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Original Research Article

Neural networks-based prediction of gingival recession in camouflage-based orthodontic treatment

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Abstract

Background and Aim: Recent advances in Artificial Intelligence (AI) and machine learning have provided dental professionals with excellent tools for forecasting the possibility of gingival recession during or after skeletal discrepancy concealment treatment. Machine learning is an effective decision-support tool for estimating the likelihood of gingival recession in treating certain skeletal malocclusions. The current study used artificial intelligence to predict the gingival recession during camouflage orthodontic treatment to disguise skeletal disparities.

Materials and Methods: Sixty-five patients with minor skeletal discrepancies treated by camouflage orthodontic treatment were selected for the study. Four factors were considered -crowding of lower anteriors, proclination of lower anteriors, spacing due to extraction of lower interior's, and canines (high risk). YES or NO were given whether the previously mentioned characteristics were present in the subjects. Orange, a machine learning tool that uses neural networks, was used to assess prediction accuracy. Test data and training and were split 80/20. Cross-validation, confusion matrix, and ROC analysis assessed model performance. This study examined precision and recall.

Results: The accuracy of the neural networks is 92%. CA (Classification Accuracy) rate of 87.5% implies that predictions were correct in 87.5% of situations.

Conclusion: Artificial intelligence solutions are intended to increase orthodontic performance and care quality. Current applications include recognizing cephalometric landmarks, categorizing skeletal components, and deciding on tooth extractions. Artificial intelligence solutions for anticipating periodontal difficulties in disguised orthodontic treatment are presently in development but will be successful shortly.

Keywords: Camouflage treatment, Gingival recession, Skeletal malocclusion, Machine learning, Artificial intelligence

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1. Introduction

The apical movement of the gingival margin concerning the cemento-enamel junction is termed gingival regression (GR).[1-2] It is also linked to attachment loss and root surface exposure to the oral environment. Among the consequences of GR comprise tooth sensitivity, root caries, hypermobility of the affected tooth, and poor aesthetics.[3-4] Lower incisor teeth are more prone to recession gingival recession, perhaps because of the thin, or frequently absent, bony lamina covering the buccal surface of these roots and the narrow, or absent, band of keratinized gingiva that is typically common in the buccal surface.[5]

In the periodontal as well as orthodontic literature, there has been much debate about the connection between gingival recession and orthodontic movement. Once gingival recession is established, the patient may experience several functional and aesthetic problems. There have been several conversations and studies regarding the potential harm orthodontic movement could do to periodontal structures.[6-10] Furthermore, it has been discovered that the chance of developing GR increases by 9.7% annually following orthodontic treatment (OT). Canines, first premolars, and first molars are more vulnerable to GR after OT in the maxilla, while central incisors and first premolars in the mandible are most at risk for GR.[11]

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In non-growing patients, treatment options for mild to moderate skeletal class III and class II discrepancies include extraction or other orthodontic procedures that mask or camouflage the skeletal discrepancies. On the other hand, an extensive skeletal disparity requires surgical correction. Dental camouflage aims to rectify the skeletal abnormalities by orthodontically repositioning the teeth in the jaws, resulting in an appropriate and acceptable dental occlusion and an aesthetic face and profile.[12-13] Although dental occlusion will be corrected, the skeletal problem or facial profile may not be addressed by camouflage treatment. Proclination of the maxillary incisors and retroclination of the mandibular incisors are common concealing factors for class III malocclusion. On the other hand, Skeletal class II is masked by proclination of the mandibular incisors and retroclination of the maxillary incisors. Before attempting to move teeth, particularly the lower incisors, it is critical to consider specific warning indications, such as thin gingival/bone biotype, gingivitis, gingival retraction before orthodontic movement, and poor oral hygiene. Gingival recession is anticipated to occur when incisor proclination and some or all of the above factors are combined.[14]

Recent studies indicate that tooth movement of the mandibular incisors in class III camouflage treatment beyond the alveolar bone predisposes gingival recession by initiating gingival attachment loss.[10,15-16] Other studies claim no evidence linking gingival recession to tooth movement.[17-18] Proclination and retroclination of mandibular incisors in masking skeletal problems have high chances of gingival recession due to the thin biotype. The patient may experience various functional and aesthetic concerns if a gingival recession occurs. Therefore, Camouflage treatment requires careful case selection to avoid harmful effects on periodontium.[19-20]

