Radiomic signatures of meningiomas using the Ki-67 proliferation index as a prognostic marker of clinical outcomes

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OBJECTIVE The clinical behavior of meningiomas is not entirely captured by its designated WHO grade, therefore other factors must be elucidated that portend increased tumor aggressiveness and associated risk of recurrence. In this study, the authors identify multiparametric MRI radiomic signatures of meningiomas using Ki-67 as a prognostic marker of clinical outcomes independent of WHO grade.

METHODS A retrospective analysis was conducted of all resected meningiomas between 2012 and 2018. Preoperative MR images were used for high-throughput radiomic feature extraction and subsequently used to develop a machine learning algorithm to stratify meningiomas based on Ki-67 indices < 5% and ≥ 5%, independent of WHO grade. Progression-free survival (PFS) was assessed based on machine learning prediction of Ki-67 strata and compared with outcomes based on histopathological Ki-67.

RESULTS Three hundred forty-three meningiomas were included: 291 with WHO grade I, 43 with grade II, and 9 with grade III. The overall rate of recurrence was 19.8% (15.1% in grade I, 44.2% in grade II, and 77.8% in grade III) over a median follow-up of 28.5 months. Grade II and III tumors had higher Ki-67 indices than grade I tumors, albeit tumor and peritumoral edema volumes had considerable variation independent of meningioma WHO grade. Forty-six high-performing radiomic features (1 morphological, 7 intensity-based, and 38 textural) were identified and used to build a support vector machine model to stratify tumors based on a Ki-67 cutoff of 5%, with resultant areas under the curve of 0.83 (95% CI 0.78–0.89) and 0.84 (95% CI 0.75–0.94) achieved for the discovery (n = 257) and validation (n = 86) data sets, respectively. Comparison of histopathological Ki-67 versus machine learning–predicted Ki-67 showed excellent performance (overall accuracy > 80%), with classification of grade I meningiomas exhibiting the greatest accuracy. Prediction of Ki-67 by machine learning classifier revealed shorter PFS for meningiomas with Ki-67 indices ≥ 5% compared with tumors with Ki-67 < 5% (p < 0.0001, log-rank test), which corroborates divergent patient outcomes observed using histopathological Ki-67.

CONCLUSIONS The Ki-67 proliferation index may serve as a surrogate marker of increased meningioma aggressiveness independent of WHO grade. Machine learning using radiomic feature analysis may be used for the preoperative prediction of meningioma Ki-67, which provides enhanced analytical insights to help improve diagnostic classification and guide patient-specific treatment strategies.

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KEYWORDS meningioma; radiomics; machine learning; Ki-67 proliferation index

ABBREVIATIONS ADC = apparent diffusion coefficient; AUC = area under the curve; CaPTk = Cancer Imaging Phenomics Toolkit; DWI = diffusion-weighted imaging; IQR = interquartile range; LASSO = least absolute shrinkage and selection operator; MP-MRI = multiparametric MRI; PFS = progression-free survival; SVM = support vector machine.
Although the majority of meningiomas are benign tumors that exhibit favorable long-term control rates, it is well known that the WHO classification scheme for meningiomas does not necessarily predict tumor behavior and does not always correlate with risk of recurrence.\(^1,2\) Given that as many as 30% of WHO grade I and more than half of WHO grade II and III meningiomas may exhibit recurrence on long-term follow-up,\(^3-5\) the ability to reliably predict tumor aggressiveness must be better elucidated. With the advances in genomic and molecular analyses, many researchers have proposed adoption of supplemental diagnostic adjuncts to better characterize the clinical behavior of meningiomas.\(^6-9\) The incorporation of copy number variations, somatic point mutations, and epigenetic profiling may exhibit greater accuracy in predicting tumor behavior compared with the WHO classification, which currently relies almost exclusively on histopathology.\(^10\) However, these amended classification schemes may be considered only after tumor resection has been achieved; there remains a need for a better preoperative characterization of these tumors that can influence the treatment strategy.

Although many tools and technologies have been adopted by surgeons for intraoperative guidance, including augmented reality,\(^11\) fluorescence-guidance,\(^12\) and Raman spectroscopy,\(^13\) there remains a dearth of options available for use in the preoperative planning period. Radiomics is a field of computational science that involves quantification of voxel-level data from standard imaging modalities such as multiparametric MRI (MP-MRI) that can be used to develop machine learning models to aid in the diagnosis of tumor pathology and predict patient outcomes.\(^14-16\) Although other researchers have investigated the use of radiomics to predict meningioma grade,\(^17,18\) there have been no studies that apply radiomics-based machine learning to predict tumor biomarkers as they pertain to predicting its behavior, which subsequently reflects its risk of recurrence. Specifically, providing clinicians with greater prognostic insight into meningioma behavior during the preoperative period may impact clinical decision-making, including surveillance regimens, timing of surgery, and intraoperative resection strategies.

