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Segmentation of masticatory muscles on ultrasonographic images using artificial intelligence in pediatric population

Firdevs Asantogrol[a,*], Burak Tunahan Ciftci[a]

[a] *Gaziantep University, Faculty of Dentistry, Department of Oral and Maxillofacial Radiology, Gaziantep, Türkiye*

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Abstract

Aim: The objective of this study is to utilize artificial intelligence for the segmentation of masticatory muscles in ultrasound images.

Materials and Methods: The study comprised a cohort of 60 pediatric patients with ultrasonographic images of the masseter, anterior temporal, and lateral pterygoid muscles, 120 images for each muscle, right and left, totaling 360 muscle images. Within the context of this research, the YOLOv8-Seg deep learning model was employed to automatically conduct the segmentation of the masseter, anterior temporal and lateral pterygoid muscles within ultrasonography images. In this study, an artificial intelligence algorithm (Roboflow, Inc., Des Moines, Iowa, USA) was developed to autonomously carry out the segmentation of the masseter, anterior temporal and lateral pterygoid muscles. A total of 120 images for each muscle group were randomly divided into training, validation and test sets.

Results: For the muscle segmentations on the test data, the true positive (TP), false positive (FP) and false negative (FN) values were 18, 0, 0 for masseter muscle, 18, 0, 0 for temporal muscle and 16, 1, 1 for lateral pterygoid muscle, respectively. The model's F1 score, precision and sensitivity values are 1.0, 1.0 and 1.0 for masseter muscle, 1.0, 1.0 and 1.0 for temporal muscle and 0.92, 0.94 and 0.94 for lateral pterygoid, respectively.

Conclusion: In summary, segmentation techniques based on deep learning for analyzing ultrasonography images of anatomical structures like masticatory muscles have great potential in clinical applications. Precise segmentation of muscles through this technology can play a crucial role in the diagnosis and follow-up of diverse medical conditions and diseases.

Introduction

The muscles that provide mandibular movements and masticatory function are four pairs: temporal, masseter, medial pterygoid, and lateral pterygoid muscles [1]. The masticatory muscles which originate from the first pharyngeal arch differentiate from the 7th week onwards. All these muscles are innervated by the mandibular branch of the 5th cranial nerve [2]. The masseter muscle is a rectangular-shaped muscle consisting of three layers: superficial, intermediate and deep. The muscle fibres start from the zygomatic arch and join downwards to form a tendon that adheres to the lateral surface of the mandibular ramus and the coronoid process. The fibres of the superficial part of the muscle extend backwards and downwards, while the fibres of the deeper part extend more vertically. The function of the masseter muscle is to facilitate the closure of the jaw, known as mandibular elevation. The deep and intermediate muscle fibres contribute to mandibular retraction, while the superficial part serves to the forward movement of the mandible [2].

The fan-shaped temporalis muscle is divided into three parts, anterior, middle and posterior, according to the direction and function of the fibres. It starts from the lateral surface of the skull and temporal fossa, passes through the zygomatic arch and attaches to the coronoid process of the mandible. The fibres of the anterior part are oriented vertically, the fibres of the middle part are obliquely directed forward, and the fibres of the posterior part extend horizontally forward and downward. Although the main function of the temporalis muscle is the elevation of the mandible, it also plays a role in the retrusion of the mandible, that is, in its posterior movement [3].

Recent studies on the lateral pterygoid muscle have revealed that the lateral pterygoid muscle consists of two parts with completely divergent functionalities. These are

*Corresponding author:
Email address: firdevsasantogrol@gmail.com (Firdevs Asantogrol)

defined as the inferior lateral pterygoid and the superior lateral pterygoid. The inferior lateral pterygoid muscle originates from the outer surface of the lateral pterygoid plate and terminates at the neck of the condyle. This muscle extends backwards, upwards and outwards. Bilateral contraction of this muscle results in mandibular protrusion, while unilateral contraction causes the mandible to move laterally towards the opposing side of contraction. When this muscle works together with mandibular depressors, it facilitates downward movement of the mandible [3]. On the other hand, the superior lateral pterygoid muscle originates from the infratemporal region of the greater wing of the sphenoid bone and extends horizontally outward and posteriorly, attaching to the joint capsule, condyle, and articular disc. The contraction of this muscle induces an anteromedial pull on the articular disc. Notably, its operation is not involved in the process of mandibular opening [4].

