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RESEARCH ARTICLE

Convolution Neural Network for Objective Myocardial Viability Assessment Based on Regional Wall Thickness Quantification From Cine-MR Images

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ABSTRACT In clinical routine, the assessment of myocardial viability is based on visual analysis of late gadolinium enhancement (LGE) sequences. This procedure remains subjective and insufficient, particularly in cases of improbable viability, where scar transmurality spans 25% to 75% of the myocardial segment total thickness. To address these challenges, this paper introduces a novel framework based on deep convolutional neural network (CNN) for objective and quantitative assessment of myocardial viability. The proposed method was validated on 73 patients with myocardial infarction and 10 healthy subjects. The initial stage involves the automatic quantification of regional myocardial wall thickness (MWT) in multiple radial directions to offer a detailed regional assessment compared to traditional techniques. This method is based on automatic segmentation of the left ventricle contours using U-Net. Afterwards, we proposed a novel protocol to automate the classification of myocardial segments into viable and nonviable classes. Additionally, we introduced MWT as a new key parameter for studying peri-infarct areas. Comparative study of our method to related works proves its superiority with an average mean absolute error (MAE) of 1.21 ± 1.00. Accurate quantification of MWT allowed the detection of myocardial segments desynchronization and the delimitation of infarction transmurality with an accuracy of 98.13%, a specificity of 99.09% and a sensitivity of 97.52% with ($p\_value < 0.001$). The obtained results proved that incorporating the proposed protocol in clinical practice may facilitate the differentiation between viable and non-viable segments, aiding in directing patient care and minimizing intra and inter-observer variability.

INDEX TERMS Automatic segmentation, regional wall thickness, cine-MRI, automatic quantification, myocardial viability, CNN.

I. INTRODUCTION

Over the last few decades, cardiovascular magnetic resonance imaging (CMR) has become widely utilized in cardiac diagnostics, establishing itself as a cornerstone imaging technique. Its exceptional precision and reliability have positioned it as the gold standard for evaluating left ventricular (LV) function and structure [1]. Recently, there has been increasing recognition of the efficacy of CMR also in evaluating myocardial viability. In this context, CMR offers two primary methods for assessing myocardial viability: contractile reserve evaluation through dobutamine stress and late gadolinium enhancement (LGE) imaging using gadolinium-based contrast agents (GBCA). The latter

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method, LGE imaging, is more frequently used and preferred in clinical practice [2]. In this method, GBCAs are administered intravenously, and due to their high affinity for extracellular space, they accumulate in areas of disrupted myocardium, such as scar tissue or areas with fibrosis. After a delay, typically around 10-20 minutes, images are acquired using LGE sequences that highlight the distribution of gadolinium within the myocardium [3]. The regions displaying increased signal intensity in these images indicate areas with changes in tissue composition, offering valuable information on myocardial viability, scar characterization, and the extent of myocardial damage. In clinical settings, evaluating myocardial viability requires careful visual examination of LGE sequences, where the thickness of hyper-enhanced regions is compared to the overall thickness of the myocardial wall. Based on the percentage of hyper-enhanced zones, myocardial segments are categorized into three main classes as follows: if the area of the infarcted zone is less than 25% of the myocardial wall thickness (MWT), the majority (87%) of the segments is viable and can recover their contractile function after revascularization, while when this area presents more than 75% of the MWT, the segment is considered non-viable and revascularization is futile. For peri-infarcted areas (between 25% and 75%), it is difficult to identify hibernating and necrotic areas which still represents a main challenge in all research involving myocardial viability assessment in MRI [4]. Hence, despite the effectiveness of this sequence in the identification and delimitation of the infarcted zones and zones at risk, it has been demonstrated that it represents irreversible myocardial injury-necrosis in the acute stage and does not distinguish hibernating from necrotic areas. Furthermore, previous research has shown that differences in LGE location and pattern are associated to patient clinical presentation and prognosis [5]. Moreover, due to the fact that not all patients with viable myocardium improved function after revascularization, viability tests may have a poorer specificity and still a clinical challenge in current practice. This is due to the lack of trustworthy regional indices for quantitative assessment of cardiac contractility. Consequently, it poses a significant barrier for cardiac function analysis and directly impacts the accuracy of myocardial viability assessment, which is crucial for the proper use of invasive treatment strategies and patient prognostication [6].

To address these challenges, this study aims to go beyond traditional methods used in clinical routine that rely on visual interpretation of hyper-enhanced zones in LGE sequences. The novel model we have developed aims to propose an automatic algorithm for objective myocardial viability assessment using convolutional neural network (CNN). The proposed method consists in classifying myocardial sub-segments into viable and non-viable based on the quantification of regional myocardial thickness and the transmurality of the scar area. In this context, the main contribution of this research is to offer a tool that aids in the diagnosis of patients with myocardial infarction, as well as in clinical decision-making regarding the necessity of revascularization procedures.

The rest of this paper is structured as follows: In section two, we review previous research related to our study. Section three outlines the dataset characteristics, details the image preprocessing steps, and thoroughly explains the proposed method for objective myocardial viability assessment. Section four presents the experimental findings, followed by a discussion of these results in section five. Finally, section six offers the conclusion.

II. LITERATURE REVIEW

To tackle difficulties associated with the analysis of LGE sequences, researchers have increasingly explored hybrid imaging approaches, like PET-MRI, as described in [7], to leverage both modalities' unique strengths and uncover complementary information while minimizing redundancies. The findings indicated that when comparing scar locations, MR imaging identified six additional infarcted areas compared to PET imaging. Furthermore, the correlation between hibernation and the extent of transmural scarring demonstrated a moderate to weak association ($r = 0.4$), which was further attenuated in the group with lower ejection fractions. In addition, Jiang et al. [8] have used stress MRI to obtain qualitative and quantitative parameters of segmental myocardium. In this research, myocardial segments supplied by coronary chronic total occlusion (CTO) target vessels were grouped based on collateral circulation assessed by angiography and categorized as negative, viable, or trans-infarcted depending on stress perfusion and LGE extent. In another clinical research [9], researchers analyzed MR images to assess both anatomical and functional aspects of the heart, including wall motion. On the LGE sequences, segments exhibiting pathology were categorized into two groups: those with less than 50% LGE (considered viable) and those with greater than 50% LGE (deemed non-viable). This methodology may lack precision and could potentially influence clinical decisions.

Additionally, in 2021, the research work of Spath et al. [10] presented a new method for the quantification of myocardial viability in patients with acute myocardial infarction (AMI). This method is based on the visualization of intracellular calcium handling using manganese-enhanced MRI (MEMRI) to distinguish between stunned and viable myocardial segments. Among the limitations of this study is that LGE and MEMRI scans were conducted 48 hours apart, potentially resulting in changes in contrast enhancement due to the dynamic nature of infarct characteristics during the first week post-revascularization.

Furthermore, a virtual native enhancement (VNE) technology, was used by Zhang et al. [14] to generate LGE-like images without contrast, combining cine-MR images and native T1 maps via artificial intelligence. While validated in hypertrophic cardiomyopathy (HCM), further studies are needed for myocardial scar assessment in post-MI patients.

Recently, the research study of Lalande et al. [12] investigated whether deep learning techniques can differentiate between non-infarct and pathological exams, with or without hyper-enhanced areas, and automatically quantified the extent of myocardial infarction. The obtained results proved that improving the segmentation of diseased areas remains a challenge due to their small size and lack of contrast with surrounding structures. Other deep learning approaches have been proposed to study myocardial infarction (MI) extent in order to quantitatively assess myocardial viability such as in [13], [14], [15], and [16].

