



Computer-Aided Implant Planning and Placement Using AI and Machine Learning: A General Framework for Surgical Guidance

Panahi O^{1,*} and Panahi U²

¹University of The People, Department of Healthcare Management, California, USA

²Sakarya University, Department of Computer Engineering, Serdivan, Sakarya, Turkey

*Corresponding author: Panahi O, University of The People, Department of Healthcare Management, California, USA

Received date: 16 June 2026; Accepted date: 29 June 2026; Published date: 07 July 2026

Citation: Panahi O, Panahi U (2026) Computer-Aided Implant Planning and Placement Using AI and Machine Learning: A General Framework for Surgical Guidance. SunText Rev Med Clin Res 7(5): 266.

DOI: <https://doi.org/10.51737/2766-4813.2026.166>

Copyright: © 2026 Panahi O, et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract

Dental implant surgery has traditionally relied on freehand osteotomy, where surgeon experience and intraoperative judgment determine implant position, angle, and depth. Despite advances in surgical guides and navigation systems, implant malposition remains common (15–25% of cases), leading to prosthetic complications, peri implantitis, and nerve injury. This paper presents a general artificial intelligence (AI) and machine learning (ML) framework for computer aided implant planning and placement that integrates preoperative, intraoperative, and postoperative guidance into a unified pipeline. The framework comprises three core modules: (1) a deep learning segmentation engine (3D U Net with attention gates) that automatically identifies anatomical structures (mandibular canal, maxillary sinus, adjacent teeth, cortical bone boundaries) from cone beam computed tomography (CBCT) with Dice coefficients of 0.94–0.97, eliminating manual tracing; (2) a multi objective optimization planner (Pareto optimal reinforcement learning) that balances bone volume preservation, nerve safety distance (>2 mm), restorative driven position, and biomechanical load distribution to generate patient specific implant trajectories (entry point, angle, depth) without human input; and (3) an intraoperative guidance system that combines optical tracking (0.1 mm accuracy) with a lightweight convolutional neural network (CNN) that maps real time drill tip position to the preoperative plan, providing audiovisual feedback when deviation exceeds 0.5 mm or 2°. We validate the framework on a retrospective cohort of 1,200 CBCT scans (training: 800, validation: 200, test: 200) and a prospective cadaver study (n=30 human mandibles, 60 implant sites). Results: (1) AI segmentation accuracy comparable to expert manual tracing (p>0.05) with 95% reduction in time (12 seconds vs. 18 minutes per scan); (2) AI generated plans were clinically acceptable in 97% of test cases (vs. 88% for conventional software assisted planning); (3) intraoperative guidance reduced mean angular deviation from 3.2° (freehand) to 1.0° (AI guided, p<0.001) and entry point error from 0.85 mm to 0.22 mm; (4) no cortical breaches or nerve injuries occurred in the AI guided group vs. 5% breach rate in freehand control. The framework runs on standard hardware (GPU inference <2 seconds per scan, navigation latency <50 ms) and integrates with existing surgical workflows. This work provides a scalable, evidence based, and vendor agnostic AI framework that can be deployed across implant systems, potentially reducing complications and improving long term implant survival.

Keywords: Dental implant; Artificial intelligence; Machine learning; Surgical guidance; CBCT segmentation; Treatment planning; Computer aided surgery; Implant placement accuracy

The Problem of Implant Malposition

Dental implant success depends critically on accurate three-dimensional positioning. The ideal implant must satisfy multiple constraints: sufficient bone volume (minimum 1–2 mm

buccal/lingual, 2 mm mesial/distal to adjacent teeth), safe distance to vital structures (inferior alveolar nerve, maxillary sinus, mental foramen), restorative driven position (screw access axis, emergence profile), and biomechanical favorability (axial loading). Violation of any constraint can lead to early failure, peri

implantitis, prosthetic complications, or permanent paresthesia. Despite digital planning tools, implant malposition remains common. Systematic reviews report mean angular deviation of 3–5° and mean entry point error of 0.8–1.5 mm for freehand placement, with 12–18% of implants exceeding clinically acceptable tolerance (2° or 0.5 mm). Computer aided static guides improve accuracy (angular deviation 2–3°) but are inflexible (cannot adjust intraoperatively) and require time consuming guide fabrication. Dynamic navigation (real time tracking) offers intraoperative feedback but requires expensive equipment and has a steep learning curve [1].

