AN AI SEGMENTER ON MEDICAL IMAGING FOR GEOMATICS APPLICATIONS CONSISTING OF A TWO-STATE PIPELINE, SNNS NETWORK AND WATERSHED ALGORITHM

Vincenzo Barrile[1, *], Francesco Cotroneo[1], Emanuela Genovese[1], Elena Barrile[2], Giuliana Bilotta[1]

[1]Department for Civil, Energetic, Enviromental and Material Engineering - DICEAM -
Geomatics Lab - Mediterranea University of Reggio Calabria, 89124 Reggio Calabria, Italy;
vincenzo.barrile@unirc.it; francesco.cotroneo@unirc.it; emanuela.genovese.728@studenti.unirc.it; giuliana.bilotta@unirc.it
[2]Università Vita Salute San Raffaele; e.barrile@studenti.unisr.it

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ABSTRACT:

As is well known, image segmentation is widely used in the fields of echocardiography and diagnostic and interventional radiology. The delineation of structural components of various organs from 2D images is a technique used in the medical field in order to identify intervention targets with increasing precision and accuracy. In recent decades, the automation of this task has been the subject of intensive research. In particular, to improve the segmentation of such images, investigations have focused on the use of neural networks, and in particular convolutional neural networks (CNNs). However, most existing CNN-based methods can produce unsatisfactory segmentation masks without precise object boundaries (Wang, Chen, Ji, Fan & Ye Li, 2022); this is mainly due to the shadows and high noise in these images. To address the problem of automated image segmentation, this work proposes a pipeline technique with two stages (applied primarily to the echocardiographic domain): the first consisting of a Self-normalising Neural Networks (SNNs) performs image denoising, while the second applies a Watershed segmentation algorithm on the cleaned image. The latter is a technique successfully applied in geomatics and land surveying. The proposed methodology may be of interest both in the medical field and in the field of Geomatics where segmentation and classification operations are required in different application areas.

1. INTRODUCTION

The interpretation of medical/geomatic images by means of segmentation processes can present various problems depending on the type of source image and the precision required by the different operative procedures. In fact, segmentation of medical and geomatic images can be challenging due to several factors, including:

- Image variability: medical and geomatic images can be highly variable in terms of contrast, brightness, noise, and texture, making it difficult to distinguish between different regions within the image.
- Presence of artifacts: images may contain artifacts such as shadow areas, blurring, or distortion, which can affect the accuracy of segmentation.
- Shape complexity: shapes of medical and geomatic structures can be complex and may exhibit significant variations among individuals, making it difficult to reliably identify areas of interest.
- Image size and resolution: images can be large and contain many details, making the segmentation process very expensive in terms of time and resources.

To overcome these challenges, advanced segmentation techniques such as machine learning and artificial intelligence can be used, which can be trained to recognize specific patterns within images. Additionally, the use of preprocessing algorithms can help improve image quality and reduce the presence of artifacts.

The assessment of cardiac function by means of echocardiography, for example, is a crucial step in everyday cardiology; however, the segmentation of the boundary of cardiac structures is a challenging procedure due to shadows and speckle noise (similar interpretation problems can be found more generally in the whole field of radiology). Manual segmentation of the cardiac border is a time-consuming process and excludes conventional segmentation for many situations such as emergency cases and image-guided robotic interventions. Therefore, providing an efficient and robust autonomous segmentation method is crucial for such applications. This work aims to investigate the possibility of introducing a segmentation algorithm (Watershed technique) widely used in the field of geomatics in this context. This technique is successfully applied in the field of geomatics and in particular in the segmentation of orographic structures, such as hills, canyons, inlets, depressions and the like (Barrile & Bilotta, 2016) (Bilotta, Calcagno & Bonfa, 2021) (Barrile, Bilotta & Pannuti, 2008) (Barrile & Bilotta, 2008). These are all situations that could be assimilated by homology to cardiac structures. As known for geomatic images, Watershed technique is based on mathematical morphology. The segmentation process begins by identifying the local minima of the image, which correspond to the lowest points of the topographic surface. These local minima are then considered as starting points for the creation of separation lines, called "watershed lines", which divide the image into regions. In this regard, Figure 1 shows an example of segmentation and classification using techniques and methods typical of geomatics (Barrile, Cacciola & Versaci, 2006). The classical algorithm applied directly to the echocardiographic image (and to

* Corresponding author

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radiological images in general), however, fails due to the considerable noise and at the same time because this technique does not practice any inference for the expected elements. In fact, Watershed methodology has some limitations that can make accurate segmentation of geomatic images difficult. Here are some of the main limitations:

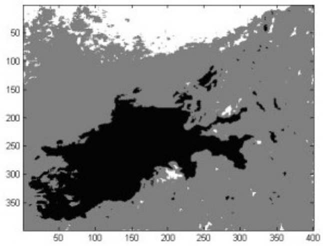

Figure 1: Example of segmentation and classification using techniques and methods typical of geomatics.

