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Artificial Intelligence-Based Prediction of Dental Implant Failure Risk Using Preoperative CBCT and Clinical Parameters: A Retrospective Cohort Study on 2,500 Implants

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Abstract

Background: Dental implant failure remains a significant clinical concern despite high overall survival rates, with 5-10% of implants failing within 5-10 years. Accurate preoperative risk stratification could enable personalized treatment planning and preventive intervention, but existing prediction tools rely on limited clinical parameters and subjective bone quality assessment.

Objective: To develop and validate an artificial intelligence (AI)-based model for predicting 5-year dental implant failure risk using preoperative cone beam computed tomography (CBCT) scans and comprehensive clinical parameters.

Methods: We conducted a retrospective cohort study of 2,500 dental implants placed in 1,800 patients at a single academic center (2016-2021), with 5 years follow up data. Preoperative CBCT scans were processed using a 3D convolutional neural network (CNN) to automatically extract quantitative bone

Parameters: bone density (Hounsfield units in planned implant region), cortical thickness (mm), and bone volume fraction. A hybrid XGBoost model integrated 28 clinical and radiographic features including patient demographics, medical history, implant parameters, and CBCT-derived measurements. Model performance was evaluated using 5-fold cross validation and compared to conventional clinical assessment.

Results: The AI model achieved 5-year implant failure prediction with AUC of 0.91 (95% CI 0.88-0.94), sensitivity 84.7%, specifically 86.2%, and accuracy 85.9%. The most important predictors included bone density in the implant recipient site (SHAP 0.24), smoking pack years (0.22), cortical thickness (0.18), implant length (0.15), and diabetes status (0.14). The model significantly outperformed conventional clinical assessment (AUC 0.71, 95% CI 0.67-0.75, p<0.001). Calibration was excellent (Brier score 0.09). Patients in the highest risk quintile had a 12-fold higher failure rate (18.2%) compared to the lowest risk quintile (1.5%).

Conclusions: AI based integration of preoperative CBCT derived bone parameters and clinical features enables accurate, objective, and early prediction of 5-year dental implant failure risk. This approach could improve preoperative counseling, guide implant selection, and enable personalized surveillance of high-risk patients.

Keywords: Dental implant; Artificial intelligence; Machine learning; CBCT; Implant failure prediction; Risk stratification; Precision dentistry

Abbreviations: ISQ: Implant Stability Quotient; CBCT: Cone Beam Computed Tomography; CNN: Convolutional Neural Network

Introduction

Background

Dental implants are a highly predictable treatment modality, with 10-year survival rates exceeding 90-95% in healthy patients. However, late implant failure typically occurring 1-5 years after placement affects 5-10% of implants and is primarily attributed to peri implantitis, occlusal overload, and progressive bone loss. Early implant loss (within 1 year) affects an additional 2-5% of cases and is often related to failed osseointegration due to poor bone quality, surgical trauma, or infection. Despite these well recognized risk factors, preoperative identification of patients at elevated failure risk remains challenging [1].

Current Limitations

The most widely used predictor of implant success is the Lekholm Zarb bone quality classification, which categorizes bone into four types (D1-D4) based on subjective visual assessment of CBCT images. This classification has significant limitations: it lacks quantitative precision, exhibits substantial inter examiner variability (Kappa 0.5-0.7), and does not incorporate other critical risk factors such as smoking, diabetes, or implant dimensions. Other clinical parameters including implant stability quotient (ISQ) measured at placement and insertion torque are intraoperative and cannot inform preoperative planning.

The Promise of AI for Implant Risk Prediction

Artificial intelligence, particularly machine learning, has demonstrated substantial promise in predicting dental implant outcomes. Several studies have reported AUC values of 0.80-0.88 for implant survival prediction using XGBoost and random forest models. However, existing studies share two critical limitations: (1) they rely on manually annotated bone quality classifications rather than quantitative CBCT-derived measurements, and (2) they have been limited by relatively small sample sizes (typically <1,000 implants). Furthermore, no prior study has demonstrated calibration of risk predictions as a prerequisite for clinical utility [2].

Objectives

This study aimed to:

1. Develop a hybrid AI model integrating automated CBCT-derived bone parameters with clinical risk factors for predicting 5-year implant failure.

2. Validate the model on a large retrospective cohort (2,500 implants) with complete 5-year follow-up.

3. Compare model performance to conventional clinical assessment.

4. Provide calibrated risk scores for preoperative clinical decision making.

Materials and Methods

Study Design and Population

We conducted a retrospective cohort study at a single academic implant center (2016-2021). The study was approved by the institutional review board (IRB #2023 0456) with a waiver of informed consent.

Inclusion criteria:

· Single or partial edentulism treated with implant supported prostheses

· Age ≥18 years

· Availability of preoperative CBCT scan (within 90 days prior to surgery)

· Minimum 5 year follow up or implant failure before 5 years

Exclusion criteria:

· Significant CBCT motion artifact

· Previous implant at the same site

· Patients receiving systemic bisphosphonates (IV or oral >3 years)

· History of head and neck radiation

A total of 1,800 patients (2,500 implants) met inclusion criteria. Implant failure was defined as implant loss (explantation) at any time during follow up, or implant mobility with radiographic evidence of complete bone loss [3].

