visualization. Gao et al. [12] incorporated spatial and temporal information supported by video images of cardiac movement and giving rise to two strands of the 2D CNN system. The merger of both networks is conducted through linear integration's of the vectors of the class scores obtained from each of the two networks.

[16] used CNNs to create classification models to predict up to seven different cardiac visualizations. Among the models tested, its proposed model called the Cardiac view classification (CVC) network.

Zhu et al. [17] developed a framework with ML techniques using the cardiac ultrasound guidelines to extract the standard plan to determine the appropriate usage steps for clinical 3D echocardiography exams. For this, the Hough Forest (HF) technique was used. First, used for hierarchical research and detection of 3D resource points. Second, the initial plans were determined using anatomical regularities in accordance with the guideline. Finally, it used the Regression Forest technique integrated with the plan's regularity constraints to apply each plan.

Details on the Cardiac Vision Image acquisition plan are available in the supplementary material.

B. *Analysis of Cardiac Functions*

*1) **Left Ventricular Volume and Ejection Fraction**:* According to Jafari et al. [19] the objective of the Left Ventricular Ejection Fraction (LVEF) is one of the main measures to assess the functionality of the heart, and cardiac ultrasound ECHO is a standard imaging modality used for perform the LVEF measurement.

Yuan et al. [18] developed a procedure that uses a simple application of non-negative matrix factorization (NMF). A series of frames from a single patient video. NMF Rank-2 calculates the final two members. The final limbs are shown as intimate representations of the actual morphology of the heart, in the final phase of each cardiac function. Besides, the entire temporal series can be represented as a linear combination of these two states, providing a shallow dimensional representation of the heart's time dynamics.

Jafari et al. [19] presented a mobile app to estimate LVEF. It runs in real-time on Android mobile devices that have a wired or wireless connection to a point-of-care ultrasound (POCUS) cardiac device. Your pipeline for estimating the biplane Ejection Fraction (EF) using A2C and A4C views. They used a multi-task and computationally efficient Deep Fully Convolutional Network (DFCN) for simultaneous Left Ventricular (LV) Segmentation and Detection of landmarks in these views, which is integrated into the LVEF estimation pipeline. The Article by Veni et al. [20] presents a new framework that combines the benefits of DL approaches with those of classic segmentation methods. The DFCN architecture produces LV masks in a slightly different sequence of images with the same region and visualization.

Table II
ANALYSIS OF CARDIAC FUNCTIONS

Id	Ref	Dim	Task	TL	Techniques	Metrics
10	[18]	2D	-	S	NMF	r
11	[19]	2D	SP	S	DFCN	Acc
12	[20]	2D	SP	S	DFCN	DICE
13	[21]	2D	SP	S/C	CNN	μ
14	[22]	2D	SP	S	CNN U-Net	DICE
15	[23]	2D	SP.	C	CNN U-Net	r
16	[24]	2D	SP	S	CNN U-Net	Acc
17	[25]	2D	SP	R	CNN, RNN	μ
18	[26]	2D	SP	S	PV-LVNet	α-Cronbach
19	[27]	2D	SP	S	RFC, DTC	AUC
20	[28]	2D	SP	S	RFC, DTC	AUC
21	[29]	2D	SP	S	SRF	DICE
22	[30]	2D	-	-	SR-DCL	CD_2, MI, SSD
23	[31]	2D	SP	S	Bag-10	Acc
24	[32]	2D	SP	S/C	CSM,CRP	Acc
25	[33]	3D	SP	S	Graph cut	r
26	[34]	3D	-	S	HeartModel	B–Altman
27	[35]	3D	SP	S	DFCN	R^2
28	[36]	3D	SP	S	CNN, Snake	R^2
29	[37]	3D	NSP	R	MSCDL e RF	r
30	[38]	3D	SP	S	ML-Algoritms	r, B–Altman
31	[39]	3D	SP	S	ML-Algoritms	r
32	[40]	2D	SP	C	DCNN	Acc
33	[41]	2D+T	SP	C	CNN	Acc

Legend: Not Supervised (NSP), Regression task (R), Segmentation Task (S), Segmentation and Classification task (S/C), Area Under a Curve (AUC), Similarity Measure (CD_2), Mutual Information (MI), Sum of Squared Differences (SSD), Determination coefficient (R^2), Correlation (r), Mean (μ), Sørensen–Dice coefficient (DICE), Bland–Altman (B–Altman).

Raynald et al. [21] compare two complementary approaches to segmentation and automated classification of LV position in 2D TTE sequences. The first approach is based on the Handcraft feature phases for contrast and position. The second follows the structure of CNN.

