Detection of Tooth Numbering, Frenulum, Gingival Hyperplasia and Gingival Inflammation on Dental Photographs Using Convolutional Neural Network Algorithms: An Initial Study

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Abstract

Objectives

The aim of this study is to perform tooth numbering using deep learning algorithms on digital dental photographs, and to evaluate the success of these algorithms in determining the presence of frenulum, gingival hyperplasia and gingival inflammation which play an important role in periodontal treatment planning.

Materials and Methods

Six-hundred-fifty-four (n = 654) intraoral photographs were included in the study. A total of 16795 teeth in all photographs were segmented and the numbering of the teeth was carried out according to the FDI system. Two-thousand-four-hundred-and-ninety-three frenulum attachments (n = 2493), 1211 gingival hyperplasia areas and 2956 gingival inflammation areas in the photographs were labeled using the segmentation method. Images were sized before artificial intelligence (AI) training and data set was separated as training, validation and test groups. Yolov5 architecture were used in the creation of the models. The confusion matrix system and ROC analysis were used in the statistical evaluation of the results.

Results

When results of study were evaluated; sensitivity, precision, F1 score and AUC for tooth numbering were 0.990, 0.784, 0.875, 0.989; for frenulum attachments were 0.894, 0.775, 0.830 and 0.827; for gingival hyperplasia were 0.757, 0.675, 0.714, 0.774; for gingival inflammation were 0.737, 0.823, 0.777, 0.802 (respectively).

Conclusions

There is a need for more comprehensive studies to be carried out on this subject by increasing the number of data and the number of parameters evaluated.

Clinical relevance

The current study showed that in the future, periodontal problem determination from dental photographs could be performed using AI systems.

Introduction

Periodontium refers to all of the tissues that support the teeth and it consists of gingiva, periodontal ligament, cementum, and alveolar bone [1]. Periodontal diseases, one of the most common diseases in the world, occur with damage to the healthy periodontium [2, 3]. Gingivitis and periodontitis, which are forms of periodontal diseases, are inflammatory diseases caused by the disruption of the balance between the microorganisms around the teeth and the host response [2, 4].

Clinical evaluations such as probing pocket depth, plaque index, gingival index, bleeding index on probing, and radiographic evaluations are used in the determination of periodontal diseases [3, 5, 6]. A comprehensive clinical examination is a critically important data collection activity necessary to arrive at a diagnosis and develop a treatment plan [6, 7]. In general, during this procedure, an examination is performed to evaluate the changes in the color, shape and texture of the gingival tissues [6–8]. In addition, some conditions such as frenulum, attached gingiva, gingival levels should be examined in detail in order not to overlook the necessity of further periodontal treatment or surgical procedures such as mucogingival surgery during the clinical evaluation [9].

The use of photography in dentistry dates back to 1848 [10]. In the following years, with the development of dentistry, the use of clinical photography has become widespread and intraoral photographs have become an integral part of patient registration and treatment planning [10–12]. Today, dental photographs are still used as one of the basic tools that enable clinicians to synthesize patient-related information and help physicians reach an accurate diagnosis [10]. Not only in a limited field of dentistry; It is used in many fields such as aesthetic dentistry, orthodontics, implantology, dental technology, oral surgery and periodontology [13].

Artificial intelligence (AI) refers to systems or machines that mimic human intelligence to perform tasks and can iteratively improve themselves based on the information they collect [14]. The use of AI in the field of health has become an increasingly popular field [15, 16]. AI systems are currently used as assistive systems for physicians in diagnosis and treatment planning. In addition, they act as decision-support mechanisms that help prevent or minimize errors that may arise from physician density, fatigue or lack of experience [15–17]. In the literature, there are many AI-based studies on the use of patient data on different medical images in the processing, interpretation and reporting [16, 18, 19]. Today, they guide physicians in the process of protecting and maintaining health in many areas such as radiography interpretation, pathological image analysis, evaluation of clinical photographs [16, 18, 19].

When the AI-based studies in field of dentistry are examined, it is seen that there are more studies on dental radiographs. In these studies, it has been tried to detect pathologies such as caries [20], apical lesion [21], dental restoration [22] and periodontal disease [23, 24] from different types of radiographs by using AI systems [25]. Despite this, it is seen that the number of studies aiming to make diagnosis and treatment planning through dental photographs using AI algorithms and evaluating the usability of these systems as assistive systems for physicians is quite limited [22, 26–30].

This study was planned with the idea that anatomical structures and some disease findings that may be important in periodontal examination can be automatically determined by using AI systems in intraoral photographs. In the light of this information, the aim of the present study is to make tooth numbering using deep learning algorithms in digital dental photographs and to determine the conditions such as the presence of frenulum, gingival hyperplasia and gingival inflammation in dental photographs with the help of these algorithms.

Material Method

Six-hundred-fifty-four intraoral profil photographs (n = 654) obtained from the photograph archive of Eskişehir Osmangazi University, Faculty of Dentistry, Department of Orthodontics were used. At the beginning of the study, approval was obtained from the Eskişehir Osmangazi University Non-Invasive Clinical Research Ethics Committee for the study plan. All stages were carried out as declared in the Helsinki Declaration guidelines (decision no: 28.09.2021-14).

Intraoral photographs of patients older than 12 years of age with similar photographic angles and image quality were included in the study. Photographs of patients with rare pathologies that cause serious anatomical variations, and photographs of patients in mixed dentition with primary teeth in their mouths were not included in the study. In addition, photographs that do not have a clear image or have wrong angles are also excluded from the study.