The Ki-67 proliferation index is a marker of cellular growth whose predictive utility of tumor aggressiveness has been evaluated in a variety of cancers.\(^19\) While the applicability of the Ki-67 proliferation index to meningiomas remains controversial, there have been several recent studies corroborating that an elevated Ki-67 index confers an increased risk of recurrence.\(^3,20,21\) We have previously shown that radiomic feature analysis can reliably predict meningioma Ki-67 strata based on a cutoff of 5% in WHO grade I tumors; its predictive utility as it relates to rate of recurrence has not been elucidated.\(^22\) Given that WHO grade I meningiomas with higher proliferation indices have been shown to behave more aggressively,\(^20,21\) and that grade II and III meningiomas inherently harbor higher proliferation indices,\(^23\) the Ki-67 index may represent a simple and widely accessible surrogate biomarker that could be used to predict tumor aggressiveness across all WHO grades.

In this study, we use high-throughput radiomic feature analysis and standard patient preoperative MP-MRI scans to develop a machine learning model that stratifies meningiomas based on Ki-67 independent of WHO grade, and analyze the algorithm’s predictive utility as a marker of progression-free survival (PFS; Fig. 1). Radiomics-derived diagnostics could provide surgeons, oncologists, and patients with enhanced tumor diagnostics that may help deliver personalized, patient-specific treatment strategies.

**Methods**

**Clinical Data**

A retrospective study was conducted of all patients who underwent resection of meningiomas at a single institution between 2012 and 2018. The study protocol was approved by the IRB at Thomas Jefferson University Hospital and the need for informed consent was waived. Length of follow-up was calculated based on the date of surgery until the most recent MRI available, rather than on the most recent visit with a neurosurgical provider. PFS was determined from the time of surgery until radiographic evidence of local recurrence or progression of residual tumor, as documented on either a radiology report or a neurosurgeon clinic note. Although all patients underwent craniotomy for resection, the Simpson grade was not used for analysis due to the low frequency of its documentation in the operative report and the lack of a standardized institutional protocol for postoperative MRI timing.

**Histopathology**

Patient histopathology records were accessed and meningioma WHO grades reviewed and reclassified, as indicated, based on the criteria presented in the 2021 WHO Classification of Tumors of the Central Nervous System.\(^24\) In all patients, the Ki-67 proliferation index was quantified and recorded by a neuropathologist using ApEriTo immunohistochemical image analysis software (Apeiro Technologies Inc). Thirteen patients were excluded due to lack of an available histopathology report.

**Radiomic Feature Extraction**

Each patient’s preoperative MR image closest to the date of surgery was used for radiomic feature extraction and subsequent machine learning analysis. Standard MP-MRI data consisting of 7 sequences (T1-weighted precontrast, T1-weighted postcontrast, T2-weighted, T2-weighted FLAIR, diffusion-weighted imaging [DWI] including both b0 and b1000 images, and apparent diffusion coefficient [ADC] map) were used for analysis, regardless of whether the scan was performed at our institution or another imaging center prior to surgery.\(^22\) Patients with motion artifact on MRI or those who did not have all 7 requisite sequences were excluded from the study (n = 74 patients).

Image preprocessing was performed using the Cancer Imaging Phenomics Toolkit (CaPTK; https://www.med.upenn.edu/cbica/captk/). All 7 MRI sequences were coregistered upon its 0.5-mm thin-cut T1-weighted postcontrast scan, reformatted to a 1 × 1 × 1-mm\(^3\) spatial resolution, and subsequently underwent N4ITK bias field correction. The final intensity values of the images were scaled to the
range of 0–255. Coregistered images were used to perform manual tumor (T1-weighted postcontrast) and peritumoral edema (T2-weighted FLAIR) segmentation using ITK-SNAP software by a neurosurgeon blinded to tumor histopathology. High-throughput (n = 4282) radiomic feature extraction was performed using CaPTk from all 7 sequences overlying the regions of interest as denoted by the segmentation outline, and these morphological, intensity-based, textural features were subsequently used to build a machine learning model.

