ORIGINAL ARTICLE

Journal of Otorhinolaryngology and Facial Plastic Surgery 2024;10(1):1-7.

https://doi.org/10.22037/orlfps.v10i1.47659

The Diagnostic Value of MRI-based-Radiomics before Surgery of Patients with Meningioma

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Article Info

Article Note:
Received: November 2024
Accepted: November 2024
Publish Online: December 2024

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Keywords:
Diagnosis;
Meningioma;
Magnetic resonance imaging;
Radiomic.

Abstract

Background: Meningioma is the most common primary brain tumor in adults, mostly seen in middle-aged women. Magnetic resonance imaging (MRI) is the primary diagnostic and follow-up tool. Recently, radiomics have been introduced to predict prognosis in patients with brain tumors, yet studies are limited.

Aim: The aim of this study was to investigate the diagnostic value of radiomics based on MRI images before surgery in patients with meningioma.

Methods: In this cross-sectional study, meningioma patients who were operated on between 2018 and 2024 were evaluated. MR imaging of the patients were observed and Radiomics features were extracted by an expert radiologist. Finally, the images were analyzed based on radiomic algorithms.

Results: LASSO test was performed and among 851 features, 10 features with non-zero correlation were selected. The accuracy of SVM was 81.25%, Precision was 0.85 with validity of 0.814±0.052. According to findings from Logistic Regression, the accuracy of the test was 87.50%, the precision was 0.89, and the validity of the test was 0.943 ± 0.070. Random Forest algorithm was also performed on the samples and it was seen that its accuracy was 87.5%, Precision 0.89, and validity 0.889 ± 0.056. The area under the curve (AUC) for SVM, Logistic Regression, and Random Forest were 0.62, 0.75, and 0.75, respectively.

Conclusion: The use of artificial intelligence based radiomic algorithms can help radiologists diagnose meningioma more accurately, but it cannot replace it.

Conflicts of Interest: The Authors declare no conflicts of interest.

Please cite this article as: Nasiri S, Teymouri A, Soleimantabar H, Afshar Moghaddam N, Teymouri A. The Diagnostic Value of MRI-based-Radiomics before Surgery of Patients with Meningioma. J Otorhinolaryngol Facial Plast Surg 2024;10(1):1-7. https://doi.org/10.22037/orlfps.v10i1.47659

Introduction

Cerebral meningioma is the most common primary brain tumor in adults mostly seen in middle-aged women (1). According to WHO classification, this disease has 3 grades: 1. Tumor with low growth rate 2. Atypical meningioma 3. Anaplastic or malignant meningioma (2). Meanwhile, grades 2 and 3 have been associated with higher recurrence rate and mortality (3). Preoperative evaluation with routine imaging has limitations such as the inability to grade pathologically based on imaging characteristics (4). Grade 1 meningioma accounts for about 81 to 95% of the disease with recurrence rate at 5 years

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estimated to be more than 10%, with some transforming to higher grade tumors (5, 6). The diagnosis of meningioma is based on history, physical examination, and radiological evaluations (7). The best radiological method to diagnose meningioma is magnetic resonance imaging (MRI) of the brain with contrast. This method can help distinguish extra-axial from intra-axial lesions because extra-axial meningiomas have homogeneous enhancement with a unique feature called dural tail. MRI of the brain helps evaluating venous sinus involvement and find cystic lesions in meningioma. This sign explains the invasion of the tumor in the brain parenchyma (8). On brain MRI without contrast, meningiomas usually appear as a hypointense lesion on T1-weighted imaging and hyperintense on T2-weighted imaging. Some meningiomas may appear isointense on brain MRI without contrast on both T1 and T2 - weighted images (7). Recently, the use of artificial intelligence in radiology has been drastically advanced with many new publications adding new information regarding its potential applications (in identification, segmentation and prediction of disease progression). The purpose of using advanced artificial intelligence techniques is to help radiologists in the diagnosis and analysis of lesions, which reduces misdiagnosis and increases diagnostic efficiency (9, 10). Radiomix is an emerging field that converts radiological images into quantitative data. Previous studies have focused more on prediction, grade, and prognosis of meningioma, and few recent studies have shown promising results in predicting the outcome of treatment in meningioma (11).