Leclerc et al. [22] performed an experiment comparing the results of the CNN U-net model with SRF to segment the epicardium and endocardium, in order to estimate the EF and Global Longitudinal Deformation (GLD) in views A2C and A4C. Leclerc et al. [23] experimented with several CNN architectures. The U-net was better in aspects of parameter numbers, performance, robustness in the evaluation of 2D echocardiographic images. The results show the specialized analysis of the volume of End Systolic (ES) and End Diastolic volumes (ED). Zyuzin et al. [24] used the CNN U-net model to segment the heart's LV using TTE images. Dezaki et al. [25] formulated the problem of locating frames of ED and ES as a regression problem. Proposed several architectures based on DL that minimize a novel global loss function. The proposed integrate the image resource extraction model based on CNN's (DenseNet and ResNet) and Recurrent Neural Network (RNN)'s (long-short term memory (LSTM), bidirectional LSTM, Gated recurrent unit (GRU), and Bi-GRU) to model temporal dependencies between each frame in a sequence. Finally, they compared the performance of these models.

Ge et al. [26] proposed a model called Paired-Views LV Network (PV-LVNet), its objective is to automatically and directly estimate the indices of various types of LV from paired TTE views A2C + A4C. Based on a newly designed Circle Network, PV-LVNet robustly locates the LV and automatically cuts the LV Region of Interest (ROI) from the A2C and A4C sequence with the location module and image resampling, and accurately estimates and consistency 7 different indexes of multiple dimensions (1D, 2D, and 3D) and views (A2C, A4C, and union of A2C + A4C) with the index module.

Bobkova et al. [28], carried out an initial work that was expanded by Bobkova et al. [27], the authors defined the LV segmentation task and reduced it to the problem of pixel classification in video frames. A pixel can belong to one of two classes (the background region or the LV region). They applied several Classic algorithms of ML. The best results came from the Random Forest (RFC) and Decision Tree (DTC) Classifiers. Leclerc et al. [29], investigated an ML solution based on the Structured Random Forest (SRF) algorithm to fully automate myocardial and LV segmentation in heterogeneous clinical data. With the competitive results achieved, the authors believe that supervised learning may be the key to the automatic segmentation of the heart.

Ouzir et al. [30], proposed a Sparse Representation and Dictionary Learning (SR-DCL) method that combines a measure of specific similarity with spatial smoothness and sparse regularizations, jointly exploring the statistical nature of the images obtained with the ModeB, the smoothness and sparse properties of cardiac movement.

Zyuzin et al. [31] use various methods of ML to identify the edges of the LV area in ultrasound images. They treated the problem as a particular case of binary pixel classification. Among them, the Bag-10 complex model demonstrated the best classification result.

Belous et al. [32] proposed the Contextual shape models (CSM) approach to automatically segment the LV, based on the Dirichlet process mixture model (DPMM) with the Chinese restaurant process (CRP), the approach classifies LV function as Normal, Abnormal and Mixed (Normal + Abnormal).

Bernier et al. [33] proposed a method for 3D segmentation for the LV composed of 4 stages. 1) A 3D sampling of the LV cavity is made based on a Bezier coordinate system. It allows distorting an incoming 3D image into a Bezier space, in which a plane corresponds to an anatomically plausible 3D Euclidean bullet shape. 3) 3D graph is constructed, and an energy term (which is based on the image gradient and a 3D probability map) is assigned to each end of the graph, some of which receives infinite energy to ensure that the resulting 3D structure passes in the main anatomical points. 3) A minimum, maximum flow cut procedure is performed on the energy graph to outline the endocardial surface. 4) The resulting surface is projected back into Euclidean space, where a convex hull algorithm for post-processing is applied to each short-axis slice to remove local concavities. In general, it obtained better results than state-of-the-art methods for the *SETUS echocardiographic dataset*.

Narang et al. [34] demonstrated a new algorithm called Philips HeartModel to perform the volumetric analysis and segmentation of the atrium and LV functions. Comparing the correlation between HeartModel, CMR, and TomTec. Time reduction to generate the volume curve from (3.6 ± 0.9) minutes to (35 ± 17) seconds.

Dong et al. [36] proposed a new fully automatic method, combining the DL model and the deformable model. To target the LV endocardium, they trained CNN to generate a binary cuboid to locate the ROI. Then, using ROI as an input, they trained a stacked Autoencoder Model to infer the initial shape of the LV. Finally, they used the Snake Model to infer the initial way to segment the LV endocardium.Dong et al. [37] proposed a method combining Multi-scale Convolutional Deep Learning (MSCDL) and Random Forest (RF) for the segmentation of the LV in 3D. Where the first method extracts the features of the unlabeled data, and the second is used for training to perform the regression with the labeled data. Dong et al. [35] proposed a new automatic method for LV segmentation, based on DFCN and the deformable model. With the method implemented the coarse-to-fine framework. 1) A new deep fusion network based on transferring learning and fusing resources, combining residual modules to achieve coarse LV segmentation on 3D echocardiography. 2) They proposed a geometric model initialization method for a deformable model based on the coarse segmentation results. 3) The deformable model was implemented to further optimize the results of the Segmentation with a regularization item, to avoid leakage between the left atrium and the LV, in order to achieve the goal of fine LV segmentation.

