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ORIGINAL ARTICLE

Performance assessment of five artificial intelligence-based algorithms for automated tooth segmentation and labeling on intraoral scans

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Abstract

Purpose: This study aimed to evaluate and compare the performance of five AI algorithms for tooth segmentation and labeling on intraoral scans, as their performance remains unclear.

Materials and Methods: A total of 100 intraoral scans in the STL file format were classified into two main groups: complete dentition (C) and partial dentition (P, fewer than 12 teeth). Each group was further divided by arch into four subgroups (n = 25 each): complete maxillary (Mx-C), complete mandibular (Md-C), partial maxillary (Mx-P), and partial mandibular (Md-P). The algorithms tested were the Tooth Group Network (Team CGIP), Dentbird Studio (Dentbird), Medit Ortho Simulation (Medit), NemoSmile 3D (Nemotec), and MovumStudio (MovumTech). Manual segmentations by an expert operator served as the ground truth. Performance was assessed using Python and five metrics, with Intersection over Union (IOU) as the primary indicator. Statistical analysis included permutation tests with the Bonferroni–Holm correction (α = 0.05).

Results: Significant differences were observed between groups and algorithms ($P < 0.05$). IOU scores ranged from 0.72 to 0.92 in complete dentition and showed greater variability in partial dentition (0–0.928). The Tooth Group Network and

MovumStudio consistently outperformed the others, with MovumStudio achieving the highest performance across all metrics and groups. Its performance matched that of a human expert when compared against a subset of the data.
Conclusions: Tooth segmentation and labeling performance vary depending on dentition completeness and algorithm choice. MovumStudio demonstrated the most robust and consistent results, comparable to expert human annotation.

KEYWORDS
artificial intelligence, digital dentistry, prosthodontics, segmentation

Artificial intelligence (AI) refers to technology that enables machines to replicate human cognitive functions, including learning and problem-solving tasks,[1,2] and includes subfields, namely machine learning (ML) and deep learning (DL).[3–5] ML allows systems to learn patterns autonomously, while DL is an advanced subset of ML that uses artificial neural networks (ANNs) to model complex and high-dimensional data.[3–6] These networks, composed of multiple interconnected layers of artificial neurons, are designed to hierarchically extract features and capture intricate relationships within the data. AI is being increasingly integrated into digital dentistry, with different AI-driven software solutions incorporated into the digital workflow, including implant recognition,[7,8] the identification of diseases and oral lesions,[9–16] dental plaque detection,[17] cephalometric analysis,[18–20] occlusion optimization,[21,22] cone beam computed tomography (CBCT) segmentation,[23,24] and the automatic design of restorations or dental devices.[25]

The primary goal of AI-based algorithms is to deliver accurate results for the specific tasks they are trained to perform, including automating repetitive processes.[26] Manual segmentation and labeling of teeth in digital files is highly time-consuming, and in prosthodontic practice, this step directly affects the efficiency and accuracy of multiple digital procedures, including virtual diagnostic waxing, restorative space evaluation, occlusion-driven design, and the fabrication of tooth- and implant-supported prostheses. For this reason, the development of fully automated algorithms capable of reliably identifying and segmenting teeth on intraoral scans is clinically relevant, as it can streamline prosthodontic workflows, reduce operator-dependent variability, and improve the predictability of digital treatment planning.[27–41]

Tooth segmentation generally involves outlining the contours of individual teeth and assigning class labels based on specific nomenclatures.[41] This process ensures that all intraoral scan surfaces representing a single crown or gingiva are assigned to their corresponding class label. Tooth segmentation has a wide range of applications in digitally assisted dentistry, including virtual extractions, implant planning,[42] autotransplantation,[43] orthodontic diagnosis,[18,20] and the design of both tooth- and implant-supported prostheses.[25] The quality of tooth segmentation is crucial for achieving reliable and long-term treatment outcomes.[44–48]

Several AI algorithms are commercially available to extract the geometric surface information of teeth from intraoral scans and classify them with the corresponding labels. Although widely used in digitally assisted dentistry workflows, automatic tooth segmentation faces several limitations, including a lack of robustness because of the high variability in tooth morphology, missing teeth, abnormal dental conditions, tooth crowding, the accuracy and postprocessing procedures of intraoral scanners, and the conversion of point clouds into three-dimensional (3D) meshes, all of which impact the geometric properties of the resulting digital files, making the outcomes of automatic tooth segmentation uncertain.[40–58]

The aim of the present study was to evaluate the performance of five AI algorithms for automatic tooth segmentation and labeling on intraoral scanner (IOS) data, including patients with complete and partially edentulous dentitions. The null hypotheses were that no significant differences would be found among the tested algorithms and that no significant differences would be observed between the complete dentition and partially edentulous dentition groups.

MATERIALS AND METHODS

The present study was conducted according to the Standards for Reporting Diagnostic Accuracy Studies (STARD) guidelines (http://www.equator-network.org/reporting-guidelines/stard/). The protocol of this study was reviewed and approved by an ethical committee (C.I. 25/050-E) in accordance with the principles outlined in the Declaration of Helsinki.

The research was conducted at the Complutense University of Madrid by using data from the postgraduate Esthetic Dentistry program. Fifty participants were selected for intraoral scanning based on the number of teeth present. The inclusion criteria were participants over 18 years of age in good general health (American Society of Anesthesiologists [ASA] Type I), without known systemic diseases and with no previous maxillofacial or dental trauma, muscular disorders, or temporomandibular joint disorders.

