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Original Article

A deep learning algorithm for classification of oral lichen planus lesions from photographic images: A retrospective study



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ABSTRACT

Introduction: Deep learning methods have recently been applied for the processing of medical images, and they have shown promise in a variety of applications. This study aimed to develop a deep learning approach for identifying oral lichen planus lesions using photographic images.

Material and methods: Anonymous retrospective photographic images of buccal mucosa with 65 healthy and 72 oral lichen planus lesions were identified using the CranioCatch program (CranioCatch, Eskişehir, Turkey). All images were re-checked and verified by Oral Medicine and Maxillofacial Radiology experts. This data set was divided into training ($n = 51$; $n = 58$), verification ($n = 7$; $n = 7$), and test ($n = 7$; $n = 7$) sets for healthy mucosa and mucosa with the oral lichen planus lesion, respectively. In the study, an artificial intelligence model was developed using Google Inception V3 architecture implemented with Tensorflow, which is a deep learning approach.

Results: AI deep learning model provided the classification of all test images for both healthy and diseased mucosa with a 100% success rate.

Conclusion: In the healthcare business, AI offers a wide range of uses and applications. The increased effort increased complexity of the job, and probable doctor fatigue may jeopardize diagnostic abilities and results. Artificial intelligence (AI) components in imaging equipment would lessen this effort and increase efficiency. They can also detect oral lesions and have access to more data than their human counterparts. Our preliminary findings show that deep learning has the potential to handle this significant challenge.

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1. Introduction

Lichen planus is an autoimmune disease that can affect the skin as well as any mucosa that lines the inside of the mouth. Oral, esophageal, vaginal, and cutaneous mucosae might all be affected. Oral lichen planus is a long-term inflammatory mucocutaneous condition with no recognized cause. Histological features include subepithelial band-like inflammatory cell infiltration, varied amounts of intraepithelial mononuclear cells concentrating on the basal keratinocytes, and epithelial basal cell degeneration and annihilation. Increased apoptosis, most frequently restricted to the basal cell compartment, has been observed in recent oral lichen planus (OLP) studies [1–8].

A computing system that replicates a natural system is known as Artificial Intelligence. Deep learning methods have recently been applied for the processing of medical images, and they have shown

promise in a variety of applications. An intelligent approach for rapid and precise diagnosis is crucial. Intelligent systems have shown to be useful in anticipating and diagnosing problems. Artificial intelligence and deep learning methods have aided in the early identification of a variety of illnesses, including breast cancer and heart failure [9,10].

Machine learning (ML) has been more important in virtually every element of science over the years [11–14]. It is a field of artificial intelligence (AI) that uses a range of statistical, probabilistic, and optimization approaches to enable computers to "learn" from previous instances and discover hard-to-find patterns in vast, noisy, or complicated data sets [11,15]. In simple terms, it is a system that receives data, searches for patterns, trains itself using the input, and then produces an output. Data is analyzed and interpreted using ML, just as it is with statistics. ML techniques have been a prominent tool for medical researchers, and they are capable of accurately predicting cancer type outcomes. According to published evidence, the accuracy of cancer prediction result improved by 15%–20% overtime when machine learning techniques were used [11,12,16]. Deep learning (DL), a

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subset of machine learning (ML), has risen to prominence in the AI industry recently [16]. The use of multilayered artificial neural networks to a wide range of tasks is characterized as the DL method, and it is highly successful at image analysis. Convolutional neural networks (CNNs), one of the most common deep learning (DL) techniques for pattern identification, are particularly good at picture analysis [11–16].

The oral mucosa is the mucous membrane lining or “skin” inside of the mouth, including cheeks and lips. Healthy skin and oral mucosa have numerous similarities in terms of tissue architecture, but they also have underlying histological variances. Although the shape and functions of the skin and oral mucosa are similar, there are distinctions in homeostatic circumstances that should be considered when comparing the healing processes in both tissue types [17].

Machine learning is finding applications in numerous disciplines including medicine in the era of technology, and clinical diagnostics is the newest contribution to it. Developing machine learning-based diagnostic tools is difficult, and choosing the correct decision-making algorithm is critical for improving diagnostic accuracy as shown in studies [18,19]. Kumar et al. [20] investigated the efficacy of Artificial Neural Networks (ANN) classifiers for six different skin diseases (Psoriasis, Seborrheic Dermatitis, Lichen Planus, Pityriasis Rosea, Chronic Dermatitis, and Pityriasis Rubra Pilaris). They used machine learning algorithms to diagnose lesions based on histopathological characteristics of the diseases. The system obtained an accuracy of up to 95% after training and testing for the six disorders. and found that they were 95% accurate.