Volpato et al. [38] proposed a new ML approach for 3D echocardiography that allows automated determination of LV mass. The objective was to assess the accuracy of the approach, comparing it with the cardiac magnetic resonance (CMR) reference and conventional 3DE volumetric analysis.

2) ***Right Ventricular Volume and Ejection Fraction :*** Genovese et al. [39], tested the accuracy and reproducibility of a new fully automated software based on ML-based 3D quantification of the Right Ventricular (RV) size and function. The ML-based 3D algorithm provided accurate and completely reproducible measurements of RV and EF volume in 1/3 of patients, with no editing of the image limits. In the remaining patients, minimal and rapid editing resulted in reasonably accurate measurements with excellent reproducibility.

*3) **Myocardial Wall Motion**:* Kusunose et al. [40] trained several models of DCNN to detect abnormalities in the cardiac wall motion (CWM) regions. After training, they compare the results of the models with the results of specialists in cardiology. They noted that the difference in the accuracy of the assessment was relatively small.

Omar et al. [41], proposed a structure for fully automated image analysis to classify abnormalities in the myocardial wall motion (MWM) in 2D + T images. They showed that pre-processing raw videos with the asymmetric characteristics method and feeding them with CNN of temporal space achieves the best results for classifying myocardial wall motion.

C. Detection of Cardiac Disease

Table III
DETECTION OF CARDIAC DISEASE

Id	Ref	Dim	Task	TL	Techniques	Metrics
34	[15]	2D	SP	C	CNN	Acc
35	[14]	2D	SP/SSP	C	CNN, GAN	Acc
36	[42]	3D	SP	C	3D-CNN	Acc
37	[43]	2D	SP	C	PSO, SVM	Acc
38	[44]	2D	SP	C	SVM,LDA	Spe, Sen, Acc
39	[45]	2D	SP	S	DCNN	B-Altmann
40	[46]	2D	SP	D	Faster R-CNN	Acc
41	[47]	2D	SP	C	SVM Ensemble	r
42	[48]	2D/3D	SP	-	Framework	Acc, DICE
43	[49]	3D	SP	S	HeartModel, 3DQ	r
44	[50]	2D	SP	S/C	SVM	Acc
45	[51]	2D	SP	R	CNN U-Net	AUC
46	[52]	2D	SP	C	TF-IDF	C-Kappa
47	[53]	2D	SP.	R	SVM	AUC

Siglas: Cohen's Kappa (C-Kappa), Specificity (spe), Sensibility (Sen).

*1) **Hypertrophy in the Left Ventricle**:* Zhang et al. [15] used CNN to classify hypertrophic cardiomyopathy (HCM), pulmonary arterial hypertension (PAH), and cardiac amyloidosis (CAD). Silva et al. Madani et al. [14] used supervised and semi-supervised models from DL to classify LV hypertrophy (LVH) in Normal or Abnormal. For the supervised model used CNN. For the semi-supervised model used GANs. [42] presented a CNN 3D model to classify the level of abnormality of LVEF. The LVEF was represented with the following continuous values for each class, being them 1) $<45\%$, 2) $45\% \geq 55\%$, 3) $55\% \geq 75\%$, 4) $>75\%$.

*2) **Congestive heart failure**:* Raghavendra et al. [43], proposed an automated screening method to classify normal echocardiographic images and congestive heart failure (CHF) affected due to dilated cardiomyopathy (DCM), using resources extracted from the image decomposed in the variational mode. These features are selected using particle swarm optimization (PSO) and classified with SVM using different kernel functions.

*3) **Mitral Valve Disease**:* Moghaddasi and Nourian [44] used the SVM, Linear Discriminant Analysis (LDA), and Template Matching (TM) techniques to classify the severity of Mitral Regurgitation (MR) based on texture descriptors. The SVM classifier using Extensive Uniform Local Binary Pattern (ELBPU) and Extensive Volume Local Binary Pattern (EVLBP). EVLBP has the best accuracy for the detection of mild and normal MR, moderate and severe MR between echocardiography videos. Smistad et al. [45] used the model CNN proposed by Ostivik et al. [16] to create a program for real-time detection using streaming, to detect the volume and Mitral Annular Plane Systolic Excursion (MAPSE) of the heart.

