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Original Article

A deep learning approach to detection of oral cancer lesions from intra oral patient images: A preliminary retrospective study

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A B S T R A C T

Introduction: Oral squamous cell carcinomas (OSCC) seen in the oral cavity are a category of diseases for which dentists may diagnose and even cure. This study evaluated the performance of diagnostic computer software developed to detect oral cancer lesions in intra-oral retrospective patient images.
Materials and methods: Oral cancer lesions were labeled with CranioCatch labeling program (CranioCatch, Eskişehir, Turkey) and polygonal type labeling method on a total of 65 anonymous retrospective intraoral patient images of oral mucosa that were diagnosed with oral cancer histopathologically by incisional biopsy from individuals in our clinic. All images have been rechecked and verified by experienced experts. This data set was divided into training (n = 53), validation (n = 6) and test (n = 6) sets. Artificial intelligence model was developed using YOLOv5 architecture, which is a deep learning approach. Model success was evaluated with confusion matrix.
Results: When the success rate in estimating the images reserved for the test not used in education was evaluated, the F1, sensitivity and precision results of the artificial intelligence model obtained using the YOLOv5 architecture were found to be 0.667, 0.667 and 0.667, respectively.
Conclusions: Our study reveals that OCSCC lesions carry discriminative visual appearances, which can be identified by deep learning algorithm. Artificial intelligence shows promise in the prediagnosis of oral cancer lesions. The success rates will increase in the training models of the data set that will be formed with more images.

1. Introduction

Oral cancer is described as malignant lesions that occur in the lip, buccal mucosa, hard palate, floor of the mouth, anterior two thirds of the tongue, and gingiva around the lower and upper teeth. Malignant tumors seen in the tonsils, soft palate, and posterior 1/3 of the tongue are referred to as oropharyngeal cancer [1–4]. Roughly 90 % of oral and oropharyngeal malignancies are oral squamous cell carcinomas (OSCC) that originate from the oral mucosa [5]. According to the most recent predictions from the American Cancer Society, there will be around 58,450 new cases of oral cavity or oropharyngeal cancer in the United States in 2024, with approximately 12,230 fatalities [3,4].

Lesions classified as oral potentially malignant disease (OPMD) may arise during malignant transformation of the oral mucosa [1,2]. The early detection of a potential malignant change related to the lesions depends on periodic follow-up and assessment of OPMDs in terms of dysplasia [6–9]. A thorough head and neck examination, a visual examination in illuminated conditions, and a palpation assessment of the oral mucosa are the fundamental steps in the oral lesion screening process [8,10]. Nevertheless, clinical examination alone is insufficient to predict the histopathological diagnosis of oral mucosal lesions, given that oral squamous cell carcinoma lesions are often diagnosed in advanced stages of the disease [10,11]. As a result, it is necessary to create auxiliary instruments that will improve clinical examination effectiveness and make it easier to find and diagnose abnormalities of the oral mucosa.

Artificial intelligence (AI) can be defined in simple terms as the use of computers or machines to perform tasks that normally require humans [12–16]. Machine learning (ML) and deep learning (DL), a subset of AI, can be used to teach machines and computers to analyze certain types of data using various algorithms [14–16]. DL, a subset of

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machine learning, has recently acquired significance in the AI industry, and it is defined as the use of multilayered artificial neural networks to a variety of tasks, including image processing [12,15,16]. Convolutional neural networks (CNNs), one of the most popular deep learning (DL) algorithms for pattern detection, excel in image analysis [15–17].

