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**ABSTRACT**

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# IMPROVEMENT OF SEGMENTATION OF UPPER AND LOWER JAW COMPUTED TOMOGRAPHY IN PATIENTS WITH MAXILLOFACIAL INJURIES AT THE ORTHOPEDIC STAGE OF REHABILITATION

The relevance of this work was due to the increasing number of patients with maxillofacial injuries requiring orthopedic rehabilitation. At the same time, specialists are increasingly relying on artificial intelligence (AI) technology. One of its most important advantages is its ability to quickly and accurately analyze huge amounts of data, providing specialists with valuable information to improve decision-making processes for planning orthopedic rehabilitation for patients with maxillofacial injuries. The synergy between AI workflows and computed tomography (CT) segmentation has the potential to improve the accuracy and efficiency of further treatment planning and patient management.

**Objective**. The aim of the study is to evaluate an improved method of CT image segmentation for patients with maxillofacial injuries, combining an automatic algorithm and manual post-processing, in order to improve segmentation accuracy and reduce processing time compared to traditional methods.

**Materials and Methods.** The study was conducted in 30 patients with maxillofacial injuries at the orthopedic stage of rehabilitation. In the course of the study, we compared the methods of CT segmentation of the upper and lower jaws: a step-by-step method (reference), automatic segmentation with AI, and an innovative method (own development). This method of CT image segmentation for patients with maxillofacial injuries combines an automatic AI algorithm and manual post-processing. It is this combination that helps to improve segmentation accuracy, which has been proven by the results of the IoU and Dice metrics.

**Results**. The improved method demonstrated higher localization accuracy and was much faster than Stepwise segmentation. The innovative segmentation method has proven to be a new solution for improving CT segmentation diagnostics, namely for localizing images with different resolutions and reducing processing time compared to conventional methods.

**Conclusion**. Our study proved the effectiveness of the improved method for patients with maxillofacial injuries and substantiated the practical application of this improved method of automatic segmentation with manual post-processing in clinical practice. Thus, an improved method for segmenting CT images for patients with maxillofacial injuries, combining an automatic algorithm and manual post-processing, improves segmentation accuracy and reduces processing time compared to traditional methods.

**Keywords:** computed tomography, maxillofacial area, injuries, prosthetic rehabilitation, digital technologies, artificial intelligence.

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## РЕЗЮМЕ

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## УДОСКОНАЛЕННЯ СЕГМЕНТАЦІЇ КОМ'ЮТЕРНОЇ ТОМОГРАФІЇ ВЕРХНЬОЇ ТА НИЖНЬОЇ ЩЕЛЕП У ПАЦІЄНТІВ З ПОРАНЕННЯМИ ЩЕЛЕПНО-ЛИЦЕВОЇ ДІЛЯНКИ НА ОРТОПЕДИЧНОМУ ЕТАПІ РЕАБІЛІТАЦІЇ

Актуальність даної роботи була зумовлена зростанням кількості пацієнтів з пораненнями щелепно-лицевої ділянки, які потребують ортопедичної реабілітації. При цьому спеціалісти все більше покладаються на технологію штучного інтелекту (ШІ). Однією з його найважливіших переваг є його здатність швидко й точно аналізувати величезні обсяги даних, надаючи спеціалістам цінну інформацію для покращення процесів прийняття рішень для планування ортопедичної реабілітації пацієнтів з пораненнями щелепно-лицьової ділянки. Синергія між робочими процесами ШІ та сегментацією ком'ютерної томографії (КТ) має потенціал для підвищення точності та ефективності планування подальшого лікування та ведення пацієнта. Мета роботи – оцінити вдосконалений метод сегментації КТ зображень для пацієнтів із пораненнями щелепно-лицевої ділянки, що поєднує автоматичний алгоритм та ручну постобробку, з метою підвищення точності сегментації та зменшення часу обробки порівняно з традиційними методами.

**Матеріали та методи**. Дослідження було проведено у 30 пацієнтів з пораненнями щелепно-лицевої ділянки на ортопедичному етапі реабілітації. В ході роботи було проведено порівняння методів сегментація КТ верхньої та нижньої щелеп: покроковий метод (еталонний), автоматична сегментація із ШІ та інноваційний метод (власна розробка).

**Обговорення.** інноваційний метод (власна розробка)метод сегментації КТ зображень для пацієнтів із пораненнями щелепно-лицевої ділянки поєднує автоматичний алгоритм ШІ та ручну постобробку. Саме таке поєднання сприяє підвищенню точності сегментації, яка була доведена за результатами метрик IoU та Dice. Вдосконалений метод продемонстрував вищу точність сегментації в порівняні з методом на основі ШІ та набагато швидший за Покрокову сегментацію. Інноваційний метод сегментації зарекомендував себе як нове рішення у вдосконаленні діагностики сегментації КТ, а саме для локалізації зображень з різною роздільною здатністю і зменшення часу обробки порівняно з загальновизнаними методами. В нашому дослідженні доведено ефективність вдосконаленого методу для пацієнтів із пораненнями щелепно-лицевої ділянки, обґрунтовано практичне застосування цього вдосконаленого методу автоматичної сегментації з ручною постобробкою в клінічній практиці.