With recent Artificial Intelligence (AI) and machine learning breakthroughs, dental professionals now have effective methods for predicting the likelihood of gingival recession during or after camouflage treatment of skeletal discrepancy. Machine learning is a powerful decision-support tool that assists in forecasting the possibilities of gingival recession in managing various skeletal malocclusions. Therefore, the present study aims to use AI technology to predict and improve the diagnosis of gingival recession in patients treated by camouflage orthodontic treatment. This helps enhance patient outcomes, speed up the evaluation process, and reduce the chances of diagnostic errors.

2. Materials and Methods

The ethical committee at Saveetha Dental College and Hospitals authorized this study. Ethical approval number IHEC/SDC/ORTHO-2201/24/033. The present study is an artificial intelligence-based study in the Department of Orthodontics at Saveetha Dental College and hospitals. Adult patients with borderline skeletal discrepancies treated with camouflage orthodontic treatment were included in the study.

A dental information management software database was used to choose 65 patients with mild to moderate skeletal class II and III who had undergone camouflage orthodontic treatment. Four factors were assessed in patients: 1) crowding of lower anteriors, 2) proclination of lower anteriors, 3) spacing due to extraction of lower anteriors, and 4) canines (high risk). YES or NO were given whether the previously mentioned characteristics were present in the subjects. Data retrieved from the database shows gingival recession and their frequencies, including 147 cases of overcrowded lower anterior teeth, 169 cases of forward tilting, 39 cases of gap between lower front teeth due to extraction, 181 cases of high-risk canines, and 208 cases of recession. The cases are classified as "YES" or "NO" based on frequency and categorization.

2.1. Neural networks

This clinical investigation involved data preprocessing, removing outliers and missing values, and splitting up the dataset into 20% testing and 80% training samples. The Orange Data Mining tool was used for analysis, and a neural network model was used to forecast accuracy and validate results. The model was tested on the testing sample, and the accuracy of predictions was evaluated using a confusion matrix. Precision and recall were also assessed as evaluation metrics. The precision metric quantifies the percentage of accurately forecasted positive cases among all positively anticipated cases. In contrast, recall measures the fraction of correctly predicted positive instances out of all positive ones. In clinical investigations, where it is critical to detect certain conditions or diseases, these measures aid in understanding the model's effectiveness in accurately classifying positive instances. This approach aims to develop a robust neural network model for accurate prediction and assessment.[21,**Error! Reference source not found.**-24]

2.2. Architecture

Neural network architecture consists of interconnected artificial neurons that perform weighted sums of inputs and apply an activation function. Numerous optimization strategies can be used to train this architecture, such as ADAM (Adaptive Moment Estimation). This specific architecture uses 20 hidden layers with varying number of neurons. The ADAM optimizer optimizes the network weights, combining adaptive learning rates and momentum-based optimization methods. The learning rate is set at -0.001, affecting the convergence speed. The model is trained for 100 iterations, updating weights and biases based on training data.

3. Results

The current investigation found that 90.4% of skeletal cases treated with camouflage resulted in gingival recession.

Canines were found to be the most frequently affected teeth. Camouflage treatment by proclination of lower anteriors was reported to have the highest incidence of gingival recession, followed by crowding in the lower anteriors. The area where the lower anteriors were extracted seems to have the least amount of gingival recession (**Table 1**).

3.1. Neural network results

The Neural Network model for recession prediction is effective in various evaluation metrics. Its high AUC (Area Under the Curve) indicates its ability to distinguish between positive and negative cases. The CA (Classification Accuracy) rate of 87.5% indicates accurate predictions in 87.5% of cases. The F1-Score (Factor of Precision and Recall) balances precision and recall, with a high F1-Score indicating good performance. The model's 87.5% recall rate demonstrates its ability to identify 87.5% of recession cases. The model's 0.982 specificity value indicates low false negatives, and a lower LogLoss value suggests more confident predictions.