CBCT Data Acquisition and Preprocessing

All CBCT scans were performed using standardized protocols (120 kV, 5 8 m As, 0.2 0.3 mm voxel size, 10 15 cm field of view). Scans were exported in DICOM format and processed using a custom pipeline.

Image preprocessing:

· Resampling to isotropic 0.3 mm^3 voxel size

· Intensity normalization using a phantom based calibration to Hounsfield units

· Region of interest (ROI) extraction centered on the planned implant site

· Cropping to a standardized volume (64×64×64 voxels, approximately 19×19×19 mm^3)

Automated Bone Parameter Extraction (3D CNN):

We implemented a 3D convolutional neural network (ResNet 18 architecture modified for 3D inputs) to automatically extract quantitative bone parameters from the ROI. The network was trained on 1,000 manually annotated CBCT volumes (inter rater ICC >0.85) to predict:

1. Bone Density: Mean Hounsfield units (HU) in the planned implant region

2. Cortical Thickness: Maximum thickness of the cortical plate (mm)

3. Bone Volume Fraction: Ratio of bone volume to total volume within the ROI

The CNN achieved Dice coefficients of 0.94 for bone segmentation, with mean absolute error of 0.38 mm for cortical thickness and 28 HU for density [4].

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Clinical Feature Extraction

Twenty-eight clinical features were extracted from electronic health records:

Demographics: Age, Sex, BMI

Medical History: Smoking (pack years), Diabetes (HbA1c), Osteoporosis, Bisphosphonate use, Cardiovascular disease, Hypertension

Local Factors: Bone quality class (subjective Lekholm Zarb), Implant site (maxilla/mandible), Implant position (anterior/posterior), Implant length, Implant diameter, Primary stability (ISQ), Insertion torque

Surgical Factors: Surgeon experience (years), Flap vs. flapless, Guided vs. freehand, Immediate vs. delayed loading, Grafting (yes/no)

Prosthetic Factors: Abutment type, Prosthesis type (single crown, bridge, overdenture)

Maintenance: Recall compliance (percentage of scheduled visits attended)

Model Development

Architecture: Hybrid XGBoost model integrating 28 clinical features with CBCT derived bone parameters (density, cortical thickness, bone volume fraction). We selected XGBoost for its superior performance in prior implant outcome studies and its ability to handle missing data (3.2% missing overall, imputed using median values).

Training And Validation: 5-fold cross validation (patient level splitting, no data leakage). Hyperparameter tuning via grid search: n_estimators=100-200, max_depth=4-8, learning_rate=0.05-0.2 [5].

Comparators:

1. Conventional clinical assessment (subjective Lekholm Zarb + clinical judgment) performed by two experienced implant surgeons (blinded to outcomes)

2. Clinical only model (without CBCT parameters)

3. CBCT only model (without clinical features)

Evaluation Metrics: AUC ROC, Accuracy, Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Brier score (calibration), and decision curve analysis (net clinical benefit).

Statistical Analysis

All analyses were conducted using Python (scikit learn, XGBoost, SHAP). Model performance was reported as mean ± SD across 5 cross validation folds. AUC comparisons used DeLong's test. Calibration was assessed via Hosmer Lemeshow test and calibration plots. Statistical significance was set at $\alpha=0.05$ with Bonferroni correction for multiple comparisons [6].

Results

Study Population

The 2,500 implants (1,800 patients) had a mean follow up of 63.2 ± 8.4 months. A total of 205 implants failed (8.2%), with failure rates of 3.1% at 1 year and 8.2% at 5 years. Failure was more common in the maxilla (10.4% vs. 6.2% in mandible, $p=0.003$), in current smokers (14.8% vs. 5.2% in non-smokers, $p<0.001$), and in patients with uncontrolled diabetes (15.2% vs. 6.8% in non-diabetics, $p<0.001$) [7].

AI Model Performance

The hybrid XGBoost model achieved a 5-fold cross validated AUC of 0.91 (95% CI 0.88-0.94), accuracy 85.9%, sensitivity 84.7%, specifically 86.2%, PPV 56.8%, and NPV 95.3%. The model was well calibrated (Brier score 0.09, Hosmer Lemeshow $p=0.21$), meaning predicted probabilities closely matched observed outcomes. The hybrid model significantly outperformed conventional clinical assessment (AUC 0.91 vs. 0.71, $p<0.001$) and clinical only XGBoost (0.91 vs. 0.84, $p=0.002$). The CBCT derived parameters contributed a 0.07 AUC improvement over clinical only features [8].

Feature Importance

CBCT derived bone density was the single most important predictor, followed by smoking, cortical thickness, and implant length. The top three CBCT parameters (density, cortical thickness, bone volume fraction) collectively accounted for 36% of model predictive power.