AI-based clinical decision support systems designed for the differential diagnosis of oral mucosal lesions can be applied to cancer screening, classification of suspicious mucosal changes, tissue diagnostics, lymph node involvement evaluation and gene expression analysis [18,19]. The use of AI applications in cancer screening increases the likelihood of early diagnosis by eliminating observer-related fatigue and detecting even a change in a single pixel in a short time, unlike accelerated workflow and conventional methods [19]. In a case-control study, the genetic information of 87 healthy persons and 84 patients with oral cancer, as well as sociodemographic data, smoking and alcohol use patterns, and several AI models were compared with specialized physicians. In determining the likelihood of acquiring oral cancer, it was discovered that both AI models outperformed specialized doctors [20]. Similar to this, Wang et al. used data from 266 individuals with suspicious oral lesions to create a customized algorithm to forecast the likelihood of malignant transformation of OPMD. It was claimed that the model that was provided could predict the risk of developing oral cancer and distinguish between lesions that were low- and high-risk with high sensitivity and specificity values [21]. Fu et al. developed an automatic DL algorithm using a CNN as a convolutional deep learning model to detect oral cancer in intraoral photographs. The algorithm, which was trained using 44,906 photographs of oral cancer lesions and healthy mucosa, was found to be able to detect oral SCC lesions with 95 % sensitivity and 89 % specificity rates [22]. In a recent study evaluating the performance of CNN algorithms in the diagnosis and classification of oral cancer and OPMDs using intraoral photographs, it was found that the algorithms were more successful than general practitioners and performed close to specialists [23].

Since early diagnosis of malignant changes is extremely important, it is crucial to use effective and noninvasive diagnostic methods in oral cancer cases. Our hypothesis is that artificial intelligence can diagnose oral cancer lesions from intraoral patient images at least as well as physicians. Therefore, the aim of this study is to evaluate the function of a diagnostic computer software designed for the detection of oral cancer lesions from intraoral patient images with deep learning algorithm.

2. Material and methods

2.1. Study design and clinical information

The study protocol of this study was approved by the Marmara University School of Medicine Clinical Research Ethics Committee on 09.02.2024 with protocol number 09.2024.209. To be included in the study sample of images, patients had to recieve histopathologically confirmed diagnoses of squamous cell carcinoma at our clinic between the years 2022 and 2024. In our study, lesion images from the most common sites of OSCC, such as the lateral border of the tongue, buccal mucosa and floor of the mouth, were used without identifying any specific site in the oral cavity.

2.2. Image acquisition and data collection

Anonymous retrospective photographic images of oral mucosa with SCC lesions were identified and labeled using the The artificial intelligence-powered CranioCatch program (CranioCatch Eskişehir Turkey) (Fig. 1). All images were re-checked and verified by G.K. who has ten years of experience as an oral medicine expert.

2.3. Deep convolutional neural network architecture

In this study, an AI algorithm was developed to perform the detection and segmentation of oral squamous cell carcinoma from photographic images by using a software program(CranioCatch, Eskisehir-Turkey). The deep learning process was performed using YOLOv5 (You Only Look Once) architecture.

YOLO is a single-stage deep learning algorithm that uses Convolutional Neural Network for object detection (Fig. 2). YOLO architecture consists of four main parts: input module, spine network, neck network and prediction network. While other algorithms use the entire image to detect objects in the image, the working principle of the YOLO algorithm generally divides the image into regions and then draws a Bounding Box surrounding the objects in each region. These boxes are called "bounding boxes" and each area calculates the probability that the object is there. A measure called "Confidence Score" is also calculated for these probabilities, which shows the similarity between the percentage of objects in the bounding box and the trained objects. YOLO passes the image through the neural network in one go, which makes the process faster [23].

The most important difference of the YOLOv5 model from other YOLO versions is the library in which it was developed. The YOLO architecture is effective in object detection because it is a regression-based approach that predicts classes and bounding boxes for the whole picture in a single run of the algorithm. YOLOv5 makes training and inference on specialised datasets extremely easy and very straightforward. Another reason for such good training and detection results of the YOLOv5 model is mosaic augmentation. In simple terms, it combines 4 different images into a single image so that the model can learn to deal with diverse and difficult images. Along with

