

RESEARCH ARTICLE

CT Radiomics for Histological Grade Assessment of Canine Soft Tissue Sarcoma: A Pilot Study

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ABSTRACT

Histological grade is an important prognostic factor in dogs with soft tissue sarcoma (STS) and is a key consideration in surgical planning. Complete surgical excision is the mainstay of treatment, and high-grade tumors generally require wider surgical margins and consideration of adjuvant therapy because of their higher risk of recurrence and metastasis. Accurate preoperative assessment of tumor grade is therefore important for treatment planning, but preoperative biopsy grading does not always match the final histological grade after surgery. Therefore, additional methods that can complement preoperative grade assessment are needed. This exploratory study investigated whether computed tomography (CT)-based radiomic features differed between low- and high-grade canine STS. Twenty-seven dogs with STS (20 low-grade [13 grade 1, 7 grade 2] and 7 high-grade [grade 3]) were included in this study. From preoperative contrast-enhanced CT images, 107 radiomic features were extracted according to the Image Biomarker Standardisation Initiative (IBSI) guidelines. Nine features were then selected through a three-stage process consisting of statistical filtering, exclusion of volume-dependent features, and hierarchical clustering. These features showed discriminatory performance for differentiating low-grade from high-grade tumors, with apparent AUC values of 0.843–0.957. GLDM-SmallDependenceLowGrayLevelEmphasis had the highest apparent AUC of 0.957 (95% CI: 0.864–1.000). Low-grade tumors tended to show higher values for low-gray-level texture features, whereas high-grade tumors showed higher values for features related to heterogeneous high-gray-level texture patterns. These findings suggest that CT-based radiomics may serve as a complementary tool for preoperative grade assessment in canine STS. Although these findings are encouraging, the reported AUC values reflect exploratory performance within this study cohort, and future prospective studies with larger cohorts and external validation are needed to confirm these findings.

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INTRODUCTION

Soft tissue sarcomas (STS) are tumors of mesenchymal origin and account for approximately 9–15% of all cutaneous and subcutaneous tumors in dogs (Bray, 2016). These tumors are locally infiltrative and may extend beyond their grossly visible margins along fascial planes. As a result, the pseudocapsule observed during surgery may underestimate the true extent of neoplastic infiltration (Bray, 2017).

Wide surgical excision is therefore the mainstay of treatment, and appropriate planning of the initial surgery is important for achieving local control (Bray, 2016; Bray, 2017). Histological grade is one of the key factors considered when determining the extent of surgery. Grade 3 tumors are associated with higher risks of local recurrence and metastasis and may require more aggressive surgical planning, together with consideration of adjuvant radiation therapy or chemotherapy. In contrast, lower-grade tumors may be managed with a less

aggressive local treatment approach (Kuntz *et al.*, 1997; McSporran, 2009; Dennis *et al.*, 2011). Accurate preoperative grading is therefore important for surgical planning and may influence postoperative outcome.

Preoperative biopsy is commonly used to estimate STS grade; however, biopsy-based grading does not always match the final histological grade determined after surgery. This discordance has been reported in approximately 40% of dogs with STS (Perry *et al.*, 2014). This discrepancy is likely attributable to sampling error, as a focal biopsy may not capture the heterogeneity of the entire tumor. These limitations may be more pronounced in markedly heterogeneous tumors or in lesions where biopsy is technically difficult or carries procedural risk (Shah *et al.*, 2025).

Radiomics may help address some of these limitations by extracting quantitative features from standard medical images, thereby capturing whole-tumor imaging characteristics that are not readily appreciated by visual inspection (Gillies *et al.*, 2016; Lambin *et al.*, 2017; Rogers *et al.*, 2020). In human oncology, magnetic resonance imaging (MRI) is widely used for assessing STS because of its excellent soft tissue contrast (Vibhakar *et al.*, 2021). In veterinary medicine, however, MRI is less commonly used because of its higher cost, limited accessibility, and longer anesthesia time. Instead, CT is more commonly used for staging and treatment planning in dogs with STS, making CT-based radiomic analysis a practical approach in current veterinary practice.

Radiomic features are commonly categorized as first-order features and second-order features, the latter also referred to as texture features. First-order features describe the distribution of voxel intensities within the region of interest (ROI), whereas second-order features quantify spatial relationships between voxels and reflect intratumoral heterogeneity (Parekh and Jacobs, 2016). These texture features can be extracted from several different matrices: the gray-level co-occurrence matrix (GLCM), the gray-level run-length matrix (GLRLM), the gray-level size zone matrix (GLSZM), the gray-level dependence matrix (GLDM), and the neighboring gray tone difference matrix (NGTDM) (van Griethuysen *et al.*, 2017).

Radiomics has been widely investigated in human oncology, including STS (Kocak *et al.*, 2023; Libling *et al.*, 2023), but remains relatively unexplored in veterinary oncology (Li *et al.*, 2025). Previous veterinary radiomic studies have mainly focused on selected tumor types, including intestinal, adrenal, and pulmonary tumors (Basran and Porter, 2022; Lee *et al.*, 2023; Jeong *et al.*, 2024).

To the authors' knowledge, no previous study has evaluated the relationship between CT radiomic features and histological grade of canine STS. Therefore, this study aimed to investigate whether CT radiomic features differ according to histological grade in canine STS and to assess whether they could provide additional imaging information for preoperative grade assessment.

