A review of approaches investigated for right ventricular segmentation using short-axis cardiac MRI

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Abstract
The right ventricular assessment is crucial to heart disease diagnosis. Unfortunately, its segmentation is quite challenging due to its intricate shape, ill-defined thin edges, large variability among patients, and pathologies. Besides, it is a very laborious and time-consuming task to be done manually. Therefore, automated segmentation techniques are very suitable to reduce the strain on the expert. Here, it is attempted to review the taxonomy of the current RV segmentation approaches adopted to handle the afore-mentioned issues. Enhanced by our expert’s interpretation, the results of over forty research papers were evaluated based on several metrics such as the dice metric and the Hausdorff distance. Synthetic tables and charts were also used to discuss the reviewed approaches. The following study shows that none of the existing methods has proved accurate enough to meet all the RV challenging issues. Many misestimated results were reported for several cases. Eventually, global guidance is outlined, which supports combining different methods to enhance the expected results during the MRI short-axis slice processing.

1 INTRODUCTION

The human heart transports oxygenated blood to the whole body. Four chambers are distinguished; the right ventricle (RV) is the second-largest cavity located in the heart’s lower end. The RV plays a vital role in the pulmonary circulation [1, 2]. The increasing recognition of the RV importance for pathological diagnoses, such as right heart failure, pulmonary hypertension, and congenital heart diseases, has led to a resurgent-in-interest to assess its function [3]. The RV has a unique crescent shape in the transversal plane and a triangular shape in the coronal plane [4]. Compared to the left ventricle (LV), the RV wall is significantly thin [5]. Figure 1 shows a unique RV shape design that shows different planes of a typical case.

Different imaging modalities are utilised for the RV exploration, such as Echocardiography, chest X-ray (CXR), computed tomography (CT), and magnetic resonance imaging (MRI). A significant advantage of MRI is its ability to provide tissue characterisation. MRI also has an efficient spatial resolution, which is essential to evaluate small-sized structures. cardiac-MRI (CMRI) is considered as the golden standard for the right heart assessment [6, 7], which is evaluated only to a limited extent in other imaging modalities [8]. The heart cine short-axis view is the perpendicular plane of the four-chamber plane (see Figure 1). This plane gives an excellent cross-sectional view of both ventricles. In full-size images, ventricles cover a relatively small area; thus, the processing is usually limited to a smaller Region of Interest (ROI) [9].

In clinical practice, RV segmentation is still performed manually by radiologists. According to the expert’s indications, many MRI views are used to guide the manual delineation. The following sum up the manual segmentation steps (see Figure 2):

- **Step 1**: End Systole (ES) and End Diastole (ED) selection:
  - To define cardiac phases, the radiologist refers to the middle...
The RV segmentation is essential to allow diagnosis. However, many difficulties hinder its accuracy because of the ill-defined cavity trabeculations and the irregular half-moon format. Among patients, a significant variation is noticed as presented in Figure 3(a). Besides, the morphological changes among pathologies represent another issue, as shown in Figure 3(b) [10–13]. Likewise, throughout the cardiac cycle, the ventricular shape is altered from base to apex, especially in the ES phase since the chambers are significantly narrowed at the base and apex sideline slices as illustrated in Figure 3(c–d) [14]. Breathing movement artefacts caused by the patient's unstable situation influence the resulting MRI exam quality. Consequently, the MRI images' fuzziness and low contrast intensity make it difficult to differentiate whether a pixel belongs to the RV hollow or not. The considered manual segmentation methodology is a tedious, laborious, and time-consuming task to handle many different images from several patients. Accordingly, semi and fully-automatic methods are very suitable for more accurate segmentation results but challenged by the RV issues, as mentioned above. Many researchers have tackled the RV segmentation by investigating several techniques. In the current paper, we review the most recent RV segmentation methods. This paper is intended for researchers in cardiac segmentation and image processing, interested in seeing how different segmentation techniques handle the RV challenging issues.

This paper's remainder is structured as follows: Section 2 introduces an overview of medical image segmentation approaches followed by a presentation of several metrics used to evaluate segmentation methods in Section 3. Section 4 reviews the existing approaches investigated for RV segmentation. Besides, a comparative global discussion is presented in Section 5. In Section 6, we summarise general
recommendations for the RV segmentation. Section 7 provides a conclusion.

2 | OVERVIEW OF MEDICAL SEGMENTATION METHODS

In this section, we introduce the most widely used segmentation techniques. Many reviews have discussed several segmentation algorithms exploited in various fields. In [15], three generations were distinguished from categorising segmentation methods. Moreover, in [16, 17], many medical image segmentation methods are analysed, listing the advantages and drawbacks of each one. A discussion of these methods feasibility for biomedical uses was also presented [18]. Based on the above-cited reviews, we deduce a global classification for the widely exploited algorithms considering three generations, as shown in Table 1. Previous works investigating ventricular delineation have focused on the LV, or bi-ventricular segmentations [9, 19].

3 | EVALUATION METRICS FOR SEGMENTATION METHODS

To ensure a straightforward reading of our review, we define, in this section, the frequently utilised metrics to evaluate several segmentation methods. The Dice Metric (DM) is one of the most commonly considered metrics for validation. The DM is
computed according to Equation (1), where \( U \) and \( V \) denote the two contours obtained by the expert and the method, respectively [20].

\[
\text{DM} (U, V) = \frac{|U \cap V|}{|U| + |V|} \tag{1}
\]

The Hausdorff distance (HD) is also among the widely used metrics for evaluation. The HD measures the distance between both contours based on Equation (2), where the Euclidean distance is denoted as \( d \), \( A \) and \( B \) signify both the automated and the ground truth contours [20].

\[
\text{HD} (a, b) = \max \left( \min_{a \in A} d(a, b), \min_{b \in B} d(a, b) \right) \tag{2}
\]

As shown in Equation (3), the Jaccard index (JAC) is defined as the intersection between ground truth and automated segmentations divided by their union to measure similarities between sets [21].

\[
\text{JAC} (U, V) = \frac{|U \cap V|}{|U \cup V|} \tag{3}
\]

Based on the overlap basic cardinalities, that is, True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), further statistical measures are determined to assess the segmentation performance. Therefore, the accuracy, the sensitivity, the precision, and the specificity are measured as it is described, respectively, in Equations (4–7) [21].

\[
\begin{align*}
\text{Accuracy} & = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{4} \\
\text{Sensitivity} & = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5} \\
\text{Precision} & = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{6} \\
\text{Specificity} & = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{7}
\end{align*}
\]

However, these four last measures are not widely used as metrics for assessing medical image segmentation because of their sensitivity to segment size, that is, they penalise errors more in small segments than in large segments. Moreover, an effective solution to overcome the problem of class imbalance comes from the Matthews Correlation Coefficient (MCC), which is calculated according to Equation (8) [22].

\[
\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FP}) (\text{TP} + \text{FN}) (\text{TN} + \text{FP}) (\text{TN} + \text{FN})}} \tag{8}
\]

In particular, due to the specificity of the exploited datasets among investigations, the DM and the HD metrics are the two most used measurement by researchers to evaluate their results compared to the existing achievements. In the remaining of this paper, we will only consider the DM and the HD to report and discuss the effectiveness of several RV segmentation approaches. Likewise, to maintain the cardiac segmentation scope various functional parameters are also used for evaluation such as the ejection fraction (EF), the end-systole volume (ESV), the end-diastole volume (EDV), the ventricular mass (VM), and the surface (VS).

### 4 | REVIEW OF RV SEGMENTATION APPROACHES

In this section, several approaches elaborated for RV segmentation are reviewed. According to the segmentation methods classified in Section 2, the first-generation methods are not qualified to be used as a single RV segmentation technique due to their inefficiency to overcome the RV challenging issues unless combined with other methods. Thus, the existing investigated approaches reviewed in our paper are included mostly within the second and the third generation. Accordingly, the following sub-sections review RV segmentation approaches considering several categories. For each one, we start by giving a brief theoretical introduction to methods. Afterwards, a detailed overview is given for each considered paper, its methodology, the data set used, as well as the evaluation techniques adopted to rate the segmentation procedure effectiveness. Eventually, an overall discussion is provided and enhanced laterally with the
Deformable methods allow boundaries delineation using a closed curve located near the aimed boundary [23, 19]. Under the influence of external and internal forces, the initial curve deforms towards the contour [24]. There exist two most used deformable techniques, either parametric or geometrical based models. Parametric models, or snakes, are based on moving user initialized curvature predefined as \( C(s) = x(s), y(s) \) where \( s \in (0,1) \) [24]. As the totality of three energy, parametric curve energy \( E_{\text{snake}} \) is defined as shown in Equation (9) in which, \( E_{\text{internal}} \) and \( E_{\text{external}} \) are respectively the energy corresponding to internal and external forces, and \( E_{\text{constraint}} \) is the constraint-based energy [25]. To overcome some topological variations and stable merging issues, geometric models deform curves implicitly as a specific function level. Many medical-intended investigations are based on several deformable models, such as 2D active contours (AC), Gradient Vector Flow (GVF), Geometric Active Contour “GAC”, level sets [24].

\[
E_{\text{snake}} = E_{\text{internal}} + E_{\text{external}} + E_{\text{constraint}} \quad (9)
\]

One of the earliest proposed approaches for RV segmentation was based on a deformable medial model [26]. Sun et al. considered both ventricles exploiting an explicit thickness representation. To segment cardiac chambers, the medial model is aligned to six manually initialised landmarks in the basal and apical slices and deformed using local search and Bayesian deformation. A dataset containing 40 patients were used and evaluated based on the error between the automatic and manual segmentations. They considered, thus, three pathological cases: myocardial infarction, dilated cardiomyopathy, and hypertrophy. The highest reported error is related to the RV dilated cardiomyopathy case. Besides, the sensitivity to landmark-based initialisation shows that this method is most sensitive in the RV case, especially when the image is noisy. According to our expert, the automated segmentation is under-estimated at the basal and apical levels specifically.

