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Original Research Article

Ai-Assisted Detection of Gingival Recession from Clinical Images: A Pilot Study

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Name of Author:

Dr. Hariprasath Gopalakrishnan[1*], Dr. Sasi Kumar PK[2], Dr. Dhivya Rajendran[3], Dr. Sakthi Saranya Devi K[4], Dr. Haseena Begum Haleel Rahman[5] and Dr. Hiruthika Kandasamy[6]

Affiliation:

[1]*Department of Periodontics, JKKN Dental College and Hospital, Komarapalayam-638183, Tamil Nadu, India.*

[2]*Department of Periodontics, JKKN Dental College and Hospital, Komarapalayam-638183, Tamil Nadu, India*

[3]*Department of Periodontics, JKKN Dental College and Hospital, Komarapalayam-638183, Tamil Nadu, India.*

[4]*Department of Oral Medicine and Radiology, JKKN Dental College and Hospital, Komarapalayam-638183, Tamil Nadu, India.*

[5]*Department of Periodontics, JKKN Dental College and Hospital, Komarapalayam-638183, Tamil Nadu, India.*

[6]*Department of Periodontics, JKKN Dental College and Hospital, Komarapalayam-638183, Tamil Nadu, India.*

Corresponding Author:

Dr. Hariprasath Gopalakrishnan

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Abstract: ***Aim***: To assess the feasibility and diagnostic accuracy of an artificial intelligence (AI) model predicting the classification of gingival recession using intraoral images, based on the classification proposed by Miller(1985). ***Materials and Methods***: This pilot study was a descriptive cross-sectional study was conducted on a sample of twelve individuals (6 males, 6 females, aged 19-65 years) presenting with gingival recession (either localized or generalized). Photographs of the interiors of the mouth were taken and the gingival recession of the mouth was classified clinically in accordance with the Miller gingival recession classification. The convolutional neural network was trained on Source Images through Google Teachable Machine with the transfer learning approach and data augmentation. The comparison of model predictions and clinical diagnosis was done. Diagnostics performance measures, agreement measures and age measures were determined. ***Results***: An AI-trained model achieved a total classification accuracy of 91.7% (11/12 cases correctly classified). Classification Sensitivity was 100% and 66.7% respectively in Classes I-III and Class IV respectively because there was one misclassification to Class II. Specificity ranged from 88.9% to 100%. The kappa obtained by Cohen was nearly the optimal agreement (κ = 0.89). There was mild recession in all age groups, with more severe defects being noted among older participants. ***Conclusion***: There is a high potential of AI-based image analysis as the screening and classification of gingivitis recession in a non-invasive way. There is a need to have larger datasets and external validation before clinical implementation.

Keywords: gingival recession, artificial intelligence, machine learning, Diagnosis, Convolutional neural network.

INTRODUCTION

Gingival recession is the apical shift or displacement of the gingival margin beyond the cementoenamel junction which exposes the root surface and causes associated problems such as: dentinal hypersensitivity, root caries, and aesthetics concerns.[1] Correct classification of recession defects is paramount to prognosis and planning of treatment.

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Till date even the new classification called Cairo's classification is available,The Miller classification is still the most widely utilized clinical system used to evaluate the presence of gingival recession.[1] Regardless, major limitations have been identified, especially in advanced defects where it may not be predictable that root coverage will be achieved completely.

Conventional diagnosis relies on periodontal probing and clinician judgment, which can be subjective and variable across examiners, has been applied to diagnose a problem, and artificial intelligence (AI), especially deep learning such as **convolutional neural network(CNN)**, has proven to have a high diagnostic performance in dental image analysis.[2-4] In periodontology, AI systems have been successfully applied to detect periodontal bone loss and stage the severity of the disease as well as predict the disease progression with the use of radiographic data.[5-8]

Recent studies have investigated the possibility of using intraoral photographs as a non-invasive source of data for periodontal check-up.[9] AI applications have also boosted in the diagnosis, risk prediction, biomarker analysis and individual treatment plan for periodontal diseases.[10-14]

Despite all these advances, AI-driven assessment of soft-tissue conditions like gingival recession is still limited. Therefore, the aim of this pilot research was to test the feasibility and diagnostic accuracy of an artificial intelligence (AI) model trained using standardized intraoral photographs to classification of gingival recession using Miller's classification(1985).

