Osmangazi Journal of Med, 2025;47(4):600-605
DOI: 10.20515/otd.1641306

Research Article
Araştırma Makalesi

Osmangazi Journal of Medicine
e-ISSN: 2587-1579

Segmentation of Meningeal Contrast Enhancement in Post-Contrast T1-Weighted Images Using the Deep Learning Method

Postkontrast T1 Ağırlıklı Görüntülerde Meningeal Kontrastlanmanın Derin Öğrenme Yöntemi İle Segment

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Ethics Committee Approval: The study was approved by Eskişehir Osmangazi University Noninterventional Clinical Research Ethical Committee Eskişehir Osmangazi University (Decision number: 29 dated: 24.05.2022).

Informed Consent: The authors declared that it was not considered necessary to get consent from the patients because the study was a retrospective data analysis.

Authorship Contributions:: Conception and design: Nevin AYDIN, Suzan SAYLISOY Analysis and interpretation of the data: Nevin AYDIN, Ugur TOPRAK, Özer ÇELİK The drafting and revising of the paper: Nevin AYDIN, Burcu MERT The final approval of the version to be published: Nevin AYDIN, Suzan SAYLISOY, Ugur TOPRAK, Burcu MERT

Copyright Transfer Form: Copyright Transfer Formwas signed by all authors.

Conflict of Interest: No conflict of interest was declared by the authors.

Financial Disclosure: The authors declared that this study received no financial support.

Received : 19.02.2025

Accepted .20.05.2025

Published :..22.05.2025

Abstract:: To evaluate the success of segmentation of meningeal contrast enhancement on post-contrast T1-weighted images using the deep learning method. The study retrospectively included 313 sections obtained from post-contrast T1-weighted sequences of 83 patients with meningeal enhancement. The dataset was divided into three groups. A total of 300 epochs of training were performed using PyTorch U-Net, and the best model was identified. The results were calculated by selecting 50% as the threshold for the intersection over union statistics. In total, images of 83 patients were evaluated, of whom 36 (43.4%) were female and 47 (56.6%) were male. The mean ± standard deviation of the patients' age was 57.06 ± 16.73 years. Of the 313 sections obtained, 251 were allocated in the training group, 31 to the validation group, and 31 to the test group. The results of the test group were as follows: 35 true positives, 12 false positives, and 12 false negatives. The precision, sensitivity, and F1 score values were all calculated to be 74%. This is one of the pioneering studies in the literature on the segmentation of meningeal contrast-enhanced areas using the deep learning-based U-net architecture. Further studies are needed in this area.
Keywords: Deep learning method, Meningeal enhancement, Pachymeningeal enhancement, Leptomeningeal enhancement, Magnetic resonance imaging

Özet: Çalışmamızın amacı; postkontrast T1 ağırlıklı görüntülerde meningeal kontrastlanmanın derin öğrenme yöntemi ile segmentasyonunun başarısını değerlendirmektir. Retrospektif olarak 2013-2020 yılları arasında meningeal kontrastlanması olan 83 hastanın postkontrast T1 ağırlıklı sekanslarından elde edilen 313 kesit çalışmaya dahil edildi. Veri seti train – validation- test grubu olarak ayrıldı. Pytorch Unet ile 300 epoch eğitim yapıldı, en iyi model kaydedildi. Birleşim Üzerinde Kesişim (The Intersection over Union, IoU, Jaccard Endeksi) istatistiğinin eşik değeri olarak %50 seçilerek sonuçlar hesaplandı. Toplamda 83 hastanın görüntüleri değerlendirilmiş olup bu hastalardan 36 (%43.4)'sı kadın, 47 (%56.6)'si erkek hasta idi. Hastaların yaş ortalaması ± standart sapması 57.06 ±16.73 idi. 83 hastanın görüntüsünden elde edilen 313 kesitte; 251 kesit eğitime, 31 kesit validasyona, 31 kesitteki etiketler test aşamasına ayrıldı. Test grubunda Doğru Bulunan: 35, Yanlış Bulunan: 12, Bulunamayan: 12 olarak tespit edildi. Çalışmamızda Precision, Sensitivity, F1 Score değerleri sırasıyla %74, %74, %74 olarak hesaplandı. Çalışmamız derin öğrenme temelli U-net mimarisi kullanarak meningeal kontrastlanma alanlarının segmentasyonunda literatürde öncü çalışmalardan biri olup bu alanda yapılacak yeni çalışmalara ihtiyaç vardır.
Anahtar Kelimeler: Derin Öğrenme, Meningeal Kontrastlanma,, Pakimeningeal Kontrastlanma, Leptomeningeal Kontrastlanma, Manyetik Rezonans Görüntüleme

