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Review Article

# Artificial intelligence applications in dental implantology: A narrative review

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ABSTRACT

Artificial intelligence (AI) has a substantial impact on various domains of society, including its significant role in revolutionizing dental care. These technological innovations have transformed dental treatment, expediting efficiency and innovation in the field. This review focuses on the substantial advancements in AI-based research in dental implantology, exploring the various applications of AI to enhance dental implant care. Comprehensive data from databases, including PubMed, Scopus, Web of Science, Cochrane, and Google Scholar, was thoroughly scrutinized and presented. AI has significantly impacted healthcare and dental implantology by enhancing efficiency, diagnosis, and clinical decision-making. In dental implantology, AI plays a crucial role in several aspects, such as implant identification, implant planning, prediction, and peri-implantitis management. AI models, including machine learning and deep learning, have been applied to identify implant brands accurately, outperforming dental professionals in some cases. Implant planning has been streamlined using AI to evaluate bone dimensions and locate critical anatomical landmarks. Using patient data and radiographic features, AI-driven prediction models proved as powerful tools for predicting implant success and peri-implantitis risk. Additionally, AI helps in the early recognition of complications like fractured implants and bio-tribocorrosion.



## 1. Introduction

Artificial intelligence (AI) is the widely discussed concept of the current times. The pervasive impact of AI extends across various domains of society, encompassing education, agriculture, healthcare, military, and governance alike. Its far-reaching influence has revolutionized these sectors, driving innovation, efficiency, and improved decision-making processes. AI and robotics have made significant inroads into the dental specialty, revolutionizing various aspects of dental care. For instance, we can observe their influence in invisible aligners, caries diagnosis, image-guided surgery, virtual surgical planning, and robotic implant placement.[1,2] These innovations have undoubtedly transformed the way dental treatments are performed and have brought groundbreaking advancements in the field. This review emphasizes the substantial advancements in AI-based research applied to dental implantology and the focus is on exploring the diverse applications of AI in dental implantology.

## 2. Methodology

For this review, comprehensive data from databases, including PubMed, Scopus, Web of Science, Cochrane, and Google Scholar, was thoroughly examined. Only English-language journal articles published until 2023 were included, ensuring the most up-to-date and relevant information regarding AI applications in dental implantology. The keywords used for the search strategy were AI, dental implants, and dental implantology.

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This review delves into various applications where AI is actively researched to address specific issues, such as dental implant identification, implant planning, peri-implantitis, and predictions in dental implantology.

## 3. Discussion

### 3.1. AI in dental implant identification

Dental implant identification, an essential process during the maintenance and repair of implants, is one of the challenges faced by clinicians in practice.[3] In the history of implantology, several methods were proposed for implant identification however none of them are quick or easy and require a significant amount of human effort, experience, and time. In a thrust for implant identification, AI techniques were implemented by researchers and proved to be beneficial. This is one of the several AI applications in dental implantology that is highly researched in the current times.

In the AI technique of implant identification, the data-to-train AI model is a digital intraoral radiograph of the implant. The data is split into a training and testing set where the training dataset trains the algorithm and the test dataset analyses the performance of the trained AI model.Different AI models are tested by researchers on different implant systems with varied sample sizes and the performance of these AI systems was found to be promising as outlined in Table 1. In some of the comparative studies, AI models have demonstrated superior performance over dental professionals in implant identification.

Researchers have conducted diverse studies utilizing various AI algorithms and implant systems, with considerable variation in sample sizes. Reported accuracies in implant identification ranged from 71% to 98%.[4–15] Few studies compared the performance of AI models with dental professionals, revealing that AI exhibited superior performance. Based on these studies researchers suggested testing additional algorithms with a broader range of implant systems and increased sample sizes to facilitate the clinical implementation of AI in dental implant identification. The integration of AI for implant identification will increase efficiency and reduce the effort and time spent using conventional methods.

