Quantification of tumor response of cystic vestibular schwannoma to Gamma Knife radiosurgery by using artificial intelligence

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OBJECTIVE  Gamma Knife radiosurgery (GKRS) is a common treatment modality for vestibular schwannoma (VS). The ability to predict treatment response is important in patient counseling and decision-making. The authors developed an algorithm that can automatically segment and differentiate cystic and solid tumor components of VS. They also investigated associations between the quantified radiological features of each component and tumor response after GKRS.

METHODS  This is a retrospective study comprising 323 patients with VS treated with GKRS. After preprocessing and generation of pretreatment T2-weighted (T2W)/T1-weighted with contrast (T1WC) images, the authors segmented VSs into cystic and solid components by using fuzzy C-means clustering. Quantitative radiological features of the entire tumor and its cystic and solid components were extracted. Linear regression models were implemented to correlate clinical variables and radiological features with the specific growth rate (SGR) of VS after GKRS.

RESULTS  A multivariable linear regression model of radiological features of the entire tumor demonstrated that a higher tumor mean signal intensity (SI) on T2W/T1WC images (p < 0.001) was associated with a lower SGR after GKRS. Similarly, a multivariable linear regression model using radiological features of cystic and solid tumor components demonstrated that a higher solid component mean SI (p = 0.039) and a higher cystic component mean SI (p = 0.004) on T2W/T1WC images were associated with a lower SGR after GKRS. A larger cystic component proportion (p = 0.085) was associated with a trend toward a lower SGR after GKRS.

CONCLUSIONS  Radiological features of VSs on pretreatment MRI that were quantified using fuzzy C-means were associated with tumor response after GKRS. Tumors with a higher tumor mean SI, a higher solid component mean SI, and a larger cystic component proportion also tended toward regression after GKRS. Further refinement of the algorithm may allow direct prediction of tumor response.

https://thejns.org/doi/abs/10.3171/2021.4.JNS203700

KEYWORDS  artificial intelligence; cyst; fuzzy C-means clustering; Gamma Knife; quantitative radiological feature; stereotactic radiosurgery; specific growth rate; vestibular schwannoma
VESTIBULAR schwannoma (VS) is the most common tumor in the cerebellopontine angle. Management options for VS include observation, surgery, and radiation. Radiosurgery is an established, noninvasive treatment for VS, with 5-year tumor control rates ranging between 81% and 100%. Despite its high tumor control rates, tumor growth persists in a minority of patients. Efforts to identify features that portend to better tumor response to radiosurgery have been ongoing. Favorable factors include smaller tumor volume and slower tumor growth before radiosurgery. However, there is no quantitative definition of cystic VS. Tumors with higher signal intensity (SI) on T2-weighted imaging (T2WI) and higher apparent diffusion coefficient values, which are thought to be related to the cystic component of the tumor, have been associated with a more favorable response after radiosurgery. However, previous studies have reported radiological features of the entire tumor, and the role of the cystic component proportion, SI of the cystic component, and SI of the solid component remains unclear. Quantification of these radiological features may aid in predicting tumor response after radiosurgery.

With the increasing role of artificial intelligence in image analytics and outcome prediction in medicine, we have developed an algorithm that can automatically segment and differentiate cystic and solid tumor components of VS. We have also investigated associations between the quantified radiological features of each component and tumor response after Gamma Knife radiosurgery (GKRS).

Methods
Patient Population
This retrospective study was based on clinical data and neuroimaging of patients with VS who underwent GKRS at Taipei Veterans General Hospital between 1993 and 2017. Our research protocol was approved and monitored by the Taipei Veterans General Hospital Institutional Review Board. A total of 323 patients satisfied the following inclusion criteria: 1) diagnosis of VS confirmed by MRI; 2) primary treatment with GKRS; 3) a minimum of 24 months of clinical and neuroimaging follow-up after GKRS; and 4) no neurofibromatosis type 2, multiple VSs, or recurrent VS. Patients with last follow-up less than 24 months after GKRS were excluded to minimize the confounding of pseudoprogression. For patients who underwent surgical intervention after GKRS, we included only data acquired before the surgical intervention.

