Prediction and Classification of Single Tooth Recession Using deep neural networks

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Single tooth recession, artificial intelligence, machine learning, predictive models, dental research, personalized care.

ABSTRACT

Background: Single-tooth recession is a common dental condition that can lead to aesthetic concerns and sensitivity. The early prediction of single tooth recession can be crucial for implementing preventive measures and conservative treatments.

Materials And Methods: The study used an Orange machine learning tool to analyze intraoral frontal images to predict and detect lower anterior recession. Three algorithms were used: Logistic Regression, Neural Network, and Naïve Bayes. The models were trained on 70 images and evaluated using a confusion matrix.

Results: The machine learning algorithms with CNN embedding successfully detected and predicted a recession. The model showed high accuracy in predicting recession in anterior teeth. For multiple lower anterior recessions, it showed an AUC of 0.964. With the advancements in artificial intelligence (AI) and machine learning, there is growing interest in utilizing these technologies to predict a single-tooth recession.

Conclusion: This article provides an overview of the current state of research in this area, discusses the challenges and opportunities, and suggests future directions for developing AI-based predictive models for single tooth recession.

1. Introduction

Single tooth recession, the apical migration of the gingival margin with exposure to the root surface, is a prevalent condition in dental practice (1-3). It can result from various factors such as periodontal disease, mechanical trauma, anatomical variations, and genetic predispositions. Early identification and prediction of single tooth recession are essential for timely intervention and prevention of further tissue loss. Traditional methods for predicting recession, such as clinical measurement of recession depth and width, have limitations in terms of accuracy and reliability (5-7).

Artificial intelligence (AI) can predict single tooth recession, enhance the diagnostic process, improve patient care, and contribute to the advancement of dental research and treatment methodologies (8). AI can detect signs of gum recession, providing timely intervention to prevent further progression and potential tooth loss. It also offers precision and consistency, saving time and cost for dental professionals (9-11). AI can also assist in creating personalized treatment plans, improve patient outcomes, and serve as an educational tool for professionals and patients. However, artificial intelligence (AI) and machine learning offer the potential to overcome these limitations and provide more accurate and efficient predictive models for single-tooth recession. In the fast-evolving landscape of technology, one phenomenon has captured the world's attention and holds tremendous potential for transforming societies, industries, and our everyday lives (12-14)

SqueezeNet-based machine learning classification model is a valuable tool for predicting gingival tooth recession due to its lightweight architecture, resource optimization, high accuracy with less complexity, scalability, and cost-effectiveness. The model's methodology involves data collection, preprocessing, model training, validation and testing, and deployment in clinical settings. The lightweight architecture allows for efficient computation and faster processing times, making it suitable for environments with limited processing power. SqueezeNet can achieve accuracy comparable to larger models, reducing the risk of overfitting. The model's compact nature allows for easy integration into dental software systems, making it cost-effective for dental practices. Continuous improvement is possible through retraining with new data. As far as we know, no studies have classified gingival tooth recession using squeeze net algorithms. So we aim to classify and predict single tooth recession using convoluted neural networks-based machine learning classification