**Висновки**. Отже, вдосконалений метод сегментації КТ зображень є більш актуальним для пацієнтів із пораненнями щелепно-лицевої ділянки, тому що поєднує автоматичний алгоритм та ручну постобробку, підвищує точність сегментації та зменшує час обробки КТ в порівнянні з традиційними методами.

**Ключові слова**: комп'ютерна томографія, щелепно-лицьова ділянка, поранення, ортопедична реабілітація, цифрові технології, штучний інтелект.

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## INTRODUCTION

The military actions taking place in Ukraine as a result of Russian aggression cause a significant increase in injuries, including those of the maxillofacial region (MFR), which lead to severe physical and psychological disabilities and disability [1, 2]. Recent studies show that the incidence of gunshot wounds to the maxillofacial area during martial law is more than 5%, of which bullet wounds account for more than 20% [3, 4]. Injuries lead to both severe damage to the maxillofacial injuries and involve other organs and systems. Therefore, the search for new methods of both diagnosis and treatment of such patients is relevant today [2, 5, 6].

The use of information systems in the medical field has been actively implemented recently, and the automation of this industry is gradually taking place. The use of digital technologies in maxillofacial surgery and dentistry is extremely necessary, as progress with the use of artificial intelligence (AI) opens up new opportunities in the diagnosis and treatment of maxillofacial injuries [5, 6].

Recent Ukrainian studies have demonstrated the successful application of machine learning algorithms to clinical datasets, further proving their feasibility in diagnostic workflows [7].

Radiological methods of visualization of key anatomical structures are important for the classification of the injury and further application of the patient's treatment strategy [8, 9]. The goal of complex treatment is to stabilize, restore the three-dimensional anatomy of the facial skeleton and provide skeletal support for proper chewing function, as well as the appearance of the soft tissues of the face [10, 11].

For diagnosis and treatment planning, computed tomography (CT) provides detailed information about a specific area, eliminating image overlap that can occur with conventional radiography [8, 9, 10]. A CT image is created using pixels according to its radio-sensitivity and displayed using Hounsfield scale units, which are compared to the known density of the tissue.

In the case of an ACL injury, it has been found that the control parameters of the CT image correlate with the parameters of the images in the image after the injury, which allows the doctor to accurately diagnose the site of the injury and eliminate the need for additional [11, 12]. In combination with digital computer technologies, this can help specialists quickly and accurately detect jaw injuries on CT images for timely treatment, which reduces the cost of treatment and prevents morbidity and late complications [13, 14].

AI, which includes deep learning systems based on medical images, has been developed to extract image features [11]. The maxillofacial region has a complex structure and is divided into several areas, such as the frontal, middle (maxilla, zygomatic bone), and mandible. Each anatomical area has different functions - chewing, phonetics, breathing, swallowing, facial expressions - and requires different treatment protocols. The lack of specific localization of maxillofacial injuries can lead to maxillofacial diseases [12, 13]. Thus, the analysis of maxillofacial fractures on CT images using multiclass detection can allow clinicians to specifically identify the location of maxillofacial fractures and provide comprehensive treatment planning for maxillofacial injuries in patients [13, 15].

In craniofacial trauma or reconstruction, landmark comparison between unaffected and affected areas is important for preoperative planning, intraoperative management, and postoperative evaluation. Physicians typically use their experience to manually or semi-automatically identify landmarks on lateral skull radiographs, CT images, incrementally on two-dimensional (2D) planes, or using three-dimensional additive (3D) models for holistic viewing and exploration [15, 16, 17].

CT image segmentation divides the image into its component parts and objects. Segmentation of CT images is considered the most challenging task in digital image processing [18, 19]. Too detailed segmentation lengthens the time of the task solution process, which requires the identification of objects separately. However, insufficiently detailed segmentation of CT images leads to errors at the end of processing. Thus, the more accurate the CT segmentation, the greater the chances of correct and accurate object recognition [15].

Improving CT segmentation of the upper and lower jaws in patients with maxillofacial injuries during the orthopedic stage of rehabilitation will lead to improved diagnosis and treatment of maxillofacial injuries, as well as improved quality of life and socialization.

Due to the increase in the number of maxillofacial injuries during the period of martial law in Ukraine, there is a need for further development and improvement of orthopedic rehabilitation methods for patients with such injuries. This problem is becoming more and more urgent, and the development of new approaches and innovative methods is becoming an urgent task for medical professionals.

