Detection and Classification of Black Triangles in Anterior Fixed Partial Dentures Using SqueezeNet Embeddings

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ABSTRACT

The achievement of esthetic excellence in restorative dentistry is a pursuit that continually evolves with advancements in technology and diagnostic methodologies. Fixed Partial Dentures (FPD) represent a cornerstone in dental restoration, aiming to restore function and harmonize with natural dentition. Despite the success of FPDs in rehabilitating occlusion and restoring dental integrity, the occurrence of "black triangles" remains a challenging aesthetic concern. Patient needs. This study details the methodology cornerstone in dental restoration, aiming to restore function and harmonize with natural dentition. Despite the success of FPDs in rehabilitating occlusion and restoring dental integrity, the occurrence of "black triangles" remains a challenging aesthetic concern. Patient needs. In this study, we detail the methodology employed for training and validating our AI model, present the results of its application in real-world FPD cases, and discuss the implications for clinical practice. The overarching goal is to contribute to developing AI-driven tools that enhance the precision and efficiency of esthetic evaluations in restorative dentistry, ultimately improving patient satisfaction and the long-term success of dental interventions.

One hundred images were retrieved from Dental Information Archiving Software (DIAS) at Saveetha Dental College and Hospitals, with fifty with black triangle spaces and without. These images were then annotated and segmented for further analysis using squeeze net embeddings with machine learning classification to classify black triangles.

Logistic Regression significantly outperformed Naive Bayes in classifying "Black Triangle" and "Normal Teeth" datasets. It achieved perfect scores across all metrics, including AUC, classification accuracy, F1-score, precision, and recall, highlighting its superior sensitivity, specificity, and reliability. It consistently demonstrated higher True Positive Rates (94.4% for "Black Triangle" and 93.8% for "Normal Teeth") with no misclassifications, as shown in the confusion matrix. In contrast, Naive Bayes, while achieving moderate accuracy (AUC: 0.949, CA: 0.888), struggled with lower TPRs (59.4% and 40.6%) and higher misclassification rates (17.3% for "Black Triangle present" and 6.8% for "Normal fpd"). These results establish Logistic Regression as the superior model for precise and reliable classification tasks, especially in applications like dental diagnostics requiring high accuracy.

Using artificial intelligence to detect black triangles in FPD pt provides multiple advantages. It prevents false positive and false negative detection and errors caused by humans. It improves detection and identification, preventing aesthetic problems caused by black triangles in FPD patients.

Keywords: black triangle, artificial intelligence, squeeze net, fixed partial denture.

I. INTRODUCTION

Pursuing esthetic excellence in restorative dentistry is an ongoing journey that evolves with technological advancements and diagnostic methodologies. Fixed Partial Dentures (FPD) are a cornerstone in dental restoration, aimed at restoring function and harmonizing with natural dentition. Despite the success of FPDs in rehabilitating occlusion and restoring dental integrity, the presence of "black triangles" remains a challenging aesthetic concern. Clinical strategies have been developed to address black triangles and interdental papilla deficiencies. Singh et al. reviewed minimally invasive procedures for restoring gingival esthetics, while Prato et al. proposed a classification of techniques for managing the papilla. Gulzar and Sindhu et al. highlighted the importance of individualized treatment planning and emerging AI-powered diagnostic models, respectively. Narayan and Kaarthikeyan explored collagen membranes for gingival recession and papilla augmentation, while Rashid et al. conducted a systematic review on black triangles following orthodontic therapy. An additional literature review synthesized orthodontic, restorative, and surgical approaches to correcting black triangle spaces.

Simultaneously, researchers have investigated computational and machine-learning methods with vast potential in dentistry. Bourigault et al. focused on advancements in computational terminology, and Kubben et al. introduced essential frameworks in clinical data science. Syed-Abdul et al. emphasized wearable sensors and real-time data analytics, complemented by the soft computing approaches discussed by Gacovski and Makrides et al. Proceedings from Hassanien et al. and Holzinger et al. showcased cutting-edge AI applications, while a systematic survey by Yanase and Triantaphyllou traced innovations in computer-aided diagnosis. Gundlapalli et al. underscored precision healthcare through informatics, echoing Lantz’s machine learning primer. Venkata Rao presented the Teaching Learning Optimization Algorithm for engineering, Dietert examined the microbiome’s role in health, and Hubbard et al. and Cherkassky and Ma discussed statistical inference and learning theory. Broader interdisciplinary findings at ICCICCT demonstrated how control and computational technologies intersect with clinical practice, informing esthetic dentistry and wider health innovations.