While considerable advancements have been achieved in aiding clinical experts to quantify MI damage and assess myocardial viability, significant challenges persist in this critical area. For instance, manual segmentation of LV contours remains subjective and susceptible to low reproducibility, resulting in high intra and interobserver variability. This stage directly impacts the accuracy of myocardial thickness quantification, upon which myocardial viability assessment relies. Furthermore, current semi-automatic methods are compromised by biases introduced during LV boundary extraction.

Motivated by the literature studies, this research work provides a novel automatic algorithm for objective myocardial assessment based on deep learning. The main contributions and objectives of this work are summarized as follows:

a) A fully automated method has been proposed for left ventricular cavity segmentation according to AHA standards. This approach provides regional assessment of myocardial segments across basal, mid, and apical slices, reducing errors associated with human intervention.
b) The segmentation of the left ventricular cavity into 17 segments, further divided into three equal sub-segments, allows for a more detailed analysis and regional quantification of myocardial thickness and thickening across all phases of the cardiac cycle. This parameter is a key indicator of myocardial viability and enables accurate quantification of the extent and severity of MI damage.
c) The quantification of regional parameters is achieved through automatic segmentation of left ventricular contours using a modified U-Net architecture, which has demonstrated superior accuracy compared to state-of-the-art methods. This approach enables precise quantification while reducing errors associated with manual segmentation commonly used in clinical practice.
d) An automatic algorithm has been proposed to classify myocardial sub-segments as viable or non-viable using a convolutional neural network (CNN) based on quantitative parameters such as RWT and scar transmurality. This approach enhances diagnostic objectivity and minimizes inter and intra-observer variability.
e) The proposed protocol allows accurate classification of sub-segment with improbable viability which remains a challenge for radiologists. This avoids unnecessary revascularization procedures, thereby improving patient outcomes and optimizing treatment strategies.

III. METHODOLOGY

A. METHOD OVERVIEW

The proposed framework comprises two main procedures as illustrated in Figure.1.

We initiate with a data preprocessing step, where the primary objective is to automatically segment the LV contours. This segmentation is achieved leveraging a deep neural network, developed as part of our previous research. Subsequently, we further segment the LV cavity into 17 segments, adhering to the standards set forth by the American Heart Association (AHA). This step facilitates the RWT quantification, serving as the initial marker of myocardial viability. In a second step, we introduce a novel objective protocol for the assessment of myocardial viability. This protocol relies on quantitative assessments using CNN. To assess the clinical impact of our method, we conducted a comparison between the diagnoses made by the radiologist using our protocol and that established through visual interpretation of LGE sequences.

B. PATIENT POPULATION AND CMR ACQUISITION

Database for our study was gathered from the Military Hospital of Tunis. The study cohort comprises seventy-three patients diagnosed with myocardial infarction, consisting of 35 males and 38 females, aged between 27 and 69 years and ten healthy subjects. All CMR examinations were acquired during end-expiration breath-hold using a 3 Tesla MRI machine (Siemens Medical solution, Erlangen, Germany) using steady-state free precession (SSFP) sequence with retrospective synchronization to the electrocardiogram (ECG). For each patient, referential segmentations of endocardial and epicardial contours carried out by an expert radiologist as well as additional information such as age, weight, height and systolic and diastolic phases were provided. The primary MRI parameters are listed as follows: slice thickness (8 mm), gap (8 mm), image size (256×256 pixel) and FOV = 320×320. Each patient included, in this study, is represented by a series of 25 images with a number of slices varying from 8 to 15 to entirely cover the LV from the base to the apex. For the same patients, the LGE sequences were acquired 10 minutes after the injection of a small quantity of GBCA of 0.2 mmol/kg by applying a T1-weighted inversion recovery gradient echo sequence (GRE-TI) to suppress normal tissue signal in the short-axis (SAX) plane of the heart to assess multiple myocardial segments. The sequence parameters used are as follows: TR (Repetition Time) = 4 ms, TE (Echo Time) = 2 ms, TI (Inversion Time) = 300 ms, size of matrix = 192×192, Field of view (FOV), slice thickness = 8 mm. It is worth noting that for this type of study formal consent is not required. We did not use either names or identifiers it was quite simply a collection of data relating to abnormalities that affect the contractile function of the myocardium.

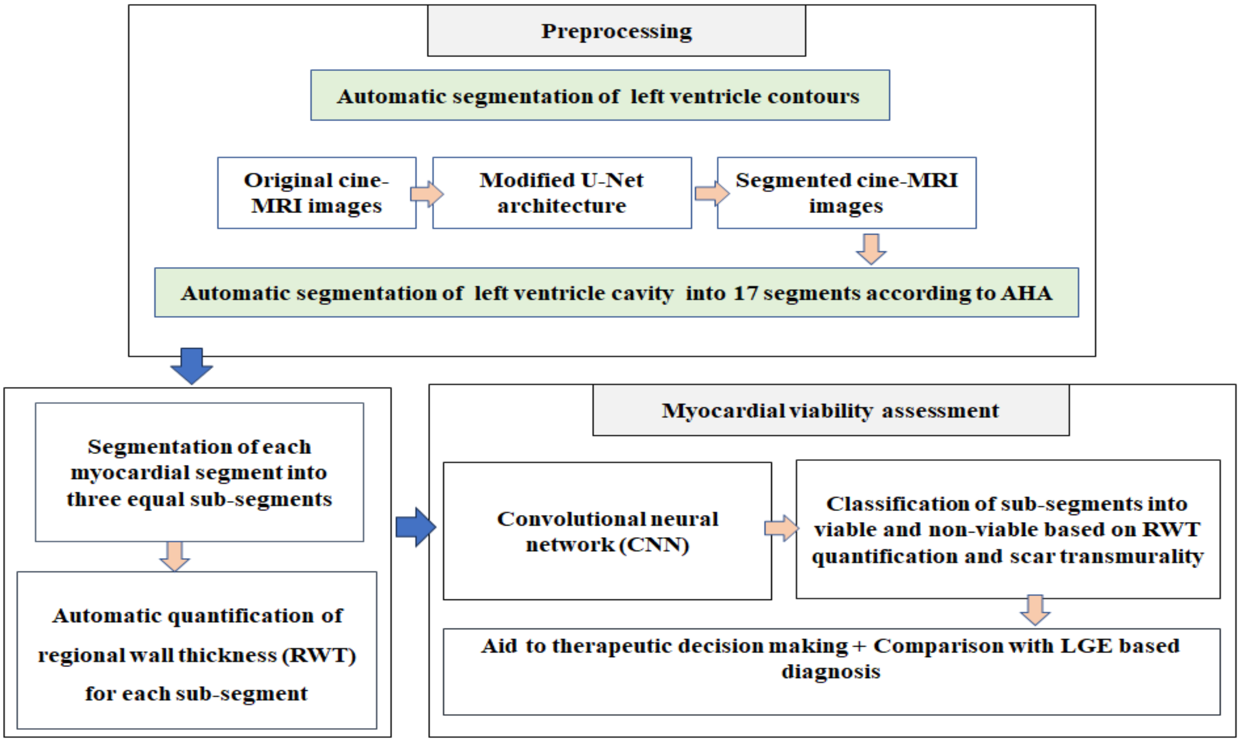


FIGURE 1. Outline of the proposed approach for regional wall thickness quantification and myocardial viability assessment.

C. PREPROCESSING

1) AUTOMATIC LV BOUNDARIES EXTRACTION USING DEEP NEURAL NETWORK

In cardiac MRI, it's possible to derive quantitative measurements directly without the need for LV contour segmentation. However, these direct methods have yet to embrace the approach of integrating segmentation for more intuitive and accurate clinical judgments. Additionally, they haven't explored the utilization of predicted contours as inputs when estimating clinical indices, despite discarding valuable background image information which plays a crucial role in data optimization [17]. For these reasons, medical experts prefer to rely on LV segmentation since it provides more accurate calculation [18]. To overcome the limitations related to manual segmentation, we employed the U-Net convolutional neural network, a tool we had previously developed, to segment all cine-MR images [19] (Figure.2)

Three changes were made to our architecture compared to the original U-Net design: it is characterized by a reduced number of blocks, average pooling operations have replaced the max pooling operations, and zero padding has been applied.

