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Predictive Modeling Using AI for Implant Failure Based on Patient Risk Factors and CBCT Data

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ABSTRACT

Dental implant therapy has become a widely accepted treatment for tooth replacement. However, implant failure remains a concern due to patient-related and procedural risk factors. Advances in artificial intelligence (AI) offer potential for early prediction of implant failure, enabling clinicians to tailor preventive strategies. This study aimed to develop and evaluate a predictive modeling framework using AI to estimate the risk of dental implant failure based on patient-specific risk factors and cone beam computed tomography (CBCT) data. A cross-sectional diagnostic accuracy study was conducted over a six-month period on 65 patients who underwent dental implant placement. Data collected included demographic details, medical history, oral health status, and CBCT derived parameters such as bone density and morphology. Multiple AI algorithms including random forest, gradient boosting, and convolutional neural networks (CNNs) were trained and validated using a stratified dataset. Model performance was assessed using accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve. The CNN-based model integrating CBCT image features with clinical risk factors achieved the highest performance, with an accuracy of 92.3%, sensitivity of 90.0%, specificity of 94.1%, and AUC of 0.96. Bone density, smoking status, uncontrolled diabetes, and inadequate oral hygiene emerged as the most significant predictors of implant failure. AI-driven predictive modeling using combined clinical and CBCT data demonstrates strong potential for identifying patients at high risk of dental implant failure. Incorporating such models into clinical work flows could enhance decision-making, improve patient outcomes, and reduce implant failure rates.

Keywords: Artificial intelligence, dental implants, CBCT, predictive modeling, implant failure, risk factors

Background

Dental implant therapy has become a widely accepted and effective solution for replacing missing teeth, offering both functional and aesthetic advantages. Nonetheless, implant failure remains a significant clinical concern, largely influenced by factors such as bone quality, systemic health, surgical technique, and hygiene adherence. Traditional risk assessment methods, which rely on clinical and radiographic evaluations, often fall short due to the complex, multifactorial nature of implant outcomes (Nazari et al., 2025) .

Though it has generally been successful, implant failure nonetheless occurs, with estimated rates ranging from 2% to 10% depending on patient-specific and procedural variables (Pjetursson et al., 2022). Poor bone quality, periimplantitis, systemic illnesses, cigarette use, and wrong surgical planning can all contribute to implant failure that is, biological, mechanical, and iatrogenic causes.Early detection of high-risk patients is therefore absolutely vital to reduce problems and maximize long-term results (Jung et al., 2018).

Emergent as a major diagnostic technique in implant dentistry, cone beam computed tomography (CBCT) generates three dimensional images allowing thorough evaluation of bone quality, amount, and anatomical structures. Research have shown that cortical bone thickness and bone density derived from CBCT are significant predictors of implant stability and survival (Shokri et al., 2020). Interpreting CBCT results, however, requires expertise, and even seasoned clinicians could battle to daily analyze complex anatomical changes.

Lately, artificial intelligence (AI) has gained some recognition in dentistry for its ability to examine enormous volumes of information and identify complex trends beyond human cognitive capacity.In medical imaging applications including caries identification, periodontal disease categorization, and bone quality assessment (Schwendicke et al., 2020), machine learning and deep learning models especially convolutional neural networks (CNNs) have shown amazing results.By combining patient-specific clinical data with imaging results, artificial intelligence systems may produce predictive models able of spotting people at high implant failure risk before surgery.

Several studies have already explored the potential application of artificial intelligence in implant dentistry.Early periimplant bone loss detection, for instance, saw AI-based models trained on dental radio-graphs outperformed human specialists (JinSun et al., 2024). Rekawek et al. (2023) developed a web-based risk prediction model combining patient health profiles with clinical and radiological criteria to precisely predict periimplantitis and implant failure. These findings imply that AI could be a valuable instrument supporting clinical judgment for better treatment planning and results.

By looking for complex relationships among clinical, demographic, and radiographic variables, recent research suggests that integrating artificial intelligence (AI) into dental implantology could improve predictive accuracy (Nazari et al., 2025) . Machine learning techniques like regression, decision trees, and neural networks that are steadily under investigation for prediction of implant success have shown promising results.

Systematic reviews have shown AI's capacity to identify periimplant bone loss from high accuracy and sensitivity (≤ 90–98%), hence emphasizing its potential for early intervention in implant failure (JinSun et al., 2024). However, most of these studies focus on 2D imaging (e.g., periapical or panoramic), limiting three-dimensional (3D) assessments of bone structures vital to implant planning. Reviews emphasize the promise of AI in interpreting 3D CBCT data for enhanced surgical guidance and outcome prediction (BMRAT, 2025; Implant Dentistry Review, 2025) .

