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A deep learning approach for masseter muscle segmentation on ultrasonography

Gaye Keser[1], Ibrahim Sevki Bayrakdar[2], Filiz Namdar Pekiner[1], Özer Çelik[3], Kaan Orhan[4,5]

[1] *Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Marmara University, Istanbul, Turkey*
[2] *Department of Dentomaxillofacial Radiology, Faculty of Dentistry, Eskişehir Osmangazi University, Eskişehir, Turkey*
[3] *Department of Mathematics and Computer, Faculty of Science and Letters, Eskişehir Osmangazi University, Eskişehir, Turkey*
[4] *Department of Dentomaxillofacial Radiology, Faculty of Dentistry, Ankara University, Ankara, Turkey*
[5] *Ankara University Medical Design Application and Research Center (MEDITAM), Ankara, Turkey*

Corresponding author: Gaye Keser, Department of Oral and Maxillofacial Radiology, Marmara University, Faculty of Dentistry, Turkey; e-mail: gayekeser@hotmail.com

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Keywords

ultrasonography; masseter muscle; deep learning; artificial intelligence

Abstract

Aim: Deep learning algorithms have lately been used for medical image processing, and they have showed promise in a range of applications. The purpose of this study was to develop and test computer-based diagnostic tools for evaluating masseter muscle segmentation on ultrasonography images. **Materials and methods:** A total of 388 anonymous adult masseter muscle retrospective ultrasonographic images were evaluated. The masseter muscle was labeled on ultrasonography images using the polygonal type labeling method with the CranioCatch labeling program (CranioCatch, Eskişehir, Turkey). All images were re-checked and verified by Oral and Maxillofacial Radiology experts. This data set was divided into training (n = 312), verification (n = 38) and test (n = 38) sets. In the study, an artificial intelligence model was developed using PyTorch U-Net architecture, which is a deep learning approach. **Results:** In our study, the artificial intelligence deep learning model known as U-net provided the detection and segmentation of all test images, and when the success rate in the estimation of the images was evaluated, the F1, sensitivity and precision results of the model were 1.0, 1.0 and 1.0, respectively. **Conclusion:** Artificial intelligence shows promise in automatic segmentation of masseter muscle on ultrasonography images. This strategy can aid surgeons, radiologists, and other medical practitioners in reducing diagnostic time.

Introduction

The masseter muscle (MM) is a quadrilateral muscle that has both superficial and deep sections. A tendinous aponeurosis, which originates from the zygomatic process of the maxilla and moves downward and backward, connects the lateral surface of the ramus of the mandible to the superficial part, which is the larger region. The deep part, which arises from the posterior bottom border of the zygomatic arch and runs downward and forward, connecting to the ramus and coronoid process, is much smaller[1–4].

The thickness of the masseter muscle has been examined extensively in relation to masticatory function and craniofacial functional processes. Occlusal morphology and biting force can impact development, facial morphology, and muscle thickness[5–8]. According to previous studies[9,10], measuring cross-sectional distances of head and neck muscles can be related to muscle palpation pain, face shape, biting force, and occlusal factors. In addition, there appears to be a relationship between masseter muscle thickness and a variety of dental arch parameters, such as alveolar process thickness and maxillary dental arch width.

The use of ultrasound imaging (US) to examine the superficial tissues of the head and neck is particularly beneficial[1,5]. Ultrasonography is a type of medical imaging that enables exact measurement of the masticatory muscle size. It can be used to diagnose, quantify, and identify changes in the proportions of the face and neck muscles, as pointed out in several articles[5,11–14]. Ultrasound can be used to get well-defined masticatory muscle images, particularly for the masseter and anterior temporal muscles, such that thickness can be estimated with excellent repeatability and speed while avoiding ionizing radiation exposure. Therefore, it is a good method for examining the perioral muscles.

