

Bits2Bites

Intra-oral Scans Occlusal Classification

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*equal contribution, _ presenting the poster

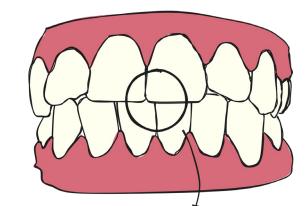


1. Introduction and Motivations

- Clinical relevance: Occlusion classification is key for orthodontic diagnosis and treatment planning.
- Gap: Existing datasets focus on segmentation or landmarks, but none of them addresses occlusal classification in 3D intra-oral scans.

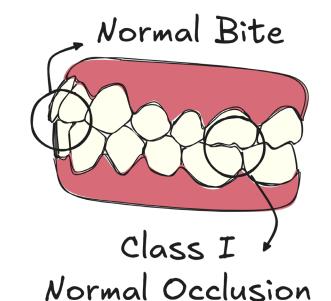


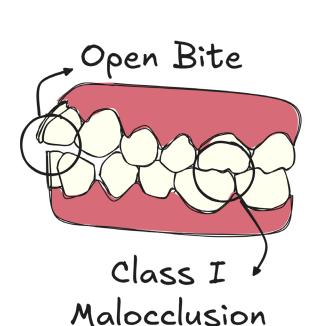


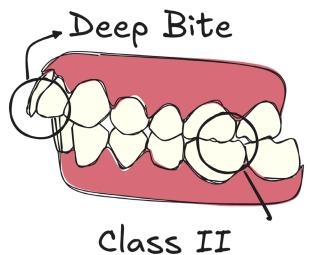


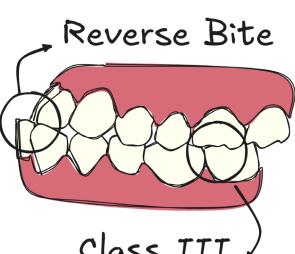
• Impact: Provides a public resource to foster Aldriven orthodontic tools.









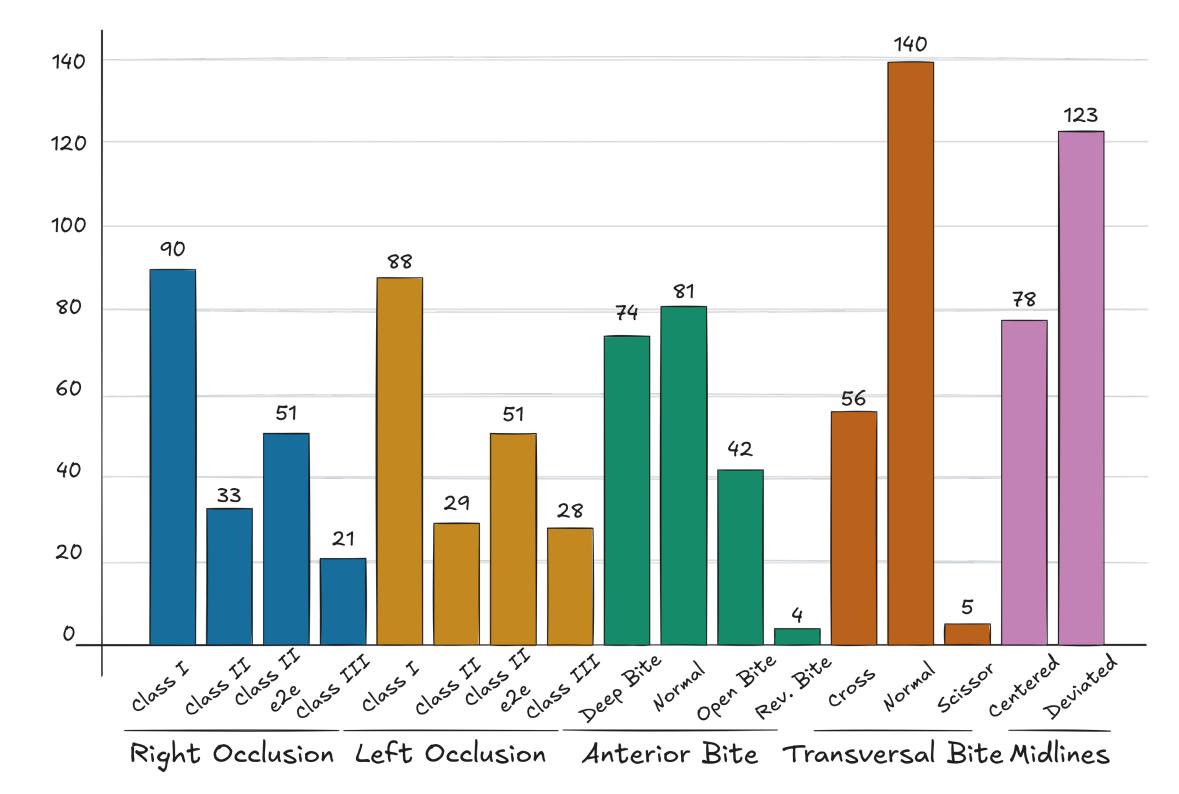


Malocclusion

Class III / Malocclusion

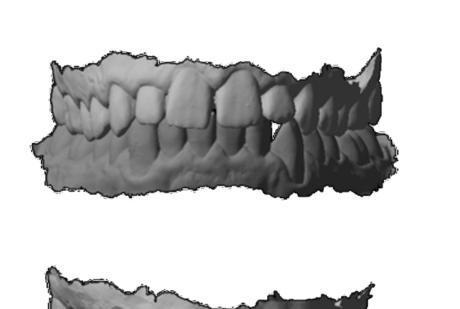
2. Dataset

- **200 paired intra-oral scans** (upper + lower arches) in STL format. All scans are aligned in a standardized coordinate system (RAS).
- Labels across 5 occlusal traits: Sagittal (left/right), Vertical bite, Transverse bite, and Midline alignment.
- Acquired with two scanners: Carestream & 3Shape TRIOS.