MATERIALS AND METHODS

Study Design and Ethical Approval:

This pilot study was a descriptive cross-sectional study conducted according to the ethical principles defined in the Declaration of Helsinki (2013), and all participants signed informed consent before taking part in the study.

Participants:

Purposive sampling was used to recruit twelve adult patients (19-65 years old) with either localized or generalized gingival recession.

Inclusion criteria:

- Age of 18 years and above.
- Presence of gingival recession (localized or generalized)

Exclusion criteria:

- Patient on Orthodontic therapy
- Systemic illness affecting periodontal conditions

Clinical Assessment:

Depth of the Gingival Recession was measured from the cementoenamel junction to the gingival margin by a UNC-15 periodontal probe. Defects were classified according to Miller's classification.[1]

Image Acquisition:

Each participant had one standard intraoral photograph that was captured at a high resolution intraoral camera under controlled light conditions with a fixed distance to reduce variability between participants.(Figure1)

Figure 1. Representative intraoral photos to be used as a training and evaluation of the artificial intelligence model.

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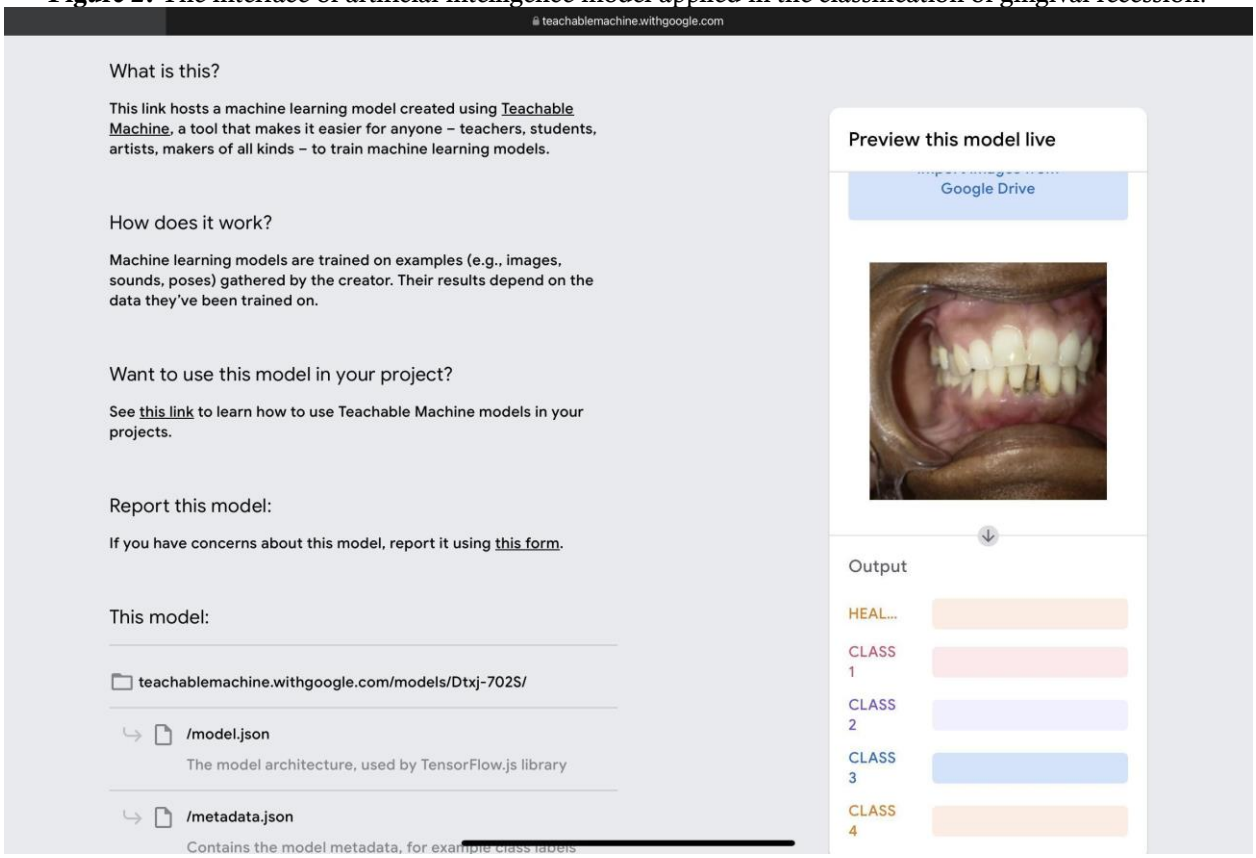
Miller's classification of gingival recession was done primarily based on clinical photographic features. It is however known that to differentiate well between Class III and Class IV defects, requires assessment of interproximal bone loss and soft tissue has to be measured, which cannot be evaluated safely through the use of two-dimensional intraoral photographs alone. The present study did not describe any radiographic data; hence, it was classified based on visual soft-tissue characteristics (the degree of recession, the height of papillary, and the position of the tooth). This weakness might have played a role in lowered precision in progressive recession categories.