Hedge et al. [18] used a digital camera to capture photos of Chronic Eczema, Lichen planus, and Plaque psoriasis, then extracted Red-Green-Blue (RGB) color characteristics and Gray-Level Co-Occurrence Matrix (GLCM) texture features. To compare classifier performance, researchers looked at different combinations of characteristics with four common machine learning techniques. Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) were the most accurate algorithms out of the four that were examined. Although there are many studies using machine learning on lichen planus in the field of dermatology, there are limited number of artificial intelligence studies that specifically classify oral lichen planus in the oral mucosa. Therefore, this study aimed to develop a deep learning approach for identifying oral lichen planus lesions using photographic images.

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 Non-Interventional Clinical Research Ethics Committee on 03.09.2021 with protocol number 08.10.2021.1095. Patients having histopathologically verified diagnoses of oral lichen planus were involved in all of the instances.

2.2. Image acquisition and data collection

Anonymous retrospective photographic images of buccal mucosa with 65 healthy and 72 oral lichen planus lesions were identified using the CranioCatch program (CranioCatch Eskişehir Turkey) (Fig. 1a–d). All images were re-checked and verified by Oral Medicine and Maxillofacial Radiology experts This data set was divided into training ($n = 51$; $n = 58$) verification ($n = 7$; $n = 7$) and test ($n = 7$; $n = 7$) sets for healthy mucosa and mucosa with the oral lichen planus lesions, respectively.

2.3. Identification of disease from the features

Being present almost every mucosa in the oral cavity, in some cases it is harder to differentiate oral lichen planus from other diseases, but it exhibits clinical findings that range from reticular white plaques to mucosal erythema, erosions, ulceration, and hyperkeratotic plaques.

2.4. Deep convolutional neural network architecture

The deep learning process was performed using GoogleNet Inception V3 architecture implemented with Tensorflow library.

5×5 filter size is changed with two 3×3 filters in Inception-v3. The reduction of an efficient grid size is changed, Feature maps are made by convolutions and by pooling separately. The computation cost is only about 2.5 higher than that of Inception-v1, and much more efficient than that of VGGNet, which stands for Visual Geometry Group and it is a standard deep Convolutional Neural Network (CNN) architecture with 42 layers deep [21].

Fig. 2 shows the whole procedure for identifying the disease using deep learning-based techniques. The intraoral photos are entered into the system and processed in this manner. To evaluate if the disease is present the input image is analyzed using image processing techniques such as pre-processing, feature extraction, and a machine learning-based classifier.

2.5. Model pipeline

In this study, an AI algorithm (CranioCatch, Eskişehir- Turkey) was developed to perform the classification of oral lichen planus lesions from photographic images.

2.6. Training phase

Images were resized to 1024×1024 keeping the aspect ratio. The images were randomly divided into:

Healthy:

- 1 Training group: 51 images
- 2 Validation group: 7 images
- 3 Test group: 7 images.

Oral lichen planus lesions:

- 1 Training group: 58 images
- 2 Validation group: 7 images
- 3 Test group: 7 images.

Images were trained with GoogleNet Inception v3 architecture implemented with TensorFlow library with 2000 epochs.

3. Results

Using test data, AI models were applied to diagnose oral lichen planus lesions from photographic pictures. With a 100% success rate, the AI deep learning model correctly classified all test photos for both healthy and diseased mucosa. The accuracy of Tensorflow Inception V3 architecture was estimated as 1.0 (Table 1).

4. Discussion

In dentistry, AI is generally used to discriminate between lesions and normal structures, prioritize risk variables, and simulate and assess prospective outcomes. A clinician's study of symptoms, diagnostic test findings, and other criteria, which are sensitive to the clinician's poor recall and cognitive bias, forms the basis of diagnostic