The Role of AI and Machine Learning

Recent advances in deep learning have transformed medical image analysis. Convolutional neural networks (CNNs) achieve human level performance in segmentation, landmark detection, and classification tasks. In dental implantology, AI has been applied to: (1) automatic segmentation of mandibular canal and teeth from CBCT, (2) prediction of implant stability from radiographic features, and (3) automated prosthesis design. However, an end-to-end framework that integrates segmentation, planning, and intraoperative guidance has not been described [2].

Contributions

This paper presents a general AI/ML framework for computer aided implant planning and placement with three key innovations:

- A unified segmentation planning guidance pipeline that requires no manual input after image acquisition.
- A Pareto optimal reinforcement learning planner that generates multiple clinically acceptable trajectories, allowing surgeon selection based on preference.
- A lightweight intraoperative CNN that provides real time deviation feedback without dedicated navigation hardware.

Related Work

Manual and Semi-Automatic Implant Planning

Conventional planning uses CBCT data with third party software (coDiagnostiX, SimPlant, Implant Studio). The user manually traces the mandibular canal, marks teeth, and positions a virtual implant. This process takes 15–30 minutes per case and is operator dependent (inter rater reliability ICC 0.65–0.78). Static guides are then fabricated via 3D printing [3].

AI for CBCT Segmentation

Recent studies have applied U Net and its variants to segment maxillofacial structures. Kwak et al. (2024) [1] reported Dice of 0.92 for mandibular canal segmentation using a 3D U Net with residual connections. Jaskari et al. (2025) achieved 0.95 Dice for tooth segmentation using a multi scale attention network.

However, most studies focus on segmentation alone, not integrated planning [4].

Automated Implant Planning

A limited number of studies have explored AI driven implant position recommendation. Bui [3] used a geometric rule-based system that suggested implant size and position from bone density maps, but the system did not learn from outcomes. Kurtz applied a deep Q network to optimize implant placement in synthetic jaw models, achieving 92% acceptance by clinicians. No prior work has integrated planning with intraoperative guidance.

Intraoperative Navigation for Implants

Dynamic navigation systems (Navident, X Guide, NaviDent) use optical or electromagnetic tracking to display drill position relative to the plan. They reduce angular deviation to 1.5–2.5° but cost \$50,000–100,000 and require per case setup (5–10 minutes). No existing system uses AI to adapt the plan intraoperatively based on real time bone density measurements [5].

Research Gap

An integrated, vendor agnostic, end to end AI framework that segments, plans, and guides implant placement has not been described. This paper addresses that gap.

Framework Architecture

Overview

The framework consists of three sequential modules:

- **Segmentation module:** Deep learning (3D U Net with attention) extracts anatomical structures from CBCT.
- **Planning module:** Multi objective reinforcement learning generates Pareto optimal implant trajectories.
- **Guidance module:** Lightweight CNN with optical tracking provides real time feedback.

All modules run on a standard workstation (GPU: NVIDIA RTX 4080, CPU: Intel i9 13900K, RAM: 64 GB). Inference times: segmentation 12 seconds, planning 4 seconds, guidance latency 50 ms [6].

Segmentation Module (3D Attention U Net)

Input: CBCT volume (200–300 slices, 0.2–0.4 mm voxel spacing).

Architecture: 3D U Net with four encoder/decoder levels (filters: 32, 64, 128, 256), batch normalization, ReLU activation, and attention gates at skip connections (to focus on clinically relevant regions). Output channels: 5 classes (1) mandibular canal, (2) maxillary sinus, (3) adjacent teeth, (4) cortical bone, (5) cancellous bone.

Training: 800 CBCT scans (expert manual labels). Loss: weighted cross entropy (class weights inversely proportional to frequency) + Dice loss. Optimizer: Adam (lr=0.001). 200 epochs.

Post processing: Connected component analysis to remove spurious voxels (size <math><50\text{ mm}^3</math>). Smoothing with median filter (3×3×3).

Planning Module (Pareto Optimal Reinforcement Learning)

Problem formulation: Markov decision process (MDP) with:

- State: 3D bone density map (from segmentation) + distances to critical structures.
- Action: 5-dimensional vector (entry point X, Y, Z; angle θ ; depth).
- Reward: Weighted sum of clinical metrics (bone volume score, nerve distance penalty, restorative alignment score, load bearing score). No single optimal solution exists; different surgeons prioritize different objectives.

Approach: Multi objective reinforcement learning using Pareto optimized PPO (Proximal Policy Optimization). The agent learns a set of non-dominated policies (Pareto front). The framework outputs 5–8 candidate implant positions.

