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Algorithms and Approaches Used in Medical Image Segmentation for Cell Migration Tracking: A Systematic Literature Review

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Abstract. Medical image segmentation plays a critical role in monitoring cellular migration, especially in tumor progression studies. This systematic literature collects the findings of 32 studies that include recent advances in computational vision methodologies applied to medical image segmentation, with a particular focus on cell migration. We can observe that traditional segmentation techniques, such as region-based methods, clustering, and edge detection, have been extensively used, but recent approaches that include deep learning architectures have been more widely used like U-Net architectures and Convolutional Neural Networks, also, findings indicate that Dice Score, Hausdorff distance, Recall and F1 score are the most used evaluation metrics. Lastly the size used for image processing was heterogeneous, ranging from 128×128 pixels, as the smallest size, to 512×512 pixels.

Keywords: Segmentation, cell migration, medical images.

1 Introduction

The term ”cell migration” refers to the process by which cells move, either individually or collectively, from one place to another in response to specific stimuli. This process is essential in various biological phenomena, whether normal or pathological, such as embryonic development and tumor cell migration [23].

This and many other mechanisms can be replicated in a laboratory setting for study through cell culture and proliferation, with the wound healing assay and the use of Boyden chambers being the most commonly used techniques to monitor the cell migration process, as well as the morphological changes that occur over time [1, 19].

Over the years, various software systems, both specific and multi-analysis, have been developed to assist in the processing and analysis of images obtained from the aforementioned techniques [30]. However, these programs present limitations and inaccuracies that must be manually corrected by the user. This entails a greater time investment, which increases as the image databases grow larger.

In recent years, the application of computer vision methodologies in different fields has become increasingly common, especially in medicine, where the interpretation and identification of pathologies based on imaging results can sometimes be inaccurate. Previous studies have shown that the use of computer vision techniques can improve the accuracy of these analyses and could potentially be used for the detection of pathologies that may be undetectable to the human eye [14, 34].

Therefore, the aim of this work is to summarize the findings of previous research related to the implementation of computer vision methodologies for the segmentation of medical images, with a focus on tracking cell migration.

2 Related Work

Recently, the implementation of segmentation techniques in medical images as a tool for disease diagnosis and monitoring has become an area of great interest. In the study conducted by Ramesh et al. in 2021 [26], a compilation of both traditional and recent methods available for medical image segmentation was carried out. They highlight region-based methods, clustering, and edge detection as the most commonly used approaches.

On the other hand, in the work presented by Gupta and Mishra in 2024 [6], a systematic review focused on deep learning-based medical image segmentation methods for polyp detection was conducted. They provided a detailed classification of the main neural network architectures applied to segmentation, including convolutional neural networks (CNNs), encoder-decoder models (such as U-Net and its variants), recurrent neural networks (RNNs), attention-based models, and generative adversarial networks (GANs).

Since there are no systematic reviews that specifically address the methods used to more accurately track tumor cell migration, the aim of this systematic literature review is to organize and present the results obtained, highlighting both the benefits and the challenges identified regarding segmentation methods in medical images applied to the study of cell migration. By gathering the available information, this review aims to provide various options that could contribute to improving current techniques and addressing key issues identified in this field of research.

Table 1. Research questions and their Motivations.

ID	Research question	Motivation
RQ1	What computer vision approaches have been used for segmentation in wound closure images at the cellular level in medical imaging?	Identify the most effective computer vision techniques applied to cellular segmentation in wound closure assays to adapt them for segmenting liver tumor cells.
RQ2	What evaluation metrics have been used to assess wound closure segmentation algorithms at the cellular level in medical imaging?	Identify the most relevant metrics for measuring the effectiveness of segmentation algorithms to evaluate the proposed approach in this work.
RQ3	What approaches or algorithms have been used to remove noise in wound closure segmentation at the cellular level in medical imaging?	Determine the most effective noise removal techniques in the context of cellular segmentation in medical imaging.
RQ4	What are the characteristics of the images used in the segmentation process of wound closure at the cellular level?	Understand the experimental conditions under which the proposed methods were evaluated to identify the most suitable approaches for our case study.