GKRS Procedure
The Leksell frame placement was performed under local anesthesia. The patient was awake for the procedure, and MRI with the patient in the stereotactic frame was performed. Radiosurgery was performed using Leksell Gamma Unit Models B, C, and Perflexion (Elekta Instruments, Inc.), depending on the year of treatment. The prescription dose was placed at an isodose level of 50%–60%, with a mean margin dose between 11 and 15 Gy. Any identifiable portion of the cochlea and brainstem received no more than 10 and 12 Gy, respectively. The trigeminal nerve received no more than 15 Gy. The overall median margin dose was 12.1 Gy. The mean and median pretreatment tumor volumes at the time of radiosurgery were 3.2 mL and 1.9 mL, respectively.

MR Image Acquisition
All pretreatment MR images were acquired using a 1.5-T scanner (Signa Horizon LX2, GE Medical Systems). Pretreatment contrast-enhanced T1-weighted imaging (CET1WI) and T2WI were used for analysis. The parameters used to acquire CET1WI were as follows: TR 367–500 msec, TE 9 msec, number of excitations 4, field of view 258.6–261.9 mm, slice thickness 2.0–3.1 mm, and pixel spacing 0.5 mm. The parameters used to acquire T2WI were as follows: TR 2833–4850 msec, TE 109 msec, number of excitations 2, field of view 258.5–262.0 mm, slice thickness 2.0–3.1 mm, and pixel spacing 0.5 mm. The subsequent analytical workflow was summarized in Fig. 1.

Image Preprocessing
After bias correction, T2WI studies were coregistered to CET1WI. Afterward, brain segmentation was performed on both T2WI and CET1WI, and both yielded images of 5 tissue types: gray matter, white matter (WM), CSF, bone, and soft tissue. All preprocessing procedures were performed using Statistical Parametric Mapping 12 software (Wellcome Department of Cognitive Neurology, London, UK, http://www.fil.ion.ucl.ac.uk/spm/). Tumor regions of interest (ROIs) were demarcated manually by experienced neurosurgeons (C.C.L. and H.C.Y.) and radiologists (H.M.W., W.Y.G., and C.J.L.).

Fuzzy C-Means Clustering
In order to investigate the impact of cystic and solid tumor components on the response after GKRS, we implemented fuzzy C-means clustering to automatically segment tumor into cystic and solid components. Fuzzy C-means clustering is an algorithm in which each data point (in our study, voxel) can belong to two clusters or more. The details of each step are described as follows.

Step 1: Generation of T2WI/T1-Weighted With Contrast Images
The cystic component often demonstrates low SI on CET1WI and high SI on T2WI, whereas the solid component often demonstrates high SI on CET1WI and low SI on T2WI. Thus, in order to enhance the contrast between cystic and solid tumor components and thereby improve the performance of fuzzy C-means clustering, we generated T2WI/T1-weighted with contrast (T1WC) images by calculating the ratio between T2WI and CET1WI (both normalized to WM mean SI) using Python (version 3.6.7). The WM mean SI was calculated by averaging the SI of WM generated by statistical parametric mapping segmentation as described above (tumor ROI was removed to eliminate its contribution of SI). In brief, T2WI/T1WC images were generated as follows:
Step 2: Median Filter

Fuzzy C-means clustering is susceptible to noises found in MRI, which could result in inadequate segmentation. Therefore, a 3D median filter was implemented to remove the noises by using Python (version 3.6.7).

Step 3: Fuzzy C-Means Clustering

Voxels in tumor ROIs on T2W/T1WC images were classified as cystic or solid component by using differences in SI. This was achieved using fuzzy C-means clustering with MATLAB software (MathWorks, Inc.), which was previously detailed. The details of fuzzy C-means clustering can be found in the Supplemental Methods. The results of fuzzy C-means clustering were verified by physicians. One example of the results of fuzzy C-means clustering is illustrated in Fig. 2.

Radiological Feature Quantification

Radiological features demonstrated on T2W/T1WC images included tumor mean SI, solid component mean SI, cystic component mean SI, cystic component proportion, and cystic component shape features (sphericity, flatness, and elongation).

The tumor mean SI was calculated by averaging the SI of the ROI on T2W/T1WC images. Solid component mean SI and cystic component mean SI were calculated by averaging the SI of solid and cystic components of tumor, respectively, segmented by fuzzy C-means clustering. The cystic component proportion was defined as the ratio of cystic component volume to total tumor volume. Cystic component shape features, including sphericity, flatness, and elongation, were obtained using the PyRadiomics package (version 2.0.1), with assessments performed on the cystic component of the tumor.