All images have been loaded into the CranioCatch software (Eskişehir, Turkey) labeling module. Initially, as a result of the joint decision of three different periodontologists (SKB, MBY, NS), the teeth were labeled and numbered with Federation Dentaire Internationale (FDI) teeth numbering system. Then, frenulum, gingival hyperplasia areas and inflammatory erythematous gingival regions were labeled using the segmentation method on the images. Images of the cases in which a consensus could not be reached on the diagnosis were excluded from the study. The parameters to be evaluated were labeled according to the following criteria:

The process of labeling and numbering teeth: All teeth were carefully labeled from the tooth margins by segmentation method. Using the FDI teeth numbering system [31], the numbering of the teeth was performed according to their regions (Fig. 1- a, b).

The process of labeling frenulums: Frenulums are muscle fibers that can be observed in different morphologies that connect the lips to the alveolar mucosa and periodontium [32]. In the present study, the relevant muscle connections and prominent mucous membrane folds were determined and labeled with the segmentation method (Fig. 1- a, c).

The process of gingival hyperplasia areas: It is the deterioration of the gingival contours following chronic inflammatory processes or with different etiologies [33]. Gingival hyperplasia in the shape mentioned in the photographs were labeled with the segmentation method by considering the borders (Fig. 1- a, d).

The process of gingival inflammation: It is known that in case of inflammation, the gingival margins appear clinically mild/moderate/severe red and brighter than normal [34]. The gingival parts showing these findings were labeled with the segmentation method (Fig. 1- a, e).

After the labeling was completed, the images were resized before the trainings. For the development of AI systems, all labeled data sets were separated in the form of training, validation and testing. Yolov5 architecture was used at different Epoch and Learning rates to create the model. The data of Epoch and Learning rates used in the study are presented in Table 1. Trials were also made with the object detection method using Yolov5 architecture in order to increase the success rates in tooth numbering.

Table 1
Parameters and data numbers used while developing an artificial intelligence system and the success results of the artificial intelligence system

DATA		MODEL NAME			
		Tooth Numbering	Frenulum	Gingival Hyperplasia	Gingival Inflammation
PARAMETERS	Epoch	500	500	500	500
	Learning Rate	0.01	0.01	0.01	0.01
	Model	Yolov5	Yolov5	Yolov5	Yolov5
NUMBER OF IMAGES AND LABELS	Number of Training Images	520	500	237	417
	Number of Education Labels	13415	2004	1004	2363
	Number of Test Images	65	62	29	51
	Number of Test Labels	1708	248	99	286
	Number of Validation Images	65	62	29	51
	Number of Validation Label	1672	241	108	307
SUCCESS OF ARTIFICIAL INTELLIGENCE SYSTEM	Found Correct for IoU Thresold: 50%	1500	186	100	205
	Found Wrong for IoU Thresold: 50%	412	54	48	44
	Not Found for IoU Thresold: 50%	15	22	32	73
	Sensitivity	0.990	0.894	0.757	0.737
	Precision	0.784	0.775	0.675	0.823
	F1 Score	0.875	0.830	0.714	0.777
	Accuracy	0.778	0.709	0.555	0.636
	AUC	0.989	0.827	0.774	0.802

In the statistical evaluation, the performance of the system was evaluated by using the confusion matrix system [20] and receiver operating characteristic (ROC) analysis. Sensitivity, precision, F1 score, accurancy were calculated with the confusion matrix system. Also, Area under the ROC curve (AUC) value results were calculated for each parameter by ROC analysis. AUC demonstrates the success of diagnostic tests. As the success of the diagnostic test used to predict the disease status increases, this value grows and approaches 1 [35].

Results

When 654 intraoral facade photographs were analyzed statistically, it was seen that a total of 16795 teeth, 2493 frenulum labels, 1211 gingival hyperplasia and 2956 gingival inflammation areas were made within the scope of the study (Table 1). When the success of the developed AI-based system was evaluated with the confusion matrix system, the sensitivity, precision, F1 score and accuracy for tooth numbering were 0.990, 0.784, 0.875, 0.778; for frenulum attachments were 0.894, 0.775, 0.830 and 709; for gingival hyperplasia were 0.757, 0.675, 0.714, 0.555; for gingival inflammation were 0.737, 0.823, 0.777, 0.636 (respectively) (Table 1). For each parameter, the real and system prediction results of some cases are shown in Fig. 2.

The graphs of the ROC analysis results were shown in Fig. 3. AUC values for tooth numbering, frenulum attachments, gingival hyperplasia and gingival inflammation were calculated as 0.989, 0.827, 0.774 and 0.802 respectively by ROC analysis (Table 1).

The training results of the evaluations made with Yolov5 were presented in Fig. 4. F1-confidence curve, presicion-confidence curve, precision-recall curve and recall-confidence curve graphics were given in Fig. 5 and labels collegrams are presented in Fig. 6.

Discussion

Inspection of conditions such as color changes, contour changes, gingival hyperplasia in the gingiva is one of the most important stages in periodontal clinical examination and disease determination [7, 36]. In addition, conditions such as deep frenulum attachments and insufficient keratinized gingiva areas should be recorded by physicians during examinations. Because these situations can disrupt the continuity of oral hygiene and sometimes cause aesthetic problems; there may be a need for surgical periodontal treatment in the relevant field in the future [7, 36]. Periodontists are specialists in the field of periodontology, a specialized field of dentistry, who carry out periodontal treatment of patients by making detailed periodontal evaluation and perform periodontal surgical treatments when necessary [37]. General dentists and dentists specialized in other fields may be inadequate in the periodontal examination and oral-mucosal status evaluation of the patients in some cases, or they may have to refer the patient to the periodontist in specialized cases [38]. It is recommended to work in coordination with a periodontist in patient planning and follow-up, especially in specialties such as orthodontics [39, 40]. However, it is not always possible to work in coordination with a periodontology specialist and to reach a specialist physician. In addition, due to the intensity, fatigue and lack of experience of the physician, some cases may be overlooked by the periodontologist. This situation brings to mind the usability of computer-aided systems that can provide decision support mechanism to physicians for diagnostic purposes.