Risk Stratification

Patients in the highest risk quintile had a 13-fold higher failure rate (18.8%) compared to the lowest risk quintile (1.4%). The model demonstrated excellent discrimination across risk strata.

Threshold Based Clinical Decision Support

At a moderate risk threshold (≥0.35), the model identified 14.2% of implants as high risk, capturing 84.7% of actual failures (sensitivity) while maintaining high specificity (86.2%). The PPV was 56.8% - meaning more than half of flagged implants would fail without intervention [9].

Calibration and Clinical Utility

The calibration plot showed excellent agreement between predicted and observed probabilities across the entire risk spectrum (calibration slope 0.98, intercept −0.04). Decision curve analysis demonstrated positive net clinical benefit across all clinically reasonable threshold probabilities (0.10-0.80), confirming the model's utility for informing implant planning and patient counseling.

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Discussion

Principal Findings

This study demonstrates that a hybrid AI model integrating automated CBCT derived bone parameters with clinical risk factors can accurately predict 5-year implant failure with an AUC of 0.91, substantially outperforming conventional clinical assessment (AUC 0.71). CBCT derived bone density was the single most important predictor, surpassing smoking and implant length. The model's excellent calibration and risk stratification capacity (13-fold difference between highest and lowest quintiles) supports its clinical utility for personalized preoperative counseling and targeted surveillance.

Comparison with Prior Work

Our model performance (AUC 0.91, accuracy 85.9%) exceeds previously reported ML models for implant survival prediction (AUC 0.80-0.88). This improvement is likely attributable to three factors: (1) the large sample size (2,500 implants vs. ≤1,800 in prior studies), (2) the integration of quantitative CBCT derived parameters rather than subjective bone quality classifications, and (3) the use of a hybrid architecture combining comprehensive clinical and radiographic features. Our SHAP analysis confirms that bone density and cortical thickness are among the top predictors, supporting the clinical importance of preoperative CBCT assessment [10].

1.1. Clinical Implications

Preoperative decision making: The model provides a calibrated risk score (0-1) that can be used for patient counseling. For example, a score of 0.45 (upper quintile) carries an 18.8% 5-year risk-information failure that may influence treatment decisions, implant selection, or the decision to proceed with alternative treatments.

Implant selection: The model's SHAP analysis reveals the relative importance of implant length (SHAP 0.15) and diameter (0.11). For high-risk patients, selection of longer or wider implants may reduce failure risk, as prior studies have demonstrated improved survival with larger diameter implants in poor bone quality. Postoperative surveillance: Patients in the highest risk quintile may benefit from intensified maintenance protocols: more frequent recall visits, enhanced home care instruction, and earlier detection of peri implantitis.

Strengths

1.1.1. **Large Sample Size:** With 2,500 implants and 1,800 patients, this is the largest study of its kind to date.

1.1.2. **Comprehensive Features:** We integrated 28 clinical features with automated CBCT derived parameters, providing a more complete risk assessment than prior models.

1.1.3. **Automated CBCT Analysis:** The 3D CNN enabled objective, quantitative bone parameter extraction with excellent accuracy, eliminating the subjectivity of traditional bone quality classification.

1.1.4. **Excellent Calibration:** The model's calibration performance (Brier 0.09) distinguishes it from prior studies that reported discriminative performance only, enhancing its clinical utility.

Limitations

1.1.5. **Retrospective Design:** The single center retrospective design may introduce selection bias; external validation is essential.

1.1.6. **Single Center Dataset:** Model performance may not generalize to other centers with different patient populations or surgical protocols.

1.1.7. **Missing Data:** While missing data was limited (3.2%), some features were unavailable for a subset of patients.

1.1.8. **No Causal Inference:** The model identifies associations, not causal relationships. Prospective validation is needed.

1.1.9. **Binary Outcome:** The model predicts implant failure, not time to failure or partial bone loss without implant loss.

1.2. Future Directions

1.2.1. **Prospective Validation:** A multi-center prospective study (N=2,000 implants) is planned to validate the model's performance in a broader clinical setting.

1.2.2. **Time to Event Prediction:** Extension of the model to predict time to failure (using survival analysis) would enable dynamic risk assessment over time.

1.2.3. **Integration with Intraoperative Data:** Incorporating intraoperative ISQ and insertion torque could further improve prediction accuracy.

1.2.4. **Patient Facing Tool:** Development of a web based or mobile risk calculator for patient counseling and shared decision making.

1.2.5. **Federated Learning:** Multi center model training without sharing raw data to improve generalizability while preserving patient privacy.

Conclusion

This retrospective cohort study of 2,500 dental implants demonstrates that an AI model integrating automated CBCT derived bone parameters with 28 clinical risk factors can accurately predict 5-year implant failure risk (AUC 0.91, accuracy 85.9%). The model significantly outperforms conventional clinical assessment and provides calibrated risk scores that can inform preoperative counseling, implant selection, and postoperative surveillance. External prospective validation is needed, but these findings suggest that AI based risk prediction may soon become a practical tool for personalized implant dentistry.

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