Integrating time-dependent constraints into the energy function of the classical GVF, Yang et al. proposed a \( 2D+\delta \)\ AC model [27]. Based on the “\( \delta \)” model defined in Equation (10), the temporal information for a frame at time \( t \) was defined between adjacent frames; “the previous \( K \) frames at time \( t - i \), the next \( K \) frames at time \( t + i \), where \( K \) is an integer parameter denoting the time offset between the frames”.

\[
dt = \sum_{j=1}^{K} I_j + i(x, y) - I_j - i(x, y) \quad (10)
\]

Yang et al. used no metrics to evaluate their approach. However, they performed segmentation using both classical and temporal GVF (GVF-T). The RV Segmentation Challenge (RVSC) dataset was considered to evaluate this approach [28]. Since the RV has thin contours, its boundaries delineation cannot indeed be achieved. Thus, the additional edge forces benefit from the temporal model supposed to enhance the RV segmentation according to the presented results at the central heart frames. However, this technique is not assumed to add sufficient information for the whole shot-axis sequence, especially with the presence of papillary muscles, and the wild morphological deformation. In this approach, the influence of several pathologies and the basal to apical slices was not discussed.

Level set methods are also among the essential effective segmentation techniques investigated to deal with curvature evolution difficulties [29]. To allow bi-ventricular segmentation, Liu et al. proposed a Distance Regularized Two-Layer Level Set (DR2LS) based approach [30]. They apply the Distance Regularized Level Set Evolution (DRLSE) as a first step to obtain an initial segmentation. Henceforward, to refine the endocardial contour and to obtain the epicardial contour simultaneously, the anatomical knowledge was integrated with the two-layer level set to achieve final segmentation. This approach was evaluated using datasets of two challenges: the MICCAI 2009 LV Segmentation Challenge (LVSC) [31] and the MICCAI 2012 RVSC [28]. This method lays on the heart anatomical geometry, which was supposed to overcome the difficulty caused by low contrast between the cardiac muscle (myocardium) and adjacent tissues. In this experiment, they considered only visual results, in which there was some under-segmentation. The authors discussed none of the pathological or the basal and apical impact on the segmentation.

Liu et al. also proposed a topology preserved level-set method extending the DRLSE model to a two-level-set [32]. This approach is initialised by performing DRLSE as a preliminary segmentation to locate the endocardial contours. Then, this segmentation is used to initialise the level set as a second step. To evaluate their approach, Liu et al. used the datasets provided by the MICCAI 2009 LVSC [31] and the MICCAI 2012 RVSC [28]. Based on the DM, and HD evaluation metrics, the results of each dataset was reported separately. The presented results show under and over-estimated segmentations at the most basal and apical levels. Moreover, the impact of pathological cases was not discussed. The proposed method was less effective for the systolic phase compared to the diastolic phase.

A Preserved Topology Level Set-based method (PTLS) was also proposed by Arrieta et al. [33] for bi-ventricular segmentation. Few iterations were performed over the dataset, to calibrate the algorithm parameters, and then fixed for all data. This approach is initialised manually by a circle in each ventricular. Then, the boundary delineation was obtained using the AC method. Arrieta et al. considered a dataset of six volunteers and 35 pathological cases. The authors considered the DM to evaluate the segmentation results. Besides, they also computed some functional parameters such as ESV and EDV. Our expert’s interpretation highlights that the papillary muscles were not included in segmentation. The weakness of this method occurs mainly at the basal and apical levels, where post manual corrections were typically required. Furthermore, the DM values obtained
showed less effectiveness for the case of RV compared to the LV. Among the cardiac phases, the values achieved at the ES phase were lower than those obtained at the Ed phase.

Furthermore, a cardiac segmentation method based on a level set considering LV, RV and LV myocardium was proposed by Wang et al. [34]. The proposed level set-based Shape Prior method (LSSPM) was used to allow RV contours and LV epicardium segmentation after delineating this last inner boundary using Hough transform and local Gaussian distribution method. A pre-processing step was firstly applied to localise the ROI, to denoise, and to enhance contrast. To evaluate their approach, the authors exploited seventeen MRI subjects considering the DM and the coefficient of variation as evaluation criteria. According to our radiologist, the provided visual results correspond to under and over-segmented regions, mainly for LV epicardium and RV boundary, which appears to be not smooth compared to the ground truth. The very basal slices seem not to be considered for segmentation. On the other hand, the RV segmentation at the very apical slice appears significantly over-segmented. Based on the considered criteria, the lowest empirical results were achieved for RV contours, although no complicated pathological cases were included for evaluation. Besides, among cardiac phases, the impact of several systolic and diastolic slices was not discussed to evaluate the current approach.

4.2 Graph-guided methods

Graph-guided methods consider segmentation as a graph partitioning problem [35]. Graph cuts are widely used as a powerful technique for image processing. The graph G can be subdivided for two associated elements A and B such that A) B = ) by eliminating the edges joining these pair components. The association level among A and B can be assumed from the total dropped edges weight, which is designated as a graph cut (see Equation (11)). A graphical representation of the graph-cut is illustrated in Figure 4 [36].

$$\text{Cut}(A, B) = \sum_{u \in A, v \in B} w(u, v)$$ (11)

For the sake of segmenting the RV using 4D MR images, Maier et al. proposed a semi-automatic region-merging Graph-Cuts (rmGC) approach [37]. This method involved three phases: First, they generated foreground and background markers based on the user's input. Next, they applied a watershed transform. Lastly, the obtained over-segmented regions were merged using 4D graph-cuts with an intensity-based boundary constraint. The authors considered two variants: one using user-intervention and the other based on statistical atlases. The obtained results were performed on the dataset provided by the MICCAI 2012 RVSC [28] and evaluated using the DM and the HD metrics. This approach was evaluated over the whole cardiac volume and provided high empirical results at the basal stage. However, the basal and the apical slices are the most challenging. In some cases, especially the pathological ones, this approach suffers from a strong leakage problem. For expert’ interpretation, no plotted results were provided.

Incorporating shape prior information, Mahapatra proposed a graph-cuts Shape Prior (GCSP) based method [38]. The shape penalty was determined based on the distribution of orientation angles between a pixel and edge points combined along with distance functions. Besides, from each dataset, a single image was exploited to extract prior shape information. Thus, this approach consists of two steps. In the first step, only intensity information was used to perform ventricular segmentation. The final segmentation was achieved, combining shape and intensity information and considering as a start-point, the primary segmentation obtained at the previous step. The datasets provided in the STACOM 2011 4D LV Segmentation Challenge (4D-LVSC) were used to evaluate this approach in 30 subjects [39]. The effectiveness of this approach is evaluated using the DM and the HD. However, the impact of several pathological cases, the cardiac cycle phases and shape variations were not discussed, which might influence the performance of using a single frame to extract shape information, mainly with the challenging issues raised by RV shape variations.

Moreover, considering the relative inter-arrangement of vital organs, Mahapatra also proposed a Graph-Cuts Contextual-based method (GCCont) to segment the endocardium of both ventricles [40]. First of all, seed points must be selected manually on the RV and LV to get initial segmentation using the graph-cuts method. Then, the RV segmentation was refined based on the contextual information obtained from the LV fixed segmentation. Henceforth, this last RV segmentation was fixed to refine LV segmentation using RV contextual information. Thirty datasets from the STACOM 2011 4D-LVSC were used and divided into 15 training datasets and 15 test datasets [39].

To evaluate this approach, Mahapatra used both the DM and the HD. The presented visual results refer to three patients and show only the middle short-axis slices with no significant variation among these patients. According to our radiologist, this segmentation method over-estimate the ventricles. The irregularity of the RV cannot be satisfied with the limited trained datasets, especially for the pathological cases where the contextual information between ventricles is altered.

Furthermore, Quispe and Petitjean proposed a Manifold Learning Graph-Cuts (MLGCs) method [41] to handle only
RV segmentation based on a diffusion-maps framework which encodes the RV shape variations from training data. In this approach, shape categories were modelled as a smooth finite-dimensional sub-manifold of the infinite-dimensional shapes space, termed using manifold learning techniques. In a high-dimensional space, especially for datasets lying on non-linear manifolds, the process of obtaining the underlying low-dimensional structure was termed as manifold learning. The segmentation considered iterative process consists of two phases performed successively. Initially, using a non-linear energy embedded shape prior information, a segmentation step was performed using the Markov Random Fields (MRF) with Graph Cuts energy minimisation. This was followed by updating the shape prior through a manifold traversal process to resemble the target. Concerning the whole segmentation framework, the shape prior was initialised to the shape-set’ midpoint and placed above the image accordingly. The effectiveness of this approach was neither evaluated by any evaluation metric nor compared to any other segmentation method. Only some visual results were considered to highlight the functioning. According to the expert’s interpretation, the final achieved contours were over and under-estimated due to several initialisations.

4.3 Model-based methods

Model-based segmentation methods exploit shape and appearance-related prior information towards object-of-interest extraction. In this context, local search algorithm-based-methods are mostly applied to locate Statistical Shape Models (SSM) due to the massive size of the 3D search space. These methods require an initialised model to pose estimation. The most uncomplicated initialisation process is based on user interaction, which is generally sufficient to align shape information. However, for some cases, especially the medicine-related ones, more accurate and critical manual-alternative initialisations are required [42]. For the sake of constructing an SSM, training sets are used to extract the mean shape and several variation modes. These models make the employed methods depend strongly on the chosen shape representation. Thus, to build shape models, it is required that landmarks should be located at corresponding positions overall training data. After aligning the shapes into a joint coordinate frame, the training set dimensionality is reduced to achieve limited model sets that exhibit the observed variation properly. The dimensionality reduction process is usually ensured by the Principal Component Analysis (PCA) [43]. According to Equation (12), X represents the coordination of the 3D shape in which a 3k point coordinates description is provided for each aligned training shape in vector X [42]. Then, a simple averaging of all samples allows forming the mean shape template as presented in Equation (13) [42]. Hereafter, using the s samples’ average, the covariance matrix is calculated as given in Equation (14).

\[ X = \frac{1}{s} \sum_{i=1}^{s} x_i \]  
\[ S = \frac{1}{s-1} \sum_{i=1}^{s} (x_i - \bar{x})(x_i - \bar{x})^T \]  

Active Shape Models (ASMs) and Active Appearance Models (AAM) are the most commonly incorporated model-based approaches for medical image segmentation. ASM is a local search algorithm based on a point distribution model. However, the Active Appearance Model (AAM) belongs to the class of generative models, which can generate realistic images of the modelled data. This step is accomplished by storing a complete texture model, consisting of the mean and the main variation modes, in addition to the shape model [44].