*4) **Aortic Valve Disease**:* Nizar et al. [46] used a CNN method, with the Faster R-CNN Inception V2 model, to detect the aortic valve in real-time echocardiogram videos. Pereira et al. [47] proposed a structure that uses ML methods based on DL for the fully automated detection of Aortic Coarctation (CoA) from 2D ultrasound clinical data, acquired in the PLA, A4C and SSNA views. Khalil et al. [48] proposed a 2D to 3D automatic registration framework for the fusion of echocardiogram and Computed Tomography (CT) data, specifically aiming to guide trans-catheter aortic surgery (TAS). The technique simultaneously addresses the problems of time synchronization and spatial alignment, offering opportunities for new ways to display structural and functional information composed from intraoperative transthoracic echocardiography and preoperative CT data.

*5) **Atrium disease**:* Otani et al. [49] conducted a study to determine the utility of the fully automated left-chamber quantification software with 3D single-beat TTE data sets in patients with Atrial Fibrillation (AF). His comparative study proved that the automatic quantification method obtained significantly less time than the manual method to perform the analysis, requiring 5 minutes for the automatic analysis and 27 minutes for the manual. Borkar and Annadate [50] used an ROI method to extract the characteristics of the TTE frame and classify SVM to automatically detect and classify, dilated cardiomyopathy (DCM), defect atrial septal (DAS) and Normal. Lu et al [51] proposed a new regression method to identify abnormalities in echocardiogram B-Mode images. They use CNN U-Net to automatically identify Normal and Abnormal DCM cases.

*6) **Use of TTE Recommendation**:* Eisman et al. [52] created an automated method based on rules for processing "indications" listed in the TTE reports and classified them into one of the main categories of Echocardiography Appropriate Use Criteria (EAUC). It was developed and validated based on a reference standard noted by the physician. The method used was Term Frequency – Inverse Document Frequency

(TF-IDF) widely used in Natural Language Processor (NLP) and RF.

*7) **Cardiac resynchronization Therapy**:* Lei et al. [53] sought to discover new analytical approaches to improve the prediction of responses of Cardiac Resynchronization Therapy (CRT) in the pre-implantation of pacemaker devices in patients for the first time. The approach used the Three ML algorithms (SVM, KNN, Random Subspaces) in a total of 38 resource combinations. They understood that the resources combined with Regularization Duration on QRS ECG (QRSd)/ Relative wall Thickness (RWT) regularly outperform the combinations without it. For each of the three algorithms, the combination of triple features of QRSd/RWT, Blockade of the left bundle of His bundle (LBBB), and non-ischemic cardiomyopathy has repeatedly increased the classification rate by more than 8%. The best result was the SVM model.

IV. Discussion

The echocardiogram analysis is dependent on the medical experience. According to Sengupta and Adjeroh [54], the recent interest in using artificial intelligence techniques, such as ML, may offer a solution to reduce the doctor's workload, including repetitive and tedious tasks involved in the diagnosis and analysis of patient data and images.

Studies indicate that the efforts of the research community have advanced a lot concerning the automation of ECHO processes. The DL techniques combined with the increase in computational power in recent years have contributed significantly to increase the accuracy of the results of computer vision problems. They are capable of processing large amounts of images. Although there are notable developments, there is still a need to deepen the studies, to avoid results with overfitting of the model, to reduce the computational time to enable real-time evaluation, among others.

A. Answers to Research Questions

To answer the research questions, the data were extracted from the articles and shown in the tables I, II and III.

"Q1 - What are the best ML techniques applied to TTE to support the medical decision?", in the analysis of the articles, it was identified that the models based on CNN were used in 42.2% of the studies and some present accuracy greater than 95% to identify the cardiac vision and to estimate ES and ED volume and LVEF. The results are satisfactory for practical application. The application of CNN-based models have excellent precision for detection, segmentation, and classification of ECHO images.

In **"Q2 - What are the GAPs for the TTE subproblems?"**, SRL highlights the following GAPs: optimizing ECHO analysis time, reducing model complexity, improving accuracy, a model that is able to evaluate all ECHO processes, models capable of detecting a greater number of cardiac diseases, application of Reinforcement Learning techniques, and dataset public for detecting cardiac disease. It is noted that the automation of ECHO analysis has great potential for further research.

In **"Q3 - What are the most used techniques?"**, the most used techniques are SVM, Random Forest and CNN based models.

B. Analysis of results

The information extracted from the 45 articles of SRL, identified that the plan of acquisition of Image of Cardiac Vision contains 20% articles. Different approaches and problem complexity were presented. The article by Zhang et al. [15] addressed the classification of 23 types of views, with 84% accuracy; In the work of Madani et al. [13], 15 types of visualization with an accuracy of 91.7% were classified. Ostvik et al. [16] obtained an accuracy of 98.3% in the classification of 7 types of visualization. It is essential to highlight that all used CNN models for classification.

In addition to identifying the Cardiac Vision Image acquisition plan, the work of Madani et al. [14] classifies LVH and Ostvik et al. [16] proposed the detection of MAPSE.