2. Methodology

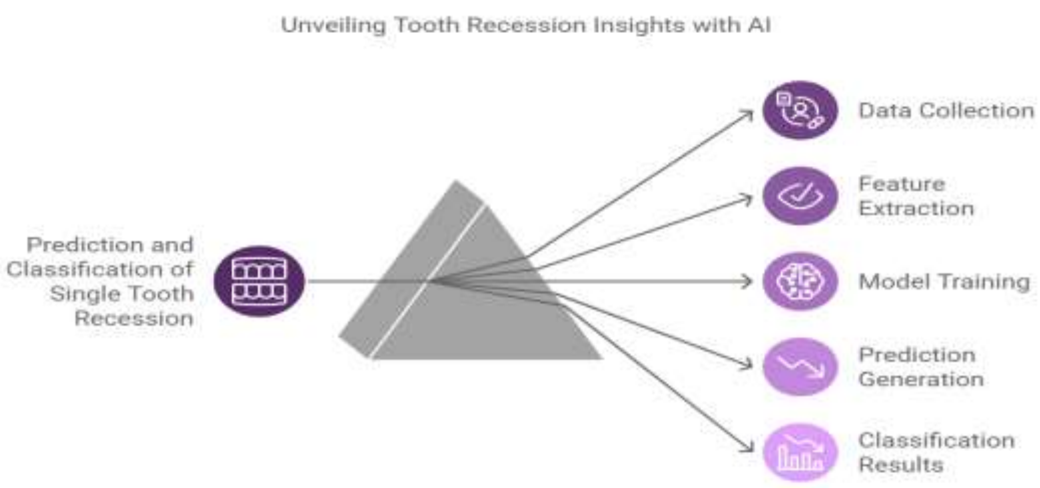

Fig. 1: workflow diagram

The intraoral frontal pictures used in this study were selected from a dental information management software database. Seventy images were acquired from Saveetha Dental College and Hospitals and divided into 35 healthy and 35 with multiple lower anterior recessions. Experts' Manual labeling provided a reference for training and evaluating the models. (fig-1)

The study utilized the Orange Data Mining tool, a machine-learning method that integrates image mining with visual analytics, resulting in interactive visualizations. It involved file loading, transformation, user interaction, model inference, and visualization using feature vectors from pre-trained deep convolutional networks. Orange's Image Embedder widget supports various embedders, including Squeeze Net, which maximizes accuracy and network complexity. The system safeguards users' privacy by storing photos on their computer, allowing comparison to more complex networks like squeezenet. Data was divided into training and testing, with 20 models cross-validated using logistic Regression, neural networks, and naive bayes. Orange uses standard Python libraries for machine learning and data manipulation (15-18).

2.1 Squeezenet architecture

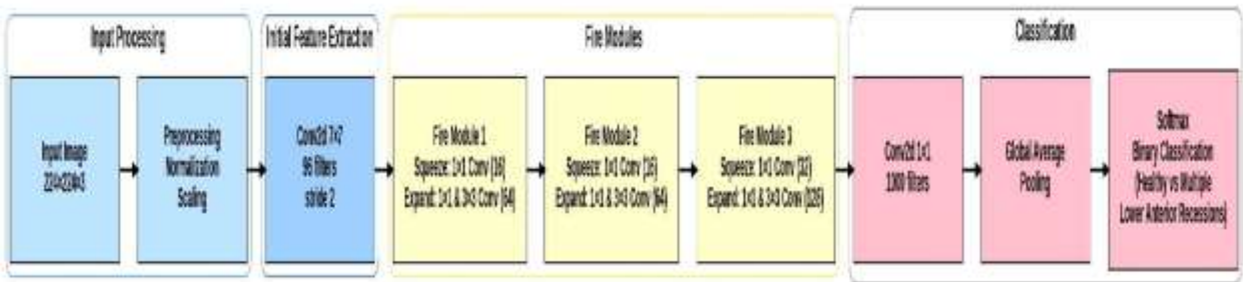

Fig. 2: shows the architecture of the model.

SqueezeNet is a deep neural network architecture that aims to achieve AlexNet-level accuracy on image classification tasks using fewer parameters. The architecture employs three main strategies: squeeze layers, expand layers, and fire modules. Squeeze layers compress input feature maps using 1x1 convolutions, while expand layers expand compressed feature maps to higher dimensions. Fire modules combine squeeze and expand layers for efficient parameter usage. Global average pooling reduces parameters and prevents overfitting. Late downsampling preserves spatial information in early layers, potentially improving fine-grained feature learning. SqueezeNet also incorporates deep compression techniques like pruning, quantization, and Huffman coding to reduce model size without compromising accuracy. (fig-2)

2.2 Naïve bayes and logistics regression architecture

Naive Bayes is a probabilistic algorithm based on Bayes' Theorem for classification tasks. It assumes that features in a dataset are independent of each other, simplifying computation and efficiency (19,20). Naive Bayes has several variations, including Gaussian, Multinomial, and Bernoulli. It is widely used in text classification, spam detection, and sentiment analysis. Logistic Regression is a statistical model used for binary classification tasks, modeling the probability that a given input belongs to a particular class. It uses the sigmoid function to map predicted values to probabilities (21-23).

2.3 Evaluation metrics

AUC-ROC is a classification model performance statistic assessing accuracy across classes, with higher AUCs indicating greater accuracy. A model with a close AUC for separability is the most accurate.

3. Results

The study utilized Orange, an open-source image analysis software package, to analyze small image sets using trained deep networks and image embeddings. Orange offers features for workflow creation, data modeling, interactive visualization, clustering, classification, Regression, outlier identification, and dimensionality reduction. It provides an efficient, laptop-compatible solution without retraining deep neural network embeddings. Orange complements other toolboxes and offers advanced users and data scientists an alternative. Naïve bayes and logistics regression showed 96% and 99% accuracy.