Maxillary, mandibular, and maximum intercuspation position (MIP) digital scans were acquired from each participant using an intraoral scanner (Primescan, Dentsply Sirona), resulting in a dataset of 50 maxillary and 50 mandibular intraoral scans in the standard tessellation language (STL) file format. Two experimental groups were created based on the number of teeth present: the C group (complete dentition)

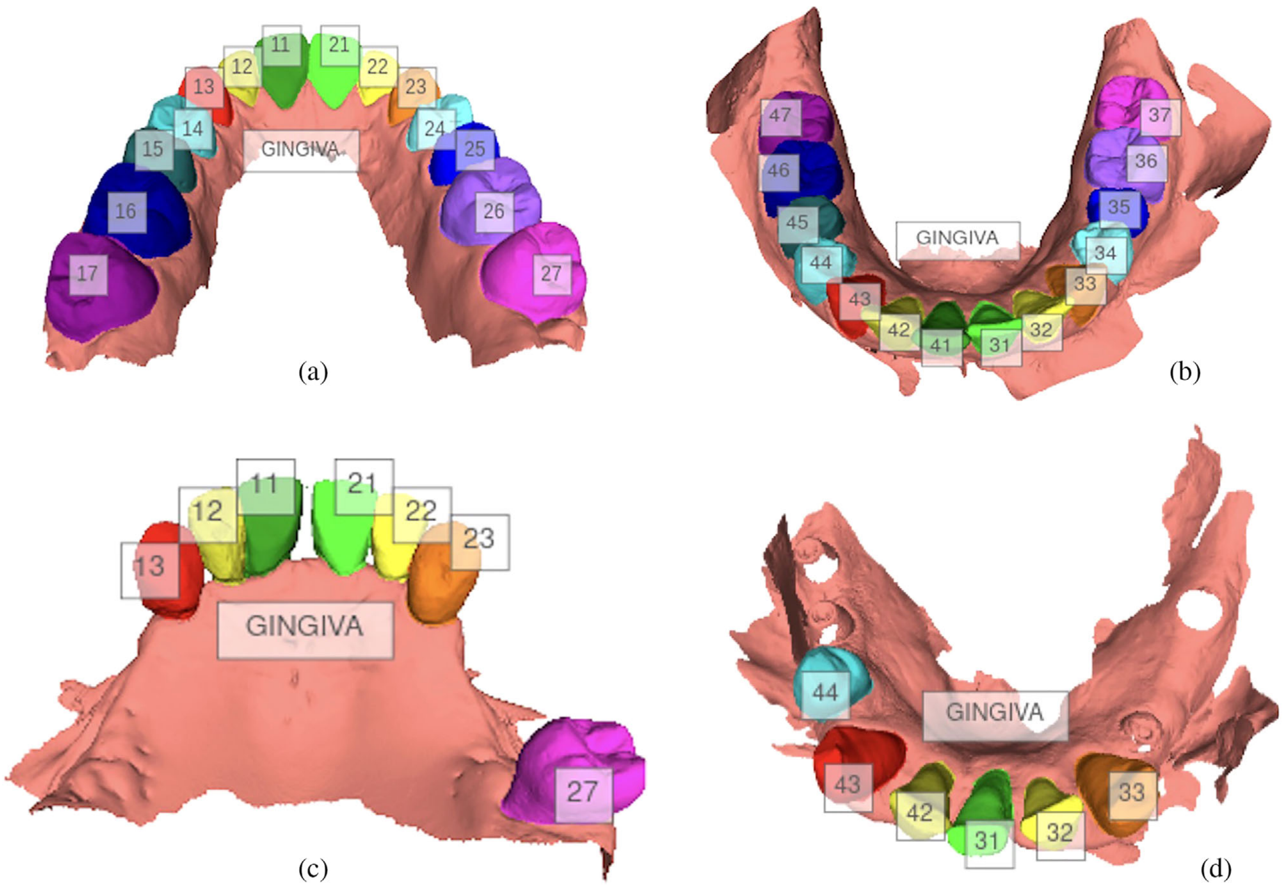


FIGURE 1 Representative ground truth tooth segmentations for each group. (a) Complete maxillary group (Mx-C). (b) Complete mandibular group (Md-C). (c) Partial maxillary group (Mx-P). (d) Partial mandibular group (Md-P).

and the P group (fewer than 12 teeth). Each primary group was further divided into two subgroups based on their anatomic location in the maxillary or mandibular regions, resulting in four classifications: Mx-C, Md-C, Mx-P, and Md-P (Figure 1a–d). Each subgroup included 25 STL files (n = 25). The scanning protocol was standardized across all test groups and performed as follows: digital scans began in the posterior area of the maxillary or mandibular arches. The scanner tip was angled at 60° toward the lingual side and moved along the dental arch to the mandibular right second molar. Subsequently, the scanner was directed occlusally from the mandibular right second molar across the dental arch back to the mandibular left second molar. Finally, the scanner was tilted 60° toward the buccal side and moved along the dental arch to complete the scanning process. The IOS (Primescan, Dentsply Sirona) and its scanning software program (Sirona Connect, v.5.1; Dentsply Sirona) had been calibrated before scanning each experimental group. All digital scans were performed by an experienced dentist (W.P.C.) with 8 years of previous experience using IOSs. The intraoral scans were performed in a room with an ambient lighting condition of 1000 lux, determined by using a luxometer (LX1330B Light Meter; Dr. Meter Digital Illuminance).