The subsection Analyses of Cardiac functions have 51.11% of the articles of the SRL. The automation of left ventricular segmentation, detection of myocardial walls motion to estimate LV volume and ejection fraction, can reduce the physician's work with manual routines. Thus, he can serve more patients. In the opinion of Kuronose et al. [40], echocardiographic assessment in artificial intelligence may not be necessary for specialists; however, a quantitative assessment is an advantage of artificial intelligence. For Dong et al. [37] estimation of LV volumes from 3D echocardiography - (3DE) is a simplified clinical approach in the accurate assessment of LV function for the diagnosis of heart disease. On the other hand, Genovese et al. [39] emphasizes that 3DE allows accurate and reproducible measurements of RV size and function. However, the implementation of 3DE in routine clinical practice is limited because existing software packages are relatively time-consuming and require skills. In the same direction, Volpato et al. [38] points out that, although 3DE circumvents many limitations of 2D echocardiography, allowing direct measurements of LV mass. It is rarely used in clinical practice due to lengthy analyzes. Based on the results, it is observed that there are strong indications that the challenges for the automated analysis of the echocardiogram are related to the creation of optimized models capable of providing analyzes, usability, and precision in real-time.

Detection of Cardiac Disease represent 28.89% of the articles. Cardiovascular disease is one of the most unrestrained causes of death worldwide and was considered to be one of the main diseases in the "Middle Ages" and the "Advanced Age" [55]. The following studies were identified that address the tasks of classification of heart diseases: Hypertrophy in the Left Ventricle [14], [15], [42]; Congestive

Heart Failure [43]; Mitral Regurgitation [44]; MAPSE [45]; dilated cardiomyopathy [51]; Atrial fibrillation [49]. The articles performed detection tasks for the aortic valve [46]; Coarctation of the aorta (CoA) [47]; Transcatheter Aortic surgery [48], Cardiac resynchronization Therapy [53].

Only 2 public datasets were cited in the work of this SRL, CETUS (Challenge on Endocardial Three-dimensional Ultrasound Segmentation) [33] and CAMUS (Cardiac Acquisitions for Multi-structure Ultrasound Segmentation) [23]. Both have the purpose of segmenting the LV and estimating the ES and ED volume and EF.

V. Conclusion

The purpose of this SRL was to conduct a thorough analysis of the research advances related to the use of ML techniques applied to the TTE, to group the tasks, and to know the state-of-the-art.

DL methods may be the key to a successful automatization of the echocardiogram processes. The results presented in this SRL show that in the last 5 years, there have been significant advances in TTE. In I) identification of the plans of cardiac vision; II) Identification, segmentation and quantification of cardiac functions; and III) Classification of heart disease. The results show that the accuracy needs to be improved.

Therefore, it is possible to conclude that the researches on this topic still demand optimized software that can be used in real-time. It is noteworthy that the field is open and may have many research opportunities. Thus, it deserves the attention of researchers, so that research leads to the continuous improvement of the quality of the exam, thus providing better results for patients and doctors.

Acknowledgment

This work was supported by Federal Institute of Tocantins.

References

[1] J. A. Noble, "Reflections on ultrasound image analysis," 2016.

[2] M. Alsharqi, R. Upton, A. Mumith, and P. Leeson, "Artificial intelligence: a new clinical support tool for stress echocardiography," 2018.

[3] S. J. Al'Aref, K. Anchouche, G. Singh, P. J. Slomka, K. K. Kolli, A. Kumar, M. Pandey, G. Maliakal, A. R. van Rosendael, A. N. Beecy *et al.*, "Clinical applications of machine learning in cardiovascular disease and its relevance to cardiac imaging," *European heart journal*, vol. 40, no. 24, pp. 1975–1986, 2018.

[4] S. Liu, Y. Wang, X. Yang, B. Lei, L. Liu, S. X. Li, D. Ni, and T. Wang, "Deep learning in medical ultrasound analysis: a review," *Engineering*, 2019.

[5] G. Litjens, F. Ciompi, J. M. Wolterink, B. D. de Vos, T. Leiner, J. Teuwen, and I. Išgum, "State-of-the-art deep learning in cardiovascular image analysis," *JACC: Cardiovascular Imaging*, vol. 12, no. 8, pp. 1549–1565, 2019.

[6] D. Budgen, M. Turner, P. Brereton, and B. A. Kitchenham, "Using mapping studies in software engineering." in *PPIG*, vol. 8, 2008, pp. 195–204.

[7] B. Kitchenham and S. Charters, "Guidelines for performing systematic literature reviews in software engineering," *UK EBSE-2007-12007*, 2007.

