Prediction of Multiple Recession in Lower Anterior Using Artificial Intelligence

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KEYWORDS
artificial intelligence, dental, gingival recession, deep learning, machine learning

ABSTRACT
Background and Aim: Soft tissue recession is the movement of the gingival edge apical to a tooth's cemento-enamel junction (CEJ) or dental implant platform. This study used intraoral frontal photos to test machine-learning methods for lower anterior tooth recession detection and multiple recession.
Materials and Methods: Orange was employed with squeeze net embedding for gingival recession images. We trained and tested logistic regression and naïve bayes algorithms on intraoral frontal images of diverse lower anterior recession kinds to predict and classify the image embeddings. Accuracy was measured via a confusion matrix and roc curve.
Results: Squeezenet-embedded machine learning systems accurately classified recession, predicting and classifying lower anterior tooth recession. The accuracy of naïve bayes and logistical regression is 96% and 100%, respectively, with class accuracy of 95% and 100%.
Conclusion: Predicting and classifying multiple lower anterior recessions using AI advances clinical practice. It has no bias or negative examination error compared to human examination. It predicts early recession better than humans.

1. Introduction

Gingival recession or soft tissue recession is defined as the displacement of the gingival margin apical to the cemento-enamel junction (CEJ) of a tooth or the platform of a dental implant(1,2). This condition is associated with losing periodontal tissues, including gingiva, periodontal ligament, root cementum, and bone at teeth, and the loss of mucosa and bone around dental implants. It was demonstrated in several epidemiological studies that gingival recession is a common finding in daily clinical practice. The prevalence ranges from 40% to 100%, depending on the population and the analysis methods. Gingival recession defects can be localized or generalized and located at labial, lingual, and interproximal tooth surfaces(3–6).

Root surface exposure by gingival recession is frequently associated with dentine hypersensitivity, root caries, non-carious cervical lesions (NCCLs), compromised plaque control, and unaesthetic appearance(6,7). Moreover, the untreated gingival recession has a tendency for further apical displacement over time despite good patient motivation. Nevertheless, not all patients with gingival recession are willing to undergo a surgical intervention to obtain soft tissue root coverage. Consequently, clinicians should select the right treatment approach while considering patient- and tooth-related factors(8).

Visual examination and radiographic imaging are subjective means of diagnosing multiple recessions in the lower anterior that can lead to diagnostic errors. In contrast, machine learning algorithms have the potential to provide more precise and quantifiable assessments of multiple recessions(9). By leveraging artificial intelligence-based classification techniques, clinicians can quickly and accurately diagnose many multiple recessions in the lower anterior. The automatic detection and classification of recessions are potential advancements for periodontists, which ensures less and more reliable diagnoses(10,11).

Deep learning has been extensively studied and designed to identify recessions in the lower anterior using various architectural approaches(12,13). Despite a smaller number of studies, the reported accuracy is promising. In several recent studies, A deep convolutional neural network (DCNN)(14) was used to classify tooth types on dental cone-beam computed tomography (CT) images with an average classification accuracy of 88.8%, with a 5% improvement after data augmentation. Research studies compared AlexNet's and GoogleNet's performance in determining distal roots, revealing high accuracy, sensitivity, and specificity(15). At the same time, GoogleNet's classification task was more accurate because its 22-layer structure has looked into how deep learning models may be used to predict the type, progression, and etiology of recessions to understand their severity based on Miller's classification. Alternative machine learning methods, such as logistic regression and neural networks, must be compared to improve the accuracy of Miller's recession classification. By comparing the predictive accuracy of these models, we can identify the most effective algorithms for classifying recession and improving the overall quality of dental care. There is a need to develop more accurate and reliable models that can automatically detect recession using a variety of digital imaging modalities. This study aims to contribute to this area of research by exploring the predictive accuracy and automatic detection capabilities of machine learning algorithms to predict multiple recessions in the lower anterior.