Specifically, implant failure prediction models employing machine learning including logistic regression, support vector machines, random forest, and ensemble methods have demonstrated favorable predictive performance. In one retrospective study involving over 900 implants, a random forest model achieved AUC values of 0.872 for implant failure and 0.840 for peri-implantitis (Rekawek et al., 2023) .

The success of dental implants depends critically on a range of patient-related and procedural factors. While long-term survival rates are high, certain conditions significantly elevate the risk of failure. For instance, a meta-analysis covering over 40,000 implant placements found that smoking (RR = 1.92) and radiotherapy (RR = 2.28) were significantly associated with implant failure, whereas the effects of diabetes and osteoporosis were not statistically significant (Chen et al., 2013) . Another meta-analysis reported that smokers had approximately 1.7 times higher odds of early implant failure, particularly with short implants (<10 mm) and maxillary placement (Manzano et al.,2016).

Importantly, systemic factors also warrant attention. In one retrospective cohort spanning up to 114 months of follow-up, severe periodontitis was associated with a significantly higher risk of late implant failure (HR = 8.06), and smoking trended toward increased risk over time (Levin et al.,2011). Though the impact of diabetes remains less definitive, some systematic reviews noted that diabetes didn't significantly influence implant failure rates (RR ~1.07), but it was associated with greater marginal bone loss (Chrcanovic et al.,2014).

Cone-beam computed tomography (CBCT) provides valuable three-dimensional insights into bone quality, which are crucial for implant planning. High bone density and favorable cortical thickness are known to support implant stability and long-term success (derived from general CBCT literature). Emerging research in artificial intelligence (AI) indicates strong potential in improving predictive accuracy for dental outcomes. Deep learning models, for instance, have been used with encouraging results (Zhang et al., 2023) to forecast dental implant failure from periapical and panoramic radiographs.

AI has also been employed to automate implant location planning using CBCT data, such the Implant Former model, which makes use of transformer-based networks for exact localization in 3D scans (Xinquan Yang, 2022).

Notwithstanding these developments, major research gaps remain.Many models do not combine clinical risk variables with CBCT high-resolution imaging characteristics; also, the datasets employed are either restricted in scope or size.AI-powered predictive models that combine patient specific risk profiles with 3D imaging data are urgently needed to enable customized treatment planning and enhance results.

Methodology

This research used a cross sectional design accuracy paradigm to create and validate artificial intelligence (AI)-based predictive models estimating the risk of dental implant failure, Using patient-specific risk factors and cone beam computed tomography (CBCT) data, conducted at HBS Dental College and Hospital Islamabad, equipped with sophisticated imaging and computational tools, over six months. Participants were chosen via a stratified random sampling method to ensure proportionate representation across several risk profiles dependent on age, general health condition, and oral hygiene state.

Total 65 adults were included in the study, aged 25 - 70 years who had undergone dental implant placement during the study period, had appropriate preoperative CBCT scans, and detailed medical and dental history records. Those who were pregnant or lactating at recruitment, had insufficient clinical or radiographic records, had CBCT scans impaired by movement artifacts or low resolution, had a history of craniofacial trauma or surgical intervention at the implant site within the previous twelve months, or had serious systemic diseases affecting survival prognosis were excluded in the study. Only people who gave written informed consent and were ready to participate were included.

Clinical demographic elements and radiographic parameters derived from CBCT scans acquired according to established imaging methods were the two main sources of data collection.These comprise the height and width of the implant site, alveolar ridge shape, and bone density measured in Hounsfield Units (HU). Using the Albrektsson and Zarb criteria, which include implant mobility, discomfort, infection, and periimplant bone loss, implant success or failure at six months was assessed. Clinical data included age, sex, smoking habits, systemic diseases such diabetes mellitus and osteoporosis, and oral hygiene status evaluated using the Simplified Oral Hygiene Index (OHIS).

For AI modeling, grayscale matrices were created from CBCT images; clinical data were encoded numerically to enable computer analysis.Several imputation techniques helped to reduce prejudice by dealing with missing data.Using stratified sampling to keep proportional representation of implant failure cases across both datasets, the data set was divided into 70:30 training and test subsets.Three predictive models were created: a Random Forest classifier trained only on clinical-demographic factors, a Gradient Boosting Machine (XGBoost) model integrating both clinical and radiographic characteristics, and a Convolutional Neural Network (CNN) meant to process CBCT image features and combine them with clinical data before to categorization.