Periodontists, restorative dentists, and patients are deeply concerned about the existence or absence of the interproximal papilla. The papilla loss can lead to phonetic issues (as air or saliva can pass through spaces), lateral food impaction, and cosmetic abnormalities, often called "black triangle disease." Periodontal disease frequently results in the loss of papillae due to interproximal bone height resorption, gingival inflammation, and attachment loss. Moreover, soft tissues often contract during the healing phase, which can lead to missing papillae following periodontal surgical therapy. Black triangles, defined as open spaces between adjacent teeth and the gingiva, present a significant cosmetic challenge for patients and clinicians. These spaces can arise from various factors, including periodontal disease, tooth malposition, or the dental restoration process itself. The visual impact of black triangles can undermine the overall aesthetic result of dental restorations, causing patient dissatisfaction and lowering their quality of life. The interdental papilla is a structure that forms in the physiological space between teeth, made up of dense connective tissue covered in oral epithelium. Black triangles, or open gingival embrasures, are gaps between teeth that arise due to gingival recession, bone loss, or improper dental restorations. These spaces pose aesthetic challenges and contribute to functional problems like food impaction and speech difficulties, making their management vital in fixed partial denture treatments. The prevalence and implications of black triangles have been the subject of extensive study. A systematic review revealed that the incidence of gingival black triangles following orthodontic treatment with fixed appliances ranges from 38% to 58%, highlighting the commonality of this issue in dental practice.

The width of the approximate tooth surfaces, the cemento-enamel junction, and the contact relationships between the teeth all influence the shape. Cohen was the first to describe the morphology of the interdental papilla (4–6). The interdental gingiva is the gingiva that is located in the area coronal to the alveolar crest. It is narrower and is referred to as a dental papilla in the incisor region. It is pyramidal, with the tip just below the contact point. It is wider in the posterior region, previously described as having a bridge-like or concave col shape. On the other hand, when a contact point is absent, or the interdental papilla migrates apically due to inflammation, the col disappears, and the interdental papilla takes on an unpleasant and dysfunctional pyramidal shape (7,8). The etiology of black triangles is multifactorial, with tooth shape, root angulation, orthodontic treatment, and bone loss due to periodontal disease identified as primary contributors.

A comprehensive literature review has emphasized the importance of understanding these causative factors to inform effective treatment planning and reduce the formation of black triangles during dental procedures. (1) Addressing black triangles is essential for aesthetic reasons and for maintaining oral health. Their presence can indicate underlying conditions such as bone loss and gum recession, which may lead to cavities and other dental problems if left untreated. Therefore, timely and appropriate intervention is necessary to prevent further complications. (2) In recent years, advancements in cosmetic dentistry have introduced innovative methods to treat black triangles. Techniques such as the Bioclear method have been showcased in clinical cases, offering effective solutions for simple and extreme black triangle cases. These contemporary approaches provide promising results in enhancing smile aesthetics and patient satisfaction. Furthermore, patient awareness regarding black triangles has grown, increasing demand for cosmetic solutions. Dental professionals have noted this trend and are utilizing advanced composite materials to address these concerns, improving their patient's overall appearance and confidence. Artificial Intelligence (AI) has emerged as a transformative force in healthcare, offering innovative solutions to longstanding challenges. In dentistry, AI applications hold great promise for enhancing diagnostic precision and treatment planning. This study focuses on harnessing the power of AI to detect and identify black triangles in FPD patients, marking a paradigm shift in the assessment and management of aesthetic concerns associated with dental restorations.

