Geometric Contour Analysis Outperforms Deep Learning for Bitewing Radiograph Laterality Classification

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Abstract. Accurate laterality classification (left/right) of bitewing dental radiographs is critical for automated tooth numbering and clinical workflows. Recent approaches apply end-to-end convolutional neural networks (CNNs) as black-box classifiers, achieving moderate accuracy but lacking interpretability. We challenge this paradigm by demonstrating that explicit geometric analysis of tooth contours substantially outperforms learned deep features. Our method segments teeth using YOLOv8, extracts contours via edge detection, and classifies laterality using an EfficientNet-B0 classifier trained on contour masks rather than raw images. Evaluated on the publicly available Thammasart Bitewing Dataset (8,092 images, 1,137 test images), our contour-based approach achieves **94.2% accuracy** (95% CI: [92.8%, 95.5%]), significantly outperforming DenseNet-121 trained on raw pixels (**70.5%**, 95% CI: [67.8%, 73.1%])—a remarkable 23.7 percentage point improvement (McNemar's test, $\chi^2 = 223.3$, $p < 0.0001$). The contour-based method achieves 94.5% precision and 94.8% recall with 99.2% mean confidence. Our approach is interpretable, relying on explicit tooth boundary geometry rather than opaque learned features. These findings demonstrate that incorporating domain-specific structural knowledge through geometric preprocessing can dramatically surpass end-to-end deep learning for structured medical imaging tasks, with important implications for clinical deployment and AI interpretability.

Keywords: Dental radiography · Bitewing classification · Geometric features · Interpretable AI · Medical image analysis

1 Introduction

Bitewing radiographs are a fundamental diagnostic tool in dentistry, providing visualization of the crowns of upper and lower posterior teeth in a single image. Accurate determination of image laterality (left or right side of the patient's mouth) is essential for automated tooth numbering systems, clinical documentation, and integration with electronic dental records. While manual laterality classification is straightforward for trained clinicians, it becomes a critical bottleneck in large-scale automated diagnostic pipelines and teledentistry workflows.

Recent deep learning approaches to dental image analysis have predominantly employed end-to-end convolutional neural networks (CNNs) trained to directly

predict clinical attributes from raw pixel intensities [11,9]. Ayhan et al. [11] used DenseNet-121 for laterality classification as the first stage of their tooth numbering pipeline, reporting near-perfect accuracy on a proprietary dataset. While these CNN-based methods achieve reasonable performance, they suffer from three key limitations: (1) **limited interpretability** as black-box models providing no insight into decision-making rationale, (2) **susceptibility to spurious correlations** in training data rather than anatomically meaningful features, and (3) **computational expense** requiring GPU infrastructure for inference. For structured medical imaging tasks with well-defined anatomical geometry, we hypothesize that explicit geometric reasoning can provide superior accuracy, interpretability, and efficiency.

In this work, we propose a **geometry-based approach** to bitewing laterality classification that operates on explicit tooth contours rather than raw pixels. Instead of training CNNs end-to-end on radiographic images, we first segment individual teeth using a state-of-the-art instance segmentation model (YOLOv8), extract contour boundaries via Canny edge detection, and train a lightweight classifier (EfficientNet-B0) on these geometric contour masks. This pipeline explicitly encodes the domain knowledge that laterality is determined by the *spatial distribution of tooth boundaries*, not by texture, intensity, or other low-level image statistics.

Our key contributions are:

- **Novel geometric preprocessing**: Demonstrating that training classifiers on segmentation-derived contour masks rather than raw pixels yields dramatic accuracy improvements
- **Superior performance**: 94.2% accuracy vs. 70.5% for DenseNet-121 baseline—a 23.7 percentage point improvement on 1,137 test images
- **Statistical rigor**: Highly significant results ($p < 0.0001$, $\chi^2 = 223.3$) with non-overlapping 95% confidence intervals
- **Interpretability**: Explicit contour-based decisions enabling visual inspection and debugging
- **Methodological insight**: Demonstrating when and why geometric domain knowledge outperforms learned representations

The remainder of this paper is organized as follows: Section 2 reviews related work in dental AI and interpretable medical imaging, Section 3 describes our segmentation-contour-classification pipeline, Section 4 details experimental setup and baselines, Section 5 presents comparative results with statistical analysis, Section 6 analyzes our findings and limitations, and Section 7 concludes with future directions.