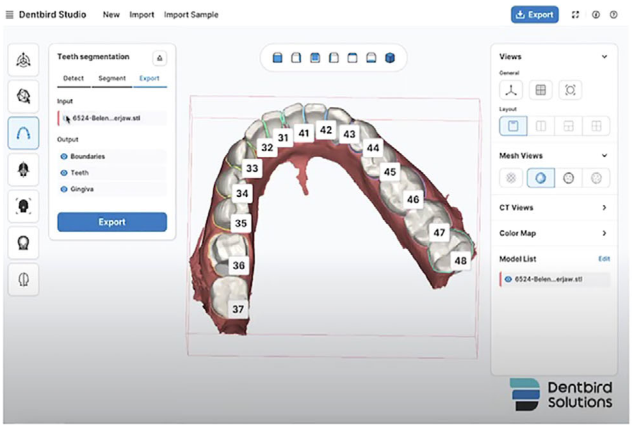
For the ground truth, an experienced clinician (W.P.C.), with 8 years of experience in using 3D computer-aided design (CAD) software programs, was responsible for manually annotating and registering the entire dataset using a CAD program specifically developed for this study in a general-purpose programming language (Python, Python Software Foundation). During the annotation process, each tooth was segmented and labeled according to its corresponding FDI notation, whereas other structures—including gingiva, scan bodies, orthodontic appliances, and artifacts—were labeled as "no-tooth" (Figure 1a–d). The inclusion of intraoral scans containing such artifacts, even if not explicitly classified as separate entities, allowed the evaluation of algorithm performance under realistic prosthodontic conditions rather than under idealized, artifact-free scenarios. The annotations were subsequently reviewed and refined, as needed, by an independent operator (C.O.M.). This curated dataset served as the reference standard for evaluating the accuracy of AI algorithms for tooth segmentation.

Five AI-based segmentation algorithms were selected for evaluation: the Tooth Group Network (Team CGIP), Dentbird Studio (Dentbird), Medit Ortho Simulation (Medit Corp), NemoSmile 3D (Nemotec), and MovumStudio (MovumTech) (Table 1, Figure 2a–c). Depending on the algorithm under evaluation, the software program may have required the user to specify whether the scan was mandibular or maxillary and/or to provide the opposing scan if only a

TABLE 1 Overview of AI-based tooth segmentation algorithms included in the study.

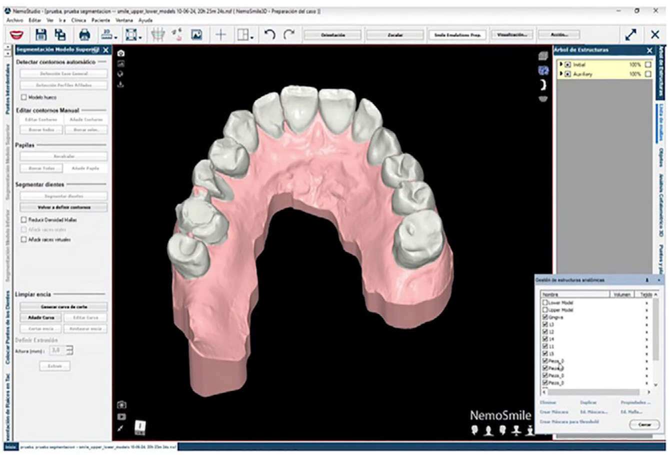
Developer	Algorithm	Version	Software program type
Team CGIP	Tooth Group Network	Final_v1	GitHub repository
Dentbird	Dentbird Studio	2.4.2	SaaS
Medit	Medit Ortho Simulation	1.3.2.48	Desktop
Nemotec	NemoSmile 3D	24.0.0.3	Desktop
Movumtech	MovumStudio	v1.0	SaaS

Abbreviations: Desktop, locally installed software program; SaaS, software-as-a-service.



(a)

(b)



(c)

FIGURE 2 User interface for tooth segmentation depending on software program. (a) Dentbird Studio. (b) Medit Ortho Simulation. (c) NemoSmile 3D.

single STL file was imported (Table 2).[25] The entire dataset was segmented using the AI-driven algorithms (Figure 3). After the dataset had been processed, segmented teeth were exported in a digital file format (STL or PLY files), depending on the software used. Subsequently, the outputs from each segmentation algorithm were standardized using the Python code to allow direct comparison with the ground truth.

The predictions on the test dataset were compared with the expert clinicians' annotations. Five performance metrics were measured: accuracy, precision, Intersection over Union (IoU), recall, and dice score. Performance metrics were defined as follows:

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}},$$

$$\text{precision} = \frac{1}{C}\sum_{i=1}^{c}\frac{\text{TP}}{\text{TP} + \text{FP}},$$

$$\text{IoU} = \frac{1}{C}\sum_{i=1}^{c}\frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}},$$

$$\text{recall} = \frac{1}{C}\sum_{i=1}^{c}\frac{\text{TP}}{\text{TP} + \text{FN}},$$

TABLE 2 Summary of requirements for each AI-based tooth segmentation algorithm.