2. Materials and Method

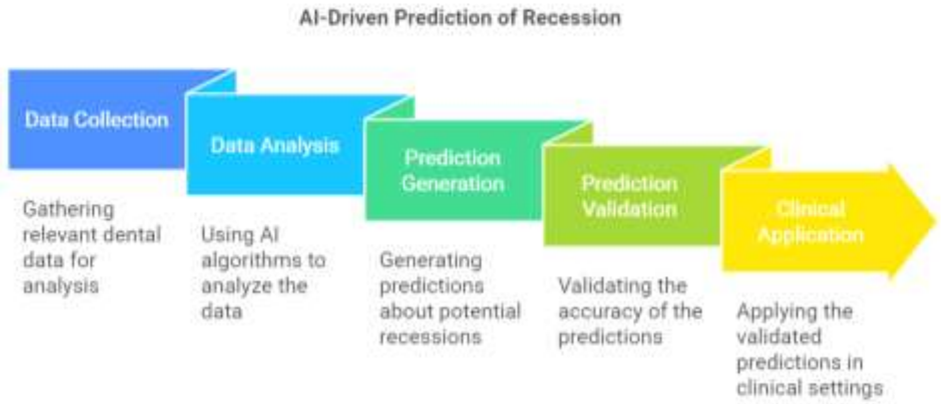

Fig-1 shows the workflow of the study.

The intraoral frontal pictures used in this study were selected from a dental information management software database. Seven hundred images were acquired from Saveetha Dental College and Hospitals and divided into 350 healthy and 350 with multiple lower anterior recessions. Experts' Manual labeling provided a reference for training and evaluating the models.

The dentist tagged every image for lower anterior multiple recessions. Orange Data Mining (16)was used for the investigation. Machine learning employs image mining and visual analytics to visualize data interactively and automatically. A typical workflow component collects, processes, visualizes, and presents analysis or user options for processing. Images are incorporated using pre-trained deep convolutional network feature vectors using squeezenet architecture. In Orange, squeeze net and other Keras Python library deep image classification models' penultimate layers are shown.(fig-1)

Squeeze Net Architecture

Convolutional neural networks like SqueezeNet(17) are becoming more popular due to their precision and small size. Its purpose was to outperform AlexNet with fewer parameters and run a network effectively. The design, benefits, and use cases of SqueezeNet will be examined in this response. SqueezeNet's architecture is built from "fire modules" that form the network. These fire modules efficiently combine spatial and channel-wise information for excellent accuracy with fewer parameters. Expand and squeeze layers make up each fire module. The squeeze layer has 1x1 convolutional filters that bottleneck and decrease input channels.

The extended layer extracts local and global contextual data using 1x1 and 3x3 convolutional filters. SqueezeNet's design uses several fire modules to learn and extract complex characteristics from incoming data with fewer parameters. Fully connected layers are then categorized as the final fire module output. Image categorization requires preprocessing images to ensure they are in the appropriate format and include the necessary information. Feature extraction, noise reduction, normalization, and image scaling may be needed. Different preprocessing methods may be utilized based on the picture categorization task. A professional image editing program rotated and cropped JPEGs to 1:1. Choose or extract significant visual qualities from photos to distinguish them across groups or categories. When embedded features are extracted, images can train machine learning algorithms for image classification.(fig-2)

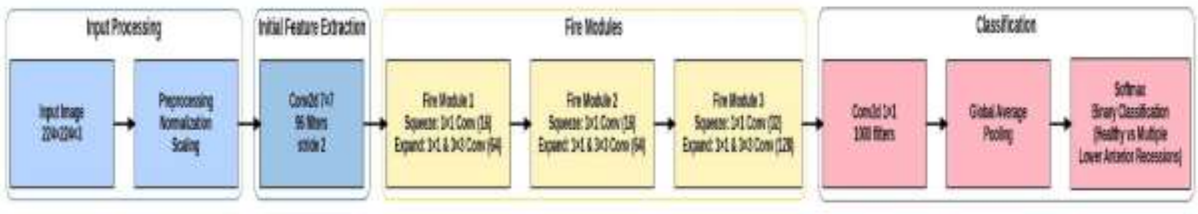

Fig-2 shows a squeeze net architecture of lower anterior teeth with multiple recessions.

Image embedding converts images into vectors. This compressed vector representation encodes image properties and qualities. Computer vision tasks, including image embedding, include picture classification, object identification, and retrieval. Converting images to vectors simplifies math and image comparisons. Image embeddings can be generated using deep learning methods like CNNs and pre-trained models like VGG16, ResNet, or squeeze net. After vectorization, photos can be used for many applications. Image embedding is a powerful method for concise, mathematical image representation, enabling computer vision applications.