3 Research Method

In this study, the guideline proposed by [15] was followed, which is a method to identify, evaluate, and synthesize evidence in systematic literature. This approach involves three main stages such as planning the review, conducting the method, and documenting the results.

3.1 Planning Stage

In this stage, the research questions and the search terms are defined, the data sources are selected and the search string is built.

Research questions: Table 1 presents the four research questions formulated to guide this work, along with the motivation behind their formulation.

Selected search terms: The search terms used to guide this search are shown in Table 2; these terms represent key aspects of the topic of interest. The appropriate selection of these key terms allowed us to obtain the necessary information for the development of this work.

Data sources: The data sources ware selected based on their relevance in the area of artificial intelligence and image processing. Furthermore, some are multidisciplinary to cover the health sector. These data sources are shown in Table 3.

Table 2. Search terms.

Search term	Related terms
Algorithm	Approach, method, technique
Image	Medical image, Medical imaging, Image analysis, Image segmentation.
Cell	Cellular, tumor cells.
Segmentation	Segmentation evaluation, Edge detection.
Counting	Count, Cell counting, Automated cell counting, Image-based cell counting.
Wound	Wound healing, wound closure, wound healing images, wound healing assay.
Cell segmentation	Tumor segmentation.
Accuracy	Metrics, precision.

Table 3. Selected sources.

Data source	Web site
ACM Digital Library	`https://dl.acm.org/`
IEEE Xplore	`https://ieeexplore.ieee.org/`
Science Direct	`https://www.sciencedirect.com/`
Springer Link	`https://link.springer.com/`

Search string: Based on the terms presented in Table 2, several search strings were proposed and evaluated using the Quasi-Gold-Standard method proposed by [40]. This method considers metrics such as recall and precision, which are described in equations (1) and (2) respectively:

$$Recall = \frac{\text{Retrieved relevant studies}}{\text{Relevant studies}}, \tag{1}$$

$$Precision = \frac{\text{Retrieved relevant studies}}{\text{Retrieved studies}}. \tag{2}$$

The search string presented below demonstrated the best performance in retrieving relevant studies, achieving 82% in the recall metric and 19.9% in the precision metric.

```
(‘‘Medical image’’ OR ‘‘image segmentation’’ OR ‘‘wound healing’’ OR ‘‘Tumor
segmentation’’ OR ‘‘Segmentation evaluation metrics’’)) AND (‘‘Accuracy’’ OR
‘‘Precision’’)
```

Selection criteria: The selection criteria used to choose the primary studies are shown in Tables 4 and 5, where the proposed inclusion and exclusion criteria can be found.

Table 4. Inclusion criteria.

ID	Inclusion criteria
IC1	The study must have been published between 2019 and 2024
IC2	The study must be written in English
IC3	Full-text access to the article must be available
IC4	The study must answer at least one research question

Table 5. Exclusion criteria.

ID	Exclusion criteria
EC1	The study must have been published between 2019 and 2024
EC2	Duplicate studies across databases
EC3	Studies available only as slides, book chapters, posters, or technical reports

De acuerdo, vamos a aplicar el mismo estilo de la tabla Selected sources a tu tabla Inclusion criteria.

Recordemos las características de ese estilo, que es el que me indicaste que querías seguir para la tabla Selected sources y que, por ende, es el que aplicaríamos aquí:

Utiliza tabularx para el control del ancho total de la tabla.

Define las columnas usando pancho para la primera columna y X para la segunda columna. Esto permite un ancho fijo para la primera y una distribución justificada para la segunda.

Incluye líneas verticales y horizontales.

Usa ara ajustar el espaciado entre filas.