**The objective of this study** was to evaluate an improved method of CT image segmentation for patients with maxillofacial injuries, combining an automatic algorithm and manual post-processing, in order to improve segmentation accuracy and reduce processing time compared to traditional methods.

**The objectives of the study were:**

- to compare three segmentation methods: a step-by-step method (reference), automatic segmentation (artificial intelligence (AI) and automatic segmentation by manual post-processing;
- evaluate the accuracy of segmentation using the IoU, Dice metrics;
- to determine the time required for each method of CT image segmentation for patients with maxillofacial injuries;
- to prove the effectiveness of the improved method for patients with maxillofacial injuries;
- to substantiate the practical application of the improved method of automatic segmentation with manual post-processing in clinical practice.

**MATERIALS AND METHODS**

The study was conducted on 30 patients with gunshot and mine-explosive injuries of the maxillofacial area at the orthopedic stage of rehabilitation. These patients were treated in the Department of Maxillofacial Surgery at the Kyiv Regional Clinical Hospital (KOCL) Central Maxillofacial Hospital (CMLH) and the National Military Medical Clinical Center "Main Military Clinical Hospital" (NMMCC "MMCH"). Among them, 6 patients had upper jaw injuries, while 24 had lower jaw injuries. All examined patients were men aged 23 to 58 years, with an average age of (34±2.33) years. All patients underwent CT segmentation using a GE Medical Systems Revolution EVO scanner.

The following methods of CT segmentation were used in the study: control method, which includes step-by-step segmentation of CT images of the maxillofacial; method 1 - automatic segmentation - an innovative method of segmentation of CT images of the maxillofacial injuries using AI algorithms; method 2 - a unique method of segmentation of CT images of patients with T maxillofacial injuries (own development) – an innovative method of CT segmentation using AI algorithms and manual post-processing by algorithm.

To assess the segmentation accuracy, we compared the two methods with the control method. For this purpose, the following metrics were used in Python software:

1. IoU (Intersection over Union) - intersection over union, measures the degree of overlap between two areas: the segmented area obtained by the algorithm and the reference (reference) area.

IoU was calculated using the formula (1):

$$IoU = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

where:
**A** – reference (benchmark) area,
**B** – is the area obtained as a result of segmentation,
**|A ∩ B|** – is the area of intersection of two regions,
**|A ∪ B|** – is the area of the two regions merging.

Comparable to the Agatston coronary calcification index in CT diagnostics, metrics such as Dice and IoU offer an objective and reproducible way to assess the quality of segmentation [20].

The obtained data was interpreted according to the IoU value, namely, IoU = 1 – perfect match of segmentation with the reference mask, IoU closer to 0 – significantly different segmented object from the reference, IoU > 0.7 – the best result in medical segmentation.

2. Dice Coefficient is a measure of similarity between two data sets (for example, between two segmentation masks), used in medical research to assess the accuracy of segmentation.

Dice Coefficient was calculated using the formula (2):

$$Dice = \frac{2|A \cap B|}{|A| + |B|} \qquad (2)$$

where:

**A** – reference (benchmark) area

**B** – the area obtained as a result of segmentation

**|A ∩ B|** – the area of intersection of two regions

Interpretation of the obtained Dice results, if Dice = 1 means a perfect match between the two areas. The higher the Dice value, the better the match, and in medicine, a Dice value > 0.8 is considered a good indicator for segmentation.

To assess the effectiveness of segmentation, we relied on the following indicators: Dice ≥ 0.80 corresponds to good quality, IoU ≥ 0.70 corresponds to an accurate overlay and is the best result in medical segmentation [21].

The study was approved by the Biomedical Ethics Commission, Protocol No. 9 of 05.12.2022, and was conducted with the written consent of the participants and in accordance with the principles of bioethics set forth in the Helsinki Declaration for the Ethical Principles of Medical Research Involving Human Subjects and the Universal Declaration of Bioethics and Human Rights (UNESCO).

Statistical data processing was performed based on the determination of the mean values of the standard error of the arithmetic mean (M±m), the reliability of the data for independent samples was calculated by Student's t-test, the difference was considered significant at $p<0.05$.

## RESULTS AND DISCUSSION

Nowadays, for the effective planning of the orthopedic stage of rehabilitation of patients with maxillofacial injuries high-quality diagnostics and accuracy of CT image segmentation are of great importance.

In this work, we used three methods of CT segmentation: control method, method 1 – automatic segmentation, method 2 – a unique method of CT segmentation of patients with maxillofacial injuries (own development). The control method, i.e., step-by-step segmentation of CT images of the maxillofacial injuries, is considered the most accurate method because it is performed by a specialist with a large amount of time.

