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Detection of Mucous Retention Cysts Using Deep Learning Methods on Panoramic Radiographs

Panoramik Radyografilerde Mukos Retansiyon Kistlerinin Derin Öğrenme Yöntemleri Kullanılarak Tespiti

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ABSTRACT

Aim: This study aimed to perform clinical diagnosis and treatment planning of mucous retention cysts with high accuracy and low error using the deep learning-based EfficientNet method. For this purpose, a hybrid approach that distinguishes healthy individuals from individuals with mucous retention cysts using panoramic radiographic images was presented.
Material and Methods: Radiographs of patients who applied to the Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Fırat University between 2020 and 2022 and had panoramic radiography for various reasons were evaluated retrospectively. A total of 161 radiographs, 82 panoramic radiographs with mucous retention cysts and 79 panoramic radiographs without mucous retention cysts, were included in the study. In the classification process, deep feature representations or feature maps of the images were created using eight different deep learning models of EfficientNet from B0 to B7. The efficient features obtained from these networks were given as input to the support vector machine classifier, and healthy individuals and patients with mucous retention cysts were classified.
Results: As a result of the model training, it was determined that the EfficientNetB6 model performed the best. When all performance parameters of the model were evaluated together, the accuracy, precision, sensitivity, specificity, and F1 score values were obtained 0.878, 0.785, 0.916, 0.857, and 0.846, respectively.
Conclusion: The proposed hybrid artificial intelligence model showed a successful classification performance in the diagnosis of mucous retention cysts. The study will shed light on other future studies that will serve the same purpose.
Keywords: Deep learning; panoramic radiography; maxillary sinus; cyst.

ÖZ

Amaç: Bu çalışmada derin öğrenme tabanlı EfficientNet yöntemi kullanılarak mukos retansiyon kistlerinin yüksek doğruluk ve düşük hata ile klinik tanı ve tedavi planlamasının yapılması amaçlanmıştır. Bu amaçla panoramik radyografik görüntüler kullanılarak sağlıklı bireyleri mukos retansiyon kisti olan bireylerden ayıran hibrit bir yaklaşım sunulmuştur.
Gereç ve Yöntemler: Fırat Üniversitesi Diş Hekimliği Fakültesi Ağız, Diş ve Çene Radyolojisi Anabilim Dalı'na 2020 ve 2022 yılları arasında başvuran ve çeşitli nedenlerle panoramik radyografi çekilmiş olan hastaların radyografileri geriye dönük olarak değerlendirilmiştir. Mukos retansiyon kisti bulunan 82 panoramik radyografi ve mukus retansiyon kisti bulunmayan 79 panoramik radyografi olmak üzere toplamda 161 radyografi bu çalışmaya dahil edilmiştir. Sınıflandırma sürecinde EfficientNet'in B0'dan B7'ye kadar sekiz farklı derin öğrenme modeli kullanılarak görüntülerin derin özellik temsilleri veya özellik haritaları oluşturulmuştur. Bu ağlardan elde edilen verimli özellikler, destek vektör makinesi sınıflandırıcısına girdi olarak verilmiş ve sağlıklı bireyler ile mukos retansiyon kisti olan hastalar sınıflandırılmıştır.
Bulgular: Model eğitimleri sonucunda EfficientNetB6 modelinin en iyi performansı sergilediği belirlenmiştir. Modelin tüm performans parametreleri birlikte değerlendirildiğinde, doğruluk, kesinlik, duyarlılık, özgüllük ve F1 puanı değerleri sırasıyla 0,878, 0,785, 0,916, 0,857 ve 0,846 olarak elde edilmiştir.
Sonuç: Önerilen hibrit yapay zeka modelinin mukos retansiyon kisti teşhisinde başarılı bir sınıflandırma performansı göstermiştir. Bu çalışmanın aynı amaca hizmet edecek gelecekteki diğer çalışmalara ışık tutacağı düşünülmektedir.
Anahtar kelimeler: Derin öğrenme; panoramik radyografi; maksiller sinüs; kist.