In this study, we aimed to evaluate the diagnostic value of Radiomics based on preoperative MRI images in patients with cerebral meningioma.

Methods

In this cross-sectional study, all patients who underwent surgery for meningioma (with definitive diagnoses) in Imam Hossein Hospital between September 2018 and September 2024 were selected. The diagnosis of meningioma was based on positive Ki67 on pathology and MRI findings. The inclusion criteria were the definite diagnosis of meningioma (with pathology confirmation), availability of MRI images (especially T2W, T1W and CET1W sequences) before their surgery in the hospital archives, no preoperative radiotherapy, and presence of positive Ki67 in pathology examination after surgical biopsy. The exclusion criteria included no confirmation of meningioma, absence MRI images, or images with artifacts, or poor quality.Finally, MRI of 52 patients were assessed. Patients who had undergone T2-weighted MRI (T2WI), T1-weighted imaging (T1WI) and contrast-enhanced T1WI (CET1) before surgery for meningioma were evaluated. T2WI sequence parameters were as follows: repetition time/echo time of 4200 /103 ms, field of view of 200×200 mm, acquisition matrix of 320×224, slice thickness of 4 mm. T1WI sequence parameters were as follows: repetition time/echo time of 9/400 ms, field of view of 200 × 200 mm, flip angle of 90°, acquisition matrix of 288 × 192, slice thickness of 3 mm. CET1 was performed with T1WI sequence parameters after rapid injection of a gadolinium-diethylenetriamine pentaacetic acid (DTPA) contrast agent. All MR images were uploaded to the software ITK-SNAP (version 3.8.0, www.itk-snap.org) and a three-dimensional region of interest (1) covering the entire tumor was defined. This manual segmentation of the tumor was performed by an experienced radiologist. Then, the radiomic features were extracted such as shape, texture, deformity, enhancement, etc. by an experienced radiologist.

Statistical analysis

All analyzes were performed with Python language (version 3.7.6) and SciPy library (version 1.4.1). A significance level of <0.05

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was considered. The tumor area was first segmented with 3D Slicer software, and after pre-processing with Python, the features of the segment area were extracted with pyradiomics library. Then, with least absolute shrinkage and selection operator (LASSO) regression, features with non-zero correlation coefficient were selected to perform machine learning. All variables were entered into the machine after pre-processing and removal of abnormal data, and svm, Logistic Regression, and random forest algorithms were evaluated. Education method was considered as 70% learning and 30% testing. As a result, the diagnostic value was reported by reporting the sensitivity, specificity, accuracy, and AUC along with the ROC curve. Also, in order to measure the validity of the results, 5-fold cross validation was conducted to evaluate the proposed model, which was reported as an average with a standard deviation (12). The relevant statistical calculations are given in the following Figure.

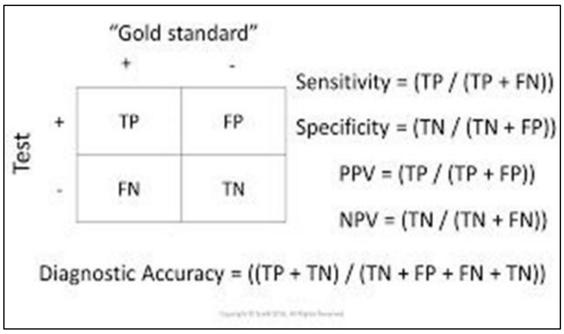

Figure 1. The method of statistical calculations of diagnostic criteria.

Results

The images of patients with a definitive diagnosis of meningioma were evaluated and analyzed with artificial intelligence algorithms. After extracting image features, LASSO test was performed and 10 features with non-zero correlation were selected from among 851 features.