Automatic segmentation (method 1) is an innovative method of CT segmentation using AI algorithms (Figures 1, 2). However, in patients with *maxillofacial injuries* at the stage of orthopedic rehabilitation, this method is ineffective due to the atypical anatomy of the upper and lower jaw areas after surgery, and the algorithm does not correctly segment the anatomical areas. Instead, this method is very accurate in segmenting "typical" patients with dentition defects, the etiological factor of which is "tooth loss due to caries complications".

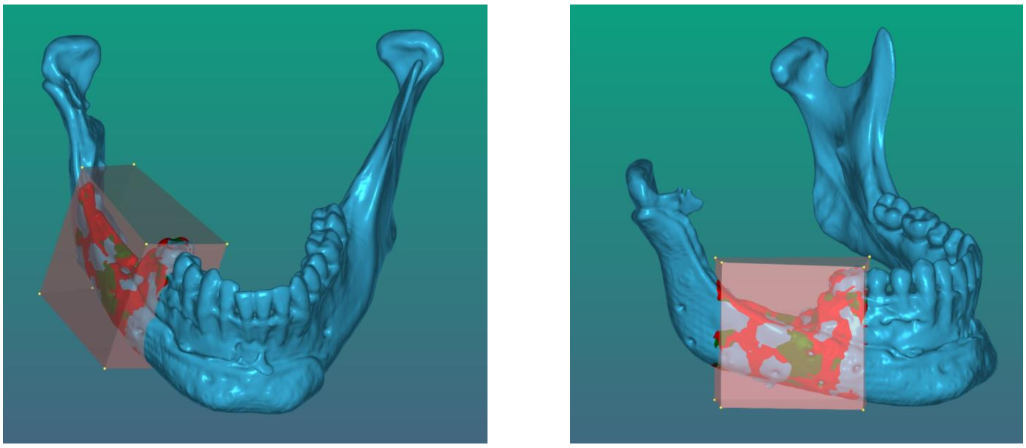


**Fig. 1. Selection of the study area of three segments of the lower jaw**

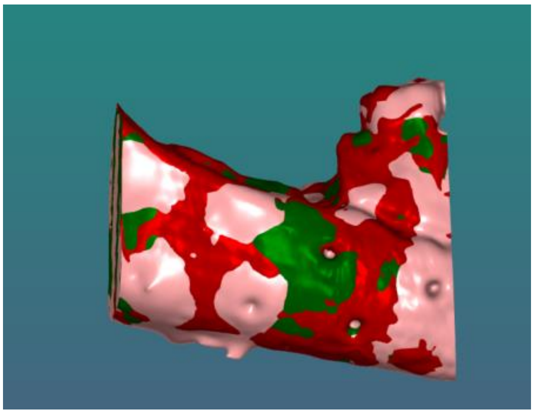
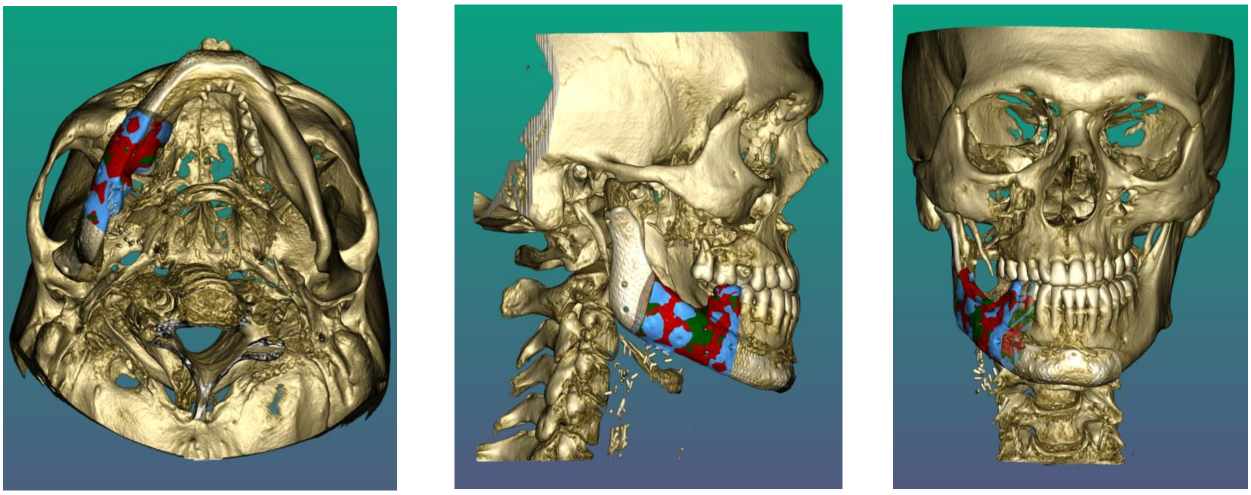


**Fig. 2. Three segments obtained by different methods (all segments are of different colors: red – segment is method 2, pink – segment is method 2, and green – segment is control method)**

Unique method of CT segmentation of patients with BLS injuries (method 2) is an innovative method of CT segmentation using AI algorithms and manual post-processing according to the algorithm (Figures 1, 2, 3). The advantage of this method is that the AI algorithm makes a primary model, which the operator can adjust to the level of step-by-step segmentation in a short time. In this case, the advantage is that the time spent on segmentation is dramatically reduced.