Ultrasonography (USG) is a non-invasive, cost-effective, and rapid imaging modality that employs sound waves to generate images, thus avoiding ionizing radiation [5]. The utilization of ultrasound imaging proves to be a highly dependable technique for the assessment of the superficial tissues of the head and neck. In particular, it allows for the visualization of masticatory muscles such as the masseter and anterior temporal muscles. It is a useful method for examining the perioral muscles due to its reproducibility and the absence of ionizing radiation exposure during image acquisition [6]. However, the accurate interpretation of USG images necessitates experience and skill. Additionally, the lateral pterygoid muscle, situated deeper within the anatomy, may not always be distinctly discernible in USG images.

Advancements in technology have brought about substantial transformations in the domains of medicine and dentistry. Among the pivotal drivers of this evolution stands artificial intelligence [7]. Artificial intelligence is characterized by the capacity of machines to execute complex tasks, encompassing activities like problem-solving, recognizing objects and words, making decisions, and emulating intelligent human behaviors [8]. It is believed that artificial intelligence will be used more and more, especially owing to its convenience for physicians and its substantial contributions to healthcare services [7]. The information derived from artificial intelligence is poised to expedite and enhance the accuracy of diagnoses [9]. In the realm of dentistry, the application of artificial intelligence to imaging techniques, particularly in dental radiology, is on the rise. Notably, the employment of artificial intelligence in the analysis of ultrasound images has also gained significant momentum as its usage continues to expand. The objective of this study is to utilize artificial intelligence for the segmentation of masticatory muscles in ultrasound images. It is anticipated that artificial intelligence will create positive developments in the prognosis of potential pathologies within this region through the segmentation of masticatory muscles. Furthermore, there is a belief that artificial intelligence will bring about convenience for medical practitioners dealing with challenging-to-interpret ultrasound images.

Materials and Methods

Study design and patient selection

The present study was carried out using the sonographic examination records of pediatric patients aged between 8-

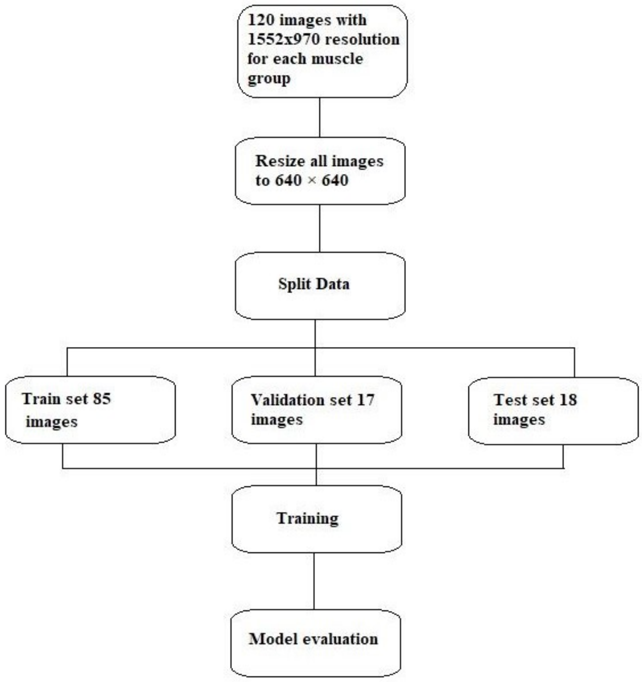

Figure 1. Artificial intelligence model pipeline for segmentation of masseter, anterior temporal, and lateral pterygoid muscles.

Figure 2. The process of polygonal labelling on ultrasonographic images using artificial intelligence.