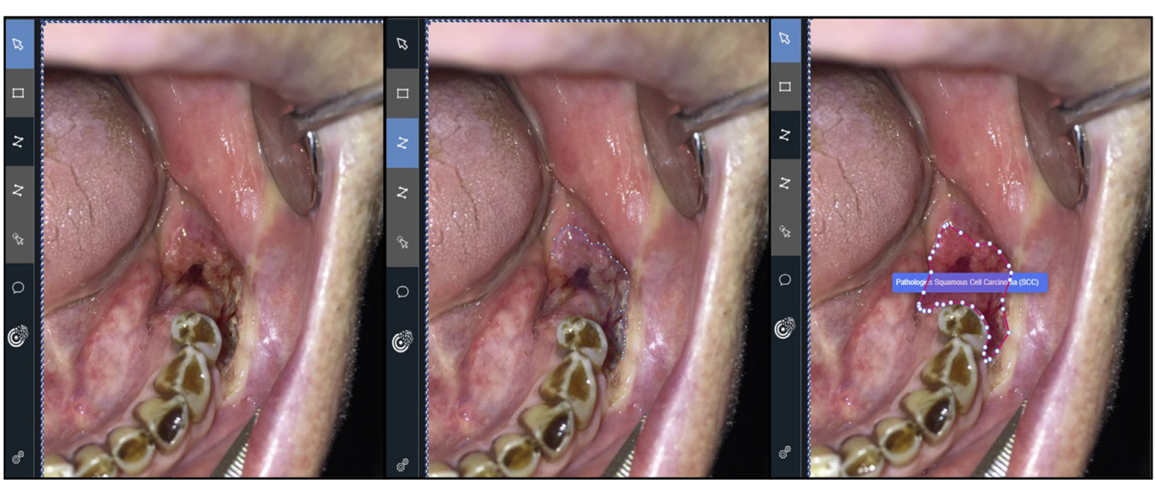

Fig. 1. Representative samples demonstrating the use of the Craniocatch (CranioCatch Eskişehir Turkey) for identifying and labeling lesions in SCC cases.

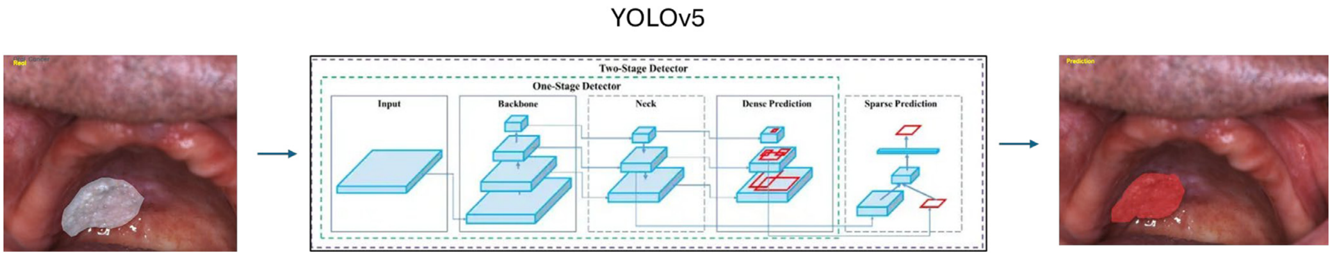

Fig. 2. An illustration of the whole approach for diagnosing SCC using deep learning-based technique, which is YOLOv5 in this study.

mosaic augmentation, it also uses other augmentation techniques [2,23].

2.4. Training phase

For the segmentation model, 65 anonymized, intra oral photographic images were resized to 640 × 448 keeping the aspect ratio. A random dataset was created by using the open-source Python programming language and Opencv, Pytorch, Numpy, Pandas, Torch Vision,Torch, Tensorboard and Seaborn libraries. To avoid using training images for re-testing, the data set was separated into three parts: 80 % training, 10 % validation, and 10 % testing:

- The training group includes 80 % of the images, representing the data set used to train the model.
- Validation group includes 10 % of images that are independent of model training and should not be seen by the model during this period. This dataset is used to evaluate the model and decide whether to terminate training or change the training variables.
- The test group consists of 10 % of the photos and is used to evaluate the trained model against training and validation data.

A total of 65 intraoral photographic images of SCC lesions were divided into:

1. Training group: 53 images
2. Validation group: 6 images
3. Test group: 6 images.

Images were trained with YOLOv5 architecture with 500 epochs.

2.5. Assessment metrics

The confusion matrix, a useful table summarizing predicted and actual situations, was used as a metric to calculate the success of the model (Fig. 3) [16].