Embedding puts a picture through a deep network to get its vector representation. Orange's Image Embedder widget supports many embedders. Squeeze Net, a deep convolutional network, optimizes accuracy and complexity for local embedding. To protect privacy, squeeze Net stores photos on users' computers rather than servers. Squeeze Net embeds accuracy evenly with more complex networks like InceptionV3. Server-based embedders may allow us to compare Squeeze Net to better-known trained deep models. The films were scanned at 11.5 pixels per millimeter and saved as "JPEG" files with reference numbers. Data was split 80/20 for training and testing, and 20 models were cross-validated using logistic regression, neural networks, and naïve bayes widgets.

AUC-ROC CURVE:

AUC-ROC measures classification model performance. The AUC-ROC statistic evaluates a model's class distinction. A higher AUC means a more accurate model. AUC-ROC curves show the sensitivity-specificity trade-off for each test cut-off. Separability AUCs are close to one in suitable models. Separability is worst in the lowest AUC model.

Precision, recall, F1 score, and ROC curve are evaluation metrics commonly used in machine learning and information retrieval tasks. Precision is the ratio of true positive predictions to the total number of positive predictions. It measures the accuracy of positive predictions, showing how well the model identifies relevant instances. Precision is calculated using the formula:

Precision = TP / (TP + FP)

Recall, also known as sensitivity or true positive rate, is the ratio of true positive predictions to the total number of positive instances. It measures the ability of the model to find all relevant instances. Recall is calculated using the formula:

Recall = TP / (TP + FN)

The F1 score is a combined metric that balances precision and recall. The harmonic mean of precision and recall provides a single value representing the model's overall performance. The F1 score is calculated using the formula:

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

The ROC (Receiver Operating Characteristic) curve is a graphical representation of the performance of a binary classifier. At different classification criteria, it graphs recall versus 1-specificity. Classifier performance evaluation often uses the area under the ROC curve (AUC-ROC). Higher AUC-ROC means greater classifier performance. These metrics evaluate machine learning models, especially in binary classification and information retrieval tasks. They reveal the model's precision-recall trade-off, discriminative capability, and ability to identify positive cases accurately.

3. Results

The study compares Naive Bayes and Logistic Regression models for classifying recessions. Naive Bayes has a high accuracy rate of 95.7%, while Logistic Regression has a perfect AUC score of 1.000. Both models have perfect precision and recall, but Logistic Regression outperforms Naive Bayes in all metrics. The F1 score measures a model's accuracy in predicting data, with Logistic Regression having a better F1 score.

Table -1 shows the accuracy of naïve bayes and logistics regression shows 96 % and 100 % and class accuracy of 95 % and 100%

Model	AUC	CA	F1	Precision	Recall
Naive Bayes	0.969	0.957	0.957	0.958	0.957
Logistic Regression	1.000	1.000	1.000	1.000	1.000

Table- 2 Confusion matrix of Naive bayes

Healthy Gingiva	97.1%	5.6%
Gingival recession	2.9%	94.4

The table shows the confusion matrix results, which indicate a classification task for identifying healthy gingiva versus gingival recession. The model correctly identified 97.1% of healthy gingiva instances, with 5.6% incorrectly classified as gingival recession. 2.9% of healthy gingiva instances were incorrectly classified as gingival recession, with 94.4% correctly identified. The higher the true positive and lower the false positive and false negative rates, the better the model identifies each class.

Table -3 shows the Confusion matrix of logistic regression.

Healthy Gingiva	100%	0%
Gingival recession	0%	100%

Table -3 results show an ideal binary classification task for identifying healthy gingiva versus gingival recession. The model has 100% accuracy in identifying healthy gingiva, with 0% false negatives and no misclassification errors. The model also has 100% accuracy in identifying gingival recession, with 100% false positives and no misclassification errors.