MATERIALS AND METHODS

Case selection: Medical records of dogs with surgically excised STS between January 2021 and July 2025 at two

veterinary hospitals (VIP Animal Medical Center, Cheongdam and Seongbuk) were retrospectively reviewed. Dogs were included if the histological grade of STS was confirmed by board-certified veterinary pathologists after surgical excision, contrast-enhanced CT images were available within two weeks before surgery, and the tumor measured ≥ 10 mm on CT. Tumors were graded according to the three-tier system described by Dennis *et al.* (2011). Dogs receiving preoperative radiation therapy or chemotherapy were excluded. Thoracic, abdominal, or retroperitoneal tumors were excluded because reliable ROI segmentation may be difficult and their biological behavior may differ from cutaneous and subcutaneous STS (Dennis *et al.*, 2011).

Image acquisition and segmentation: Contrast-enhanced CT images were acquired using the same 16-channel scanner (Brivo CT 385; GE Medical Systems) at both participating institutions, with the following parameters: 100–120 kVp, 80–110 mA, 1.0 s rotation time, pitch 0.938, and slice thickness of 0.625–2.5 mm. Contrast medium (iohexol, 600–750 mg I/kg) was administered intravenously, and post-contrast images were acquired 40–50 s after injection. Because of the retrospective design, reconstruction kernel, matrix size, field of view, and contrast injection rate were not standardized.

Tumor segmentation was performed on the contrast-enhanced CT images using 3D Slicer (v5.8.1). The ROIs were manually delineated by one author (SL), who was blinded to the histological grade, and reviewed by a veterinarian with more than ten years' experience in diagnostic imaging. To assess intraobserver reproducibility, 37% of the tumors were segmented a second time after a 4-week interval. A Dice Similarity Coefficient (DSC) ≥ 0.70 was considered acceptable (Zijdenbos *et al.*, 1994; Wong *et al.*, 2021).

Preprocessing and feature extraction: CT images were preprocessed in accordance with the Image Biomarker Standardisation Initiative (IBSI) guidelines. Images and masks were resampled to isotropic voxel dimensions of $1.0 \times 1.0 \times 1.0$ mm³ using B-spline and nearest-neighbor interpolation, respectively. Range-based re-segmentation retained voxels between –50 and 350 HU, followed by gray-level discretization using a fixed bin width of 25 HU. Radiomic features were extracted using the PyRadiomics library (v3.1.0), yielding 107 features: 14 shape, 18 first-order, and 75 second-order features.

Feature selection framework: Tumors were divided into two groups: low-grade (grades 1–2) and high-grade (grade 3). A three-stage feature selection framework was used to identify radiomic features associated with histological grade while minimizing potential confounding and redundancy.

In the first stage, features that differed significantly between low- and high-grade tumors were identified using the Mann–Whitney U test with Benjamini–Hochberg false discovery rate (FDR) correction ($q < 0.05$). Cliff's delta was also used to account for the small sample size, and features with large effect sizes ($|\delta| \geq 0.474$) were retained.

In the second stage, after feature extraction, features correlated with tumor volume (Spearman's $|\rho| \geq 0.7$) or

previously reported to be highly sensitive to slice-thickness variation were excluded to reduce confounding and acquisition-related instability. Slice-thickness-sensitive features were defined according to Shafiq-ul-Hassan *et al.* (2017) as those showing >50% variation related to the original slice thickness despite resampling.

In the third stage, hierarchical clustering was applied to reduce redundancy among the remaining features. Ward's clustering was performed using a distance threshold of $1 - |r| < 0.3$, and the feature with the largest absolute Cliff's delta was selected from each cluster.

Statistical analysis: All statistical analyses were conducted in Python (v3.11). Because of the small sample size, continuous and categorical variables were compared using the Kruskal–Wallis and chi-square tests, respectively ($P < 0.05$). The apparent discriminatory performance of the selected features was assessed using ROC curve analysis. AUC 95% CIs were estimated using 2,000 class-stratified bootstrap resamples. AUC values for features inversely associated with grade 3 STS were corrected as $1 - \text{AUC}$.

RESULTS

Study population: A total of 27 dogs with STS were included in this study. There were 13 grade 1, 7 grade 2, and 7 grade 3 tumors. Tumors were most commonly located in the extremities ($n=15$), followed by the trunk ($n=6$) and head and neck region ($n=6$). Age, sex, and tumor location did not differ significantly among histological grades (Table 1).

Twenty-two dogs had primary and five had recurrent tumors. Regional lymph node metastasis was confirmed in four dogs, and pulmonary metastasis was identified in two dogs. Among the evaluated cases, metastasis was more frequently identified in grade 3 tumors than in grades 1–2 tumors, although lymph node evaluation was not performed in all dogs. The distribution of primary, recurrent, and metastatic tumors according to histological grade is presented in Table 2.

Segmentation reproducibility: The mean and median DSC for intraobserver reproducibility were 0.78 and 0.81, respectively (range: 0.70–0.92), exceeding the predefined acceptability threshold of 0.70.

Binary grouping validation: Exploratory grade-wise comparisons were performed to assess whether binary grouping of grades 1–2 versus grade 3 was appropriate. Radiomic feature differences were observed more frequently between grade 3 and lower-grade tumors, whereas only eight of 107 features differed between grade 1 and grade 2 tumors. These findings supported the use of low-grade (grades 1–2) and high-grade (grade 3) groups for subsequent feature selection.

Feature selection: In the first stage, 66 of the 107 features met the statistical significance and large effect size criteria. Most of these features showed higher values in grade 3 tumors, and shape and second-order texture features predominated. The distribution and direction of effect sizes are shown in the volcano plot (Fig. 1).