Based on this information, in the current study, it was aimed to develop an AI system that automatically evaluates periodontal status from intraoral photographs, which are widely used for patient follow-up and recording in all areas of dentistry, and to measure the success of this system. In this study, the success of AI supported systems in the detection of periodontal disease findings such as erythematous-inflamed gingiva and enlarged gingiva and anatomical structures such as the frenulum, which plays an important role in mucogingival evaluation, was evaluated.

As in many fields of medicine, the usability of AI systems in image processing and interpretation in dentistry, especially in areas such as radiology and pathology, has been demonstrated, and it has been confirmed by academic studies that they can be a decision-support mechanism for physicians [16–19]. When the AI-based periodontology studies are examined, it is seen that these systems are very successful in the interpretation of intraoral and extraoral dental radiographs; also, it is seen that information such as the presence of bone loss, the presence of periodontal disease and the severity of the disease can be determined automatically with AI [23, 41, 42].

In the literature, detection of lesions such as squamous cell carcinoma [26], lichen planus [43] using AI systems in intraoral photographs; detection of dental applications such as dental prostheses, restorations and fissure sealants [29, 44, 45]; in addition, there are many studies on the detection of conditions such as dental caries [28, 46], white spot [18], and anomalies such as microdontia, rotation, and supernumerary [47]. All of these studies about AI, which has attracted great interest in dentistry in recent years, support the usability of these systems for intraoral photographs and dental cameras in the dental field in the coming years.

In one of these studies, Fu et al. (2020) had tried to determine oral squamous cell carcinoma with CNN using 1469 intraoral photographs and compared the results of 21 observers (expert, medical student, non-medical student) with the results of AI in their study [26]. As a result of this study, they had reported that AI systems have a performance comparable to the specialist physician in determining the relevant pathology, and that the system performs significantly better than an average medical student [26]. Similarly, Keser et al. (2021), in their study, had tried to determine the oral lichen planus lesions related using inception v3 architecture (an AI system) on 65 intraoral photographs of healthy induviduals and 72 patients with oral lichen planus [43]. They also had reported that the AI system used in this study was 100% successful in detecting the presence/absence of the lesion, that is, in its classification [43].

Zhang et al. (2020) had carried out a study on the automatic detection of dental caries by CNN-based AI systems on a large dataset containing 3932 photographs [28]. As a result of this study, they had reported that the system gave very successful results in detecting the related pathology and that the use of these systems in caries screening in crowded populations could be beneficial [28]. Kühnisch, et al. (2022) also had carried out a similar study and reported that CNN-based AI systems can be used in caries detection, but these systems need to be improved [46]. Although different situations have been evaluated with AI systems, our study shows that AI systems can be successfully used in the future in determining dental status, tooth numbering and anatomical formation from intraoral photographs similarly.

Takahashi et al. (2021) had found that metallic colored restorations were recognized by the ai-systems with a higher accuracy rate, as a result of their study on prosthesis and restoration detection using AI systems (This study was carried out on 1904 dental photographs) [29]. In another study, Engels et al. (2022) had reported that AI systems showed success in the range of 92.9–99.2% in the determination of different restorations such as non-restorative tooth, composite restoration, cement restoration, amalgam restoration, gold restoration and ceramic restoration [44]. On the other hand, Schlickenrieder et al. (2021) had reported the usability of CNN systems in the determination of fissure sealant in intraoral photographs. Even if the related studies are not directly related to the field of periodontology, it supports that all kinds of pathology, restoration and dental conditions can be detected with AI systems [45].

When the literature is examined, it can be seen that these systems can be used in a wide variety of pathology detections. Askar et al. (2021), in their study using 434 photographs, had reported that CNN systems showed satisfactory results in the determination of cases such as White spot and fluorosis, and that new studies should be carried out on large data sets for more successful results [18]. Rogodos et al. (2022) had used 38486 intraoral photographs to evaluate 10 dental anomalies including rare anomalies (such as mammalons, hypoplasia, Microdontia) by AI systems and obtained successful results [47].

It is known that the success of the system increases as the number of data increases in AI systems. Therefore, in the current study, the number of data was tried to be kept as wide as possible. As can be seen, although many conditions such as caries, restoration, prosthesis, and anomalies have been evaluated with AI systems in the literature, tooth numbering has not been performed in any of these studies. In the present study, the system's ability to identify teeth and perform tooth numbering was also studied. Thus, it is aimed to analyze the related pathology, dental disease and which tooth is associated with the condition. As far as we know, the present study is the first study in which tooth numbering is done from photographs using AI systems. This parameter is very important for dental evaluations. Because, not only in periodontology, but also in all AI studies to be developed in the dental field, it allows the automatic determination of which tooth is associated with the relevant pathology, restoration or dental condition. In summary, It can enable the localization of related pathologies and conditions to be determined and subsequently converted into a written report.

The studies most similar to the aim of the present study were studies of Alalharith et al. (2020), You et al. (2020) Xu et al. (2022) and Li et al. (2021) [27, 30, 48, 49]. Because in these studies, AI systems that will help the physician in periodontal evaluation such as the detection of gingivitis findings and the determination of dental plaque, as well as inform the patient, had been studied. Alalharith et al. (2020) had tried to detect tooth detection and gingival inflammation using CNN systems on 134 photographs [48]. This study also had evaluated inflammatory and erythematous site detection, similar to the current study. But Alalharith et al. (2020) had used the object detection method in their studies [48], while the segmentation method, which is a more ideal method, was used in the current study. It can be said that the current study is more comprehensive and superior to this study in terms of it has larger data set, the use of segmentation method in evaluations, and the evaluation of different parameters. On the other hand, in the study carried out by Li et al. (2021), 3932 intraoral photographs obtained from 625 patients were used [30]. In this study, similar to the study of Alalharith et al. (2020), they had tried to determine the signs of gingivitis, soft appendages and calculus with the objective detection method [48]. Although similar results and system success were reported in the detection of inflammation with the results of the current study, the fact that the object detection method was used in this study can be considered as a disadvantage of the study.