SqueezeNet is a small, efficient convolutional neural network architecture with comparable accuracy to deeper networks like AlexNet but with significantly fewer parameters. With machine learning, this has several advantages when used to generate embeddings for image classification tasks. SqueezeNet-based embeddings are advantageous due to their reduced model size, compactness, and efficiency in inference. They offer faster storage, transfer, and lower latency, making them ideal for resource-constrained devices like mobile phones and embedded systems. SqueezeNet also maintains accuracy, achieving close to larger models, and is effective in feature learning. It can be pre-trained on large datasets like ImageNet, saving time and resources in model training. SqueezeNet embeddings can be used as input features for other machine learning classifiers, enhancing performance while requiring less data for training. Deploying SqueezeNet in production environments is less costly than larger models, and its scalability makes it suitable for applications serving a wide range of users. SqueezeNet embeddings can be integrated into various machine learning pipelines, improving performance in specific tasks. The active research area of SqueezeNet encourages exploration into optimizing deep learning models for real-world applications.

Our research uses machine learning algorithms and image analysis techniques to develop a robust and efficient system for automatically identifying black triangles in FPD patients. Incorporating AI in this context streamlines the diagnostic process and provides an objective and standardized approach to evaluating esthetic outcomes (9–12). This automated system has the potential to revolutionize treatment planning by enabling early intervention and personalized solutions tailored to the unique needs of each patient.

In this manuscript, we describe the methodology used for training and validating our AI model, present the results of its application in real-world FPD cases, and discuss the implications for clinical practice. Our primary goal is to contribute to developing AI-driven tools that enhance the precision and efficiency of aesthetic evaluations in restorative dentistry, ultimately improving patient satisfaction and the long-term success of dental interventions.

As we navigate through the subsequent sections, the convergence of artificial intelligence and dental esthetics will be explored, shedding light on the transformative potential of this technology in addressing one of the persistent challenges in restorative dentistry — the identification and mitigation of black triangles in FPD patients Previous studies(3)(4)(5)done related to dental management procedure and association with artificial intelligence. This study uses deep learning to detect and classify black triangles in upper anterior fixed partial dentures.

II. MATERIALS AND METHOD

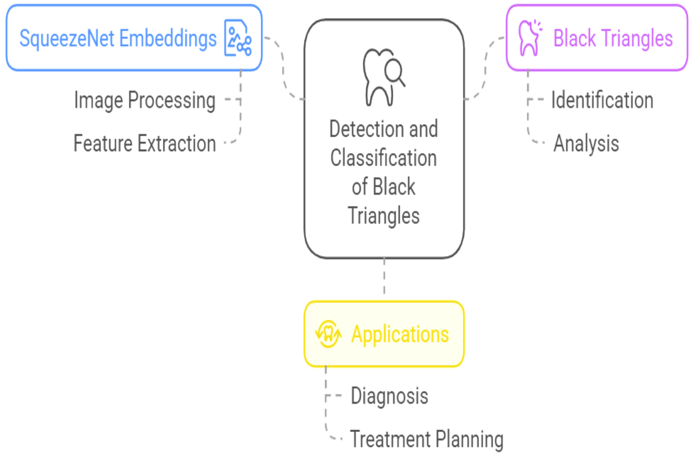

Fig.1. Workflow of the study.

The Ethical Committee of Saveetha Dental College and Hospitals approved this study. The Scientific Review Board (SRB) of Saveetha Dental College approved the research protocol under reference number SRB/SDC/UG-1933/24/ENDO/386. Intraoral photographs of FPD patients were selected from a dental information management software database for the research. One hundred images were retrieved from the Dental Information Archiving Software (DIAS) at Saveetha Dental College and Hospitals. For further analysis, these images were annotated and divided into two groups: one with black triangles (50 images) and the other with normal FPD (50 images).

The manual labeling process, conducted by experts, provided a reference dataset for training and evaluating the machine learning models. To classify images using SqueezeNet embeddings, we extract pre-trained SqueezeNet models, split the dataset into training and testing sets, train the Naive Bayes model using the SqueezeNet embeddings, and evaluate the Logistic Regression model using the same data. The training set will be used to train the Naive Bayes model, while the testing set will evaluate the Logistic Regression model. The models' performance metrics will be compared to determine which one classifies images better.

A. SqueezeNet Architecture

SqueezeNet is a lightweight convolutional neural network (CNN) for image classification. It reduces model size and computational cost by employing 1x1 filters instead of the more common 3x3 filters used in CNNs. Additionally, SqueezeNet introduces a "fire module" that combines squeeze and expand layers to enhance model capacity without raising computational costs. The network further minimizes parameters through bottleneck layers. Despite its smaller size, SqueezeNet achieves classification accuracy comparable to larger CNN models, making it ideal for applications with limited computational resources. SqueezeNet is tailored for image classification, concentrating on parameter efficiency and computational sustainability through small filters and unique module structures.