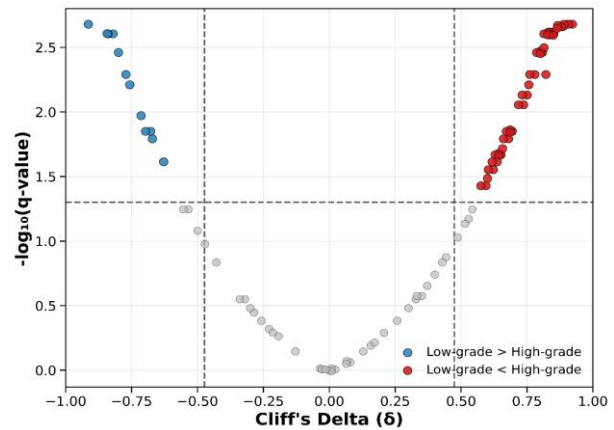


Fig. 1: Volcano plot showing the statistical significance and effect size (Cliff's delta) of radiomic features comparing low-grade and high-grade canine STS. Dashed lines indicate the selection threshold of $|\delta| \geq 0.474$ and $q < 0.05$. Red and blue dots indicate features higher in grade 3 and grades 1–2 tumors, respectively, whereas gray dots indicate features that did not meet the selection criteria.

Table 1: Demographic and clinical characteristics of the study population by histological grade.

	Grade 1 (n=13)	Grade 2 (n=7)	Grade 3 (n=7)	P-value ^a
Age (years)	11 (4–13)	11 (6–14)	13 (9–17)	0.087
Body weight (kg)	5.9 (2.3–12.0)	6.8 (3.0–12.8)	5.5 (2.2–16.4)	0.79
Sex	CM 7 (53.8%)	6 (85.7%)	4 (57.1%)	0.278
	SF 6 (46.2%)	1 (14.3%)	3 (42.9%)	
Tumor location	Extremities 7 (53.8%)	5 (71.4%)	3 (42.9%)	0.44
	Trunk 3 (23.1%)	2 (28.6%)	1 (14.3%)	
	Head/Neck 3 (23.1%)	0 (0.0%)	3 (42.9%)	

^aP-values were calculated using the Kruskal–Wallis test (continuous variables) or chi-square test (categorical variables); $P < 0.05$ was considered statistically significant. Continuous data are presented as median (range). Abbreviations: CM, castrated male; SF, spayed female.

Table 2: Tumor characteristics and metastatic status according to histological grade

Characteristic	Grade 1 (n=13)	Grade 2 (n=7)	Grade 3 (n=7)
Tumor status			
Primary	12	6	4
Recurrent	1	1	3
Regional lymph node^a			
Present	0	1	3
Absent	4	4	2
Not evaluated	9	2	2
Distant metastasis^b			
Pulmonary	0	1	1
Other organs	0	0	0

^aConfirmed regional metastases were diagnosed via cytological or histological examination, whereas 'not evaluated' indicates cases where assessment was not performed. ^bPulmonary metastases were identified as multiple pulmonary nodules on CT. One grade 3 dog had hepatic lesions suspicious for metastasis on CT; however, this was not included as cytological or histological confirmation was not obtained.

Next, features strongly correlated with tumor volume were removed, and all shape features were excluded in this stage (Fig. 2). Four additional features were excluded because of previously reported sensitivity to slice-thickness variation (Shafiq-ul-Hassan *et al.*, 2017).

Finally, inter-feature correlations among the remaining features were assessed to reduce the feature redundancy. The corresponding heatmap is provided in Fig. 3. Based on these inter-feature similarities, hierarchical clustering grouped the features into nine clusters. One representative feature was selected from each cluster, resulting in nine final radiomic features (Fig. 4). The full names of abbreviated feature labels are provided in Table 3.