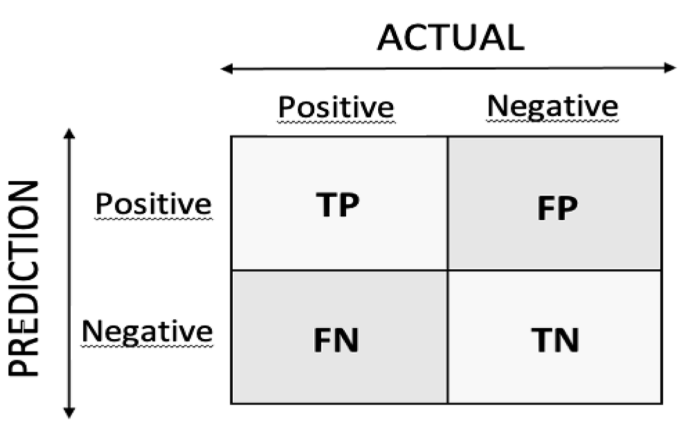

Fig. 3. Confusion matrix.

The following procedures and metrics were used to assess the success of the AI model:

- Initially true positive (TP), false positive (FP) and false negative (FN) rates were calculated.

TP: Result where the model accurately predicted the positive class.
FP: Result where the model incorrectly predicted the positive class.
FN: The result where the model incorrectly predicted the negative class.

The following metrics were then calculated using the TP, FP and FN values:

- **Sensitivity (Recall):** TP/ (TP + FN)
- **Precision:** TP/ (TP + FP)
- **F1 Score:** 2TP/ (2TP + FP + FN)
- mAP: $\frac{\sum_{c=1}^{C} \mathrm{Avarageprecision}(C)}{C}$ where C is the total number of output classes.

These assessment parameters range from 0 to 1, with higher values indicating greater detection accuracy.

3. Results

Using test data, DL model was were applied to detect oral squamous cell carcinoma lesions from photographic pictures (Fig. 4). The precision, sensitivity and F1 scores of AI model estimation performance values and graphs are shown in Table 1 and Fig. 5. The precision sensitivity and F1 scores in Table 1 are 0.667, respectively. These values indicate that the success of the algorithm is close to 1 on the scale between 0 and 1.

Fig. 5 shows Precision-confidence curve, Recall -confidence curve, F1-confidence curve and Precision−recall curve performance graph of YOLOv5-based AI model. The Recall-cofidence curve shows the recall score obtained by the model at a given confidence level. The maximum value of the curve is the confidence level at which the model achieves the highest recall score. In this case, the maximum value is 0.95. Moreover, the Recall-confidence curve in the YOLOv5 algorithm displays the model's recall score at each confidence level. The greatest value of the curve is the confidence level at which the model obtains its highest recall score. In that instance, the highest value is 0.95. Similarly, the maximum value for Precision-Recall curve is 0.85.

As seen in the Precision - confidence graph, precision increases as the confidence level increases. However, when the confidence level is too high, the precision starts to decrease. This is due to the fact that when the algorithm is very confident that the objects it detects are correct, it is more likely to make false positives. In the graph, the precision "OSCC" reaches 1.00 at a confidence level of 0.525.