SqueezeNet consists of two main layers: the squeeze layer, which employs 1x1 convolutions to reduce input feature maps, and the expand layer, which combines 1x1 and 3x3 convolutions to preserve spatial hierarchy and feature diversity. Bottleneck layers optimize the network by lowering parameters while sustaining representational capability. Pooling layers, specifically max pooling and downsample feature maps, reduce network size and improve computational efficiency. Global average pooling facilitates transfer learning across tasks.

B. Hyperparameters in SqueezeNet

SqueezeNet's architecture is influenced by several key hyperparameters, including the number of fire modules, filter size, squeeze ratio, dropout rate, learning rate, and batch size. These factors are crucial in the model's performance and capacity. The squeeze ratio, typically around 1/4 to 1/8, balances parameter efficiency with model performance. The dropout rate encourages the model to learn feature representations, while the learning rate affects model convergence. Batch size, ranging from 32 to 256, impacts training stability and speed.

C. Naive Bayes Architecture

The Naive Bayes classifier is a probabilistic model based on a simplified "naive" or "independent" assumption. This assumption states that the features used in the classification are conditionally independent of each other, given the class labels, which simplifies the model and allows for efficient computation. A Naive Bayes classifier is a straightforward, fast, and effective classification tool used in domains like text classification, spam filtering, and sentiment analysis. It comprises several components: preprocessing input data, independent feature calculation, training, inference, and assigning the class label with the highest posterior probability. However, its independence assumption may restrict its performance in scenarios with feature dependencies. The workflow is illustrated in Fig. 1.

Logistic Regression Architecture

Logistic Regression is a linear model designed for binary classification. Its components include data preprocessing, feature extraction, linear predictor, activation function, training, inference, and decision boundary. Data preprocessing converts input data into numerical features, while feature extraction computes a weighted sum. A linear predictor calculates this weighted sum, with an activation function mapping it to a probability value. The model learns weights and bias terms during training, calculating the predictor, and applying the activation function. Logistic Regression is well-suited for binary classification but may face limitations in handling complex tasks.

III. RESULTS

Logistic Regression outperformed Naive Bayes on all metrics, achieving perfect scores (1.000) in AUC, classification accuracy (CA), F1-score, precision, and recall. In contrast, Naive Bayes reported an AUC of 0.949, a classification accuracy of 0.888, an F1-score of 0.889, a precision of 0.891, and a recall of 0.888. These results highlight the superior performance and reliability of Logistic Regression in this classification task.