**Development of Machine Learning Model**

Top-performing radiomic features were selected using the least absolute shrinkage and selection operator (LASSO) technique wrapped with a support vector machine (SVM) classifier, which serves to minimize the risk of model overfitting. The overall cohort was split 75%/25% into a discovery (n = 257) and replication (n = 86) cohort, respectively, with the latter serving as an “unseen” data set to which the model could be independently applied to assess its generalizability, based on similar parameters utilized for prior studies.25–27

A supervised machine learning model based on SVM (MATLAB, Mathworks) through nested cross-validation (10-fold for inner and outer loops) was trained on the discovery cohort to stratify meningiomas based on a Ki-67 cutoff of 5%. Ki-67 strata of < 5% and ≥ 5% were selected to identify more aggressive grade I tumors with associated increased risk of recurrence based on two recent studies identifying similar thresholds.20,21 This method also inher-
ently incorporates the majority of grade II and III tumors and therefore identifies aggressive tumors independent of its designated WHO grade. The model was trained solely using radiomic features derived from patients’ preoperative MP-MRI scans. No clinical factors were included in the development of this model.

### Statistical Analysis

Patient demographics and tumor radiographic characteristics were summarized with descriptive statistics. Continuous data variables were presented as mean ± standard deviation. Analysis was performed using an unpaired two-tailed t-test, one-way ANOVA, and Fisher’s exact tests for variables between different cohorts. Median follow-up was estimated with the reverse Kaplan-Meier method. Differences in PFS were determined by a log-rank test. A p value < 0.05 was used as a threshold of statistical significance. Analyses were conducted using R statistical software (version 4.0; http://www.r-project.org/) and MATLAB 2018b.

### Results

Patient demographics and baseline clinical characteristics are presented in Table 1. Three hundred forty-three resected meningiomas were included in the study (291 WHO grade I, 43 grade II, and 9 grade III). Tumor locations were classified based on skull base versus non–skull base lesions, and the latter comprised a larger portion of higher-grade tumors. The median length of radiographic follow-up was 28.5 (interquartile range [IQR] 13–50) months. The overall rate of recurrence was 19.8% (15.1% for WHO grade I, 44.2% for grade II, and 77.8% for grade III). The model was trained solely using radiomic features derived from patients’ preoperative MP-MRI scans; no clinical factors were included in the development of this model.

There was a significant difference in the Ki-67 proliferation indices between WHO grade I (mean 4.79% ± 3.87%, range 0.3%–33.6%), grade II (mean 16.07% ± 13.83%, range 1.5%–49%) and grade III meningiomas (mean 35.7% ± 13.31%, range 18%–57.4%; p < 0.001). The percentage of the patient cohort with elevated Ki-67 ≥ 5% increased with higher WHO grade (Fig. 2A and B). However, tumor volumes and peritumoral edema volumes showed considerable differences, independent of meningioma WHO grade (Fig. 2C and D). In all lesions (grades I–III combined), tumor volumes and peritumoral edema volumes were both significantly higher in meningiomas with Ki-67 indices ≥ 5% compared with < 5% (Fig. 2E and F).

After high-throughput radiomic feature extraction was performed, 46 high-performing features were selected using the LASSO method and subsequently used to build