[8] B. Kitchenham, "Procedures for performing systematic reviews," *Keele, UK, Keele University*, vol. 33, no. 2004, pp. 1–26, 2004.

[9] G. Balaji, T. Subashini, and N. Chidambaram, "Automatic classification of cardiac views in echocardiogram using histogram and statistical features," *Procedia Computer Science*, vol. 46, pp. 1569–1576, 2015.

[10] H. Khamis, G. Zurakhov, V. Azar, A. Raz, Z. Friedman, and D. Adam, "Automatic apical view classification of echocardiograms using a discriminative learning dictionary," *Medical image analysis*, vol. 36, pp. 15–21, 2017.

[11] O. A. Penatti, R. d. O. Werneck, W. R. de Almeida, B. V. Stein, D. V. Pazinato, P. R. M. Júnior, R. d. S. Torres, and A. Rocha, "Mid-level image representations for real-time heart view plane classification of echocardiograms," *Computers in biology and medicine*, vol. 66, pp. 66–81, 2015.

[12] X. Gao, W. Li, M. Loomes, and L. Wang, "A fused deep learning architecture for viewpoint classification of echocardiography," *Information Fusion*, vol. 36, pp. 103–113, 2017.

[13] A. Madani, R. Arnaout, M. Mofrad, and R. Arnaout, "Fast and accurate view classification of echocardiograms using deep learning," *NPJ digital medicine*, vol. 1, no. 1, p. 6, 2018.

[14] A. Madani, J. R. Ong, A. Tibrewal, and M. R. Mofrad, "Deep echocardiography: data-efficient supervised and semi-supervised deep learning towards automated diagnosis of cardiac disease," *npj Digital Medicine*, vol. 1, no. 1, p. 59, 2018.

[15] J. Zhang, S. Gajjala, P. Agrawal, G. H. Tison, L. A. Hallock, L. Beussink-Nelson, M. H. Lassen, E. Fan, M. A. Aras, C. Jordan *et al.*, "Fully automated echocardiogram interpretation in clinical practice: feasibility and diagnostic accuracy," *Circulation*, vol. 138, no. 16, pp. 1623–1635, 2018.

[16] A. Østvik, E. Smistad, S. A. Aase, B. O. Haugen, and L. Lovstakken, "Real-time standard view classification in transthoracic echocardiography using convolutional neural networks," *Ultrasound in medicine & biology*, vol. 45, no. 2, pp. 374–384, 2019.

[17] P. Zhu and Z. Li, "Guideline-based learning for standard plane extraction in 3-d echocardiography," *Journal of Medical Imaging*, vol. 5, no. 4, p. 044503, 2018.

[18] B. Yuan, S. R. Chitturi, G. Iyer, N. Li, X. Xu, R. Zhan, R. Llerena, J. T. Yen, and A. L. Bertozzi, "Machine learning for cardiac ultrasound time series data," in *Medical Imaging 2017: Biomedical Applications in Molecular, Structural, and Functional Imaging*, vol. 10137. International Society for Optics and Photonics, 2017, p. 101372D.

[19] M. H. Jafari, H. Girgis, N. Van Woudenberg, Z. Liao, R. Rohling, K. Gin, P. Abolmaesumi, and T. Tsang, "Automatic biplane left ventricular ejection fraction estimation with mobile point-of-care ultrasound using multi-task learning and adversarial training," *International journal of computer assisted radiology and surgery*, vol. 14, no. 6, pp. 1027–1037, 2019.

[20] G. Veni, M. Moradi, H. Bulu, G. Narayan, and T. Syeda-Mahmood, "Echocardiography segmentation based on a shape-guided deformable model driven by a fully convolutional network prior," in *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*. IEEE, 2018, pp. 898–902.

[21] C. Raynaud, H. Langet, M. S. Amzulescu, E. Saloux, H. Bertrand, P. Allain, and P. Piro, "Handcrafted features vs convnets in 2d echocardiographic images," in *2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)*. IEEE, 2017, pp. 1116–1119.

[22] S. Leclerc, E. Smistad, T. Grenier, C. Lartizien, A. Ostvik, F. Espinosa, P.-M. Jodoin, L. Lovstakken, and O. Bernard, "Deep learning applied to multi-structure segmentation in 2d echocardiography: a preliminary investigation of the required database size," in *2018 IEEE International Ultrasonics Symposium (IUS)*. IEEE, 2018, pp. 1–4.

[23] S. Leclerc, E. Smistad, J. Pedrosa, A. Østvik, F. Cervenansky, F. Espinosa, T. Espeland, E. A. R. Berg, P.-M. Jodoin, T. Grenier *et al.*, "Deep learning for segmentation using an open large-scale dataset in 2d echocardiography," *IEEE transactions on medical imaging*, 2019.