INTRODUCTION

Panoramic radiography is the most preferred imaging method for diagnosis and treatment planning in dentistry due to its features such as low cost, low radiation dose, and comprehensive view of the anatomical structures in the maxillofacial region (1). Maxillary sinuses are structures adjacent to the oral mucosa, their borders and contents can be viewed in panoramic images and they are important anatomical structures that should be taken into consideration in dentistry practices (2). Mucous retention cysts (MRC) and pseudocysts are defined as dome-shaped, well-circumscribed radiopacities, formed because of fluid accumulation in the sinus membrane. MRC is called a “true cyst” because it has a thin epithelial lining that is formed due to obstruction of the salivary gland ducts, whereas “pseudocysts” lack an epithelial wall and result from diffuse subepithelial accumulation of inflammatory exudate. Since both are radiologically indistinguishable, many investigators have described them as sharply circumscribed, dome-shaped radiopaque formations arising from the antral wall, without differentiating between MRC and pseudocysts on radiographic images (2,3).

Inflammatory and traumatic causes such as allergy, barotrauma, and rhinitis are frequently considered in the etiology of mucosal cysts; and headache, nasal congestion, facial pain, and postnasal discharge are rarely suspected. The pain in this area can be confused with toothache, and it is known that dental infections also cause MRC (4,5). The presence of MRC increases the possibility of complications in surgical procedures planned for reasons such as missing teeth and residual ridge insufficiency in the posterior maxilla (3,6). Therefore, during the clinical examination, a careful sinus examination and the detection of MRC, which often does not cause subjective findings, are required.

Deep learning methods, which aim to solve problems that are solved by human intelligence and skills, with artificial intelligence (AI) are rapidly developing in the field of health. These methods, supported by digital data, have begun to be widely used in dentistry, where data flow is continuous. It is possible to detect and distinguish anatomical and pathological structures in panoramic radiographs with AI-based deep learning methods (7,8). Convolutional neural network (CNN) is one of the AI-based deep learning methods and has been used in many research such as the diagnosis of caries, periapical lesions, cysts, tumors, and cancers on dental radiological images (8-10). The increasing use of these AI-supported innovative technologies helps more careful radiographic interpretations by preventing asymptomatic lesions from being undiagnosed due to the pain-focused dental approach of most physicians and missed by inexperienced or unaware physicians, contributing to higher sensitivity and fewer errors. In addition, it aims to contribute to the education of physicians during the training process, facilitate the work of physicians, and improve the management of patients and treatment results (11). EfficientNet, one of the advanced deep learning models, used for the accurate diagnosis of MRC, provides reliable results due to its high sensitivity and low error rates (12,13).

In this study, it was aimed to contribute to the clinical diagnosis and treatment planning of MRC with higher precision and fewer errors by using AI-based deep learning methods, to improve clinical decision-making processes and to manage patients' health conditions more effectively. For this purpose, a hybrid approach is presented to distinguish healthy individuals from individuals with MRC using panoramic radiographs.

MATERIAL AND METHODS

The radiographs of patients applied to the Department of Oral and Maxillofacial Radiology of Fırat University Faculty of Dentistry between 2020 and 2022 and were taken panoramic radiography for various reasons were evaluated retrospectively. A total of 205 panoramic radiographs, which were taken on the Planmeca Promax (Helsinki, Finland) 2D Digital Panoramic X-ray Device, were evaluated and 44 films with poor image quality were excluded. 82 panoramic radiographs with MRC and 79 panoramic radiographs without MRC were included in the study (Figure 1). Ethical approval was obtained from the Fırat University Non-Interventional Clinical Research Ethics Committee (23.02.2023, 03-15).