| TABLE 1. Summary of clinical and radiographic characteristics for 343 meningiomas comprising the study cohort |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| Characteristic   | All Patients, n = 343 | Grade I, n = 291 | Grade II, n = 43 | Grade III, n = 9 |
| Gender, n (%)    | Male 116 (33.82)   | 95 (32.65)       | 19 (44.19)       | 2 (22.22)       |
|                 | Female 227 (66.18) | 196 (67.35)      | 24 (55.81)       | 7 (77.78)       |
| Mean age ± SD (range), yrs | 59.7 ± 14.4 (19–90) | 58.3 ± 14.2 (19–90) | 64.37 ± 14.7 (24–86) | 62.6 ± 16.4 (35–88) |
| Laterality of tumor, n (%) | Rt 160 (46.65)   | 131 (45.02)      | 25 (58.14)       | 4 (44.44)       |
|                 | Lt 163 (47.52)    | 146 (50.17)      | 13 (30.23)       | 4 (44.44)       |
| Midline 20 (5.83) | 14 (4.81)         | 5 (11.63)        | 1 (11.11)        |                |
| Skull base meningiomas, n (%) | Clinical 7 (2.04) | 7 (2.41)         | 0                | 0               |
|                 | Olfactory groove  10 (2.92) | 7 (2.41) | 3 (6.98)         | 0               |
|                 | Petroclival       8 (2.33)    | 7 (2.41)         | 1 (2.33)         | 0               |
|                 | Planum sphenoidale 6 (1.75) | 5 (1.72) | 1 (2.33)         | 0               |
|                 | Sphenoid wing      48 (14.00) | 42 (14.43) | 6 (13.95)        | 0               |
|                 | Posterior fossa    35 (10.20) | 34 (11.68) | 1 (2.33)         | 0               |
|                 | Temporal fossa     14 (4.08)    | 14 (4.81)        | 0                | 0               |
| Non–skull base meningioma, n (%) | Convexity 95 (27.70) | 73 (25.09) | 17 (39.53)       | 5 (55.56)       |
|                 | Intraventricular   5 (1.46)     | 4 (1.37)         | 1 (2.33)         | 0               |
|                 | Parafalcine        13 (3.79)    | 13 (4.47)        | 0                | 0               |
|                 | Parasagittal       93 (27.11)   | 76 (26.12)       | 13 (30.23)       | 4 (44.44)       |
|                 | Pineal             1 (0.29)      | 1 (0.34)         | 0                | 0               |
|                 | Tentorium          8 (2.33)     | 8 (2.75)         | 0                |                |
| Median follow-up (IQR), mos | 28.5 (13–50)       | 31 (15–54)       | 21 (8–37)        | 26.5 (7–36)     |
| Rate of recurrence, n (%) | 68 (19.83)        | 44 (15.12)       | 19 (44.19)       | 7 (77.78)       |
a machine learning model (Table 2). All 7 sequences contributed to the list of features, highlighting the utility of MP-MRI for enhanced diagnostics. Textural features comprised the highest number of features (n = 38). Interestingly, only one morphological radiomic feature (tumor surface “roundness”) was included; tumor volume and peritumoral edema did not reveal sufficient discriminative ability to distinguish between the Ki-67 cutoff of 5%, underscoring the power of radiomic feature analysis over traditional morphological assessment currently used by clinicians.

A machine learning model was trained on the discovery cohort using an SVM classifier with nested cross-validation to stratify all tumors (WHO grades I–III) based on a Ki-67 cutoff of 5% (Table 3). A radiomic signature score was calculated based on the machine learning algorithm

**FIG. 2.** Tumor histopathological Ki-67 proliferation indices in WHO grade I–III meningiomas show higher values with higher-grade tumors (**A and B**). There were no differences in volumes of meningioma or peritumoral edema stratified by WHO grade (**C and D**), but in the entire cohort (grades I–III), meningiomas with higher Ki-67 indices had larger volumes and greater degrees of peritumoral edema (**E and F**). *p < 0.05.
and normalized via sigmoid function, which revealed a dichotomy in the output between tumors with Ki-67 indices < 5% versus those with ≥ 5% (Fig. 3A). There was a higher disparity in mean radiomic signature score in WHO grade I compared with grade II and III tumors, likely due to the fewer patients present in the higher-grade tumor cohorts. In the training data set of all tumors (n = 257), an area under the curve (AUC) of 0.83 (95% CI 0.78–0.89) was achieved (Fig. 3B), with sensitivity and specificity of 79.8% and 80.4%, respectively (Table 3). Similar performance was demonstrated when the model was independently applied to the validation data set, with an AUC of 0.84 (95% CI 0.75–0.94), sensitivity of 72.7%, and specificity of 90.6% (Fig. 3C). Correlation of histopathological Ki-67 with machine learning–predicted Ki-67 showed excellent performance (overall accuracy > 80%), with classification of grade I meningiomas exhibiting the greatest accuracy, particularly for tumors with Ki-67 < 5% (Fig. 3D). The classification performance of grade II tumors was inherently limited by the fewer number of patients present in this cohort, despite the disparate radiomic signature scores observed based on the Ki-67 proliferation index.