Algorithm	Arch differentiation (Maxilla/Mandible)	Opposing arch required	Alignment
Tooth Group Network	Required	Not required	Required
Dentbird Studio	Not required	Not required	Not required
Medit Ortho Simulation	Required	Required	Required
NemoSmile 3D	Required	Required	Not required
MovumStudio	Not required	Not required	Not required

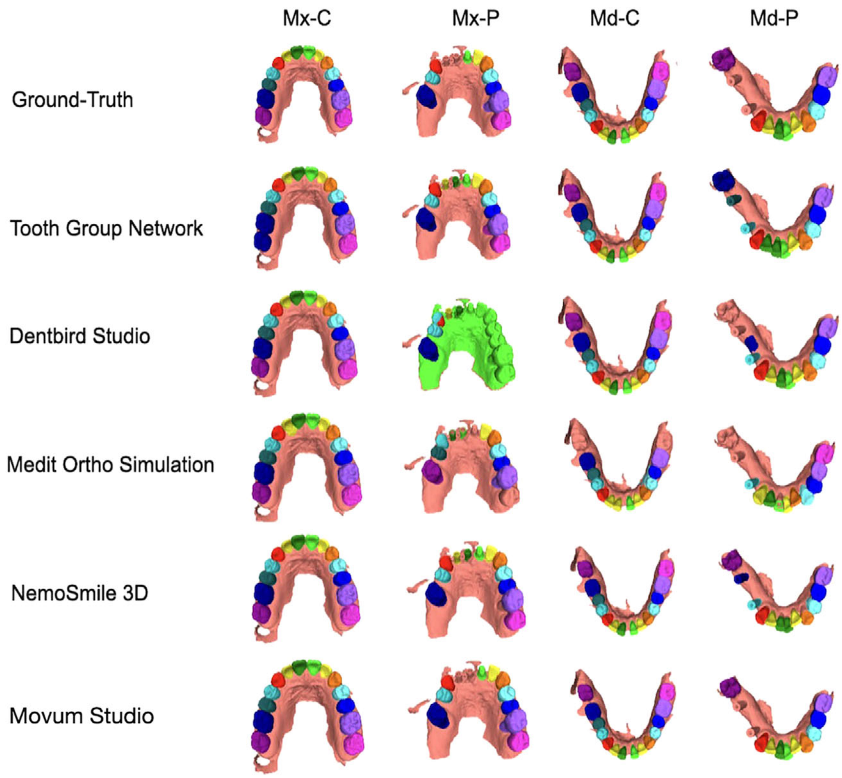


FIGURE 3 Representative results of tooth segmentations for each software program, algorithm, and group. Rows correspond to software program and algorithms. Columns correspond to groups.

and

$$\text{dice} = \frac{1}{C} \sum_{i=1}^{c} \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}},$$

where TP, TN, F, and FN are true positive, true negative, false positive, and false negative, respectively, and where C refers to the number of classes (teeth and gingiva) present in each scan (Figure 4a–e).

Once the performance metrics for each segmentation were calculated, two statistical analyses were conducted for each metric using permutation tests. The first analysis assessed whether there were significant performance differences between pairs of algorithms (10 pairwise repeated-measures comparisons). The second analysis evaluated whether performance differed significantly between the C and P groups for each software (four independent sample comparisons). In the first case, the test statistic was the median of paired differences, whereas in the second case, it was the difference in medians. All hypothesis tests were conducted with 10,000 permutations. The null hypothesis stated that both samples originated from the same population, while the alternative suggested they came from different populations. The median was preferred over the mean due to its robustness to outliers (especially failed segmentations) and its suitability under heteroscedasticity. For the first analysis, a Bonferroni–Holm correction was applied to adjust for multiple comparisons. A significance level of 0.05 was used in all tests.[55,56]

Finally, an additional analysis was performed to evaluate whether the IoU—the most representative metric of medical image segmentation—of the best performing algorithm was comparable to that of a human expert annotator. A subset of 12 intraoral scans from the initial dataset (3 Mx-C, 3 Md-C, 3 Mx-P, and 3 Md-P) was randomly selected and re-annotated by a second human expert (C.O.M.). A pairwise permutation test identical to that described in the first analysis was then applied to compare the segmentations produced by the best performing algorithm and the second human annotator.

All statistical analysis calculations were performed using the proprietary Python software code (Python v3.8, Python Software Foundation).[26–29]