The study found that neural networks outperformed other algorithms in detecting and classifying depressions in the anteroinferior region. Naïve Bayes and logistic Regression performed better in detecting single-tooth recession. This suggests that machine learning algorithms can improve the accuracy and efficiency of detecting single tooth recession, allowing early detection of gingival recession and reducing subjectivity and bias. (fig-3,4,5,6)

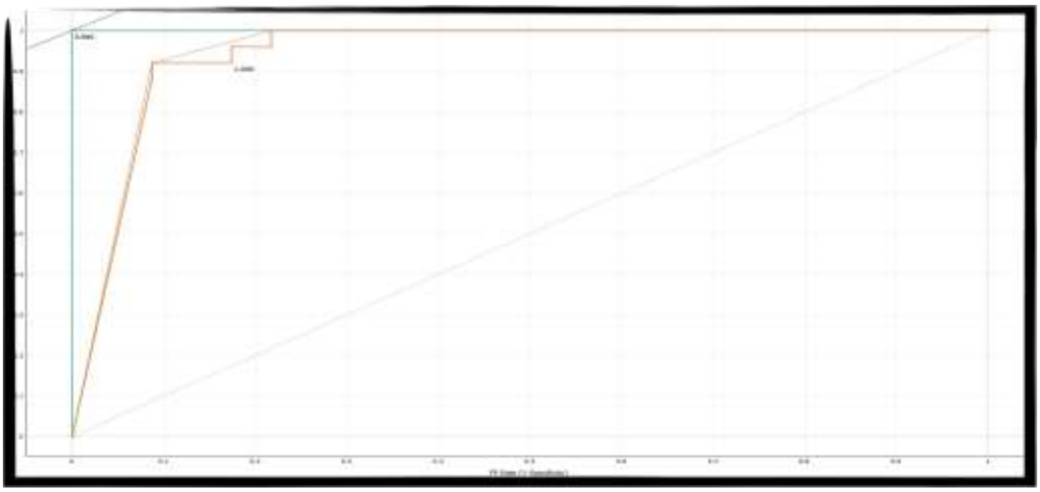

Fig. 3: ROC analysis of normal gingiva

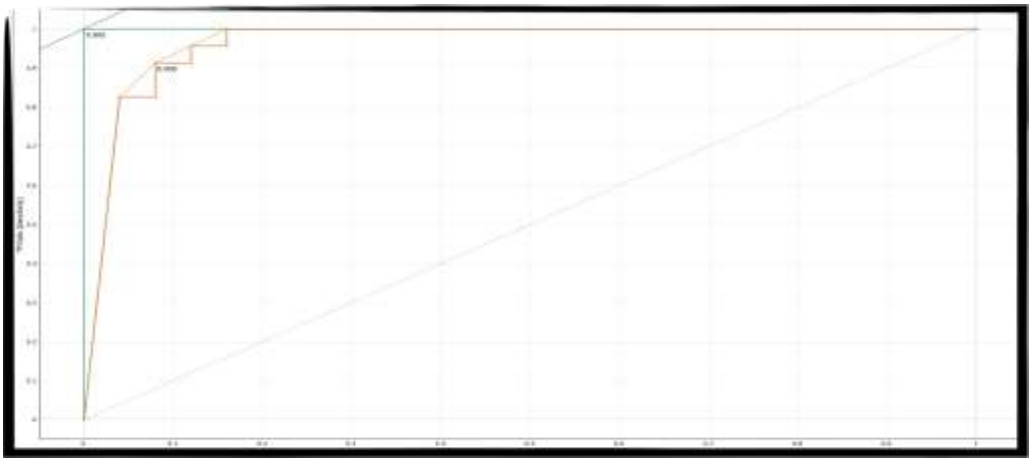

Fig. 4: ROC analysis of single tooth recession

Actual \ Predicted	withoutrecession	withrecession	Σ
withoutrecession	85.2 %	9.5 %	25
withrecession	14.8 %	90.5 %	23
Σ	27	21	48

Fig. 5: Confusion matrix of naive bayes

Actual \ Predicted	withoutrecession	withrecession	Σ
withoutrecession	100.0 %	0.0 %	25
withrecession	0.0 %	100.0 %	23
Σ	25	23	48

Fig. 6: Confusion matrix of logistics regression.