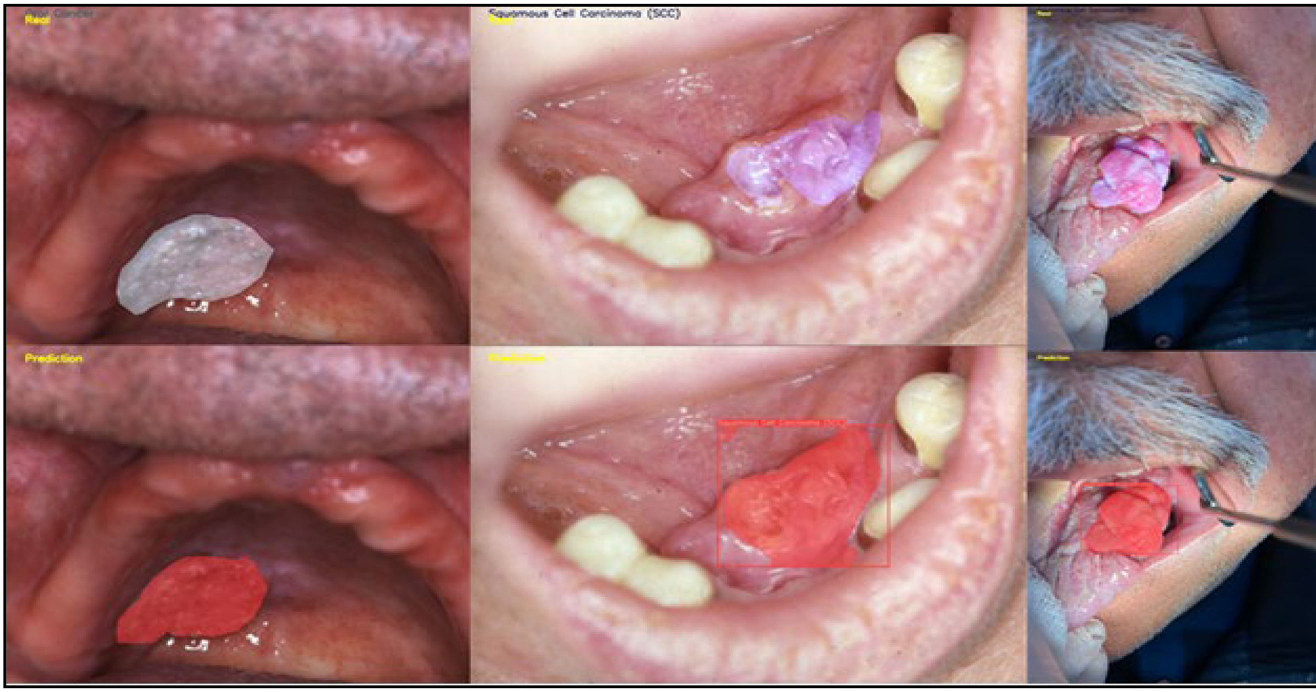

Fig. 4. The YOLO v5 algorithm's segmentation of the cancer lesion is remarkably near to reality in the prediction of oral cancer lesions (Real: manually labeled images, Prediction: images detected by the model).

4. Discussion

OSCC represents one among the world's most frequent cancers, with many nations witnessing an increase in its prevalence Early identification is essential for better prognosis, treatment, and outcome [1,2,8]. We hypothesized that, like physicians, artificial intelligence will be able to identify oral cancer lesions from intraoral patient photos. Thereby, the goal of this study is to assess the effectiveness of a deep learning algorithm-based diagnostic computer program designed for the detection of oral cancer lesions using intraoral patient photos.

DL has been presented as a means of enhancing precision medicine by increasing early detection and thereby minimizing cancer-related mortality and morbidity [2,18,24]. Dental practitioners are nowadays under a lot of pressure since they must assess many more patients or cases that are more complex than in the past. These professionals may be able to solve these challenges with the assistance of AI. The described algorithms in studies, like human observers, is becoming progressively sensitive and accurate [2,12].

Clinical images are becoming increasingly prevalent in medicine to provide deep learning solutions to automatic systems that assist with decisions for disease diagnosis, prognosis, and therapy customization, among other purposes to improve the efficiency of the medical industry [2,20,22,24]. They are gradually being utilized as input data in cancer studies to build a deep learning model that predicts clinical outcomes. Jubair et al. applied a CNN classifier to classify 716 clinical images as benign, malignant, or oral potentially malignant condition (OPMD). When compared to 62 board-certified dermatologists, the deep learning approach provided an effective method of screening for oral cancer, with a sensitivity score of 0.805 [25]. Uthoff et al. used CNN to detect precancerous and cancerous tumors. CNN outperformed experts with senstivity and precision scores of 0.85 and 0.88, respectively, as an approach for effective management of oral cancer through early detection in identifying precancerous and cancerous lesions. The authors stated that more datasets can improve the CNN model's performance [26]. Moreover Fu et al. created an automated deep learning technique for detecting OCSCC in photographic pictures that uses convolutional neural networks on 44,409 clinical photos gathered from 11 hospitals in China, including all biopsy-proven OCSCC photographs and normal controls. The authors also tested the algorithm's performance against that of seven oral cancer specialists using a clinical validation dataset. The deep learning algorithm achieved a sensitivity score of 0.949, comparable to human specialists. The researchers suggest that this model could be used as a clinical tool for cancer screening, early detection, and therapeutic efficacy assessment [26].