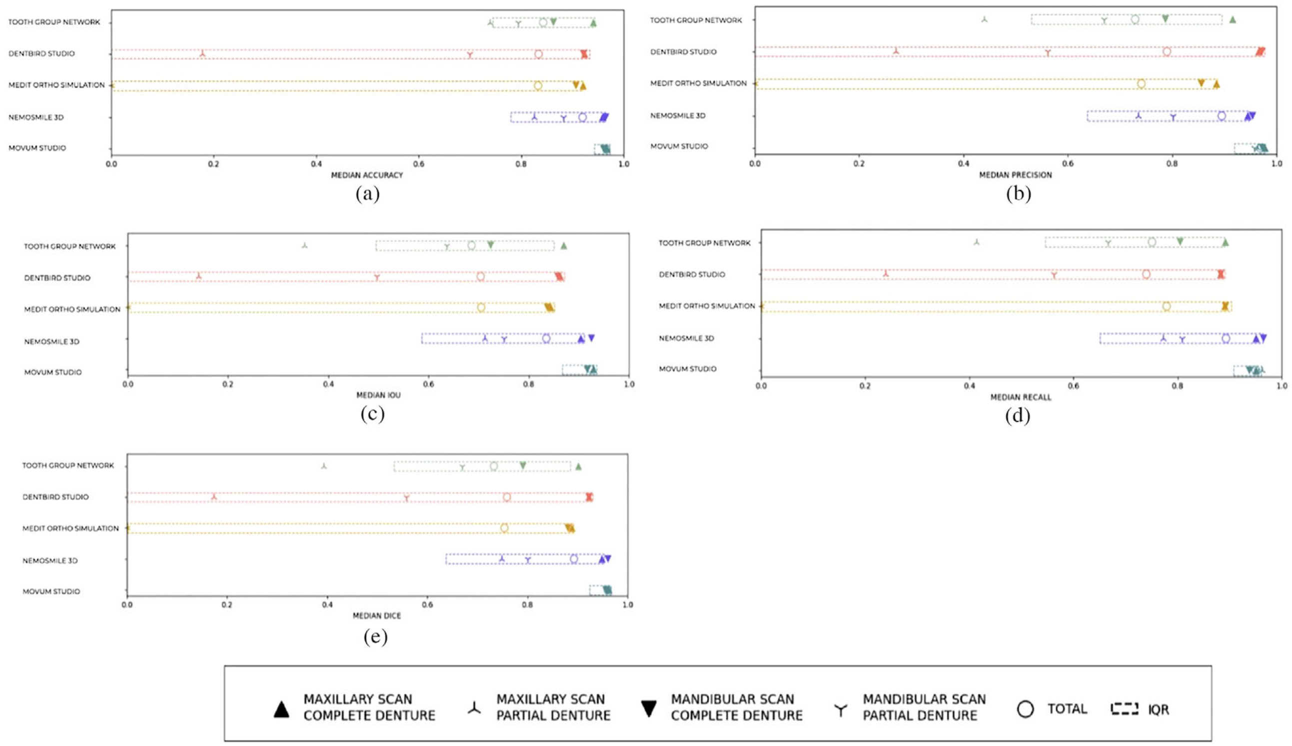


FIGURE 4 Median performance for each software program and subset. (a) Accuracy. (b) Precision. (c) IoU. (d) Recall. (e) Dice Score. *X*-axis: CSS. *Y*-axis: Software.

TABLE 3 Median performance of AI-based tooth segmentation algorithms.

Algorithm	Successful segmentations	IoU [IQR]	Accuracy [IQR]	Precision [IQR]	Recall [IQR]	Dice [IQR]
Tooth Group Network	100/100	0.686 [0.495–0.85]	0.843 [0.744–0.944]	0.729 [0.53–0.895]	0.751 [0.546–0.89]	0.733 [0.533–0.886]
Dentbird Studio	74/100	0.704 [0–0.871]	0.834 [0–0.934]	0.79 [0–0.977]	0.74 [0–0.891]	0.759 [0–0.93]
Medit Ortho Simulation	64/100	0.705 [0–0.851]	0.833 [0–0.92]	0.741 [0–0.886]	0.779 [0–0.903]	0.754 [0–0.892]
NemoSmile 3D	82/100	0.835 [0.586–0.911]	0.92 [0.78–0.965]	0.895 [0.637–0.948]	0.893 [0.651–0.964]	0.893 [0.637–0.953]
Movum Studio	100/100	0.925 [0.867–0.936]	0.966 [0.943–0.973]	0.969 [0.919–0.977]	0.95 [0.908–0.961]	0.96 [0.924–0.967]

RESULTS

The overall median performance of each algorithm is summarized in Table 3. The MovumStudio algorithm consistently outperformed all others across all measured metrics, achieving the highest median values for accuracy (0.966 [IQR: 0.943–0.973]), precision (0.969 [IQR: 0.919–0.977]), IoU (0.925 [IQR: 0.867–0.936]), recall (0.950 [IQR: 0.908–0.961]), and dice score (0.960 [IQR: 0.924–0.967]). NemoSmile 3D had the second best performance, with median values of accuracy (0.920 [IQR: 0.780–0.965]), precision (0.895 [IQR: 0.637–0.948]), IoU (0.835 [IQR: 0.586–0.911]), recall (0.893 [IQR: 0.651–0.964]), and dice score (0.893 [IQR: 0.637–0.953]), followed by the Tooth Group Network, while Dentbird Studio and Medit Ortho Simulation exhibited lower performance and a significant number of unsuccessful segmentations.

Pairwise statistical analyses revealed significant differences in performance among algorithms (Table 4). MovumStudio demonstrated statistically significant superiority across all metrics ($p < 0.01$). Notable results included precision (median of difference [MoD] = 0.1634 compared with Medit Ortho Simulation) and IoU (MoD = 0.2079 compared with the Tooth Group Network). NemoSmile 3D outperformed the Tooth Group Network and Medit Ortho Simulation in precision (MoD = 0.0563 compared with Tooth Group Network, $p < 0.01$), IoU (MoD = 0.0622, $p < 0.01$), and dice score (MoD = 0.0703, $p < 0.01$). Dentbird Studio

TABLE 4 Pairwise comparisons of AI-based tooth segmentation algorithms for accuracy, precision, Intersection over Union (IoU), recall, and dice scores. Values expressed as median of differences (MoD).