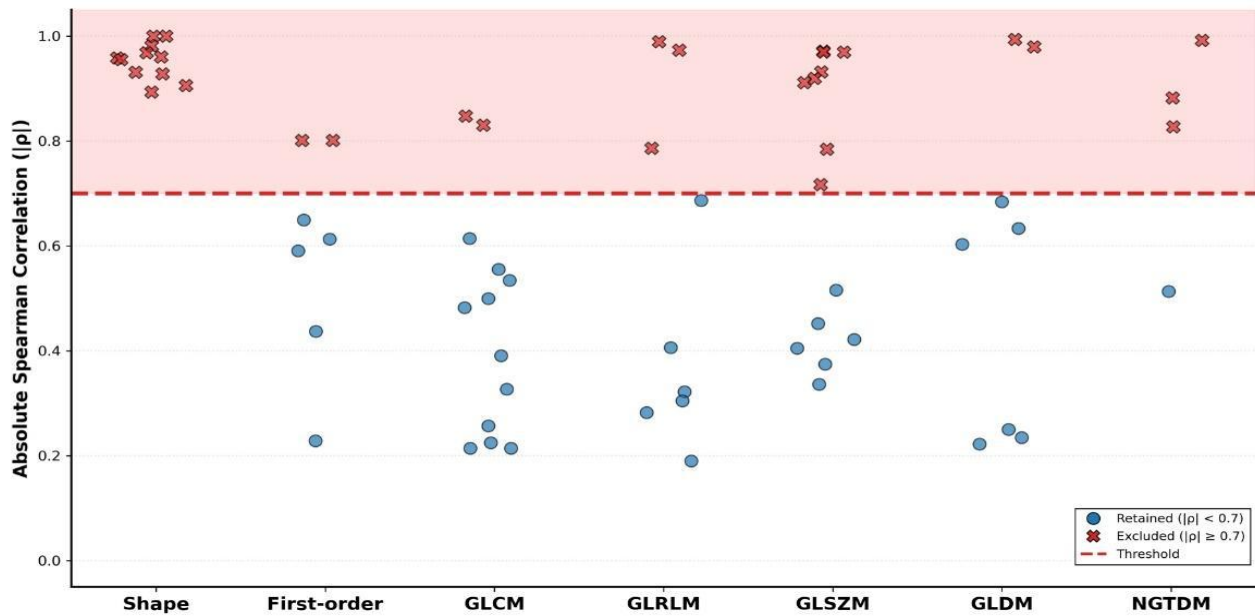


Fig. 2: Absolute Spearman correlation coefficients between radiomic features and tumor volume. The dashed line indicates the exclusion threshold ($|\rho| \geq 0.7$). Blue circles represent retained features, and red X markers represent excluded features. Abbreviations: GLCM, gray-level co-occurrence matrix; GLRLM, gray-level run-length matrix; GLSZM, gray-level size zone matrix; GLDM, gray-level dependence matrix; NGTDM, neighboring gray tone difference matrix.

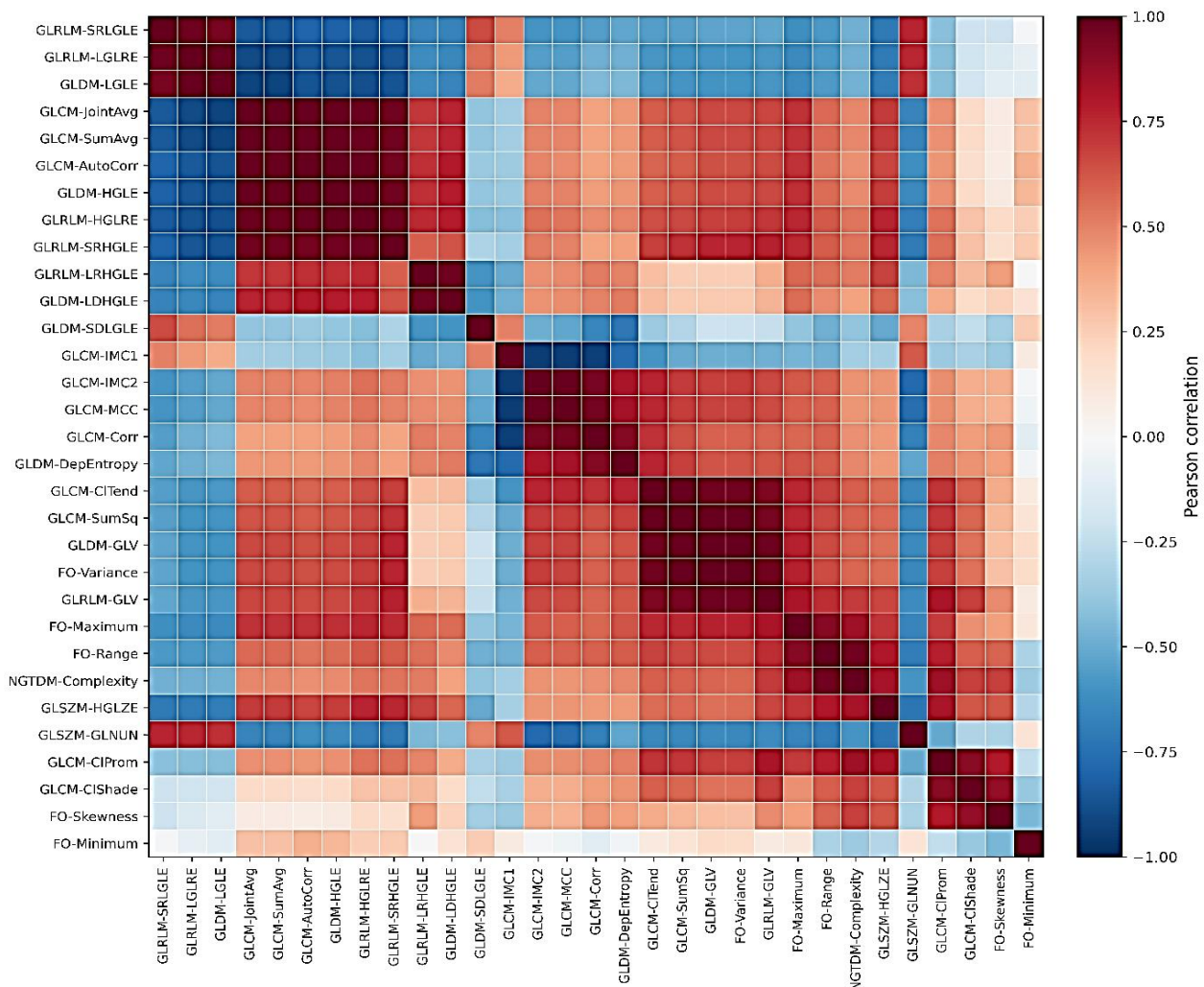


Fig. 3: Correlation heatmap of the 31 retained radiomic features after stability and volume-dependency filtering. Cell colors represent Pearson correlation coefficients between feature pairs, ranging from -1 to 1. For readability, feature labels are shown in abbreviated form, and the corresponding full feature names are provided in Table 3. Abbreviations: FO, first-order; GLCM, gray-level co-occurrence matrix; GLRLM, gray-level run-length matrix; GLSZM, gray-level size zone matrix; GLDM, gray-level dependence matrix; NGTDM, neighboring gray tone difference matrix.

