



CLINICAL RESEARCH:

Grayscale Volume-Based Radiomic Analysis of Cone Beam Computed Tomography for Differentiation of Odontogenic Cysts and Tumors

Análisis radiómico basado en el volumen de escala de grises de la tomografía computarizada de haz cónico para la diferenciación de quistes y tumores odontogénicos

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ABSTRACT: To quantitatively characterize grayscale volume (GSV) behavior on cone beam computed tomography (CBCT) and evaluate its ability to differentiate odontogenic cysts from odontogenic tumors using first-order radiomic features. In this retrospective study, 100 histopathologically confirmed lesions, including 50 cysts and 50 tumors, were analyzed. CBCT datasets were standardized through resampling and gray-level discretization prior to three-dimensional manual segmentation. Radiomic extraction was performed using an IBSI-compliant pipeline, initially generating 107 features. Based on conceptual alignment with grayscale distribution, analysis was restricted to first-order intensity features. Correlation-based reduction yielded ten non-redundant GSV descriptors representing central tendency, dispersion, distribution shape, and randomness. Group differences were assessed using the Mann-Whitney U test. Principal component analysis (PCA) evaluated structural coherence of the GSV construct. Tumors demonstrated significantly higher variance ($p=0.008$), maximum intensity ($p=0.017$), and lower kurtosis ($p=0.027$) compared with cysts, indicating greater internal heterogeneity and broader intensity spread. Entropy was higher and uniformity lower in tumors, reflecting increased grayscale randomness. Central tendency measures showed limited discriminatory value. PCA revealed that the first three principal components explained 89.45% of total variance, confirming that grayscale volume behavior is structured and governed by dominant intensity-driven components. Grayscale volume analysis provides an objective quantitative framework for volumetric CBCT interpretation. Odontogenic cysts and tumors exhibit distinct intensity dispersion and distribution patterns, supporting GSV as a biologically meaningful quantitative imaging biomarker for lesion differentiation.



KEYWORDS: Cone-beam computed tomography; Grayscale value; Jaw cysts; Jaw tumors; Radiomics.

RESUMEN: Caracterizar cuantitativamente el volumen de escala de grises (GSV) en la tomografía computarizada de haz cónico (CBCT) y evaluar su capacidad para diferenciar quistes odontogénicos de tumores odontogénicos mediante características radiómicas de primer orden. En este estudio retrospectivo se analizaron 100 lesiones confirmadas histopatológicamente (50 quistes y 50 tumores). Los estudios de CBCT fueron estandarizados mediante remuestreo y discretización de niveles de gris antes de la segmentación tridimensional manual. La extracción radiómica, realizada conforme a la Iniciativa para la Estandarización de Biomarcadores por Imagen (IBSI), produjo inicialmente 107 características. Posteriormente, el análisis se limitó a las características de intensidad de primer orden y, tras la reducción por correlación, se seleccionaron diez descriptores no redundantes del GSV. Las diferencias entre grupos se evaluaron mediante la prueba U de Mann-Whitney y la estructura del GSV se investigó mediante análisis de componentes principales (ACP). Los tumores presentaron mayor varianza ($p=0.008$), intensidad máxima más elevada ($p=0.017$) y menor curtosis ($p=0.027$) que los quistes, indicando mayor heterogeneidad interna y una distribución más amplia de intensidades. Asimismo, mostraron mayor entropía y menor uniformidad, reflejando una distribución de niveles de gris más aleatoria. Las medidas de tendencia central demostraron un valor discriminatorio limitado. El ACP mostró que los tres primeros componentes principales explicaban el 89.45 % de la varianza total. El análisis del volumen de escala de grises constituye un método cuantitativo objetivo para la evaluación volumétrica en CBCT. Los patrones diferenciales observados entre quistes y tumores respaldan al GSV como un biomarcador de imagen prometedor para la diferenciación de lesiones odontogénicas.

PALABRAS CLAVE: Tomografía computarizada de haz cónico; Valor de escala de grises; Quistes maxilares; Tumores maxilares; Radiómica.