The final result of the segmentation step is a segmented cine-MRI image. This is achieved by overlaying the mask obtained from the neural network output onto the original cine-MRI image, resulting in a cine-MRI image with delineated contours. After applying histogram equalization to enhance image contrast, the two contours are detected using the "get_contour" function developed in Python. Finally, the perimeters of the two contours are calculated to distinguish the endocardial contour (narrow perimeter) from the epicardial contour (wide perimeter). When displaying, red and green colors are assigned to the two contours, respectively.

2) AUTOMATIC SEGMENTATION OF THE LV CAVITY ACCORDING TO AHA STANDARDS

In clinical settings, segmentation of the heart into 17 segments according to American Heart Association (AHA) standards [20] is typically conducted semi-automatically. Radiologists manually identify key anatomical points: the center of the LV cavity and the upper and lower intersection points between the LV and the right ventricle (RV). Subsequently, software tools are used to obtain myocardial segments. Nevertheless, this process is laborious and susceptible to fatigue-induced errors. In this sub-section, we propose an automatic method to divide the LV into 17 segments for each segmented image. In our work, this step is crucial as it allows RWT quantification for each myocardial segment. AHA segmentation was performed using Python software (version 3.7) in two main steps: heart sections characterization and slices' segmentation.

The characterization of cardiac sections is based on myocardium division into 4 regions by referring to the presence or not of papillary muscles (PM): basal section, mid-section, apical section and the apex. In effect, slices identified as mid-cavity whenever PM are present. To identify basal

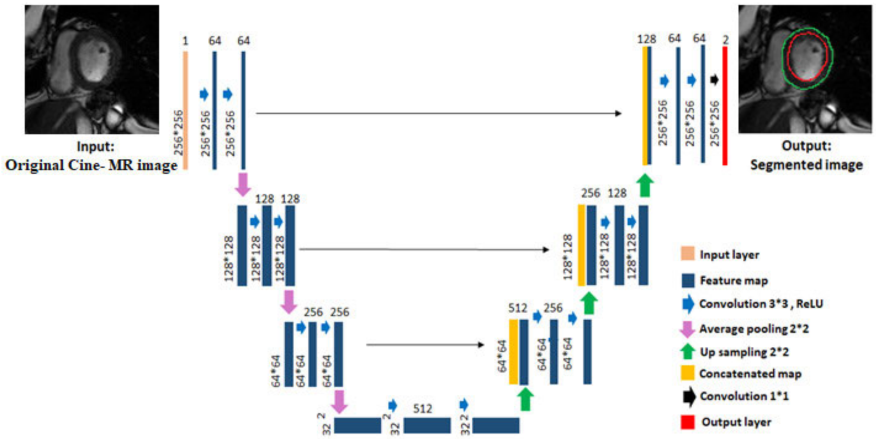


FIGURE 2. The proposed neural network architecture for automatic LV contours extraction.

and apical slices, we compare the endocardial perimeter of the studied section with that of the mid-section. Thus, if its perimeter is larger, it is a basal slice otherwise, it belongs to apical sections.

Regarding the apex, it is the part of the myocardium characterized by the absence of the blood pool. After identifying myocardium sections, we segment them according to AHA standards: basal and mid-sections are both divided into 6 segments separated by approximately 60°, apical slices are divided to 4 segments separated by approximately 90° and the 17^{th} segment is the apex. To identify myocardial segments (A: anterior, IS: Inferoseptal, I: Inferior, IL: Inferolateral, AL: Anterolateral, AS: Anteroseptal, S: septal and the apex), we need practically to locate three anatomical points: the centroid "O" of the LV cavity and the upper and lower intersection points of the LV and RV that we named P and M respectively. The centroid is the point belonging to the LV cavity equidistant with the majority of the endocardial contour points. To locate the two other points on the segmented MR images, we converted the pixel intensity from cartesian coordinates (x, y) to polar coordinates (R, θ). This operation simplifies analyzes as the LV is characterized by an approximately radial motion and a circular boundary of the epicardium. Conversion between cartesian and polar coordinates is given as [21]:

$$K(x, y) \Longleftrightarrow K_1(R, \theta) \text{ where } x = R\cos\theta,\ y = R\sin\theta \quad (1)$$

$$R = \sqrt{x^2 + y^2} \quad (2)$$

where (x,y) are the cartesian coordinates of the point K, (R, θ) are the polar coordinates, R is the radius of the circle with the center "O" passing through K, and θ is the angle that the radius makes with the abscissa axis. The limits of the inter-ventricular septum represented by the two points P and M are the intersection of the two straight lines (OP) and (OM) with the epicardial contour. The AHA automatic segmentation process is shown in Figure.3.

D. AUTOMATIC QUANTIFICATION OF REGIONAL MYOCARDIAL WALL THICKNESS

As previously mentioned, myocardial wall thickness (MWT) is the primary indicator of myocardial viability which provides an initial indication of the heart function. In clinical routine, this parameter is usually assessed at the end-diastolic (ED) and the end-systolic (ES) phases from the manually segmented sequences. In this research, we offer an automated approach for the quantification of RWT. In several radial directions based on fully automatic LV contours' extraction and AHA segmentation results. Our method's fundamental idea is to divide cardiac segments of each of basal median and apical sections into three sub-segments to accurately delineate infarcted areas which makes a total number of 49 segments. Then, we calculate MWT and thickening over the entire cardiac cycle for each sub-segment. Thus, basal and median sections are segmented every 20 degrees and apical section every 30 degrees while knowing that this method has been validated by an expert radiologist. This allows to accurately localize the infarcted area as well as its transmurality. Then, the distance between the endocardial and epicardial contours and the crossing sites of the rays emanating from the center of the LV cavity "O" is estimated using Python software in order to quantify MWT values. Consequently, we propose calculating MWT at 18 locations for each acquisition (image). This results in more than 360 thickness values since each patient is represented by 25-30 acquisitions, as illustrated in Figure. 4.

From RWT values quantified automatically at each instant, we calculate myocardial thickening between acquisitions by subtracting the two thickness values related to the corresponding acquisitions. From ED and ES thickness, it is possible to deduce by difference, the absolute thickening (ATh) and finally, the relative thickening (RTh) as follows [22]:

$$ATh = Diastolic\ thickening - Systolic\ thickening \quad (3)$$

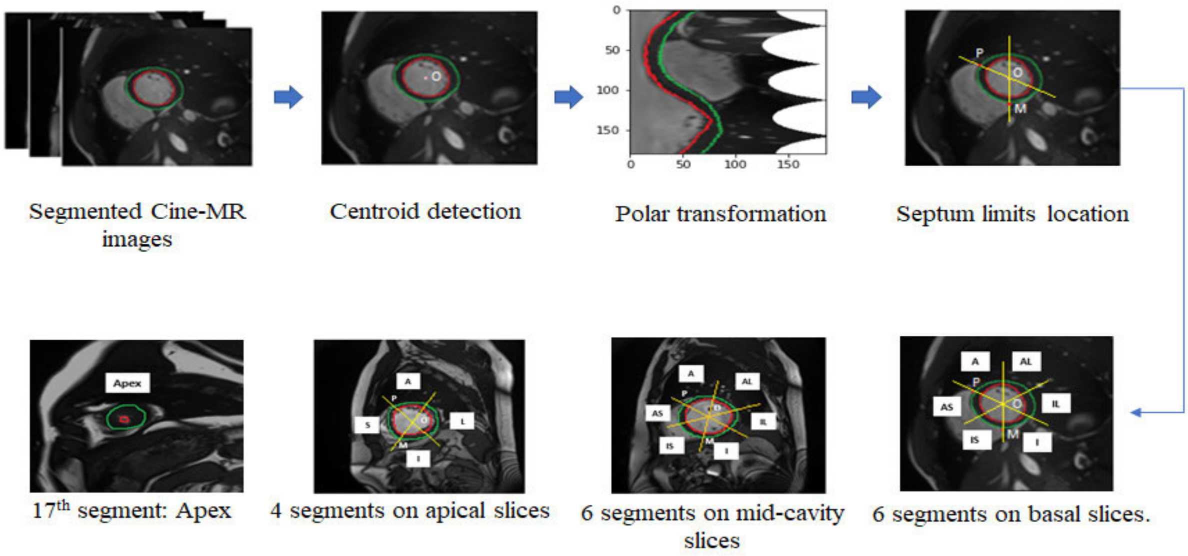


FIGURE 3. Automatic left ventricle segmentation into 17 segments according to AHA standards.