You et al. (2020) had used the CNN method to detect dental plaque around primary teeth and reported that AI systems detected plaque at a higher accuracy rate than the dentist in their study on 886 photographs. In this study, the segmentation method was used and in this respect, it is similar to the current study [27]. However, the fact that only one parameter had been evaluated and studied only in primary tooth photographs can be considered as a disadvantage of this study.

Xu et al. (2022) had carried out a study using the Googlenet model, and in this study, they had aimed to analyze the plaques around the teeth with the object detection method [49]. Only 400 images were used in the study of Xu et al. (2022) [49]. In these two studies, they had worked on a critical parameter in terms of periodontology, namely the determination of plaque, and presented acceptable success rates [27, 49]. It should not be forgotten that plaque control is the basic principle in the treatment of periodontal disease, and this issue should be more comprehensively focused in future AI-based periodontology studies on the intraoral photographs.

Although the related study presented in the article had not been evaluated before in AI-based studies performed in photographs and had evaluated various parameters that may be periodontally important, it had some limitations. The first of these was the limited number of data and the fact that it was carried out only on intraoral facade photographs. Studies in which the type of photography is diversified by increasing the number of data will provide more meaningful results. In addition, the decisions of many auditors were not recorded and were not compared with the relevant CNN system. These can be considered as the limitations of the study. Had the study been conducted in this way, it would undoubtedly have presented more interpretable results. These issues should be taken into consideration in future studies, and more comprehensive studies should be carried out with photographs taken from different cameras and of different quality, in which more parameters are evaluated. It is obvious that AI systems, which gained importance in many fields, will take place in the diagnosis and treatment planning in dentistry in the coming years. Academic studies to be carried out will accelerate this acceleration.

Conclusion

The present study has shown that the determination of periodontal problems from dental photographs can be performed using AI systems in the future. There is a need for more comprehensive studies on more data to be obtained from different centers and in which more parameters will be evaluated. In order to better understand the success of AI systems, the decisions of physicians with different experience in diagnosis and treatment planning should be evaluated in future studies and compared with AI systems.

Declarations

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Ethical Approval: The study protocol was carried out according to the Helsinki Declaration of 1975, as revised in 2002 and also approved by the Human Ethical Committee of Ondokuz Mayis University (Eskişehir Osmangazi University Non-Invasive Clinical Research Ethics Committee, decision no: 28.09.2021-14).

Competing interests: The authors declare that they have no conflict of interest.

Authors' contributions: All authors have made substantial contributions to conception and design of the study. SKB, MU, ISB, MBY and NS have been involved in data collection and ÖÇ has been involved in data analysis. SKB, MU, ISB, MBY, NS, OK, AB, BCUS and RJ have been involved in data interpretation and drafting the manuscript. SKB, ISB and KO has been involved in revising it critically and have given final approval of the version to be published.