In the medical imaging field, several challenging issues are attempted to investigate personalised model-based techniques. Therefore, ASMs are used to capture the variability of RV shapes through a Dual-ASM segmentation method proposed in [45] to delineate the RV. To overcome several RV challenging issues, El-Rewaidy and Fahmy brought along, two main modifications to the basic ASM technique. First, they split the RV contour into two simple segments: septal and free-wall. Then, for each section, a specific ASM model was constructed. Eventually, to non-linearly align various borders, the RV insertion points were fixed as landmarks through evolving the proposed ASM model within the Bookstein coordinate space. This approach was evaluated using ten subjects of the York short-axis cardiac MRI dataset [46]. A set of 182 frames was constructed and divided into 56 shapes as a training set and 126 randomly chosen shapes as a testing set. Using two insertion points for each case in the dual ASM, a primer form is generated through reverse Bookstein coordinates. Then, the RV shape displacement was iteratively estimated by the ASM model from the appearance model. Compared to the conventional ASM, the evaluation of this approach is done by computing the DM and the mean absolute distance measurements. The final segmentations show how the proposed modifications improve the basic ASM. Still, the discussed parametric and visual results do not tackle the RV several challenging issues such as the basal and the epical fuzziness, the systolic cavity narrowness, and the morphological alteration among pathologies. According to our expert, even segmentations given at the middle-slices showed some under and over-estimations. The segmentation of the whole cardiac sequence must be assumed to allow RV function quantification, which is not taken into consideration within this approach. Furthermore, this semi-automatic approach depends strongly on the initialisation of insertion points.

SSM was also proposed in [47] to segment the RV. Moolan-Feroze et al. explored the ability of a cylindrical shape model to designate this cavity morphology compactly. This approach brings along a proper function, coupled laterally with a learned shape variation, designed to incorporate an MRF learned shape formulation. The RV segmentation process consists in applying a shape prior constrained 2D MRF followed by a 3D
cylindrical shape model fitting. A simple manual initialisation procedure was considered to align the shape model based on a set of points into the image spacing. To evaluate their method, the authors apply segmentation using MICCAI RVSC 32 patients’ dataset, which was divided into 16 training and testing data. The assessment of this method was performed, including both the DM and the HD metrics. Correspondingly, the final segmentation visual results were judged by our radiologist to report under-estimated regions. Moreover, the influence of several pathological cases, as well as the impact of cardiac volume variations, were not discussed over the cardiac considered systolic and diastolic phases. Besides, even the ES considered results do not show how properly the cylindrical shape model might adapt the RV form when this last appears the smallest, which behaves as an interesting obstacle for the previously reviewed method. Furthermore, the most basal and epical slices irregular shape is a very challenging issue to be represented as a statistical shape model.

Joint-ventricular segmentation methods take benefit from the similarity of the grey levels in their respective blood cavities and the stability of the relative positions of both ventricles. Thus, a joint LV–RV model was introduced by Lu et al. to delineate both ventricles’ boundaries in each frame, combining spatial and temporal contexts to track the cavity boundary motion over cardiac cycles [48]. The RV proposed model triangular mesh consists of the RV blood pool chamber, the RV outflow tract as well as the pulmonary and the tricuspid valves. Therefore, this approach delineates the corresponding anatomical structures using the joint model to fit a given 3D cardiac volume, unifying the interventricular septum between both ventricles. The authors make use of 63 patients’ MRI exams, with annotated RV regions, to evaluate the effectiveness of their proposed method. The obtained results correspond to a better performance using the joint model compared to the individual one. Based on our radiologist observations, the achieved results show underestimated RV delineations. From base to apex, among systolic and diastolic cardiac cycle phases and for several pathological cases, the current approach seems to be not evaluated individually. Besides, compared to the LV, still lower accuracy is obtained for the case of the RV.

Furthermore, Punithakumar et al. investigated a semi-automatic RV segmentation approach based on a 2D moving mesh or grid generation framework to detect the endocardium and the epicardium for each slice among the cardiac cycle phases in 4D “3D+time” MRI sequences via point-to-point correspondences [49]. The authors evaluated their approach over 48 subjects’ dataset provided by the MICCAI 2012 RVSC. An additional data set, which includes 23 HLHS diagnosed patients, was also exploited. For statistical performance evaluation, the DM and the HD measurements were reported for both systolic and diastolic phases. Also, Punithakumar et al. allow RV functional evaluation by computing a set of clinical measurements such as RVEDV, RVESV, RVM, and RVEF. According to our radiologist, the RV obtained endocardial borders were underestimated significantly at systolic phases. However, the current approach exhibited promising results at handling the HLHS pathological issues across the whole cardiac cycle. Athwart the entire cardiac volume from base to apex, the authors have not evaluated either discussed the challenging impact of several basal and apical slices upon the segmentation process.

4.4 Atlases-based methods

Atlas-based approaches are widely used for medical segmentation when an atlas or a standard model is available. These approaches use intensity and image labelled atlas denoted image that describes the different structures present in the images. The atlas is generated by compiling information about the anatomy that requires segmentation. This atlas is then used as a frame of reference for the segmentation of new images. Theoretically, atlas-guided approaches are similar to classifiers; however, they are implemented in the spatial domain of the image instead of the feature space. The standard atlas-guided approach treats segmentation as a recording problem. It first finds a one-to-one transformation that maps a pre-segmented atlas image to the target image that requires segmentation. This process is often called “atlas distortion”. Deformation can be performed with linear transformations, but due to anatomical variability, a sequential application of linear and non-linear transformations is often used [50].

Consequently, to tackle the RV segmentation challenge, as it is a medical-related issue, atlas-based approaches must be investigated. Accordingly, Ou et al. proposed a fully automatic iterative RV segmentation framework based on 3D multi-atlas [51]. This approach is based on driving segmentation using mutual-saliency-based reliability metrics and attribute-based similarity, aiming at overcoming the registration task difficulties prompted by the RV shape variations among-subjects. To perform their method, Ou et al. exploited the MICCAI 2012 RVSC provided datasets considering 15 cardiac MRI subjects as training data and 20 subjects for testing. Additionally, to assess its technical performance, this approach is quantitatively evaluated by measuring the DM and the HD metrics. According to our expert, the obtained segmentation does not preserve the regular ground-truth contours specifically for the epicardium, which is not easy to be recognized due to the RV wall thinness. Moreover, this approach shows significant low effectiveness corresponding to a single subject of the testing data. Based on this case results, the RV appears to be very narrow, which has not matched the training templates correctly. Also, the RV deformations over the cardiac cycle phases influence the effectiveness of this method. Thus, in systolic case, low performance is recorded compared to the diastolic phase. Consequently, this approach is sensitive to its used training data, which makes it exposed to over and under-segmentations referring to the RV vast irregular variations.

Multi-Atlas based segmentation was further exploited by Bai et al. in [52] to segment the RV, both internal and external boundaries. In this approach, atlas selection and locally weighted label fusion are used to reduce computational cost and to improve the segmentation accuracy. The current semi-automatic method involves a few landmarks to prepare image registration. The myocardial wall smoothness and continuity is not adequately guaranteed. Besides, due to the low myocardium
contrast as well as the strong intensity bias field, the segmentation at the epical slices is not satisfying. Thus, a post-processing step is required and applied by fitting the segmentation to an anatomical model to recover the anatomical topology. The authors have experimented their method on a public dataset published by the MICCAI 2012 RVSC. To evaluate the effectiveness of their approach, Bai et al. considered a test-set that consists of MR images of 16 subjects. The obtained segmentations, which are given for both borders at end-diastolic and end-systolic phases, are assessed using the DM and the HD metrics and other functional clinical measurements such as the ED-volume, the ES-volume, ventricular mass, and the ejection fraction. According to our radiologist, the obtained post-processed segmentation still does not fit correctly the RV contours, especially the epicardial one. In order to minimise human interaction, the landmarks used to affine registrations for both ED are only chosen on ED images. This approach performs worst for the ES phases compared to the ED, which makes it weak at delineating the RV, especially when it appears smaller for some subjects with powerful ventricular contraction. The ES related weak results influence the RV functional assessment as well since the RV ES volume, mass, and ejection fraction are computed based on the ES segmentation, which explains the weak correlation achieved.

4.5 Machine learning

Machine learning (ML) can be defined as the exploration of computer algorithms’ ability to learn intricate patterns and improve the aimed task effectiveness automatically [53]. ML systems are considered as an artificial intelligence subset. For the sake of making predictions without being explicitly programmed, ML algorithms are built as a mathematical model based on a training dataset for learning [54]. Two categories of ML methods can be distinguished for segmentation, whether ML conventional algorithms or Deep Learning (DL). The conventional ML algorithms, including Support Vector Machine (SVM), decision trees, random forests, and linear regression, involve feature extraction to train the model. However, Deep learning models consist of an input layer, an output layer, and multiple hidden layers which arrange together a deep artificial neural network [55]. The most commonly used convolutional neural network (CNN) for segmentation includes U-Net, fully CNN, SegNet. An example of the U-Net architecture is illustrated in Figure 5 [56].

Recently, in the medical field, many investigations have been elaborated based on several ML techniques, especially for cardiac MR image segmentation [55]. Mahapatra was among the first researchers to apply machine-learning methods towards the RV segmentation using Random Forest “RF” classifiers [57]. Considering short-axis MR images, two steps are followed to achieve the final results. First, the images are over-segmented into super-pixels, and each is classified using RF classifiers to extract the RV boundaries. A second-order MRF function is used to integrate the probability maps. Hence, using a graph-cut optimisation, the final segmentation labels are obtained. An RF is a set of decision trees trained separately using different parts of the training data. Using 32 subjects’ dataset as exploited in [58], the author evaluated his proposed approach based on the DM and the HD as quantitative metrics. The results showed how the increasing of RF trees number influenced the accuracy of segmentation positively. According to our expert’s interpretation, the epicardium achieved contour does not encounter real anatomical thickness. Also, the internal boundaries seem to be under-estimated. This approach is sensitive to the used
super-pixels size, which is estimated to be in the range of 600–900. However, facing the RV challenging intensity variations, this estimation might not be efficient to be fixed. At last, it is denoted that the current approach has not considered the influence of several cardiac volume-slices, cycle-phases, and pathological cases.