- Over-segmentation: the watershed methodology can lead to over-segmentation of the image, meaning the subdivision into regions that are too small and detailed. This can make it difficult to understand the image and interpret the results.
- Scale dependence: the watershed segmentation is highly dependent on the scale of the image. This means that the segmentation result can vary depending on the chosen scale, which can make reproducibility and result comparability difficult.
- Sensitivity to noise: the watershed methodology is sensitive to noise present in the image. This can cause the formation of unwanted watershed lines and the creation of incorrect segments.

To overcome these limitations, pre-processing techniques can be used to improve image quality and reduce noise. Additionally, hybrid approaches can be used, such as combining watershed techniques with machine learning approaches, to improve segmentation accuracy and overcome the limitations of watershed methodology alone. The idea is therefore to use a two-stage pipeline, the first consisting of a neural network of type SNNs - SELU (Scaled exponential linear units) that performs image denoising, while the second applies the Watershed algorithm on the cleaned image.
The methodology, even if little used, has some advantages related to the speed of the results obtained in all those situations where timely intervention is of fundamental importance, being able to overlook a minor error that could still be made manually by an expert. In the proposed procedure, a fundamental part is played by the noise-cleaning process. This process is not noise agnostic but aims to generate a derived image on which the Watershed algorithm will find little difficulty in producing the expected output. The inference process produced by the neural network is not to identify the constituent elements of the cardiac structures but to 'identify' the type of noise that when added to these structures complicates the application of Watershed's algorithm. In recent years, research into the problem of segmentation of echocardiographic images has intensified enormously, especially with regard to convolutional neural networks (CNNs) in this context (Chen, Qin, Qiu, Tarroni, Duan, Bai et al., 2020). Enormous steps forward compared to traditional techniques have been demonstrated (Lei, Fu, Roper, Higgins, Bradley, Curran et al., 2021) (Fu, Lei, Wang, Curran, Liu & Yang, 2021) (Fu, Lei, Wang, Curran, Liu & Yang, 2020) (Chen, Wang, Zhang, Fung, Thai, Moore et al., 2022) (Wang, Yang, Rong, Zhan & Xiao, 2019) (Li, Chen, Fang & Zhao, 2017) (Li, Jiang, Kambhamettu & Shatkay, 2018), however, two questions still remain open:

- Even networks that show very good performance may manifest inefficiencies when applied to input images with many shadows and noise distributed very un-evenly with respect to the cases of the training set.
- The training of a good model requires the construction of a training set that is very large in number of occurrences and cases; large when considering the training sets required in other fields for the classification and/or segmentation of the same number of categories.

The two points are connected. In order to make a correct inference and given the type of noise that plagues these images, it is necessary for the training process to present as many situations as possible. Added to this problem is the fact that in this sector, the production of reliable training sets is very costly in terms of money, time and the professional skills that have to be involved. Here too, the proposed methodology uses neural networks, which, however, do not have the task of carrying out the segmentation, something that is delegated to a deterministic, classical algorithm, which in some way guarantees the 'universality' of the approach even in the face of extreme variability of the input data. Figure 2 shows the proposed two-stage pipeline.

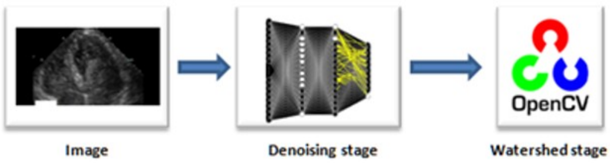

Figure 2: Two-stage segmentation pipeline Stage 1: AI image denoising, Stage 2: Watershed algorithm.