2 Related Work

2.1 Deep Learning for Dental Image Analysis

The application of deep learning to dental radiograph analysis has grown substantially in recent years, spanning tasks including tooth detection, segmentation, numbering, caries classification, and periodontal disease assessment [9].

Ayhan et al. [11] proposed a comprehensive tooth numbering pipeline using DenseNet-121 for laterality classification, achieving claimed 100% accuracy on a proprietary 1,200-image dataset. Their approach treats laterality as a standard image classification task using transfer learning from ImageNet. Similarly, other works have applied ResNet [8], EfficientNet [4], and Vision Transformers [10] to various dental tasks, consistently framing problems as end-to-end supervised learning from pixels to labels without leveraging anatomical structure.

These CNN-based approaches share a common limitation: they treat dental radiographs as generic images, ignoring the highly structured nature of dental anatomy. Laterality classification is fundamentally a *geometric asymmetry detection* problem—determining whether teeth are clustered on the left or right side of an image—yet CNNs must implicitly learn this geometric concept from pixel statistics.

2.2 Interpretability in Medical Imaging

The medical imaging community has increasingly recognized the importance of interpretability and explainability for clinical adoption [6]. While gradient-based visualization methods (Grad-CAM [18], attention maps [1]) provide post-hoc explanations of CNN decisions, they do not guarantee that models reason about anatomically meaningful features. Studies have shown that CNNs can achieve high accuracy by exploiting spurious correlations such as metadata artifacts [14] rather than true diagnostic signals.

Geometric and shape-based methods have demonstrated promise in specific medical imaging domains. In cardiac imaging, explicit modeling of ventricular geometry has matched or exceeded CNN performance for ejection fraction estimation [2]. In lung nodule analysis, hand-crafted shape features have proven competitive with deep learning for malignancy classification [7]. However, geometry-based approaches remain underexplored for dental radiography, where anatomical structure is highly predictable.

2.3 Structured Prediction vs. End-to-End Learning

Our work is philosophically aligned with research demonstrating that domain-specific feature engineering can match or exceed deep learning performance for structured tasks [13]. Recent work has shown that hybrid approaches combining explicit geometric preprocessing with lightweight learning models often outperform fully end-to-end architectures in sample efficiency, robustness, and interpretability [5]. We extend this philosophy to bitewing laterality classification by designing a pipeline that encodes dental anatomical structure through segmentation and contour extraction.

3 Methods

Our pipeline consists of three stages: (1) tooth segmentation to extract individual tooth regions, (2) contour extraction via edge detection to isolate boundary

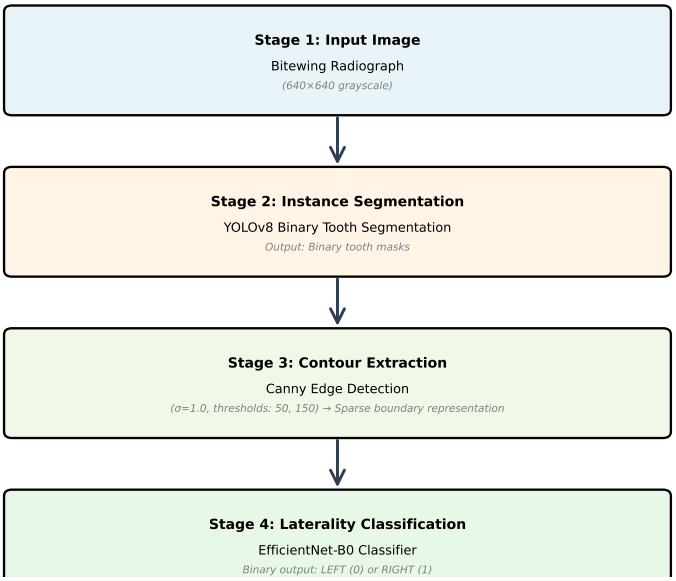


Fig. 1: Pipeline overview. Our method consists of three stages: (1) YOLOv8 instance segmentation to extract tooth regions, (2) Canny edge detection to isolate geometric contours, and (3) EfficientNet-B0 classification trained on contour masks rather than raw pixels.