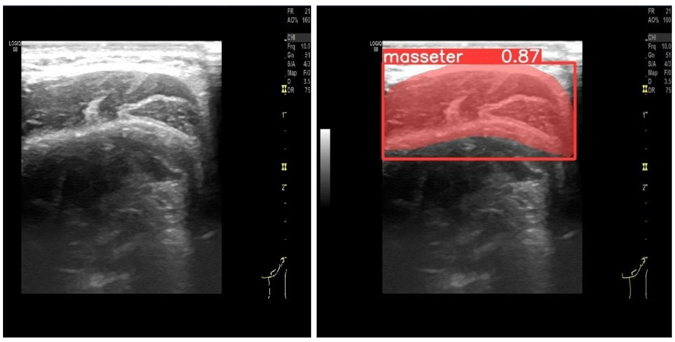

Figure 3. Segmentation of the masseter muscle on ultrasonographic images using artificial intelligence.

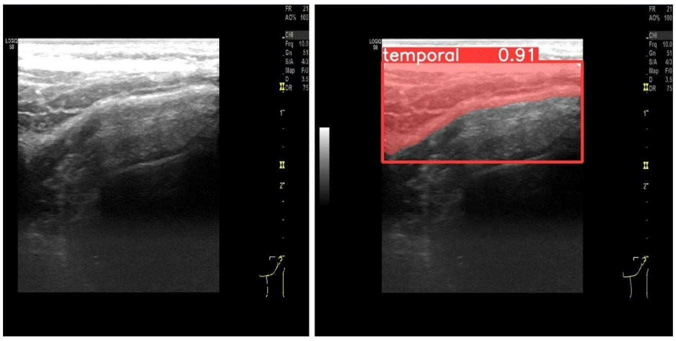

Figure 4. Segmentation of the anterior temporal muscle on ultrasonographic images using artificial intelligence.

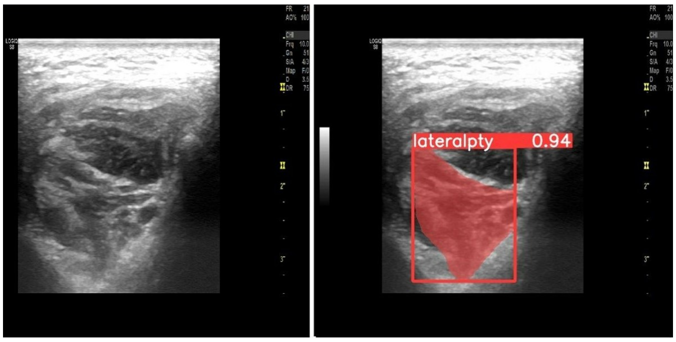

Figure 5. Segmentation of the lateral pterygoid muscle on ultrasonographic images using artificial intelligence.

15 years who applied to Gaziantep University Faculty of Dentistry. The study comprised a cohort of 60 pediatric patients with USG images of the masseter, anterior temporal and lateral pterygoid muscles, 120 images for each muscle, right and left, totalling 360 muscle images. The study was conducted in accordance with the principles of the Declaration of Helsinki and ethical approval was received for the study from the Gaziantep University Clinical Research Ethics Committee (protocol number: 2023/309).

Creation of dataset for ultrasonographic images

All patients included in the study were evaluated using a GE LOGIQ S8 with XDclear USG device (GE Healthcare, Waukesha, WI, US) in the Department of Oral and Maxillofacial Radiology and 9L-D (2-8 MHz) and ML 6-15-D Matrix Array (4-15 MHz) linear probes and standard water-based acoustic coupling gel. The scan depth was set to 40 mm to examine the masseter, temporal and lateral pterygoid muscles. The frame rate was set to 300 frames per second. Throughout the USG examinations, patients were instructed to recline in a comfortable supine position and maintain stillness while refraining from swallowing. Muscle assessments were conducted with the patient at rest, without any occlusal contact between the teeth. To ensure this condition, patients were guided to close their lips, swallow saliva, take a deep breath, and position their jaws in a state of rest.

During the examination of the masseter muscle, the probe was positioned at a perpendicular (transversal) angle to the masseter muscle fibres, specifically in the thickest region of the muscle near the level of the occlusal plane. This placement was parallel to the long axis of the corpus mandibulae and approximately in the middle of the mediolateral part of the mandibular ramus. When conducting an examination of the anterior temporal muscle, the probe was situated on the upper edge of the zygomatic bone, until the temporal muscle appeared on the ultrasound screen. Subsequently, the probe was slightly adjusted in a cranial direction to ensure that the zygomatic arch remained parallel, and the probe was positioned between the lateral canthus of the eye and the anterior hairline. While evaluating the lateral pterygoid muscle, the probe was aligned along the zygomatic arch and inferiorly above the mandibular sigmoid notch. At this point, the muscle was identified as a hypoechoic, triangular-shaped area between the coronoid and condylar processes of the mandible, particularly when the jaw was opened to its maximum extent.