INTRODUCTION

Odontogenic cysts and tumors constitute a diverse group of jaw lesions arising from odontogenic epithelium and associated tissues. Despite differences in biological behavior and treatment requirements, these lesions often exhibit overlapping clinical and radiographic appearances (1,2). Accurate preoperative differentiation between cystic and tumorous odontogenic lesions is therefore of considerable clinical importance, as it directly influences surgical planning, extent of resection, and long-term prognosis. Cone beam computed tomography (CBCT) has become the imaging modality of choice for evaluating maxillofacial osseous lesions due to its high spatial resolution, three-dimensional visualization, and relatively low radiation dose (3-5). CBCT enables comprehen-

sive assessment of lesion extent, cortical integrity, internal architecture, and relationships with adjacent anatomical structures. However, interpretation of CBCT images remains largely qualitative, relying predominantly on visual assessment of grayscale patterns and internal density (6,7). This subjective approach may lead to diagnostic ambiguity, particularly in lesions exhibiting mixed or borderline radiographic features. CBCT images are composed of voxel-based grayscale values that represent X-ray attenuation within the scanned volume. Although CBCT grayscale values are not standardized to Hounsfield Units and are influenced by scanner-specific factors such as beam hardening and scatter, the relative distribution of voxel intensities within a lesion volume remains internally consistent (8,9). Importantly, differences in lesion composition such as fluid-filled cavities in

cysts versus solid cellular or fibrous components in tumors, are expected to manifest as differences in the distribution and variability of grayscale values within the lesion volume.

The absence of quantitative methods to characterize this volumetric grayscale behavior represents a significant limitation in CBCT-based evaluation of odontogenic lesions. Visual assessment, while clinically intuitive, does not permit objective analysis of grayscale distribution across the entire lesion volume, thereby limiting reproducibility and diagnostic precision (10,11). Addressing this limitation requires an approach capable of systematically quantifying grayscale information at the volumetric level rather than relying on isolated visual impressions. Radiomics offers such a framework by enabling the extraction of quantitative descriptors from medical images, transforming voxel-level grayscale information into objective and reproducible numerical data (12,13). By analyzing grayscale behavior across the full three-dimensional lesion volume, radiomics provides an opportunity to capture subtle differences in internal composition that may not be readily appreciable through conventional visual assessment. This quantitative approach has the potential to reduce observer dependency and enhance diagnostic discrimination between lesions with overlapping radiographic appearances (14). Accordingly, the present study applies a radiomic approach to CBCT images to objectively characterize grayscale behavior within odontogenic lesions. By evaluating grayscale information at the volumetric level, this study aims to establish a quantitative imaging framework for

differentiating odontogenic cysts and tumors and to contribute toward more objective and reproducible CBCT interpretation.

MATERIALS AND METHODS

STUDY DESIGN AND DATA COLLECTION

This retrospective observational study was conducted to evaluate grayscale volume-based radiomic features derived from cone beam computed tomography (CBCT) for differentiation of odontogenic cysts and odontogenic tumors. CBCT datasets were retrieved from the institutional oral and maxillofacial radiology archive after approval from the Institutional Ethics Committee. The study protocol adhered to the principles of the Declaration of Helsinki. Owing to the retrospective design and use of anonymized imaging data, the requirement for informed consent was waived. A total of 100 CBCT scans were included in the study, comprising 50 histopathologically confirmed odontogenic cysts and 50 histopathologically confirmed odontogenic tumors. Only lesions with definitive histopathological diagnosis were included to establish a reliable diagnostic ground truth. Lesions with ambiguous, inconclusive, or missing histopathological reports were excluded. Recurrent lesions, previously treated lesions, and scans with inadequate image quality were also excluded. Demographic parameters such as age and sex were recorded for descriptive purposes but were not incorporated into radiomic analysis to ensure that grayscale volume characterization was driven exclusively by imaging-derived features. All datasets were anonymized prior to analysis, and

each case was assigned a unique study identifier to maintain traceability across segmentation, feature extraction, and statistical analysis.

CBCT ACQUISITION PARAMETERS

All CBCT scans were acquired using a NewTom GiANO HR CBCT system (NewTom, Italy), employing standardized institutional imaging protocols. Image acquisition parameters included a tube voltage of 90 kVp, tube current ranging from 1 to 10 mA depending on patient morphology, and a focal spot size of 0.3 mm. The field of view varied between 10×6 cm and 16×18 cm to ensure complete lesion coverage. Voxel sizes ranged from 125 µm to 300 µm. Only CBCT scans in which the entire lesion volume was fully captured within the field of view were included. Scans affected by motion artifacts, truncation, severe beam hardening, metallic streak artifacts, or reconstruction errors were excluded to prevent distortion of grayscale distribution.