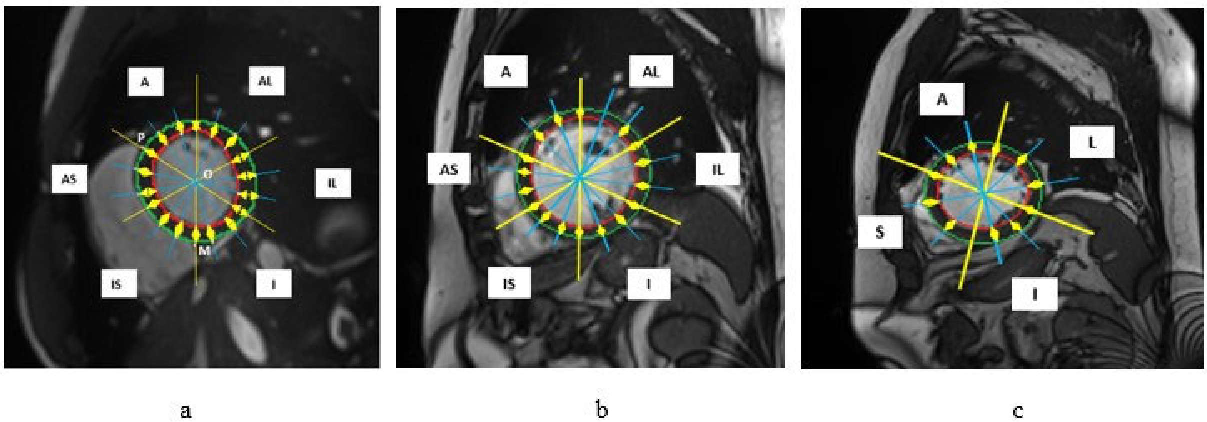


FIGURE 4. Example of myocardial segmentation for every 20° for basal (a) and median (b) sections and for every 30° for apical section (c) for MWT quantification (quantified distances are represented by the yellow arrows).

$$RTh\ (\%) = \frac{Absolute\ thickening}{Diastolic\ thickening} * 100 \quad (4)$$

To evaluate the performance of the proposed method for RWT quantification, we compare them with the reference values provided by the Circle cvi42 software used in clinical practice.

E. MYOCARDIAL VIABILITY ASSESSMENT BASED ON CONVOLUTIONAL NEURAL NETWORK

In cardiac MRI, studying the viability of myocardial segments in peri-infarct zones, where scar transmurality represents between 25 and 75% of the myocardial segments total thickness, poses a significant challenge for the radiologist. The challenge arises from the diverse composition of these areas, where a combination of viable and scarred tissue creates overlapping signal intensities on MRI images. This overlap complicates the distinction between the two types of tissue. Furthermore, motion artifacts caused by cardiac movement further complicate the assessment of myocardial viability in these areas.

After a long discussion with the two radiologists who participated in this study, we introduce, in this paper, a novel protocol for objective myocardial viability assessment. In this protocol, we automated the classification of segments with known response to revascularization as follows:

- Segments with transmurality less than 25% are considered as viable as approved in clinical routine.
- Segments with transmurality greater than 75% are considered non-viable as approved in clinical routine.
- For peri-infarcted areas (25% $<$ transmurality $<$ 75%), where conventional assessments may be uncertain, priority is given to MWT with a threshold of 5.5 mm as described in Figure 5. This means that if myocardial segment is too much thinned (MWT $<$ 5.5 mm), a large part of myocytes is definitively lost so the segment is considered as non-viable.

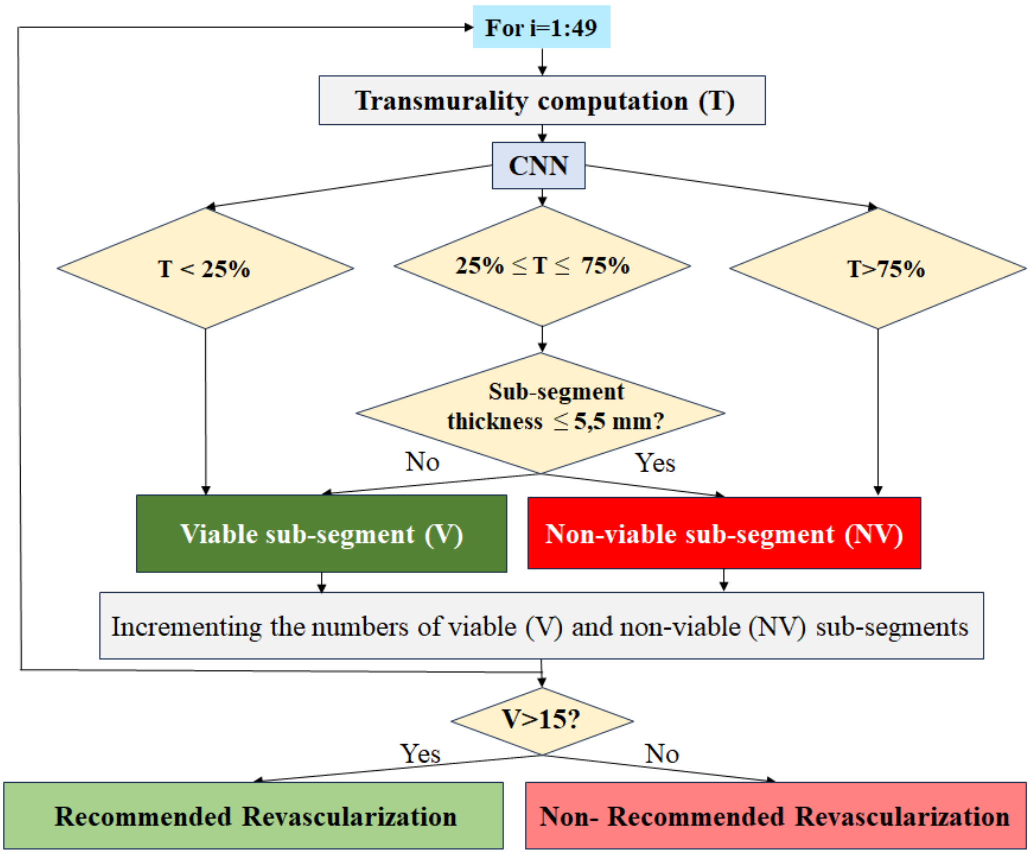


FIGURE 5. Explanatory diagram of the proposed protocol for objective myocardial viability assessment.

