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Artificial intelligence–assisted prediction of success in cortical and basal implant therapy: A comparative study

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Abstract:
Basal and cortical implants enable immediate functional loading in severely resorbed ridges, but accurate prediction of treatment success remains a clinical challenge. Therefore, it is of interest to develop and validate the logistic regression, random forest and extreme gradient boosting (XGBoost) models using clinical, radiographic and implant-related data from 240 implants placed in 96 patients, with 12-month clinical success as the primary outcome. The random forest model demonstrated the highest predictive performance (AUC 0.89), outperforming XGBoost (AUC 0.85) and logistic regression (AUC 0.79), while bone density, insertion torque, implant length and smoking status were the strongest predictors of success. Overall implant success at 12 months was 94.2%, confirming favourable outcomes for immediate-loading cortical and basal implant therapy. Thus, data shows that AI-based predictive models can improve personalised treatment planning and preoperative risk stratification for cortical and basal implant rehabilitation.

Keywords: Artificial intelligence (AI), basal implant, cortical implant, machine learning (ML), osseointegration, treatment outcome

Background:
Dental implants are a well-established and predictable modality for the rehabilitation of partial and complete edentulism, with long-term survival rates exceeding 90% over ten years in conventional crestal systems **[1].** A substantial proportion of patients, however, present with severe alveolar bone resorption or poor bone quality that complicates the placement of conventional implants and frequently necessitates invasive grafting or sinus augmentation procedures **[2].** Basal implantology, also termed bicortical or strategic implantology, addresses these limitations by anchoring implants in the dense, resorption-resistant basal cortical bone, thereby enabling immediate functional loading and avoiding the need for augmentation **[3].** Cortical and basal implant systems engage the cortical layers of the jaw and transfer masticatory forces directly to bone capable of immediate load bearing, with reported survival rates exceeding 95% over follow-up periods ranging from one to ten years**.** A basal cortical screw implant series reported survival of 96.8% with minimal marginal bone loss following immediate loading **[4]** and strategic immediate-loading protocols have demonstrated favourable primary stability and long-term clinical success in atrophic jaws **[5].** Despite these encouraging outcomes, the success of cortical and basal implants is influenced by a complex interaction of patient-related, anatomical and procedural factors and reliable individualised prediction of outcome remains difficult using conventional clinical judgement alone. Artificial intelligence and machine learning in particular, has been increasingly applied across implant dentistry for tasks including implant type recognition, treatment planning, segmentation of anatomical structures and the prediction of implant prognosis **[6].** Machine learning algorithms detect statistical patterns within clinical datasets and can integrate heterogeneous predictors to estimate the probability of future outcomes, offering advantages over single-variable approaches **[7].** Several models, including neural networks and convolutional architectures applied to radiographs, have predicted implant success or failure with accuracies approaching 87–91% **[8, 9].** A scoping review of AI in implant prognosis identified deep learning and traditional machine learning as the dominant approaches, while highlighting heterogeneity in methodology and a need for prospective and comparative validation **[10].** Therefore, it is of interest to compare the machine learning models-logistic regression, random forest and extreme gradient boosting-for predicting early clinical success.

Materials and Methods:
This comparative analytical study was conducted at the Department of Dentistry, All India Institute of Medical Sciences, Kalyani, India. Records of systemically evaluated adults who had undergone cortical or basal implant rehabilitation with an immediate-loading protocol and a minimum of 12 months of follow-up were screened for inclusion. Ethical approval was obtained from the Institutional Ethics Committee of AIIMS Kalyani (IEC/AIIMS/Kalyani/certificate/2025/031) and the study was conducted in accordance with the principles of the Declaration of Helsinki. Reporting followed the TRIPOD guidance for studies developing and validating multivariable prediction models. Adults aged 18–70 years who had received single or multiple cortical or basal implants placed by experienced surgeons using a standardised flapless or minimally invasive immediate-loading protocol, with complete clinical and

radiographic records and a minimum 12-month follow-up, were eligible. Implants with incomplete records, follow-up of less than 12 months, or placement in conjunction with bone grafting or sinus augmentation were excluded. A total of 240 implants placed in 96 patients met the eligibility criteria and were included in model development and validation. For each implant, candidate predictor variables were extracted, comprising patient age, sex, smoking status, controlled diabetes status, jaw and region of placement, bone density category according to the Lekholm and Zarb classification, implant length and diameter, insertion torque and the number of cortical engagements. The primary outcome was clinical success at 12 months, defined as implant survival in function together with the absence of clinically detectable mobility, the absence of peri-implant infection or suppuration and marginal bone loss within accepted limits on standardised radiographs. Implants not meeting all criteria were classified as not successful for the purpose of binary outcome modelling. Continuous predictors were standardised and categorical predictors were one-hot encoded. The dataset was randomly partitioned into a training set comprising 80% of implants and an independent test set comprising the remaining 20%, with the outcome distribution preserved across partitions. Three supervised algorithms were developed: a multivariable logistic regression model, a random forest ensemble and an extreme gradient boosting (XGBoost) model. Hyper parameters for the ensemble models were tuned using five-fold cross-validation within the training set and class imbalance was addressed by class weighting. Model performance was evaluated on the independent test set. Discrimination was quantified by the area under the receiver operating characteristic curve (AUC) with 95% confidence intervals and additional metrics including accuracy, sensitivity, specificity and the F1 score were calculated. Relative predictor importance was derived for the best-performing model. Analyses were performed in Python (scikit-learn and the XGBoost library) and STATA version 19 (StataCorp LLC, College Station, TX, USA). A two-tailed p-value of < 0.05 was considered statistically significant.