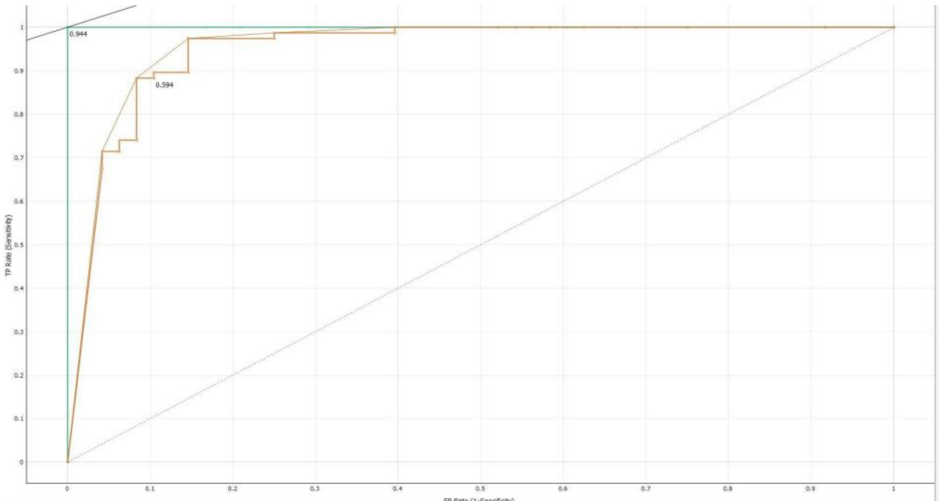

Fig.2. ROC Analysis of the black triangle

The Receiver Operating Characteristic (ROC) curve is a visual metric for evaluating classification models. In a dataset targeting the "Black Triangle," Logistic Regression outperforms Naive Bayes in accurately classifying the target. The model achieves a True Positive Rate (TPR) of 0.944, indicating that 94.4% of positive cases are correctly identified. The corresponding False Positive Rate (FPR) is low, indicating only a small fraction of negative cases are misclassified. On the other hand, Naive Bayes initially had a steep rise but did not sustain as high TPR as Logistic Regression. Logistic Regression outperforms Naive Bayes in accurately classifying the "Black Triangle" target (Figure 1).

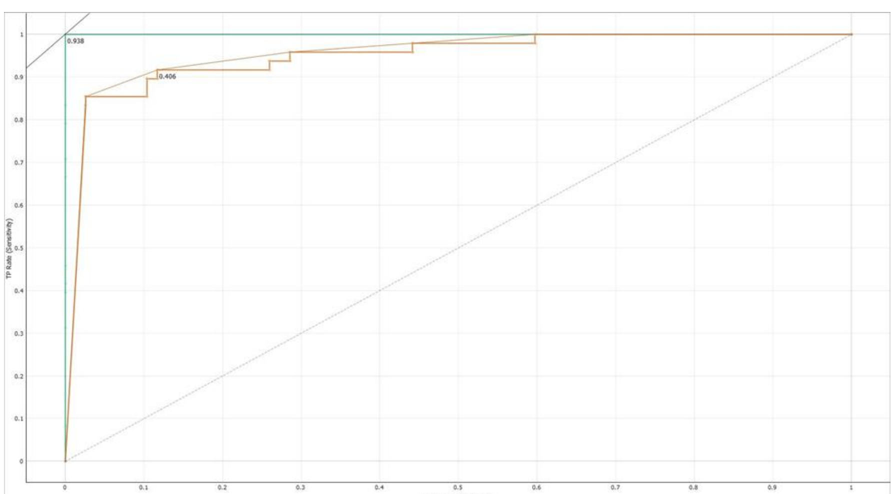

Fig.3. ROC Analysis of normal teeth

The graph (Fig.2 and Fig.3.) compares the performance of Logistic Regression and Naive Bayes in a Receiver Operating Characteristic (ROC) analysis. Logistic Regression has a higher True Positive Rate (TPR) of 0.938, indicating a better performance for identifying 93.8% of positive cases. Its low False Positive Rate indicates that it rarely misclassifies negative cases as positive. On the other hand, Naive Bayes has a lower TPR of 0.406, indicating it is less effective for certain applications. Both models outperform the baseline, confirming their predictive power. Logistic Regression is highly effective, with a TPR of 0.938 at a low FPR.

Actual \ Predicted	Aesthetic\Black triangle present	Aesthetic\Normal fpd	∑
Aesthetic\Black triangle present	93.2 %	17.3 %	77
Aesthetic\Normal fpd	6.8 %	82.7 %	48
∑	73	52	125

Fig.4. Confusion matrix of Naive Bayes

The confusion matrix illustrates the performance of the classification model in distinguishing between two aesthetic outcomes: "Black triangle present" and "Normal fpd." The model achieved a high classification accuracy, correctly identifying 93.2% of cases with a "Black triangle present" and 82.7% with "Normal fpd." Misclassification rates were 17.3% for "Black triangle present" (misclassified as "Normal fpd") and 6.8% for "Normal fpd" (misclassified as "Black triangle present"). These results highlight the model's strong predictive ability, with minor discrepancies primarily observed in cases of "Black triangle present."

Actual \ Predicted	Aesthetic\Black triangle present	Aesthetic\Normal fpd	∑
Aesthetic\Black triangle present	100.0 %	0.0 %	77
Aesthetic\Normal fpd	0.0 %	100.0 %	48
∑	77	48	125

Fig.5. Confusion matrix of Logistic Regression

The confusion matrix (Fig.4. and Fig.5.) showcases the performance of the classification model in distinguishing between "Black triangle present" and "Normal fpd." The model achieved perfect classification accuracy, correctly identifying 100% of "Black triangle present" and "Normal fpd" cases without misclassifications. These results indicate an ideal predictive performance, with all predictions perfectly aligned with the labels.