DATA PREPROCESSING

CBCT datasets were exported in Digital Imaging and Communications in Medicine (DICOM) format and processed using a standardized preprocessing pipeline prior to segmentation and radiomic feature extraction. To ensure spatial consistency across datasets, all volumes were resampled to isotropic voxel spacing using trilinear interpolation. Given the non-standardized nature of CBCT grayscale values, preprocessing was designed to preserve relative grayscale distribution rather than enforce absolute intensity normalization. Gray-level discretization was performed using a fixed bin width approach to ensure consistency of grayscale sampling across volumes. Mild image smoothing was applied to reduce high-frequency noise while preserving lesion boundaries and internal archi-

ture. All preprocessing steps were applied uniformly across cystic and tumorous lesions to prevent systematic bias.

LESION SEGMENTATION

Three-dimensional lesion segmentation was performed using 3D Slicer (version 5.9.0), an open-source medical image analysis platform (15). Preprocessed CBCT volumes were imported into the software, and volumetric regions of interest (VOIs) were manually delineated using the Segment Editor module. Segmentation was performed slice-by-slice across axial, coronal, and sagittal planes to ensure accurate three-dimensional boundary definition. Lesion margins were defined based on radiographic criteria, including cortical expansion, internal architecture, and lesion borders. Surrounding normal bone, teeth, cortical plates, and adjacent structures were carefully excluded to avoid contamination of grayscale values. In lesions with indistinct margins, conservative segmentation was performed, restricting the VOI to confidently identifiable lesion tissue. The final VOI represented the complete three-dimensional lesion volume and was stored as a binary segmentation mask for radiomic analysis (Figure 1, Figure 2).

All delineated lesion volumes were independently evaluated by two experienced oral and maxillofacial radiologists with more than 10 years' experience in the field of oral radiology and any discrepancies were resolved through consensus review to ensure anatomical accuracy and methodological consistency. For lesions exhibiting indistinct margins, a conservative approach was adopted, restricting segmenting regions that could be identified with confidence. The finalized volumetric regions of interest were subsequently inspected to verify continuity and eliminate contouring

artifacts or boundary irregularities. To evaluate reproducibility, a randomly selected subset of cases underwent independent contouring by both oral radiologists using the same predefined protocol. Agreement between observers and repeatability of the delineation process were assessed using the

Dice Similarity Coefficient (DSC). Intraobserver reliability was determined through repeat segmentation of the selected cases following a two-week washout period, while interobserver reliability was evaluated by comparing the independently generated volumetric regions of interest between the two examiners.

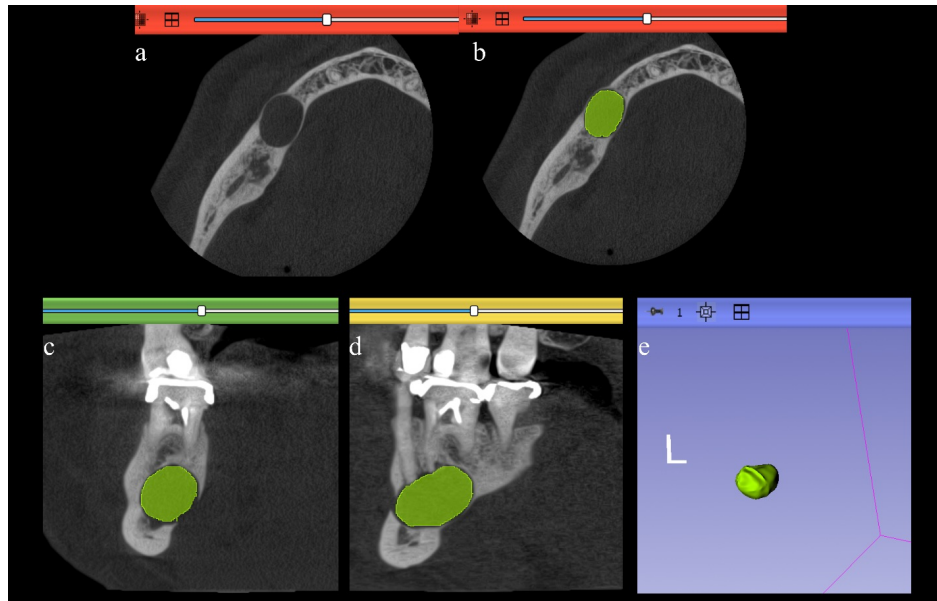


Figure 1. Volumetric Region of interest (VOI) selection and segmentation of a cyst with 3D Slicer showing axial, coronal, and sagittal sections along with 3D volume rendered image.