For example, during our work, we created a digital algorithm for calculating three-dimensional objects of the upper and lower jaw and determined its effectiveness. For medical segmentation, two metrics are used: IoU and Dice, which helps to get a complete picture of the algorithm's efficiency. The data obtained are presented in Table 1.

IoU evaluates how accurately the segmented area coincides with the reference area, taking into account their mutual intersection and total area. Dice Coefficient is similar to IoU, but focuses more on the mutual intersection of regions. These two metrics had a value greater than 0.9 and significantly exceeded the value of method 1 for both the maxilla and mandible, indicating the high efficiency of the innovative method of CT segmentation using AI algorithms and manual post-processing according to the algorithm in patients with maxillofacial injuries.



**A** **B** **C**

**Fig. 3. View of segmented areas in the CT reconstruction mode (A - side view, B - front view, C - bottom view) (All methods in one mask)**

*Table 1 – Comparison of the accuracy of CT segmentation methods in patients with maxillofacial injuries, n=30 (M±m)*

| Indicator | Method 1 paired with the control method | Method 2 in conjunction with the control method | p* |
|---|---|---|---|
| IoU maxilla, (n = 6) | 0.50±0.07 | 0.92±0.01 | <0.05 |
| IoU mandible, (n = 24) | 0.46±0.05 | 0.93±0.01 | <0.05 |
| Dice upper jaw, (n = 6) | 0.65±0.07 | 0.96±0.01 | <0.05 |
| Dice lower jaw, (n = 24) | 0.60±0.05 | 0.96±0.01 | <0.05 |

*Notes: * – significant difference between the indicators (p levels were calculated using Student's t-test)*

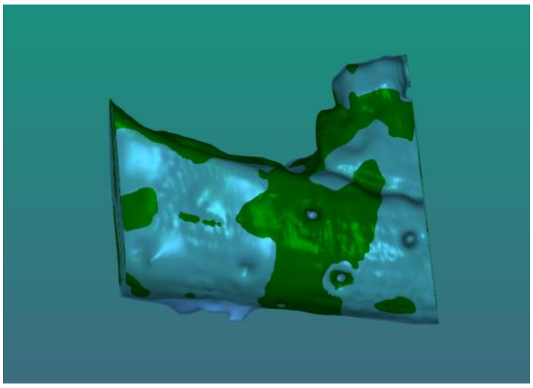


**Fig. 4. Correlation of AI to step-by-step CT segmentation of patients with CLL injuries (method 1 and control)**

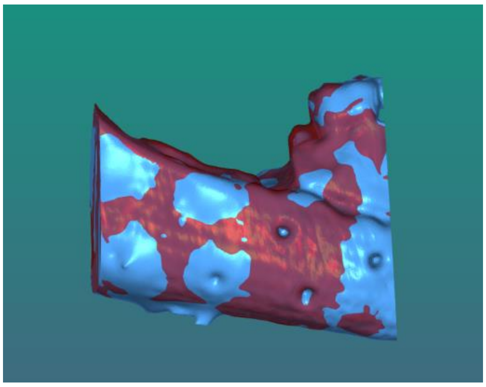


**Fig. 5. Ratio of AI segmentation with post-processing to AI segmentation of CT scans of patients with maxillofacial injuries (method 1 and method 2)**

It should be noted that CT segmentation in patients with *maxillofacial injuries* by the control method took the longest time, from 45 minutes to 98 minutes (Fig. 6).

For method 1 (automatic segmentation), the segmentation time was the same in all cases and amounted to 1 minute. Whereas the time spent on segmentation by method 2 (own development of a unique method of CT segmentation of patients with *maxillofacial* injuries (by the author) was sharply reduced and ranged from 7 to 23 minutes, the average time was significantly (p<0.05), which allows us to consider this method to be the best (Table 2).