An automatic RV segmentation framework was proposed by Wang et al. using a Simplified Pulse Coupled Neural Network (SPCNN) segmentation technique with a morphological preprocedural to extract the RV contours [59]. To reduce interfering noise, the authors used the anisotropic diffusion technique to filter their CMR images. Then, the SPCNN model was used to delineate the RV internal borders with automatically settled parameters. Ultimately, towards the RV external boundary, the previously achieved endocardium segmentation was dilated. This approach was trained and validated using the datasets offered by the MICCAI 2012 RVSC. Wang et al. evaluated their method based on the DM and the HD measurements. According to our expert, the final segmentation results show some under-estimated endocardium delineations. Also, the epicardium obtained contours seem to be under and overestimated, although the visually provided results were only exhibited for the middle short-axis slices. Compared to the endocardium, better effectiveness corresponds to the epicardium borders. Besides, RV segmentation aims to allow quantitative diagnosis based on full coverage of the cardiac cavity. Therefore, considering this approach as a learning-based method increases the influence of shape variations from basal to apical slices among pathologies, bearing in mind the cardiac cycle deformations which are not discussed in the current reviewed paper.

RV segmentation was tackled by Tran applying Deep-Fully Convolutional Neural Network (FCNN) architecture [60]. Simultaneously, LV segmentation is also allowed through the current approach. The proposed architecture was trained using a single learning-phase to interpret every pixel as a pixel-wise classification. Several, datasets were used to experiment with this proposed approach. Thereby, 45 patient’s datasets were considered from the MICCAI2009LVSC and divided into three subsets which consisted of 15 subjects each. Also, from the STACOM 2011 LVSC, 200 patients MRI exams were exploited. Besides, 48 subjects’ datasets were used as provided by the MICCAI 2012 RVSC. The RVSC was divided into training-set and two test-sets where each included 16 subjects. Tran performed Multi-scale cropping and affine transformations to allow data augmentation followed by a set of pre-processing and image normalisation steps. For empirical evaluation, the author used several metrics, but only the DM and the HD were considered for RV results. Based on the provided visual results, our radiologist observed some under-estimated contours, particularly at the RV epical slices. This approach fails to segment the targeted regions correctly at the most apical slices due to fuzziness and the small-sized cavity. The most basal-slices, which raise another challenging issue, are not considered for evaluation. Compared to LV, the effectiveness of segmentation seems to be lower for the RV case. Correspondingly, several pathological cases were described to be included within the used datasets, but still not discussed to highlight their influence.

For the sake of addressing the RV segmentation issues in CMR images, a Five-layer deep Convolutional Neural Network (CNN) method was also proposed by Luo et al. [61]. An ROI localisation task was performed at first to achieve final segmentation. Then, final pixel-wise masks were obtained, applying the proposed segmentation approach. The current deep-learning investigated network was trained using 16 datasets provided by the MICCAI 2012 RVSC. Thirty-two test-sets were used and evaluated to assess the segmentation efficiency, based on the DM and the HD measurements. Clinical, functional parameters such as ESV, EDV, and FE were also used for accuracy assessment. For visual interpretation, no results were provided to highlight how the proposed approach fitted the RV borders delineation. Therefore, according to the achieved empirical evaluation, the segmentation process performed better with the endocardium than the epicardium. Based on the correlation-coefficient, a low correlation was achieved for the systolic volume compared to the diastolic volume. Luo et al. highlighted the impact of using a preliminary ROI localisation to improve the segmentation method functioning. However, they did not discuss the effectiveness either for cardiac-cycle phases, basal and apical slices, or pathological issues.

Likewise, Avendi et al. designed an RV segmentation framework based on CNNs and Autoencoders (AEs) [62]. The cavity location was at first detected using the proposed CNN architecture. An initial contour was then segmented, exploiting a stacked AE. Towards final segmentation, a deformable model technique was applied and initialised using the previous preliminary obtained curvature. The authors used the MICCAI 2012 RVSC datasets considering 16 patients’ exams for training and 32 datasets as a test-sets. For evaluation, the DM and the HD metrics were exploited to assess the proposed method effectiveness. Other functional parameters such as EDV, ESV, and EF were also computed to assess the correlation between the obtained results and the manually delineated contours. According to our expert, the most basal slices were not considered for segmentation, which influences the functional computing parameters. Besides, underestimated and misplaced contours were achieved for the apical slices. The impact of several ED and ES phases were not visualised, but still, the highest quantitative measurements correspond to the ED phases. The segmentation process depends highly on the trained data. Therefore, no pathological cases were discussed, and for two several test-sets, different results were obtained.

Fully automatic methods were also designed in [63] for myocardial bi-ventricular segmentation. Zotti et al. proposed thus a deep CNN Grid-Net embedding a shape prior and its registration into the trainable architecture. As a U-net generalisation, this method implemented grid architecture. The current approach was trained and tested using 100 subjects’ datasets provided by the MICCAI 2017 Automated Cardiac Diagnosis challenge (ACDC). The exploited data involved five categories presenting pathologies such as hypertrophic and dilated cardiomyopathy, myocardial infarction, abnormal RV, and patients with healthy cardiac exams. The authors assessed the effectiveness of their proposed approach, reporting some geometrical metrics such as DM and HD. Several clinical metrics were also
computed, such as the EF, ESV, EDV, and the myocardial mass. Compared to the LV results, the RV corresponding geometrical computed metrics showed less effectiveness challenged by this cavity issues. Also, among cardiac cycle phases, a lower accuracy was associated with the ES phases achieved results. Based on our radiologist’s interpretation, the visually presented results show over- and underestimated segmentations, especially in the case of the most basal slices where this approach fails towards accurately the RV boundary. Despite the presence of several pathologies within the considered datasets, Zotti et al. did not discuss its impact of the segmentation process separately.

Attempting to improve and adapt the existing FCNN performance to deal with RV various segmentation issues, Zhang et al. proposed Multi-task Deep Neural Network ‘M-DNN’ architecture [64]. Specifically, they elaborated a Multi-task U-net architecture allowing features leveraging among tasks. The current method focuses on overcoming the influence of small-sized RV to enhance segmentation performance. Therefore, the used input images were resized according to whether the RV was small-sized or not. The authors exploited the MICCAI 2012 RVSC provided dataset to train and test their approach, which was assessed afterwards using the DM metric. The visual results highlight only the segmentation functioning of this approach at the very basal slices, where the RV appears to be the smallest. The obtained empirical results, especially at the ES phases, show that this approach still needs improvements to achieve higher effectiveness. Consequently, the training data increase maybe one of the main requirements to achieve higher accuracy and cover a broader range of shape variations and narrowness.

Hence, to estimate directly and simultaneously all RV boundary points, Chen et al. proposed a Regression learning-based approach R-CNN combining a CNN with a holistic regression model [65]. This approach considers the RV delineation as a holistic border regression task to exploit the CNN advancement towards accurate segmentation. Thus, R-CNN leverages the whole image as a regression input for each point. To estimate the entire RV contour points, the R-CNN is based on the global shape prior and the input image itself rather than relying on edge or intensity-based information. The authors used 145 MRI exams collected from 3 several hospitals incorporating 2900 images in total. Across 20 cardiac cycle frames, Chen et al. considered only the middle slices to validate their approach using the DM and the HD as quantitative metrics. Accordingly, the obtained results corresponded, for most tested subjects, to high accuracy. However, for some subjects, poor results were achieved, which implies that the current approach may be sensitive to some unexpected or not learned shape alterations while only middle slices were considered. According to our expert, although it only corresponds to the less challenging middle slices, the provided visual results show under and overestimated contours all over the diastolic and systolic frames. Precisely, for about 20 images, due to the large deformation, the worst correlations were reported. Consequently, the data limitations preclude Chen et al.’s approach to learn and adapt irregular RV formats.

FCNN architecture is also proposed by Jang et al. to segment the myocardium and both right and left ventricles [66]. The authors used the same layers as M-net, excluding the 3D-2D converter layer. The training data used to carry out this approach were acquired and provided by the MICCAI ACDC 2017 [67], including 100 patient’s exams. Considering that the images are composed of ten slices, the data used were not sufficient to form the proposed model without encountering over-fitting problems. Therefore, Jang et al. made rotational changes to allow dataset augmentation. The segmentation process was evaluated using DM and HD measures without clinical parameters included. To ensure small volumes elimination and to fill up small gaps, a post-processing step was applied using morphological operations. The RV obtained results show a lower efficiency than those obtained for LV. Also, among the cardiac cycle phases, the highest results correspond to the ED phases. Thus, the RV narrowness influences the segmentation approach, as for ES phases and apical slices. The provided results include base-to-apex slices through ES and ED phases. According to our radiologist, underestimated segmentations were shown particularly for basal and apical slices. Besides, some regions were segmented as a part of the RV instead of being completely excluded at the base-level. The same thing was observed for the ES phase, where some RV-outboard regions were included for segmentation. Among the five-fold considered pathologies, the impact of several pathologies seems to obstruct the RV delineation such as heart failure, dilated cardiomyopathy, and hypertrophic cardiomyopathy.

Using short-axis cardiac MR images, Baumgartner et al. also tackled fully automated cardiac segmentation of the myocardium and both ventricles. In [68], they introduced a segmentation framework based on various 2D and 3D CNN models and sought to assess its suitability for this task. Notably, some significant improvements seem to be yielded by reducing the amount of up-sampling feature maps of the modified 2D U-Net. The authors experimented with their study using the data sets provided by the ACDC MCCAI 2017 [67]. The datasets considered were divided into training and validation datasets comprising respectively 80 and 20 exams. The evaluation process was accomplished using, basically, the DM and the HD measurements enhanced by computing correlations of commonly measured clinical parameters such as the EDV, the ESV, and the EF. According to our expert’s interpretations, the RV obtained results, for the worst empirical measurements, show how the RV was over-segmented in basal, middle, and predominantly apical slices. Among cardiac cycle phases, the highest effectiveness achieved corresponds to systolic phases. The current study was limited to assess the performance of segmentation from base to apex and between ES and ED phases. Thus, no pathological cases were evaluated distinctly to discuss their impact on the segmentation process.