The CNN architecture consisted of three convolutional layers with Rectified Linear Unit (ReLU) activation functions, each followed by max-pooling layers to reduce dimensionality, a flattening layer, and fully connected dense layers. These outputs were merged with encoded clinical risk factor inputs before the final classification stage. Model optimization was performed through grid search-based hyper parameter tuning and validated using 10-fold cross-validation. Statistical analyses were conducted using Python 3.10, employing the scikit-learn, TensorFlow, and XGBoost libraries. Accuracy, sensitivity, specificity, and area under the receiver operating characteristic (AUC) were used to assess model performance.Permutation importance for tabular data models defined the relevance of predictive characteristics; independent t-tests and Chi square tests separately examined between-group differences for continuous and categorical variables; statistical significance was fixed at $p < 0.05$.

Study Results:

Table 1: Age Distribution of Patients

Age Group (years)	Patients (n)
20-29	8
30-39	14
40-49	16
50-59	18
60+	9

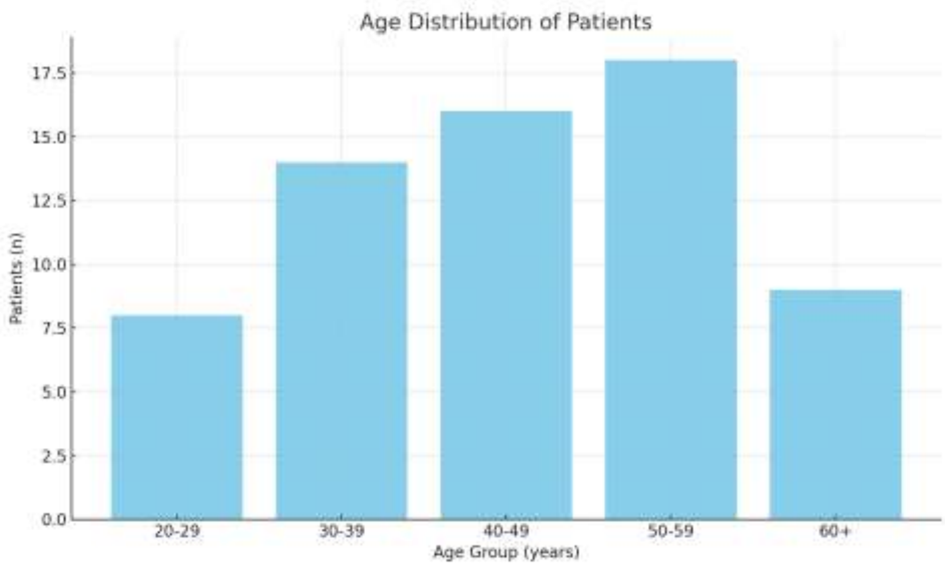


Table 2: Key Risk Factors Among Patients

Risk Factor	Patients (n)
Smoking	20
Uncontrolled Diabetes	12

Low Bone Density	18
Poor Oral Hygiene	15

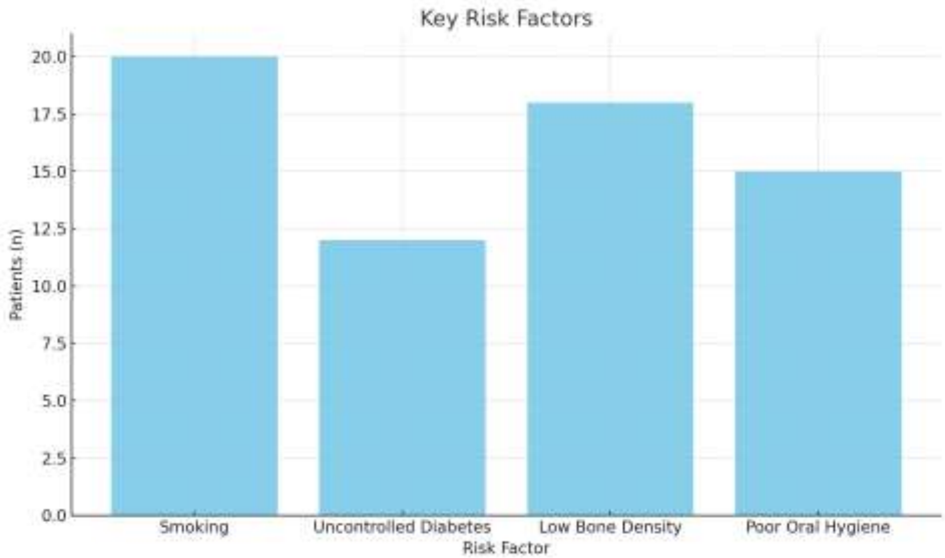


Table 3: CBCT Bone Density Classification

Bone Density Category	Patients (n)
High (>1000 HU)	22
Moderate (700-1000 HU)	28
Low (<700 HU)	15