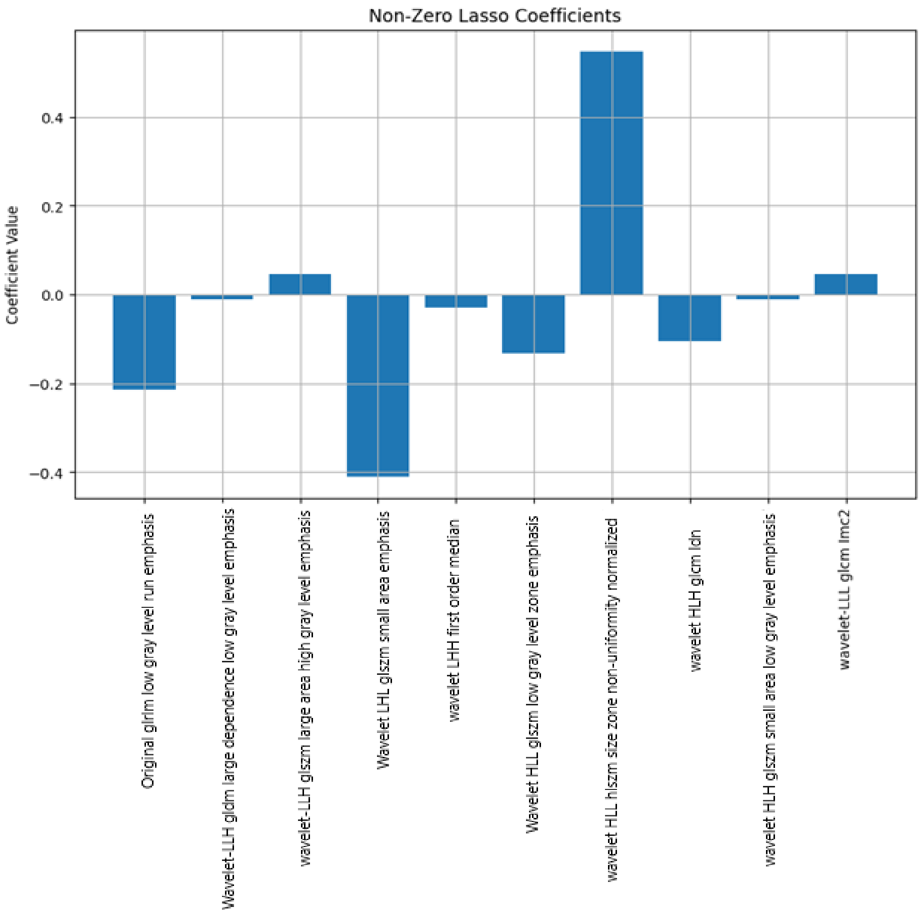

Figure 2. LASSO test results

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We assessed results of different radiomic algorithms including SVM, Logistic Regression, and Random-Forest for meningioma diagnosis. The results of SVM algorithm are seen in Figure 3. The accuracy for test Set was 81.25% (95% CI: 62.13%, 99.37%), weighted average precision (95% CI): 0.850 (0.675, 99.03), weighted average recall (95% CI): 0.812 (0.621, 0.98.2), weighted average F1-score (95% CI): 0.767 (0.559, 0.974), and 5-fold cross validation accuracy was 0.814 ± 0.052. the area of under curve (AUC) was 0.62.

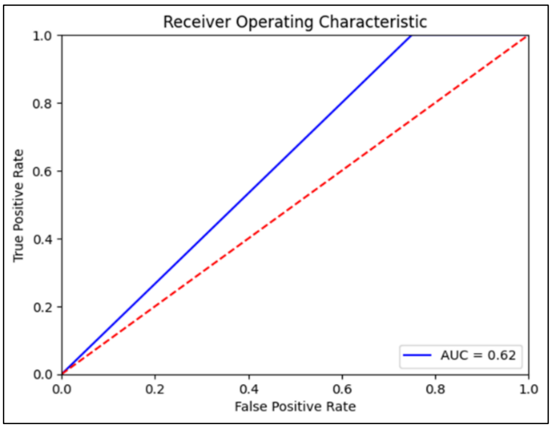

Figure3. The results of SVM algorithm

The results of Logistic Regression are seen in Figure 4. The accuracy for test Set was 87.50% (95% CI: 71.30%, 98.70%), weighted average Precision (95% CI): 0.89 (0.73, 96.84), weighted average Recall (95% CI): 0.88 (0.713, 96.07), weighted average F1-score (95% CI): 0.86 (0.69, 94.20), 5-fold cross validation accuracy: 0.943 ± 0.070, and AUC was 0.75.