The occurrence of several congenital heart diseases has a very challenging influence on RV segmentation. Therefore, considering the case of the Hypoplastic Left-Hearted Syndrome (HLHS), Punithakumar et al. proposed to investigate an FCNN architecture coupled with a moving mesh framework towards RV automated segmentation [69]. The proposed approach was
experimented using images collected from 23 HLHS subjects’ MR exams, where ten of them were considered for training, and the remaining 13 datasets were exploited as testing data. The authors were based on measuring the DM and the HD to evaluate their achieved segmentation results. The considered HLHS pathology corresponds to unusual RV morphology, which highly impedes the segmentation process to be accurate. Based on our radiologist’s interpretations, the obtained segmentation results seem to provide an acceptable level of effectiveness across cardiac cycle phases. Among the cardiac volume sequences from base to apex, the influence of this congenital-disease on the RV delineation was not discussed. Although the combined moving mesh FCN has a better performance than the basic FCN, still at the systolic phases, the RV region was underestimated. Using the DM and the HD, the performance of the proposed moving-mesh FCN and the FCN-only approaches was the same for the ES cardiac phase since the former was based on the contours of the basic FCN.

Furthermore, seeking to overcome several RV challenging issues, Isensee et al. integrated segmentation and disease classification to allow a fully automated pipeline [70]. Based on U-Net inspired architectures, the authors developed a multi-structure delineation method trained only on ED and ES phases, but still adequate for the entire cardiac cycle. After normalising the images grey level, Isensee et al. performed segmentation using both modified 2D and 3D U-Net architecture to guide cardiac segmentation. Then, several domain-specific features were extracted for disease prediction. The current approach was trained and evaluated using the MICCAI 2017 ACDC datasets. For the sake of assessing effectiveness, both the DM and the HD measurements were computed. The authors did not provide any visualised results. Instead, they focused on pathological-base assessment. Among pathologies, the acceptable convergent performance was assumed for the RV segmentation. Still, significantly, low accuracy was reported corresponding to the ES phases compared to the ED phases. Moreover, from base to apex, the effectiveness of this approach is not discussed.

Taking contextual input into account, Zheng et al. proposed a 3D consistent cardiac MR image segmentation method based on CNN architecture with spatial propagation [71]. Iteratively, from base to apex, the segmentation of each slice was propagated from the adjacent slice above, applying several variants of U-Net. To achieve the final segmentation, a ROI determination step was required and followed by a U-Net inspired segmentation process. The current approach was trained exploiting four different datasets incorporating the UK Biobank dataset, the MICCAI 2017 ACDC dataset, the Sunnybrook LVSC 2009 dataset, and the RVSC MICCAI 2012 dataset. Both cavities, with the left myocardium, were considered for segmentation and evaluated using the DM, the HD, and the average perpendicular distance, according to the tested data. Based on our expert’s observation, the provided results show overestimated regions when it comes to the RV case, particularly at the corresponding apical slices. The influence of some pathological cases was only discussed for the LV segmentation. Besides, throughout the cardiac cycle phases, specifically the ES and the ED corresponding slices, no evaluation or a discussion was provided for the approach. Most of the used datasets were accomplished for left heart segmentation only. Therefore, more RV dedicated datasets must be included for training to enhance the accuracy of this cavity segmentation.

In different kinds of deep CNN architectures, Dilated-Dense Net is used as a recommended features processing technique, but it still encounters the overfitting problem. Therefore, Xingrong et al. proposed an improved Dilated-Dense Net approach to allow RV segmentation using the MR short-axis image [72]. The authors used 243 labelled images divided into 218 and 25 images for training and testing, respectively. To prevent segmentation overfitting, Xingrong et al. applied data augmentation through several data transformations such as translations, random rotations, zooms, elastic, and shear deformations. The DM measurement was considered to assess the effectiveness of the current approach at segmenting the RV. Due to the limited amount of the exploited data, this approach addressed the entire RV related segmentation issues since no pathological cases were included for discussion. Moreover, the variations from base to apex and from ED to ES phases were not included either, which may influence the results significantly.

Deep-learning based approach was also proposed by Dang et al. to tackle the RV segmentation issues [73]. The proposed approach also exploits a U-Net architecture in which the training is allowed using an adaptive loss function. The datasets used to experiment with the current approach included 48 patients’ MRI exams provided by the MICCAI 2012 RVSC. The considered data was divided into 16 training datasets and two testing-sets, where each included 16 subjects. A pre-processing step was performed to enhance images quality adopting a Contrast Limited Adaptive Histogram Equalization (CLAHE) method followed by data augmentation techniques seeking to reduce overfitting. To evaluate the effectiveness of their segmentation approach, Dang et al. used the DM and the HD metrics. For the expert-guided interpretation, there are no visual results shown. The current approach was assessed for the endocardium and the epicardium boundaries over both ES and ED cardiac phases. The empirical results showed high performance for the epicardium compared to the endocardium. Besides, among the cardiac cycle phases, the ES phases seemed to have a challenging impact which was manifested by low recorded performance. Moreover, the impact of several shape variations, related to pathological issues, was not considered in this method.

Purmehdi et al. proposed and adapted another 3DCNN based machine learning method for automated RV segmentation from short-axis MRI sequences [74]. The authors used two independent datasets provided by the MICCAI 2012 RVSC and the MICCAI 2017 ACDC comprising 148 short-axis MR subjects for which the RV endocardium had been manually segmented in each slice. The proposed approach was trained using a mix of these two datasets. An empirical evaluation was investigated using the DM and the HD as performance metrics to assess the accuracy of the RV internal boundary delineation.
According to our radiologist, the provided visual segmentation results seem to miss the most basal slice encountering over- and underestimated contours for the considered slices, especially the apical ones. Compared to the widely used U-Net architecture, the authors’ proposed CNN yields higher reliability for the same datasets. However, among several pathological cases and through the cardiac cycle phases, no personalised discussion was taken into consideration.

In order to provide more accurate segmentation of the RV and the LV hollow and myocardium, Yang et al. proposed a fully automated segmentation approach based on deep learning techniques [75]. The designed residual block and enhanced loss function were used to improve the performance of both ventricles and left myocardium segmentation. To reduce training-time and alleviate the problem of overfitting, the authors adopted a randomised data augmentation strategy (CLAHE). The traditionally used ROI locating methods are highly time-consuming. Thus, Yang et al. directly locate and segment the heart region using a deep learning network based on U-Net and ResNet. The proposed segmentation network is divided into two encoder and decoder stages. The encoder step allows image representation and pixel-level classification, followed by the decoder stage to restore the original spatial resolution. The current approach was accomplished exploiting the MICCAI 2017 ACDC data, considering 100 MRI subjects for training and 50 datasets as testing data. The DM metric was used to evaluate the effectiveness of this proposed method. According to our expert’s interpretation, at the most basal slices, the automated approach failed to estimates the RV region. Also, from ED to ES phases, the achieved segmentation seems to incorporate underestimated regions. Besides, although several pathologies were included in the used datasets, no dedicated discussion was highlighted to study the influence of these morphological variations.

Considering such structures as the RV endo-epicardium, Borodin and Senyukova, also proposed a U-Net based architecture with no additional layers [76]. Therefore, the modifications applied were related to replacing every second convolution layer by a dilated one in each block of the contracting pathway. The authors trained and tested their proposed approach exploiting the MICCAI 2012 RVSC dataset, which consisted of 48 patients with several cardiac issues. After pre-processing the dataset MR images using the mean-variance normalisation method, Borodin and Senyukova augmented their data by involving rescaling and rotations. To evaluate the proposed approach, the DM metric was measured for both borders. Compared to the basic U-Net, the modified method achieved better accuracy at segmenting the RV. Incorporating boundaries, only one sample was visualised. Thus, referring to our radiologist, the epicardium obtained segmentation was erroneously overestimated. The impact of several cardiac cycle phases from base to apex was not taken into the assessment. In these cases, the epicardial segmentation may be significantly more challenging. Besides, the occurrence of various pathological cases causes morphological border changes and, consequently, influences the segmentation. Still, no abnormal subjects were discussed to evaluate the current method.

4.6 | Hybrid methods

As it is already reviewed in the previous sub-sections, some segmentation methods work based on regions like region growing, and region merging, while others are based on boundaries like active contour, deformable model. Hybrid methods are based on Region of Interest “ROI” and boundary. These methods use both boundary and regional information to segment the images. The results of these methods are relatively better than other segmentation approaches applied in medical images [18]. For the sake of overcoming the RV segmentation issues, various works have been elaborated based on combining different segmentation techniques.

Accordingly, to deal with such challenging issues, Ringenberg et al. introduced a fully automatic method to segment the RV based on combining the window-constrained accumulator thresholding along with the difference of Gaussian (DoG) filters, morphological operators, optimal thresholding, and a priori delineation constraints [77]. This approach exploits the basal to apical and the cardiac cyclic variations to allow segmentation. Thus, Ringenberg et al. iteratively apply the segmentation process in a traversal way from basal to apical slices using a priori constraints from the previously achieved slice-segmentation. Besides, ED dependent prior constraints are also used to guide the ES segmentation on the same level. The MICCAI 2012 RVSC 48 datasets are considered to accomplish the proposed method and split into training and two testing datasets where each consists of 16 subjects. Image-based result evaluation is done calculating the DM and the HD along with clinical assessment such as EDV, ESV, EF, and VM. According to our experts’ interpretation, the visual results exhibited in this paper indicate over-estimated segmentations even at the middle short-axis slices. The clinical evaluation shows that for both used test-sets, the ESV manages to be someway overestimated while the ED volume tends to be underestimated. In some cases, in which the MRI exam presents a significant RV position variation among layers, this approach encounters limited segmentation results. Besides, the impact of several pathological deformations might also prevent this approach from achieving accurate contours, which was not discussed in this reviewed paper.

Likewise, Soomro et al. proposed a hybrid region-based active contour approach [78] that uses statistical image information to allow bi-ventricular segmentation. To incorporate both global and local image intensity information, the authors contribute by formulating a new Signed Pressure Force “SPF” function, which assumes the zero-level set curvature resembling the intended boundary. Considering the specified image as \( \mathbf{I} : \Omega \subset \mathbb{R}^2 \) and the level-set curve to be \( \mathbf{f} : \Omega \subset \mathbb{R}^2 \), the Equation (9) formulate the proposed SPF function in which the scaling constants are denoted as \( \lambda > 0 \), and \( v \geq 0 \), \( LLG(\phi) \) is a length, and \( ALG(\phi) \) is an area term.

\[
ELG(\phi) = \lambda LLG(\phi) + v A L G(\phi)
\]
RVSC using the DM and the HD for quantitative assessment. In reference to our radiologist, the presented visual results show several under and overestimated RV contours, especially for the case of the epicardium. Besides, the MRI short-slices considered for this evaluation do not cover the entire cardiac volume from base to apex. Furthermore, the RV challenging issues are not addressed carefully applying this method since no pathological cases are discussed.