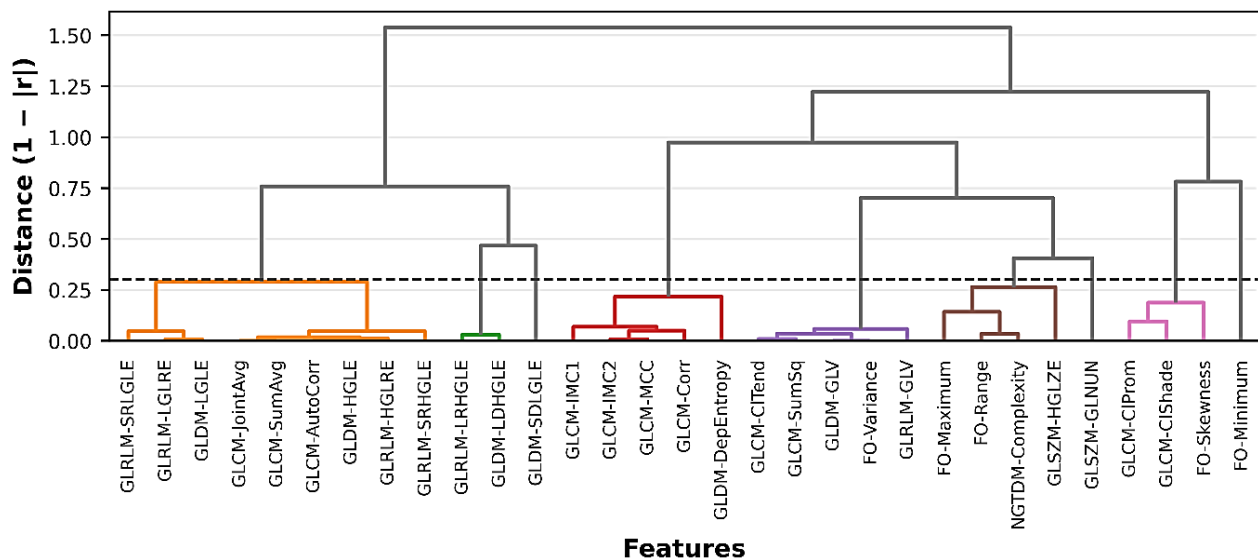


Fig. 4: Hierarchical clustering of the 31 retained radiomic features. Clustering was performed using Ward's method based on inter-feature correlations. The dashed line indicates the threshold used to define nine feature clusters ($|r|=0.7$; distance=0.3). For readability, feature labels are shown in abbreviated form, and the full names are provided in Table 3. Abbreviations: FO, first-order; GLCM, gray-level co-occurrence matrix; GLRLM, gray-level run-length matrix; GLSZM, gray-level size zone matrix; GLDM, gray-level dependence matrix; NGTDM, neighboring gray tone difference matrix.

Table 3: Full names of abbreviated radiomic feature labels used in Figures 3 and 4.

Full feature name	Figure label
FirstOrder-Maximum	FO-Maximum
FirstOrder-Minimum	FO-Minimum
FirstOrder-Range	FO-Range
FirstOrder-Skewness	FO-Skewness
FirstOrder-Variance	FO-Variance
GLCM-Autocorrelation	GLCM-AutoCorr
GLCM-ClusterProminence	GLCM-CIProm
GLCM-ClusterShade	GLCM-CIShade
GLCM-ClusterTendency	GLCM-CITend
GLCM-Correlation	GLCM-Corr
GLCM-Imc1	GLCM-IMC1
GLCM-Imc2	GLCM-IMC2
GLCM-JointAverage	GLCM-JointAvg
GLCM-MCC	GLCM-MCC
GLCM-SumAverage	GLCM-SumAvg
GLCM-SumSquares	GLCM-SumSq
GLDM-DependenceEntropy	GLDM-DepEntropy
GLDM-GrayLevelVariance	GLDM-GLV
GLDM-HighGrayLevelEmphasis	GLDM-HGLE
GLDM-LargeDependenceHighGrayLevelEmphasis	GLDM-LDHGLE
GLDM-LowGrayLevelEmphasis	GLDM-LGLE
GLDM-SmallDependenceLowGrayLevelEmphasis	GLDM-SDLGLE
GLRLM-GrayLevelVariance	GLRLM-GLV
GLRLM-HighGrayLevelRunEmphasis	GLRLM-HGLRE
GLRLM-LongRunHighGrayLevelEmphasis	GLRLM-LRHGLE
GLRLM-LowGrayLevelRunEmphasis	GLRLM-LGLRE
GLRLM-ShortRunHighGrayLevelEmphasis	GLRLM-SRHGLE
GLRLM-ShortRunLowGrayLevelEmphasis	GLRLM-SRLGLE
GLSZM-GrayLevelNonUniformityNormalized	GLSZM-GLNUN
GLSZM-HighGrayLevelZoneEmphasis	GLSZM-HGLZE
NGTDM-Complexity	NGTDM-Complexity

Table 4: Characteristics and discriminative performance of nine representative radiomic features.