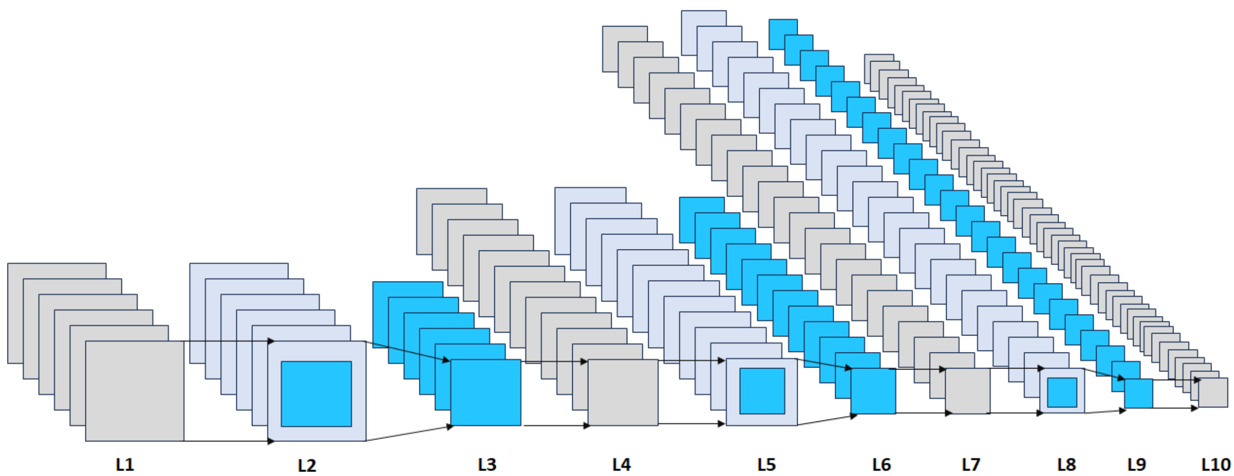


FIGURE 6. Proposed CNN for myocardial segments classification according to viability.

Regarding transmurality computation, radiologists initially performed a visual analysis of the LGE sequences to estimate the transmurality of the scar area for each sub-segment as approved in clinical routine. This visual estimation serves as a reference for our quantitative method. Our approach involves applying thresholding technique to the LGE sequences to isolate the hyper-enhanced regions, representing scar tissue. Then, we calculated the percentage of the extracted area compared to the myocardial sub-segment total thickness. The quantitative results were reviewed and validated by the radiologists to ensure accuracy.

The algorithm, used in our work, for the classification of sub-segments into viable and non-viable and assistance in making therapeutic decision is presented in Algorithm 1.

The CNN architecture proposed for the classification of the myocardial sub-segments into viable and non-viable is composed of 10 layers as shown in Figure.6:

L1: input layer which is a convolution layer with 6 kernels of size 3*3

Algorithm 1 The Classification Algorithm

N: total number of sub-segments = 49
V: number of viable sub-segments
NV: number of non-viable sub-segments
WT: wall thickness
for i = 1 : N **do**
  Transmurality computation **(T)**
   if T < 25%
   Increment the number of viable segments: (V ← V+1)
   else if T > 75%
   Increment the number of non-viable segments: (NV ← NV+1)
   else if 25% < T < 75%
    if WT < 5,5 mm
    Increment the number of non-viable segments: (NV ← NV+1)
    else
    Increment the number of viable segments: (V ← V+1)
end
if V > 15
 revascularization operation is recommended
else
 revascularization operation is not recommended

L2, L5 and L8: ReLU activation layers.
L3, L6 and L9: Max-pooling layers.
L4: Convolution layer with 12 kernels of size 3*3.
L7: Convolution layer with 24 kernels of size 3*3.
L10: output layer which is a fully convolution layer with 48 kernels of size 3*3.

The input images for our neural network undergone three types of segmentation: automatic delineation of LV contours, automatic segmentation according to AHA standards and segmentation of each segment into three equal parts. Quantitative measurements of RWT were provided and each sub-segment was manually classified according to wall thickness. These images serve as the ground truth for the CNN. Short-axis MR images from 35 patients with myocardial infarction and 10 healthy subjects were used to train the neural network over 50 epochs using Adam optimizer. The training process lasted approximately 2 hours and 23 minutes using Python software (version 3.7) running on a 64-bit Intel(R) Xeon (R) central processing unit (CPU) E5–1607 v4 @ 3.10 GHz. Validation was conducted on 15 patients, while the neural network's performance was assessed using data from 23 patients. The time required for the prediction was estimated to be around two seconds. Once the classification of segments is completed, computation of viable segments and non-viable segments is important for the prediction of contractile function recover and help doctors to make the appropriate therapeutic decision in these cases. In our study, we calculate the viable and the non-viable segments percentage as follows:

$$viable\ segments\ percentage\ (\%) = \frac{Total\ number\ of\ viable\ segments}{(18+18+12+1)} * 100 \tag{5}$$

$$non-viable\ segments\ percentage\ (\%) = \frac{Total\ number\ of\ non-viable\ segments}{(18+18+12+1)} * 100 \tag{6}$$

In this context, it has been demonstrated in previous clinical studies [23] that a number greater than 5/17 dysfunctional-but-viable segments is recommended to consider the myocardium as hibernating and able to recover its contractile function after revascularization. Thus, we need about 15 viable sub-segments to consider that revascularization is useful.

F. STATISTICAL ANALYSIS

The effectiveness of the proposed framework was assessed on several levels. We start by evaluating the performance of left ventricular contour segmentation through the calculation of the Dice Similarity Coefficient (DSC) and the Hausdorff Distance (HD) as follows [24]:

$$DSC = \frac{2TP}{2TP+FP+FN} * 100 \tag{7}$$

$$HD = \max(\max p \subset C_A\, d(p, C_B), \max q \subset C_B\, d(q, C_A)) \tag{8}$$

In the context of automatic segmentation, a true positive (TP) occurs when the model accurately identifies a positive class, while a true negative (TN) occurs when the model correctly identifies a negative class. A false positive (FP) refers to cases where the model incorrectly classifies a negative class as positive, and a false negative (FN) occurs when the model incorrectly classifies a positive class as negative. C_A and C_B are the automatic and referential contours, respectively and d (p, C) is the minimum distance which separates the point p of contour C.

TABLE 1. Performance of the proposed architecture for LV endocardial (Endo) and epicardial (Epi) segmentation in terms of DSC and HD.

	Mean DSC (%)		Mean HD (mm)	
	Endo	Epi	Endo	Epi
Healthy subjects	97.88 ± 3.6	98.55 ± 2.1	6.102 ± 3.3	5.212 ± 2.4
Patients with myocardial infarction	97.64 ±	98.7 ± 1.8	7.202 ± 1.1	5.457 ± 4.1

In addition, we examined the precision of regional wall thickness (RWT) quantification and assessed the effectiveness of the myocardial viability assessment protocol.

Regarding quantification, the mean absolute error (MAE) between the ground truth values (y) and the quantified ones ŷ is calculated with standard deviation (SD) for all frames as:

$$MAE(y, \hat{y}) = \frac{1}{N}\sum\nolimits_{i=1}^{N} |y^i - \hat{y}^i| \quad (9)$$

Continuous variables were expressed as a mean ± standard deviations (SD).

To evaluate the impact of the proposed protocol, we used several common performance measures such as inter and intra-observer variability and calculate sensitivity, specificity and accuracy as follows:

$$sensitivity\,(\%) = \frac{TP}{(TP + FN)} * 100 \quad (10)$$

$$specificity\,(\%) = \frac{TN}{(TN + FP)} * 100 \quad (11)$$

$$accuracy\,(\%) = \frac{(TP + TN)}{(TP + TN + FP + FN)} * 100 \quad (12)$$

In the context of myocardial viability assessment, true positive (TP) refers to the number of segments correctly identified as non-viable, true negative (TN) refers to the number of segments correctly identified as viable, false positive (FP) refers to the number of segments incorrectly identified as non-viable and false negatives (FN) refers to the number of segments incorrectly identified as viable.

