



Application of Machine Learning and Computer Vision in Oral Surgery and Implant Outcome Prediction

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Abstract

Oral surgery and dental implantology have traditionally relied on surgeon experience, two-dimensional radiographs, and clinical judgment to predict treatment outcomes. However, postoperative complications including implant failure, peri implantitis, nerve injury, and poor esthetics remain common, with failure rates of 5–10% over 10 years. Machine learning (ML) and computer vision (CV) offer transformative potential to shift from experience based to data driven, personalized outcome prediction. This paper provides a comprehensive review and proof of concept framework for applying ML/CV to three critical tasks in oral surgery: (1) preoperative risk stratification – predicting patient specific implant survival probability using tabular data (age, smoking, bone density, medical history) with ensemble methods (random forest, XGBoost) achieving AUC of 0.89–0.94; (2) surgical computer vision guidance – real time segmentation of anatomical structures (mandibular canal, maxillary sinus, tooth roots) from intraoperative video using a lightweight U Net (10 ms inference, 0.94 Dice), enabling augmented reality overlay of high risk zones; and (3) postoperative outcome forecasting – predicting 5 year marginal bone loss and peri implantitis risk from preoperative CBCT and intraoperative force/torque data using a hybrid CNN LSTM architecture (mean absolute error 0.28 mm for bone loss, AUC 0.91 for peri implantitis). We validate each component on retrospective clinical datasets: (1) 2,500 implant cases with 5 years follow up (failure rate 7.2%); (2) 500 intraoperative video segments (100 seconds each) from 50 implant surgeries; (3) 1,200 implants with complete preoperative, intraoperative, and 5-year postoperative data. Results demonstrate that ML/CV can outperform standard clinical indices (e.g., implant stability quotient, ISQ) in predicting failure (AUC 0.92 vs. 0.71, $p < 0.001$). Furthermore, a combined model integrating all three modalities achieves AUC of 0.96 for 5-year implant survival. We discuss deployment considerations (edge computing for real time CV, HIPAA compliant cloud training), limitations (dataset bias, need for prospective validation), and future directions (federated learning across centers, integration with electronic health records). This work establishes that ML and computer vision are not futuristic concepts but clinically deployable tools that can improve preoperative counseling, intraoperative safety, and long-term implant prognosis.

Keywords: Machine learning, computer vision, oral surgery, dental implant, outcome prediction, deep learning, surgical guidance, risk stratification

Introduction

The Challenge of Outcome Prediction in Oral Surgery

Dental implant placement is one of the most common surgical procedures worldwide, with over 5 million implants placed annually in the United States alone. While overall survival rates exceed 90–95% at 10 years, individual patient risk varies dramatically. Early implant loss (within 1 year) affects 2–5% of

cases, while late losses from peri implantitis affect 10–20% of patients over 10–15 years. Other complications include nerve injury (0.5–3% for mandibular implants), sinus perforation (2–10% for maxillary posterior implants), and esthetic failures (5–15% in the anterior maxilla). Current clinical prediction relies on surrogate markers: implant stability quotient (ISQ) measured at placement (correlates poorly with long term survival, $R^2 = 0.31$), bone density classification (Lekholm & Zarb, subjective), and patient factors

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(smoking, diabetes) assessed dichotomously (present/absent) rather than as continuous risk scores. The result is imprecise counseling: a surgeon cannot tell a patient their specific 5-year failure probability, only a population average estimate [1].

Machine Learning and Computer Vision: A Paradigm Shift

Machine learning excels at discovering nonlinear, multivariate relationships that are invisible to human clinicians. Computer vision enables real time analysis of surgical video or radiographic images. Together, they offer:

- Preoperative risk calculators that integrate dozens of patient specific features into a single probability score.
- Intraoperative guidance that highlights anatomical hazards in real time, reducing cognitive load.
- Postoperative forecasting that predicts long term outcomes from early data, enabling early intervention.

Contributions

This paper provides

- A systematic evaluation of ML models for implant survival prediction using a large retrospective cohort (N=2,500).
- A proof of concept CV system for real time segmentation of high-risk anatomy from surgical video.
- A hybrid CNN LSTM model for forecasting 5-year marginal bone loss and peri implantitis.
- Clinical deployment recommendations and identification of key barriers.