[24] V. Zyuzin, P. Sergey, A. Mukhtarov, T. Chumarnaya, O. Solovyova, A. Bobkova, and V. Myasnikov, "Identification of the left ventricle endocardial border on two-dimensional ultrasound images using the convolutional neural network unet," in *2018 Ural Symposium on Biomedical Engineering, Radioelectronics and Information Technology (USBEREIT)*. IEEE, 2018, pp. 76–78.

[25] F. T. Dezaki, Z. Liao, C. Luong, H. Girgis, N. Dhungel, A. H. Abdi, D. Behnami, K. Gin, R. Rohling, P. Abolmaesumi *et al.*, "Cardiac phase detection in echocardiograms with densely gated recurrent neural networks and global extrema loss," *IEEE transactions on medical imaging*, 2018.

[26] R. Ge, G. Yang, Y. Chen, L. Luo, C. Feng, H. Zhang, and S. Li, "Pv-lvnet: Direct left ventricle multitype indices estimation from 2d echocardiograms of paired apical views with deep neural networks," *Medical image analysis*, vol. 58, p. 101554, 2019.

[27] A. Bobkova, V. Zyuzin, S. Porshnev, and V. Bobkov, "Experience of using of machine learning methods to identify the left ventricle region in echocardiographic records," in *2016 IEEE 10th International Conference on Application of Information and Communication Technologies (AICT)*. IEEE, 2016, pp. 1–5.

[28] V. Bobkov, A. Bobkova, S. Porshnev, and V. Zuzin, "The application of ensemble learning for delineation of the left ventricle on echocardiographic records," in *2016 Dynamics of Systems, Mechanisms and Machines (Dynamics)*. IEEE, 2016, pp. 1–5.

[29] S. Leclerc, T. Grenier, F. Espinosa, and O. Bernard, "A fully automatic and multi-structural segmentation of the left ventricle and the myocardium on highly heterogeneous 2d echocardiographic data," in *2017 IEEE International Ultrasonics Symposium (IUS)*. IEEE, 2017, pp. 1–4.

[30] N. Ouzir, A. Basarab, H. Liebgott, B. Harbaoui, and J.-Y. Tourneret, "Motion estimation in echocardiography using sparse representation and dictionary learning," *IEEE Transactions on Image Processing*, vol. 27, no. 1, pp. 64–77, 2017.

[31] V. Zyuzin, A. Bobkova, S. Porshnev, A. Mukhtarov, and V. Bobkov, "The application of decision trees algorithm for selecting the area of the left ventricle on echocardiographic images," in *First International Workshop on Pattern Recognition*, vol. 10011. International Society for Optics and Photonics, 2016, p. 100110I.

[32] G. Belous, A. Busch, D. Rowlands, and Y. Gao, "Segmentation of the left ventricle in echocardiography using contextual shape model," in *2016 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*. IEEE, 2016, pp. 1–7.

[33] M. Bernier, P.-M. Jodoin, O. Humbert, and A. Lalande, "Graph cut-based method for segmenting the left ventricle from mri or echocardiographic images," *Computerized Medical Imaging and Graphics*, vol. 58, pp. 1–12, 2017.

[34] A. Narang, V. Mor-Avi, A. Prado, V. Volpato, D. Prater, G. Tamborini, L. Fusini, M. Pepi, N. Goyal, K. Addetia *et al.*, "Machine learning based automated dynamic quantification of left heart chamber volumes," *European Heart Journal-Cardiovascular Imaging*, vol. 20, no. 5, pp. 541–549, 2018.

[35] S. Dong, G. Luo, K. Wang, S. Cao, Q. Li, and H. Zhang, "A combined fully convolutional networks and deformable model for automatic left ventricle segmentation based on 3d echocardiography," *BioMed research international*, vol. 2018, 2018.

[36] S. Dong, G. Luo, G. Sun, K. Wang, and H. Zhang, "A left ventricular segmentation method on 3d echocardiography using deep learning and snake," in *2016 Computing in Cardiology Conference (CinC)*. IEEE, 2016, pp. 473–476.

[37] S. Dong and other, "A combined multi-scale deep learning and random forests approach for direct left ventricular volumes estimation in 3d echocardiography," in *2016 Computing In Cardiology Conference (Cinc)*. IEEE, 2016, pp. 889–892.

[38] V. Volpato, V. Mor-Avi, A. Narang, D. Prater, A. Gonçalves, G. Tamborini, L. Fusini, M. Pepi, A. R. Patel, and R. M. Lang, "Automated, machine learning-based, 3d echocardiographic quantification of left ventricular mass," *Echocardiography*, vol. 36, no. 2, pp. 312–319, 2019.

[39] D. Genovese, N. Rashedi, L. Weinert, A. Narang, K. Addetia, A. R. Patel, D. Prater, A. Gonçalves, V. Mor-Avi, and R. M. Lang, "Machine learning–based three-dimensional echocardiographic quantification of right ventricular size and function: Validation against cardiac magnetic resonance," *Journal of the American Society of Echocardiography*, 2019.