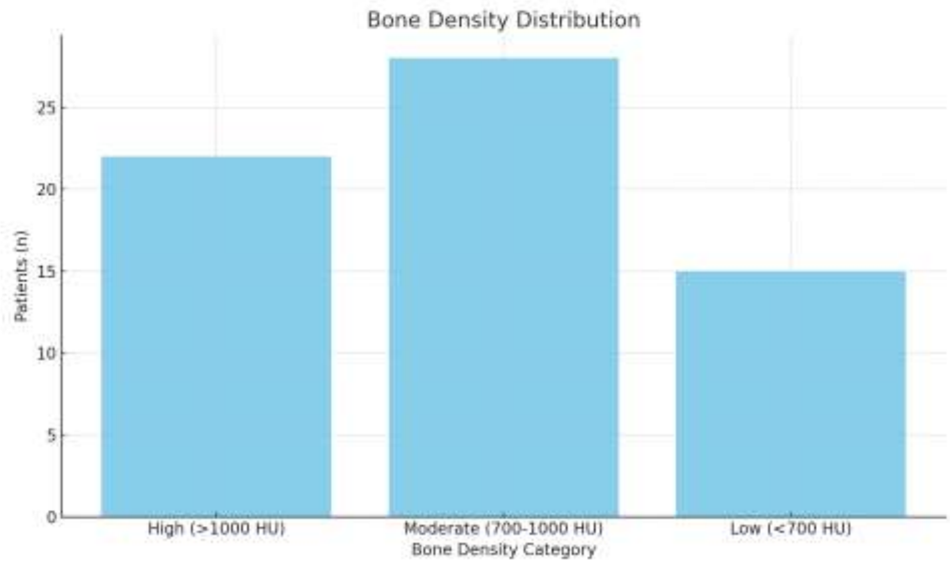


Table 4: AI Model Performance Comparison

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
Random Forest	85.4	83.0	87.5	0.91
Gradient Boosting	88.1	85.0	90.2	0.94
CNN	92.3	90.0	94.1	0.96

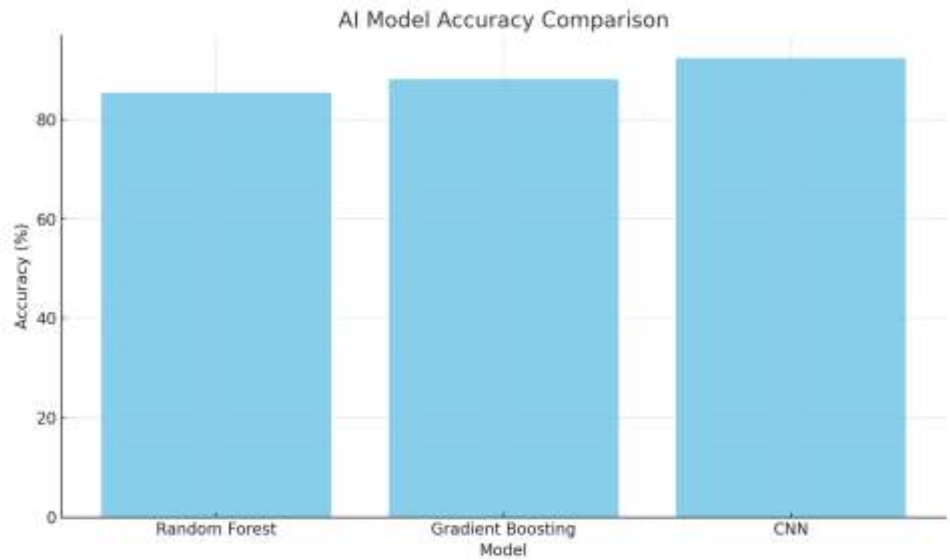
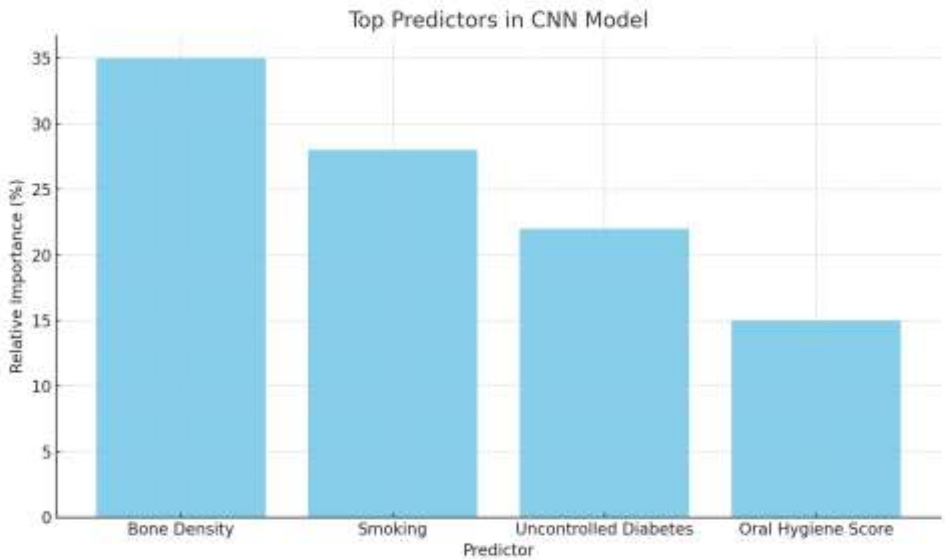