Follow-Up and Outcomes

Follow-up neuroimaging and clinical evaluations were done after GKRS and volumetric measurement was per-
formed at every follow-up neuroimaging session. Note that neuroimaging studies were independently reviewed by experienced neurosurgeons.

An exponential fitting model was shown to be a good fit for estimation of volumetric change of tumor after GKRS;\textsuperscript{13} therefore, tumor response to GKRS could be assessed by specific growth rate (SGR).\textsuperscript{9,10} which was derived from the following formula:

\[
SGR = \frac{\ln(V_t/V_0)}{t},
\]

where \(V_0\) is the tumor volume at the time of GKRS treatment, and \(V_t\) is the tumor volume at last follow-up, with \(t\) equaling the time period after GKRS at last follow-up.

**Statistical Analysis**

Descriptive statistics for continuous variables were reported as means, medians, and ranges. Categorical variables were reported as frequencies. Linear regression was used to assess the correlation of clinical variables and radiological features with SGR after GKRS. We first investigated the correlation of clinical variables (age, sex, maximum dose, margin dose, and tumor volume) and radiological features of the entire tumor (tumor mean SI) with SGR after GKRS. Afterward, to further investigate the impact of the cystic and solid tumor components on SGR after GKRS, clinical variables as described above and radiological features of cystic and solid tumor components (solid component mean SI, cystic component mean SI, cystic component proportion, cystic component sphericity, cystic component flatness, and cystic component elongation) were correlated with SGR after GKRS. Variables that were found to be significant at the 0.10 level in univariable analyses were entered into a multivariable linear regression model. Statistical significance was defined as \(p < 0.05\). All statistical analyses were performed using SPSS (version 24; IBM Corp.).

**Results**

**Patient and Tumor Characteristics**

The baseline characteristics are summarized in Table 1. In brief, the patient cohort comprised 136 males and 187 females with a mean age of 51.9 years (median 53.3 years, range 14.9–82.3 years). The mean follow-up period was 75.7 months (median 65.6 months, range 24.1–201.0 months), and the mean pretreatment tumor volume was 3.2 mL (median 1.9 mL, range 0.1–17.1 mL). The mean maximum dose was 21.1 Gy (median 21.1 Gy, range 15.4–24.6 Gy), and the mean marginal dose was 12.1 Gy (median 12.0 Gy, range 11.0–15.0 Gy).

**Correlation Between Clinical Variables or Radiological Features of the Entire Tumor and SGR**

Clinical variables included age, sex, maximum dose, margin dose, and pretreatment tumor volume. Radiological features of the entire tumor included tumor mean SI. Variables that proved significant at the 0.10 level in univariable linear regression models were considered potential prognostic factors and were entered into a multivariable linear regression model.

Among clinical variables, increasing age (\(p = 0.002\)), increasing pretreatment tumor volume (\(p < 0.001\)), and male sex (\(p = 0.071\)) were associated with a lower SGR after GKRS in univariable linear regression models. For radiological features, a higher tumor mean SI on T2W/T1WC images (\(p < 0.001\)) was associated with a lower SGR after GKRS in univariable linear regression models. These variables were entered into a multivariable linear regression model.

The multivariable linear regression model revealed that increasing age (\(p = 0.036\)), increasing pretreatment tumor volume (\(p = 0.001\)), and higher tumor mean SI on T2W/T1WC images (\(p < 0.001\)) were independently associated with a lower SGR after GKRS (i.e., better response to GKRS). Univariable and multivariable linear regression models for predictors of SGR using radiological features of the entire tumor are summarized in Table 2 and Fig. 3.

**Correlation Between Clinical Variables or Radiological Features of Cystic and Solid Tumor Components and SGR**

We further investigated the impact of the cystic and solid tumor components on SGR after GKRS. Clinical variables remained the same, whereas radiological features were further differentiated into cystic and solid tumor components, which included solid component mean SI, cystic component mean SI, cystic component proportion, cystic component sphericity, cystic component flatness, and cystic component elongation. Similarly, variables that proved significant at the 0.10 level in univariable linear regression models were considered potential prognostic factors and were entered into a multivariable linear regression model.