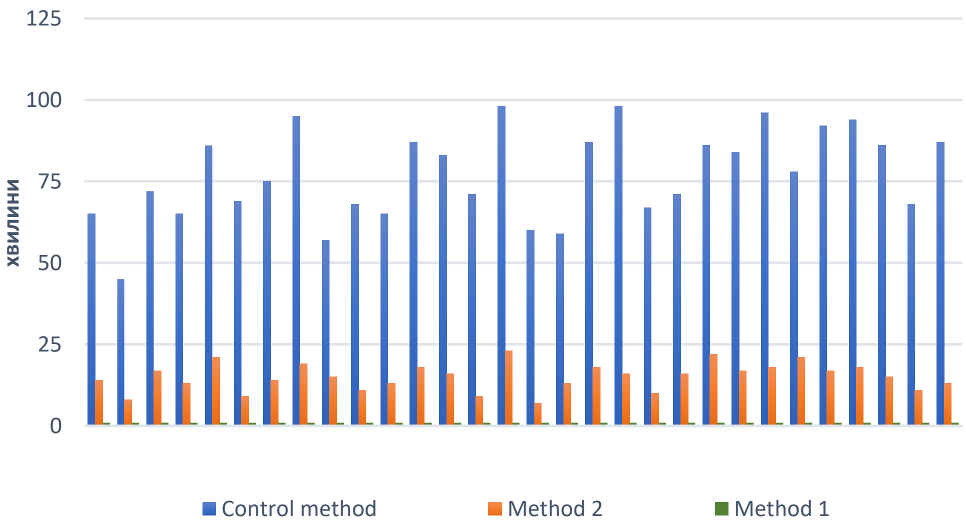



**Fig. 6. Distribution of CT segmentation time using different methods in patients with maxillofacial wounds**

*Таблиця 2 – Comparison of the time required for different methods of CT segmentation in patients with maxillary wounds, n= 30 (M±m)*

| Indicator, minutes | Control method | Method 1 | Method 2 | p |
|---|---|---|---|---|
| Upper jaw, n=6 | 68.5±4.25 | 1.0±0 | 13.83±2.23 | <0.05 |
| Mandible, n=24 | 79.29±2.89 | 1.0±0 | 15.38±0.80 | <0.05 |

*Note: * – significant difference between the control method and method 2 (p<0.05 calculated by Student's t-test)*

According to the data obtained, the efficiency of CT image segmentation using Method 2 was evaluated. At a Dice Coefficient value of ≥ 0.80, which corresponds to excellent quality of CT segmentation in medicine [21], when using method 2 in combination with the control method, this indicator was 0.96±0.01, both for the upper and lower jaw. Accordingly, at an IoU value ≥ 0.70, which corresponds to an accurate overlay of areas and indicates the best segmentation of CT images, it was 0.92±0.01 for the upper jaw and 0.93±0.01 for the lower jaw. The minimum error for method 2 was 0.03, compared to the control processing time of < 5 seconds, indicating that this method is fast.

The average time required for manual processing using method 2 was compared. It was found that the processing time for segmentation of the upper jaw using method 2 compared to the control method was reduced by 5.0 times ($p<0.05$) for the upper jaw and by 5.1 times ($p<0.05$) for the lower jaw. Thus, the use of method 2 significantly reduces the processing time of CT image segmentation for patients with injuries of the maxillofacial area compared to the control method (Stepwise segmentation).

In clinical practice, most doctors rely on manual or semi-automatic methods of CT segmentation of maxillofacial areas, which leads to poor results [22, 23, 24, 25]. Therefore, the development of methods for automatic segmentation of the maxillofacial area is a very relevant issue. However, there are many problems with the segmentation of the maxillary teeth, the boundaries between the upper and lower teeth are difficult to distinguish, the upper and lower jawbones are also connected in the condylar process, which creates fuzzy boundaries that are difficult to segment.

Image segmentation refers to the task of labeling image voxels as a specific class. In the context of maxillofacial surgery, this stage of image segmentation is commonly used to distinguish bone structures from soft tissue or air [26]. Although a wide variety of statistical methods have been developed for bone segmentation, they usually require human intervention to obtain accurate results, mainly due to the lack of reliable Hounsfield units and limited signal-to-noise ratio in scanning. Therefore, it is desirable to automate this task as much as possible, thereby freeing the medical professional from this time-consuming and time-consuming task, as well as improving the accuracy and consistency of segmentation results [27].

At present, maxillofacial CT segmentation mainly includes traditional segmentation and AI methods. In classical segmentation methods, the combination of template image and registration method can effectively semi-segment the jaws, but template reconstruction and manual processing are time-consuming [16, 22]. Although these classical methods have achieved some segmentation results, they are relatively complex and time-consuming, with low-quality images. Scientists have found that the model developed with the help of AI provides highly accurate 3D localization of maxillofacial structures even in complex cases [16, 17]. Landmarks, those defined by complex anatomical curves or specific directional projections, tend to exhibit larger errors, which requires constant training and practice to improve the accuracy of landmark localization consistency [19, 28, 29]. AI-powered models help clinicians conduct accurate and efficient localization analysis due to their clinical accuracy, reliability, and generalizability. Whereas traditional manual landmark identification is time-consuming and requires considerable experience [18, 30]. Based on the above, our work proposes an improved method of CT segmentation for maxillofacial injuries at the orthopedic stage of rehabilitation.