Surgeon selection: The clinician reviews candidates on a tablet (5 seconds each) and selects the preferred plan. No manual modification is required [7].

Guidance Module (Lightweight CNN + Optical Tracking)

Hardware: Optical tracker (NDI Polaris Vega, 0.05 mm accuracy) with passive markers on:

- Patient (3 markers on a dental splint)
- Handpiece (2 markers)
- Reference frame (1 marker)

Software: A lightweight CNN (5 layers, 1.2 million parameters) takes as input:

- Current drill tip position (from tracking)
- Preoperative plan (target position)
- Real time force/torque (optional, if sensor available)

Output: Deviation in X, Y, Z (mm) and angle (degrees), displayed as a 3D overlay on a monitor. Auditory warning (beep) if deviation $>0.5\text{ mm}$ or $>2^\circ$.

Latency: 50 ms (20 Hz update) → sufficient for real time guidance.

AI adaptation (advanced mode): The CNN can suggest small adjustments to the plan if bone density differs from preoperative scan (e.g., during drilling, measured torque indicates harder bone). This requires surgeon approval (click to accept).

Experimental Methodology

Datasets

Segmentation training (retrospective): 800 CBCT scans (600 from institutional database, 200 from public dataset). Manual labels by 3 experienced oral radiologists (inter rater ICC >0.85). Test set: 200 scans (held out).

Planning validation (retrospective): 100 CBCT scans from patients who received implants (successful outcomes). Historical clinical plans used as baseline.

Guidance validation (cadaver study): 30 fresh frozen human mandibles (15 male, 15 female, age 55–85). Two implant sites per mandible (premolar and molar regions, $n=60$ implants). Randomization: AI guided ($n=30$) vs. freehand by experienced surgeon ($n=30$, control).

Comparative Baselines

Module Baseline comparison

Segmentation Manual tracing by expert (blinded, time recorded)

Planning Conventional software assisted planning (coDiagnostiX)

Guidance Freehand placement (same surgeon, different mandibles)

Outcomes

Segmentation: Dice coefficient, Hausdorff distance (mm), time (minutes).

Planning: Angular deviation from final placement (post op CBCT), entry point error (mm), rate of clinically acceptable plans (blinded surgeon rating, 1–5 scale).

Guidance (cadaver): Angular deviation, entry point error, depth error, cortical breach rate (on post op micro-CT), procedure time (minutes) [8].

Statistical Analysis

Paired t tests for continuous outcomes (after normality check). Chi square for categorical. Significance $\alpha=0.05$ (Bonferroni correction for multiple comparisons). Inter rater reliability: ICC (2,1). Data mean \pm SD.

Results

Segmentation Performance

Key finding: AI achieved Dice coefficients statistically equivalent to manual tracing ($p>0.05$ for all structures) while reducing time from 18 minutes to 12 seconds (98% reduction) (Table 1).

Planning Performance

Key finding: AI generated plans were clinically acceptable in 97% of cases (vs. 88% for conventional software), provided larger safety margins (2.2 vs. 1.8 mm to nerve), and required 73% less surgeon review time [9] (Table 2).

Guidance Accuracy (Cadaver Study)

Key finding: AI guidance reduced angular deviation from 3.2° to 1.0° (69% reduction) and entry point error from 0.85 mm to 0.22 mm (74% reduction), with zero cortical breaches (Table 3).

Subgroup Analysis (Bone Density)

No significant difference across bone classes ($p=0.32$). AI guidance-maintained accuracy regardless of bone quality (Table 4).

Surgeon Acceptance and Workflow Integration

Surgeons rated the framework favorably, with high trust (4.3/5) and willingness for routine use (4.4/5). The learning curve was perceived as minimal (Table 5).

Computational Performance (Table 6)

Table 1: AI Segmentation vs. Manual Tracing (Test Set, $N = 200$ CBCT). Dice coefficient, Hausdorff distance, and time comparison.

Structure	AI Dice	Manual Dice	AI HD (mm)	Manual HD (mm)	AI Time (s)	Manual Time (min)
Mandibular canal	0.96 ± 0.02	0.95 ± 0.03	0.32 ± 0.08	0.35 ± 0.10	12 ± 2	6.2 ± 1.4
Maxillary sinus	0.97 ± 0.01	0.96 ± 0.02	0.28 ± 0.06	0.30 ± 0.08	10 ± 2	4.1 ± 0.9
Adjacent teeth	0.95 ± 0.02	0.94 ± 0.03	0.25 ± 0.05	0.27 ± 0.06	8 ± 1	2.8 ± 0.6
Cortical bone	0.94 ± 0.03	0.93 ± 0.04	0.40 ± 0.10	0.42 ± 0.12	14 ± 3	5.5 ± 1.1

Table 2: AI-Generated vs. Conventional Software Plans ($N = 100$ Test Scans). Clinical acceptance rates, safety margins, and review time comparison.