AI Model Development:

100 images were collected for each classes (from I to IV) of gingival recession from existing sources and trained in Google Teachable Machine which is free to use.

Clinically captured Images were labeled according to recession class and uploaded to Google Teachable Machine. Data augmentation techniques like rotation, mirroring, brightness adjustments were applied to improve model robustness. Transfer learning with a MobileNet-based convolutional neural network architecture was used.(Figure2)

Figure 2. The interface of artificial intelligence model applied in the classification of gingival recession.



Statistical analysis:

Statistical Data analysis was performed using IBM SPSS(Statistical Package for the Social Sciences) Statistics Version 26.0 (IBM Corp., Armonk, NY, USA). Continuous variables were summarized as mean +/- standard deviation, while categorical variables were represented as frequencies and percentages.

The diagnostic performance of the artificial intelligence model was evaluated by:

- calculating overall accuracy,
- sensitivity, and
- specificity.

A confusion matrix was created to illustrate the classification performance of the model and pinpoint certain patterns of misclassification across the four Miller classes.

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To evaluate the agreement between the predictions of the AI model and the clinical ground truth diagnosis, Cohen kappa coefficient (k) was used. Participants were classified into three age groups (19-30, 31-50, >50 years) to note the demographic trends. Since this pilot study is purely exploratory and the sample size (n=12) is small, there was no need to become overly assertive with inferential statistical testing, confidence intervals and more sophisticated predictive measures (like ROC-AUC or F1-scores). As a result, all the findings are described in a descriptive format to demonstrate the possibility of establishment of larger, better trials in the future.

RESULTS

Characteristics of participants:

A total of twelve participants were represented (six males, six females). Age ranged from 19 to 65 years. The numbers of the four classes of Miller were equal (Table 1).

Table 1. Demographic Characteristics of Participants (n = 12)

Variable	Value
Age range (years)	19–65
Mean ± SD	~46 ± 14*
Male	6 (50%)
Female	6 (50%)
Class I	3 (25%)
Class II	3 (25%)
Class III	3 (25%)
Class IV	3 (25%)

*Approximate mean based on available records

Primary Outcome: Diagnostic Accuracy:

The AI model made the accurate predictions on 11out of the 12 clinical cases, making its initial accuracy 91.7. At the performance measured by specific categories of gingival recessions, this AI model had 100% sensitivity to mild and moderate defects (Class I: 3/3; Class II: 3/3; Class III: 3/3). Regardless, sensitivity decreased for severe defects, accurately identifying Class IV in 2/3 cases (66.67%).

Specificity was also very high in all categories with the highest specificity at 88.9% (8/9) in Class II and at 100% (9/9) in the rest of the classes.(Table 2) The overall specificity between these AI-generated classifications and the clinical diagnosis of the periodontist was near perfect, marked by a Cohen's kappa coefficient of 0.89.

Thus, the AI trained model correctly classified 11 of the 12 clinical cases, yielded an overall initial accuracy of 91.7%. When evaluating performance by specific recession categories, the model demonstrated 100% sensitivity for detecting mild to moderate defects (Class I: 3/3; Class II: 3/3; Class III: 3/3). Specificity remained consistently high across all categories, ranging from 88.9% (8/9) for Class II to 100% (9/9) for the remaining classes.(Table 2) The overall agreement between the AI-generated classifications and the periodontist's clinical diagnosis was almost perfect.