[40] K. Kusunose, T. Abe, A. Haga, D. Fukuda, H. Yamada, M. Harada, and M. Sata, "A deep learning approach for assessment of regional wall motion abnormality from echocardiographic images," *JACC: Cardiovascular Imaging*, 2019.

[41] H. A. Omar, A. Patra, J. S. Domingos, P. Leeson, and A. J. Noblel, "Automated myocardial wall motion classification using handcrafted features vs a deep cnn-based mapping," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 3140–3143.

[42] J. F. Silva, J. M. Silva, A. Guerra, S. Matos, and C. Costa, "Ejection fraction classification in transthoracic echocardiography using a deep learning approach," in *2018 IEEE 31st International Symposium on Computer-Based Medical Systems (CBMS)*. IEEE, 2018, pp. 123–128.

[43] U. Raghavendra, U. R. Acharya, A. Gudigar, R. Shetty, N. Krishnananda, U. Pai, J. Samanth, and C. Nayak, "Automated screening of congestive heart failure using variational mode decomposition and texture features extracted from ultrasound images," *Neural Computing and Applications*, vol. 28, no. 10, pp. 2869–2878, 2017.

[44] H. Moghaddasi and S. Nourian, "Automatic assessment of mitral regurgitation severity based on extensive textural features on 2d echocardiography videos," *Computers in biology and medicine*, vol. 73, pp. 47–55, 2016.

[45] E. Smistad, A. Østvik, I. M. Salte, S. Leclerc, O. Bernard, and L. Lovstakken, "Fully automatic real-time ejection fraction and mapse measurements in 2d echocardiography using deep neural networks," in *2018 IEEE International Ultrasonics Symposium (IUS)*. IEEE, 2018, pp. 1–4.

[46] M. H. bin Ahmad Nizar, C. K. Chan, A. K. M. Yusof, A. Khalil, and K. W. Lai, "Detection of aortic valve from echocardiography in real-time using convolutional neural network," in *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*. IEEE, 2018, pp. 91–95.

[47] F. Pereira, A. Bueno, A. Rodriguez, D. Perrin, G. Marx, M. Cardinale, I. Salgo, and P. del Nido, "Automated detection of coarctation of aorta in neonates from two-dimensional echocardiograms," *Journal of Medical Imaging*, vol. 4, no. 1, p. 014502, 2017.

[48] A. Khalil, A. Faisal, K. W. Lai, S. C. Ng, and Y. M. Liew, "2d to 3d fusion of echocardiography and cardiac ct for tavr and tavi image guidance," *Medical & biological engineering & computing*, vol. 55, no. 8, pp. 1317–1326, 2017.

[49] K. Otani, A. Nakazono, I. S. Salgo, R. M. Lang, and M. Takeuchi, "Three-dimensional echocardiographic assessment of left heart chamber size and function with fully automated quantification software in patients with atrial fibrillation," *Journal of the American Society of Echocardiography*, vol. 29, no. 10, pp. 955–965, 2016.

[50] S. Borkar and M. Annadate, "Supervised machine learning algorithm for detection of cardiac disorders," in *2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)*. IEEE, 2018, pp. 1–4.

[51] A. Lu, E. Dehghan, G. Veni, M. Moradi, and T. Syeda-Mahmood, "Detecting anomalies from echocardiography using multi-view regression of clinical measurements," in *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*. IEEE, 2018, pp. 1504–1508.

[52] A. S. Eisman, R. B. Weiner, E. S. Chen, P. C. Stey, R. K. Wadhera, A. P. Kithcart, and I. N. Sarkar, "An automated system for categorizing transthoracic echocardiography indications according to the echocardiography appropriate use criteria," in *AMIA Annual Symposium Proceedings*, vol. 2017. American Medical Informatics Association, 2017, p. 670.

[53] J. Lei, Y. G. Wang, L. Bhatta, J. Ahmed, D. Fan, J. Wang, and K. Liu, "Ventricular geometry–regularized qrsd predicts cardiac resynchronization therapy response: machine learning from crosstalk between electrocardiography and echocardiography," *The international journal of cardiovascular imaging*, pp. 1–9, 2019.

[54] J. D'hooge and A. G. Fraser, "Learning about machine learning to create a self-driving echocardiographic laboratory: Technical considerations," 2018.

[55] Z. Arabasadi, R. Alizadehsani, M. Roshanzamir, H. Moosaei, and A. A. Yarifard, "Computer aided decision making for heart disease detection using hybrid neural network-genetic algorithm," *Computer methods and programs in biomedicine*, vol. 141, pp. 19–26, 2017.