Paper Organization

Section 2 reviews prior ML/CV applications in oral surgery. Section 3 describes datasets and methods. Section 4 presents results. Section 5 discusses limitations and deployment. Section 6 concludes.

Related Work

Machine Learning for Implant Outcome Prediction

Prior studies have used logistic regression, random forests, and support vector machines to predict implant failure. Papaspyridakos et al. (2024) reported AUC of 0.82 using patient demographics and bone quality. Alarifi et al. (2025) used XGBoost on 1,800 implants, achieving AUC 0.88. However, these models used only preoperative tabular data; none incorporated intraoperative sensor data (torque, ISQ) or postoperative imaging [2].

Computer Vision in Oral Surgery

CV has been applied to segment mandibular canal (Dice 0.92–0.96) and teeth (Dice 0.94–0.97) from CBCT. Real time intraoperative segmentation from endoscopic or surgical microscope video is more challenging due to lighting variations, blood, and motion artifacts. A 2024 study by Kim et al. reported 0.88 Dice for mandibular canal segmentation from surgical video, but latency was 200 ms (too slow for real time guidance).

Hybrid Models for Longitudinal Prediction

Long short-term memory (LSTM) networks have been used to model time series medical data. No prior study has combined CNN extracted features from CBCT with LSTM processed intraoperative time series to predict long term implant outcomes.

Research Gap

An integrated framework that combines preoperative ML risk stratification, intraoperative CV guidance, and postoperative outcome forecasting has not been described. This paper provides the first such end-to-end proof of concept.

Materials and Methods

Datasets

Dataset 1 (Preoperative risk stratification): 2,500 implants placed in 1,800 patients (2015–2020) at a single academic center. Inclusion: single or partial edentulism, ≥ 18 years, minimum 5 year follow up (or failure before 5 years). Variables (32 features): demographics (age, sex, BMI), medical history (smoking, diabetes, osteoporosis, bisphosphonates), local factors (bone density class, site, implant dimensions), surgical factors (surgeon experience, flapped vs. flapless, ISQ at placement). Outcome: implant failure (loss of osseointegration, explantation) within 5 years (7.2% failure rate).

Dataset 2 (Computer vision): 500 intraoperative video segments (each 100 seconds, 30 fps, 1080p) from 50 implant surgeries. Frames manually annotated for: mandibular canal, mental foramen, tooth roots, sinus floor (n=15,000 annotated frames). Train/validation/test: 70/15/15%.

Dataset 3 (Postoperative forecasting): 1,200 implants with complete data: preoperative CBCT (segmented), intraoperative time series (ISQ, insertion torque, drilling force), and 5 years follow up (marginal bone loss from serial radiographs, peri implantitis diagnosis per 2018 classification). Outcomes: 5-year marginal bone loss (mm, continuous) and peri implantitis (binary).

Preoperative Risk Stratification Models

We compared five ML algorithms:

Model Description

Logistic regression Baseline linear model

Random forest (RF) 500 trees, max depth 10
 XGBoost 100 estimators, learning rate 0.1
 Support vector machine (SVM) RBF kernel
 Neural network (NN) 3 hidden layers (64, 32, 16), dropout 0.3
 Training: 5-fold cross validation (patient level splitting, no data leakage). Hyperparameter tuning via grid search.
 Outcome: 5-year implant failure. Metrics: AUC, sensitivity, specificity, Brier score (calibration).

Computer Vision Model (Real Time Segmentation)

Architecture: Lightweight U Net with MobileNetV3 encoder (pre trained on ImageNet, fine-tuned). Output: 4 classes (background, mandibular canal, tooth roots, sinus). Input: single RGB frame (640×480, resized to 256×256). Loss: Dice + focal loss ($\alpha=0.25$, $\gamma=2$) [3].
 Optimization: Quantization to int8 (TensorFlow Lite). Target latency: <50 ms on edge device (NVIDIA Jetson Orin Nano).
 Metrics: Dice coefficient, pixel accuracy, inference time.
 Augmentation: Random brightness ($\pm 30\%$), contrast ($\pm 20\%$), rotation ($\pm 10^\circ$), elastic deformation (to simulate tissue manipulation).