Model

This study presents a hybrid approach to distinguish between healthy individuals and individuals with MRC using panoramic images. The proposed model consists of three stages; data preprocessing, feature extraction, and classification. After the dataset was created, the images were resized according to the standard input size of the EfficientNet deep network in the first stage. Images of 600*600 size were converted to 224*224 size to be fed to the CNN model. In the second stage, eight different EfficientNet models from B0 to B7 and feature maps representing deep features of the images were generated. In the last step, the features obtained from each model were used as input to the support vector machine (SVM) classifier to distinguish healthy individuals and individuals with MRC. Sensitivity, specificity, precision, accuracy, and F1-score criteria were used to compare the performance of the networks. These evaluation criteria were considered to determine the classification ability of each model and to evaluate the overall effectiveness of the study. The flow diagram including all stages of the proposed study was presented in detail (Figure 2).

Data Collection and Data Preprocessing

In this stage, the panoramic radiographs of the patients who applied to the Department of Oral and Maxillofacial Radiology of Fırat University Faculty of Dentistry were used. The radiographic images used in this study were selected from patients with an informed consent form. Patient records were protected in accordance with medical ethics rules. The data obtained at this stage was resized to be given as input to the EfficientNet network in the next stage.

Feature Extraction and Classification

The EfficientNet deep network model was used in the feature extraction stage of the study. By optimizing the size of models, EfficientNet reduces the computational cost and provides high accuracy. Although the success of the models used for the first time in the ImageNet dataset increases in parallel with the model complexity, the computational costs of these models are quite high. As a solution to this problem, EfficientNet uses eight different