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Figures

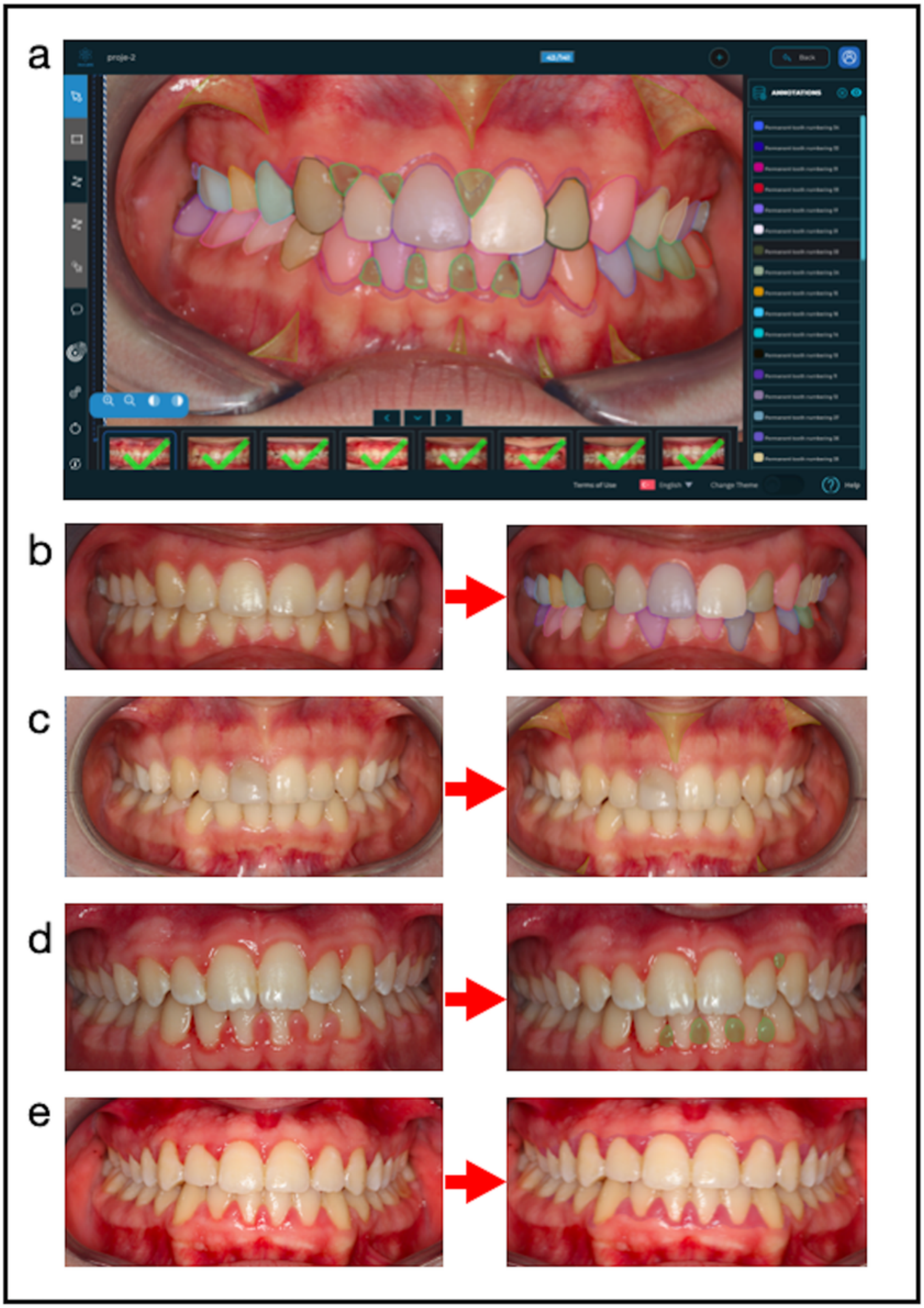

Figure 1

Examples of the labeling process performed on different patients for each parameter in the CranioCatch labeling module. **a.**Labeling process for all parameters on a patient's intraoral photograph in CranioCatch labeling module; **b.** Labeling process for tooth numbering on a patient's intraoral photograph; **c.** Labeling process for frenulum on a patient's intraoral photograph; **d.** Labeling process for gingival hyperplasia on a patient's intraoral photograph; **e**. Labeling process for gingival inflammation on a patient's intraoral photograph.

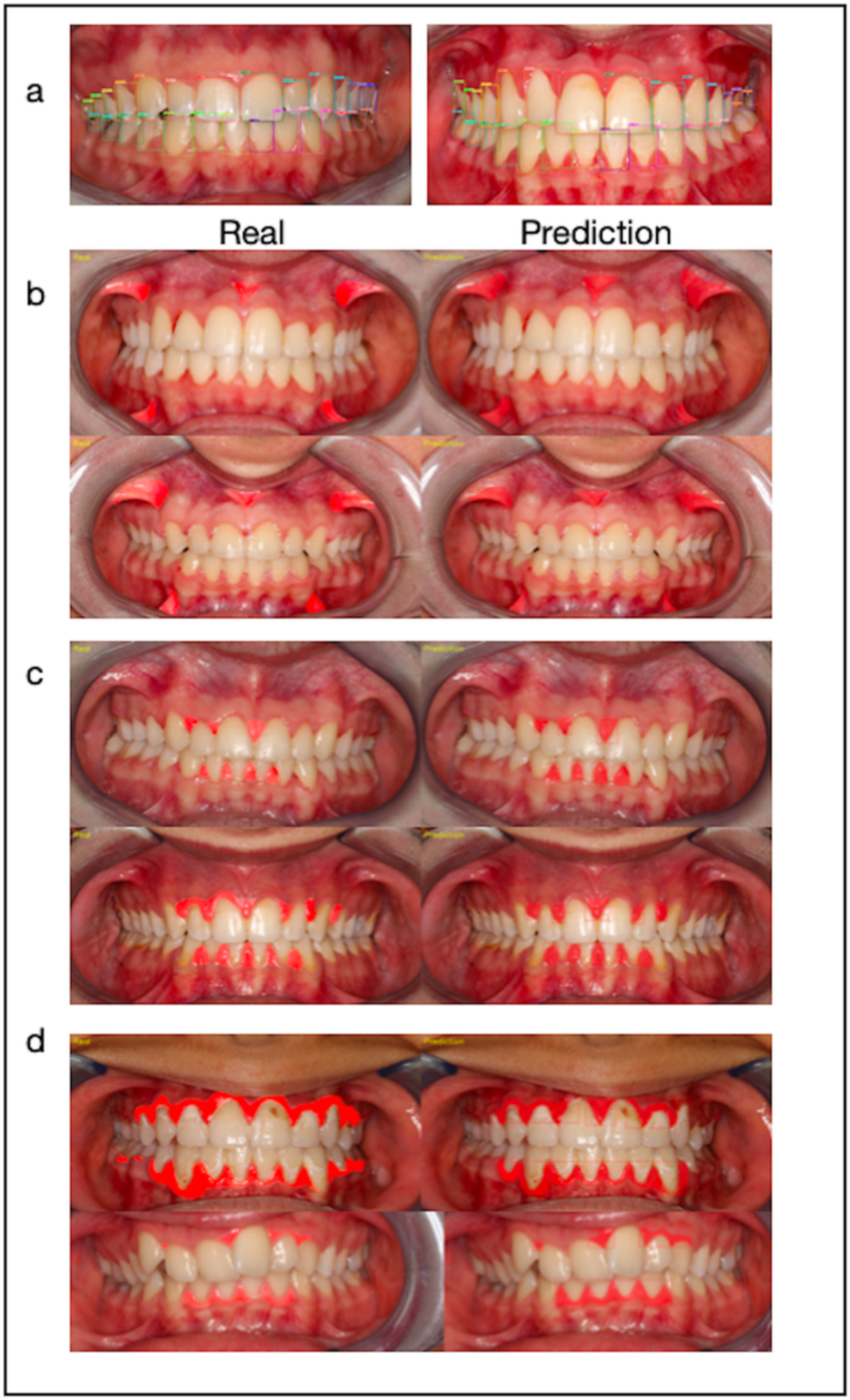

Figure 2

Examples of tooth numbering, frenulum, gingival hyperplasia and gingival inflammation detection of artificial intelligence systems in intraoral photographs of different patients. **a.**System predictions of tooth numbering in two different patients' intraoral photo; **b.** System predictions of frenulum in two different patients' intraoral photo; **c.** System predictions of gingival hyperplasia in two different patients' intraoral photo; **d.** System predictions of gingival inflammation in two different patients' intraoral photo.