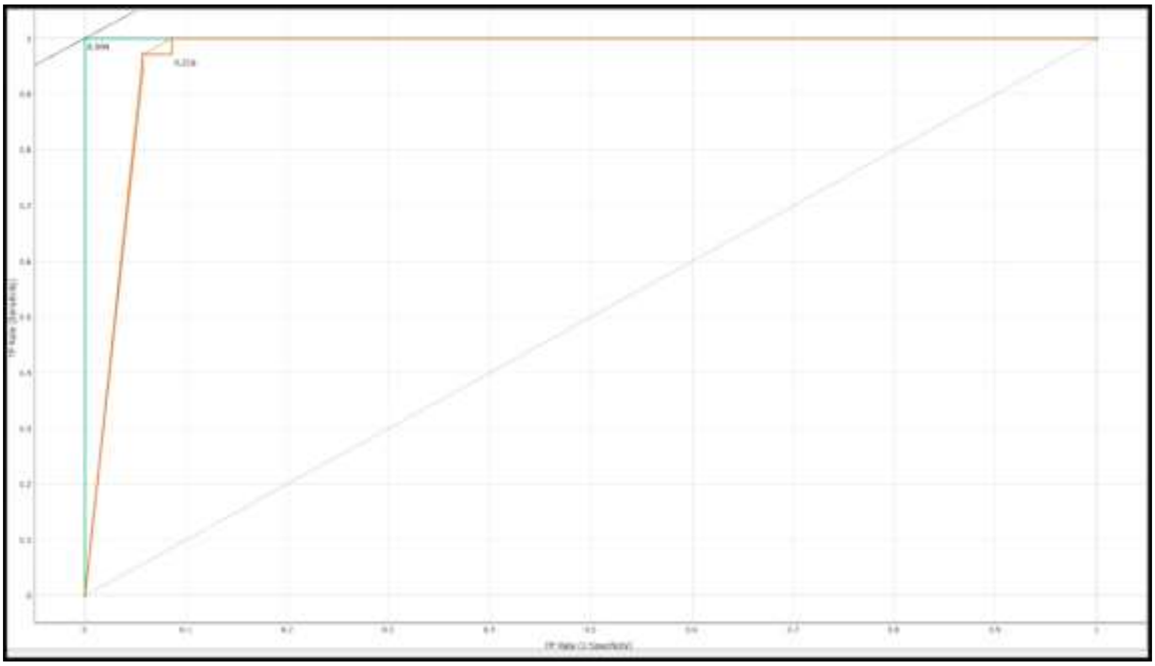

Fig:3 -ROC analysis of normal gingiva

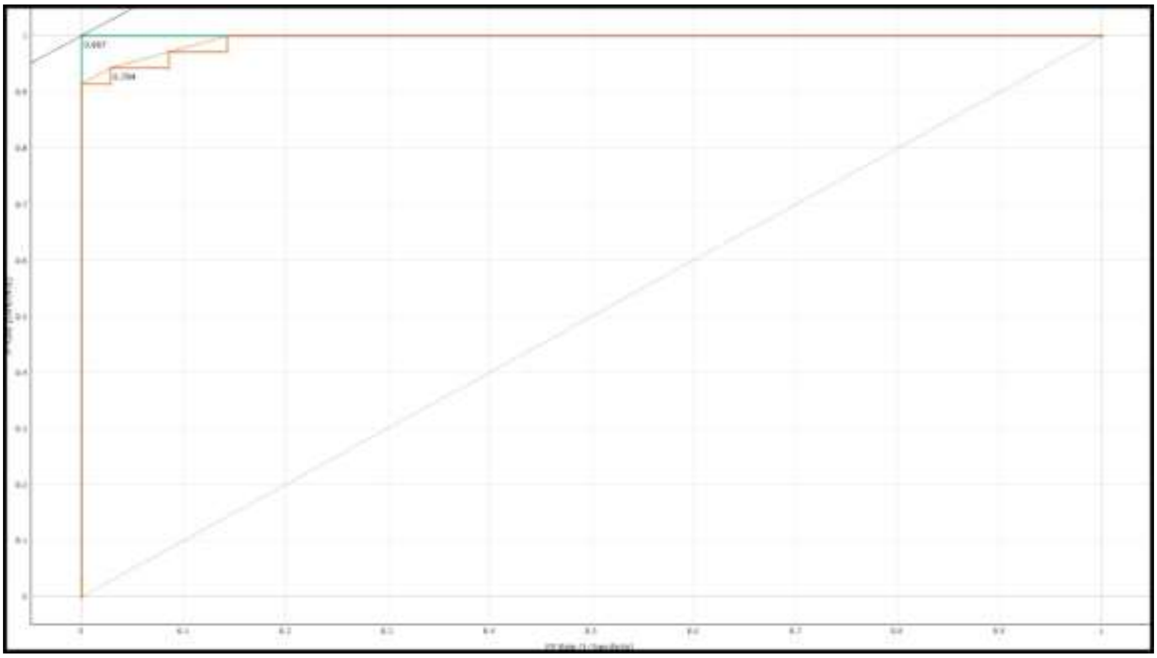

Fig 4- ROC analysis of multiple recessions in lower anterior

4. Discussion

Multiple gingival recession is a common periodontal condition that presents aesthetic concerns and dentine hypersensitivity for patients(3,4,18–20). The etiopathogenesis of gingival recession involves multiple factors, and new methods for testing and eliminating these factors are still being sought. The direct causes of gingival recession include low-level and long-lasting trauma, such as aggressive brushing, and chronic inflammatory periodontal disease(7). Predisposing factors for gingival recession include decreased alveolar bone crest thickness, thin gingival margins, dehiscence, and fenestration. The periosteum, firmly inserted into the cortical bone, is crucial in bone vitality and feasibility(8,9,21). Surgical procedures involving the periosteum can result in the loss of the cortical bone surface layer and subsequent resorption. However, the periosteum remains present even when the buccal bone plate is thin and delicate.

Managing multiple adjacent gingival recession defects can be challenging due to anatomical factors such as thin gingival biotypes and sub-optimal width of keratinized tissue. Surgical management of multiple gingival recessions can be achieved using a subepithelial connective tissue graft combined with a double lateral bridge flap, resulting in complete root coverage. The diagnostic reliability of the automatic classification was excellent, with a Pearson correlation coefficient of 0.73 overall for the whole jaw(10,22,23). Deep learning detected the radiographic bone level (CEJ level) on panoramic radiographs as a simple jaw structure. Next, the percentage rate study of radiographic bone loss included tooth long-axis, periodontal bone, and CEJ levels. Radiologists' diagnoses were correlated with the automatic technique by a Pearson correlation coefficient of 0.73 ($p < 0.01$) and an intraclass correlation value of 0.91 ($p < 0.01$). This underscores the accuracy and consistency of the automatic method in classifying periodontitis stages based on radiographic bone loss of individual teeth(14,24). Similar to our study, naïve bayes and logistics regression accuracy show 96 % and 100 %, and class accuracy is 95 % and 100%.(fig-3.4)(table-1,2,3).