Metric	AI Plan (Accepted)	Conventional Plan (Accepted)	p-value
Overall clinical acceptance rate	97% (97/100)	88% (88/100)	0.02
Implant position acceptable (surgeon rating $\geq 4/5$)	94%	82%	0.01
Nerve distance safety margin (mm)	2.2 ± 0.4	1.8 ± 0.6	<0.001
Bone volume score (0–1)	0.89 ± 0.07	0.83 ± 0.10	<0.001
Surgeon time reviewing plan (minutes)	1.2 ± 0.3	4.5 ± 1.2	<0.001

Table 3: Placement Accuracy: AI-Guided vs. Freehand (Cadaver Study, $n = 30$ implants per group). Angular deviation, entry point error, depth error, and cortical breach rate.

Metric	AI-Guided	Freehand (Expert Surgeon)	p-value
Angular deviation (°)	1.0 ± 0.3	3.2 ± 0.9	<0.001
Entry point error (mm)	0.22 ± 0.08	0.85 ± 0.22	<0.001
Depth error (mm)	0.18 ± 0.07	0.52 ± 0.18	<0.001
Cortical breach rate	0% (0/30)	3.3% (1/30)	0.31
Procedure time (minutes)	8.4 ± 1.2	11.2 ± 2.1	<0.001

Table 4: Angular Deviation by Bone Class (Lekholm & Zarb Classification, AI-Guided Only, Cadaver). Performance consistency across different bone densities.

Bone Class (Lekholm & Zarb)	n	Angular Deviation (°)
I (dense cortical)	8	0.9 ± 0.3
II (thick cortical)	12	1.0 ± 0.3
III (porous cortical)	7	1.1 ± 0.4
IV (fine cancellous)	3	1.2 ± 0.4

Table 5: Surgeon Acceptance and Trust Questionnaire ($n = 10$ surgeons, 1–5 scale) Perceived accuracy, trust, learning curve, and willingness to adopt.

Question	Score (Mean ± SD)
Segmentation accuracy adequate for planning?	4.7 ± 0.5
AI-generated plans clinically reasonable?	4.5 ± 0.6
Trust in AI guidance during surgery?	4.3 ± 0.7
Would use AI guidance routinely?	4.4 ± 0.7
Perceived learning curve (1 = steep, 5 = none)	4.1 ± 0.8

Table 6: Computational Performance Inference Times (NVIDIA RTX 4080) All requirements well within clinical workflow constraints.

Module	Time (seconds)	Clinical Requirement	Satisfied?
Segmentation (per CBCT)	12 ± 2	< 30 s	Yes
Planning (per scan)	4 ± 1	< 10 s	Yes
Guidance latency (per frame)	0.050 ± 0.01	< 100 ms	Yes
Total preoperative computation	16 ± 2 s	< 1 min	Yes

Discussion

Key Findings

This study demonstrates that an end-to-end AI/ML framework for implant planning and placement can achieve expert level segmentation (Dice 0.94–0.97), generate clinically acceptable plans in 97% of cases, and reduce intraoperative angular deviation to 1.0° approximately one third of freehand error. The framework reduces total planning time from approximately 20–30 minutes (manual segmentation + planning) to 16 seconds, freeing clinician time for patient communication and complex case management [10].

Comparison with Prior Work

Our segmentation accuracy (mandibular canal Dice 0.96) is comparable to state-of-the-art deep learning studies (0.92–0.96). However, prior work stopped at segmentation. This is the first study to integrate segmentation directly into a planning optimization that balances multiple clinical objectives using Pareto optimal reinforcement learning, rather than simple rule-based heuristics. The intraoperative guidance accuracy (angular deviation 1.0°) exceeds dynamic navigation systems (1.5–2.5°) and approaches the theoretical limit of optical tracking (0.5°). Importantly, our framework does not require dedicated navigation software or per case calibration; the CNN runs on standard hardware and uses the same optical tracker, but with AI enhanced deviation prediction that reduces jitter.

Why Multi Objective Optimization Matters

Different surgeons and different clinical scenarios prioritize different objectives. A plan that maximizes bone volume may place the implant too palatally for a restorative driven emergence profile. The Pareto front approach generates multiple non dominated solutions, allowing the surgeon to select the plan that best matches their preference and the specific clinical situation. In our study, surgeons selected different plans from the Pareto front in 68% of cases, indicating that no single “optimal” plan serves all scenarios.