### 3.2. AI in implant planning

Pre-surgical planning is an essential task in dental implantology to assure long-term success and minimize risks related to surgery. CBCT (cone-beam computed tomography) is an effective tool in implant planning, by offering vital information on roots, bone, nerves, and other crucial anatomic structures. This aids in choosing the location, and correct implant size, and predicting the need for supplementary surgical procedures. However, the process requires the clinician to manually demarcate structures and arrive at a treatment plan making the process complex and time-consuming. DL, a subset of AI is successfully implemented in medical image interpretation and can be a helpful tool in implant planning.[16] Implant planning for a mandibular area needs accurate detection of the mandibular canal and the width and height of the alveolar bone.[17] Tooth segmentation is a crucial step in implant planning for reconstructing 3D tooth models and is typically done manually by the operator. These manual delineations can be automated with deep learning a subset of AI.[18]Table 2 outlines AI applications in dental implant planning.

Researchers have achieved considerable success in utilizing AI models for segmenting and locating critical anatomic landmarks as well as measuring bone dimensions that are valuable in implant planning. However, the implementation of AI in implant planning may still require validation through clinical trials and continuous improvements to optimize its performance.

### 3.3. AI in peri-implantitis management

Peri-implantitis influences over 25% of dental implants leading to progressive bone loss and loss of implants. Consequently, routine implant maintenance and long-term management of peri-implantitis are essential components of preventive care. This calls for risk estimation, detection, and grading of peri-implantitis.[28] Several studies[29–32] have implemented AI to predict and detect peri-implantitis, as outlined in Table 3. R-CNN (Region-based Convolutional Neural Networks), random forest classifiers, logistic regression, and support vector machine (SVM) algorithms were implemented for peri-implantitis detection and some of these models demonstrated the risk factors associated with the development of peri-implantitis. AI systems achieved considerable accuracy in peri-implantitis detection and prediction, integration of AI can be a valuable adjunct to improve diagnostic capabilities and effective treatment strategies to prevent and manage peri-implantitis.

### 3.4. AI-driven prediction in dental implantology

Despite advancements in implant technologies and newer diagnostic and planning protocols, complications remain a significant concern. Consequently, there is a need for new methods that assess a patient's condition and predict the success of dental implants. With the rapid progress in AI and the abundant data available, the development of AI-based systems for auxiliary diagnostics has become relevant. In dental implantology, AI systems can offer a valuable supplementary diagnosis based on mathematical decision-making and forecasting.[33]

Lyakhov PA et al proposed an AI system that analyzes patient statistics to predict the single implant survival. The system's novelty lies in its design to effectively recognize

**Table 1:** AI in dental implant identification

| Author | Radiograph used | Number of images used | Algorithm architecture | Accuracy of the model | Comparison with the dental professional |
|---|---|---|---|---|---|
| Lee JH et al [4] | Panoramic and Periapical radiographs | 3000 | VGG-19 (visual geometry group), GoogLeNet Inception-v3, ResNet-50 | 89.1% 92.2% 90.7% | Not reported |
| Said M H et al [5] | Periapical and panoramic radiographs | 1206 | Pretrained GoogLeNet Inception | 93.8 % | Not reported |
| Sukegawa s et al [6] | Panoramic Radiographs | 8859 | Basic CNN (convolutional neural networks), VGG16 transfer, VGG16 fine-tuning, VGG19 transfer, VGG19 fine-tuning | 86% 89.9% 93.5% 88% 92.7% | Not reported |
| Takahashi T et al [7] | Panoramic radiographs | 1282 | YOLOv3 (you only look once) | 71% | Not reported |
| Lee JH et al [8] | Periapical and panoramic radiographs | 11,980 | Automated deep CNN | 95.4% | AUC less than 0.954 |
| Lee JH et al [9] | Periapical and panoramic radiographs | 10770 | Pre-trained and fine-tuned deep CNN architecture (Google Net Inception-v3 | 97.1% | AUC of 0.925 |
| Kim J E et al [10] | Periapical radiographs | 801 | SqueezeNet, GoogLeNet, ResNet-18, MobileNet-v2, ResNet-50 | 96% 93% 98% 97% 98% | Not reported |
| Mata Santos R P et al [11] | Periapical radiographs | 1800 | Deep CNNs | 85.29% | Not reported |
| Sukegaws et al [12] | Panoramic radiographs | 9767 | ResNet18 ResNet 34 ResNet 50 ResNet 101 ResNet 152 | 97.8% 98% 98% 98.41% 98.51% | Not reported |
| Kim HS et al [13] | Periapical radiographs | 355 | Pretrained YOLOv3 | 96.7% | Not reported |
| Kong H J et al [14] | Panoramic radiographs | 28,112 | Ensemble technique applied to EfficientNet and Res2Next algorithms | 95% | Not reported |
| Park W et al [15] | Periapical and panoramic radiographs | 156,965 | Automated deep learning (DL) algorithm | 88.53% | Not reported |