Stage 1 is therefore represented by a neural network with supervised learning. The training set, as will be discussed in more detail later, will be generated by processing the echocardiographic images used in this work. For each image, more than twenty derived images can be generated to form the training set. This work used the CAMUS (Cardiac Acquisitions for Multi-structure Ultrasound Segmentation) dataset (Leclerc, Smistad et al., 2019) and some images provided by clinical laboratories in the manner prescribed by law. The CAMUS dataset is a collection of echocardiographic image data created to support research on automatic heart segmentation in ultrasound images. The dataset contains ultrasound images of the heart acquired from different modalities such as transthoracic and transesophageal echocardiography. The CAMUS dataset has been used for the development and validation of automatic heart segmentation algorithms in exam, with the aim of improving the accuracy of the study. Below (Figure 3), an image extracted from the CAMUS dataset which was then used successfully in the results validation phase is reported.

As for the neural network dedicated to the image denoising stage, the type of neural network chosen for the classifier is SNN (Self-normalising Neural Networks) (Fu, Lei, Wang, Curran, Liu & Yang, 2021) whose structure and characteristics are shown in Figure 4, all using Tensorflow that has been widely used to develop machine learning models in different fields such as image recognition, automatic translation, and medical diagnosis.

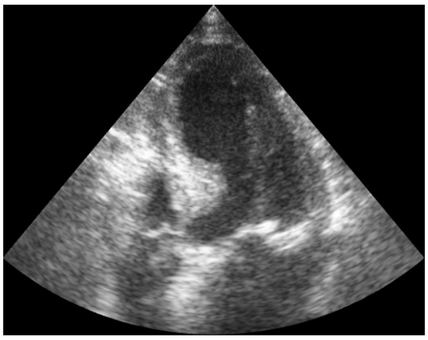

Figure 3: Example of the CAMUS dataset.

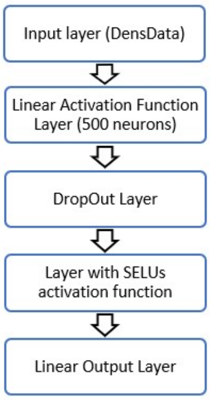

Figure 4: SNN Neural Network structure.

The OpenCV library was used for the Watershed techniques. Software based on OpenCV and Python was then built to create the training set.
The aim of this work is therefore to introduce a ”hybrid” pipeline methodology, shown in Figure 5 into the context under consideration, where the techniques of the last stage are often used in geomatics; it is therefore not intended to be conclusive. All useful steps for its implementation, and the results obtained, will be listed.

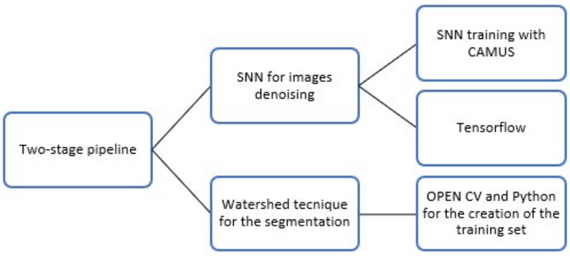

Figure 5: Hybrid pipeline scheme used for experimentation.

2. MATERIALS AND METHODS

2.1 Using SNN Neural Networks with ’SELUs’ Layer

During the experiments, when training the neural network, only SNN models were used that had at least one layer made up of neurons with a SELUs (Scaled exponential linear units) activation function (Klambauer, Unterhiner, Mayr & Hochreiter, 2017).

In this scenario, it seemed useful and not too expensive in computational terms to use SNNs (Self-normalizing Neural Networks). These networks are robust to noise and disturbances and do not show large variations in training errors. SNNs have the main characteristic of being self-normalizing neural networks and therefore do not require pre-processing of inputs with scaling / normalization activities or batch processes. The heart of this type of network is the use of the SELU activation function, which in addition to guaranteeing the property of self-normalization of the data guarantees convergence towards the zero mean and unitary variance in training errors; convergence in the training process is so accelerated and you don’t need to do continuous random initializations to avoid local minima. Therefore, the SELU learns faster and better than other activation functions without the need for further processing, and this is especially true when the training set is quite noisy.
This type of activation function has been introduced very recently in the AI landscape and was chosen here mainly due to its high performance in the learning phase and the fact that it does not require any kind of normalisation of the input data, which is why such networks are referred to as Self-normalising Neural Networks. Its form and expression are shown in Figure 6.