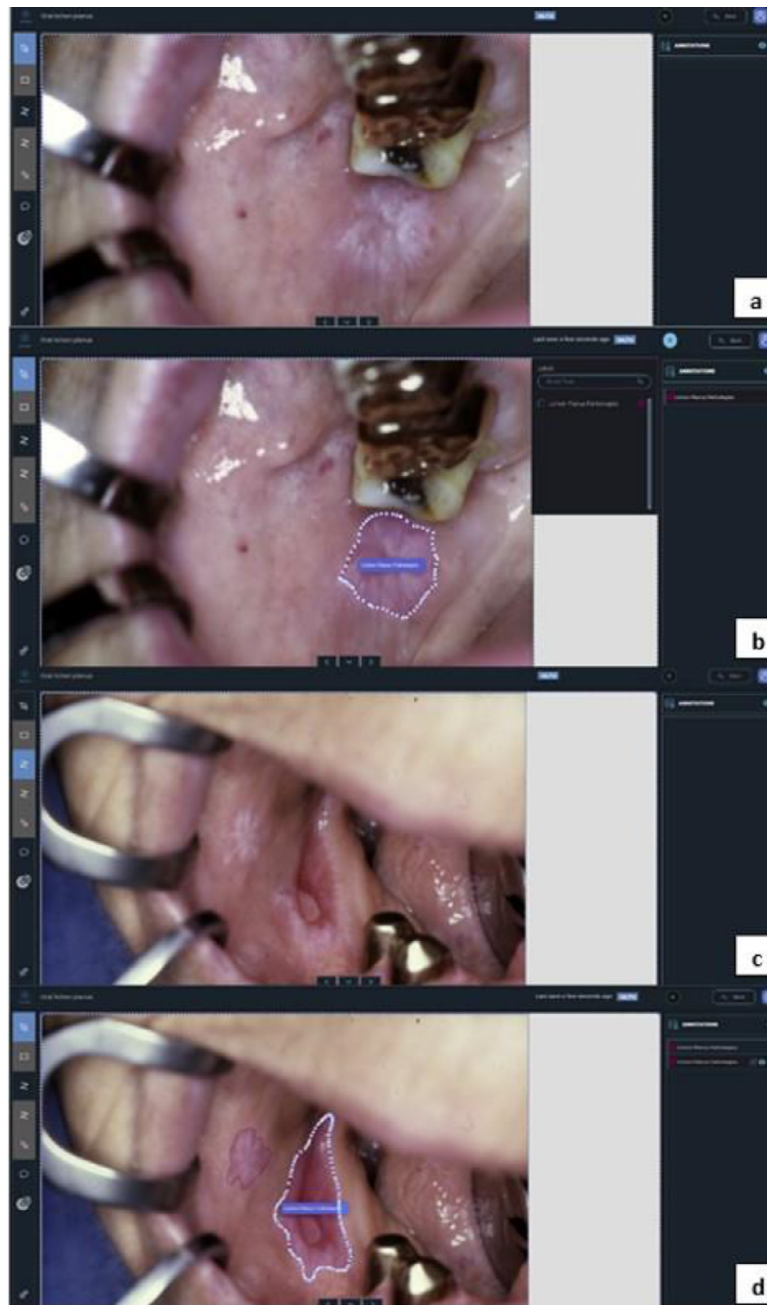


Fig. 1. (a–d) Representable samples showing the application of the Craniocatch in detecting and labeling lesions in OLP cases.

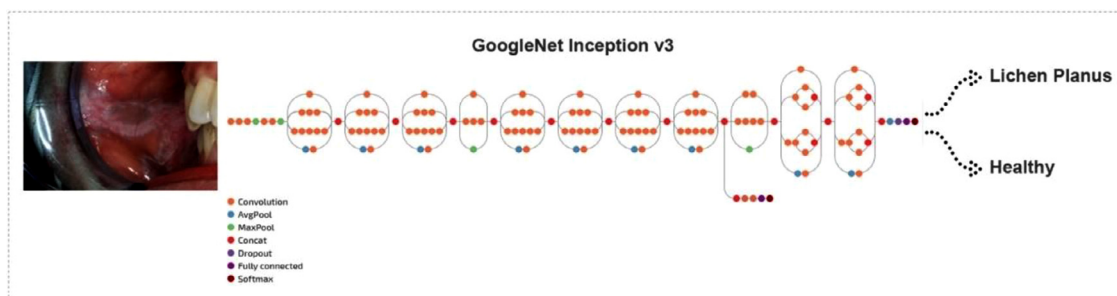


Fig. 2. An artificial intelligence model was developed using Tensorflow Inception V 3 architecture, which is a deep learning approach. Fig. 2 shows the whole procedure for identifying skin disease using deep learning based techniques. The intra oral photos are entered into the system and processed in this manner. To evaluate if the disease is present the input image is analyzed using image processing techniques such as pre-processing, feature extraction, and a machine learning-based classifier.

Table 1

The AI deep learning model correctly classified all test photos for both healthy and diseased mucosa.