Algorithm 1	Algorithm 2	IoU (MoD)	Accuracy (MoD)	Precision (MoD)	Recall (MoD)	Dice (MoD)
Dentbird Studio	Movum Studio	−0.1193**	−0.0832**	−0.0994**	−0.1156**	−0.1005**
Dentbird Studio	Medit Ortho Simulation	0.0003	0.0000	0.0488**	0.0000	0.0007
Dentbird Studio	NemoSmile 3D	−0.0353**	−0.0293**	0.0193	−0.0629**	−0.0206**
Dentbird Studio	Tooth Group Network	−0.0203	−0.0162	0.0097	−0.0274	−0.0111
Movum Studio	Medit Ortho Simulation	0.1598**	0.1156**	0.1634**	0.1389**	0.1464**
Movum Studio	NemoSmile 3D	0.0445**	0.0207**	0.0374**	0.0104	0.0249**
Movum Studio	Tooth Group Network	0.2079**	0.1078**	0.2084**	0.1564**	0.1843**
Medit Ortho Simulation	NemoSmile 3D	−0.0623**	−0.0481**	−0.0656**	−0.0597**	−0.0620**
Medit Ortho Simulation	Tooth Group Network	−0.0631**	−0.0455**	−0.0843**	−0.0457**	−0.0642**
NemoSmile 3D	Tooth Group Network	0.0622**	0.0308**	0.0563**	0.0713**	0.0703**

Note: Statistically significant differences are indicated by an asterisk (*).
Abbreviation: MoD, median of differences.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

performed comparably with the Tooth Group Network for complete dentitions, with no significant differences in IoU or dice score ($p > 0.05$). However, it demonstrated significantly lower robustness for partially edentulous arches, with reductions in accuracy (MoD = −0.0832, $p < 0.01$) and IoU (MoD = −0.1193, $p < 0.01$), compared with MovumStudio against NemoSmile 3D. Dentbird Studio showed lower precision (MoD = −0.0293, $p < 0.01$), IoU (MoD = −0.0353, $p < 0.01$), and dice score (MoD = −0.0206, $p < 0.01$). The Tooth Group Network was statistically outperformed by both NemoSmile 3D and MovumStudio. Median differences included lower precision (MoD = 0.0563, $P < 0.01$) and IoU (MoD = 0.0622, $p < 0.01$) compared with NemoSmile 3D and significant deficits in accuracy (MoD = −0.1078, $p < 0.01$), precision (MoD = −0.2084, $p < 0.01$), and dice score (MoD = −0.1843, $p < 0.01$) compared with MovumStudio.

Statistically significant differences in performance were observed between complete (C) and partially edentulous (P) dentition groups for all algorithms except MovumStudio (Table 5). MovumStudio showed no significant difference in accuracy between the C and P groups (DiM = −0.0001, $p > 0.05$). In contrast, Medit Ortho Simulation exhibited pronounced decreases in accuracy (DiM = 0.9148, $p < 0.001$), precision (DiM = 0.8815, $p < 0.001$), and dice score (DiM = 0.8846, $p < 0.001$). Dentbird Studio showed significant reductions in accuracy (DiM = 0.5679, $p < 0.001$), precision (DiM = 0.4581, $p < 0.001$), and IoU (DiM = 0.4831, $p < 0.001$). Tooth Group Network also displayed significant reductions in accuracy (DiM = 0.1528, $p < 0.001$), precision (DiM = 0.2942, $p < 0.001$), and dice score (DiM = 0.2912, $p < 0.001$). NemoSmile 3D exhibited a minor but statistically significant decrease in accuracy (DiM = 0.0860, $p < 0.01$), with corresponding reductions in precision (DiM = 0.1944, $p < 0.001$) and dice score (DiM = 0.1945, $p < 0.001$). For maxillary segmentations in the P group, MovumStudio achieved the highest accuracy at 0.967 (IQR: 0.933–0.982), followed by NemoSmile 3D (0.735 [IQR: 0.143–0.870]), Tooth Group Network (0.440 [IQR: 0.320–0.727]), Dentbird Studio (0.270 [IQR: 0–0.811]), and Medit Ortho Simulation (0.000 [IQR: 0–0.476]). For mandibular segmentations in the P group, MovumStudio again demonstrated the highest accuracy at 0.963 (IQR: 0.909–0.976), followed by NemoSmile 3D (0.802 [IQR: 0–0.908]), Tooth Group Network (0.669 [IQR: 0.530–0.743]), Dentbird Studio (0.561 [IQR: 0–0.790]), and Medit Ortho Simulation (0.000 [IQR: 0–0.489]).

Regarding the comparison between human and automatic segmentation, the second human annotator achieved a median IoU of 0.9312 [0.895–0.951] when compared with the main annotator (W.P.C.). The best-performing algorithm, MovumStudio, achieved a median IoU of 0.9221 [0.874–0.946] for the same subset of 12 intraoral scans, showing a performance comparable to that of the second human annotator. The pairwise permutation test, identical to that described in Table 4, yielded a Median of Differences (MoD) of 0.0004 and a p-value (rounded to four decimal places) of 1, indicating no statistically significant difference between the two.

TABLE 5 Differences in performance metrics (DiM) for AI-based tooth segmentation algorithms between complete and partially edentulous patients.