Deep learning architecture

Within the context of this research, the YOLOv8-Seg deep learning model was employed to automatically conduct the segmentation of the masseter, anterior temporal, and lateral pterygoid muscles within ultrasonography images.

The YOLOv8-Seg model employs a CSPDarknet53 backbone to serve as its foundational feature extractor. Additionally, it integrates a C2f module, which takes the place of the traditional YOLO neck architecture. Subsequent to this, two segmentation heads are employed. These heads are responsible for producing semantic segmentation masks that correspond to the original input image.

Much like the YOLOv8 model, the YOLOv8-Seg incorporates detection heads. These detection heads consist of five detection modules and a prediction layer. The YOLOv8-Seg model has showcased exceptional performance across various object detection and semantic segmentation evaluation metrics. Importantly, this high level of performance is maintained while still delivering impressive speed and efficiency.

For practical use, YOLOv8-Seg can be executed using the command line interface (CLI) or alternatively installed as a PIP package. The model also offers a range of integrations tailored for tasks like labeling, training, and deployment [10].

Model pipeline

In this study, an artificial intelligence algorithm (Roboflow, Inc., Des Moines, Iowa, USA) was developed to autonomously carry out the segmentation of the masseter, anterior temporal and lateral pterygoid muscles (Figure 1). Muscles within the imaging domain were delineated using polygonal labels (Figure 2).

Figures 3, 4, and 5 show both the original images and the images that have been segmented using the deep learning model.

Model training

For each muscle group, a total of 120 images were randomly partitioned into training, validation, and test sets as detailed below:

- Training Set: 85 images

- Validation Set: 17 images.
- Test Set: 18 images

To augment the training dataset and enhance the model's performance, various transformations were applied automatically to the training data, including orientation adjustment, resizing to 640x640 pixels, translation (both horizontal and vertical), rotation within the range of -15° to +15°, grayscale conversion (applied to 25% of the images), and blurring (up to 2.5 pixels).

Statistical analysis

A confusion matrix was used to evaluate and analyse the performance of the artificial intelligence model. The segmented muscle images were compared with the annotations provided by the oral radiologist. Through this comparison, true positive (TP), false negative (FN), and false positive (FP) values were identified, allowing for comprehensive evaluation.

TP refers to cases in which the model correctly predicts a positive outcome that corresponds to the actual positive state. FN refers to cases in which the model incorrectly predicts a negative outcome while the actual state is positive. FP refers to cases in which the model incorrectly predicts a positive outcome while the actual state is negative. Subsequently, the following metrics were computed utilizing TP, FP and FN values:

- Sensitivity: TP/ (TP + FN)
- Precision: TP/ (TP + FP)
- F1 Score: 2TP/ (2TP + FP + FN).

Results

The performance of the model was objectively assessed using a confusion matrix. The confusion matrix plots for the segmentation of the masseter, anterior temporal and lateral pterygoid muscles are illustrated in Figure 6.

The prediction values for segmentation of ultrasonographic images of masseter, anterior temporal and lateral pterygoid muscles in children using the YOLOv8 deep learning model were determined to be as follows: 100% for the masseter muscle, 100% for the temporal muscle, and 88% for the lateral pterygoid muscle.

For the muscle segmentations on the test data, the TP, FP and FN values were 18, 0, 0 for masseter muscle, 18, 0, 0 for temporal muscle and 16, 1, 1 for lateral pterygoid muscle, respectively. These values were then utilized to calculate sensitivity, precision, and F1 scores, which are presented in Table 1.

Table 1. Precision, accuracy and F1 scores for the segmentation of masseter, anterior temporal, and lateral pterygoid muscles.