Aquí tienes el código para tu tabla Inclusion criteria con ese estilo:

Fragmento de código

3.2 Conduction Stage

The selection process was divided into three stages, during which the inclusion and exclusion criteria were applied to identify the primary studies. In the first stage, IC1 and IC2 were applied, while in stage 2, EC1 and EC2 were applied. In the third and final stage, IC3 and IC4 were applied. This process can be observed in Figure 1.

The results of the primary study selection process described in Figure 1 are outlined in Table 6, where it can be observed that after applying stage 3, a total of 32 primary studies were obtained.

3.3 Reporting Stage

A narrative synthesis was carried out following the steps presented by [24]. In this synthesis, an analysis of the findings was performed, identifying patterns in plots and tabulations.

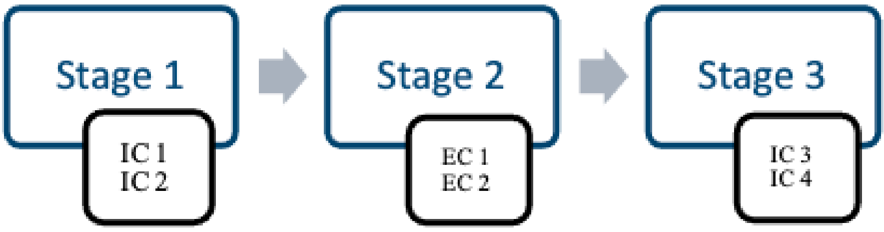

Fig. 1. Primary studies selection process.

Table 6. Results of selection process by stage.

Source	Initial stage	Stage 1	Stage 2	Stage 3
Springer Link	307	139	122	7
ScienceDirect	152	47	20	2
IEEE Xplore	18	18	18	10
ACM DL	377	352	122	13
Total	854	556	282	32

4 Results

The automated search was conducted in the data sources shown in Table 3, with ACM DL accounting for 41% of the relevant studies as shown in Fig. 2, followed by IEEE Xplore with 31%. Table 7 lists the selected studies and their corresponding data sources.

Additionally, the distribution of articles by publication type was identified, as shown in Fig. 3. Of the total articles, 69% were published in journals and 31% in conferences.

Finally, regarding the distribution of publications by year, as can be seen in Fig. 4, 21 of the 32 selected studies were published in 2024, while 8 were published in 2023 and 2022, showing research topic is current and relevant.

4.1 RQ1. What computer vision approaches have been used for segmentation in wound closure images at the cellular level in medical images?

During this work, two main computer vision approaches for segmentation were identified: texture and color. The studies that addressed this research question and used color as an approach were mainly based on genetic algorithms [19, 30], while those that used texture primarily implemented deep learning techniques [11, 16]. In both cases, their study objects were different types of tumors, and they used images obtained through imaging techniques such as magnetic resonance imaging and computed tomography, as well as images obtained from cell migration assays, including the wound closure assay.

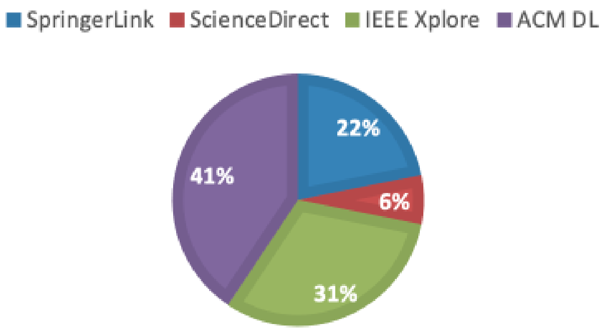

Fig. 2. Distribution of primary studies by data source.

Table 7. Selected Primary Studies

Data source	Primary studies
Springer Link	[10] [16] [11] [18] [17] [37] [8]
ScienceDirect	[14] [4]
IEEE Xplore	[25] [29] [22] [13] [20] [28] [38] [12] [27] [32]
ACM DL	[21] [36] [9] [3] [39] [31] [2] [5] [35] [7] [41] [42] [33]

4.2 RQ2. What evaluation metrics have been used to assess wound closure segmentation algorithms at the cellular level in medical images?