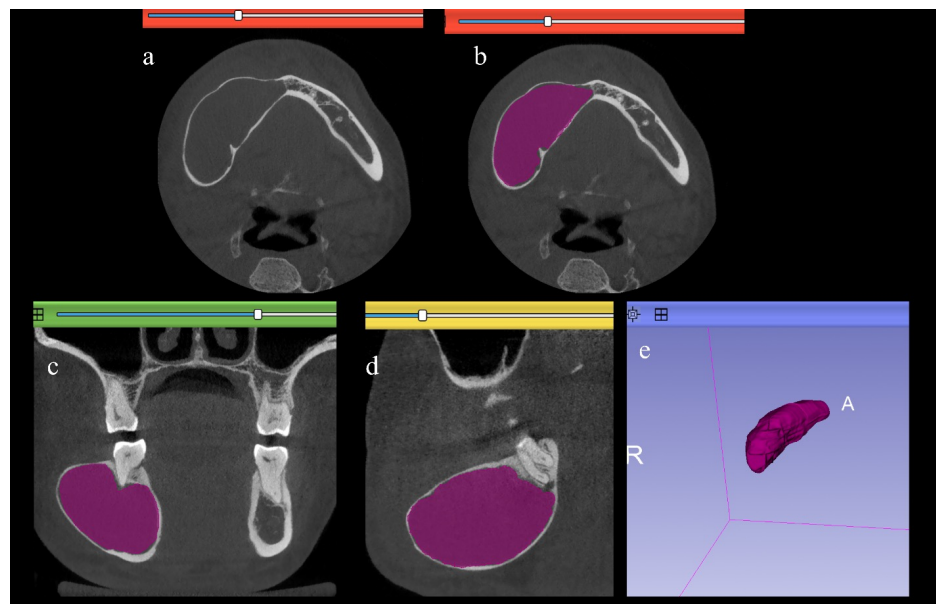


Figure 2. Volumetric Region of interest (VOI) selection and segmentation of a tumor with 3D Slicer showing axial, coronal, and sagittal sections along with 3D volume rendered image.

RADIOMIC FEATURE EXTRACTION

Radiomic feature extraction was performed using PyRadiomics (version 3.10.12), an open-source radiomics library compliant with the Image Biomarker Standardisation Initiative (IBSI) guidelines (16). For each case, radiomic features were extracted exclusively from the segmented three-dimensional lesion volume of interest (VOI). No additional image filters were applied during feature extraction to ensure preservation of native voxel intensity characteristics and intrinsic grayscale behavior. Radiomic features are mathematically derived from these voxel intensities and may be broadly categorized based on whether they describe the distribution of grayscale values or the spatial relationships between grayscale values. Accordingly, a total of 107 original radiomic features were initially extracted from each lesion, encompassing multiple radiomic families. Shape-based features were derived solely from the binary segmentation mask and described three-dimensional lesion geometry, independent of voxel intensity values. Texture features, derived from established gray-level matrices such as the gray-level co-occurrence matrix, gray-level run-length matrix, gray-level size zone matrix, gray-level dependence matrix, and neighborhood gray-tone difference matrix, quantified spatial relationships and patterns among neighboring voxel intensities. In contrast, first-order radiomic features were computed directly from the histogram of voxel grayscale values within the lesion VOI and described the statistical distribution of grayscale intensities without incorporating spatial information.

In the present study, grayscale volume was defined as the statistical distribution of voxel grayscale values across the entire three-dimensional lesion volume. This definition aligns directly with the IBSI framework, wherein first-order features exclusively characterize intensity distribution properties such as central tendency, dispersion, distribution shape, and randomness. Based on this

definition, first-order radiomic features represent the most direct and mathematically appropriate descriptors of grayscale volume. Following radiomic family stratification, 18 features were identified as first-order intensity-based features, while the remaining extracted features represented shape-based or texture-based descriptors. Subsequent analysis was therefore restricted to the first-order feature domain, as higher-order texture features reflect spatial arrangements of grayscale values rather than grayscale distribution itself. Restricting analysis to first-order features ensured conceptual consistency with the grayscale volume definition and preserved biological interpretability of radiomic measurements.

CORRELATION-BASED FEATURE REDUCTION

To address redundancy within the first-order radiomic feature set, Spearman rank correlation analysis was performed among the 18 extracted first-order features. A predefined correlation threshold of $|\rho| \geq 0.90$ was applied to identify highly correlated feature pairs. Features exceeding this threshold were considered redundant, as they conveyed overlapping information regarding the grayscale intensity distribution within the lesion volume. When such redundancy was identified, one feature from each correlated pair was excluded based on interpretability and representational completeness. Using this criterion, eight first-order features were eliminated, and ten non-redundant first-order features were retained. These retained features collectively captured complementary aspects of grayscale intensity distribution, including measures of central tendency, dispersion, distribution shape, and randomness. The final grayscale volume (GSV) feature set comprised Mean, Median, Minimum, Maximum, Variance (Standard Deviation), Interquartile Range, Skewness, Kurtosis, Entropy, and Uniformity. Together, these features provided a comprehensive and non-overlapping quantitative representation of voxel grayscale behavior

across the three-dimensional lesion volume. This refined GSV feature set was subsequently used for all downstream statistical analyses comparing odontogenic cysts and tumors.