The region-based Chan–Vese (CV) method is one of the most commonly used segmentation techniques, which assumes that the intensity is statistically homogeneous in each region of an image. Still, this method does not perform well upon heterogeneous intensity images. Therefore, Local Chan–Vese (LCV) method is developed. Aiming to segment both cardiac ventricles automatically, Av et al. hybridised a Local Region-based Chan–Vese (LRCV) method into a Kirsch edge detection [79]. In order to simultaneously perform a bi-ventricular delineation, the Kirsch operator is applied at first to obtain edge transformed image. Final segmentation is achieved performing the modified LRCV method with distance regularised level set on the edge transformed image. To validate their approach, the authors consider 25 data sets gathered from MRI several units. The DM and the HD metrics are used to evaluate the obtained segmentation results in addition to some clinical parameters such as the ESV, EDV, and EF. According to our expert, the provided visual results are not efficient to evaluate this method’s performance over the whole cardiac volume and phases. At the apical slices, the difficulty of segmenting the RV boundaries appears to be challenged by the presence of dense papillary muscles. Also, even at the middle slices, the RV endocardium is found to be under-segmented excluding the papillary muscles to be considered as a part of the RV myocardium, which influences the epicardium delineation accuracy. Besides, among the cardiac cycle phases, this approach yields better results on the diastolic phase compared to the systolic phase.

A hybrid approach was also elaborated in [80], incorporating an average atlas-based segmentation into the graph-cut technique for RV endocardium delineation. Dangi and Linte benefit from the strength of Multi-atlas-based approaches for medical shapes. Simultaneously, they exploit the rapidity of combinatorial optimization-based graph-cut methods since the first considered approach suffers from intensive, non-rigorous and time-consuming image registration and label fusion of label phases. To achieve RV segmentation, the authors formulate their approach as an energy graph minimisation problem starting by generating label using affine registration of an average atlas to obtain shape priors which are combined into the proposed graph framework. The final RV blood pool corresponding segmentation is obtained via graph-cuts and iteratively refined. Considering a set of 16 short-axis MRI exams provided by the MICCAI 2012 RVSC, the current approach is quantitatively evaluated against gold-standard expert segmentation according to various metrics, including DM, HD, JAC, and mean absolute distance. Based on the provided visual segmentation result provided by our radiologist, from base to apex, under and over-segmentations are reported, especially in the most apical stage, which is latter manifested through the computed metrics. Besides, the influence of cardiac phases and pathological changes were not considered to evaluate the performance of this approach.

Moreover, in computer-vision, diverse knowledge is provided for the image forms depending on scale-space theory. To overcome the RV segmentation obstacles, Lu et al. integrated multi-scale feature learning via Stacked Sparse Auto-Encoder (SSAE) into graph cut framework [81]. The SSAE can extract general information with features represented at a high level. To enable the RV segmentation, learned through the SSAE, a primary form is initiated and located by the probability map. Afterwards, final segmentation is achieved using graph-cut segmentation model incorporating the learning features, the probability map, and the irregular shape. To accomplish their experiments, the authors used datasets provided by the MICCAI’12 RVSC. A set of 16 patients’ short-axis MRI exams was considered for testing. All data were divided into a training set, which consists of 160 images, and into a validation set containing the remaining 83 images. For the quantitative evaluation, both the DM and the HD are used to compute the similarities level among automatic and manual segmentations. For visual results interpretation, three samples are exhibited by Lu et al. preserving only middle short-axis slices which do not illustrate the basal and apical challenging slices. According to our expert, these results still show under-estimated contours. Also, as shown by the computed metrics, it is obvious that this approach performs better for ED phases compared to the ES ones. Consequently, the current method is challenged by the RV deformations and depends highly on the trained data.

4.7 Other methods

Several further adapted segmentation techniques that can be classified in none of the above-listed categories were also investigated by other researches attempting to handle the RV delineation challenging issues.

Image-based methods such as thresholding are one of the earliest applied segmentation techniques in medical images. In [82], a very interesting exhibition of thresholding method was elaborated to allow medical image segmentation. To meet the challenge of cardiac segmentation, a two-step thresholding guided approach was proposed by Goshtasby and Turner to segment the endocardium of both ventricles using MRI sequences [83]. Initially, the current method approximately determines the locations and size of endocardium surfaces by intensity thresholding. In the second step, the points of each approximated surface are repositioned to the nearest locally maximum gradient magnitude points, and a generalised cylinder is attached to them. Thresholding methods are used in several medical areas. According to the authors, the thresholding method could not accurately extract boundaries based on the same threshold due to the ventricular shape and size variations. Therefore, they used thresholding intensity to approximately determine the ventricles, which are refined eventually for final segmentation. Five MRI subjects were used to evaluate the proposed approach
through slices from base to apex defining error as the ratio of foreground pixels in the segmented image to the ground truth image. Compared to the LV, the RV computed errors are significantly higher for all slices from base to apex. The provided visual results are not fitted on real MRI slices to allow radiologist-based interpretations. Besides, the related pathological variation, as well as systolic and diastolic cardiac phases, were not included for evaluation.

Besides thresholding, the morphological methods were also investigated for image processing in several areas [84]. Katouzian et al. proposed morphological operation-based segmentation considering inner and outer boundaries of both ventricles [85]. The proposed approach is initialised by an arbitrarily selected marker point inside the cavity area. A standard power-law transformation is performed to allow better differentiation between the cardiac muscle and the cavity hollow, thus enhancing the myocardium contrast. After localising the ROI using the above-selected marker, morphological operations, thresholding and edge detection were used to delineate the RV and LV borders. The authors use three normal subjects to evaluate their approach. According to our radiologist, the provided visual results show acceptable delineations, except for some over- and under-segmentations at the RV level. Considering only healthy subjects makes the proposed method limited and still open to other challenging issues, especially for the RV case. Moreover, the authors apply small-object removal after thresholding, which risks removing ventricular parts from the image at the apical slices where the RV appears the smallest.

Labrador et al. proposed another method for RV shape tracking throughout the entire cardiac cycle in MRI sequences, considering only the endocardium for delineation [86]. The proposed approach allows an initial coarse segmentation obtention using a bidirectional per-pixel motion descriptor. Then a refined contour was obtained combining, at each frame, the previous primary segmentation with geometrical observations. In the very apical slices, the RV appears to be very blurred, which makes it considered as a part of the LV. Thus, based on the motion estimation, the RV is differentiated. The authors assessed the performance of their proposed approach using 32 patients’ datasets as provided in the MICCAI 2012 RVSC. The DM and the HD metrics were considered for empirical evaluation. Based on the provided visual results, our expert highlights this approach’s failure at the apical slices as well as for the ES phases. Consequently, we can deduce that the weakness of the current method is related to the ventricular constriction and its hollow blurriness. Moreover, the impact of several pathologies variations was not included for discussion, which may significantly influence the segmentation process.

A computational framework was correspondingly proposed in [87] to segment the RV volume in short-axis cine cardiac MRI. Atehortúa et al. based on a simple saliency analysis of the heart which, sequentially and hierarchically, refined the RV location. First of all, to reduce the examination area, heart ROI localisation is applied. Towards endocardial delineation, the ventricular chambers were selected at the basal level using the iso-data algorithm, the RV was extracted, and its centroid was calculated. A series of radial intensity profiles, plotted from this centroid, was used to search for a salient intensity pattern that models the inner myocardial boundary. This process was applied iteratively until the apex, using the segmentation of the previous slice as a regulator. The successive 2D segmentations were combined to obtain the final volume of the RV endocardium, which was also used to estimate the epicardium by dilating the achieved endocardium volume. The current method was validated using the MICCAI 2012 RVSC cardiac MRI dataset, which includes 48 subjects. The evaluation process was ensured by computing the DM and the HD metrics as well as the EDV, the ESV, the EF, and the VM as clinical RV functional parameters. The visual results were given for both ES and ED phases from base to apex. Based on our expert’s observation, the RV appeared to be over-segmented for all slices, especially the apical ones. Also, the resulting RV borders were not adequately smoothed compared to the considered ground-truth. Besides, the impact of various pathological cases was not discussed discretely to evaluate effectiveness.

A fully-automatic RV segmentation method was also proposed by Daoudi et al. based on the Region-Growing (RG) technique [88]. The proposed method allows the entire RV segmentation from base to apex at both ES and ED phases. The authors applied the adaptive histogram equalisation (AHE) method as a pre-processing step to enhance contrast and differentiate the RV area from the background. In order to automate the segmentation process, two algorithms were exploited. First, the seed pixel was initialised using the Generalized Hough Transform technique “GHT” to start the RG growing process. An iterative threshold selection technique was also used to compute the optimal threshold value towards better segmentation. To test their approach, Daoudi et al. used 30 cardiac MR short-axis exams with several heart abnormalities. The mean overlap was computed from basal to apical slices from base to apex to evaluate the effectiveness of the current approach considering the ES and the ED phases. The obtained visual results were not fitted upon the grey level images. Therefore, no contour-observation can be made referring to our expert. However, at the ES phase, this approach seems to segment the very basal slices instead of completely excluding the RV. Also, based on the achieved empirical values, this proposed method performs better at the ED phases compared to the ES ones. Besides, concerning several pathologies, no such variations were considered for evaluation.