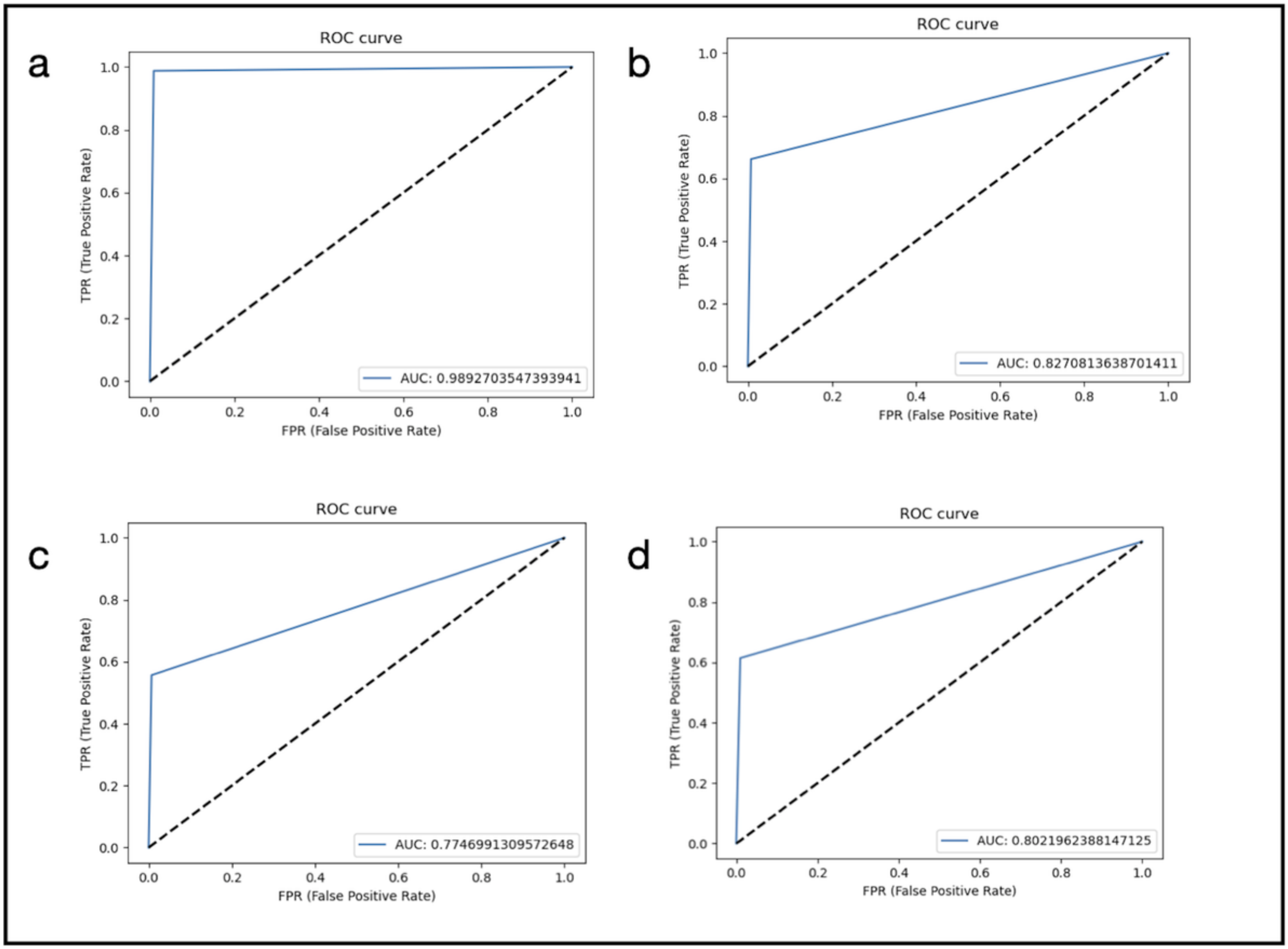

Figure 3

The graphs of the ROC analysis results. **a.** For tooth numbering; **b.** For frenulum; **c.** For gingival hyperplasia; **d.** For gingival inflammation.