### Table 1. Clinical variables in 323 patients and radiological features of VSs

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
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<tbody>
<tr>
<td>Age in yrs</td>
<td>51.9 (53.3, 14.9 to 82.3)</td>
</tr>
<tr>
<td>Sex: male/female</td>
<td>136:187</td>
</tr>
<tr>
<td>Maximum dose in Gy</td>
<td>21.1 (21.1, 15.4 to 24.6)</td>
</tr>
<tr>
<td>Margin dose in Gy</td>
<td>12.1 (12.0, 11.0 to 15.0)</td>
</tr>
<tr>
<td>Pretreatment tumor vol in mL</td>
<td>3.2 (1.9, 0.1 to 17.1)</td>
</tr>
<tr>
<td>Follow-up in mos</td>
<td>75.7 (65.6, 24.1 to 201.0)</td>
</tr>
<tr>
<td>SGR per month</td>
<td>−0.012 (−0.010, −0.064 to 0.036)</td>
</tr>
<tr>
<td>Tumor mean SI on T2W/T1WC images</td>
<td>1.2 (1.0, 0.6 to 4.5)</td>
</tr>
<tr>
<td>Solid component mean SI on T2W/T1WC images</td>
<td>2.6 (2.3, 0.7 to 6.4)</td>
</tr>
<tr>
<td>Cystic component mean SI on T2W/T1WC images</td>
<td>0.9 (0.9, 0.5 to 2.4)</td>
</tr>
<tr>
<td>Cystic component proportion in %</td>
<td>14.7 (12.1, 2.3 to 58.5)</td>
</tr>
<tr>
<td>Cystic component sphericity</td>
<td>33.3 (31.0, 16.3 to 72.1)</td>
</tr>
<tr>
<td>Cystic component flatness</td>
<td>0.5 (0.5, 0.0 to 0.9)</td>
</tr>
<tr>
<td>Cystic component elongation</td>
<td>0.7 (0.8, 0.3 to 1.0)</td>
</tr>
</tbody>
</table>

All values except for sex represent the mean (median, range).
Among radiological features of cystic and solid tumor components, higher solid component mean SI on T2W/T1WC images \((p < 0.001)\), higher cystic component mean SI on T2W/T1WC images \((p < 0.001)\), larger cystic component proportion \((p < 0.001)\), higher cystic component sphericity \((p = 0.003)\), and lower cystic component flatness \((p = 0.013)\) were associated with a lower SGR after GKRS in univariable linear regression models. These variables were entered into a multivariable linear regression model as described above.

The multivariable linear regression model revealed that increasing pretreatment tumor volume \((p = 0.008)\), higher solid component mean SI on T2W/T1WC images \((p = 0.039)\), and higher cystic component mean SI on T2W/T1WC images \((p = 0.004)\) were independently associated with a lower SGR after GKRS (i.e., better response to GKRS). Increasing age \((p = 0.072)\) and larger cystic component proportion \((p = 0.085)\) were associated with a trend toward a lower SGR. Univariable and multivariable linear regression models for predictors of SGR using radiological features of cystic and solid tumor components are summarized in Table 3 and Fig. 3.

### Case Illustrations

Figure 4 illustrates a case with a good reduction in tumor volume after GKRS. This was a 70-year-old woman with a right-sided VS. The tumor had a high tumor mean SI (T2W/T1WC images) of 2.50, a high solid component mean SI (T2W/T1WC images) of 1.55, a high cystic component mean SI (T2W/T1WC images) of 0.80, a low cystic component proportion \((p = 0.013)\) were associated with a lower SGR after GKRS (i.e., better response to GKRS). Increasing age \((p = 0.072)\) and larger cystic component proportion \((p = 0.085)\) were associated with a trend toward a lower SGR. Univariable and multivariable linear regression models for predictors of SGR using radiological features of cystic and solid tumor components are summarized in Table 3 and Fig. 3.