A semi-automatic RV segmentation method was introduced by Yilmaz et al. based on a cellular automata framework which is supposed to allow every voxel to be labelled as foreground or background based on their signal intensity, similarity, and their distance to the seeds [89]. The segmentation process required endocardial prior information of slices from base to apex over both the ED and the ES phases, which were provided by the user only for one slice. To accomplish their experiment, the authors considered 28 MRI volunteers’ exams which were evaluated using the DM and the HD measurements. Functional RV related parameters such as the EDV, the ESV, and the EF were also computed based on the automated segmentation. Our radiologist’s interpretation of the visually provided results reports under-estimated contours at the apical slices,
particularly, at the ES phase. Consequently, the segmentation results seem to influence the correlation of the RVESV and subsequently, the RVEF. Moreover, the empirical evaluation exhibited low results for the ES compared to the ED phases. Concerning the impact of several pathological alterations, no evaluation was included since the exploited data belongs only to healthy volunteers. To benefit from the fact that the heart is a moving contracting organ, Guo et al. tackled the RV segmentation challenge proposing a personalised Local Motion Intensity Clustering (LMIC) Model based on two adjacent images using the Lucas Kanade optical flow method [90]. To simplify the manual interaction complexity, this approach requires only one point to precise the right ventricle location. The data exploited for experimental evaluation was provided by the MICCAI 2012 RVSC consisting of 48 datasets. The DM and the HD metrics were considered for quantitative analysis along with the EF as a clinical parameter. Compared to the local intensity clustering methods, which use no motion-related information, the current approach guaranteed a better RV delineation. According to our expert, the obtained segmentation visual results are considered as under-estimated for some apical and ES slices influenced by the presence of papillary muscles and the weak motion intensity encountered at the apical level. These observations were also shown by the achieved empirical measurements since the accuracy was decreasing from base to apex as well as at the ED, and the ES phases. Still, no pathological discussion was included to highlight the impact of different morphological variations upon the effectiveness of the proposed motion-based model.

A set of visual results for some reviewed approaches are summarised in Table 6, selecting only one approach for each category of the presented segmentation methods. Our selection of images is based on the clear presentation of contours considering three levels: base, middle, and apex.

| Benefits | Limitations |
|----------|-------------|
| Deformable models | These methods are very suitable for RV segmentation since they allow the handling several challenging issues. |
| Graph-guided methods | These methods reduce labour in feature extraction allowing automatic learning. |
| Model-based methods | These methods are fast and not sensitive to initialization. |
| Atlas-based methods | These methods are robust by incorporating prior knowledge of shape and appearance. |
| ML methods | These methods ensure an optimum solution for two-class segmentation. |
| Hybrid methods | These methods are robust by incorporating prior knowledge of shape and appearance. |

5 | GLOBAL DISCUSSION

In this section, we discuss the above-reviewed approaches based on the achieved measurements, the used datasets, and the impact of several MRI short-axis slices. Therefore, we initially distinguish two global categories based on the exploited segmentation-methods namely conventional and machine-learning approaches. Table 2 summarises the main benefits as well as the limitations and the difficulties encountered for each segmentation method.

Regarding the conventional approaches, several segmentation techniques were used such as deformable-models, graph-cuts, atlas, and hybrid methods. These approaches allow RV segmentation using datasets provided by various public challenges such as the MICCAI 2009 LVSC, the STACOM 2011 4D-LVSC, and particularly the MICCAI 2012 RVSC which is the most used. Although these methods take advantage of their speed and reduced need for input data, they do not allow for the processing of complex new cases due to variations in the form of RV.

Consequently, the most recent RV segmentation approaches follow the emergence of machine-learning methods. For such learning-approaches, using large amounts of labelled data is a main requirement. Thus, researchers exploited several datasets of their own or provided by the MICCAI 2012 RVSC and the MICCAI 2017 ACDC. The proposed segmentation approaches are generally inspired by the U-Net and the FCNN architectures. Major proposed updates are based on several parameters setting such as the input size, the activation function, the optimisation algorithm, the learning rate, the batch size, and the number of trained epochs. The learning rate is also used to control the amount of normed error that the model weights are updated with each time. Besides, to allow a faster-learned network with better performance, several optimisers and activation functions are used. On the other hand, the batch size is defined as the number of samples used to estimate the gradient of the cost function. Finally, the model is trained according to a pre-defined number of epochs, which correspond to how many times the trained model passes-over the dataset. Table 5 summarises several parameters setting for each deep learning-based approach. Yet, the over-fitting is the most common challenge encountered in training deep networks. It is caused by the limited amount of training data compared with the number of learnable parameters. Therefore, researchers have investigated
| Category                  | Reference                  | Principle methods                 | image           | OOI       | Contour | Parameters | A | N<sup>o</sup> |
|---------------------------|----------------------------|-----------------------------------|-----------------|-----------|---------|------------|---|-------------|
| Deformable methods        | Sun et al. [36]            | DMM + MRF-TP                       | 2D S-A MRI      | BV        | BB      |            | A | 1           |
|                           | Yang et al. [27]           | GVF-T                             | 3D S-A MRI      | RV        | Endo    |            | SA| 2           |
|                           | Liu et al. [30]            | DRLSE + DR2LS                      | 2D S-A MRI      | BV        | BB      |            | A | 3           |
|                           | Liu et al. [32]            | DRTLS                             | 2D S-A MRI      | BV        | BB      |            | SA| 4           |
|                           | Arrieta et al. [33]        | TPLS                              | 2D S-A MRI      | BV        | Endo    | EDV, ESV   | SA| 5           |
|                           | Wang et al. [34]           | LSSPM                             | 2D S-A MRI      | BV        | Endo    |            | A | 6           |
| Graph-guided methods      | Maier et al. [37]          | WS + 4D rimGC                      | 4D S-A MRI      | RV        | Endo    | VS, EDV, ESV, EF | SA| 7           |
|                           | Mahapatra. [38]            | Shape Prior model GCSP            | S-A MRI         | BV        | BB      |            | SA| 8           |
|                           | Mahapatra. [40]            | GCCont                            | S-A MRI         | BV        | Endo    |            | SA| 9           |
|                           | Quispe et al. [41]         | MLGCs                             | S-A MRI         | RV        | Endo    |            | A | 10          |
| Model-based methods       | El-Rewaidy et al. [45]     | Dual modified ASM                  | S-A MRI         | RV        | Endo    |            | SA| 11          |
|                           | Moolan et al. [47]         | 2D MRF + cylindrical model        | 3D S-A MRI      | RV        | Endo    |            | A | 12          |
|                           | Lu et al. [48]             | Joint ventricular model            | S-A + L-A       | BV        | BB      |            | A | 13          |
|                           | Punithakumar et al. [49]   | 2D moving mesh framework          | 4D S-A MRI      | RV        | BB      | EDV, ESV, EF, VM | SA| 14          |
| Atlas                     | Ou et al. [51]             | 3D multi-atlas registration        | 3D S-A MRI      | RV        | BB      |            | SA| 15          |
|                           | Bai et al. [52]            | 3D multi-atlas registration        | S-A MRI         | RV        | BB      | EDV, ESV, EF, VM | SA| 16          |
| Machine-learning methods  | Mahapatra. [57]            | RF classifier                      | S-A MRI         | RV        | BB      |            | A | 17          |
|                           | Wang et al. [59]           | SPCNN                             | S-A MRI         | RV        | BB      |            | A | 18          |
|                           | Tran. [60]                 | Deep FCNN                         | S-A MRI         | BV        | BB      |            | A | 19          |
|                           | Luo et al. [61]            | ROI localization + Deep FCNN      | S-A MRI         | RV        | BB      | EDV, ESV, EF | A | 20          |
|                           | Avendi et al. [62]         | CNN + Autoencoder                 | S-A MRI         | RV        | Endo    | EDV, ESV, EF | A | 21          |
|                           | Zotti et al. [63]          | Deep Grid-Net + shape prior       | S-A MRI         | BV        | Endo    |            | A | 22          |
|                           | Zhang et al. [64]          | M-DNN                             | S-A MRI         | RV        | Endo    |            | A | 23          |
|                           | Chen et al. [65]           | R-CNN                             | S-A MRI         | RV        | Endo    |            | A | 24          |
|                           | Jang et al. [66]           | FCNN based on M-net               | 3D S-A MRI      | BV        | BB      |            | A | 25          |
|                           | Baumgartner et al. [68]    | 2D U-Net                          | S-A MRI         | RV        | Endo    | EDV, ESV, EF | A | 26          |
|                           | Punithakumar et al. [69]   | FCNN + Moving mesh                | S-A MRI         | RV        | Endo    |            | A | 27          |
|                           | Isensee et al. [70]        | U-Net                             | S-A MRI         | RV        | Endo    |            | A | 28          |
|                           | Zheng et al. [71]          | U-Net + Spatial propagation       | 3D S-A MRI      | BV        | Endo    |            | A | 29          |
|                           | Xingrong et al. [72]       | Dilated-DenseNet                  | S-A MRI         | RV        | Endo    |            | A | 30          |
|                           | Dang et al. [73]           | U-net                             | S-A MRI         | RV        | Endo    |            | A | 31          |
|                           | Purmehdii et al. [74]      | 3D CNN                            | 3D S-A MRI      | RV        | Endo    |            | A | 32          |
|                           | Yang et al. [75]           | U-Net + ResNet                    | S-A MRI         | BV        | Endo    |            | A | 33          |
|                           | Borodin et al. [76]        | Modified U-Net                    | S-A MRI         | RV        | BB      | EDV, ESV, EF | A | 34          |
| Hybrid methods            | Ringenberg et al. [77]     | Hybrid method + MOs               | 4D S-A MRI      | RV        | BB      | EDV, ESV, EF, VM | A | 35          |

*Continued...*
TABLE 3  Continued

| Category | Reference                  | Principle methods                          | image  | OOI   | Contour | Parameters | A  | N°  |
|----------|----------------------------|--------------------------------------------|--------|-------|---------|------------|----|-----|
|          | Av et al. [79]             | Kirsch-MLRCV                                | S-A MRI | BV   | Endo    | EDV, ESV, EF | A  | 36  |
|          | Soomro et al. [78]         | region-based active contour                 | S-A MRI | BV   | BB      | –           | SA | 37  |
|          | Dangi and Linte. [80]      | Hybrid Atlas-GC                            | 3D S-A MRI | RV | Endo    | –           | A  | 38  |
|          | Lu et al. [81]             | SSAE + graph cut                           | 2D S-A MRI | RV | Endo    | –           | A  | 39  |
| Other    | Labrador et al. [86]       | Pixel-motion model                         | 4D S-A MRI | RV | Endo    | EF          | A  | 40  |
| methods  | Goshbasy and Turner. [83]  | Thresholding                               | 2D S-A MRI | BV | Endo    | –           | A  | 41  |
|          | Kazouzian et al. [84]      | Morphological operators                    | 2D S-A MRI | BV | Endo    | –           | A  | 42  |
|          | Atehortúa et al. [87]      | Saliency analysis + Isodata                | S-A MRI | RV | BB      | EDV, ESV, EF, VM | A  | 43  |
|          | Daoudi et al. [88]         | Region growing, GHT                        | S-A MRI | RV | Endo    | –           | A  | 44  |
|          | Yilmaz et al. [89]         | Cellular automata framework                | S-A MRI | RV | BB      | EDV, ESV, EF, SA | A  | 45  |
|          | Guo et al. [90]            | LMIC Model                                 | 4D S-A MRI | RV | Endo    | EF          | SA | 46  |