Artificial intelligence (AI) is described as the use of computers or machines to undertake tasks that would typically be performed by people[15–19]. Machine learning and deep learning (DL) are an artificial intelligence field that may be used to educate machines and computers how to analyze various types of data using different techniques. AI algorithms are employed in a range of sectors, including engineering, the stock market, and medicine, among others[17–21]. Artificial intelligence principles and actual potential, as well as its impact on our personal and professional life, are still unknown to many people, including physicians and physicists.

AI algorithms have a lot of potential in dentistry, especially in imaging[15–20]. In recent years, AI applications in dentistry have aroused much interest in fields such as caries diagnostics, pathology detection, orthodontic treatment planning, robotic surgery, and dental implant installation[22–25]. Dental radiology research has been emphasized due to its adaptation of image processing tools. Artificial intelligence (AI)-based computer-aided detection and diagnosis are being utilized to improve the quality, efficiency, and affordability of US imaging, which has led to an increase in US acceptability for musculoskeletal assessments[26]. As a result, the purpose of this study is to evaluate the effectiveness of a deep convolutional neural network (D-CNN)-based AI system for masseter muscle detection and segmentation on US images.

Materials and methods

Study design and clinical information

This study was performed in line with the principles of the Declaration of Helsinki.The study protocol was approved by the Marmara University School of Medicine Non-Interventional Clinical Research Ethics Committee on 03.09.2021 with protocol number 09. 2021.990.

Data preparation

US images of 388 patients admitted to the Marmara University Faculty of Dentistry were used in this retrospective study.

Ultrasonography image dataset

The retrospective assessments were performed with the use of an Aloka Prosound 6 (Hitachi Aloka Medical Systems, Tokyo, Japan) equipped with an 8 MHz-wide bandwidth linear active matrix transducer (ranging from 1 to 15 MHz). The ultrasonograms were recorded in MM mode with an image depth of 3.5 cm and an echo gain of 80–90 dB.

Each patient was sitting upright, with the head in the normal posture. The sufferers were told to relax. The muscle image was obtained by scanning both sides of the masseter muscle perpendicular to the anterior border of the muscle and the surface of the mandibular ramus at about 2.5 cm above the inferior border of the mandible with no or little pressure.

Deep convolutional neural network architecture

The deep learning process was performed using the U-net architecture[27]. This architecture operates with less training photos and produces more exact segmentations. The primary idea of is to add consecutive layers to a traditional contracting network, where pooling operators are substituted with upsampling operators. As a result, these layers improve the output resolution. The U-net architecture performs well in biomedical segmentation applications[28,29].

Model Pipeline

An AI algorithm (CranioCatch, Eskisehir, Turkey) was created in this research to perform autonomous segmentation of masseter muscles (Fig. 1, Fig. 2).

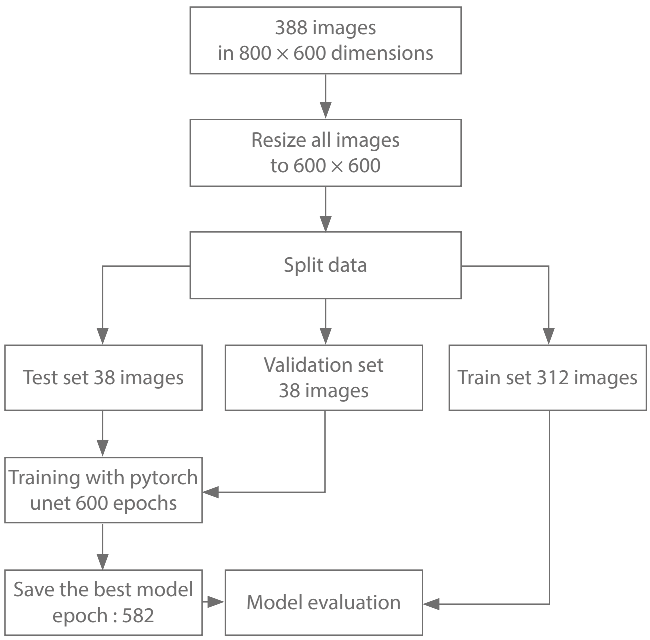

Fig. 1. *AI Model (CranioCatch, Eskisehir-Turkey) Pipeline for Masseter Muscle Segmentation in USG Images*