Algorithm	IoU (DiM)	Accuracy (DiM)	Precision (DiM)	Recall (DiM)	Dice (DiM)
Tooth Group Network	0.2809***	0.1528***	0.2942***	0.2553***	0.2912***
Dentbird Studio	0.4831***	0.5679***	0.4581***	0.4345***	0.5091***
Medit Ortho Simulation	0.8404***	0.9148***	0.8815***	0.8916***	0.8846***
NemoSmile 3D	0.1869***	0.0860**	0.1944***	0.1694***	0.1945***
MovumStudio	0.0032	−0.0001	0.0149***	−0.0109	0.0022

Note: Statistically significant differences are indicated by an asterisk (*)
Abbreviation: DiM, difference in medians.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

DISCUSSION

This study evaluated the performance of five AI algorithms for automated tooth segmentation on intraoral scans. Although there have been some prior studies on a limited number of participants,[39,40] the authors are unaware of a previous study that compared multiple AI algorithms for tooth segmentation under actual clinical conditions. It is important to note that this study does not consider the internal architecture of the analyzed algorithms, nor does it include any information regarding the data used for their training, as most of these systems are commercial and proprietary. Therefore, the evaluation is strictly limited to the performance of the algorithms on previously unseen real clinical data.

AI-powered software programs for automated tooth segmentation and labeling play a crucial role in digitally assisted dentistry, offering considerable time savings compared with the traditional manual methods commonly used in prosthodontic, orthodontic, and surgical treatments. Previous studies on tooth segmentation have indicated that AI-assisted techniques generally achieve higher accuracy than manual approaches.[27–40] However, accuracy can vary depending on the operator's expertise, with more experienced users often achieving better results. The findings from the present research demonstrated that the performance of AI-based tooth segmentation algorithms was significantly influenced by the number of teeth present in the intraoral scans and by the specific algorithm used. Based on the findings of this study, MovumStudio consistently outperformed all other algorithms across all metrics, demonstrating the highest level of performance in every tested scenario (Table 6). Consequently, the null hypothesis that no significant differences would be found among the tested algorithms and between the complete dentition and partially edentulous groups was rejected.

Average values for tooth segmentation performance have been reported to range from 0.813 to 0.98.[28,29,34,36,37] However, many of these studies lacked consistent metrics for performance evaluation, failed to differentiate between maxillary and mandibular arches, and did not take into consideration the number of teeth present in the arch. Moreover, most studies have not used actual clinical digital files for training, making comprehensive comparisons across studies challenging. The IoU metric has been widely considered the benchmark for evaluating semantic tooth segmentation because of its ability to provide a more precise assessment of segmentation quality. Unlike accuracy, which can be inflated by class imbalances, IoU focuses on the overlap between predicted and ground-truth regions, penalizing both false positives and false negatives, making IoU particularly valuable in clinical applications where spatial precision and boundary accuracy are essential. Additionally, IoU has been reported to be more robust in multiclass scenarios, such as distinguishing individual teeth, and better reflects performance across datasets with varying class distributions, offering a more reliable evaluation of segmentation algorithms.[59] Wang et al[28] reported an IoU of 92.2 ±3.8 for tooth segmentation in complete dentate intraoral scans and an IoU of 89.3 ±8.0 for partially edentulous patients using a convolutional neural network. Similarly, Vinayahalingam et al[29] achieved an average IoU score of 0.915 for tooth segmentation on intraoral scans. In the present investigation, the best average IoU was obtained by the MovumStudio algorithm, 0.929 [0.916–0.936]. For maxillary scans with a complete dentition, MovumStudio achieved an IoU of 0.929 [0.916–0.936], outperforming other algorithms, including NemoSmile 3D (0.904 [0.848–0.91]) and Tooth Group Network (0.87 [0.763–0.922]). In partially edentulous maxillary arches, MovumStudio's IoU remained stable at 0.928 [0.793–0.954], while other algorithms, including Dentbird Studio and Medit Ortho Simulation, exhibited significant declines, with IoUs of 0.142 [0–0.721] and 0 [0–0.461], respectively. This discrepancy highlights the limitations of less robust algorithms when processing complex or incomplete dentitions. For mandibular scans, similar trends were observed. MovumStudio achieved an IoU of 0.917 [0.874–0.927] in complete dentitions and maintained strong performance in partially edentulous arches (0.916 [0.802–0.937]). By contrast, NemoSmile 3D, the second-best performer, showed a moderate decline in IoU for partially edentulous mandibular arches (0.751 [0–0.815]). The poorer performance of Medit

TABLE 6 Median performance of AI-based tooth segmentation algorithms across maxillary and mandibular intraoral scans for complete and partially edentulous patients.