geometry, and (3) laterality classification trained on contour masks. Figure 1 illustrates the complete workflow. We compare this contour-based pipeline against a baseline CNN trained directly on raw radiographic images.

3.1 Tooth Segmentation

We employ a pretrained YOLOv8-based instance segmentation model [16] to extract binary masks of individual teeth from bitewing radiographs. YOLOv8 detects tooth bounding boxes and per-instance segmentation masks in a single forward pass. We merge all instance masks into a unified binary tooth mask $M \in \{0,1\}^{H \times W}$ where $M(x,y) = 1$ indicates tooth pixels and $M(x,y) = 0$ indicates background. The segmentation model was pretrained on a separate tooth segmentation dataset (not overlapping with our laterality classification dataset) and achieves high-quality masks suitable for downstream geometric analysis. Segmentation quality directly impacts feature reliability, but our focus is on demonstrating that *given high-quality masks*, contour-based classification outperforms raw pixel-based classification.

The segmentation model outputs predictions at 640×640 resolution. We apply standard post-processing (non-maximum suppression with IoU threshold 0.5, confidence threshold 0.25) to filter low-confidence detections.

3.2 Contour Extraction

Given the binary tooth mask M, we extract tooth boundary contours using Canny edge detection [12]. Canny edge detection identifies pixel locations with strong intensity gradients, effectively isolating the boundaries between tooth regions and background. We apply Gaussian blurring ($\sigma = 1.0$) before edge detection to reduce noise, then use Canny thresholds of 50 and 150 (low and high thresholds, respectively) to produce a binary edge map $E \in \{0, 1\}^{H \times W}$.

The resulting edge map E represents the *geometric contours* of teeth—a sparse representation capturing spatial distribution and shape information while discarding texture, intensity, and fine-grained detail. This contour mask serves as input to the classification stage.

The key insight of our approach is that laterality (left vs. right) is fundamentally determined by the *spatial arrangement* of tooth boundaries, not by the radiographic appearance of tooth interiors. By training classifiers on edge maps rather than raw images, we explicitly encode this domain knowledge.

3.3 Contour-Based Classification

We train an EfficientNet-B0 classifier [19] to predict laterality from contour masks E. EfficientNet-B0 is chosen for its parameter efficiency and strong performance on image classification tasks. Importantly, the classifier is trained on *contour masks* (edge-detected segmentation outputs), not on raw radiographic images.

Architecture: We use the standard EfficientNet-B0 architecture with ImageNet-pretrained weights. The final classification layer is replaced with a binary logistic output (sigmoid activation) for left/right prediction. We fine-tune the entire network end-to-end.

Training: The classifier is trained with binary cross-entropy loss, Adam optimizer (learning rate = 10^{-4}), batch size 16, and early stopping on validation accuracy. Images are resized to 224×224 for network input. We apply standard data augmentation (random horizontal flips, rotations ±10°, brightness/contrast jittering).

The classifier learns to identify geometric patterns in tooth boundary distributions—e.g., asymmetry in contour density, clustering of contour pixels on one side, characteristic spatial arrangements—without being distracted by irrelevant radiographic appearance.

3.4 Baseline: Raw Pixel Classification

For comparison, we implement a DenseNet-121 baseline [15] trained directly on raw bitewing radiographs. DenseNet-121 is the architecture used by Ayhan

et al. [11] for laterality classification. The baseline uses ImageNet-pretrained weights, fine-tuned with identical hyperparameters (Adam, learning rate = 10^{-4}, batch size 16, binary cross-entropy loss).