Representative feature	Cluster size	Cliff's δ^a	q-value ^b	Spearman ρ	AUC ^c	95% CI
GLRLM-ShortRunLowGrayLevelEmphasis	9	-0.829	0.003	-0.406	0.914	0.786–1.000
GLRLM-LongRunHighGrayLevelEmphasis	2	0.843	0.003	0.687	0.921	0.800–1.000
GLDM-SmallDependenceLowGrayLevelEmphasis	1	-0.914	0.002	-0.684	0.957	0.864–1.000
GLCM-ClusterProminence	3	0.729	0.009	0.391	0.864	0.693–0.979
FirstOrder-Minimum	1	-0.736	0.012	-0.65	0.868	0.721–0.986
GLCM-Correlation	5	0.757	0.006	0.614	0.879	0.714–1.000
GLCM-ClusterTendency	5	0.686	0.014	0.327	0.843	0.671–0.964
GLSZM-HighGrayLevelZoneEmphasis	4	0.829	0.003	0.422	0.914	0.771–1.000
GLSZM-GrayLevelNonUniformityNormalized	1	-0.757	0.006	-0.375	0.879	0.714–0.986

^aCliff's δ effect size ($|\delta| \geq 0.474$ indicates large effect). Positive values indicate higher values in grade 3; negative values indicate higher values in grades 1–2. ^bP-values adjusted using Benjamini–Hochberg FDR correction ($q < 0.05$). ^cAUC values for features with negative Cliff's δ were corrected as $1 - \text{AUC}$. Abbreviations: AUC, area under the receiver operating characteristic curve; CI, confidence interval; GLCM, gray-level co-occurrence matrix; GLRLM, gray-level run-length matrix; GLSZM, gray-level size zone matrix; GLDM, gray-level dependence matrix.

DISCUSSION

In this exploratory study, a subset of CT radiomic features showed differences between low- and high-grade canine STS. After excluding the volume-dependent and redundant features, nine representative radiomic features showed apparent discriminatory performance for separating grade 3 tumors from grades 1–2 tumors, with AUC values ranging from 0.843 to 0.957. Although these findings suggest that CT radiomics may provide grade-related imaging information, they should be interpreted cautiously because of the small sample size and lack of independent validation (Yip and Aerts, 2016).

Of the nine selected features, four had higher values in grades 1–2 tumors, whereas five had higher values in grade 3 tumors. This suggests that low- and high-grade STS may differ in the spatial organization of voxel intensities.

GLDM-SmallDependenceLowGrayLevelEmphasis and GLRLM-ShortRunLowGrayLevelEmphasis showed higher values in low-grade tumors, both of which describe fine-scale, low-gray-level texture patterns. FirstOrder-Minimum and GLSZM-GrayLevelNonUniformityNormalized also showed higher values in grade 1–2 tumors, which may reflect differences in the distribution and organization of lower-attenuation voxels (Engellau *et al.*, 2005; Coindre, 2006; Ganeshan and Miles, 2013).

In contrast, five features had higher values in grade 3 tumors. The GLCM-based features, including Cluster Prominence, Cluster Tendency, and Correlation, suggest greater variation in voxel intensities, consistent with increased intratumoral heterogeneity (Ganeshan and Miles, 2013). GLRLM-LongRunHighGrayLevelEmphasis and GLSZM-HighGrayLevelZoneEmphasis also showed higher values in grade 3 tumors, indicating more prominent high-gray-level runs or zones within the tumor. Together, these findings suggest that high-grade tumors may contain more heterogeneous and spatially complex enhancement patterns than low-grade tumors (Parekh and Jacobs, 2016; Lubner *et al.*, 2017).

These findings show some overlap with previous human STS studies. Peeken *et al.* (2019) reported that GLRLM-LowGrayLevelRunEmphasis was related to tumor grade and survival in human STS. In the present study, a similar GLRLM feature, GLRLM-ShortRunLowGrayLevelEmphasis, was selected and showed higher values in low-grade tumors. Although these features are not identical, both describe low-gray-level run-length patterns, suggesting that similar texture information may be relevant to STS grading across species.

Several methodological considerations should be noted. First, grades 1 and 2 were grouped as low-grade and grade 3 as high-grade tumors. A similar binary approach has also been used in previous human STS radiomic studies (Peeken *et al.*, 2019; Xu *et al.*, 2020). However, the optimal approach to dichotomizing histological grade remains uncertain even in human STS radiomics studies, where intermediate (grade 2) tumors have been grouped with either low- or high-grade tumors (Shah *et al.*, 2025).

Because grade 2 tumors may show heterogeneous biological behavior, grouping them with grade 1 tumors may underestimate the malignancy of some cases.

Although most of the grade 2 tumors behaved similarly to low-grade tumors in the present cohort, one grade 2 tumor had both regional and pulmonary metastasis, indicating aggressive behavior that overlapped with grade 3 tumors. Larger studies are therefore needed to evaluate whether alternative grouping strategies or analyses based on the full three-tiered grading system can better account for grade 2 heterogeneity.

Second, Cliff's delta was used as an additional feature selection criterion because of the small sample size. In small cohorts, P-values alone may not adequately reflect the magnitude of between-group differences, whereas effect size provides complementary information that is less dependent on sample size (Nakagawa and Cuthill, 2007). This approach allowed the feature selection process to consider both statistical significance and the magnitude of grade-associated differences.

Third, tumor volume was considered as a potential confounder because several radiomic features have been reported to correlate with tumor volume independently of true intratumoral heterogeneity (Traverso *et al.*, 2020). Such features may appear discriminative simply because larger tumors have higher feature values, rather than because they reflect grade-related texture differences. Therefore, features strongly correlated with tumor volume were excluded before final feature selection.