Algorithm	Successful segmentations	IoU [IQR]	Accuracy [IQR]	Precision [IQR]	Recall [IQR]	Dice [IQR]
Maxillary scan, completely dentate (*N* = 25)						
Tooth Group Network	25/25	0.87 [0.763–0.922]	0.941 [0.877–0.964]	0.916 [0.808–0.978]	0.892 [0.81–0.94]	0.902 [0.804–0.959]
Dentbird Studio	21/25	0.863 [0.776–0.901]	0.924 [0.867–0.949]	0.966 [0.851–0.987]	0.883 [0.791–0.916]	0.923 [0.819–0.948]
Medit Ortho Simulation	23/25	0.844 [0.78–0.895]	0.921 [0.882–0.955]	0.885 [0.827–0.926]	0.891 [0.847–0.957]	0.889 [0.837–0.943]
NemoSmile 3D	22/25	0.904 [0.848–0.91]	0.959 [0.936–0.968]	0.945 [0.886–0.949]	0.951 [0.923–0.964]	0.949 [0.891–0.952]
Movum Studio	25/25	0.929 [0.916–0.936]	0.968 [0.965–0.972]	0.978 [0.973–0.981]	0.951 [0.94–0.957]	0.963 [0.956–0.967]
Maxillary scan, partial dentition (*N* = 25)						
Tooth Group Network	25/25	0.352 [0.302–0.682]	0.739 [0.671–0.846]	0.44 [0.32–0.727]	0.414 [0.376–0.746]	0.393 [0.329–0.731]
Dentbird Studio	15/25	0.142 [0–0.721]	0.178 [0–0.835]	0.27 [0–0.811]	0.239 [0–0.751]	0.174 [0–0.777]
Medit Ortho Simulation	9/25	0 [0–0.461]	0 [0–0.773]	0 [0–0.476]	0 [0–0.484]	0 [0–0.48]
NemoSmile 3D	19/25	0.712 [0.109–0.831]	0.825 [0.745–0.916]	0.735 [0.143–0.87]	0.772 [0.109–0.873]	0.748 [0.124–0.872]
Movum Studio	25/25	0.928 [0.793–0.954]	0.967 [0.933–0.982]	0.964 [0.808–0.973]	0.963 [0.81–0.978]	0.962 [0.813–0.976]
Mandibular scan, completely dentate (*N* = 25)						
Tooth Group Network	25/25	0.724 [0.623–0.902]	0.863 [0.787–0.956]	0.787 [0.67–0.967]	0.805 [0.72–0.929]	0.791 [0.676–0.948]
Dentbird Studio	21/25	0.858 [0.69–0.894]	0.922 [0.815–0.941]	0.972 [0.758–0.984]	0.883 [0.714–0.91]	0.923 [0.734–0.944]
Medit Ortho Simulation	23/25	0.837 [0.715–0.908]	0.907 [0.849–0.947]	0.856 [0.746–0.943]	0.892 [0.781–0.954]	0.881 [0.764–0.951]
NemoSmile 3D	23/25	0.925 [0.86–0.931]	0.965 [0.926–0.972]	0.954 [0.903–0.959]	0.965 [0.921–0.971]	0.961 [0.896–0.964]
Movum Studio	25/25	0.917 [0.874–0.927]	0.961 [0.942–0.966]	0.973 [0.964–0.978]	0.938 [0.913–0.95]	0.957 [0.932–0.962]
Mandibular scan, partial dentition (*N* = 25)						
Tooth Group Network	25/25	0.636 [0.493–0.7]	0.794 [0.758–0.848]	0.669 [0.53–0.743]	0.666 [0.534–0.749]	0.669 [0.533–0.732]
Dentbird Studio	17/25	0.497 [0–0.746]	0.7 [0–0.904]	0.561 [0–0.79]	0.562 [0.0–0.756]	0.558 [0.0–0.772]
Medit Ortho Simulation	9/25	0 [0–0.454]	0 [0–0.65]	0 [0–0.489]	0 [0–0.514]	0 [0–0.501]
NemoSmile 3D	18/25	0.751 [0–0.815]	0.883 [0–0.914]	0.802 [0–0.908]	0.809 [0–0.889]	0.8 [0–0.895]
Movum Studio	25/25	0.916 [0.802–0.937]	0.963 [0.909–0.976]	0.957 [0.828–0.968]	0.952 [0.838–0.968]	0.956 [0.836–0.967]

Ortho Simulation and Dentbird Studio in both maxillary and mandibular partial dentition arches further emphasizes the challenges faced by these algorithms in processing complex dental configurations.

The findings suggest that the Nemotec and Tooth Group Network algorithms performed correctly in patients with a complete dentition but experienced a noticeable decline in performance when applied to partially edentulous patients. Additionally, Medit Ortho Simulation and Dentbird Studio encountered challenges in partially edentulous patients, particularly in the maxillary arch. These results emphasize the varying capabilities of AI algorithms and the critical importance of selecting the most suitable tools based on specific clinical needs and the complexity of individual patients. The differences in IoU across the tested AI algorithms can be attributed to variations in algorithm architecture, training datasets, and validation methodologies.

Finally, as the difference in median IoU between the manual segmentation performed by C.O.M. and that produced by MovumStudio was only 0.0004 and not statistically significant, intraoral AI segmentation technology appears to have reached a level of maturity suitable for routine clinical use.

Limitations of the present study include the sample size ($n = 25$ per subgroup; $N = 100$ in total), which may limit the statistical power and generalizability of the results, and the use of only one intraoral digital scanner. Larger datasets and the inclusion of scans acquired with different devices would be required to confirm the consistency of these findings across broader populations and scanning systems.

CONCLUSION

Based on the findings of this clinical study, significant differences were observed among the tested algorithms, highlighting variations in their ability to accurately segment and label teeth in intraoral scans. Partially edentulous arches exhibited significantly lower performance compared with complete dentate arches. Among the evaluated systems, the MovumStudio algorithm consistently achieved the highest scores across all performance metrics for tooth segmentation, demonstrating superior results in both maxillary and mandibular intraoral digital scans. Its performance was statistically comparable to that of a human expert annotator.

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CONFLICT OF INTEREST STATEMENT

The authors declare the following potential conflicts of interest related to the MovumTech algorithm evaluated in this study: G.C.S is a current employee of MovumTech. X.B.A holds equity or stock ownership in MovumTech. O.G.M serves on the Board membership and holds equity or stock ownership in MovumTech. J.G.A holds equity or stock ownership in MovumTech. W.P.C serves on the board membership and equity or stock ownership in MovumTech. C.O.M holds equity or stock ownership in MovumTech. All other authors declare no competing interests.

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