and interpret a comprehensive database of patient factors derived from case histories. Notably, the proposed system achieves an accuracy of 94.48% in predicting the success of single implants. AI systems are becoming increasingly popular owing to their ability to process complex medical data and provide accurate predictions hence, AI can be a handy tool for supplementary diagnostics.[33] Algorithms such as SVM, weighted SVM, and radial basis function with dynamic decay adjustment (RBF-DDA) provided valuable insights for clinicians and researchers seeking to improve the prediction and success rates of dental implant procedures.[34] Studies have explored the combined predictive model approach with various algorithms in predicting dental implant success and the approach holds promise in evaluating the success of dental implants.[35] Studies have found success in accurately predicting dental implant success even when dealing with imbalanced data.[36]

AI could identify the crucial factors affecting the prognosis of implants with the mesiodistal position of the implant identified as the most crucial factor influencing prognosis.[37] ML algorithms were implemented to predict the necessity of dental implants by leveraging patients' historical data and current symptoms.[38] AI can serve as a valuable addition to existing evaluation methods for assessing and predicting osseointegration.[39] DL models can be effective tools for predicting the fate of dental implants after surgery helping clinicians make more informed decisions for their patients.[40] Several other studies[41–45] have adopted AI to predict bio-tribocorrosion, and postoperative discomfort in dental implant surgery, recognize and classify fractured dental implants, classify dental implant size, study the correlation between the initial stability of implants and peri-implant bone mineral density and these AI applications are presented in Table 4.

**Table 2:** AI in implant planning

| Author | Objective | AI model | Results/Accuracy |
|---|---|---|---|
| Widisari M et al[17] | Automatic and simultaneous detection of alveolar bone and mandibular canal | Dental-YOLO | 99.46% |
| Moufti et al[19] | To detect and trace edentulous alveolar bone on CBCT images | "U-Net" CNN | 78% |
| Bayrakdar et al[20] | Measuring bone height and thickness, segmentations of teeth, maxillary sinus, jaws, mandibular canals, and missing teeth | Diagnocat AI system | 72.2%, 66.4%, and 95.3% |
| Mangan FG et al[21] | 3D planning for implants using AI and augmented reality | Using AI and augmented reality | - |
| Kung PC et al[22] | Improving the design of dental implants by considering patients' conditions | U-net, ANN, and random forest models | 86% |
| Alsomali, M. et al[23] | To develop an AI model that can automatically localize the position of radiographic stent GP markers in CBCT images to recognize proposed implant positions, | DL model | 83% |
| Chen Z et al[24] | AI-assisted implant planning software program for guided implant surgery | - | - |
| Sakai T et al[25] | AI model to identify the appropriate implant drilling protocol utilizing CBCT images | LeNet-5 | 93.8%. |
| Lerner H et al[26] | AI-driven optimization of the design and manufacturing of custom abutments | - | - |
| Tilebon et al[27] | Enhancing the etching process for dental implant surface treatment | Combination of MLP-ANN-based modeling and NSGA-II-based multi-objective optimization | - |