CT acquisition variability is another important consideration in this retrospective study. Although isotropic voxel resampling was performed according to IBSI recommendations, the original slice thickness varied across cases. Features known to be highly sensitive to slice-thickness variation were therefore excluded from the final analysis (Shafiq-ul-Hassan *et al.*, 2017). Additional preprocessing steps, including range-based re-segmentation and fixed bin-width discretization, were applied to improve the robustness of radiomic feature extraction. However, these measures could not completely eliminate acquisition-related bias arising from unstandardized parameters such as reconstruction kernel and field of view.

This study had several limitations. The small sample size ($n=27$) limited the generalizability of the findings. In addition, ROC analysis was performed in the same cohort used for feature selection. Therefore, the reported AUC values represent apparent discriminatory performance and may overestimate performance in independent cohorts. Because internal cross-validation, nested validation, and external validation were not performed, these findings should be regarded as preliminary feature-discovery results rather than validated predictive performance. Future studies should validate these features in larger, independent cohorts.

Although intraobserver reproducibility showed acceptable agreement, interobserver reproducibility was not assessed in the present study. Since radiomic features can be sensitive to segmentation variability, future studies should include interobserver reproducibility analysis. Also, the identified radiomic features were not directly compared with histological tumor characteristics, such as necrosis, cellularity, or vascularity, and their biological basis remains unclear. In addition, the potential influence of different histological subtypes on radiomic feature expression was not evaluated and should be investigated in further studies.

CT-based radiomic assessment could provide complementary preoperative information on tumor grade in canine STS, if validated in larger cohorts. This information may help guide the initial treatment plan, including the extent of surgery, staging for metastatic disease, and consideration of adjuvant therapy. This could be particularly useful when the results of the biopsy are equivocal or when biopsy is technically difficult or has potential risk during the procedure.

In addition to preoperative grade assessment, radiomics may also provide prognostic information. CT-based radiomic features in human STS patients have shown prognostic value when treated with neoadjuvant radiation therapy (Peeken *et al.*, 2019; De Angelis *et al.*, 2024). Further work is needed to determine whether the radiomic features identified in this study, or refined features derived from larger cohorts, are associated with treatment response, local recurrence, metastasis, or survival.

Conclusions: The findings of this exploratory study suggest that selected CT-based radiomic features may provide additional imaging information for preoperative grade assessment in canine STS. The selected radiomic features showed apparent discriminatory performance between low- and high-grade tumors. These results should be regarded as preliminary because the cohort was small and independent validation was not performed.

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Ethics statement: This animal study was approved by the Institutional Animal Care and Use Committee of the Jeonbuk National University, Iksan-si, Jeonbuk-do, Republic of Korea (approval no. NON2024-188). Written informed consent was obtained from all dog owners at the time of hospital admission. All imaging procedures were performed as part of routine diagnostic care, and no additional procedures were performed specifically for this study.

Authors contribution: SL conceived and designed the study, performed data analysis, and drafted the manuscript. JK and SK collected clinical data and provided case materials. KL supervised imaging methodology and data interpretation. HY supervised the study, critically revised the manuscript, and served as the corresponding author. All authors interpreted the data, revised the manuscript for important intellectual content, and approved the final version.

Conflict of interest: The authors declare no conflicts of interest related to this study.