Table 1: ML Model Performance for 5-Year Implant Failure Prediction (N = 2,500 implants); Metrics reported: AUC, sensitivity, specificity, Brier score, and calibration slope.

Model	AUC	Sensitivity	Specificity	Brier Score	Calibration Slope
Logistic Regression	0.76 ± 0.03	0.68	0.71	0.18	0.92
Random Forest	0.89 ± 0.02	0.82	0.84	0.12	0.95
XGBoost	0.91 ± 0.02	0.85	0.86	0.10	0.97
SVM (RBF)	0.79 ± 0.03	0.72	0.74	0.16	0.88
Neural Network	0.90 ± 0.02	0.84	0.85	0.11	0.96

Table 2: Top Feature Importance (XGBoost, Mean SHAP Value); Most predictive features for 5-year implant failure (N = 2,500 implants).

Rank	Feature	SHAP Value	Direction (Higher Risk)
1	Bone density class (D1–D4)	0.32	D4 (soft bone) → highest risk
2	Smoking (pack-years)	0.28	Positive correlation with failure
3	ISQ at placement	0.25	Lower ISQ → higher failure risk
4	Insertion torque (Ncm)	0.22	<15 Ncm → high risk
5	Diabetes (HbA1c)	0.20	>7.5% → higher risk
6	Implant length (mm)	0.18	<10 mm → higher risk
7	Surgeon experience (years)	0.15	<5 years → higher risk
8	Osteoporosis (yes/no)	0.14	Yes → higher risk

Table 3: Real-Time Segmentation Performance (Intraoperative Video); Metrics reported: Dice coefficient, pixel accuracy, and inference time.

Structure	Dice Coefficient	Pixel Accuracy	Inference Time (ms)
Mandibular canal	0.92 ± 0.04	0.96 ± 0.02	12 ± 3
Mental foramen	0.88 ± 0.05	0.94 ± 0.03	12 ± 3
Tooth roots	0.94 ± 0.03	0.97 ± 0.02	12 ± 3
Maxillary sinus floor	0.93 ± 0.03	0.96 ± 0.02	12 ± 3
Mean (all structures)	0.92	0.96	12

Table 4: Comparison with Prior Work (Computer Vision for Surgical Guidance) Mandibular canal segmentation performance comparison.

Study	Structure	Dice	Latency (ms)	Hardware
Kim et al. (2024)	Mandibular canal	0.88	200	Desktop GPU
Proposed	Mandibular canal	0.92	12	Edge (Jetson)

Table 5: 5-Year Outcome Prediction Performance (N = 1,200 implants) Metrics reported: Marginal bone loss MAE and peri-implantitis AUC, with calibration measured by Brier score.

Model	Marginal Bone Loss MAE (mm)	Peri-implantitis AUC	Calibration (Brier)
ISQ only (baseline)	0.62 ± 0.08	0.71 ± 0.04	0.22
Preop tabular only	0.48 ± 0.06	0.82 ± 0.03	0.16
Intraoperative only (LSTM)	0.44 ± 0.05	0.85 ± 0.03	0.14
CBCT only (CNN)	0.41 ± 0.05	0.84 ± 0.03	0.13
Hybrid CNN-LSTM (proposed)	0.28 ± 0.04	0.91 ± 0.02	0.08

Table 6: CNN-LSTM Ablation Study Contribution of each modality to prediction performance.

Model Variant	Bone Loss MAE	Peri-implantitis AUC
Full hybrid model	0.28	0.91
- CBCT features (tabular + LSTM only)	0.38	0.86
- LSTM (CNN + tabular only)	0.36	0.87
- Tabular (CNN + LSTM only)	0.32	0.89
- Both CBCT and LSTM (tabular only)	0.48	0.82

Table 7: Clinical Utility – Net Reclassification Improvement ML reclassification compared to ISQ alone.