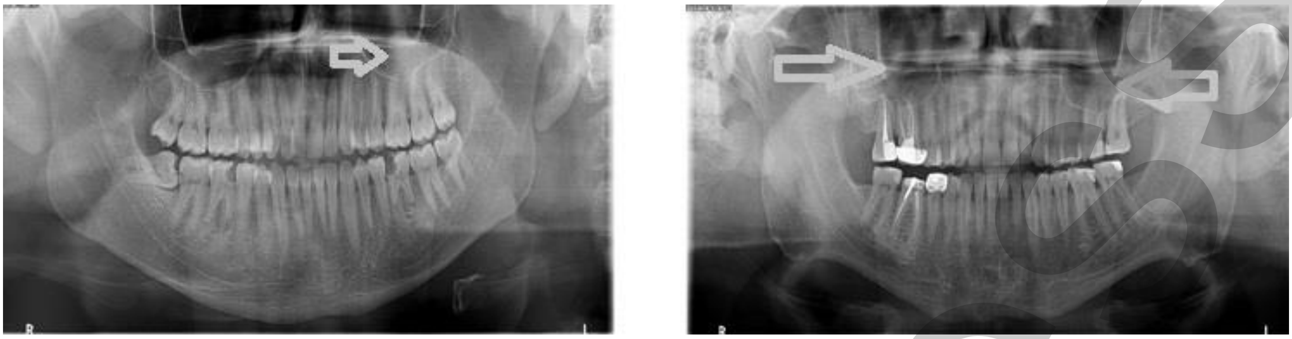

Figure 1. Data set sample images

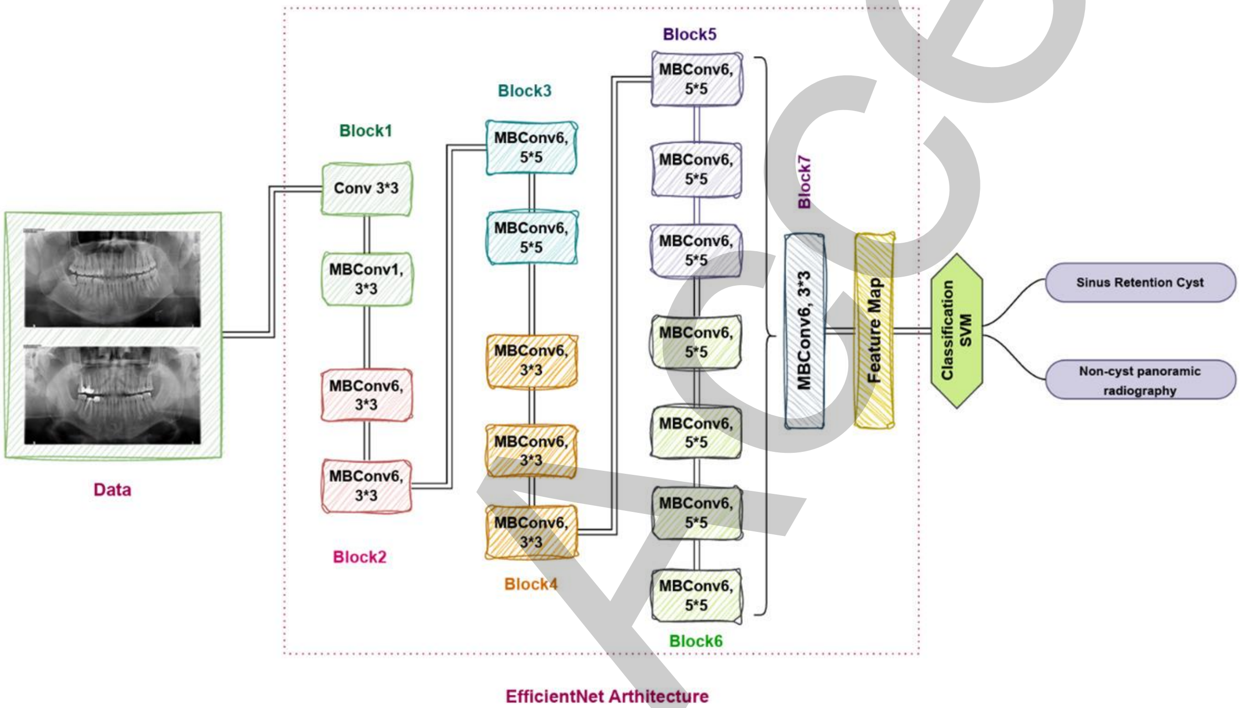

Figure 2. Proposed work process flow

CNN versions from B0 to B7, greatly increase the accuracy rate without adding more parameters (14). EfficientNet uses a new activation function known as Swish instead of the traditional ReLU activation function. This helps the model to learn and extract features. EfficientNet achieves significant success by providing more effective and efficient approaches for smaller models (15). In this study, feature maps of the data were created using 8 different versions of the EfficientNet model, from 0 to 7. Each version establishes a balanced relationship between depth, width, and resolution dimensions. This diversity provides suitable options for feature extraction in a variety of tasks such as data mining, image processing, and classification and flexibility for various application scenarios.

Classification is a data mining function that assigns features to specific groups. Its main purpose is to precisely anticipate the target class for each sample in the data (16). Classification has important applications in computer vision, medicine, engineering, and many other fields. It plays an important role in determining the conditions of patients, especially in the diagnosis of diseases in medicine. In this stage, features obtained from EfficientNet network versions were classified using SVM for each version. The results obtained were evaluated using precision, sensitivity, specificity, F1-Score, and accuracy metrics (17). Calculations of the evaluation metrics used are given with the complexity matrix (Figure 3).

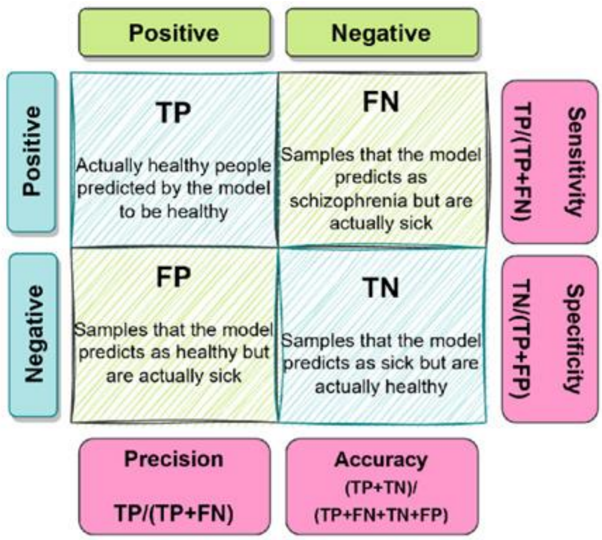

Figure 3. Performance evaluation metrics

These evaluations in the classification stage investigate whether EfficientNet networks can distinguish between healthy people and people with MRC. The metrics given in Figure 3 were used to objectively evaluate the performance of the classification algorithms and understand the results.