Previous studies used a deep convolutional neural network (DCNN) to classify tooth types on dental cone-beam computed tomography (CT) images(24). The network trained on ROIs from 42 training and 10 test cases, with an average classification accuracy of 88.8% using augmented training data augmented by image rotation and intensity transformation and other studies deep CNN algorithm achieved diagnostic accuracies of 89.0% (80.4-93.3), 88.0% (79.2-93.1), and 82.0% (75.5-87.1) on the premolar, molar, and both models, with the premolar model providing the best AUC for dental caries detection(15,25–27). Here, we applied deep learning squeeze net algorithms for embedding and used machine learning algorithms for classification instead of detection with good class accuracy.

Machine learning techniques may aid the diagnosis and treatment planning of multiple gingival recessions. Still, no specific references to machine learning in this context were found in the provided abstracts. The study employed Orange, an open-source software package for image analysis built on top of the Orange visual programming data mining framework(28). Orange includes features in the penultimate layer, such as workflow creation, data modeling, and interaction in deep networks. Encoding pictures with attributes from this layer and employing machine-learning algorithms such as random forests or logistic regression enabled transfer learning. This approach provided a laptop-compatible and efficient solution that does not require retraining the deep neural network embedding. Orange aims to provide an interactive and accessible environment for image analytics with high functionality that is adaptable to specific needs. In comparison with previous studies related to machine learning on predicting multiple recessions in lower anteriors, several algorithms can detect lower anterior recession in various circumstances(25).

Naive Bayes detected and classified many lower anterior recessions better than the other two methods. Logistic regression detected several lower anterior recessions better than the other two techniques(6,8,21–23). This study confirms that neural networks like skilled dentists can recognize several lower anterior recessions. This study has major clinical implications. Machine learning techniques can improve lower anterior detection accuracy and efficiency with numerous recessions. Automated detection helps clinicians diagnose periodontitis early and prevent it. Machine learning techniques can also reduce subjectivity and prejudice in detecting many lower anterior teeth manually.

5. Conclusion

Machine learning algorithms can accurately detect multiple recessions. Further research is needed to validate these findings using larger sample sizes and imaging modalities. Additionally, future research should focus on the clinical implementation of machine learning algorithms in dental practice.

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