	Masseter	Anterior Temporal	Lateral Pterygoid
F1	1.0	1.0	0.92
Sensitivity	1.0	1.0	0.94
Precision	1.0	1.0	0.94

The Receiver Operating Characteristic (ROC) curves and the corresponding area under the curve (AUC) values for the segmentation of ultrasonographic images of the masseter, anterior temporal, and lateral pterygoid muscles in pediatric cases can be observed in Figure 7.

Discussion

Artificial intelligence has been actively used in many fields such as medicine, automotive, finance, education, production, robotics, security and agriculture in recent times. This has captivated the attention of numerous researchers due to its noteworthy potential. Dentistry is a field that follows this prevailing trajectory, and the implementation of artificial intelligence holds immense promise, particularly within the realm of Oral and Maxillofacial Radiology. Recent studies of artificial intelligence in Oral and Maxillofacial Radiology mainly focus on the utilization of convolutional neural networks for image classification [11], detection [12] and segmentation [13]. These artificial intelligence systems have been developed to cater to various aspects including radiographic diagnosis, image analysis, and forensic dentistry [14]. Various types of radiographic images, including panoramic radiographs, cephalometric radiographs, cone beam computed tomography images, and intraoral radiography images, are commonly utilized in artificial intelligence studies [15].

Analyzing ultrasonography images using artificial intelligence techniques is a more extensively explored and prominent area within the field of medicine compared to dentistry. Artificial intelligence is commonly employed in a range of medical conditions, including cancer [16], liver and kidney diseases [17, 18], and ischaemic heart disease [19]. Moreover, there has been a noticeable rise in the utilization of artificial intelligence approaches for interpreting oral and maxillofacial ultrasonography images in recent years. Belikova et al. conducted a study on an artificial intelligence algorithm that tracks temporomandibular joint (TMJ) movements on ultrasonography images during mandibular opening and closing movements. They achieved a tracking accuracy of 2.14 mm error margin in monitoring the movements of the TMJ [20]. Kise et al. assessed the effectiveness of artificial intelligence algorithms in analyzing ultrasonography images of submandibular salivary glands in three different conditions; obstructive sialadenitis, Sjögren's syndrome and healthy glands. The study encompassed 50 patients within each category, and the deep learning system exhibited sensitivities of 55.0%, 83.0%, and 73.0% in the obstructive sialadenitis, Sjögren's syndrome, and control groups, respectively [21]. Ariji et al. used intraoral Doppler ultrasound images of 33 patients to predict late cervical lymph node metastasis in early tongue cancer and found the sensitivity and specificity of the artificial intelligence system to be 84% and 87.1%, respectively [22].

Nguyen et al. analysed 1400 images to automatically determine the enamel-cement junction in ultrasound images using convolutional neural networks and reported that the distances between the enamel-cement boundary and the alveolar crest measured by artificial intelligence correlated

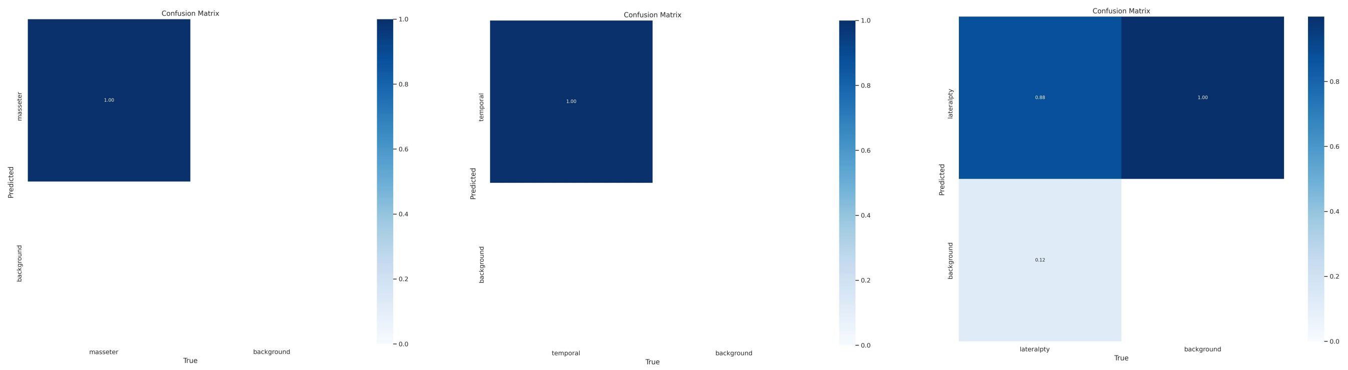

Figure 6. Confusion matrix plots are presented, with those for masseter muscle segmentation on the left, for anterior temporal muscle segmentation in the middle, and for lateral pterygoid muscle segmentation on the right.