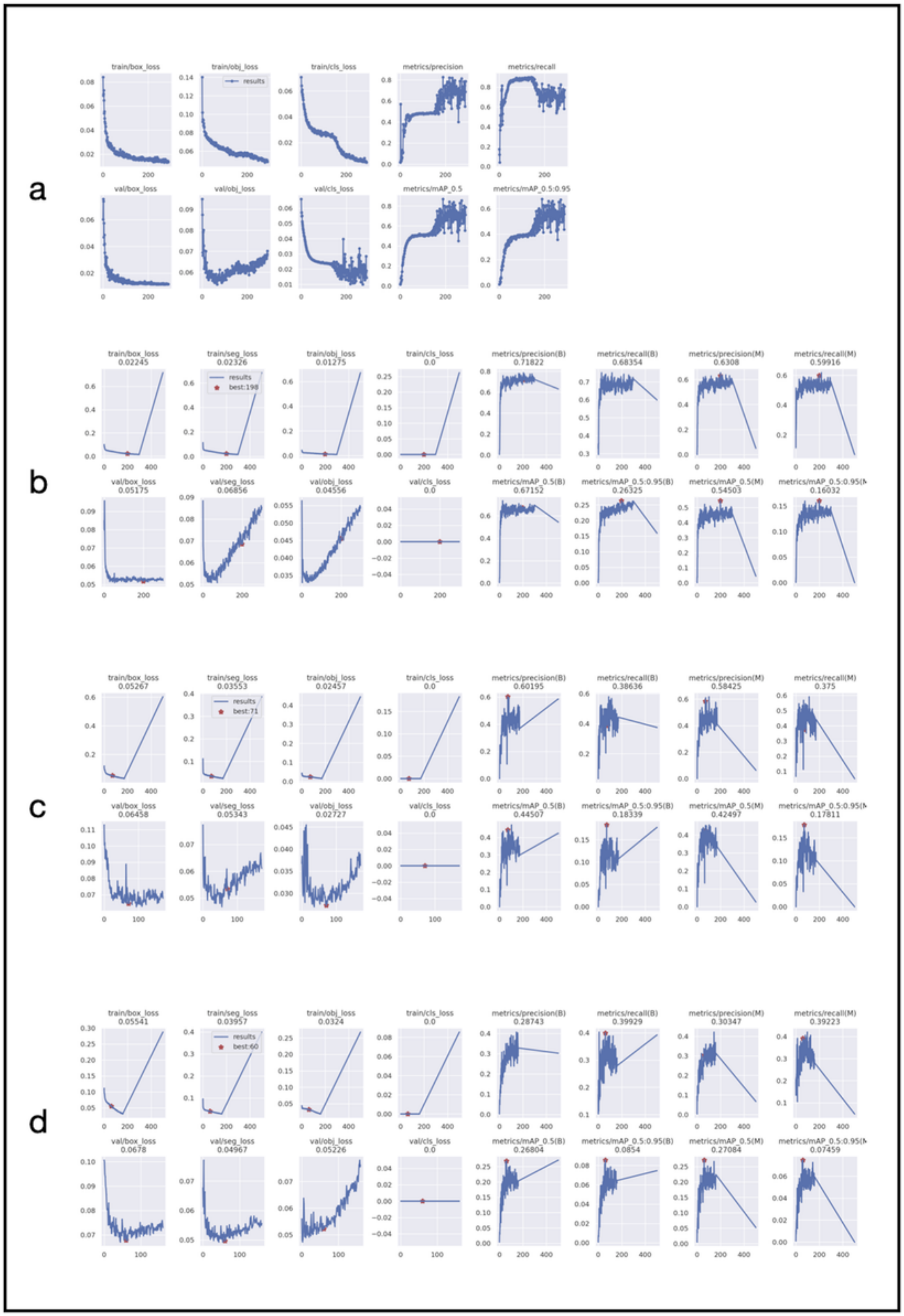

Figure 4

The training results by Yolov5. **a.** For tooth numbering; **b.** For frenulum; **c.** For gingival hyperplasia; **d.** For gingival inflammation.