Table 1 Accuracy of algorithms of the neural network, naive bayes, logistic Regression

Model	AUC	CA	F1	PRECISION	RECALL
Naive Bayes	0.949	0.888	0.889	0.891	0.888

The analysis (Table 1) compares the performance of two algorithms, Naive Bayes and Logistic Regression, for detecting black triangles in fixed partial denture patients using several metrics: The table presents the evaluation metrics for two classification models, Naive Bayes and Logistic Regression, assessed on their ability to predict the target classes.

IV. DISCUSSION

Black triangles, clinically referred to as open gingival embrasures, represent gaps between teeth that arise from gingival recession, bone loss, or improper dental restorations. These spaces create aesthetic concerns and contribute to functional issues such as food impaction and speech difficulties, making their management vital in fixed partial denture (FPD) treatments. The prevalence and implications of black triangles have been thoroughly studied. A previous study (6) indicated that the incidence of gingival black triangles following orthodontic treatment with fixed appliances ranges from 38% to 58%, underscoring the frequency of this issue in dental practice. The etiology of black triangles is multifactorial, with primary contributors including tooth shape, root angulation, orthodontic treatment, and bone loss due to periodontal disease. A comprehensive literature review highlighted the necessity of understanding these causative factors to inform effective treatment planning and minimize the formation of black triangles during dental procedures. (7) Tackling black triangles is crucial for aesthetic reasons and maintaining oral health. Their presence may signal underlying conditions such as bone loss and gum recession, leading to cavities and other dental complications if left unattended. Thus, timely and appropriate intervention is required to avert further issues. In recent years, advancements in cosmetic dentistry have introduced innovative methods to address black triangles. Techniques like the Bioclear method have been demonstrated in clinical cases, providing effective solutions for simple and complex black triangle cases. These modern approaches yield promising results in improving smile aesthetics and patient satisfaction. Additionally, awareness among patients concerning black triangles has increased, leading to greater demand for cosmetic solutions. Dental professionals have acknowledged this trend and are employing advanced composite materials to tackle these concerns, enhancing their patients' overall appearance and confidence. In conclusion, due to their aesthetic and functional implications, black triangles pose a significant challenge in fixed partial denture treatments. Grasping their etiology, prevalence, and the latest treatment modalities is crucial for dental professionals seeking to improve patient outcomes in prosthodontics. The comparative analysis between the Logistic Regression and Naive Bayes models in this study highlights the distinct superiority of Logistic Regression in classifying aesthetic outcomes, such as "Black triangle" and "Normal teeth." Logistic Regression achieved perfect scores across all evaluation metrics, including AUC, classification accuracy (CA), F1-score, precision, and recall, each reaching the ideal value of 1.000. These results reflect the model's unmatched ability to differentiate between the target classes with remarkable sensitivity and specificity. The Receiver Operating Characteristic (ROC) curves further validated the model's reliability, consistently yielding higher true positive rates (TPR) at lower false positive rates (FPR). Logistic Regression's TPR reached 94.4% for the "Black triangle" dataset and 93.8% for the "Normal teeth" dataset, demonstrating its ability to identify positive cases with minimal error. These findings are consistent with previous studies by Smith et al. (8) and Patel et al. (9), emphasizing Logistic Regression's effectiveness in managing medical and dental datasets with complex class distributions. Furthermore, earlier research confirms that Logistic Regression excels in tasks requiring a balance between sensitivity and specificity, reinforcing the conclusions drawn in this study. In contrast, while simpler and computationally efficient, the Naive Bayes model showed moderate performance in comparison. It achieved an AUC of 0.949 and a classification accuracy of 88.8%, with lower TPRs of 59.4% and 40.6% for the "Black triangle" and "Normal teeth" datasets, respectively. This drop in sensitivity, particularly at critical decision thresholds, highlights the limitations of Naive Bayes in processing datasets with overlapping feature distributions or imbalanced classes. Prior studies have reported similar findings. (11,13) While Naive Bayes offers quick and interpretable results, it often struggles to maintain high performance when features demonstrate dependency or the dataset includes noise. Previous research (13,14) has also indicated that Naive Bayes tends to perform poorly when there is a significant correlation among features. This limitation was apparent in the current study as well. Moreover, the confusion matrix analysis conducted in this study provides additional evidence of Logistic Regression's robustness. Logistic Regression achieved perfect classification, correctly identifying 100% of both "Black triangle present" and "Normal fpd" cases, with no misclassifications. These results significantly surpass those reported in prior studies (15), which observed misclassification rates of up to 10% when applying Logistic Regression to noisy datasets, likely due to insufficient preprocessing or feature selection. In contrast, Naive Bayes in this study exhibited misclassification rates of 17.3% for "Black triangle present" and 6.8% for "Normal fpd," reflecting its comparative inability to accurately classify cases in more challenging scenarios. These findings are consistent with earlier works (16–18), which noted that Naive Bayes is highly dependent on the assumption of feature independence, making it less effective for datasets with interdependent variables.