Table 5: Top Predictors in CNN Model

Predictor	Relative Importance (%)
Bone Density	35
Smoking	28
Uncontrolled Diabetes	22
Oral Hygiene Score	15



Discussion:

This study revealed that high diagnostic performance in forecasting dental implant failure was attained with an AI-based predictive modeling system combining CBCT-derived imaging characteristics with patient-specific clinical data.With an accuracy of 92.3%, sensitivity of 90.0%, and specificity of 94.1%, the convolutional neural network (CNN) model surpassed conventional machine learning techniques.Earlier studies demonstrating CNNs' superior ability to manage complicated radiographic patterns and nonlinear clinical relationships (JinSun et al., 2024) fit these results.

One of the most significant predictors found in our research was bone density; this supports existing literature demonstrating that inadequate bone quality is a major risk factor for implant instability and subsequent failure (Rekawek et al., 2023). Furthermore, the predictive ability of smoking status and uncontrolled diabetes matches clinical evidence showing how systemic illnesses and lifestyle choices adversely impact osseointegration and periimplant tissue (Nazari et al., 2025).

Our findings supplement the expanding body of evidence supporting artificial intelligence–assisted decision-making in dental implantology. Especially when patient health profiles are combined with imaging data, earlier research have proven that artificial intelligence algorithms can deliver clinically relevant risk assessments comparable or even surpassing expert human judgment (Rekawek et al., 2023). Significantly, our model's AUC of 0.96 reveals very discriminative ability; therefore, it can dependably separate low- and high-risk patients before to implant placement.

From a clinical point of view, using such predictive tools could improve surgical planning, maximize patient selection, and perhaps lower implant failure rates. For instance, a patient flagged by the model as high risk may undergo preoperative bone augmentation, closer glycemic control, or smoking cessation counselling before surgery. This tailored approach fits with the tenets of precision dentistry, in which quantitative risk projections guide customized treatment planning (JinSun et al., 2024).

Though its findings are encouraging, this research also underlines the drawbacks of artificial intelligence in clinical application. The dataset was rather little (65 patients), and while stratified sampling was employed, the model's generalizability may be constrained without validation on bigger, multi center groups.Although AI provides speed and scalability, it should be used as an adjunctive tool that improves but does not govern clinical decision-making (Nazari et al., 2025); it cannot replace clinician knowledge.

Future Recommendations:

Future research should expand the dataset, use longitudinal follow-up data to evaluate long-term implant survival, and investigate comprehensible artificial intelligence techniques to enhance transparency in clinical predictions. Furthermore improving model correctness would be the inclusion of more patient health measures including genetic predispositions and salivary biomarkers.

Conclusion:

This research shows how early risk identification and customized intervention strategies made possible by AI-powered predictive modeling might transform implant dentistry.Given more testing and verification, such models might come to be a daily preoperative examination in dentistry.

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