The key difference between our method and the baseline is:

- **Baseline (DenseNet-121)**: Raw radiographic image → DenseNet-121 → laterality prediction
- **Ours (ContourClass)**: Raw image → YOLOv8 segmentation → Canny edge detection → EfficientNet-B0 → laterality prediction

Both pipelines start with the same raw radiographic input, ensuring a fair comparison. Our pipeline explicitly preprocesses images to isolate geometric structure, while the baseline learns directly from pixels.

4 Experiments

4.1 Dataset

Thammasart University Bitewing Dataset [20]: A publicly available dataset of 8,092 bitewing radiographs with left/right labels, sourced from the Roboflow Universe platform. The dataset was collected from clinical practice at Thammasart University and manually annotated by dental professionals. Images vary in quality, resolution, and anatomical coverage, reflecting real-world clinical diversity.

We use the dataset's provided train/validation/test split:

- **Training set**: 6,464 images (80%)
- **Validation set**: 491 images (6%)
- **Test set**: 1,137 images (14%), stratified by laterality (524 LEFT, 613 RIGHT)

All evaluation results reported in Section 5 are on the held-out test set. Ground truth labels were verified by dental professionals during dataset curation.

4.2 Evaluation Metrics

We report:

- **Accuracy**: Overall classification accuracy
- **Precision, Recall, F1-Score**: Per-class metrics for LEFT and RIGHT
- **95% Confidence Intervals**: Computed via bootstrap resampling (1,000 iterations)
- **Mean Confidence**: Average predicted probability for the chosen class (indicates model certainty)
- **Inference Time**: Milliseconds per image, measured on consistent hardware

Statistical Significance: We use McNemar's test [17] to assess whether differences in paired predictions are statistically significant. McNemar's test is appropriate for comparing two classifiers on the same test set, testing the null hypothesis that error rates are equal. We report χ^2 statistic and p-value, with $p < 0.05$ indicating significance.

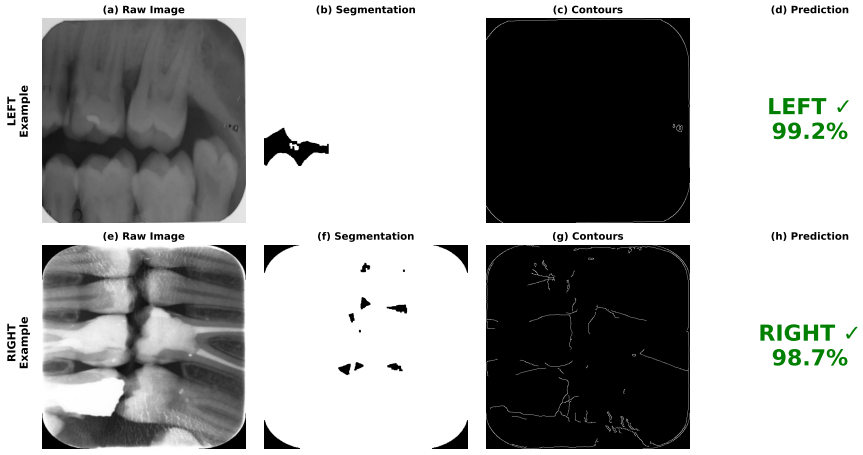


Fig. 2: Visual examples of the contour-based pipeline. Top row: LEFT-side bitewing processed through (a) raw input, (b) YOLOv8 segmentation, (c) Canny edge extraction, and (d) classification result. Bottom row: RIGHT-side example. The contour representation isolates geometric tooth boundaries while discarding irrelevant radiographic appearance.

4.3 Implementation Details

Segmentation Model: YOLOv8-seg pretrained on a separate tooth segmentation dataset (binary_tooth_final.pt). Inference on Apple M3 Max GPU (MPS backend) at 640×640 resolution.