G. CLINICAL VALIDATION

To evaluate and validate the effectiveness of the proposed protocol, we used the test database composed of cine-MRI images of 23 patients. Two cardiac MRI specialists, one with three years and the other with seven years of experience, were involved in this study to appraise how our method influences the accuracy of myocardial viability assessment. As a first step, radiologists make their therapeutic decisions separately, then collectively based on visual analysis of Cine-MRI sequences and hyper-enhanced regions on the LGE sequences. Two months later, radiologists examine the Cine-MRI images along with quantitative measurements of MWT and thickening of the same patients. For each patient, we conducted a follow-up on the therapeutic decisions made by the radiologists after interpreting the LGE sequences to assess improvement in contractile function after revascularization. During this protocol, radiologists examine, for each patient, a number of myocardial segments depending on the acquisitions' number. Then, the segments were classified in two classes: normal and pathological segments.

The pathological class is divided into two sub-classes: viable and non-viable segments according to the scare area which represents the percentage of the infarcted area of the entire thickness of the myocardial segment at the ED phase. This manual classification carried out by the expert radiologists represents the reference for automatic classification using CNN.

IV. EXPERIMENTAL RESULTS

A. RESULTS OF AUTOMATIC SEGMENTATION OF LEFT VENTRICLE CONTOURS USING U-NET

In this sub-section, we will study through Table 1 the performance of the proposed neural network for the segmentation of the LV contours in terms of DSC and HD. The obtained results presented in Table 1 demonstrate a strong correlation between manual and automated segmentation that reached 98.7% and 5.212 mm in terms of DSC and HD respectively.

By comparing the endocardial and epicardial segmentation results, we notice that, the accuracy of endocardial segmentation appears to be lower than that of epicardial segmentation for healthy subjects and patients with myocardial infarction. This discrepancy can be attributed to the presence of trabeculae and papillary muscles in the left ventricular cavity, particularly in the mid-sections. These structures are closely associated with the endocardium, which complicates the segmentation process and reduces its precision. A comparative analysis demonstrated the superior performance of our method over the most advanced segmentation techniques proposed in the literature.

B. RESULTS OF AUTOMATIC QUANTIFICATION OF REGIONAL WALL THICKNESS

Figure.7 shows a comparison between the mean wall thickness of a healthy subject's 17 myocardial segments over a whole cardiac cycle and a patient with transmural MI in the basal, middle and apical segments.

By comparing the quantification results in the left column (healthy subject) with the right column (patient with MI), we notice that the curves related to the healthy subject Figure.7 (a,b,c,d) have a bell shape distorted to the right and a peak at the systolic phase, which corresponds to the seventh acquisition. In addition, all cardiac segments reach their maximum thickness together around acquisitions 6-9. However, for the patient with MI, Figure.7 (e,f,g,h), curves are characterized by an aspect of asynchronization and some

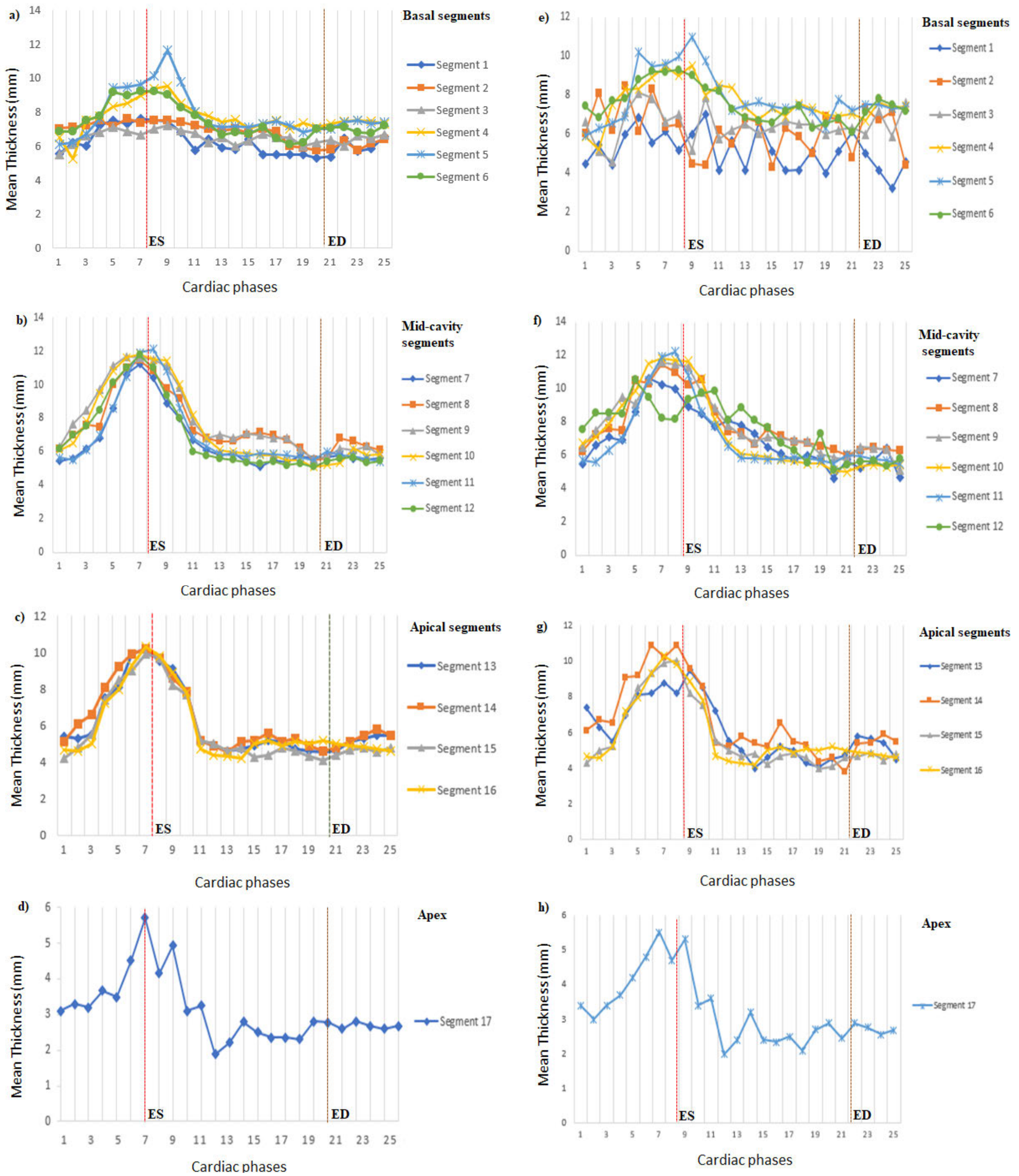


FIGURE 7. Comparison of mean segmental wall thickness across cardiac cycle: healthy subject (a,b,c,d) vs patient with transmural MI (e,f,g,h) for basal, mid, and apical segments.

segments have lost the general bell shape: (segments 1 and 2) of the basal slice, (segments 7 and 12) of the middle slice and the 14th segment of the apical slice. This allows to easily locate myocardial segments affected by MI and identify the occluded coronary artery which are the left anterior descending artery (LAD) and the left circumflex artery (LCX) in this case.

For the same patients, we track myocardial thickening over the entire cardiac cycle at basal, middle and apical slices using our automatic method as illustrated in Figure.8.