Risk Category (by ISQ)	N	Actual Failures	ML-Predicted High-Risk (Reclassified)	Net Reclassification Improvement
Low risk (ISQ > 70)	850	12 (1.4%)	8 (0.9%) reclassified to high risk	+0.12 (p < 0.001)
Medium risk (ISQ 60–70)	900	45 (5.0%)	68 (7.6%) reclassified to high risk	+0.18 (p < 0.001)
High risk (ISQ < 60)	750	123 (16.4%)	12 (1.6%) reclassified to low risk	+0.09 (p = 0.03)

Table 8: Computational Requirements for Clinical Deployment Hardware, inference time, memory, and storage requirements.

Module	Hardware	Inference Time	Memory (RAM)	Storage
Preoperative XGBoost	CPU (any)	0.2 s	128 MB	50 MB
Intraoperative CV (U-Net)	NVIDIA Jetson Orin	12 ms	2 GB	500 MB
CNN-LSTM Forecasting	GPU (RTX 3060)	0.5 s (offline)	4 GB	2 GB
Total (real-time guidance)	Edge device	< 50 ms	2.5 GB	600 MB

Postoperative Outcome Forecasting (CNN LSTM)

Architecture

- CNN branch: 3D CNN (3 conv layers) extracts spatial features from CBCT (mandibular canal proximity, bone density map). Output: 128 dim vectors.
- LSTM branch: 2-layer LSTM (64 units) processes intraoperative time series (ISQ, torque, force) over 100 time points (1 Hz). Output: 64 dim vectors.
- Fusion: Concatenate CNN + LSTM outputs → 2 dense layers (64, 32) → two outputs: (1) marginal bone loss (linear regression), (2) peri implantitis probability (sigmoid) [4].

Training: Multi task loss = MSE (bone loss) + binary cross entropy (peri implantitis). Adam optimizer, lr=0.001, batch size=32, early stopping.

Statistical Analysis

AUC compared using DeLong’s test. Calibration assessed via Hosmer Lemeshow test. Significance $\alpha=0.05$ (adjusted for multiple comparisons where noted). All analyses in Python (scikit learn, TensorFlow, PyTorch) [5].

Results

Preoperative Risk Stratification

Key finding: XGBoost achieved highest AUC (0.91), significantly outperforming logistic regression (p<0.001) and ISQ (AUC 0.71, p<0.001). Calibration was excellent (slope 0.97) (Table 1) (Table 2).

Computer Vision Guidance

Key finding: The lightweight U Net achieved 0.92 mean Dice at 12 ms inference (83 Hz), exceeding the real time requirement (>30 Hz). Quantization to int8 preserved accuracy (0.91 Dice, 0.02 drop) [6] (Table 3).

Comparison with Prior Work

Our model is 16× faster with higher accuracy, enabling true real time guidance (Table 4).

Postoperative Outcome Forecasting

Key finding: The hybrid CNN LSTM model reduced marginal bone loss prediction error by 55% compared to ISQ alone (0.28 vs. 0.62 mm MAE) and improved peri implantitis AUC from 0.71 to 0.91 (table 5). All components contributed significantly ($p < 0.01$ for each removal) (Table 6).

Integrated Risk Score (Combined Model)

When we integrated all three modules (preoperative XGBoost risk score + intraoperative CV anatomy detection + CNN LSTM forecasting), the combined model achieved AUC of 0.96 (95% CI: 0.94–0.98) for predicting 5-year implant survival, compared to 0.91 for the best standalone model ($p = 0.01$) [7-8]. ML reclassification identified 76 additional high-risk patients (who would have been missed by ISQ alone) and correctly downgraded 12 low risk patients (avoiding unnecessary intervention) (Table 7).

Deployment Benchmarks

All components run on commercially available hardware. The CV module meets real time requirements (<50 ms). Preoperative and forecasting modules run offline (overnight batch) (Table 8).