The most used metrics by the authors to evaluate the performance of segmentation algorithms were average precision, F1-score, and Dice score, reported in 10 of the 32 selected articles, with values ranging between 80% and 90% for each metric across all studies. This can be seen in more detail in Table 8.

4.3 RQ3. What approach or algorithm is used to remove noise in wound closure segmentation at the cellular level in medical images?

A wide variety of algorithms and techniques were found for noise removal and analysis of medical images, but two of them stood out: U-Net, which is used in 14 of the 32 analyzed articles, and Convolutional Neural Networks (CNNs), used in five of the 32 analyzed articles. This can be seen in more detail in Table 9.

4.4 RQ4. What are the characteristics of the images used in the segmentation pro-cess of wound closure at the cellular level?

We observed that the image sizes used in the analyzed studies were heterogeneous, ranging from 128x128 pixels, as the smallest size, to 512x512 pixels, as the largest size. Both grayscale and RGB images were used.

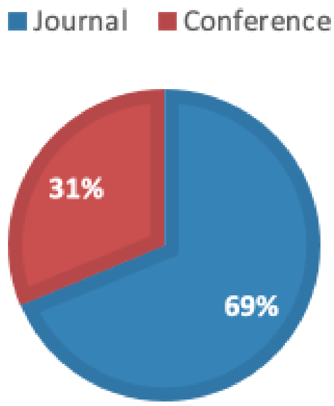

Fig. 3. Distribution of primary studies by publication type.

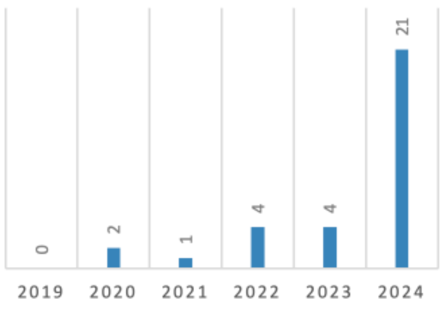

Fig. 4. Distribution of primary studies by publication year.

Table 8. Distribution of Primary Studies by evaluation metrics used.

Evaluation metrics	Primary studies
Intersection over Union (IoU)	[11]
Dice Score	[18] [29] [22] [38]
Hausdorff distance	[18] [17] [22]
Structural Similarity Index (SSIM)	[4]
Mean Squared Error (MSE)	[4]
Percentage of Misclassification (PM)	[29]
Peak signal-to-noise ratio (PSNR)	[17] [29]
Recall	[11] [17] [38]
Precision	[11] [27]
F1 score	[17] [38] [21]
Accuracy	[27] [21]

Table 9. Distribution of Primary Studies by Computer vision approach.

Approach	Primary studies
Spatial-channel Convolution Optimization (ASCO)	[11]
U-Net	[18] [37] [29] [22] [13] [28] [38] [12] [21] [36] [31] [35] [7] [41]
Deep Attention Integrated Networks (DAINets)	[33]
Encoder-decoder network for segmentation and a sub network for classification	[41] [42]
Arithmetic Optimization Algorithm (AOA)	[17]
Ultrasound Network (US-Net)	[3]
Contextual Attention Network (CAN)	[32]
Convolutional Neural Networks (CNN)	[14] [8] [27] [39] [5]
CA-Unet network	[25]
Prediction Wound Progression Framework (PWPF)	[4]

5 Conclusions and Future Work

This systematic review highlights the growing reliance on U-Net and CNN-based architectures for medical image segmentation, particularly in tracking cellular migration. These models have shown superior segmentation accuracy compared to traditional methods. However, several challenges remain, including the need for extensive labeled datasets, and the difficulty of generalizing models to different imaging modalities.

Future research should prioritize focus on improving datasets availability and synthetic data generation. Another crucial approach would be to refining existing models to achieve better generalization across diverse imaging conditions and reduce the need for manual corrections. Addressing these challenges will contribute to the development of more reliable and efficient segmentation tools for biomedical applications.

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