Table 1
The precision, sensitivity and F1 scores of AI model estimation performance values.

	Measurement Value		
	Precision	Sensitivity	Recall
Oral Squamous Cell Carcinoma lesion	0.667	0.667	0.667

Tanriver et al. proposed a CNN model for diagnosing oral lesions that combines object identification with classification tasks. YOLOv5l is used in their proposed pipeline to detect lesion areas in the whole image, and EfficientNet-b4 is used to categorize the discovered lesion regions into three groups. The selected networks demonstrated high accuracy and inference time, making them suitable for real-time applications. For the test set, the YOLOv5l model outperformed all other versions, with an average precision (AP) of 0.644 [27].

The COCO (Common Objects in Context) dataset, which is a large-scale object detection, segmentation and captioning dataset, has been widely used to train and evaluate deep learning models in object detection (such as YOLO, Faster R-CNN and SSD), instance segmentation (such as Mask R-CNN) and keypoint detection (such as OpenPose). YOLOv5, which is available in four distinct versions, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, has achieved strong detection results on the PASCAL VOC and COCO datasets; [28,29] hence, this present study uses the YOLOv5 detection network to produce bounding boxes for objects.

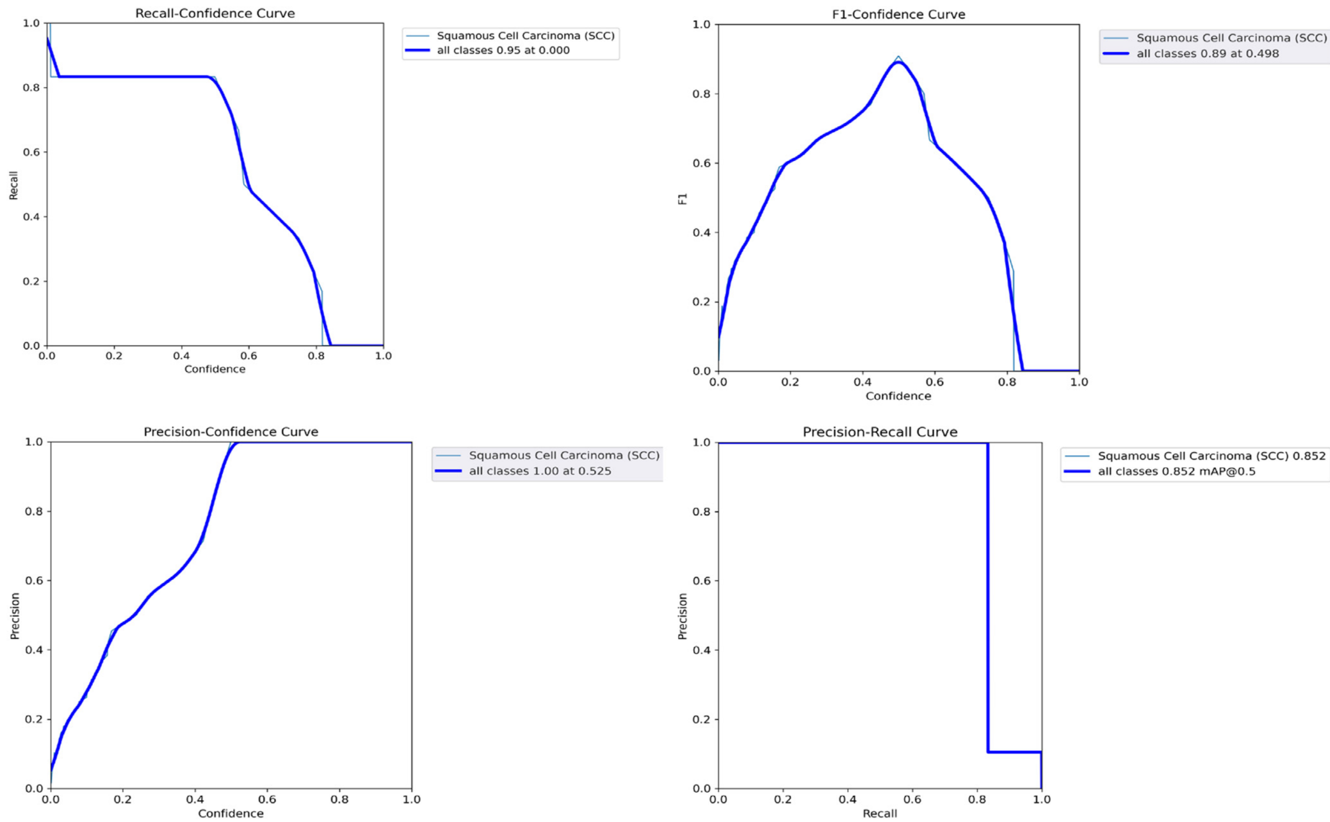

Fig. 5. Precision confidence curve, Recall confidence curve, F1 confidence curve and Precision−recall curve performance graph of YOLOv5-based AI model.

Consequently, using the YOLOv5 architecture, our study achieved somewhat similar precision,sensitivity, and F1 scores to Tanriver et al., which were all 0.667.

Besides, Warin et al. established an automatic classification and detection model for oral cancer screening using CNN deep learning techniques. The study included 700 clinical oral images from the oral and maxillofacial centers, which were divided into 350 photos of oral squamous cell carcinoma and 350 photos of healthy oral mucosa. The classification and detection models were generated using DenseNet121 and the faster R-CNN, respectively. The DenseNet121 model achieved classification scores of 0.99, 0.99 and 0.98 for precision, F1 score and sensitivity, respectively [30].

Plenty of studies in the literature have attempted to "demonstrate" that AI-based systems may be utilized as an additional diagnostic tool for oral cancer lesions. The bulk of the investigations were conducted retrospectively, with limited data from a small number of patients. To optimize the learning capacity of AI-based systems, large-scale databases and enormous volumes of accurately labeled data are required. The confidentiality of patients should be addressed while developing these databases, and data security must be assured [2,15,18].