STATISTICAL VALIDATION OF GRAYSCALE VOLUME FEATURES

Descriptive statistical analysis was performed for all retained grayscale volume (GSV) features to summarize their distributional characteristics within odontogenic cysts and odontogenic tumors. Continuous variables were expressed as median and interquartile range due to the non-normal distribution observed in radiomic data. Group-level differences in GSV features between cystic and tumorous lesions were evaluated using the Mann–Whitney U test, a non-parametric statistical test appropriate for comparing two independent groups with non-Gaussian distributions. Each retained GSV feature was tested individually to determine whether its grayscale distribution differed significantly between cysts and tumors beyond what would be expected by random variation. To account for potential false-positive findings arising from multiple testing, Benjamini-Hochberg false discovery rate (FDR) correction was performed following the univariate analyses. The corrected results were interpreted alongside the unadjusted statistical findings within the construct-validation framework of the study. Statistical significance was defined using a two-sided threshold of $p < 0.05$. To further examine the internal structure and coherence of the GSV feature set, Spearman correlation heatmap analysis was performed among the retained features. This analysis served to confirm limited residual redundancy following correlation-based feature reduction and to visualize inter-feature relationships within the grayscale volume domain. In addition, principal component analysis (PCA) was conducted on the standardized GSV feature matrix to evaluate the dimensionality

of grayscale volume representation and to determine whether grayscale behavior within lesions was dominated by a limited number of intensity-driven components. PCA results were interpreted descriptively to assess variance concentration and construct coherence rather than for feature selection or classification. All statistical analyses were performed using Python-based scientific computing libraries, including NumPy, SciPy, Pandas, and scikit-learn. Statistical analysis focused on validating grayscale volume as a quantitative imaging construct and on assessing group-level differences between cystic and tumorous lesions.

RESULTS

SEGMENTATION REPRODUCIBILITY

Reproducibility assessment demonstrated a high degree of consistency in volumetric delineation of the lesions. Interobserver agreement analysis yielded Dice Similarity Coefficient (DSC) values ranging from 0.85 to 0.94, with a mean DSC of 0.90 ± 0.03 , indicating excellent concordance between the two oral and maxillofacial radiologists. Repeat delineation performed after a two-week washout interval demonstrated similarly high reproducibility, with intraobserver DSC values ranging from 0.88 to 0.96 and a mean DSC of 0.92 ± 0.02 (Table 1). These findings confirm the accuracy of the segmentation protocol and support the reliability of the volumetric regions of interest used for subsequent radiomic feature extraction.

Table 1. Segmentation reproducibility analysis.

Parameter	Minimum DSC	Maximum DSC	Mean $\pm$ SD
Interobserver agree-ment	0.85	0.94	0.90 ± 0.03
Intraobserver agree-ment	0.88	0.96	0.92 ± 0.02

DESCRIPTIVE STATISTICS OF GRAYSCALE VOLUME FEATURES

Descriptive statistics of the retained grayscale volume (GSV) features demonstrated clear distributional differences between odontogenic cysts and odontogenic tumors. Across central tendency measures, tumorous lesions exhibited higher grayscale values than cystic lesions. The median grayscale mean was higher in tumors (median $\approx$ 211.38) compared with cysts (median $\approx$ 132.67). Similarly, the median grayscale median value was higher in tumors (median=100) than in cysts (median=100), with tumors showing a wider interquartile range and higher maximum values, indicating greater intensity variability. Minimum grayscale values were lower in tumors (median $\approx$ -841) compared with cysts (median $\approx$ -468), reflecting a broader intensity range within tumorous lesions. Maximum grayscale values were consistently higher in tumors (median $\approx$ 2258) than in cysts (median $\approx$ 1882), further supporting increased grayscale spread