Table 2. Diagnostic Performance of the AI Model by Miller Classification

Class	True Positives	False Positives	False Negatives	Sensitivity (%)	Specificity (%)
I	3	0	0	100	100
II	3	1	0	100	88.9
III	3	0	0	100	100
IV	2	0	1	66.7	100

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Overall Accuracy: 91.7%
Cohen's κ: 0.89

Secondary Outcome:
Misclassification Pattern: There was one instance of a misclassification of Class IV recession as Class II. There was no misclassification between Classes I-III.(Table 3)

Table 3. Confusion Matrix of AI Predictions vs Clinical Diagnosis

Classes	Predicted class I	Predicted class II	Predicted class III	Predicted class IV
Actual Class I	3	0	0	0
Actual Class II	0	3	0	0
Actual Class III	0	0	3	0
Actual Class IV	0	1	0	2

Age- and Sex-Based Observations:
There was mild recession (Classes I-II) in all groups of age, including younger participants. The cases of moderate or severe defects (Classes III-IV) were more common among the participants who were older than 45. Nonetheless, the small sample size did not allow establishing any statistical relationship between age or sex and the severity of recession.

DISCUSSION

Summary of Key Findings:
This pilot study showed that the accuracy of determining gingival recession using an AI model trained on standardized intraoral photographs is high (91.7%) and the model has an almost perfect agreement with clinical diagnosis (κ = 0.89). Performance was excellent with mild to moderate defects but was lower for severe recession.

Interpretation in correlation with Existing Evidence:
Gingival recession is a prevalent periodontal condition that needs proper classification for its prognosis and treatment planning.[1] The Miller system is still widely used despite having shortcomings in the area of advanced defects.[1,17]

AI applications in dentistry has proven to be strong in terms of dental diagnosis of the periodontal bone loss and staging of the disease.[5-8] Reviews highlight its potential to minimise observer variability and increase diagnostic precision.[2-4]

Recent evidence has shown that intraoral photographs have the potential to be useful non-invasive sources of data for use in the automated assessment of periodontitis.[9] The present study is an extension of these findings to an evaluation of soft tissues.

Reduced sensitivity for severe defects is likely characteristic of the morphological complexity of advanced recession and limitations of the classification system itself.[17] In periodontology, AI studies and autonomous diagnostic tools are a growing focus of study because of the potential of the latter to transform the field and predict risk.[10,15,16]

Age-Related Interpretation:
The finding of the increased severity of recession in older subjects is consistent with the epidemiological evidence that indicates there is cumulative periodontal damage over time. However, when a recession occurs in the younger individual it does confirm a multifactorial etiology involving trauma, phenomenology, and local factors.

Strengths:
- Standardized protocol for imaging
- Balanced representation of recession classes
- High Agreement to Clinical Diagnosis
- Non-invasive methodology

Limitations:
- Small pilot sample
- Single-center recruitment
- One image per participant
- Lack of external validation
- Cross-sectional design

The other limitation is the fact that two-dimensional intraoral photographs are used to classify gingival recession. Although photographic analysis suffices to detect mild defects, such as class I and II, more severe classes of recession necessitate the determination of interproximal bone and attachment loss which is impractical to be detected using the soft-tissue images alone. Failure to have a radiographic correlation can hence result in misclassification of Miller Class III and IV defects and this explains the lower model performance in these groups. Future studies involving the use of radiographic or three-dimensional data,

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could contribute to the accuracy of the diagnostic or clinical applicability of automated classification systems.

Clinical Implications:
AI-assisted photographic analysis may be valuable to support the screening, triage, and monitoring of gingival recession, especially in tele-dentistry scenarios or fulfilling the required resource limitations.

Controversies:
The industrialization of clinical decision-making with AI brings a few concerns from reliability in populations, ethical aspects, and standardized imaging protocols.

Future Research Directions:
Larger multicenter datasets, quantitative clinical measure, external cohorts validation, as well as evaluation in the real world should be considered for future studies.

Hypothesis: Using AI models trained on big, diverse datasets may be able to provide diagnosis equivalent to that of specialist clinical assessment.

CONCLUSION

By making standardized intraoral photographs, AI models can make high levels of accuracy in order to predict the extent of gingival recession according to Miller's classification(1985). The system was characterized by a high level of performance as mild to moderate defects, and a performance that was acceptable in terms of severe lesions. The results emphasize the possibilities of AI because it could be a fast, non-invasive and objective screening solution that could enhance clinical decision making, promote application of tele-dentistry services and periodontal surveillance data gathering on a large scale. Nonetheless, larger multicenter research works which undergo external validation are pivotal in order to confirm clinical applicability.

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CONFLICT OF INTEREST:

No conflicts of interest to declare.

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