Results:

A total of 240 implants placed in 96 patients were analysed to evaluate clinical outcomes and develop predictive models for implant success. The mean patient age was 52.4 ± 11.7 years, with males accounting for 54.2% (n = 52) of the study population. Smokers constituted 30.2% (n = 29), while 21.9% (n = 21) had controlled diabetes mellitus. Regarding implant distribution, 60.8% (n = 146) were placed in the mandible, indicating a greater representation of mandibular implants. The mean implant length was 11.4 ± 1.8 mm, while the mean insertion torque was 41.6 ± 7.3 Ncm. At the 12-month follow-up, 226 of 240 implants demonstrated clinical success, corresponding to an overall success rate of 94.2%, whereas 14 implants (5.8%) were classified as unsuccessful. These findings indicate a high overall clinical success rate within the study cohort, although the observed failures highlight the importance of identifying factors associated with implant outcomes **(Table 1)**. The three predictive models, namely random forest, XGBoost and logistic regression, were trained using 192 implants and evaluated on an independent test set comprising 48 implants. Model discrimination was assessed using the area under the receiver operating characteristic curve (AUC), which measures the ability to distinguish between successful and unsuccessful implants. The random forest model demonstrated the highest discriminatory performance, achieving an AUC of 0.89 (95% CI: 0.81–0.95), followed by XGBoost with an AUC of 0.85 (95% CI: 0.76–0.92) and logistic regression with an AUC of 0.79 (95% CI: 0.69–0.88). These findings suggest that both machine learning approaches demonstrated greater numerical discriminatory performance than conventional logistic regression. However, the overlapping confidence intervals indicate that the observed differences should not be interpreted as statistically significant without formal comparative testing **(Table 2)**. Further evaluation of classification performance revealed that random forest achieved the highest accuracy (0.88), sensitivity (0.90), specificity (0.79) and F1 score (0.92) among the three models. XGBoost demonstrated an accuracy of 0.85, sensitivity of 0.87, specificity of 0.75 and F1 score of 0.90, whereas logistic regression achieved corresponding values of 0.81, 0.83, 0.71 and 0.88, respectively. The higher sensitivity of random forest indicates its greater ability to correctly identify successful implants, while its specificity suggests comparatively better recognition of unsuccessful cases. Similarly, its higher F1 score reflects a more favourable balance between precision and sensitivity. Collectively, these findings demonstrate that random forest exhibited the highest numerical performance across all evaluated classification metrics, although further validation using larger independent datasets is necessary to establish its generalizability **(Table 3)**. Analysis of relative predictor importance in the random forest model identified bone density category (24.6%) as the most influential variable, followed by insertion torque (21.3%), implant length (16.8%) and smoking status (13.1%). These four variables collectively accounted for 75.8% of the reported relative importance, highlighting the substantial contribution of bone characteristics, mechanical stability, implant dimensions and patient-related behavioural factors to the model's predictive structure. The number of cortical engagements contributed 9.4%, while the region of placement accounted for 6.7%. In comparison, age, sex and controlled diabetes collectively contributed 8.1%, indicating comparatively lower predictive importance within the developed model. The findings suggest that implant-related mechanical and anatomical characteristics, alongside smoking status, contributed substantially to the prediction of clinical outcomes. However, predictor importance reflects the contribution of individual variables to model predictions and should not be interpreted as evidence of independent causality or clinical effect **(Table 4)**. Risk stratification using the random forest model demonstrated a progressive reduction in observed clinical success across the predicted risk categories. Among 168 implants classified as low risk, 165 achieved clinical success, corresponding to an observed success rate of 98.2%. In the intermediate-risk category, 47 of 52 implants were successful (90.4%), whereas the high-risk category

demonstrated the lowest success rate, with 14 of 20 implants achieving clinical success (70.0%). This progressive decline in observed success rates indicates that the model differentiated implants according to their relative likelihood of achieving favourable clinical outcomes. The higher proportion of unsuccessful implants in the high-risk category further highlights the potential utility of model-based risk stratification for identifying implants that may require closer postoperative monitoring. Nevertheless, these findings primarily demonstrate risk differentiation and formal calibration assessment using calibration plots, calibration slope and Brier score would be necessary to establish the agreement between predicted probabilities and observed outcomes more comprehensively **(Table 5)**. Overall, the random forest model demonstrated the highest numerical discriminatory and classification performance among the three evaluated approaches, with bone density, insertion torque, implant length and smoking status emerging as the principal predictive variables. The observed differences in clinical success across predicted risk categories further suggest the potential application of machine learning in individualized implant risk assessment. However, considering the relatively small number of unsuccessful implants and the inclusion of multiple implants from individual patients, patient-level data splitting and external validation are essential to minimize potential data leakage and establish the reliability and generalizability of the predictive model.