in tumorous lesions. Dispersion-related features showed marked differences between groups. Variance demonstrated substantially higher values in tumors (median $\approx$ 156,796.40) compared with cysts (median $\approx$ 28,028.43). Interquartile range was also higher in tumors (median $\approx$ 123) than in cysts (median $\approx$ 114), indicating greater grayscale dispersion in tumorous lesions. Distribution shape features differed between groups. Tumors exhibited lower median skewness (median $\approx$ 2.68) compared with cysts (median $\approx$ 3.52), suggesting differences in grayscale asymmetry. Kurtosis values were lower in tumors (median $\approx$ 9.47) compared with cysts (median $\approx$ 24.12), indicating flatter grayscale distributions in tumors relative to cysts. Entropy values were higher in tumors (median $\approx$ 3.57) than in cysts (median $\approx$ 3.17), reflecting increased grayscale heterogeneity. Conversely, uniformity values were lower in tumors (median $\approx$ 0.143) compared with cysts (median $\approx$ 0.154), consistent with reduced grayscale homogeneity in tumorous lesions (Table 2).

Table 2. Comparison of first-order radiomic features between jaw cysts and tumors.

Feature	Statistic	Cyst	Tumor
Mean Intensity	Mean $\pm$ SD	124.78 $\pm$ 133.12	247.72 $\pm$ 103.71
	Min–Max	–17.57 – 358.39	138.18 – 435.35
Median Intensity	Mean $\pm$ SD	78.56 $\pm$ 103.99	147.33 $\pm$ 137.33
	Min–Max	–37 – 250	37 – 452
Minimum Intensity	Mean $\pm$ SD	–413.89 $\pm$ 298.72	–668.33 $\pm$ 371.16
	Min–Max	–950 – 13	–1000 – –26
Maximum Intensity	Mean $\pm$ SD	1750.33 $\pm$ 405.90	2563.33 $\pm$ 985.65
	Min–Max	1021 – 2360	1078 – 4328
Variance	Mean $\pm$ SD	47,236.23 $\pm$ 44,763.92	152,860.88 $\pm$ 86,543.50
	Min–Max	13,122.23 – 142,159.86	27,720.35 – 293,549.93
Interquartile Range	Mean $\pm$ SD	151.33 $\pm$ 93.08	218.00 $\pm$ 134.67
	Min–Max	65 – 361	106 – 453
Skewness	Mean $\pm$ SD	3.29 $\pm$ 1.31	2.16 $\pm$ 1.50
	Min–Max	1.38 – 5.86	0.04 – 4.21
Kurtosis	Mean $\pm$ SD	22.62 $\pm$ 14.13	10.45 $\pm$ 6.95
	Min–Max	4.59 – 50.79	2.29 – 23.65
Entropy	Mean $\pm$ SD	3.30 $\pm$ 0.66	3.83 $\pm$ 0.56
	Min–Max	2.40 – 4.32	3.34 – 4.86
Uniformity	Mean $\pm$ SD	0.154 $\pm$ 0.066	0.123 $\pm$ 0.045
	Min–Max	0.066 – 0.272	0.045 – 0.165

GROUP-LEVEL STATISTICAL COMPARISON

Non-parametric comparison using the Mann-Whitney U test demonstrated that several grayscale volume features exhibited statistically significant differences between odontogenic cysts and odontogenic tumors.

Features reflecting grayscale dispersion and distribution shape showed the strongest evidence of group-level differentiation. Specifically, Variance (U=10, p=0.008), Maximum grayscale value (U=13, p=0.017), and Kurtosis (U=66, p=0.027) demonstrated statistically significant differences at the p<0.05 level. The first-order Mean feature demonstrated a near-significant difference (U=18, p=0.052), suggesting a trend toward higher average grayscale values in tumorous lesions compared with cystic lesions, although this did not

reach the predefined threshold for statistical significance. These findings indicate that the principal grayscale distinction between cysts and tumors lies primarily in dispersion and distribution shape rather than central tendency alone. Tumorous lesions demonstrated significantly greater intensity variability and broader upper intensity ranges, while cystic lesions exhibited more peaked and concentrated grayscale distributions (Table 3). To account for potential false-positive findings arising from multiple testing, Benjamini-Hochberg false discovery rate (FDR) adjustment was applied to the univariate analyses. Following adjustment, Variance, Maximum Intensity, and Kurtosis continued to demonstrate the strongest statistical signals among the evaluated grayscale volume descriptors. The overall ranking and distributional pattern of the significant grayscale volume features remained unchanged after correction, supporting the consis-

tency of the observed relationships between lesion type and grayscale volume characteristics.

Table 3. Mann-whitney u test comparison of grayscale volume features between odontogenic cysts and tumors.