4. Discussion

Several recent studies have explored AI techniques for predicting a single-tooth recession. For example, researchers have employed machine learning algorithms to analyze various risk factors, including periodontal biotypes, tooth anatomy, oral hygiene habits, and genetic markers, to develop predictive models for recession (23). These studies have demonstrated promising results regarding AI-based models' accuracy and predictive ability in identifying individuals at high risk of developing single-tooth recession. Furthermore, integrating data from clinical examinations, imaging techniques, and patient demographics has shown potential for improving the precision of AI models in predicting recession patterns at the individual tooth level.

Despite the potential benefits of AI in predicting a single-tooth recession, several challenges need to be addressed. One of the key challenges is the availability of high-quality data for training AI algorithms. Large-scale longitudinal studies with comprehensive clinical and imaging data are essential for developing robust and generalizable predictive models. Additionally, the interpretability of AI predictions and integrating AI tools into the clinical workflow are important considerations for successfully implementing AI-based predictive models in dental practice. (24). Furthermore, the ethical and legal implications of using AI in dentistry must be carefully addressed, particularly in patient privacy and data security.

The application of artificial intelligence (AI) and machine learning (ML) in dentistry has shown immense potential for advancing diagnostics and personalized care. This study demonstrated the effectiveness of machine learning algorithms, particularly convolutional neural networks (CNNs), in predicting and classifying single-tooth recession. The findings highlight the utility of AI in reducing diagnostic subjectivity, improving accuracy, and enabling early intervention (25).

4.1 Comparison with Existing Literature

Our results align with previous studies emphasizing AI's role in dentistry. Researchers such as Tandon and Rajawat (2020) and Schwendicke et al. (2020) have noted the advantages of AI in diagnosing and managing periodontal diseases (26,27). This study corroborates these findings, particularly in single-tooth recession classification, by achieving an AUC of 0.964 using advanced algorithms like SqueezeNet. The lightweight architecture of SqueezeNet demonstrated high efficiency, comparable to larger models, making it a practical choice for clinical applications.

4.2 Algorithm Performance

Among the tested algorithms, neural networks outperformed logistic regression and Naïve Bayes in detecting and classifying recessions in the lower anterior region. However, Naïve Bayes and logistic regression exhibited higher precision in detecting single-tooth recession. These findings suggest that combining models or using ensemble methods might further enhance predictive accuracy and reliability (28).

4.3 Challenges and Limitations

Despite the promising results, several challenges persist.

1. Data Quality and Quantity: The study was limited to 70 intraoral images, which may restrict the generalizability of the findings. Larger datasets with diverse demographic and clinical variations are necessary to train robust models (29).
2. Model Interpretability : While neural networks achieved high accuracy, their black-box nature poses challenges in understanding the rationale behind predictions. Future research should focus on enhancing the interpretability of AI models for better acceptance in clinical practice.
3. Integration into Clinical Workflow: Implementing AI-based tools in dental practice requires seamless integration with existing dental software systems. User-friendly interfaces and clinician training are essential for adoption (30).
4. Ethical Concerns: The use of patient data necessitates strict adherence to privacy and security protocols to prevent misuse and ensure ethical compliance (31-32).

4.4 Future Directions

This study opens avenues for further exploration in AI applications for periodontal conditions. Future research should focus on:

- Expanding datasets through multicentric studies for improved model generalizability.
- Exploring ensemble models or hybrid approaches to leverage the strengths of different algorithms.
- Integrating AI tools with real-time imaging systems for immediate clinical use.
- Addressing ethical concerns by developing robust data governance frameworks (33).

4.5 Clinical Implications

The study underscores the potential of AI to revolutionize periodontal care. AI-based predictive tools can assist clinicians in identifying patients at risk for single-tooth recession, enabling timely preventive measures. Moreover, these tools can enhance patient education by visually demonstrating recession risks, thereby improving treatment adherence and outcomes (34,35).

5. Conclusion

In conclusion, applying artificial intelligence and machine learning in predicting single tooth recession holds great promise for advancing personalized dental care and improving patient outcomes. While challenges such as data availability, interpretability, and implementation barriers must be carefully addressed, the potential benefits of AI-based predictive models for single-tooth recession prediction are substantial. Collaborative efforts across interdisciplinary fields, standardized data collection, and technological advancements will drive the development and implementation of AI tools in predicting and managing single-tooth recession in dental practice.

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