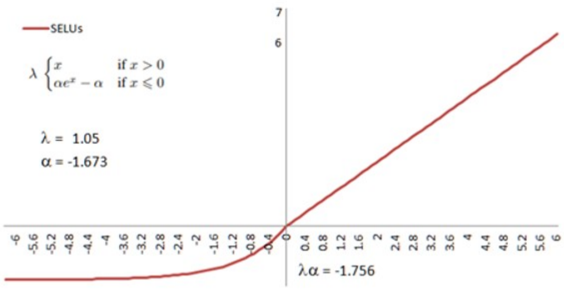

Figure 6: SELUs (Scaled exponential linear units) activation function used for Self-normalising Neural Networks.

The ”SELU” non-linearity keeps the data standardized and the gradients from getting too small or too large. The effects are comparable to batch normalization while requiring significantly less computation. Furthermore, the convergence property of SNNs towards zero mean and unit variance allows training of deep networks with many levels and makes learning extremely solid.
The SELUs activation function offers considerable advantages that make it preferable even to RELU (Rectified Linear Unit), the latter being widely used within CNN convolutional networks. Some of these include:

- They make the network self-normalising;
- SELUs does not have vanishing gradient problem;
- Compared to ReLUs, SELUs neurons cannot die;
- SELUs learn faster and better than other activation functions without the need for further processing.

The parameterisation in Figure 6 is the default defined in the design environment and is taken from the literature.

2.2 The Watershed Technique

The Watershed segmentation technique has always been used successfully in the field of geomatics and especially in the segmentation of orographic structures, such as hills, canyons, mountain

ranges and the like. These are all situations that could be assimilated by homology to cardiac structures as far as the problems inherent in segmentation techniques are concerned, except for the typical and particularly problematic noisiness of echocardiographic images.
This segmentation technique treats the image as a topographic map, with the intensity of each pixel representing height. For example, dark areas may intuitively be considered 'lower' height and may represent depressions. Bright areas, on the other hand, may be considered 'high', acting as hills or mountain ridges, or vice versa. Various algorithms can be used to calculate these 'catchment areas'. One of the most popular algorithms is Watershed-by-flooding. Basically, a source of water is assumed to be located in catchment areas, the low-lying areas. These catchments are flooded and the areas where flood waters from different catchments meet are identified. Barriers in the form of pixels are then constructed in these areas. As a result, these barriers act as partitions in the image and the image is considered segmented in this way.
As can be understood, the AS IS application of the technique is unthinkable directly to the echocardiographic image, but a pre-processing of the latter is required so that the noise present does not invalidate the assumptions made by this technique. And it is precisely for this purpose that the first processing stage consisting of the SNN network is provided. Here the inference of the neural network must be towards a function capable of "flattening" or "highlighting" those pixels whose noisy value could cause the Watershed technique to fail.

2.3 Creation of the training set for the denoising stage

The purpose of creating the training set is to allow the modelling of an SNN operating in the denoising stage within the proposed pipeline. As mentioned, it must "identify" the type of noise that when added to the cardiac structures in the cardiographic image complicates the application of the Watershed algorithm. It follows that the training set must be generated with this specificity in mind and with truth checks using the Watershed stage, as shown in Figure 7.

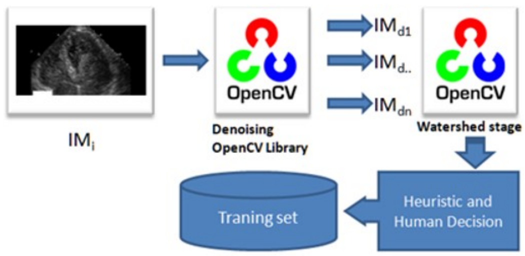

Figure 7: Creation of the training set for the denoising stage.