One of the primary limitations of this paper is that it examines deep learning with limited sample sizes. In addition, the lack of demographic data in our analysis stems from the fact that the information was gathered retrospectively. Future research will attempt to incorporate additional data and compare several deep learning algorithms to assess each one's performance.

To our knowledge, this is the first study in Turkey that focuses just on the detection of OSCC using a deep learning system from photographic images. With the results of this study, other deep learnig oral squamous cell carcinoma detection studies to be conducted in Turkey will contribute to the data pool.

5. Conclusion

AI has several applications in the health-care industry. Increased work, increased job complexity, and potential doctor tiredness may imperil diagnostic abilities and outcomes. AI components in imaging equipment would reduce this effort and boost efficiency. They can also identify oral lesions and have access to more information than humans do. Ultimately, we showed a DL model, YOLOv5, portrays promising results in oral cancer lesion detection from intraoral patient photos. We believe that this research will serve as a model for developing new studies for oral cancer screening, assisting inexperienced clinicians and remote healthcare providers in detecting malignant lesions in the oral cavity.Our first results indicate that deep learning has the ability to address this critical obstacle. With greater ability to handle huge amounts of data, future AI research should continue to emphasize human interests as its primary aim.

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Ethics approval

The study protocol of this study was approved by the Marmara University School of Medicine Clinical Research Ethics Committee on 09.02.2024 with protocol number 09.2024.209.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Gaye Keser: Writing – original draft, Software, Investigation, Data curation, Conceptualization. **Filiz Namdar Pekiner:** Writing – review & editing, Data curation, Conceptualization. **İbrahim Şevki Bayrakdar:** Validation, Software, Resources. **Özer Çelik:** Software. **Kaan Orhan:** Validation, Supervision.

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