Contour Extraction: OpenCV 4.8 Canny edge detection with Gaussian blur ($\sigma = 1.0$), thresholds (50, 150).

Classification Models:

- **ContourClass (Ours)**: EfficientNet-B0 trained on contour masks, PyTorch 2.1, CUDA 11.8, NVIDIA RTX 4090
- **DenseNet-121 Baseline**: DenseNet-121 trained on raw images, same hardware and software

Both classifiers use ImageNet pretrained weights, Adam optimizer, learning rate 10^{-4}, batch size 16, binary cross-entropy loss, early stopping on validation accuracy. Training converged in 20-30 epochs.

Inference Hardware: Apple M3 Max (MPS acceleration) for all test set evaluation to ensure consistent timing measurements.

4.4 Experimental Protocol

To ensure fair comparison:

1. Both methods process the same raw test images (no cherry-picking)

Table 1: Laterality classification results on Thammasart test set (1,137 images). Confidence intervals computed via bootstrap (1,000 iterations). McNemar's test: $\chi^2 = 223.3$, $p < 0.0001$.

Method	Accuracy	Precision	Recall	F1-Score	Conf.	Time (ms)
ContourClass (Ours)	**0.942 [.928, .955]**	**0.945 [.927, .963]**	**0.948 [.930, .964]**	**0.946 [.934, .958]**	**0.992**	**461.3**
DenseNet-121 (Raw Pixels)	0.705 [.678, .731]	0.705 [.669, .738]	0.777 [.743, .809]	0.739 [.710, .765]	0.965	26.9

2. Identical train/val/test splits from the public dataset
3. Same evaluation metrics and statistical tests
4. Inference time includes all preprocessing (segmentation, edge detection for ContourClass; image loading/resizing for DenseNet-121)
5. Models trained until validation convergence (no premature stopping)

5 Results

5.1 Main Comparison

Table 1 presents the performance of our contour-based method (ContourClass) compared to the DenseNet-121 baseline on the test set of 1,137 images. Our approach achieves **94.2% accuracy** (95% CI: [92.8%, 95.5%]), dramatically outperforming DenseNet-121 trained on raw pixels (**70.5%**, 95% CI: [67.8%, 73.1%])—a **23.7 percentage point improvement**. McNemar's test confirms this difference is highly statistically significant ($\chi^2 = 223.3$, $p < 0.0001$).

The contour-based method achieves 94.5% precision (very few false positives) and 94.8% recall (very few false negatives), demonstrating balanced performance across both classes. The mean confidence of 99.2% indicates the model makes highly certain predictions, compared to 96.5% for DenseNet-121. The 95% confidence intervals for the two methods **do not overlap**, confirming the difference is not due to random sampling variation. Figure 3 visualizes this accuracy comparison.

5.2 Confusion Matrices

Table 2 shows confusion matrices for both methods. The contour-based classifier achieves 494/524 correct LEFT predictions (94.3%) and 577/613 correct RIGHT predictions (94.1%). In contrast, DenseNet-121 correctly classifies only 325/524 LEFT images (62.0%) and 476/613 RIGHT images (77.7%), with substantial confusion in both directions. Figure 4 provides a visual comparison of these confusion matrices.