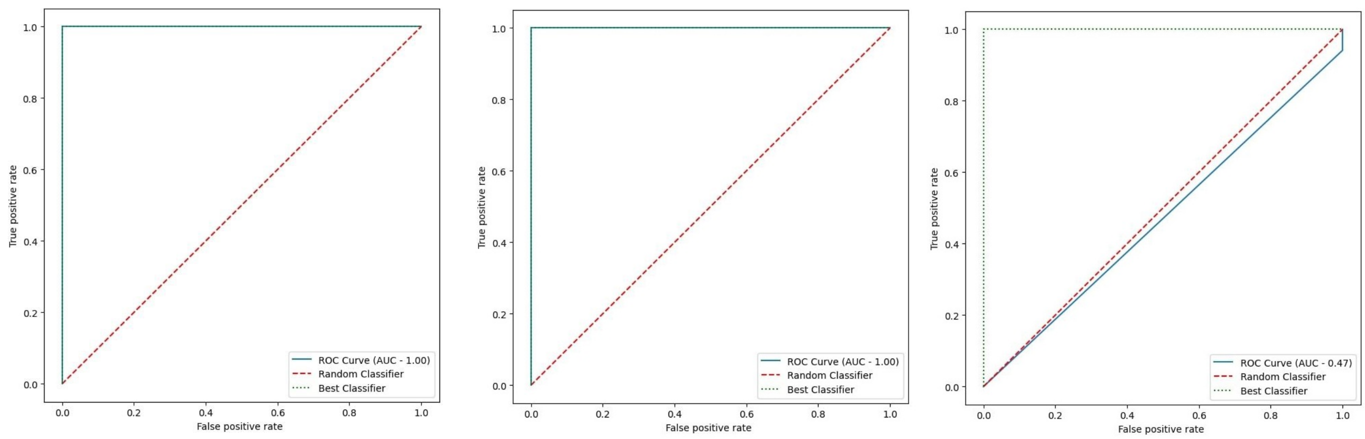

Figure 7. Receiver operating characteristic (ROC) curve and area under the curve (AUC) plots for masseter muscle segmentation on the left; for anterior temporal muscle segmentation in the middle, and for lateral pterygoid muscle segmentation on the right.

significantly with manual labelling (R=0.933, p<0.001) [23].

In the current literature, only a limited number of studies have investigated the segmentation of the masseter muscle in the field of dentistry [6, 23]. However, it is imperative to analyze the masseter muscle and other masticatory muscles in the diagnosis and follow-up of common muscle pathologies and muscle-related TMJ disorders. These pathologies include local muscle tenderness, myospasm, myofascial pain, and centrally mediated myalgia. Myofascial pain is typically identified through muscle palpation. The origin of the pain is the myofascial trigger point, a highly localized and tender region within a contracted muscle that can be easily discerned via palpation [24]. Myospasm pertains to involuntary muscle contractions leading to muscle spasms [25]. Centrally mediated myalgia refers to widespread muscle discomfort attributed to the central nervous system [26].

The diagnosis and management of such disorders can have significant effects on patients' pain, functional abilities, and overall quality of life. Pathological conditions affecting not only the masseter muscle but also other masticatory muscles can lead to symptoms like difficulties in mouth opening and closing, facial pain, headache and discomfort with jaw movements.

Temporomandibular disorders (TMDs) encompass a broad spectrum of clinical indications and manifestations that pertain to the masticatory muscles, TMJ, and related structures. It was commonly believed that TMDs primarily impacted adults. Nonetheless, investigations into the prevalence of these conditions have revealed that comparable signs and symptoms are equally prevalent among children and adolescents [27].