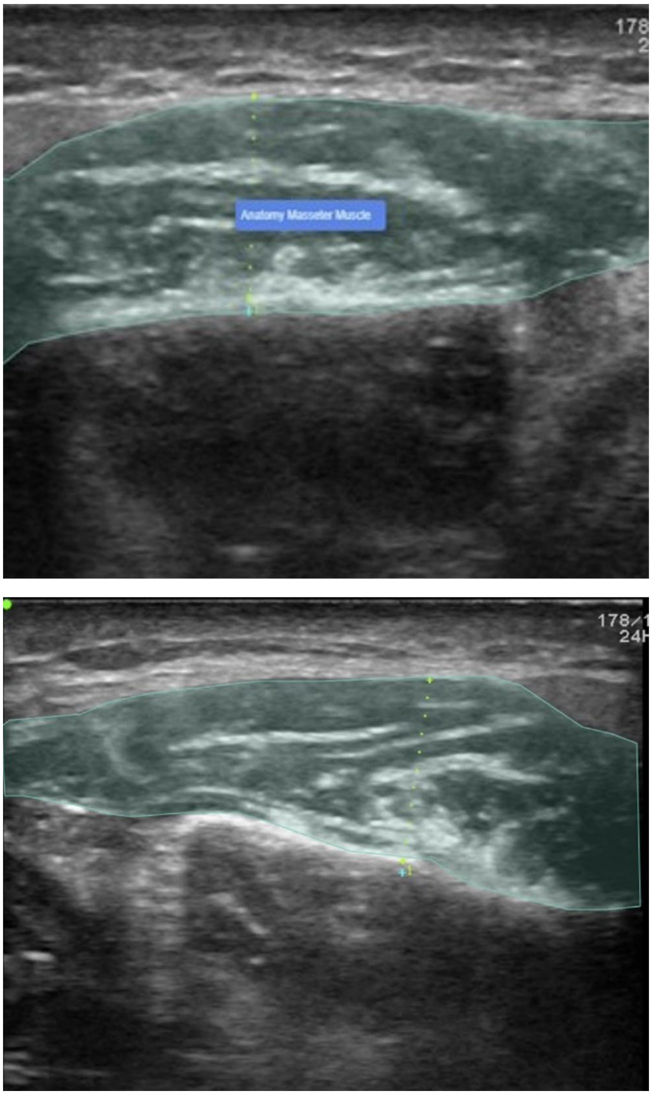

Fig. 2. *The images show the Masseter Muscle Measurements performed using AI Models (CranioCatch, Eskisehir- Turkey)*

Training phase

The images were randomly divided into:
1. Training group: 312 images
2. Validation group: 38 images
3. Test group: 38 images.

Statistical analysis

The confusion matrix, an informative table that summarizes the expected and actual conditions, was used as a metric to calculate the model's success. The following processes and metrics were used to measure the success of the AI model:

True positive (TP), false positive (FP), and false negative (FN) rates were calculated:
- TP: the outcome in which the model correctly predicts the positive class.
- FP: the outcome in which the model incorrectly predicts the positive class.
- FN: the outcome in which the model incorrectly predicts the negative class.

The following metrics were then calculated using the TP, FP, and FN values:
- Sensitivity (Recall): TP/(TP + FN)
- Precision: TP/(TP + FP)
- F1 Score: 2TP/(2TP + FP + FN)

Results

In our study, the artificial intelligence (AI) deep learning model U-net provided the detection and segmentation of all test images, and when the success rate in the estimation of the images was evaluated, the F1, sensitivity and precision results of the model were 1.0, 1.0 and 1.0, respectively, indicating perfect precision and recall (Tab. 1).

Discussion

Ultrasound imaging is a powerful diagnostic technique for musculoskeletal examinations. It is noninvasive and delivers real-time imaging without the use of ionizing radiation. It' is also popular for evaluating ligaments, muscles, and tendons, as well as superficial cancers and peripheral nerves[26,30,31].