### TABLE 2. Association between clinical variables and radiological features of the entire tumor and SGR after GKRS in the univariable and multivariable linear regression models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Univariable, p Value</th>
<th>Unstandardized Coefficient</th>
<th>SE</th>
<th>Standardized Coefficient</th>
<th>p Value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (yrs)</td>
<td>0.002*</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.102</td>
<td>0.036†</td>
<td>0.000 to 0.000</td>
</tr>
<tr>
<td>Male sex (male = 1, female = 0)</td>
<td>0.071‡</td>
<td>-0.002</td>
<td>0.001</td>
<td>-0.053</td>
<td>0.270</td>
<td>-0.004 to 0.001</td>
</tr>
<tr>
<td>Maximum dose (Gy)</td>
<td>0.162</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marginal dose (Gy)</td>
<td>0.738</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pretreatment tumor vol (mL)</td>
<td>&lt;0.001§</td>
<td>-0.001</td>
<td>0.000</td>
<td>-0.167</td>
<td>0.001*</td>
<td>-0.001 to 0.000</td>
</tr>
<tr>
<td>Tumor mean SI (T2W/T1WC images)</td>
<td>&lt;0.001§</td>
<td>-0.011</td>
<td>0.001</td>
<td>-0.428</td>
<td>&lt;0.001§</td>
<td>-0.014 to -0.009</td>
</tr>
</tbody>
</table>

* \(p < 0.01\); † \(p < 0.05\); ‡ \(p < 0.1\); § \(p < 0.001\).
ponent mean SI (T2W/T1WC images) of 5.95, and a large cystic component proportion of 0.22. Based on these features, this VS was predicted to regress after GKRS. After undergoing GKRS, this patient received regular follow-up evaluations that included MRI every 6 months. There was significant tumor volume reduction in follow-up assessments (SGR −0.057).

Figure 5 illustrates a stable case without significant tumor regression following GKRS. This was a 38-year-old woman with a right-sided VS. Its tumor mean SI (T2W/T1WC images), solid component mean SI (T2W/T1WC images), cystic component mean SI (T2W/T1WC images), and cystic component proportion were 0.58, 0.54, 1.62, 0.05, respectively, all of which were lower than those of the previous example. Consequently, this VS was less likely to regress in volume after GKRS based on our model. This patient received regular follow-up evaluations for 30 months, but the tumor volume remained unchanged (SGR −0.005).

Discussion

This study attempts to identify pretreatment radiological...
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The cal features of VS on MRI associated with tumor response after GKRS. The radiological features were analyzed via its components (i.e., cystic and solid tumor components). We generated T2W/T1WC images and performed fuzzy C-means clustering to segment the tumors into cystic and solid components. We then extracted quantitative radiological features of the entire tumor and cystic and solid tumor components, and then correlated these features with SGR after GKRS. Our results demonstrated that, after adjusting for important clinical variables, VSs with a higher tumor mean SI, a higher solid component mean SI, and a higher cystic component mean SI on T2W/T1WC images were more likely to regress in volume after GKRS. Those with a larger cystic component proportion trended toward regression after GKRS.

Previous studies on VSs treated with radiosurgery have identified several prognostic factors for tumor response after radiosurgery, including tumor volume, pretreatment growth rate, and presence of cyst. Radiological features derived from pretreatment MRI including SI on T2WI and apparent diffusion coefficient values were also shown to be potential prognostic factors for tumor response after radiosurgery. This has been thought to be related to the presence of a cystic component. However, to our knowledge, there is no study on automated segmentation or quantification of cystic and solid tumor components of VS. This is the first study to perform an automated segmentation with fuzzy C-means clustering and quantification of radiological features of VS by using cystic and solid components, and to correlate these features with tumor response to GKRS.

Fuzzy C-means clustering is one of the most commonly used unsupervised clustering techniques in the field of medical imaging. It is well established in lesion segmentation performed using medical images. It has also been used for segmentation of lesions into different tissue types based on SI. In this study we first generated T2W/T1WC images to enhance the contrast between cystic and solid tumor components, subsequently performed fuzzy C-means clustering to automatically segment VSs into cystic and solid components, and then performed further analysis.

Our results demonstrated that VSs with a higher tumor mean SI on T2W/T1WC images were more likely to regress in volume after GKRS. Furthermore, higher mean SI on T2W/T1WC images was an independent predictor of regression in volume after GKRS in both the cystic and solid components of VS. Therefore, both components have independent features that inform tumor response to GKRS. Differences in solid component mean SI may reflect the difference in ratio of Antoni A to Antoni B regions. Antoni A regions are highly cellular, and these regions demonstrate low SI on T2WI and high SI on CET1WI. In contrast, Antoni B regions are areas with loose tissue, demonstrating high SI on T2WI and low SI on CET1WI. Consequently, VSs with higher solid component mean SI on T2W/T1WC images may indicate a higher percentage of Antoni B regions in the tumor, and these were more likely to regress after GKRS. Our results also suggested that VSs with a larger cystic component proportion trended toward regression after GKRS, which supports the hypothesis given that the Antoni B regions contain the radiologically detectable cyst. Moreover, if we considered cellularity of VSs as a spectrum instead of classifying them into Antoni A and Antoni B regions, our results suggested that tumors with a lower cellularity and thereby a higher solid component mean SI on T2W/T1WC images would be more likely to regress after GKRS.