How to cite/ Atıf için:, Aydin N, Saylısoy S, Toprak U, Mert B, Çelik Ö. Segmentation of Meningeal Contrast Enhancement in Post-Contrast T1-Weighted Images Using the Deep Learning Method, Osmangazi Journal of Medicine, 2025;47(4):600-605

1. Introduction

Meningeal contrast enhancement is categorized into two types: pachymeningeal (dura-arachnoid) and leptomeningeal (pia-arachnoid) [1]. In post contrast magnetic resonance imaging (MRI), the normal dura mater appears as a thin, linear, and interrupted structure [2]. Thick linear or nodular enhancement can be observed in pachymeningeal enhancement. Leptomeningeal enhancement refers to the observation of gyriform or serpentine enhancement of pial surfaces, including the subarachnoid spaces [1]. Meningeal enhancement should be considered in cases where there is meningeal thickening, enhancement in long segments, intense enhancement, or nodular enhancement [3].Contrast-enhanced MRI provides superior visualization of meningeal enhancement than contrast-enhanced computed tomography. Identifying meningeal enhancement on MRI images is a useful diagnostic tool that can be utilized in many conditions, such as infection, tumoral spread, and inflammation [1,4].

In recent years, deep learning has been increasingly prevalent across various scientific disciplines [5]. Utilizing artificial intelligence techniques in MRI examinations can reduce the workload in daily clinical practice and shorten the diagnosis process. With the use of convolutional neural networks in MRI, successful models have emerged for segmentation [6,7]. The present focus, especially in the field of MRI examinations, is on segmentation using deep learning methods. However, there is no study in the literature evaluating meningeal enhancement with these methods.

This study aimed to evaluate the success of segmentation of meningeal enhancement on post-contrast T1-weighted images using the deep learning method.

2. Material and Methods

Ethics: The study was initiated after receiving ethical approval on May 24, 2022, with the decision number 2022-29. In this study, written informed consent has obtained from the participant.

Patient Population

Contrast-enhanced brain MRI examinations performed between 2013 and 2020 were retrospectively screened from the hospital's Picture Archiving and Communication Systems using the keywords "pachymeningeal enhancement", "leptomeningeal enhancement", and "meningeal enhancement". The images of 229 patients with meningeal enhancement on post-contrast examinations were evaluated. Among these patients, those under 18 years were excluded. After also eliminating images of inadequate examination quality, those with motion artifacts, those with insufficient or questionable contrast enhancement, and those without contrast enhancement, the images of 83 patients were included in the study. The diagram for patient selection is shown in Fig. 1.

MRI Scan and Analysis

Axial sections were recorded in the post-contrast T1-weighted sequences of the patients. A total of 313 sections obtained from 83 patients were used in the study. MRI examinations were performed using a 3T MRI scanner (General Electric, Discovery 750W with GEM Suit). In patients with more than one examination, only one examination of each patient was included in the sample. The following imaging parameters were used for 3T MRI: pixel resolution, 754x1005; echo time, 17 msn; repetition time, 750 msn; zoom, 1.96x; window center/window width, 370/570; and slice thickness, 5 mm. All images were resized to 512x512. The mask images of the labeled regions of the images were created and saved using the same names. Then, the dataset was divided into training, validation, and testing groups at a ratio of 80, 10, and 10%, respectively. A total of 300 epochs of training were performed using PyTorch U-Net, and the best model was noted. The results were calculated by selecting 50% as the threshold value for the intersection over union (IoU, Jaccard index) statistic [8]. Using the true positive (TP), false positive (FP), and false negative (FN) values, the sensitivity, precision, and F1 score values were calculated according to the formulas given below.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \qquad [9]$$

$$\text{Precision} = \frac{TP}{TP + FP} \qquad [10]$$

$$\text{F1 score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Sensitivity}}} \qquad [11]$$

Statistical Analysis

Continuous data was presented as mean ± standard deviation values and categorical data as percentages. IBM SPSS Statistics 21.0 (IBM Corp. Released 2012. IBM SPSS Statistics for Windows, Version