Model accuracy Is 92%, with good predictions.(**Table 2**)

3.2. Confusion matrix

The model accurately predicts gingival recession with a False Positive Rate of 0%, True Positive Rate of 50%, True Negative Rate of 100%, and False Negative Rate of 50%. However, it misses 50% of cases with gingival recession, indicating room for improvement. The model's accuracy is based on 0% false positives and 100% true negatives, indicating potential for improvement.(**Figure 1**)

Table 1: Results

Crowding of lower interior's	Proclination of lower anterior	Spacing due to extraction of lower interiors	Canines (high risk)	Recession
147	169	39	181	Yes = 208 NO = 22

Table 2: Accuracy Table

Model	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
Neural Network	0.929	0.875	0.891	0.938	0.875	0.474	0.982

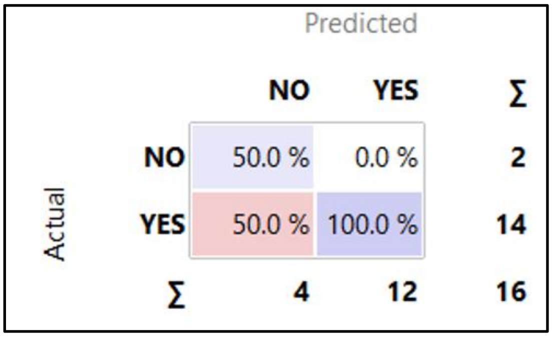

Figure 1: Confusion matrix

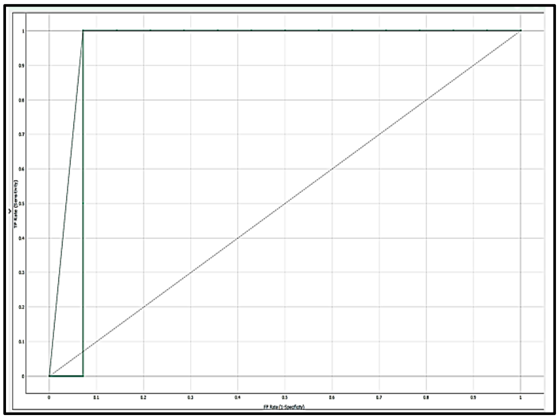

Figure 2: ROC curve of the NO classes

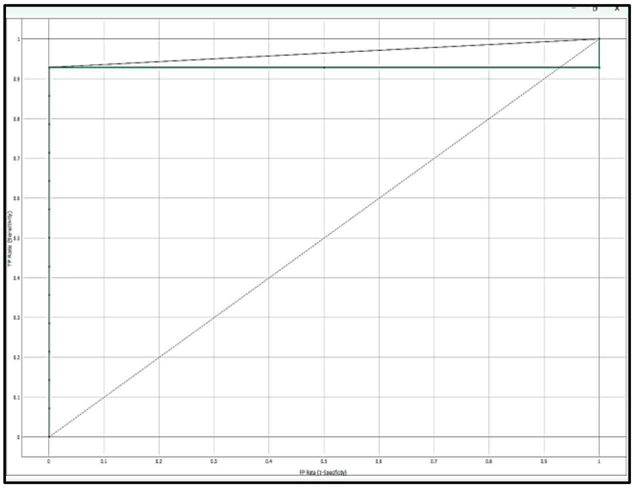

Figure 3: Roc curve - No classes

3.4. Lift curve

The lift curve is a graphical representation that compares the effectiveness of a predictive model to a random model. It is used in scoring and ranking models, especially in marketing and customer analytics. To create a lift curve, data is sorted and divided into segments, and the response rate is calculated for each segment. The cumulative response rate is then divided by the overall response rate, and the lift is plotted against the segment numbers. This helps in decision-making, such as determining the optimal segment for marketing campaigns or identifying areas for improvement. Improvement. It compares the model's predictions to a random guess line, showing how better the model identifies the positive class. A steeper curve indicates better performance, while higher lifts indicate better model performance. The lift curve visually represents a model's effectiveness in binary classification tasks. (**Figure 4** & **Figure 5**)