Regarding cystic component mean SI on T2W/T1WC images, there are relatively limited studies. Cystic component SI may indicate different cystic contents. For ex-

FIG. 5. Illustrative case 2. A 38-year-old woman with right-sided VS treated with GKRS. Left: Axial CET1WI, T2WI, and T2W/T1WC images, and the result of fuzzy C-means clustering of the VS prior to GKRS. Tumor mean SI (T2W/T1WC images) 0.58, solid component mean SI (T2W/T1WC images) 0.54, cystic component mean SI (T2W/T1WC images) 1.62, cystic component proportion 0.05. Right: Three consecutive axial slices of CET1WI of the VS prior to GKRS and at 6, 12, 18, 24, and 30 months after GKRS (left to right). The SGR after GKRS was −0.005.
ample, it may be associated with concentration of proteins or lipid, hemoglobin degradation products, or mineral substances in cystic contents. However, there is a lack of association of cystic contents with tumor response to radiosurgery. Further studies are warranted. Our results also suggested that increasing pretreatment tumor volume of VS is associated with a better chance of regression in tumor volume after GKRS. At a first glance, this may contradict results of previous studies. However, those studies focused on large VSs with tumor volumes greater than 6–15 mL and argued that these tumors respond unfavorably to radiosurgery compared to those with smaller volume. In contrast, most of the tumors included in this study were smaller by the definitions of those studies, and therefore were not in the range of their conclusions.

Shape features of cystic component were not related to tumor response to GKRS in this study. Macrocystic VSs have been shown to respond better to radiosurgery than microcystic VSs. Macrocystic VSs should have larger cystic component sphericity than microcystic ones given that the cystic part of the former should be more sphere-like than that of the latter. However, our results did not find a significant correlation between cystic component sphericity and SGR after GKRS. Similarly, other shape features including elongation and flatness did not predict SGR after GKRS. The relationship between shape of cystic component and tumor response warrants further investigation.

This study used SGR as a measure of tumor response to GKRS. Some studies assessed tumor control by change in tumor diameter. However, they used absolute change of diameter for all sizes of tumor, which is subject to error depending on tumor shape. Other studies used volume reduction ratio, which was calculated as the absolute change in volume divided by pretreatment volume. However, time elapsed was not accounted for. Even if some studies divided volume reduction ratio by the period of time between different volume measurements, it was oversimplified to directly divide it. In contrast, SGR accounts for both change in tumor volume and time. Moreover, an exponential fitting model has been shown to be a good fit for estimating tumor volume change after GKRS, and so it was reasonable to use SGR after GKRS as a measure of tumor response.

The limitations of our study must be considered. First, the study was subject to the inherent shortcomings of its retrospective design, such as selection bias. In addition, the study was performed at a single high-volume center, which may be subject to referral bias. Additionally, the model developed within the study has not been independently validated, and thus its out-of-sample validity remains undetermined. Nevertheless, this study comprised a relatively large number of patients and identified several quantitative radiological features as prognostic factors for tumor response of VSs to GKRS.

Conclusions

Radiological features of VSs on pretreatment MRI quantified using fuzzy C-means were associated with tumor response after GKRS. Tumors with a higher tumor mean SI, a higher solid component mean SI, and a higher cystic component mean SI on T2W/TTWC images were more likely to regress in volume after GKRS. Those with a larger cystic component proportion also trended toward regression after GKRS. Further refinement of the algorithm may allow direct prediction of tumor response.

Acknowledgments

This work was financially supported in part by the Ministry of Science and Technology, Taiwan, under the project MOST 109-2221-E-038-010 and MOST 109-2314-B-075-051-MY2, and in part by Taipei Veterans General Hospital, Taipei, Taiwan, under the project V109B-002.

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Disclosures
The authors report no conflict of interest concerning the materials or methods used in this study or the findings specified in this paper.

Author Contributions

Supplemental Information
Online-Only Content
Supplemental material is available with the online version of the article.

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