REFERENCES

- Basran PS and Porter I, 2022. Radiomics in veterinary medicine: overview, methods, and applications. *Veterinary Radiology & Ultrasound* 63(Suppl 1):828-839. doi: 10.1111/vru.13156.
- Bray JP, 2016. Soft tissue sarcoma in the dog - part 1: a current review. *Journal of Small Animal Practice* 57:510-519. doi: 10.1111/jsap.12556.
- Bray JP, 2017. Soft tissue sarcoma in the dog - part 2: surgical margins, controversies and a comparative review. *Journal of Small Animal Practice* 58:63-72. doi: 10.1111/jsap.12629.
- Coindre JM, 2006. Grading of soft tissue sarcomas: review and update. *Archives of Pathology & Laboratory Medicine* 130:1448-1453. doi: 10.5858/2006-130-1448-GOSTSR.
- De Angelis R, Casale R, Coquelet N, *et al.*, 2024. The impact of radiomics in the management of soft tissue sarcoma. *Discovery Oncology* 15:62. doi: 10.1007/s12672-024-00908-2.
- Dennis MM, McSporran KD, Bacon NJ, *et al.*, 2011. Prognostic factors for cutaneous and subcutaneous soft tissue sarcomas in dogs. *Veterinary Pathology* 48:73-84. doi: 10.1177/0300985810388820.
- Engellau J, Bendahl PO, Persson A, *et al.*, 2005. Improved prognostication in soft tissue sarcoma: independent information from vascular invasion, necrosis, growth pattern, and immunostaining using whole-tumor sections and tissue microarrays. *Human Pathology* 36:994-1002. doi: 10.1016/j.humpath.2005.07.008.
- Ganeshan B and Miles KA, 2013. Quantifying tumour heterogeneity with CT. *Cancer Imaging* 13:140-149. doi: 10.1102/1470-7330.2013.0015.
- Gillies RJ, Kinahan PE and Hricak H, 2016. Radiomics: images are more than pictures, they are data. *Radiology* 278:563-577. doi: 10.1148/radiol.2015151169.
- Jeong J, Choi H, Kim M, *et al.*, 2024. Computed tomography radiomics models of tumor differentiation in canine small intestinal tumors. *Frontiers in Veterinary Science* 11:1450304. doi: 10.3389/fvets.2024.1450304.
- Kocak B, Baessler B, Bakas S, *et al.*, 2023. CheckList for Evaluation of Radiomics research (CLEAR): a step-by-step reporting guideline for authors and reviewers endorsed by ESR and EuSoMI. *Insights into Imaging* 14:75. doi: 10.1186/s13244-023-01415-8.
- Kuntz CA, Dernell WS, Powers BE, *et al.*, 1997. Prognostic factors for surgical treatment of soft-tissue sarcomas in dogs: 75 cases (1986-1996). *Journal of the American Veterinary Medical Association* 211:1147-1151.
- Lambin P, Leijenaar RTH, Deist TM, *et al.*, 2017. Radiomics: the bridge between medical imaging and personalized medicine. *Nature Reviews Clinical Oncology* 14:749-762. doi: 10.1038/nrclinonc.2017.141.
- Lee K, Goh J, Jang J, *et al.*, 2023. Feasibility study of computed tomography texture analysis for evaluation of canine primary adrenal gland tumors. *Frontiers in Veterinary Science* 10:1126165. doi: 10.3389/fvets.2023.1126165.
- Libling WA, Korn R and Weiss GJ, 2023. Review of the use of radiomics to assess the risk of recurrence in early-stage non-small cell lung cancer. *Translational Lung Cancer Research* 12:1575-1589. doi: 10.21037/tlcr-23-5.
- Li S, Yu F and Gao Y, 2025. The application of artificial intelligence in veterinary oncology: a scoping review. *BMC Veterinary Research* 22:28. doi: 10.1186/s12917-025-05192-y.
- Lubner MG, Smith AD, Sandrasegaran K, *et al.*, 2017. CT texture analysis: definitions, applications, biologic correlates, and challenges. *Radiographics* 37:1483-1503. doi: 10.1148/rg.2017170056.
- McSporran KD, 2009. Histologic grade predicts recurrence for marginally excised canine subcutaneous soft tissue sarcomas. *Veterinary Pathology* 46:928-933. doi: 10.1354/vp.08-VP-0277-M-FL.
- Nakagawa S and Cuthill IC, 2007. Effect size, confidence interval and statistical significance: a practical guide for biologists. *Biological Reviews* 82:591-605. doi: 10.1111/j.1469-185X.2007.00027.x.
- Parekh V and Jacobs MA, 2016. Radiomics: a new application from established techniques. *Expert Review of Precision Medicine and Drug Development* 1:207-226. doi: 10.1080/23808993.2016.1164013.
- Peeken JC, Bernhofer M, Spraker MB, *et al.*, 2019. CT-based radiomic features predict tumor grading and have prognostic value in patients with soft tissue sarcomas treated with neoadjuvant radiation therapy. *Radiotherapy and Oncology* 135:187-196. doi: 10.1016/j.radonc.2019.01.004.
- Perry JA, Culp WTN, Dailey DD, *et al.*, 2014. Diagnostic accuracy of pre-treatment biopsy for grading soft tissue sarcomas in dogs. *Veterinary and Comparative Oncology* 12:106-113. doi: 10.1111/j.1476-5829.2012.00333.x.
- Rogers W, Thulasi Seetha S, Refaee TAG, *et al.*, 2020. Radiomics: from qualitative to quantitative imaging. *The British Journal of Radiology* 93:20190948. doi: 10.1259/bjr.20190948.

- Shafiq-ul-Hassan M, Zhang GG, Latifi K, *et al.*, 2017. Intrinsic dependencies of CT radiomic features on voxel size and number of gray levels. *Medical Physics* 44:1050-1062. doi: 10.1002/mp.12123.
- Shah A, Alessandrino F, Palmerini E, *et al.*, 2025. Radiomics in soft tissue sarcoma: toward precision imaging in oncology. *Cancers* 17:3661. doi: 10.3390/cancers17223661.
- Traverso A, Kazmierski M, Zhovannik I, *et al.*, 2020. Machine learning helps identifying volume-confounding effects in radiomics. *Physica Medica* 71:24-30. doi: 10.1016/j.ejmp.2020.02.010.
- van Griethuysen JJM, Fedorov A, Parmar C, *et al.*, 2017. Computational radiomics system to decode the radiographic phenotype. *Cancer Research* 77:e104-e107. doi: 10.1158/0008-5472.CAN-17-0339.
- Vibhakkar AM, Cassels JA, Botchu R, *et al.*, 2021. Imaging update on soft tissue sarcoma. *Journal of Clinical Orthopaedics and Trauma* 22:101568. doi: 10.1016/j.jcot.2021.101568.
- Wong J, Baine M, Wisnoskie S, *et al.*, 2021. Effects of interobserver and interdisciplinary segmentation variabilities on CT-based radiomics for pancreatic cancer. *Scientific Reports* 11:16328. doi: 10.1038/s41598-021-95152-x.
- Xu W, Hao D, Hou F, *et al.*, 2020. Soft tissue sarcoma: preoperative MRI-based radiomics and machine learning may be accurate predictors of histopathologic grade. *AJR American Journal of Roentgenology* 215:963-969. doi: 10.2214/AJR.19.22147.
- Yip SSF and Aerts HJWL, 2016. Applications and limitations of radiomics. *Physics in Medicine Biology* 61:R150-R166. doi: 10.1088/0031-9155/61/13/R150.
- Zijdenbos AP, Dawant BM, Margolin RA, *et al.*, 1994. Morphometric analysis of white matter lesions in MR images: method and validation. *IEEE Transactions on Medical Imaging* 13:716-724. doi: 10.1109/42.363096.