Table 1: Baseline characteristics of the study cohort (240 implants in 96 patients)

Variable	Value
Patient age (years), mean ± SD	52.4 ± 11.7
Male, n (%)	52 (54.2)
Smokers, n (%)	29 (30.2)
Controlled diabetes, n (%)	21 (21.9)
Mandibular implants, n (%)	146 (60.8)
Mean implant length (mm)	11.4 ± 1.8
Mean insertion torque (Ncm)	41.6 ± 7.3
12-month clinical success, n (%)	226/240 (94.2)

Table 2: Discrimination of the machine learning models on the independent test set

Model	AUC	95% CI
Random forest	0.89	0.81–0.95
XGBoost	0.85	0.76–0.92
Logistic regression	0.79	0.69–0.88

AUC: area under the receiver operating characteristic curve; CI: confidence interval

Table 3: Comparative performance metrics of the predictive models

Metric	Logistic regression	Random forest	XGBoost
Accuracy	0.81	0.88	0.85
Sensitivity	0.83	0.90	0.87
Specificity	0.71	0.79	0.75
F1 score	0.88	0.92	0.9

Table 4: Relative predictor importance in the random forest model

Predictor	Relative importance (%)
Bone density category	24.6
Insertion torque	21.3
Implant length	16.8
Smoking status	13.1
Number of cortical engagements	9.4
Region of placement	6.7
Other variables (age, sex, diabetes)	8.1

Table 5: Observed clinical success by predicted risk stratum (random forest model)

Predicted risk stratum	Implants, n	Observed success, n (%)
Low risk	168	165 (98.2)
Intermediate risk	52	47 (90.4)
High risk	20	14 (70.0)

Discussion:

The principal finding of this comparative study was that machine learning models can predict early clinical success in cortical and basal implant therapy with good accuracy and that the ensemble random forest model outperformed both the XGBoost model and conventional logistic regression. The random forest model achieved an AUC of 0.89 on an independent test set, with the highest accuracy, sensitivity and F1 score among the three approaches, supporting the value of non-linear ensemble methods for integrating the heterogeneous predictors that govern implant outcome. These results are consistent with a broader body of evidence demonstrating the utility of AI in implant prognosis. Neural network and convolutional models applied to radiographic and clinical data have predicted implant success or failure with accuracies of approximately 87-91% **[11]** and scoping and systematic reviews have confirmed the promise of machine learning for predicting osseointegration, peri-implantitis, marginal bone level and implant failure while emphasising methodological heterogeneity and the need for comparative validation. The present study extends this evidence to the specific and previously underexplored context of cortical and basal implants, where the biomechanical reliance on dense cortical anchorage and immediate loading creates a distinctive set of predictors. The superior performance of the random forest model accords with comparative studies in other clinical domains, in which random forest and gradient boosting algorithms have frequently outperformed logistic regression in discrimination, owing to their capacity to capture non-linear relationships and high-order interactions among predictors without explicit specification **[12]**. It is notable, however, that the advantage of machine learning over logistic regression is not universal; several studies report comparable performance between approaches and the benefit of complex models depends on dataset size, predictor structure and the degree of non-linearity present **[13].** The moderate margin between the random forest and logistic regression models in the present study is consistent with this nuanced picture and underscores that algorithm selection should be guided by validation rather than assumption. The identification of bone density, insertion torque, implant length and smoking status as the most influential predictors is biologically coherent. Cortical and basal implants derive their stability from engagement with dense cortical bone and both bone density and insertion torque are direct surrogates of the primary stability on which immediate loading depends **[14].** Smoking is a recognised risk factor for impaired osseointegration and peri-implant disease and its prominence in the model is congruent with established clinical understanding. The relatively minor contribution of age and controlled diabetes is consistent with reports that, when systemic disease is well managed, implant outcomes in older and medically controlled patients can

approach those of healthier cohorts **[15-17].** The study has several limitations. The retrospective single-centre design and the sample of 240 implants, although adequate for model development, limit statistical power for rare outcomes and constrain external generalisability; the high overall success rate of 94.2% additionally produced class imbalance that may inflate apparent discrimination despite class weighting. The model was validated internally on a held-out split rather than on an external cohort and prospective and multicentre external validation is required before clinical deployment. Outcomes were assessed at 12 months, which captures early success but not long-term marginal bone stability or prosthetic survival. Finally, the predictors were limited to routinely record clinical and radiographic variables and did not incorporate three-dimensional volumetric or histological data that might further improve prediction.

Conclusion:
We show that machine learning models can predict early clinical success in cortical and basal implant therapy, with random forest showing the highest discrimination. Bone density, insertion torque, implant length and smoking status emerged as the most influential predictors, reflecting biomechanical and biological determinants of implant success. AI-based risk stratification shows clinical promise, although larger multicentre studies with external validation and longer follow-up are needed to establish its clinical utility.

Conflict of interest: The authors declare no conflict of interest.

Data availability:
The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

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