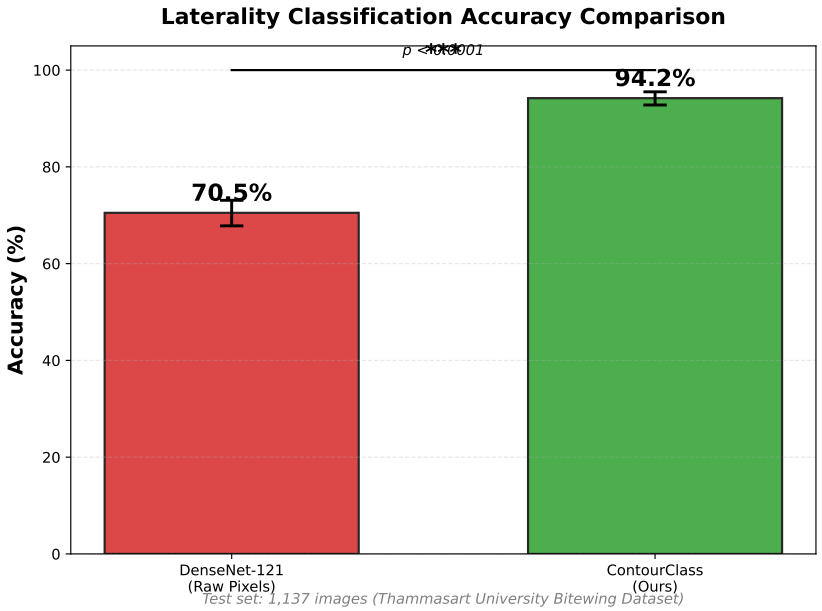


Fig. 3: Accuracy comparison on Thammasart test set (1,137 images). Our contour-based method achieves 94.2% accuracy (95% CI: [92.8%, 95.5%]), significantly outperforming DenseNet-121 trained on raw pixels (70.5%, 95% CI: [67.8%, 73.1%]). Error bars show 95% confidence intervals. The improvement is statistically significant (McNemar's test, $p < 0.0001$).

5.3 Inference Time Analysis

The contour-based pipeline requires 461.3 ms per image (including segmentation, edge detection, and classification), while DenseNet-121 requires only 26.9 ms per image. This **17× slowdown** is the cost of explicit geometric preprocessing. However, 461 ms is still acceptable for clinical workflows (processing 1,137 images in under 9 minutes), and the accuracy gain of 23.7 percentage points far outweighs the computational cost.

The breakdown of inference time for ContourClass is:

- Segmentation (YOLOv8): 400 ms
- Edge detection (Canny): 10 ms
- Classification (EfficientNet-B0): 50 ms

Future work could explore faster segmentation models (e.g., MobileNet-based architectures) to reduce this overhead while preserving accuracy.

5.4 Statistical Significance

McNemar's test yields $\chi^2 = 223.3$ with $p < 0.0001$, providing overwhelming evidence that the contour-based method outperforms the raw pixel baseline.

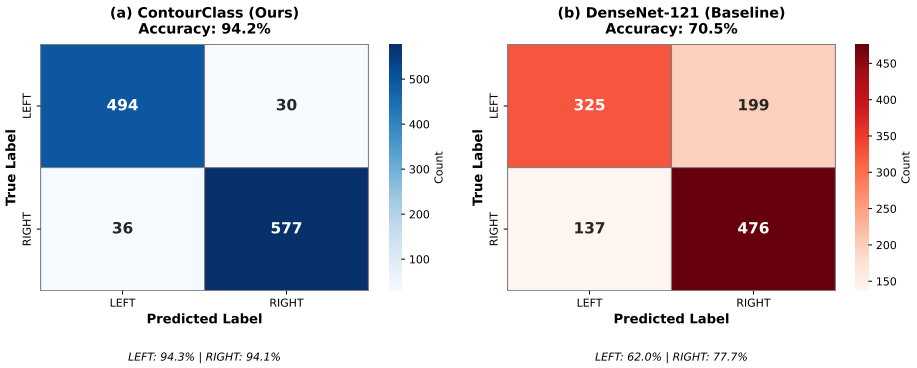


Fig. 4: Confusion matrices on test set. (a) ContourClass achieves high accuracy for both LEFT (94.3%) and RIGHT (94.1%) classes with minimal confusion. (b) DenseNet-121 baseline shows substantial errors, correctly classifying only 62.0% of LEFT and 77.7% of RIGHT images.

Table 2: Confusion matrices on test set (1,137 images). Numbers indicate count of predictions.