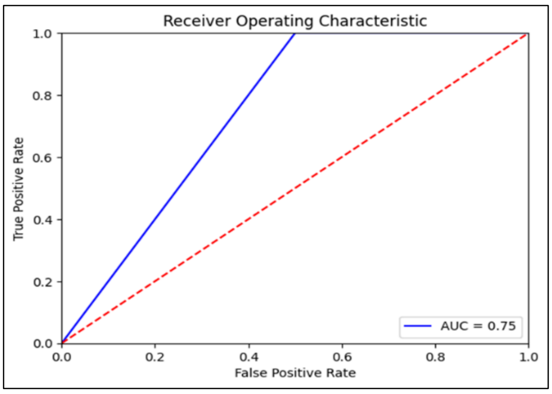

Figure4. The results of Logistic Regression algorithm

In Figure 5, The result of Random Forest is demonstrated. Based on our evaluation, the accuracy for test Set was (95% CI): 87.5 (73.8, 96.01), weighted average Precision (95% CI): 0.893 (0.741, 95.044), weighted average Recall (95% CI): 0.875 (0.713, 92.037), weighted average F1-score (95% CI): 0.859 (0.688, 96.030), 5-fold cross validation accuracy: 0.889 ± 0.056, and the AUC was 0.75.

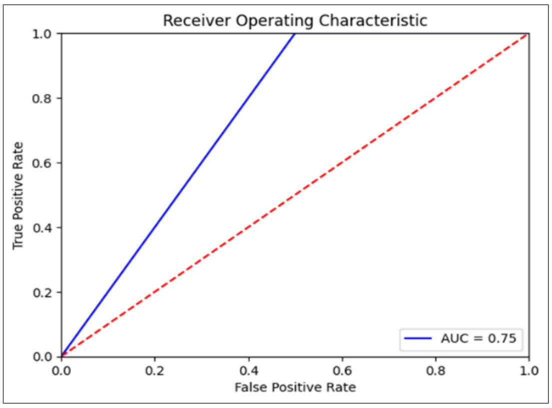

Figure 5. the result of Random Forest algorithm

Discussion

Our results showed that the accuracy of SVM was 81.25%, precision was 0.85 and validity was 0.814 ± 0.052. Logistic Regression revealed that the accuracy of the test was 87.50%, the precision was 0.89, and validity was 0.943 ± 0.070. Random Forest algorithm was also performed on the samples and it was seen that its accuracy was 87.5%, Precision 0.89 with validity of 0.889 ± 0.056. The AUC for SVM, Logistic Regression, and Random Forest were 0.62, 0.75, and 0.75, respectively, which indicates that Logistic Regression and Random Forest are better methods than SVM for meningioma diagnosis.

Zhai et al. designed a nomogram to predict meningioma consistency based on radiomics. AUC for train and test groups was calculated as 0.861 and 0.960, respectively. Also, this model benefited from sufficient calibration in both groups. This study showed that a designed nomogram is able to non-invasively estimate tumor consistency with acceptable accuracy (2). In our study, the consistency of the tumor

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was not checked, and the diagnostic value of radiomics was compared to radiologists' decision. It was seen that the AUC for both Logistic Regression and Random Forest in meningioma diagnosis were 0.75, which is close to 1, so it can be said that this detection rate is acceptable but not perfect. The remarkable point in the two studies was that, despite the difference in the investigated content (both studies were conducted on meningioma, but they differed in how each utilized AI), both studies had acceptable levels of AUC, but these results show that AI is still unable to replace the decision-making abilities of a radiologist.