The improved method of CT image segmentation for patients with maxillofacial injuries combines an automatic algorithm and manual post-processing. This combination helps to improve segmentation accuracy, which has been proven by the results of the IoU and Dice metrics. The improved method demonstrated higher localization accuracy compared to others, with an average processing time of 15 minutes per case, thus proving to be a new solution in improving CT segmentation diagnostics, namely for localizing images with different resolutions and reducing processing time compared to generally accepted methods. Our study proved the effectiveness of the improved method for patients with maxillofacial injuries and substantiated the practical application of this improved method of automatic segmentation with manual post-processing in clinical practice.

**Practical application.** Thus, we can recommend the practical application of the innovative method of CT segmentation of patients with maxillofacial injuries using AI algorithms and manual post-processing according to the algorithm, given the reduced time for segmentation and the best result of segmentation accuracy according to the IoU and Dice metrics. Implementation of improved method 2 can minimize the workload of medical staff and increase the efficiency and consistency of the treatment planning process.

## CONCLUSIONS

1. The advanced method (automatic segmentation with manual post-processing) provides high accuracy compared to the automatic method for patients with a history of maxillofacial injuries.

2. Compared to stepwise segmentation, the improved method significantly reduces processing time, making it optimal for clinical use.

3. The proposed approach can be used for fast and accurate CT segmentation in the diagnosis and planning of orthopedic rehabilitation of patients.

## AUTHOR CONTRIBUTIONS

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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None.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## REFERENCES

1. Ivchenko DV, Varzhapetyan SD, Mishchenko OM, et al. [Experience in the treatment of combat injuries of the maxillofacial area with titanium implants in modern warfare]. Pathologia. 2022;19(2):154-159. https://doi.org/10.14739/2310-1237.2022.2.260598. Ukrainian.
2. Oren D, Dror AA, Zoabi A, Kasem A, Tzadok L, Kablan F, Morozov NG, Safory E, Sela E, Srouji S. The impact of delayed surgical intervention following high velocity maxillofacial injuries. Sci Rep. 2021;11(1):1379. https://doi.org/10.1038/s41598-021-80973-7.
3. Gulyuk A, Pedchenko D. [Features of diagnostics and primary surgical treatment of wounds in patients with gunshot wounds of the maxillofacial region]. Journal of Dentistry. 2023;121(4):41–46. DOI: https://doi.org/10.35220/2078-8916-2022-46-4.8
4. Brozhyna B, Pavlenko O. The need for orthopedic rehabilitation of patients with maxillofacial injuries. Journal of dentistry. 2023;125(4):63–67. https://doi.org/10.35220/2078-8916-2023-50-4.11. Ukrainian.
5. Tsur N, Talmy T, Radomislensky I, Almog O, Gendler S. Traumatic maxillofacial injuries: Patterns, outcomes, and long-term follow-up of a military cohort. Dent Traumatol. 2023;39(2):147-156. https://doi.org/10.1111/edt.12801.
6. Gvazava S, Margvelashvili V, Chikhladze N, et al. A retrospective study of the maxillofacial injuries in two emergency departments in tbilisi, georgia. Georgian Med News. 2023;(339):13-19. PMID: 37522767.
7. Babienko VV, Shanyhin AV, Rozhnova AM, Strakhov YeM, Korkhova AS. Dependence of vitamin D level on laboratory and anthropometric indicators: application of machine learning methods for screening in adults. Odesa Medical Journal. 2024;5:74-78. https://doi.org/10.32782/2226-2008-2024-5-12
8. Xu J, Liu J, Zhang D, et al. A 3D segmentation network of mandible from CT scan with combination of multiple convolutional modules and edge supervision in mandibular reconstruction. Comput Biol Med. 2021;138:104925. https://doi.org/10.1016/j.compbiomed.2021.104925.
9. Warin K, Limprasert W, Suebnukarn S, et al. Maxillofacial fracture detection and classification in computed tomography images using convolutional neural network-based models. Sci Rep. 2023;13(1):3434.https://doi.org/10.1038/s41598-023-30640-w.
10. Qiu B, van der Wel H, Kraeima J, et al. Automatic Segmentation of Mandible from Conventional Methods to Deep Learning-A Review. J Pers Med. 2021;11(7):629. https://doi.org/10.3390/jpm11070629.
11. Wang X, Xu Z, Tong Y, et al. Detection and classification of mandibular fracture on CT scan using deep convolutional neural network. Clin Oral Investig. 2022;26(6):4593-4601. https://doi.org/10.1007/s00784-022-04427-8.
12. Mai HY, Lee DH. Impact of Matching Point Selections on Image Registration Accuracy between Optical Scan and Computed Tomography. Biomed Res Int. 2020;2020:3285431. DOI:10.1155/2020/3285431.
13. Kim M-J, Liu Y, Oh SH, et al. Automatic Cephalometric Landmark Identication System Based on the Multi-Stage Convolutional Neural Networks with CBCT Combination Images. Sensors. 2021;21(2):505.
14. Qiu B. (Automatic Segmentation of the Mandible for Three-Dimensional Virtual Surgical Planning. [Thesis fully internal (DIV), University of Groningen]. University of Groningen. 2021. https://doi.org/10.33612/diss.179140520.
15. Hendrickx J, Gracea RS, Vanheers M, et al. Can artificial intelligence-driven cephalometric analysis replace manual tracing? A systematic review and meta-analysis. Eur J Orthod. 2024;46(4):cjae029. https://doi.org/10.1093/ejo/cjae029.
16. Bonny T, Al Nassan W, Obaideen K, et al. Contemporary Role and Applications of Artificial Intelligence in Dentistry. F1000Res. 2023;12:1179. https://doi.org/10.12688/f1000research.140204.1.