USG is the preferred diagnostic method for assessing the condition of masticatory muscles and TMJ in pediatric patients. This method is easily accessible, offers real-time assessment and does not involve ionising radiation. Furthermore, It is an inexpensive, non-invasive, and swift procedure. USG has been used to demonstrate the relationship of masticatory muscles to bruxism and thus temporomandibular disorders in children [28,29]. In addition to these commonly observed symptoms, there are studies in the literature in which masticatory muscles were examined by ultrasonography in anomalies such as cleft lip and palate [30], unilateral posterior crossbite [31], facial asymmetry [32], and Class II malocclusion [33]. Therefore, utilizing artificial intelligence to analyze ultrasonographic images of masticatory muscles will aid medical professionals in diagnosing and treating conditions such as bruxism, TMDs, and other afflictions that impact masticatory muscles.

In the study conducted by Orhan et al., the segmentation of the masseter muscle was performed using deep learning architectures including U-Net, PSPNet and FPN. The accuracy rates obtained with these methods are reported as 0.985, 0.947 and 0.969, respectively. These results show that all three methods are acceptably successful. The study also emphasized that clinicians can greatly benefit from these methods when performing segmentation and thickness measurement of the masseter muscle through ultrasonography. These findings reveal the potential of deep learning-based segmentation methods in the evaluation of the masseter muscle in clinical practice [34]. Keser et al. segmented the masseter muscle using the U-Net architecture and found F1, sensitivity and precision values of 1.0, 1.0 and 1.0, respectively [6]. In the present study, the YOLO architecture was implemented and the sensitivity, precision and F1 scores for masseter muscle segmentation were found to be 1.0, 1.0 and 1.0, respectively, in accordance with other studies in the literature.

To the best of our knowledge, our study marks the first successful attempt to segment not only the masseter muscle but also the temporal and lateral pterygoid muscles in ultrasound images, employing artificial intelligence systems. Furthermore, our research is groundbreaking as it pioneers this segmentation process using ultrasound images specifically from pediatric patients. The outcomes of our study revealed an exceptionally high achievement rate of 100% in the segmentation of the masseter and temporal muscles.

Limitations

The success of artificial intelligence in segmenting the lateral pterygoid muscle was found to be relatively lower compared to that of the masseter and anterior temporal muscles. Although ultrasonography is more useful in the examination of superficial masticatory muscles, there may be some difficulties in detecting more deeply located muscles [35]. Ultrasound examination of the lateral pterygoid muscle may not be easy, even for experienced clinicians, due to its deeper location and the obstruction caused by the ramus when the mouth is closed. However, muscle thickness correlates with age and tends to be lesser in children than in adults [36]. Taking all these factors into account, the lower success in segmenting the lateral pterygoid muscle can be attributed to the anatomical limitations mentioned above and the insufficient availability of training data.

Conclusion

In summary, segmentation techniques based on deep learning for analyzing ultrasonography images of anatomical structures like masticatory muscles have great potential in clinical applications. Precise segmentation of muscles through this technology can play a crucial role in the diagnosis and follow-up of diverse medical conditions and diseases.

Artificial intelligence-assisted muscle segmentation can improve the accuracy of clinical practice and make diagnostic processes faster and more reliable. Particularly, investigations involving ultrasound images of pediatric patients could potentially facilitate earlier diagnoses and treatment interventions for this specific patient group.

Through the utilization of this technology, clinicians are empowered to attain outcomes that are not only more precise and objective, but also to respond more promptly to treatment needs and to effectively monitor the progression of patient treatments. Artificial intelligence-assisted muscle segmentation holds significant potential as a tool for early diagnosis of muscle-related pathologies and the advancement of more efficient treatment approaches. As a result, this improvement will have a positive effect on patients' quality of life by enhancing the quality of both diagnosis and treatment procedures.

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Conflict of interest

The authors declare that they have no conflict of interest in the publication.

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Author contributions

Conception: F.A., B.T.Ç. - Design: F.A., B.T.Ç. - Supervision: F.A.- Materials: F.A., B.T.Ç. - Data Collection and/or Processing: B.T.Ç. - Analysis and/or Interpretation: B.T.Ç. – Literature Review: F.A., B.T.Ç. - Writing: F.A, B.T.Ç.. - Critical Review: F.A.

Ethical approval

Ethical approval was received for this study from Gaziantep University Clinical Research Ethics Committee (protocol number: 2023/309).

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