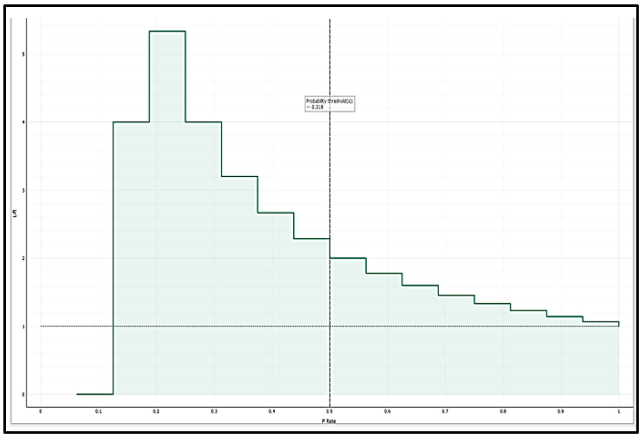

Figure 4: Lift curve of the no class

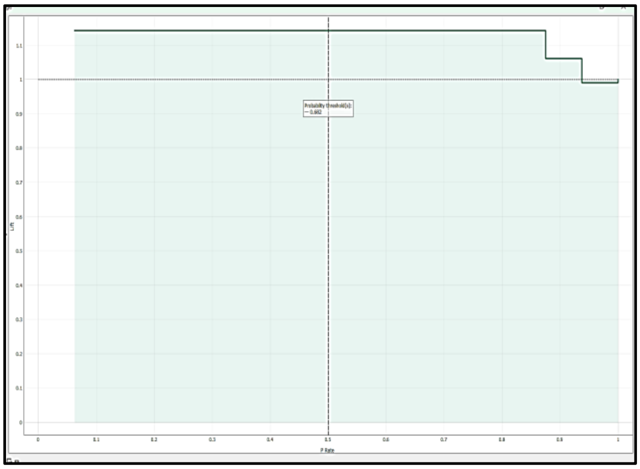

Figure 5: Lift curve of the yes class

3.3. Roc curve

The Receiver Operating Characteristic (ROC) curve is a graphical representation of the performance of a binary classifier system when its discrimination threshold is modified. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) across different threshold values. To generate a ROC curve, train a model, make predictions, change the classification threshold, calculate TPR and FPR, plot the ROC curve, and calculate the Area Under the Curve (AUC) metric. (**Figure 2** & **Figure 3**)

4. Discussion

The goal of orthodontic camouflage treatment is to use dental compensations to conceal the skeletal disparity. When extractions are necessary, the upper arch (first premolars) is usually the site of the treatment to address the incisor protrusion. Furthermore, functional appliances are typically used to modify growth, but in adult patients, they are also used to adjust the position of the teeth.[25-28] While the treatment has many advantages, there are also potential concerns, such as those related to periodontal tissue health.[29] There have been several discussions and research in periodontics and orthodontics on the possible damage that orthodontic movement could cause to periodontal structures. Teeth moved orthodontically into unfavorable positions relative to their supporting base due to osseous dehiscence, fenestrations, gingival recession, and apical soft tissue migration. Gingival recession, particularly in the anterior teeth, can harm the dentition's look, frequently impairing aesthetics.[29-30]

Consequently, orthodontists must understand the likelihood of gingival recessions and other periodontal complications following camouflage therapy for skeletal malocclusion. Therefore, to determine the prognosis of camouflage therapy, it is necessary to estimate the probabilities of such complications using some diagnostic technique. Artificial intelligence (AI) can be described as a system's capacity to emulate human intelligence or as the ability to make sound decisions based on a gold standard.[31] Machine learning (ML) is a branch of artificial intelligence that facilitates the processing, analysis, and interpretation of data by computers and other devices to assist in overcoming real-world issues. These issues include developing software and websites, organizing patient appointments, treatment forecasts, robotic surgeries, 3D printing, storing, sharing, and safeguarding data online, and national security and defense. When given the correct data, algorithms are capable of learning on their own and executing tasks. The algorithm aims to give intelligent machines the ability to forecast results based on historical data. Using the data provided, machine learning algorithms and techniques help train a model to predict and conform to future outcomes.[32-34] thus, the current study aimed to estimate the likelihood of gingival recession in patients receiving camouflage therapy using machine learning.