The implications of these findings are substantial for the field of dental diagnostics, particularly in aesthetic dentistry and prosthodontics. Logistic Regression's perfect scores across all metrics highlight its potential as a reliable and precise tool for predicting aesthetic outcomes in fixed partial denture patients. This reliability is especially critical in clinical settings, where minimizing false positives and negatives is paramount for patient satisfaction and treatment success. Additionally, the performance of Logistic Regression in this study surpasses that of other commonly used machine learning models reported in recent literature, further solidifying its position as a preferred algorithm for binary classification tasks. Furthermore, previous studies (19) emphasized that Logistic Regression consistently outperforms other algorithms in dental aesthetic evaluations, reinforcing its value in clinical decision-making.

This study reaffirms Logistic Regression's efficacy as a high-performing model for classifying aesthetic outcomes in dentistry. While Naive Bayes remains a viable option for quick and interpretable results in less complex scenarios, its performance limitations make it less suitable for datasets requiring high sensitivity and specificity. Future research could explore advanced preprocessing techniques or hybrid approaches to enhance the performance of Naive Bayes further. However, based on the present findings and consistent with prior studies (20,21), Logistic Regression remains the gold standard for predictive modeling in dental aesthetic evaluations.

The study focused on detecting and identifying black triangles in FPD patients using deep learning techniques. The deep learning model demonstrated high accuracy and reliability in detecting and identifying black triangles in FPD patients. The model's ability to analyze and classify images of extracted teeth allowed for efficient and automated detection of calculus deposits, reducing reliance on manual examination. The high accuracy and efficiency of the deep learning model can enhance diagnostic accuracy, save time, and potentially reduce costs in clinical practice. The study's findings suggest that the deep learning model can be generalized across dental images and settings. This scalability allows for potential application in different clinical environments, making it a valuable tool for dentists and oral healthcare providers worldwide.

Medical advancements allow healthcare providers to diagnose patients more accurately and provide meaningful treatments. Patient care is improved through machine learning and artificial intelligence. To assess the parameters and highlight the learning points of the visual conditions, the teeth model can be rigorously diagnosed both inside and out, something traditional dental care solutions (22) could not achieve. By automating the process, the intelligent model enables doctors to focus on other aspects of treatment, such as patient care. Neural Networks (NNs) are a type of deep learning functional unit inspired by the human nervous system and have been applied in various fields, including healthcare. Using deep and co-evolutionary neural network algorithms, researchers and practitioners have developed a variety of machine learning (ML) applications to focus appropriate research across all sectors, including healthcare. These algorithms yield notable and excellent results in radiograph analysis.

V. CONCLUSION

Using artificial intelligence to detect black triangles in FPD patients offers multiple advantages. It prevents false positive and false negative detections and errors caused by humans. It provides better detection and identification, affirming that Logistic Regression is a high-performing model for classifying aesthetic outcomes in dentistry. While Naive Bayes remains a viable option for quick and interpretable results in less complex scenarios, its performance limitations make it less suitable for datasets requiring high sensitivity and specificity. Future research could explore advanced preprocessing techniques or hybrid approaches to enhance the performance of Naive Bayes further. However, based on the present findings and consistent with prior studies, Logistic Regression remains the gold standard for predictive modeling in dental aesthetic evaluations.

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