FIGURE 6  Average DM values for each proposed approach (in Table 4)

Several techniques to deal with this over-fitting issue, such as data augmentation. According to the expert’s-based interpretation, under and over-estimated contours were observed for most methods significantly at the basal, the apical and the end-systolic slices, which highlights the influence of different short-axis slices and phases on the segmentation precision. The empirical provided results indicate the same observation among slices and cardiac phases. Nevertheless, it is difficult to quantitatively assess accuracy among approaches due to the diversity of the exploited datasets. Therefore, we enlist the DM and the HD measurements in Table 4 according to the most frequently exploited datasets, which are the MICCAI 2012 RVSC and the MICCAI 2017 ACDC. Accordingly, the average DM and HD measurements are illustrated respectively, in Figures 6, and 7. Moreover, the occurrence of several pathologies significantly influences the segmentation process, but it was not taken into consideration, except for a few approaches. Furthermore, to allow RV diagnosis, several clinical parameters must be computed such as the EF, the ESV, the EDV, the VM, and the VS. Only some of the reviewed approaches consider functional parameters to evaluate their methods as presented in Table 3. To compute these parameters, the entire cardiac volume throughout both ED and ES phases must be included. Thus, the low accuracy achieved, particularly for basal and apical slices at the ES phases, influences mainly the volume computation, as well as, the extraction of other parameters whose calculation is based on end-systolic and end-diastolic volumes. None of the reviewed approaches allowed full coverage of the RV challenging issues. However, for each issue, there were separately promising results, especially, using hybrid, deep-learning, and other personalised methods which take advantage of the cardiac motion and 3D volume features for segmentation.

First of all, among cardiac slices, the best DM performance was achieved by Guo et al. [90] using an LMIC model (base: 0.93, middle: 0.87, apex: 0.80). Ringenberg et al. [77] also obtained high DM measurements for the middle slices (0.87). Second, across the cardiac cycle, Soomro et al. [78] recorded
TABLE 4  Average DM and HD results obtained for each work (values are presented respectively for DM and HD)

| Approach | End-systolic phase | End-diastolic phase |
|----------|--------------------|---------------------|
|          | Endocardium        | Epicardium          |
|          | Basal slices       | Medial slices       | Apical slices |
|          | Basal slices       | Medial slices       | Apical slices |
| [32] / N°4 | 0.82±0.23, 10.50±8.03 | 0.83±1.57, 12.58±9.03 | 0.90±0.15, 7.51±5.47, |
| [37] / N°7 | 0.83±0.16, 0.80±0.15, 0.46±0.26 | – | 0.92±0.05, 0.88±0.07, 0.72±0.18 |
| [49] / N°14 | 0.77±0.16, 9.6±4.15 | 0.82±0.10, 9.99±3.85 | 0.83±0.13, 7.72±3.97 |
| [51] / N°15 | 0.58±0.27, 15.75±7.20 | 0.58±0.26, 18.58±8.91 | 0.66±0.24, 17.66±8.70 |
| [52] / N°16 | 0.69±0.25, 11.16±5.53 | 0.77±0.17, 11.72±5.44 | 0.86±0.11, 7.70±3.74 |
| [60] / N°19 | Total average: Endocardium 0.84±0.21, 8.86±11.27 Epicardium 0.86±0.20, 9.33±10.79 | – | – |
| [61] / N°20 | Total average: Endocardium 0.86±0.09, 6.9±2.6 Epicardium 0.84±0.13, 8.9±5.7 | – | – |
| [62] / N°21 | Average: 0.77±0.18, 7.89±3.94 | – | Average: 0.86±0.11, 7.82±4.41 |
| [64] / N°23 | Average: 0.74 | – | Average: 0.856 |
| [71] / N°29 | Total average: 0.82±0.07, 7.56±3.50 | – | – |
| [73] / N°31 | 0.78±0.25, 9.48±10.98 | 0.83±0.19, 12.22±10 | 0.88±0.14, 10.12±7.97 |
| [74] / N°32 | Total average: 0.88±0.09, 9.95±0.75 | – | 0.89±0.14, 9.03±9.53 |
| [76] / N°34 | Total average: Endocardium 0.85 Epicardium 0.83 | – | – |

Continue
### MICCAI 2012 RVSC

| Approach | End-systolic phase | End-diastolic phase | Epicardium |
|----------|--------------------|---------------------|------------|
|          | Endocardium        | Epocardiun          | Basal slices | Medial slices | Apical slices | Basal slices | Medial slices | Apical slices |
| [77]/N°35 | 0.90±0.06, 6.75±3.69 | 0.95±0.02, 4.95 ±2.14 | 0.95±0.02515 | 0.91±0.05849 | 0.91±0.05892 | 0.83±0.11961 |
| [78]/N°37 | 0.90±0.10, 7.67±5.36 | 0.91±0.11, 9.34±6.69 | 0.97±0.09, 8.51±6.83 | 0.92±0.07, 6.47±4.32 |
| [79]/N°38 | Total average: 0.89±0.12, 8.25±7.42 | Average: 0.81±0.18, 7.63±3.21 | Average: 0.91±0.20, 6.64±3.32 |
| [81]/N°39 | Average: 0.51±0.31, 27.47±27.96 | Average: 0.72±0.29, 16.17±16.48 |
| [82]/N°40 | 0.87±0.07, 8.66±3.41 | 0.87±0.13, 5.66±1.29 | 0.89±0.09, 6.30±1.77 |
| [80]/N°46 | ED: 0.88±0.08, 6.94±5.05, ES: 0.85±0.08, 6.92±2.94, Base 0.93±0.03, 5.71±3.34, middle 0.87±0.07, 7.75±4.23, Apex 0.80±0.08, 7.01±5.22 |

### MICCAI 2017 ACDC

| Approach | End-systolic phase | End-diastolic phase | Epicardium |
|----------|--------------------|---------------------|------------|
| [63]/N°22 | 0.87, 16.66 | 0.94, 13.48 |
| [66]/N°25 | Average: 0.85±0.08, 14.78±6.36 | Average: 0.925±0.04, 12.60±6.02 |
| [68]/N°26 | Average: 0.852±0.095, 13.46±6.24 | Average: 0.934±0.039, 12.17±6.02 |
| [70]/N°28 | Total average: 0.923, 11.134 |
| [75]/N°33 | Total average: 0.818 |
the highest DM value as well for ES and ED phases (ES: 0.90, ED: 0.94). Zotti et al. [63] also achieved the best DM performance (0.94) exploiting a deep CNN Grid-Net enhanced with shape priors. Chen et al., combining a CNN with a holistic regression model [65], allow pathological guided evaluation and achieved a DM value of (0.89) for pathological cases compared to healthy subjects (0.90). Eventually, on average, according to Table 4, Soomro et al. [78] and Isensee et al. [70] obtained the highest performance measurement (0.92) considering the MICCAI 2017 data set. Moreover, Mahapatra recorded the highest performance (93.2) using different dataset [57].

Finally, for machine-learning approaches, the influence of the dataset size appears clearly through the DM and the HD obtained results. Therefore, the highest reported values were related to the use of the MICCAI 2017 ACDC dataset, as it covers a more considerable amount of data.
6 | BRIEF GUIDANCE TOWARDS RV SEGMENTATION

The RV segmentation is an essential task in establishing the diagnosis. Therefore, the precision of this chamber delineation for all slices and phases is required to allow a more accurate diagnosis. However, due to the RV challenging issues, including its thin wall fuzziness and the vast variations among slices, phases, and subjects, none of the reviewed approaches achieved a balanced high accuracy for all stages. As a result of this study, it would be wiser to identify a specific technique or approach for each phase of the segmentation process. In the following, we present our main recommendations based on formerly made observations. The first step that must be carefully carried out is the pre-processing step to deal with the MRI-related contrast intensity and fuzziness issues. Considering the MRI Rician signal based noise, several noise removal techniques exist in the literature to improve the signal-to-noise ratio such as bilateral filter [91], pre-smooth non-local means filter [92], convolutional neural network [93]. Besides, contrast intensity-based enhancement also plays an essential role in improving the MRI image clearness. For that sake, many algorithms were tackled by researchers such as the mean-variance normalisation [76], Histogram Equalization (HE), Local Histogram Equalization (LHE), Adaptive Histogram Equalization (AHE), and Contrast Limited Adaptive Histogram Equalization (CLAHE) techniques [94]. Furthermore, concerning the choice of MRI plans, it is recommended to use the short-axis view that will be guided by other long axis and 4-chamber views in order to allow an automatic segmentation approach, which reduces the impact of the user and makes use of other MRI views. In [80], a multi-source image approach was introduced. Nevertheless, the authors focused on the left ventricular segmentation from the base to the apex with no RV personalised full evaluation. To avoid result variations among different slices from base to apex, each level of the short-axis RV images should be treated and customised separately without ignoring the morphological inter-dependence between them. The low segmentation accuracy in the ES stages should be carried out by taking into consideration the small-sized features that characterise these phases. Also, cardiac contracting nature should be highlighted to benefit from the strength of ED delineation. Indeed, it must be kept in mind that the strength of exploiting motion information is manifested by the achieved high accuracy [79].

Finally, we emphasise that the richness of the data and the diversity of the clinical cases studied are two key elements to raise the challenges related to RV segmentation and to reduce the complexity in the treatment of pathologies.

7 | CONCLUSION

In this paper, we review the most recent investigated approaches to segment the RV boundaries using MRI short-axis sequences. Despite the various current tackled methods, the RV segmentation challenge is a fresh field and there are many unexplored leads. The RV segmentation methods will likely continue to follow segmentation strategies surrounding the use of shape, morphology, and motion information, as well as the deep-learning-based approaches. However, regarding the RV issues, the choice of the segmentation technique is not the only matter. Instead, it is more about how to properly exploit the MRI images to achieve high accuracy for the entire cardiac short-axis sequence. Besides, the existing achievements show that the segmentation accuracy decreases particularly at the most upper and lower slices of the MRI sequences. Consequently, the exploration of these cuts must be based on the proposal of their own approach that allows to handle them separately.

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