In the present study, the neural network model predicted the output with 92% accuracy based on previously imported input. Based on the confusion matrix, the model accurately predicts gingival recession with a 0% false positive rate, 50% true positive rate, 100% true negative rate, and 50% false negative rate. Still, it misses 50% of cases, showing opportunity for improvement. The effectiveness of the AI models in identifying dental plaque and identifying gingivitis and periodontal disease was assessed in a systematic review conducted by Mr. Leon et al. They stated that although AI models for periodontology applications are still in the early stages of development, they could offer a potent diagnostic instrument.[35]

Numerous studies have been conducted using machine learning in the field of orthodontics. They were mostly employed as diagnostic and treatment planning tools. Artificial intelligence and machine learning have several uses in orthodontics, according to a literature review by SN Aisiri et al. Between 64% and 97%, he found that most systems and approaches have good-to-excellent accuracy. It is anticipated that accuracy at the lower end of this range will increase as sample sizes increase and additional data becomes available. Algorithms are predicted to improve, allowing for more complex data management, particularly in digital dentistry, where patient records are maintained as digital images, necessitating additional time, experience, and training.[36] Neural networks were utilized in a study by P. Li and colleagues to forecast orthodontic treatment choices, including extraction-non-extraction, extraction patterns, and anchorage patterns. They stated that the neural network models showed a sensitivity of 94.6% and specificity of 93.8%, with an accuracy of 94.0% for extraction-non-extraction prediction. Additionally, the technique demonstrated 92.8% accuracy for anchorage patterns and 84.2% accuracy for extraction patterns, indicating that it can successfully direct orthodontists with less experience in treatment planning.[37]

The study's small sample size, with a recession of 208 and no recession of 22 in 65 patients, may limit the model's generalizability to larger populations. Despite this, the neural network model for recession prediction has demonstrated strong performance in various evaluation metrics, including high AUC, classification accuracy rate, F1-Score, recall rate, specificity value, and LogLoss value. These metrics suggest the model effectively identifies gingival recession cases despite its limitations. However, caution should be exercised when extrapolating results to broader contexts. Imbalance in datasets refers to a situation where one class has more samples than another, such as in recession prediction. Accuracy can be misleading in such situations, as it only calculates correctly predicted samples' ratios.

Another study concluded that the ML-based AI model predicted treatment plans with 84% accuracy compared to those determined by orthodontists' professional opinions. Additionally, it determined the relative significance of particular diagnostic data in treatment planning calculations.[35] AI can help orthodontists save time while providing accurate diagnostic assessments and prognostic forecasts to improve performance and care quality. Studies show that current uses include cephalometric landmark identification, skeletal categorization, and decision-making regarding tooth extraction.**Error! Reference source not found.** A scoping review reported similar findings. The amount of research on the use of AI and ML in orthodontics has skyrocketed.[38] The most frequently researched domains were diagnostic and treatment planning, automated anatomic landmark identification and analysis, and growth and development evaluation.**Error! Reference source not found.**

Future directions for neural network models for predicting gingival recession include feature engineering, model optimization, ensembling, incorporating external data sources, and improving interpretability. However, limitations include generalizability, data quality, clinical context, model complexity, and ethics. Generalizability requires validation on diverse datasets, while data quality depends on the quality of input data. Model complexity requires careful preprocessing and cleaning, and ethics should be ensured by assessing training data for potential biases and implementing fair practices in model development and deployment to predict gingival recession in camouflaged orthodontic patients.

5. Conclusion

Machine learning models may be inadequate for making expert conclusions due to a lack of training data and technological skills. Nevertheless, if AI develops and diagnostic tools get better, orthodontists may find them to be a helpful Clinical Decision Support System. These models save time and provide accuracy comparable to that of expert dentists by offering a framework for diagnosis, treatment flexibility, and viability. Artificial intelligence systems aim to improve orthodontic performance and care quality. Current applications include identifying cephalometric landmarks, categorizing skeletal structures, and deciding tooth extractions. Artificial Intelligence techniques for anticipating periodontal issues in camouflaged orthodontic treatment are currently under development but can be used effectively shortly.

6. Source of Funding

None.

7. Conflict of Interest

None.

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