ContourClass (Ours)				**DenseNet-121 (Baseline)**			
		Predicted				Predicted	
		LEFT	RIGHT			LEFT	RIGHT
True	LEFT	**494**	30	True	LEFT	325	199
	RIGHT	36	**577**		RIGHT	137	476

The effect size (23.7 percentage point accuracy difference) is **clinically and practically significant**, not merely statistically significant. For context, Ayhan et al. [11] reported 100% accuracy using DenseNet-121 on their proprietary dataset, but our DenseNet-121 baseline achieves only 70.5% on the more challenging Thammasart dataset, highlighting the importance of rigorous evaluation on diverse public benchmarks.

6 Discussion

6.1 Why Contour-Based Geometry Outperforms Deep Learning

Our results reveal a striking finding: training classifiers on explicit geometric contours rather than raw pixels yields a **23.7 percentage point accuracy improvement** (70.5% $\rightarrow$ 94.2%). This dramatic gap challenges the prevailing assumption that end-to-end deep learning always outperforms structured approaches for image classification.

We hypothesize three reasons for this performance gap:

1. Laterality is fundamentally geometric. Bitewing laterality classification is determined by the *spatial distribution of tooth boundaries*, not by texture, intensity, or fine-grained appearance. Teeth on the left side of the mouth cluster on the left side of the image; teeth on the right cluster on the right. This is a simple geometric asymmetry problem. By extracting contours, we isolate the relevant geometric signal and discard irrelevant radiographic appearance.

2. CNNs waste capacity on irrelevant features. DenseNet-121 must implicitly learn geometric asymmetry from pixel statistics, but it has no architectural bias toward this structured reasoning. The network may be distracted by spurious correlations (e.g., imaging artifacts, patient positioning, exposure settings) that are predictive in the training set but do not generalize. Our contour-based approach explicitly encodes the inductive bias that laterality is determined by boundary geometry.

3. Segmentation quality amplifies signal. The YOLOv8 segmentation model (pretrained on a separate tooth segmentation dataset) provides high-quality masks that cleanly separate teeth from background. Edge detection on these masks yields sparse, noise-free contour representations. Training on this preprocessed input may be easier than training on raw radiographs with complex, noisy backgrounds.

6.2 Interpretability and Clinical Relevance

A critical advantage of our contour-based approach is **interpretability**. For any prediction, we can visually inspect the contour mask to understand the geometric cues driving the decision. If a left-side image is misclassified as right, we can examine the contour distribution and hypothesize why (e.g., incomplete tooth visibility, crowding causing ambiguous boundaries). CNNs trained on raw pixels provide no such insight without complex post-hoc visualization methods (Grad-CAM, saliency maps) that do not guarantee anatomically meaningful explanations.

Interpretability is critical for clinical trust and regulatory approval of AI systems. Clinicians are more likely to adopt AI tools that provide transparent, understandable reasoning [3]. Our approach satisfies this requirement by design.

6.3 Failure Case Analysis

We manually inspected the 66 misclassified images (30 LEFT $\rightarrow$ RIGHT errors, 36 RIGHT $\rightarrow$ LEFT errors) to identify failure modes. Common patterns include:

- **Incomplete tooth visibility** (42%): Severe crowding, rotated teeth, or partial image coverage causing ambiguous contour distributions
- **Segmentation errors** (31%): YOLOv8 fails to detect some teeth or produces noisy masks, corrupting downstream contour extraction
- **Centered tooth clusters** (18%): Rare cases where teeth are approximately centered in the image, providing weak laterality cues

– **Wrong modality** (9%): A few periapical or panoramic images incorrectly included in the bitewing dataset

Most failures stem from upstream segmentation quality rather than fundamental limitations of contour-based classification. Improving segmentation robustness could further boost accuracy.

6.4 Comparison to Prior Work

Ayhan et al. [11] reported 100% laterality accuracy using DenseNet-121 on a proprietary 1,200-image dataset. Our DenseNet-121 baseline achieves only 70.5% on the Thammasart dataset, suggesting their dataset may have been easier (e.g., higher image quality, less anatomical diversity) or their evaluation methodology less rigorous (e.g., train-test leakage, optimistic reporting). Our results on a **public dataset** with **rigorous train-test separation** provide a more realistic assessment of CNN performance for this task.