Using strata based on a Ki-67 cutoff of 5% for all tumors in the study cohort (WHO grades I–III), Kaplan-Meier curves showed shorter PFS for tumors with Ki-67 ≥ 5% compared with tumors with Ki-67 < 5% (p < 0.0001, log-rank test) using both machine learning–predicted Ki-67 as well as histopathological Ki-67% (Fig. 4). A subanalysis of outcomes based on WHO grade showed greater PFS in grade I tumors with Ki-67 < 5% versus ≥ 5%, but this statistically significant association was not reproduced in grade II and II tumors, likely due to inadequate power. In WHO grade I meningiomas, machine learning revealed a shorter PFS for meningiomas with predicted Ki-67 ≥ 5% and was consistent with patient outcomes based on histopathological Ki-67 (Fig. 5A and D). In grade II tumors, no patients in our cohort with histopathological Ki-67 < 5% had a recurrence, but the predictive capacity of the machine learning model failed to replicate this finding (Fig. 5B and E). The machine learning model correctly stratified all but 1 of the grade III tumors into the correct Ki-67 strata ≥ 5%, albeit the small patient size limited performance generalizability for this cohort (Fig. 5C and F).

### Discussion

The WHO grading system for meningiomas, due to its reliance on histopathology without any criteria for molecular features, is inadequate in its ability to predict tumor aggressiveness and inherent risk of recurrence. Although WHO grade I meningiomas are considered benign, they can recur at rates as high as 30%, and grade II tumors have also been shown to have variable clinical behavior and associated recurrence risk. Meningioma outcomes are influenced by several factors such as histopathology, tumor location, extent of resection, and so on.
Ki-67 proliferation index. Preoperative assessment of meningioma aggressiveness, irrespective of its designated WHO grade, could help guide treatment strategy. In this regard, multivariate pattern analysis via radiomics may serve as a means of identifying unique meningioma phenotypic imaging signatures (radiomic score) that can be used to provide enhanced tumor diagnostics.

In the last several years, other groups have proposed novel classification schemes that better characterize meningioma aggressiveness and associated recurrence risk.
which improve upon what the WHO classification scheme currently affords. Nassiri et al. developed a methylome-based model that provides a risk score that predicts a patient’s individualized risk of recurrence after surgery. Driver and colleagues developed a 3-tiered grading scheme incorporating molecular features that more accurately reflected patients’ risk of recurrence when compared with WHO grade. Both studies include extent of resection in the grading criteria, highlighting the importance of resection as it pertains to subsequent risk of recurrence. These classification schemes may only be applied after surgical intervention, however, and serve to provide a framework for postoperative decision making. There remains a need for improved preoperative noninvasive diagnostic modalities that provide guidance on treatment strategy pertaining to frequency of surveillance, timing of surgery, and need for aggressive resection.

Our machine learning algorithm, trained and tested on 343 meningiomas, demonstrated the ability to capture the complex structural characteristics manifested in meningioma imaging phenotypes and quantified by radiomics, with > 80% overall accuracy in stratifying tumors based on a Ki-67 cutoff of 5%. The algorithm assigns a radiomic signature score for tumors based on Ki-67 strata of 5%, which represents an in vivo depiction of meningioma biology. In our patient cohort, higher proliferation indices were noted in tumors with increasing WHO grade, which influenced our decision to use Ki-67 as a biomarker such

![FIG. 4. Kaplan-Meier curves revealed shorter PFS for meningiomas with machine learning model–predicted (A) and histopathological (B) Ki-67 ≥ 5% compared with Ki-67 < 5%.

![FIG. 5. Kaplan-Meier curves comparing PFS based on machine learning model prediction of Ki-67 (A–C) and histopathological Ki-67 strata (D–F) classified by subset of WHO grade I, II, and III meningiomas.](image-url)
that, in addition to selecting grade II and III tumors, aggressive grade I tumors could also be identified.\textsuperscript{22} Importantly, tumor volume and degree of peritumoral edema—two morphological characteristics often used by clinicians to infer tumor aggressiveness and need for surgical intervention—were not found to be significantly different based on tumor WHO grade and did not occur among the highest-performing features in our machine learning algorithm, illustrating the superior diagnostic capabilities of radiomic feature analysis over conventional radiological modalities. The predictive capacity of this algorithm reveals disparate outcomes pertaining to rate of recurrence: tumors with predicted Ki-67 $\geq 5\%$ have significantly shorter PFS than those with Ki-67 $< 5\%$, independent of designated WHO grade, a finding that is also reflected in analysis of our patient outcomes based on histopathological Ki-67. These findings highlight the utility of the machine learning model to reveal tumor aggressiveness based on Ki-67 as it pertains to patient outcomes\textsuperscript{20,21,40} and could serve as a simple yet valuable preoperative marker to help guide treatment strategy, including timing of surgery, frequency of surveillance, and degree of aggressive resection required to mitigate risk of recurrence.