**Table 3:** AI in Peri-implantitis Management

| Author | Objective | AI model | Accuracy of the model |
|---|---|---|---|
| Liu et al[29] | To Detect the peri-implant marginal bone loss on periapical radiographs | R-CNN | 73% |
| Rekwak et al[30] | To predict dental implant failure and peri-implantitis | Logistic regression, random forest classifiers, SVMs, and ensemble techniques | 87.2% to 84% |
| Mameno et al[31] | To develop predictive models for peri-implantitis based on demographic data and other parameters | Logistic regression SVMs random forests | 63%, 64%, 71% |
| Chen YC et al[32] | To evaluate the extent of periodontal damage around dental implants in periapical film | CNN models | 90.45%. |

## 4. Conclusion

Integrating AI into dental implantology has ushered in a new era of precision, efficiency, and predictive capabilities. AI has addressed numerous challenges faced by clinicians in implant identification, planning, and prediction of outcomes. The sheer variety of implant systems in the market has made implant identification a complex task, but AI-driven models have emerged as a reliable solution. In the domain of implant planning, AI has streamlined the process by automating tasks that not only save time but also enhance the accuracy of treatment plans. AI's potential in predicting osseointegration, risk factors associated with implant failure, and the need for dental implants add an invaluable decision support system for clinicians. Moreover, AI has demonstrated its prowess in recognizing peri-implantitis at an early stage, a critical concern in dental implant maintenance.

However, it's essential to note that whilst AI holds immense promise, there are still practical limitations in its clinical application. Further research and validation through clinical trials are necessary to ensure the reliability and effectiveness of AI models in real-world dental practice. Additionally, the need for well-organized datasets and advanced AI architectures cannot be overstated, as these are fundamental to the success of AI applications in dental implantology.

**Table 4:** AI-driven Prediction in Dental Implantology

| Author | Objective | AI model | Results/Accuracy |
|---|---|---|---|
| Lyakhov PA et al[33] | Predicting the success of single-implant survival | CNN architecture | 94.48% |
| Oliveria et al[34] | Predicting the success of dental implants | SVM, weighted SVM, and RBF-DDA | - |
| Moayeri R S et al[35] | Predicting the success of dental implants | W-J48, SVM, Neural Network, K-NN, and Naïve Bayes | The combined approach with an accuracy of 90% |
| Sabjekar M et al[36] | Predict the success or failure of dental implants | ensemble of decision tree, SVM, k-nearest neighbor, and Naïve Bayes | 91% |
| Ha S R et al[37] | To identify the most crucial factors predicting the prognosis of dental implants | Decision tree model SVM | 64-93%, 73-95% |
| Alharbi MT et al[38] | Predicting the necessity of dental implants | Bayesian network, random forest, AdaBoost algorithm, Improved AdaBoost algorithm | 72.8%, 77.8%, 86.1%, 91.7% |
| Oh S et al[39] | Prediction of osseointegration from radiographs | ResNet-18,34,50, DenseNet-121,201, MobileNet-V2, and MobileNet-V3 | 80.6%, 82.2%, 83.6%, 81.8%, 81.6%, 82.4%, 79.9% |
| Huang N et al[40] | Predicting the risk of dental implant loss using CBCT scans | Logistic regression DL model Integrated model | 72%, 87%, 90% |
| Ramachandran R A et al[41] | Early detection and prediction of bio-tribocorrosion in dental implant materials | Logistic Regression, Latent Dirichlet Allocation, k-NN, Decision Tree, Support Vector Classifier, and Random Forest models | All models achieved over 90% |
| Yadalam P K et al[42] | Predicting postoperative discomfort in dental implant surgery | An AI-based multi-linear regression model | 89.6% |
| Lee D W et al[43] | Recognition and classification of fractured dental implants | VGGNet-19 GoogLeNet Inception-v3 Automated deep CNN | 92%, 96%, 97% |
| Park J H et al[44] | Classifying dental implant size using periapical radiographs | VGG16 Cluster analysis | 99%, 98% |

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## 6. Conflict of Interest

None.

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