The first step in creating the training set, as shown in Figure 7, is to subject a single IMi image to a custom pseudo-random algorithm constructed using the OpenCV library and the functions of the Computational Photography and denoising package. The software is applied n times to the same image, changing each time, and randomly, the filter parameters offered by the library and the sub-regions of the image where to apply it most relevantly.
In this way, IMd11 ... IMd1n images are generated. Each of these constitutes the input of the segmentation stage represented by OpenCV's Watershed algorithm and thus produces the IMs11 ... IMs1n images, i.e. the images containing the segmentation. Finally a heuristic algorithm assesses whether the produced images do not have a segmentation fallacy, if this is the case they are discarded otherwise they are included in the training set. Here, of course, it is possible that there are false positives, but the discard was certainly with no errors. The heuristic algorithm provides for rejection when the polygons generated have a number and area that definitely do not correspond to reality.
For the elimination of false positives, human intervention is required, but the operator's activity is here delegated to a check operation and not to manual segmentation as training for the network. For the purpose of this work, a false-positive filtering operation was performed that focused on eliminating glaring errors, no thresholds as described by the anatomical sciences were considered.
The algorithm for creating the training set is a generate-and-test type, however given the boundaries given to the parameters, the possible permutations make the approach compatible with currently commercially available computational resources. The final training set matches each IMi with the set of undiscarded IMd11 ... IMd1n images.
In the case study, No. 200 images from the CAMUS dataset were used, the generated training set initially had about 4200 occurrences, after manual intervention it was reduced to about 3300 occurrences. The process was run independently on several workstations at the same time (each equipped with eight eleventh-generation Intel core i7 logic processors). Each workstation processed one image at a time (the stop to single processing was given when the 4-hour processing time was exceeded). Once the training set was obtained, we then proceeded to define the neural network model and carry out supervised training. A number of inputs equal to 20x20x3 (Pixel Matrix of 20 units and the three RGB channels) were then defined for both networks. It should be noted that the central part of the images was stretched. This is because the individual images in the datasets (regardless of the area covered) represent a single class, or rather, a single semantic unit. Below we list the structure of the SNN neural network showing the layers of which it is made up and their characteristics:

- Input layer (DensData);
- Linear Activation Function Layer (500 neurons);
- DropOut Layer. With 30 per cent activation rate. Layer only present during training, helps prevent overfitting;
- Layer with SELUs activation function;
- Linear Output Layer.

And finally, training was launched. The training time was approximately 8 hours (workstation with eight eleventh-generation Intel core i7 logic processors). In order to show the advantages of the methodology proposed even in the medical field, it is highlighted how these new types of neural networks are starting to spread successfully in various application areas from which the advantages compared to traditional methods are highlighted (Tripathi & Sharma, 2021) (Zhu, Shi, Song, Tao, Tan & Zhang) (Zhu, Abdalla, Tang & Cen, 2022).

3. RESULTS

Once the training was finished, the performance of the network in the pipeline sense was evaluated, or rather the methodology was unit-tested. For this purpose, No. 500 images not belonging to the training set were used and fed into the pipeline. The outputs were marked by human sifting as valid or invalid. The discernment between the two categories was made by setting as invalid those cases where the segmentation was clearly in discordance with cardiac structures, no discriminating thresholds of medical relevance were considered. Using this criterion, the network and the entire pipeline operated successfully on average in 94 % of the cases. Consequently, two case studies (A and B) carried out using the proposed methodology are reported. Figure 8 (Case A) shows the case when the Watershed algorithm is used without the denoising stage. Figure 9 (Case A) shows instead when the proposed pipeline is used. Figure 10 (Case B) shows the whole pipeline segmentation, denoising stage and Watershed stage, applied to another image of the CAMUS dataset.

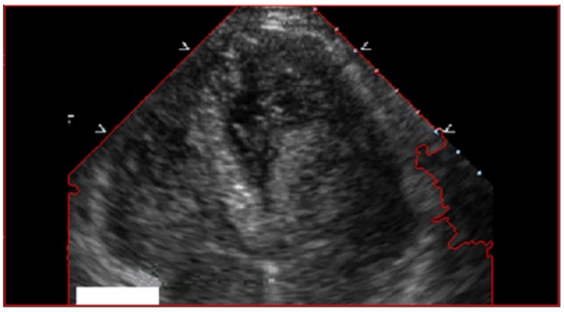

Figure 8: Watershed segmentation applied without denoising stage.

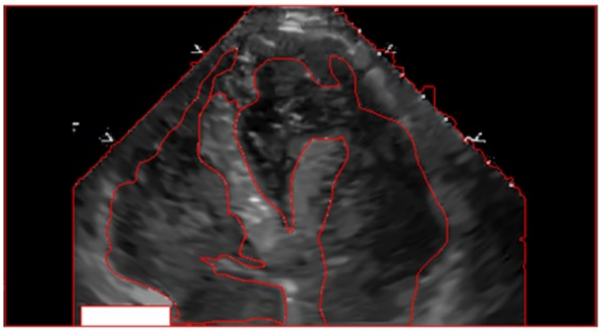

Figure 9: Example of whole pipeline segmentation, denoising stage and Watershed stage.