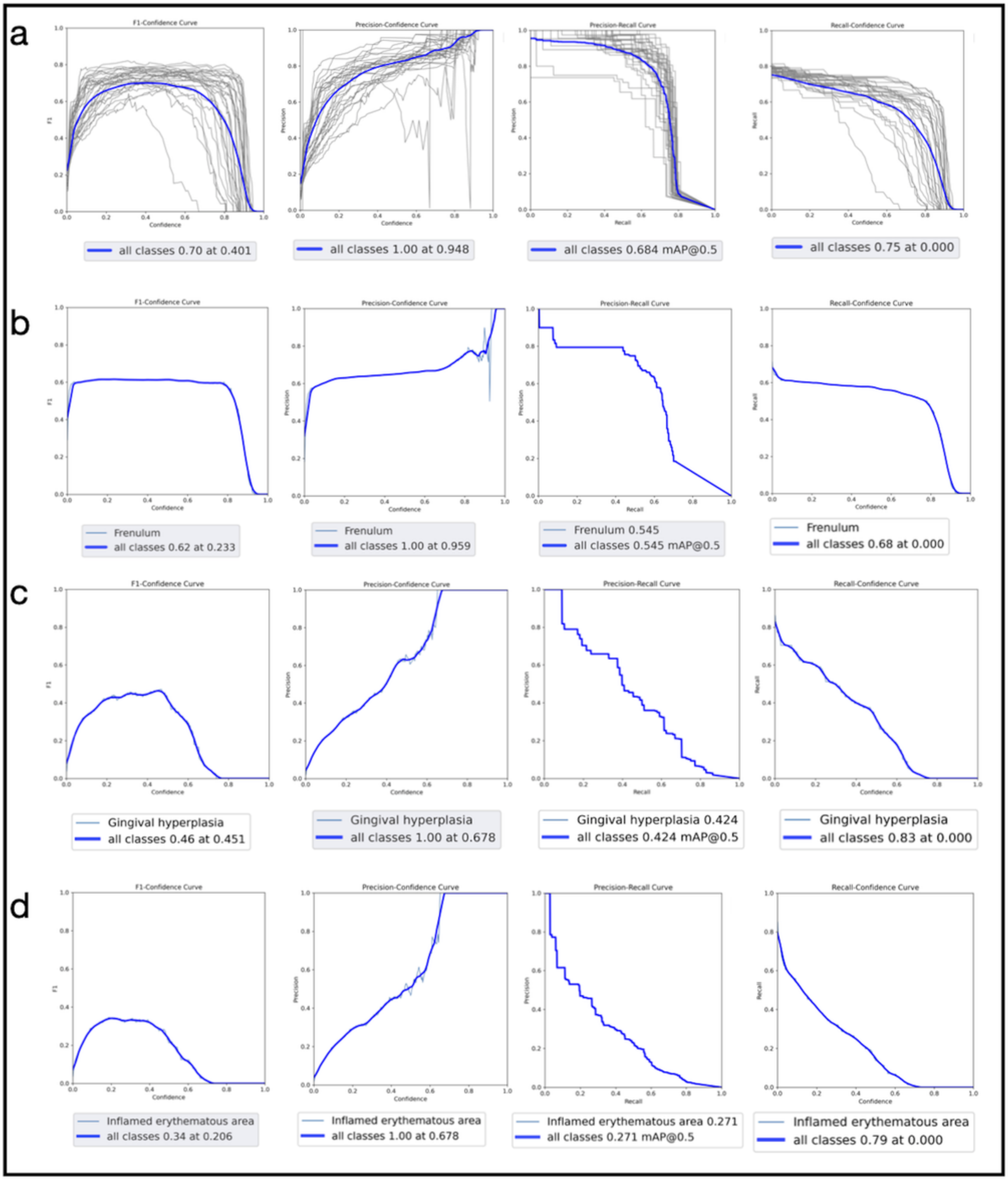

Figure 5

F1-confidence curve, presicion-confidence curve, precision-recall curve and recall-confidence curve graphics. **a.** For tooth numbering; **b.** For frenulum; **c.** For gingival hyperplasia; **d.** For gingival inflammation.

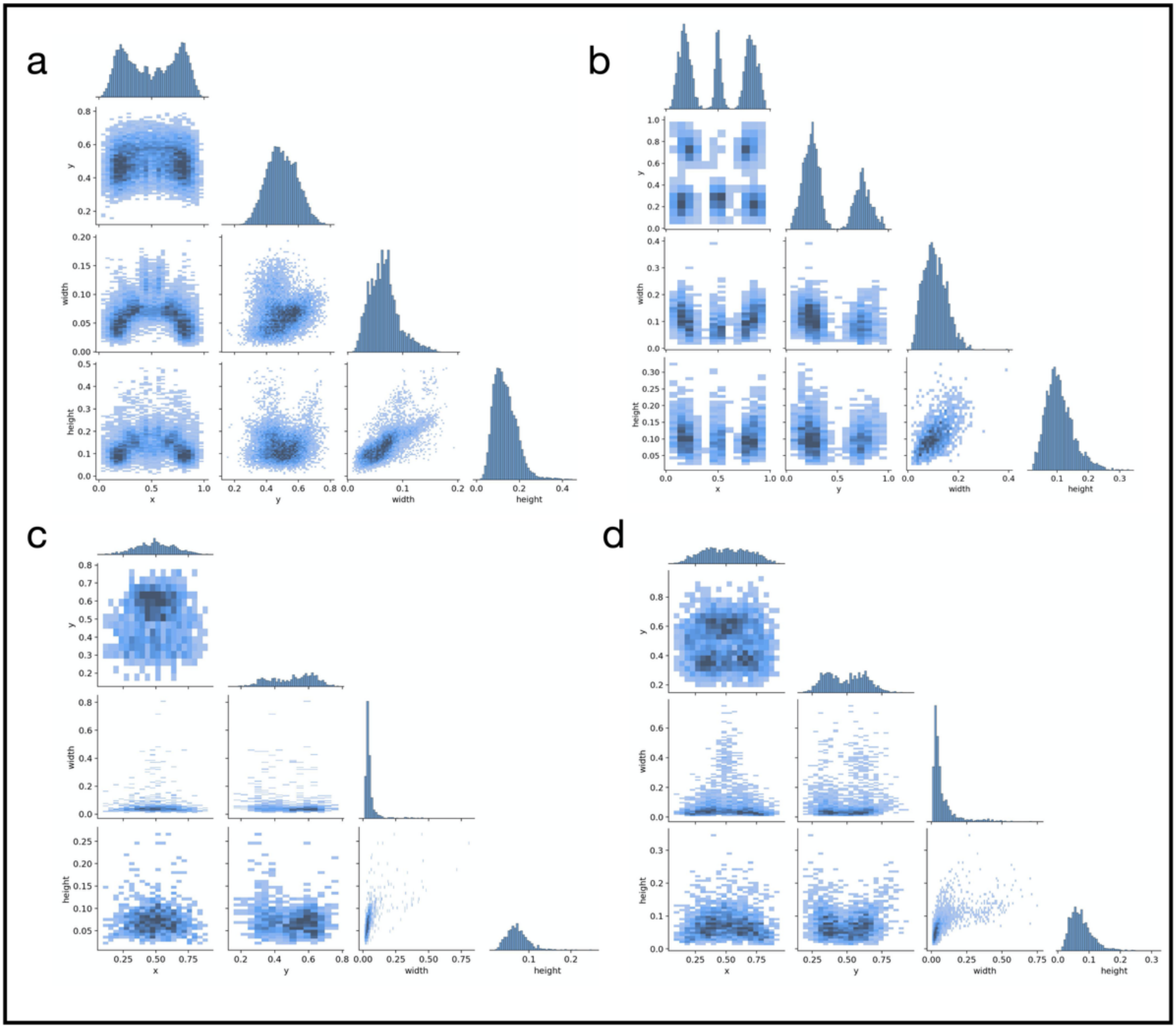

Figure 6

Labels correlograms. **a.** For tooth numbering; **b.** For frenulum; **c.** For gingival hyperplasia; **d.** For gingival inflammation.