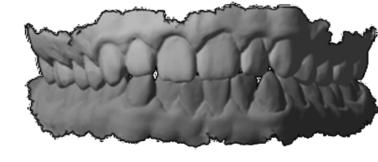
3. Intra-oral Scans

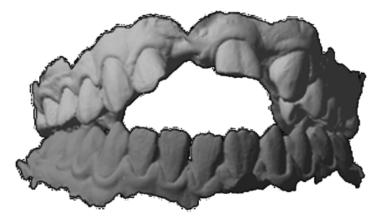
IOS samples randomly chosen from the dataset.







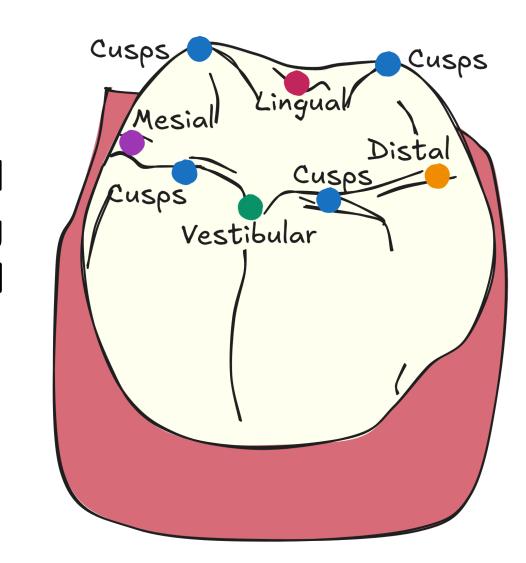




4. Teeth Landmarks

For every intra-oral scan, we predicted different landmarks for each tooth using the winner of MICCAI2024 3DTeethLand Challenge.

Both model and weights are available at: https://github.com/nnistelrooij/3dteethland



5. Methods

We built our baselines on the **Pointcept** framework, using PointTransformer V3 and SPUNet. To assess the best input type, we compared mesh vertices only, predicted landmarks only, and their combination.

We also contrasted two learning strategies: a shared backbone with five task-specific heads (multi-task) versus separate models for each task (single-task).



Evaluation followed a **5-fold cross-validation** scheme, with results reported as mean and standard deviation across folds.

6. Results

Study about different input features. All classification metrics are macro-averaged across the five occlusal tasks and reported as mean ± std (%) over the 5 cross-validation folds. Inference time is the average time in seconds to process a single scan.

Input Features	\mathbf{Model}	Accuracy	Precision	Recall	F1-Score	Time (s)
Mesh		0.69 ± 0.03	0.62 ± 0.02	0.61 ± 0.04	0.60 ± 0.03	0.11
Landmarks	PointTr.V3	0.70 ± 0.04	0.62 ± 0.04	0.63 ± 0.05	0.61 ± 0.04	0.04
Mesh + Landmarks		0.71 ± 0.03	0.64 ± 0.03	0.64 ± 0.02	0.63 ± 0.03	0.11
Mesh		0.64 ± 0.01	0.56 ± 0.03	0.58 ± 0.03	0.56 ± 0.04	0.05
Landmarks	SPUNet	0.60 ± 0.02	0.56 ± 0.06	0.56 ± 0.06	0.58 ± 0.05	0.02
$\operatorname{Mesh} + \operatorname{Landmarks}$		0.65 ± 0.01	0.59 ± 0.05	0.61 ± 0.04	0.58 ± 0.05	0.05

Multi-Task Learning (MTL) vs. Single-Task Learning (STL). All classification metrics are macro-averaged across the five occlusal tasks and reported as mean ± std over the 5 cross-validation folds. Inference time is the average time in seconds to process a scan.

Model	Learning Strategy	Accuracy	Precision	Recall	F1-Score	Time (s)
PointTr.V3	Single-Task (STL) Multi-Task (MTL)		0.66 ± 0.14 0.64 ± 0.03			
SPUNet	Single-Task (STL) Multi-Task (MTL)		0.61 ± 0.13 0.59 ± 0.05			

Per-task F1-score (%) across occlusal classification tasks. Results are macro-averaged over 5-fold cross-validation and reported as mean ± std (%).

\mathbf{Model}	Strategy	Right Occl.	Left Occl.	Anter. Bite	Tran. Bite	Midline	Avg.
PointTr.V3	$\begin{array}{c} \mathrm{STL} \\ \mathrm{MTL} \end{array}$			0.77 ± 0.14 0.74 ± 0.14			
SPUNet	STL MTL			0.78 ± 0.13 0.68 ± 0.15			