21.0. Armonk, NY: IBM Corp.) program was used for the implementation of statistical analyses.

3. Results

In total, images of 83 patients were evaluated, of whom 36 (43.4%) were female and 47 (56.6%) were male. The mean ± standard deviation age of the patients was 57.06 ± 16.73 years. The number of sections taken from the patients was between 1 and 8. The imaging of the patients was performed with the preliminary diagnosis of an operated intracranial mass, infection, lymphoma, metastasis, Sturge-Weber syndrome, and edema. Pachymeningeal involvement was observed in 34 of the patients, leptomeningeal involvement in 37, and a mixed pattern in 12 (Table 1). Of the 313 sections obtained from the images of 83 patients, 251 were allocated to training, 31 to validation, and 31 to testing. The total number of labels was 723, including 591 labels in the training group, 73 labels in the validation group, and 59 labels in the test group (Table 2). The results of the test group based on the 50% threshold value of IoU were as follows: 35 TPs, 12 FPs, and 12 FNs. Segmentation and the U-Net architecture in TP samples are shown in Fig. 2 and Fig. 3. The precision, sensitivity, and F1 score values were calculated to be 74%, 74%, and 74%, respectively.

Table 1. General characteristics of the patients

	Number of patients (n = 83), n (%)
Sex	
Female	36 (43.4%)
Male	47 (56.6%)
Age, mean ± standard deviation	57.06 ± 16.7
Number of sections (minimum-maximum)	1.00-8.00
Imaging reason	
Metastasis	51 (61.4%)
Infection	11 (13.2%)
Operated intracranial mass	10 (12.1%)
Lymphoma	8 (9.6%)
Sturge-Weber syndrome	2 (2.4%)
Edema	1 (1.2%)
Meningeal enhancement	
Pachymeningeal	34 (40.9%)
Leptomeningeal	37 (44.5%)
Mixed	12 (14.6%)

Table 2. Numbers of images and labels in the training, validation, and test groups

Total number of images	**Number of images in the training group**	**Number of labels in the training group**	**Number of images in the validation group**	**Number of labels in the validation group**	**Number of images in the test group**	**Number of labels in the test group**
723	251	591	31	73	31	59

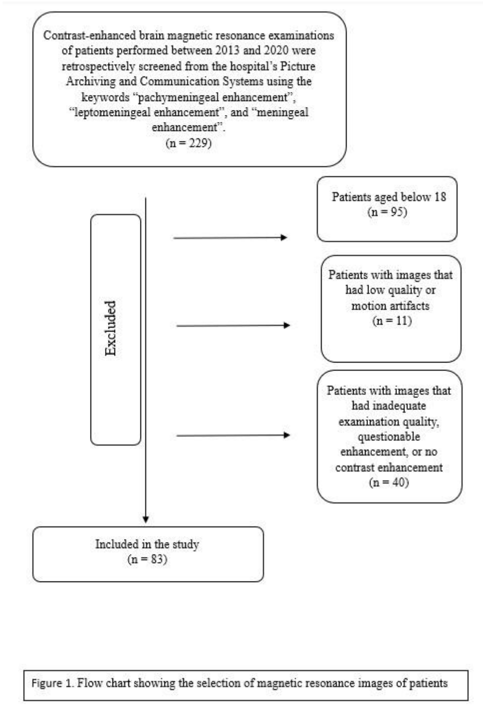

Figure 1. Flow chart showing the selection of magnetic resonance images of patients

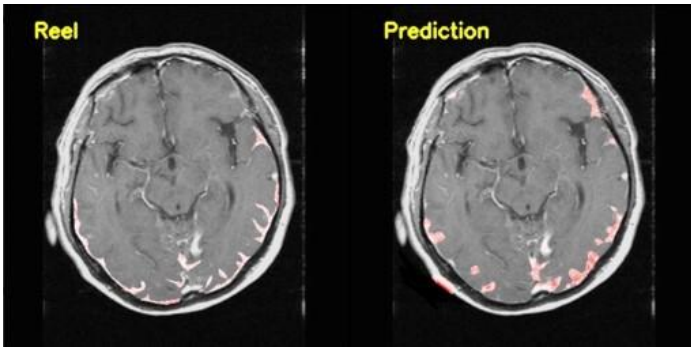

Figure 2. Raw image data and segmentation output of meningeal enhancement areas in a contrast-enhanced T1-weighted axial image