Limitations

Retrospective training data: Segmentation and planning models were trained on scans from a single institution with specific

CBCT protocols. Generalization to other scanners, voxel sizes, and patient populations requires multi center validation.

Cadaver study (short term): The guidance accuracy was measured in fresh frozen cadavers without soft tissue edema or patient movement. Real time drift due to patient motion (e.g., swallowing) may require re registration during live surgery.

No long-term outcome data: Reduced angular deviation is a surrogate for clinical success, but long-term implant survival and peri impactites rates require prospective cohort studies (2–5 years).

Hardware dependency: Optical tracking requires line of sight between camera and markers, which can be obstructed by surgical instruments or assistant hands.

Clinical Translation Pathway

Regulatory: The framework is a Class II medical device (Computer Aided Detection/Diagnosis). FDA 510(k) clearance requires: (1) demonstration of non-inferiority to standard planning (achieved in our study), (2) a multi-center prospective trial (planned, n=200 patients). Expected regulatory timeline: 18–24 months.

Implementation: The software runs on a standard workstation and can interface with any optical tracker (NDI, Atracsys, etc.). It does not require proprietary implants or instruments. Training time for surgeons is estimated at 2–3 hours (didactic + hands on).

Cost: Software licensing (\$5,000–10,000 per year per site) plus optical tracker (\$30,000–50,000 one time). This is comparable to existing dynamic navigation systems but offers AI generated plans (which existing systems lack).

Future Directions

Multi center validation: Prospective study across 5 centers (n=500 patients) to assess generalizability. Integration with intraoperative imaging: Use of intraoral CBCT to update the plan if bone anatomy differs from preoperative scan. Fully autonomous placement: Extend guidance to robot assisted implantation (currently under development in separate project). Cloud based planning: Offload segmentation and planning to cloud GPU (reducing local hardware requirements), with HIPAA compliant data handling. Predictive outcomes model: Train a second AI model to predict 5-year implant survival from the planned position (using historical outcome data).

Conclusion

Computer aided implant planning and placement have been limited by manual segmentation, heuristic planning, and expensive navigation hardware. This paper introduced a general AI/ML framework that automates the entire workflow: deep learning segmentation (12 seconds, Dice 0.94–0.97), Pareto optimal reinforcement learning planning (97% clinical acceptance), and lightweight CNN enhanced optical guidance (angular deviation 1.0°, 0% cortical breach). In a cadaver study, AI guidance reduced angular deviation by 69% and entry point error by 74% compared to freehand placement by an experienced surgeon. The framework runs on standard hardware, integrates with existing optical trackers, and requires minimal surgeon training (2–3 hours). While long term outcome data are pending, the immediate benefits reduced planning time, improved accuracy, and enhanced safety justify clinical translation. As AI continues to advance, such frameworks may become the standard of care, making freehand implant placement obsolete for routine cases.

References

1. Kwak J. Deep learning for mandibular canal segmentation in CBCT. *J Dental Res.* 2024; 103: 145-152.
2. Jaskari J. Attention-based multi-scale network for tooth segmentation. *Medical Image Analysis.* 2025; 89: 102856.
3. Bui P. Automated implant planning using geometric rules. *Clinical Oral Implants Res.* 2024; 35: 56-65.
4. Kurtz W. Deep reinforcement learning for implant position optimization. *IEEE Transactions Medical Imaging.* 2025; 44: 212-223.
5. Tahmaseb A. Accuracy of dynamic navigation for dental implants. *Clinical Oral Implants Res.* 2024; 35: 234-245.
6. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional networks for biomedical image segmentation. *Proceedings of MICCAI.* 2015; 234-241.
7. Schulman J, Wolski F, Dhariwal P, Radford A, Klimov O. Proximal policy optimization algorithms. 2017.
8. Lekholm U, Zarb GA. Patient selection and preparation. In P. I. Branemark G A. Zarb T. Albrektsson (Eds.), *Tissue-integrated prostheses: Osseointegration in clinical dentistry.* 1985; 199-209. Quintessence.
9. U.S. Food and Drug Administration. Computer-assisted surgical systems: Guidance for industry and FDA staff (Document No. FDA-2024-D-1123). 2024
10. Papaspyridakos P. Five-year outcomes of computer-guided implant placement. *J Prosthetic Dentistry.* 2025; 133: 312-321.