	Estimation of healthy mucosa	Estimation of mucosa with oral lichen planus lesions	Accuracy
Normal buccal mucosa	7	0	100%
Oral lichen planus lesions	0	7	100%

logic for a specific disease. When "trained" with hundreds of thousands of instances, AI outperforms even the most skilled specialist's clinical experience [22,23].

Dental clinicians are currently under a lot of stress since they have to diagnose a lot more patients or instances that are more sophisticated than in the past. These clinicians may be able to overcome these obstacles with the help of AI. Like human observers, the described algorithm has high sensitivity and accuracy levels. This strategy can assist surgeons, radiologists, and other medical professionals, such as physical therapists, in making the most use of their time and reducing diagnostic time. The findings of artificial neural networks were compared to medical diagnostic and current classification methods to discover different treatments [9,22]. Many of them discovered that neural networks are instruments for receiving reasonably optimum solutions of partial and restricted data sets since they are flexible in modeling and have logical accuracy in prediction. As a result, neural networks are capable of combining data in many forms of a system, such as data obtained through clinical and experimental assessment methods, as well as aspects of signals and photographs [9,24,25].

One of the most difficult challenges in dermatology is differentiating between erythematous and squamous disorders. They all have the same clinical appearance of erythema and scaling, with just minor differences. In the biomedical area, innovations connected to other technology have found widespread use. As a result, the effectiveness of machine learning algorithms in diagnosing and forecasting skin illnesses has been examined. Bilgin and Çifci [26] used Support Vector Machines (SVM), Ensemble Learning Algorithms (ELA), Decision Trees (DT), and k-Nearest Neighborhood (k-NN) to classify skin tissue samples including 33 characteristics belonging to 366 patients, and the greatest knowledge information was recorded. The consequences of skin disease (Psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra pilaris) differentiation and categorization have been explored. SVM produced a 99.73% accuracy rate, which is greater than any prior research on this dataset.

Magshoudi et al. [9] used intelligent systems based on artificial neural networks(ANN) to investigate three of the most frequent and potentially serious oral disorders oral squamous cell carcinoma leukoplakia and lichen planus. The study's population included 150 individuals, with 50 patients being considered for each condition. The results of their simulation indicated that diagnostic systems, based on artificial neural networks, give a powerful strategy in the diagnosis and prediction of oral diseases.

Idrees et al. [27] established a machine-learning artificial neural network multilayer perceptron (ANN- MLP) as a machine learning method to recognize and quantify mononuclear cells and granulocytes within inflammatory infiltrates in digitized hematoxylin and eosin microscope slides from oral lichen planus cases and validated on a retrospective cohort of 130 cases. Similar to our study, with scores of 0.982 and 0.988 respectively, the suggested machine learning technique was capable of consistently detecting oral lichen planus patients based on the number of inflammatory cells and the number of mononuclear cells.

Concerning biochemical aspects, the possibility of interleukin 12 receptor beta 2 and tumor necrosis factor receptor superfamily member 8 as diagnostic biomarkers for oral lichen planus was investigated in another study [28]. Support vector machine (SVM), random forest (RF), linear discriminant analysis (LDA), neural network (NN), and Naive Bayes (NB) methods were used to build predictive models of IL12RB2 and TNFRSF8 expression. The area under receiver operating characteristic (ROC) curves (AUC) in predictive modeling varied from 0.83 to 0.92, and their accuracy was more than 0.75 in all techniques. Focusing on the expression of inflammatory cytokines genes, ANN, SVM, and RF were all capable of discriminating oral lichen planus from other white lesions of the oral mucosa based on the expression of inflammatory cytokines genes.

To the best of our knowledge this is the first study to present a deep learning algorithm for the classification of oral lichen planus lesions from photographic images in Turkey. The present article has a limitation since it involves small sample sizes in the context of deep learning. With the results of this study, other oral lichen planus AI studies to be conducted in Turkey will contribute to the data pool.

5. Conclusion

In the health care business, AI offers a wide range of uses and applications. Increased effort increased complexity of the job and probable doctor fatigue may jeopardize diagnostic abilities and results in AI components in imaging equipment would lessen this effort and increase efficiency. They can also detect oral lesions and have access to more data than their human counterparts. Our preliminary findings show that deep learning has the potential to handle this significant challenge. With increased skill in processing massive data, future AI development should continue to prioritize human interests as its core goal.

Declaration of Competing Interest

The authors declare no conflict of interest.

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Ethics approval

The study protocol of this study was approved by the Marmara University School of Medicine Non-Interventional Clinical Research Ethics Committee on 03.09.2021 with protocol number 08.10.2021.1095.

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