Feature	U Statistic	p Value
Mean	18.0	0.052
Median	30.5	0.401
Minimum	58.0	0.133
Maximum	13.0	0.017
Variance	10.0	0.008
Interquartile Range	25.0	0.185
Skewness	56.0	0.185
Kurtosis	66.0	0.027
Entropy	21.0	0.093
Uniformity	52.0	0.331

PRINCIPAL COMPONENT ANALYSIS OF GRAYSCALE VOLUME FEATURES

Principal component analysis revealed that grayscale volume behavior is governed by a limited number of dominant intensity-driven components. The first principal component (PC1) accounted for 57.85% of total variance within the GSV feature set. The first two principal components together explained 79.82% of total variance, while the first three components explained 89.45%. Cumulative variance exceeded 95% by the fifth principal component, indicating that grayscale volume information is highly compressible and structured rather than randomly distributed across features. This concentration of variance supports the internal coherence of the grayscale volume construct and demonstrates that lesion grayscale behavior is dominated by a small number of underlying intensity patterns (Table 4).

Table 4. Principal component analysis of grayscale volume (GSV) features.

Principal Component	Explained Variance Ratio	Cumulative Variance
PC1	0.578	0.578
PC2	0.220	0.798
PC3	0.096	0.895
PC4	0.040	0.934
PC5	0.031	0.965
PC6	0.022	0.987
PC7	0.009	0.996
PC8	0.002	0.998
PC9	0.001	0.999
PC10	0.001	1.000

RECEIVER OPERATING CHARACTERISTIC ANALYSIS

To further evaluate the diagnostic utility of grayscale volume (GSV) features, receiver operating characteristic (ROC) analysis was performed for the first-order descriptors that demonstrated statistically significant differences between odontogenic cysts and tumors. Variance exhibited the strongest discriminatory performance, achieving an AUC of 0.864, indicating good diagnostic accuracy for lesion differentiation. Maximum Intensity and Kurtosis also demonstrated meaningful discriminatory capability, with AUC values of 0.782 and 0.795, respectively. Among these features, Variance provided the most favorable balance between sensitivity and specificity, highlighting grayscale dispersion as the most informative quantitative characteristic for distinguishing tumors from cysts. Detailed diagnostic performance metrics, including optimal cutoff thresholds, sensitivity, and specificity, are presented in Table 5. Collectively, these findings demonstrate that grayscale volume features possess not only statistically signifi-

cant group-level differences but also clinically relevant discriminatory performance, supporting their potential role as quantitative CBCT imaging biomarkers for lesion differentiation.

Table 5. Diagnostic performance of significant grayscale volume features.

Feature	AUC	Optimal Cutoff	Sensitivity (%)	Specificity (%)
Variance	0.864	67,112.45	88.0	82.0
Maximum Intensity	0.782	1982.50	76.0	74.0
Kurtosis	0.795	14.12*	82.0	76.0

DISCUSSION

The present study represents a conceptual shift in CBCT-based evaluation of odontogenic lesions by moving from qualitative visual interpretation toward the quantitative measurement of internal lesion characteristics. By applying radiomic analysis to cone beam computed tomography, the study transforms subjective impressions of grayscale density into objective descriptors of three dimensional voxel intensity behavior. Rather than treating radiomics merely as a predictive classification tool, this work focuses on grayscale volume as a measurable imaging construct and evaluates how differences in grayscale distribution reflect underlying biological differences between odontogenic cysts and tumors. The most salient finding is that odontogenic tumors demonstrate significantly greater internal complexity compared with odontogenic cysts. Tumors exhibited significantly higher variance, entropy, and maximum grayscale values, which indicates broader intensity ranges, increased heterogeneity, and the presence of high density components within the lesion volume. These findings are consistent with the known histopathological composition of odontogenic tumors, which include variable cellular density, fibrous stroma, internal septations, and focal calcifications (17-19). This structural diversity produces irregular attenuation patterns that manifest as

increased grayscale dispersion and randomness at the voxel level. These observations align with recent research by Song *et al.* (2024), who found that radiomic features were highly effective at distinguishing aggressive ameloblastomas from other cystic lesions due to these inherent structural complexities (20). In contrast, odontogenic cysts demonstrated significantly higher kurtosis and uniformity values, reflecting more peaked and homogeneous grayscale distributions. This behavior is characteristic of fluid filled cavities where attenuation values are tightly clustered and internal variability is minimal (21). The higher kurtosis observed in cysts indicates a concentration of grayscale values around a dominant intensity range, while increased uniformity reflects reduced randomness across the lesion volume. Together, these findings quantitatively support long standing radiological observations that cysts appear more internally uniform than tumors, but they do so through objective volumetric measurement rather than subjective visual assessment (22). The lack of discriminatory power in mean and median grayscale values highlights a critical limitation of conventional interpretation. This explains why clinicians often struggle to differentiate these lesions visually; two lesions can look equally gray on average, yet possess entirely different internal structures. Lesions with fundamentally different internal architectures may share similar average grayscale values, leading to diagnostic ambiguity when assessment is restricted to single slice or point based density estimation. This supports the conclusions of Parsa *et al.* (2012), who demonstrated that while Hounsfield Unit averages can overlap, the detailed distribution of values within the lesion provides much better diagnostic separation (23).