Discussion

Principal Findings

Three main findings emerge. First, ML substantially outperforms traditional clinical indices for implant failure prediction: XGBoost achieved AUC 0.91 vs. 0.71 for ISQ ($p < 0.001$). The top predictors bone density, smoking, ISQ, torque is measurable before or at placement, enabling preoperative risk counseling [9]. Second, real time CV guidance is feasible on edge hardware with 0.92 Dice at 12 ms latency. This is 16× faster than prior work, making intraoperative AR overlay clinically practical. Third, hybrid CNN LSTM forecasting integrates spatial (CBCT) and temporal (intraoperative) data to predict 5-year outcomes with unprecedented accuracy (bone loss MAE 0.28 mm, peri implantitis AUC 0.91). The combined model (all three modules) achieved AUC 0.96.

Clinical Implications

Preoperative phase: Patients with ML predicted high risk (e.g., AUC risk score >0.8) could receive enhanced consent, longer healing periods, or alternative treatment (e.g., shorter span prostheses). Low risk patients could be reassured and may avoid unnecessary follow up imaging.

Intraoperative phase: Real time overlay of mandibular canal and sinus on the surgical field could reduce nerve injuries and sinus perforations. In our simulation, the CV system alerted the surgeon to impending canal proximity in 94% of simulated high risk drilling paths (tested on 50 prerecorded videos) [10].

Postoperative phase: Patients predicted to have high bone loss (>0.5 mm/year) could be enrolled in more frequent recall (every 6 months vs. annually) or receive adjunctive chlorhexidine therapy.

Limitations

Retrospective, single center data: Models were trained on data from one institution with specific surgical protocols (flapless, guided surgery predominant). External validation at 2–3 centers is required.

Labeling bias for CV: Annotators were oral surgeons ($n = 3$). Inter rater variability for mandibular canal boundaries on video was 0.05–0.10 Dice, which sets an upper bound on achievable model performance.

No prospective validation: All models were tested on held out retrospective data. A prospective trial (e.g., ML guided vs. standard care) is needed to demonstrate improved clinical outcomes (lower failure rates, fewer nerve injuries).

Black box concerns: XGBoost provides SHAP values (feature importance), but some surgeons remain uncomfortable with non-interpretable neural networks for the CNN LSTM forecasting module.

Data privacy: Training on multi center data requires federated learning; sending raw CBCT or video to a central server raises HIPAA compliance issues.

Deployment Roadmap

Phase 1 (6–12 months): External validation on 1–2 additional centers (retrospective). Develop FHIR interface for EHR integration.

Phase 2 (12–24 months): Prospective observational study ($n = 500$) to confirm ML predicted risk scores correlate with outcomes.

Phase 3 (24–36 months): Randomized controlled trial: ML guided risk stratification + CV guidance vs. standard care. Primary outcome: 2-year implant survival.

Phase 4 (36+ months): Commercialization (FDA 510(k) for CV guidance module as Class II device; risk calculator as software as medical device).

Future Directions

Federated learning: Train models across 5–10 centers without sharing raw data, improving generalizability.

Multimodal foundation models: Use self-supervised learning on 100,000+ unlabeled CBCT scans to pre train a “dental foundation model,” then fine tune for specific tasks.

Real time force feedback integration: Combine CV (anatomy location) with force/torque sensing to alert surgeon when drilling force exceeds safe limit for that bone density.

Patient facing app: Provide patients with personalized risk score and evidence-based recommendations (e.g., “your predicted 5-year failure risk is 12%; quitting smoking would reduce this to 6%”).

Conclusion

Oral surgery and implant outcome prediction have remained stubbornly experience based, despite decades of clinical research. Machine learning and computer vision offer a path to data driven, personalized prediction. This paper demonstrated that: (1) XGBoost predicts 5year implant failure with AUC 0.91, outperforming ISQ (0.71); (2) a lightweight U Net segments high risk anatomy from intraoperative video at 12 ms latency (83 Hz), enabling real time guidance; (3) a hybrid CNN LSTM model forecasts 5year marginal bone loss (MAE 0.28 mm) and peri implantitis (AUC 0.91). When integrated, the combined model achieved AUC 0.96 for implant survival. These models run on commercially available hardware (edge GPU for CV, CPU for risk calculator). While prospective validation and regulatory clearance remain, the technical barriers have been overcome. ML and computer vision are not futuristic concepts—they are clinically deployable tools ready for the next phase of translation. Adopting them could reduce implant failures.

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