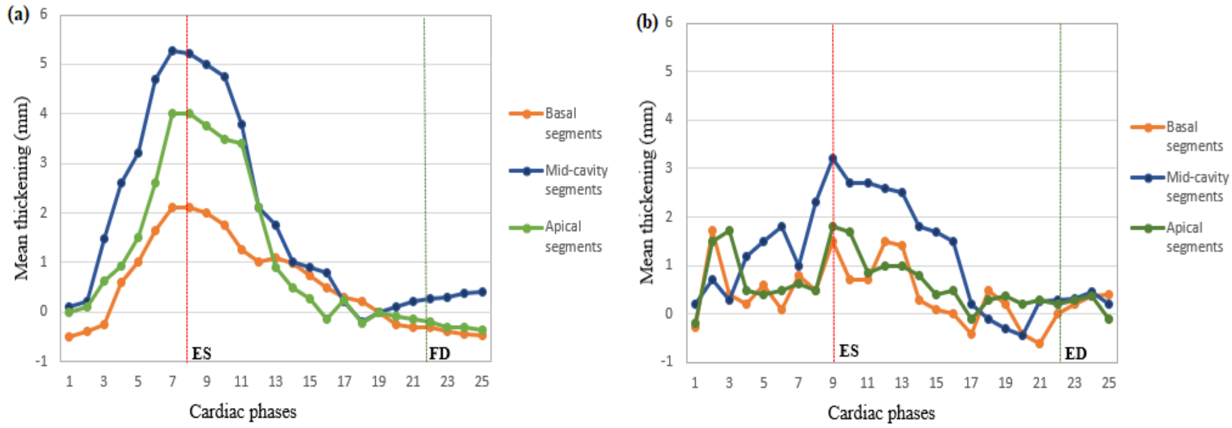


FIGURE 8. Mean myocardial thickening in basal, median and apical slices for healthy subject (a) and patient with MI (b).

TABLE 2. Performance of the proposed method for RWT quantification in terms of MAE for healthy subject and patient with MI.

	Myocardial segment	Healthy subject	Patient with MI
Basal segments	1	1.20±1.02	1.21±1.21
	2	1.29±1.10	1.25±1.19
	3	1.32±1.20	1.27±1.01
	4	1. 18±1.08	1.09±1.02
	5	1.24±1.04	1.13±1.04
	6	1.19±1.03	1.21±1.22
Mid-cavity segments	7	1.13±1.20	1.17±0.77
	8	1.27±0.81	1.25±1.08
	9	1.22±1.01	1.28±0.92
	10	1.19±0.45	1.17±1.22
	11	1.04±0.91	1.02±0.84
	12	1.22±1.22	1.31±1.03
Apical segments	13	1.31±1.01	1.23±0.82
	14	1.34±1.20	1.25±1.09
	15	1.27 ±1.01	1.29±0.89
	16	1.31±1.05	1.27±1.21
Apex	17	1.24±1.02	1.31±0.76

Myocardial thickening curves for the healthy subject indicate a synchronization of movement between myocardium segments and a dyssynchronization between them for the patient with MI. Moreover, the maximum contraction is delayed from the 7th to the 9th acquisition and the thickening is reduced over the entire cardiac cycle. The quantification outcomes show the efficiency of the proposed method in quantifying RWT for each segment at each instant of the cardiac cycle. This allows the identification of pathological segments affected by MI or synchronization pathologies. Corresponding quantitative analysis for these patients is presented in Table 2.

The ground truth and the RWT values measured using the proposed method correspond well, according to an overall analysis of the Table 2. However, we noted that apical segments are characterized by the highest MAE values compared to basal and mid-sections due to the insufficient MRI resolution. This had directly impacted the segmentation accuracy and consequently the quantification performance.

C. CLINICAL IMPACT OF THE PROPOSED MYOCARDIAL VIABILITY PROTOCOL

Visual analysis of cine-MRI images combined with the LGE sequences and analysis performed two months later combining cine-MRI images with quantitative results led to the following therapeutic decisions (Table 3):

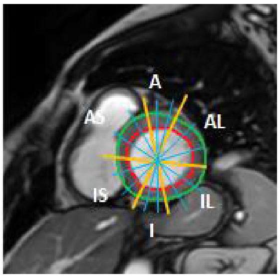
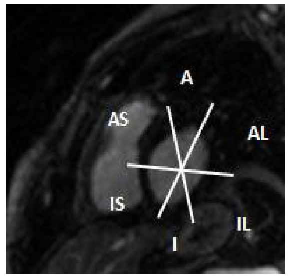
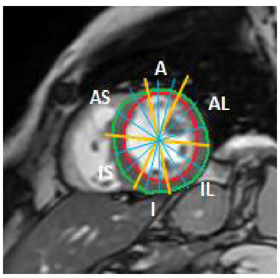
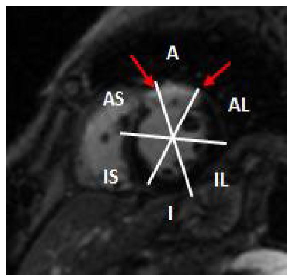
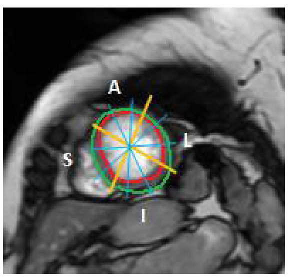
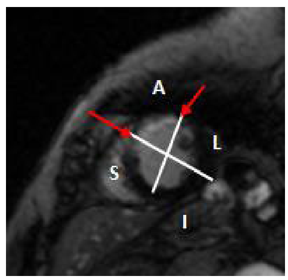
During the proposed protocol, quantitative analysis was provided to radiologists to study the viability of 49 myocardial segments for 23 patients at the ED phase (1127 segments in total). Healthy and pathological segments were identified with an accuracy of 98.4%, sensitivity of 97.77% and a specificity of 96.8% ($p < 0.0017$).

After visual interpretation the radiologist with 3 years of experience decided that 19 patients from 23 patients (82.6%) with MI undergo revascularization. However, the radiologist with 7 years of experience decided that only 16 patients (69.6%) need to undergo this operation. The inter-observer variability was 13% for these first analyzes.

TABLE 3. Therapeutic decision with visual and quantitative analysis.

	Therapeutic decision: revascularization		Intra-variability observer
	Visual analysis	Quantitative analysis	
Radiologist with 3 years of experience	19 patients	17 patients	8.69 %
Radiologist with 7 years of experience	16 patients	18 patients	8.66 %
Together	18 patients	15 patients	13.05 %
Inter-variability observer	13 %	4.36 %	-

TABLE 4. Classification results of myocardial segments based on visual and quantitative analysis for a patient with MI.

Slices	Diagnosis based on quantitative analysis		Diagnosis based on qualitative analysis	
	Cine-MRI	Classification results	LGE	Classification results
Basal		All sub-segments are viable		All segments are viable
Median		Five sub-segments are non-viable		One non-viable segment
Apical		Five sub-segments are non-viable		One non-viable segment

After quantitative analysis, radiologists with 3 and 7 years of experience decided that 17 and 19 patients undergo reoxygenation operation respectively. For these second analyzes, inter-observer variability decreases by 8.64% and becomes 4.36%.

To assess the clinical impact of our method, we followed the improvement of contractile function in patients who underwent revascularization. It turned out that three patients did not register any improvement in myocardial contractility. This corresponds perfectly to the number of patients eliminated by the two radiologists after quantitative analyzes. This proves that the integration of our protocol in clinical practice allowed to avoid unnecessary revascularization operations. Myocardial viability was assessed using CNN for 1127 segments and we had (TP = 670, TN = 436, FP = 4, FN = 17). The obtained results are confirmed by clinical analyzes and confirm the effectiveness of the proposed protocol in the objective study of myocardial viability which achieves a performance of 98.13% in terms of accuracy, 97.52% in terms of sensitivity and 99.09% in terms of specificity with p-value < 0.0001.

To thoroughly assess the clinical implications of the proposed protocol, we examined classification outcomes derived from both visual interpretation of LGE sequences and quantitative analysis methods for a patient with acute myocardial infarction affecting the median and apical slices. In Table 4,

TABLE 5. Performance of the proposed automatic method for RWT quantification compared to state-of-the-art methods in terms of MAE ± SD.