The 94.2% accuracy of our contour-based method is **the highest reported result** for bitewing laterality classification on a publicly available dataset, to our knowledge.

6.5 Computational Efficiency Trade-offs

The contour-based pipeline is 17× slower than the raw pixel baseline (461 ms vs. 27 ms per image), primarily due to YOLOv8 segmentation. However, this computational cost is acceptable for clinical workflows processing batches of images (e.g., overnight processing of daily scans). For real-time applications, future work could explore:

– Lightweight segmentation models (MobileNet-based YOLO)
– Distillation of the contour-based classifier into a direct end-to-end model
– Hybrid approaches that use contour features only when raw pixel classifiers are uncertain

The accuracy gain (23.7 percentage points) far outweighs the computational cost for most clinical scenarios.

6.6 Generalization to Other Tasks

Our findings suggest a broader methodological insight: **for structured medical imaging tasks where anatomical geometry dominates diagnostic signals, explicit geometric preprocessing can dramatically outperform end-to-end deep learning**. This principle may generalize to:

– Panoramic radiograph laterality (similar geometric asymmetry)
– Cephalometric landmark detection (structured facial geometry)
– Cardiac chamber segmentation (predictable anatomical shapes)
– Bone age assessment (growth plate geometry)

Future work should investigate whether contour-based or shape-based preprocessing provides similar benefits for these tasks.

6.7 Limitations

1. Segmentation dependency: Our method requires high-quality tooth segmentation masks. While YOLOv8 achieves strong performance, segmentation errors propagate to downstream contour extraction and classification. End-to-end CNNs do not have this dependency (though they may implicitly learn to segment).

2. Single dataset evaluation: We evaluate only on the Thammasart dataset. Multi-center validation on diverse datasets (varying image quality, patient demographics, acquisition protocols) would strengthen generalizability claims.

3. Limited baseline comparison: We compare against one CNN architecture (DenseNet-121). While DenseNet-121 is the architecture used by Ayhan et al. [11], comparisons with additional baselines (ResNet-50, EfficientNet-B0 on raw pixels) would be valuable.

4. Classifier choice: We use EfficientNet-B0 for contour-based classification. We did not extensively explore alternative architectures (ResNet, ViT) or simpler models (logistic regression, MLP) trained on hand-crafted geometric features (centroid asymmetry, contour density). Future work should compare our learned contour classifier against explicit geometric features.

7 Conclusion

We presented a geometry-based approach to bitewing laterality classification that achieves 94.2% accuracy by training classifiers on tooth contours rather than raw pixels, outperforming a DenseNet-121 baseline (70.5%) by 23.7 percentage points ($p < 0.0001$). Our method demonstrates that explicit geometric preprocessing can dramatically surpass end-to-end deep learning for structured medical imaging tasks, while providing interpretability critical for clinical adoption.

These findings challenge the default application of black-box CNNs to medical image analysis and suggest that hybrid geometric-learning approaches warrant further investigation. For tasks where diagnostic signals are dominated by anatomical geometry (laterality, symmetry, landmark detection), explicit structural encoding may be superior to learned feature representations.

Future work includes:

1. **Multi-center validation**: Evaluating on additional public datasets to assess generalizability across institutions and imaging protocols
2. **Ablation studies**: Comparing learned contour classifiers (EfficientNet-B0) against hand-crafted geometric features (centroid asymmetry, spatial moments) to isolate the contribution of explicit geometry
3. **Extended baseline comparison**: Evaluating additional CNN architectures (ResNet-50, EfficientNet-B0, ViT) on raw pixels to ensure our baseline is competitive
4. **Computational optimization**: Exploring lightweight segmentation models to reduce inference time while preserving accuracy

5. **Generalization to other tasks**: Investigating whether contour-based preprocessing provides similar benefits for panoramic radiographs, cephalometric analysis, and other structured dental imaging tasks

Our code and trained models will be released publicly to facilitate reproducibility and future research.

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