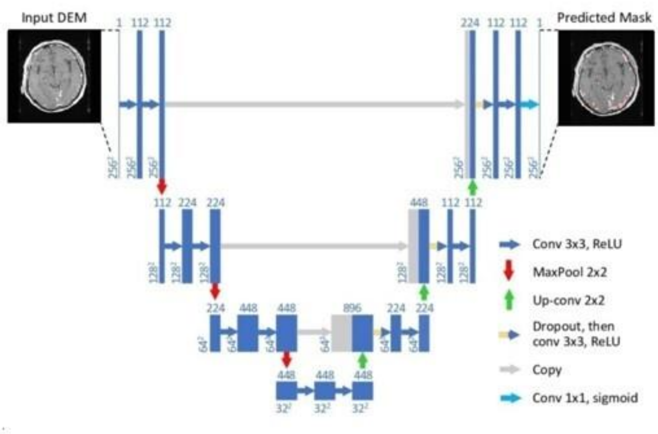

Figure 3. U-Net architecture of a segmentation sample

4. Discussion

In this study, we evaluated the success of segmentation using the deep learning method for segmenting leptomeningeal and pachymeningeal enhancement areas on the T1-weighted images of post-contrast MRI scans. By employing the U-Net architecture based on a convolutional neural network algorithm, we achieved average success in segmenting meningeal enhancement areas, with precision, sensitivity, and F1 score values of 74% each. This may be because even experts in this field have difficulty making a diagnosis in some cases when deciding on pachymeningeal and leptomeningeal enhancement on post-contrast T1-weighted images in routine examinations. While parenchymal brain metastases show a better contrast pattern compared to the surrounding brain parenchyma, the thin anatomical structure of leptomeninges might sometimes cause radiologists to overlook the apparent contrast enhancement in this area [12-14]. In the current study, leptomeningeal enhancement areas were relatively high in number. Pachymeningeal enhancement represents the dura mater or dura and the arachnoid membrane and shows thicker anatomical structures than the leptomeninges [15]. Therefore, pachymeningeal enhancement can be diagnosed more easily than leptomeningeal enhancement in MRI examinations. In our study, we did not evaluate pachymeningeal and leptomeningeal enhancement by segmenting them into separate groups, considering that as the number of groups increased, the number of patients decreased, and some patients presented with both contrast enhancement patterns. In this regard, there is a need for further studies that segment pachymeningeal and leptomeningeal enhancement areas by dividing them into separate groups. To the best of our knowledge, in the literature, there is no artificial intelligence study on meningeal enhancement. Therefore, our study is considered one of the pioneering studies in this field.

In recent years, artificial intelligence studies in neuroimaging have particularly focused on MRI imaging of meningiomas, and there are many studies on this subject [16-18]. In a volumetric study on meningiomas using multiparametric MRI, a deep learning model and manual segmentation were compared, and the authors found automatic segmentation to be correlated with manual segmentation [16]. In another study, segmentation and grading of meningiomas were undertaken in multiparametric MRI using contrast-enhanced T1- and T2-weighted images, and the segmentation was deemed successful according to the Dice coefficient. The segmentation model developed was relatively more successful in automatic volumetric evaluation compared to studies that used external validation. In meningioma grading, the combination of contrast-enhanced T1-weighted images and T2-weighted images yielded more successful results in modeling [17]. The current study employed only contrast-enhanced T1-weighted images obtained from MRI examinations. We also did not utilize external validation.

Another artificial intelligence-based study performed predictions for high-grade (II-III) and low-grade (I) meningiomas using automatic segmentation and radiomics before surgery [18]. Although radiomic features were not incorporated into our study, this feature may be used in a future study focusing on the etiological causes of meningeal enhancement.

Among the limitations of our study are its retrospective and single-center design. Other limitations can be considered as the aggregation of pachymeningeal and leptomeningeal enhancement areas into a single group and the relatively small number of cases.

In conclusion, our study is one of the pioneering studies in the literature on deep learning-based segmentation of meningeal enhancement on contrast-enhanced T1-weighted images in cranial post-contrast MRI examinations. There is a need for further studies in this field.

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Abbreviations

MRI: Magnetic Resonance Imaging