	Regional wall thickness (RWT) (mm)						
	IS	I	IL	AL	A	AS	Average
Max flow [26]	1.53±1.73	3.23±2.83	4.15±3.17	5.08±3.95	3.47±3.25	1.76±1.80	3.21±1.98
Muti feature+RF [26]	1.70±1.47	1.71 ±1.34	1.97±1.54	1.82±1.41	1.55±1.33	1.68±1.43	1.73±0.97
SDL+AKRF [27]	1.98±1.58	1.67±1.40	1.88±1.63	1.87±1.55	1.65±1.45	2.04±1.59	1.85±1.03
MCDBN+RF [28]	1.78±1.40	1.68±1.41	1.92±1.45	1.66±1.20	1.20±1.01	1.63±1.23	1.65±0.77
ResRNN [29]	1.22±1.02	1.47±122	1.78±1.53	1.60±1.30	1.31±1.08	1.25±0.97	1.44±0.74
CSRNet [30]	**1.06±0.87**	1.33±1.14	1.33±1.09	1.32±1.09	1.08±0.92	**0.97±0.80**	**1.16±0.97**
Indices-Net [31]	1.39±1.13	1.51±1.21	1.65±1.36	1.53±1.25	1.30±1.12	1.28±1.00	1.44±0.71
FullLVNet [32]	1.32±1.09	1.38±1.1	1.57±1.35	1.60±36	1.34±1.11	1.26±1.10	1.41±0.72
DMTRL [33]	1.26±1.04	1.18±0.93	1.59±1.29	1.57±1.34	1.32±1.10	1.25±1.01	1.39±0.68
Proposed	1.33 ±1.04	**1.12±1.01**	**1.27±1.00**	**1.31±0.98**	**0.98±0.78**	1.29±1.23	1.21±1.00

we present the cine-MRI images and their corresponding obtained from the LGE sequences where the hyper-enhanced pathological zones are delimited by the red arrows.

For the basal slice, both diagnoses indicate that all myocardial segments are viable.

Regarding mid-cavity slice, diagnosis based on visual interpretation of LGE sequences identifies a single non-viable myocardial segment (the anterior segment) while the diagnosis based on quantitative analysis identified 5 non-viable sub-segments (the anterior segment, a sub-segment of the anterolateral segment and a sub-segment of the anteroseptal segment).

For this slice, the visual analysis highlights 5 viables segments. However, the quantitative analysis reveals 13 viable sub-segments. This shows that two sub-segments belonging to the anteroseptal and the anterolateral segments which are adjacent were incorrectly identified as viable during visual analysis.

Similarly, for the apical slice, the initial qualitative analysis identified 3 viable segments. However, the regional quantitative analysis revealed that two sub-segments, belonging to the lateral and septal segments, were incorrectly identified as viable in the qualitative analysis. This led to a total identification of 7 viable sub-segments. The obtained results proved that integrating our protocol into clinical practice enables the objective assessment of myocardial viability mainly for segments with improbable viability. Additionally, it allows accurate delimitation of myocardial infarction' extent. This approach effectively guides clinical decisions, thereby reducing the need for unnecessary revascularization procedures.

V. DISCUSSION

In this study, we proposed an automatic framework for objective myocardial viability assessment based on RWT quantification. As a first step, the effectiveness of the proposed method for regional wall thickness quantification was assessed by calculating MAE for 73 patients with MI and 10 healthy subjects and made comparison with the state-of-the-art methods including Max flow model [25], Multi-features + RF [26], SDL + AKRF [27], MCDBN + RF [28], ResRNN [29], CSRNet [30] and end-to-end methods such as Indices-Net [31], FullLVNet [32] and DMTRL [33]. Results are summarized in Table 5.

Table 5 clearly illustrates that our proposed method achieves accurate RWT quantification compared to other approaches. Specifically, it outperforms the Max Flow method, exhibiting a MAE of 1.21 ± 1.00 versus 3.21 ± 1.98. This discrepancy can be attributed to the Max Flow method's dependency on manual segmentation of the initial frame, leading to increased estimation errors. In our study, LV boundaries were automatically extracted using U-Net, surpassing prior methods with a DSC of 98.7% and an HD of 5.512 mm. Our method also surpasses the top-performing direct method (MCDBN + RF), particularly in regional MWT quantification, with a notable difference of 0.44 in terms of MAE. Moreover, for the inferior (I), inferolateral (IL), anterolateral (AL) and anterior (A) segments, our method is characterized by the lowest MAE (1.12 ± 1.00, 1.27.100, 1.131 ± 0.98 and 0.98 ± 0.78) respectively. However, for the quantification of RWT of the inferoseptal (IS) and anteroseptal (AS) segments, we note that CSR-Net method yields the lowest MAE of 1.06 ± 0.87 and 0.97 ± 0.80 respectively. Comparison with state-of the art methods shows that the proposed automatic method has a great potential to achieve more accurate quantification results of RWT.

In other study [34], MWT quantification was carried out, similarly to our work from automatically segmented contours using a combination of two CNNs. This method achieved an accuracy of 94% for both endocardial and epicardial segmentation. Since the quantification accuracy relies on the segmentation quality, our method appears more accurate compared to this method because U-net is more appropriate for medical image segmentation and provides more accurate results [24]. In the same work, RWT was quantified in six radial directions according to AHA compared to 18 radial directions for our work which results in the study of 49 segments instead of 17 segments.

The obtained results prove the usefulness of our method for the diagnosis of synchronization pathologies by evaluating myocardial thickening overall the entire cardiac cycle. Moreover, sub-segmental regional analysis allowed the quantification of MI transmurality with high performance. In addition, our method highlights myocardial segments that have been misclassified as healthy which may hide myocardial abnormality with an accuracy of 98.13%, a sensitivity of 97.52% and a specificity 99.09% with p-value < 0.0001. Based on quantification results of clinical parameters (thickness, thickening and scar area) which represent a predictors of contractile function recovery in myocardial hibernation, we studied the myocardial viability of 49 segments for 23 patients with AMI. The involvement of quantified parameters in the diagnostic process reduced inter-observer variability by 8.64% and intra-observer variability. The study of myocardial segments viability shows a strong correlation between decisions taken after quantitative analysis and whether or not contractile function improves in patients who have undergone reoxygenation surgery. This proves the usefulness of the decision support protocol in avoiding unnecessary revascularization operations. Among the limitations of this study, we cite that it has been validated only on a 2D database. It is therefore preferable to test its effectiveness using a 3D and 4D database. Another potential disadvantage of the proposed method is that it was only evaluated on MR images acquired in short-axis view. However, long-axis images give additional information that might be useful in RWT measurement and myocardial viability evaluation.

VI. CONCLUSION

In clinical practice, assessing myocardial viability relies heavily on visually interpreting LGE sequences, a process prone to subjectivity. This can introduce variability in diagnoses and treatment decisions, highlighting the need for more objective and quantitative methods to enhance diagnostic accuracy and improve patient outcomes. This paper introduces an automated framework for objective myocardial viability assessment, leveraging deep neural networks and focusing on RWT quantification. The findings affirm the effectiveness of our method in detecting and quantifying LV abnormalities, such as synchronization pathologies and hypokinesia. The quantified parameters were useful for accurate classification of myocardial sub-segments into viable and non-viable categories and the delimitation of MI extent. The comparison between the obtained results with and without involvement of the proposed method in the diagnostic process proves that it can be used as a promising diagnostic aid tool to guide patient management.

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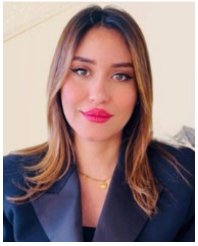

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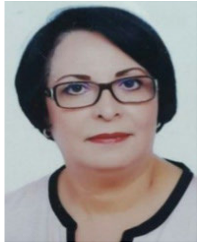

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