Zhang et al., developed a radiomics model to predict the risk of brain invasion in meningioma based on MRI. 16 features were significantly associated with brain invasion. Gender in combination with MRI in predicting brain invasion in training and test groups had AUC 0.857 and 0.819, respectively, and sensitivity 72.8 and 90.1%. This study showed that clinical risk factors in combination with radiomics characteristics will lead to the development of a model capable of predicting brain invasion in meningioma (3). In the current study, it was seen that the best radiomic tests for meningioma diagnosis were Logistic Regression and Random Forest, and the AUC for both of these tests was 0.75, similar to the results of Zhang et al. It can be said that the use of radiomics can be helpful in diagnosing and evaluating the extent of meningioma invasion in the brain.

In the study of Ko et al., MRI radiomics was used to predict progression or recurrence of meningioma. A total of 128 patients with grade I meningioma were included in the study. 32 first order features and 75 texture features were extracted. SVM was used to evaluate the statistical significance of each along with the prognosis of the disease, and 4 more significant features were selected to calculate the score. In multivariate analysis, subtotal resection, bone invasion (HR: 7.31), low ADC (HR: 4.67), and high SVM score (HR: 8.13) were significantly more in the recurrence or progression group. In case of using SVM, the AUC equal to 0.80 with a cut-off score of 0.224 was obtained. This study showed that the use of radiomics can be useful in adopting the appropriate treatment plan according to the recurrence or progression of the disease (4). In our study, AUC for SVM was 0.62 and F1-score was 0.767, which are different from the study of Ko et al. This difference can be explained by the difference in the studied patients because the current study was on patients with meningioma with any grade, but the study by Ko et al. was only performed on patients with grade 1 meningioma.

Oga et al., conducted a systematic review of studies to evaluate the results of radiomic MRI and machine learning in meningioma. The total (possible range, -8 to 36) and percentage of radiomic quality scores were 6.96 ± 4.86 and 19 ± 13%, respectively, with moderate to good reproducibility between readers. The meta-analysis showed an overall AUC of 0.88 with a standard error of 0.02 (5). In our study, the AUC was evaluated between different methods and was not reported in general, but the AUC for different radiomics were 0.62 and 0.75, which indicates the appropriate diagnostic value of radiomics for the diagnosis of meningioma. Patel et al., investigated the use of radiomics in meningioma in a systematic review and found that for the diagnosis and segmentation, radiomic models had an average accuracy of 93.1 ± 8.1%.

Meningioma classification had an average accuracy of 95.2% ± 4.0%. Tumor grading had an average AUC of 0.85 ± 0.08. Correlation with biological characteristics of meningioma had a mean AUC of 0.07 ± 0.89. The prognosis of the clinical course had a mean AUC of 0.83 ± 0.08. The quality of the studies was generally low with an average of 5.9 ± 6.7 (6). As shown by Patel et al., the quality of studies on the use of artificial intelligence is low, and this can be due to the novelty of these methods, their

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required improvement, and the unfamiliarity of some radiologists with these methods. Similar to our study, the use of radiomics can help with the diagnosis of meningioma, but its diagnostic power is still lower than that of radiologists. This issue indicates the need to increase the accuracy of artificial intelligence to detect radiological findings.

Conclusion

Use of artificial intelligence-based radiomics can help radiologists diagnose meningioma more accurately, but AI cannot replace radiologists at this stage. According to our findings, the diagnostic value of radiomics are suitable for meningioma diagnosis, and Logistic Regression and Random Forest have better diagnostic performance than SVM. An advantage of our study was the evaluation of different types of radiomics, as various applications of artificial intelligence, for the diagnosis of all types of meningioma which was less attended to in previous studies.

Acknowledgments

None to declare.

Conflicts of Interest

The authors declare no conflicts of interest.

Financial Support

The authors declared that there was no funding support for this study.

Ethical approval:

IR.SBMU.MSP.REC1403.112.

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