By avoiding the hand-crafted engineering phases that define ML pipelines, DL transformed the field of end-to-end learning. Deep Neural Networks automatically detect patterns in data and perform admirably in a variety of applications, such as radiology[32,33], dermatology[34], and ophthalmology[35].

AI-based musculoskeletal imaging improved greatly in the previous decade, boosting anatomical structure visualization and automating quantitative assessments. According to current research on AI-based musculoskeletal US[26,30], DL methods may become next-generation diagnostic tools for monitoring the state of joints, bones, cartilage, ligaments, and muscles.

Only one study in the literature assessed the effectiveness of a deep convolutional neural network (D-CNN)-based artificial intelligence (AI) system for masseter muscle segmentation using ultrasonography (USG) images. In this investigation, Orhan *et al*.[36] included a total of 195 anonymised US images. U-net, Pyramid Scene Parsing Network (PSPNet), and Fuzzy Petri Net (FPN) architectures

Tab. 1. *Evaluation for diagnostic performance by AI model set for masseter muscle segmentation*

	U-Net Model
F1	1.0
Sensitivity	1.0
Precision	1.0

were used in the deep learning process. Muscle thickness was measured with the use of US software and manual segmentation. Following automated muscle measurements, a neural network model (CranioCatch, Eskisehir-Turkey) was employed to determine the muscles. The test dataset was used to calculate accuracy, Receiver Operating Characteristic (ROC) area under the curve (AUC), and Precision-Recall Curves (PRC) to compare a human observer with the AI model. AI was statistically compared to manual segmentation and measures ($p < 0.05$). Only two examples of muscles were not recognized by PSPNet, and the AI models detected and segmented all test muscle data for FPN and U-net (false negatives). FPN, PSPNet, and U-net had 0.985, 0.947, and 0.969 accuracy, respectively. Similarly, in our study, the artificial intelligence (AI) deep learning model, U-net, provided the detection and segmentation of all test images, and when the success rate in the estimation of the images was evaluated, the F1, sensitivity and precision results of the model were 1.0, 1.0 and 1.0, respectively.

Although AI-based musculoskeletal US has shown significant promise in terms of overcoming high variability and operator dependency, there are a few limitations to be mindful of. First, there is a distinction between 2D and 3D imaging, which is often utilized in radiology clinics. Due to the complexity of musculoskeletal systems and multiple joints, image preprocessing techniques, such as rigid or non-rigid image registration, are required for the large-scale usage of DL for US. Without a thorough grasp of functional anatomy, even for US professionals, diagnosis based on 2D US is difficult. The narrow 2D US image planes are difficult to duplicate and locate, which is a drawback for creating a large, standardized medical image collection. Recent AI-based 3D US imaging approaches may be able to overcome 2D US limitations[37,38]. As a result, 3D medical US reconstruction, visualization, and segmentation methodologies appear to be promising.

Although the present algorithm showed promising results, this study had a significant limitation. Further studies are needed to determine the estimation success of segmentation using larger data sets, as well as to examine additional types of architectures.

Conclusion

AI has a wide range of functions and applications in the health-care industry. Increased effort and likely doctor's weariness may risk diagnostic abilities and outcomes. Artificial intelligence components in imaging equipment would reduce this effort and boost efficiency. Our first findings indicate that deep learning has the capability to deal with this significant obstacle. Future AI research should continue to emphasize human interests as its primary purpose, as expertise in processing large amounts of data improves.

Conflict of interest

The authors do not report any financial or personal connections with other persons or organizations which might negatively affect the contents of this publication and/or claim authorship rights to this publication.

Author contributions

Original concept of study: GK, ISB, FNP, KO. Writing of manuscript: GK, ISB. Analysis and interpretation of data: OC. Final acceptation of manuscript: FNP, KO. Collection, recording and/or compilation of data: GK. Critical review of manuscript: ISB, FNP, KO.

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