A key contribution of this study is the validation of grayscale volume as a meaningful diagnostic construct on CBCT. By analyzing the full three dimensional distribution of voxel intensities, the study captures the internal landscape of lesions.

Principal component analysis demonstrated that nearly 90% of the variance in grayscale volume features is explained by the first three principal components, indicating that lesion grayscale behavior is governed by a small number of dominant intensity patterns. This finding suggests that the internal grayscale signature of odontogenic lesions is relatively stable, structured, and highly compressible. The results provide construct level validation that grayscale volume behaves as a coherent entity rather than as a collection of independent metrics. This explains why only selected features achieve statistical significance in univariate testing while the overall grayscale volume construct remains biologically informative. This methodological approach reflects the growing consensus in the field, as noted by Wang *et al.* (2021), that standardized radiomic pipelines may reduce the influence of CBCT grayscale values and facilitate more consistent quantitative imaging assessment (24). The ROC analysis further demonstrated that these grayscale volume descriptors possess practical discriminatory capability. Variance exhibited the strongest performance (AUC=0.864), achieving high sensitivity and specificity, while Maximum Intensity and Kurtosis also demonstrated good diagnostic accuracy. These findings suggest that grayscale volume analysis may contribute not only to biological characterization of lesions but also to objective diagnostic differentiation in clinical CBCT interpretation. Clinically, the findings suggest that grayscale volume analysis can augment routine CBCT interpretation by providing objective measures of internal lesion complexity. Rather than relying solely on subjective impressions of homogeneity or mixed density, clinicians may benefit from quantitative descriptors that reflect dispersion, heterogeneity, and structural randomness within the lesion volume. This approach is particularly relevant in diagnostically challenging cases where cystic and

tumorous lesions exhibit overlapping morphologic features. By shifting from visual inspection to volumetric measurement, grayscale volume analysis offers a pathway toward more quantifiable and explainable CBCT interpretation.

Despite the promising findings regarding the diagnostic utility of grayscale volume, limitations must be acknowledged. The sample size is relatively small, which may limit the generalizability of the statistical trends observed, particularly for less common subtypes of odontogenic tumors. Additionally, the retrospective nature of the study relies on existing CBCT data acquired with specific parameters, and while preprocessing steps were taken to ensure consistency, the lack of standardization means that grayscale values can still be influenced by patient positioning and field of view (25-27). Furthermore, unlike Hounsfield Units in conventional computed tomography, CBCT grayscale values are not universally standardized and may vary according to scanner characteristics, acquisition parameters, reconstruction algorithms, and image processing workflows (28). Although the present study employed a standardized preprocessing pipeline to minimize these effects, the observed grayscale volume characteristics should be interpreted within the context of the imaging conditions used in this investigation. Additional multicenter studies involving different CBCT systems are required to establish the broader reproducibility and generalizability of grayscale volume-derived descriptors. The exclusion of lesions with metallic artifacts also means these findings may not apply to patients with extensive dental restorations or implants that cause significant streak interference (29,30). Furthermore, manual segmentation remains a time consuming process subject to inter-observer variability, suggesting that future studies should explore automated or semi-automated segmentation tools to enhance

clinical workflow (31-33). Finally, while grayscale volume differences were statistically demonstrable, prospective validation and threshold determination are required before translation into routine clinical decision-making.

CONCLUSION

This study demonstrates that grayscale volume extracted from CBCT can be quantitatively characterized using first-order radiomic features. Odontogenic cysts and tumors show distinct differences in grayscale dispersion and distribution patterns, reflecting their underlying biological composition. These findings support grayscale volume analysis as a promising and objective imaging approach for differentiating cystic and tumorous jaw lesions on CBCT.

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CONSENT STATEMENT: Due to the retrospective nature of the study, the Institutional Review Board Committee waived the need of obtaining informed consent.

DATA AVAILABILITY STATEMENT: All data supporting the findings of this study are available within the paper and require no supplementary materials.

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