17. Mai HY, Lee DH. Impact of Matching Point Selections on Image Registration Accuracy between Optical Scan and Computed Tomography. Biomed Res Int. 2020;2020:3285431. https://doi.org/10.1155/2020/3285431.
18. Liu B, Liu C, Xiong Y, et al. Accuracy and Reliability of 3D Cephalometric Landmark Detection with Deep Learning January 2025. https://doi.org/10.21203/rs.3.rs-5777684/v1.
19. Schwendicke F, Chaurasia A, Arsiwala L, et al. Deep learning for cephalometric landmark detection: systematic review and meta-analysis. Clin Oral Investig. 2021;25(7): 4299-4309.
20. Ishchenko MS, Romaniuk OR. The Prognostic Value of the Coronary Calcium Score for Detecting Significant Coronary Artery Stenosis Based on CT Coronary Angiography in Patients with Coronary Artery Disease. Ukrainian Journal of Cardiovascular Surgery. 2025;33(1):19-26. https://doi.org/10.63181/ujcvs.2025.33(1).19-26
21. Ding AS, Lu A, Li Z, et al. Automated Registration-Based Temporal Bone Computed Tomography Segmentation for Applications in Neurotologic Surgery. Otolaryngology–Head and Neck Surgery. 2022;167(1):133-140. https://doi.org/10.1177/01945998211044982.
22. Apostolakis D, Michelinakis G, Kamposiora P, Papavasiliou G. The current state of computer assisted orthognathic surgery: A narrative review. J Dent. 2022;119:104052. https://doi.org/10.1016/j.jdent.2022.104052.
23. Zhao Y, Zeng K, Zhao Y, et al. Deep learning solution for medical image localization and orientation detection. Med Image Anal. 2022;81:102529. https://doi.org/10.1016/j.media.2022.102529.
24. Chim S, Lee JG, Park HH. Dilated skip convolution for facial landmark detection. Sensors. 2019;19(24): 5350. https://doi.org/10.3390/s19245350.
25. Huang Y, Huang H. Stacked attention hourglass network based robust facial landmark detection. Neural Netw. 2023;157:323-335. https://doi.org/10.1016/j.neunet.2022.10.021.
26. Minnema J, Ernst A, van Eijnatten M, et al. A review on the application of deep learning for CT reconstruction, bone segmentation and surgical planning in oral and maxillofacial surgery. Dentomaxillofac Radiol. 2022;51(7):20210437. **https://doi.org/10.1259/dmfr.20210437.**
27. Park S, Kim H, Shim E, et al. Deep Learning-Based Automatic Segmentation of Mandible and Maxilla in Multi-Center CT Images. Applied Sciences. 2022;12(3):1358. https://doi.org/10.3390/app12031358.
28. Hendrickx J, Gracea RS, Vanheers M, et al. Can articial intelligence-driven cephalometric analysis replace manual tracing? A systematic review and meta-analysis. Eur J Orthod. 2024;46(4):cjae029. https://doi.org/10.1093/ejo/cjae029.
29. Bermejo E, Taniguchi K, Ogawa Y, et al. Automatic landmark annotation in 3D surface scans of skulls: Methodological proposal andreliability study. Comput Methods Programs Biomed. 2021;210:106380. https://doi.org/10.1016/j.cmpb.2021.106380
30. Shujaat S, Riaz M, Jacobs R. Synergy between artificial intelligence and precision medicine for computer-assisted oral and maxillofacial surgical planning. Clinical oral investigations. 2023;27(3):897–906. https://doi.org/10.1007/s00784-022-04706-4.


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