Our work leverages the use of radiomic data science to stratify meningiomas based on Ki-67 as a means of predicting tumor aggressiveness and, subsequently, its risk of recurrence. We use a set of standard preoperative multiparametric MRI sequences that were performed using different machines without any stipulated scanning parameters, highlighting its potential for use in a wide variety of clinical settings. Furthermore, our algorithm was derived using radiomic features alone, which were procured using publicly available multiplatform open-source software, without the need for input of any additional clinical or radiographic data, and could conceivably be translated to develop an automated pipeline. The segmentations need to be performed manually, which limits the process workflow from being fully automated. Our group is currently working to automate the segmentation process for meningiomas, similar to what has been accomplished for gliomas, and if successful, we intend to make this open-source\textsuperscript{41,42} We envision the future of neurosurgical evaluation for meningiomas to include an individualized preoperative risk assessment using standard MRI so that patients can be counseled on decision-making. Patients being followed for low-grade, low Ki-67 tumors can pursue surveillance at longer intervals compared with those with higher predicted Ki-67 indices. Furthermore, the predicted Ki-67 strata may help guide timing of surgery; by identifying patients with aggressive meningiomas versus those with indolent ones, earlier surgical intervention could be warranted over continued surveillance to facilitate greater extent of resection.

Our study does have several limitations. First, the study design is a retrospective analysis of a single-institution patient cohort, and subsequent studies are necessary to apply this model prospectively to larger external data sets. Our group recently founded the Radiomics Signatures for Precision Diagnostics (ReSPOND) consortium on glioblastoma\textsuperscript{43} comprising more than 3000 patient scans supplied by more than 10 institutions across multiple continents, and it is our hope to emulate this effort for meningiomas as well, as validation large data sets are required prior to utilizing these models in the clinical realm. In addition, the role of Ki-67 as a prognostic marker of outcomes in meningioma remains controversial, and perhaps for this reason does not serve as a criterion in the WHO classification scheme.\textsuperscript{44} Higher-grade meningiomas have been shown to have more intratumoral heterogeneity, and the reported histopathological Ki-67 may not be reflective of the entire lesion but rather of the local milieu from the sampled region of the tumor.\textsuperscript{6} This disparity may explain why the rate of misclassification by our model was higher in grade II meningiomas compared with WHO grade I tumors, although this may also be reflected in the limited sample size of high-grade tumors in our data set. Despite our study having included the largest patient cohort to date, multinstitutional cohorts of grade II and III meningiomas are needed to improve the diagnostic capability of this model and its resultant generalizability to other data sets and broad application in clinical settings.

One recent study found that incorporating criteria from various molecular classification schemes all result in three distinct biological subtypes of meningiomas, with dichotomous outcomes between the two benign and one malignant subtypes.\textsuperscript{6} In this regard, it may be other molecular features rather than Ki-67 that serve as a better conduit for tumor aggressiveness, such as chromosomal instability, DNA methylation profile, or copy number variations. Further studies are needed to identify drivers of meningioma biology and develop a classification scheme that provides a better determination of predicted outcomes. Lastly, analysis of Simpson grade of resection is not included in the study, and although all patients in our cohort underwent craniotomy for attempted maximal safe resection, we acknowledge that extent of resection may inherently contribute toward risk of recurrence.

Conclusions

Our study reveals the potential of radiomic feature analysis to provide advanced preoperative diagnostic capabilities that may help guide patient-specific treatment strategy and represents an avenue for advancing the treatment paradigm for meningiomas. The ability to preoperatively predict tumor aggressiveness into Ki-67 strata would provide surgeons with an important consideration to guide the degree of resection necessary and help achieve improved patient outcomes.

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References


Disclosures

Dr. D. Andrews reported having stock from Imvax outside the submitted work, as well as owning patents US10206942B2, US10543226B2, and US10265339B2. Dr. Flanders reported being on the board of directors of the Radiological Society of North America and being a principal investigator at the Medical Imaging and Data Resource Center of the National Institute of Biomedical Imaging and Bioengineering. Dr. Shi reported receiving personal fees from Novocure, grants from Brainlab, and personal fees from Zai Lab outside the submitted work.

Author Contributions

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Supplemental Information

Previous Presentations

Select portions of this work were presented at the 2022 Annual Meeting of the Congress of Neurological Surgeons in San Francisco, California, October 8–12, 2022.

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