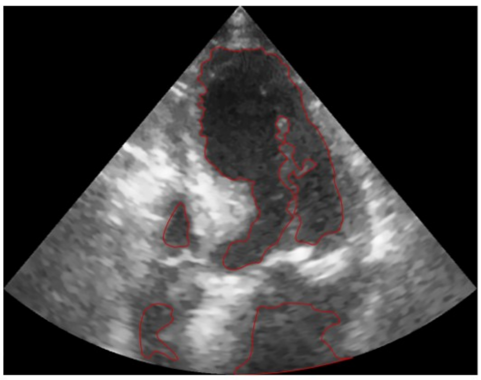

Figure 10: Example of the whole pipeline segmentation applied to another image of the CAMUS dataset.

In Figure 9 and Figure 10 the boundaries tracing the cardiac structures (red polygons) superimposed on the image generated by the denoising stage are shown. As can be seen, the application of the methodology provides appreciable results, about 94% of the cases, highlighting the advantage of the methodology speed in terms of time. To verify its reliability, it seemed appropriate to carry out a verification of the results obtained by the two-stage pipeline by comparing these both with the manual method done by medical personnel in the sector (Figure 11) (proceeding to extrapolate the portions of the image of interest, scaling the results so as to make them comparable with the automatic segmentation by we carried out) either with a segmentation algorithm designed specifically for medical images implemented in ITK-SNAP version 3.0 software (Figure 12) (Yushkevich, Pashchinskiy, Ognuz et al., 2019), applied to another image extracted from CAMUS.

Figure 11: Segmentation operated by medical personnel in the sector.

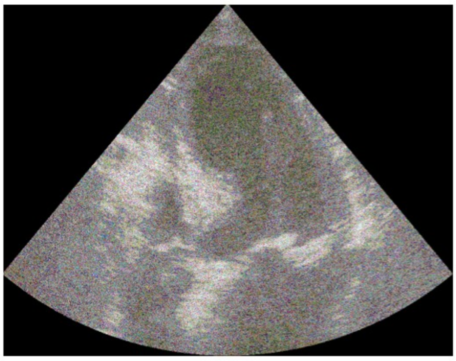

Figure 12: Segmentation operated by ITK-SNAP.

As can be seen from the comparison between Figure 9-10 and 10-11, the results obtained from the proposed methodology are completely comparable both with manual segmentation and with the procedure used by the ITK-SNAP software, resulting the proposed methodology more performing in some portions of the images and less performing in others. From the same images of the results obtained, it is also evident that in some cases the ITK-SNAP algorithm failed to define polygonal boundaries comparable with the results obtained from the multi-stage segmenter. However, this problem does not arise in the case of using the program with low-noise images such as magnetic resonance imaging (MRI).

For the completeness of the analysis, highlighting primarily that one of the advantages of the proposed method lies in the image segmentation times compared to traditional methods, we wanted to evaluate the similarity metrics between manual/ITK-SNAP segmentation and the proposed segmentation. In this regard, it was chosen to use the Intersection over Union (IoU) performed on different portions of the images by measuring the overlap between the two segmentations. The result of the similarity analysis after evaluating also false negatives and false positives shows an IoU

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of 0.94, indicating that images are on average comparable, highlighting different results in different regions where the algorithm works best and others where performance can improve.

4. CONCLUSION

This work proposed a preliminary investigation into the use of a two-stage pipeline for the segmentation of echocardiographic /radiographic/ geomatics images. The first denoising stage implemented by means of an SNN and a deterministic stage implemented by a Watershed algorithm from the experiences of geomatics. The first results, reported here, seem to show that while the direct application of the Watershed algorithm is not possible, the use of the pipeline could instead be a promising methodology, presenting results that are on average 94% comparable with the other methodologies present in the literature, overcoming the problem of training set generation when comparing segmentation techniques that exclusively use convolutional SNNs, with evident advantages in time consuming such as for example for many situations of emergency and image-guided robotic interventions.
The results produced does not want to be exclusively quantitative (measuring the performance of the algorithm by comparison) but tries to demonstrate the validity of the approach identified by highlighting how the creation of automatic intelligent algorithms applied to such images is particularly complex. Automatic medical image segmentation through SNN (self-normalizing Neural Networks) is in fact a continuously evolving research field, and there are numerous possible future developments. One is the use of increasingly larger datasets to improve segmentation accuracy. With larger datasets, it is possible to train SNN models more accurately, thus improving their generalization and segmentation capabilities for new images. Another possibility is to improve the computational efficiency of SNNs.

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