RESULTS

In the first stage of the proposed method, feature extraction was performed on panoramic radiographs with the feature extractor EfficientNet models (B0 to B7) to detect MRC. The extracted features were represented in 1xn size according to the output feature of the EfficientNet model and were given as input to the SVM algorithm.

The accuracy value alone may not be sufficient to reliably evaluate the performance of the proposed model. Therefore, various metrics such as F1 score, sensitivity, and specificity were also used in the experiments. Sensitivity measures the test's ability to identify true positive results, while specificity measures the rate of missing false positive results in those without the disease condition. When used together, these measurements help fully evaluate the model's performance. In this study, it is observed that the highest performance is achieved with the EfficientNetB6 model (Table 1). As the parameters of the model, the rates of 0.878, 0.785, 0.916, 0.857, and 0.846 were obtained for accuracy, precision, sensitivity, specificity, and F1 score, respectively.

The proposed system demonstrated a high classification performance by helping to diagnose MRC. The findings show that the image processing and machine learning methods of the proposed study can be used effectively in the diagnosis of MRC. Experimental results show that the model stands out as a potential clinical aid in the MRC diagnostic process.

DISCUSSION

A correct and complete examination is possible by evaluating the patient history (anamnesis) and radiological findings as a whole and integrating them with current technological developments. The use of AI in head and neck imaging during radiological detection of anomalies that cannot be noticed by the human eye or anomalies that are overlooked due to physician inexperience and fatigue has been rising in the last 20 years (18). For this purpose, digital imaging methods such as panoramic radiography and advanced imaging methods such as cone-beam computed tomography (CBCT), ultrasonography (USG), and magnetic resonance imaging (MRI) have been rapidly integrated into this new system (7,19-22). Panoramic radiographs, which are the most frequently used routinely, have become pioneers in providing sufficient data for AI-based learning methods because they allow the evaluation of a wide area including teeth and jaws, have low radiation dose, cost-effective, easily accessible and easy to apply (1,8). The development of CNN provides useful results to clinicians in the detection of normal structures, diagnosis of abnormal structures, treatment planning, and follow-up (22,23). In this study, a hybrid classification process was carried out using EfficientNet and SVM, one of the CNN models, to detect MRC in panoramic radiographs, which do not give any subjective findings, and diagnosis is often missed by clinicians due to overlapping of anatomical structures such as the nasal floor and hard palate.

Murata et al. (24) have aimed to diagnose maxillary sinusitis from radiographs using deep learning methods with 400 healthy individuals and 400 patients with inflamed maxillary sinus. They increased the amount of data for healthy and patient groups up to 6000 samples, increasing the total number of data up to 12000. They designed the learning process as 200 epochs and included 120 data, 60 patients with diseases and 60 healthy, in the training input set. They reached 0.875 accuracy, 0.867 sensitivity, 0.883 specificity, and 0.875 area under the curve (AUC) performance values. The obtained results were examined mutually with the predictions of two radiologists and two research assistants. They stated that there is not a significant difference with radiologists, but they achieved a higher performance compared to research assistants. In the proposed study, the accuracy rate was calculated as 0.878 compared to this study, a higher success rate was achieved with the proposed method even though we used a smaller data set. The reasons for the difference in model performance include many different factors such as choosing the right model and setting the parameters correctly.

Kuwana et al. (25) used the radiographic images of 416 inflamed maxillary sinuses and 171 maxillary sinus cysts to detect cysts and inflammation in the maxillary sinus in panoramic radiographs. The obtained data were divided into 3 different groups, training, test1, and test2 to be used in the training and testing process. Using the training data, they carried out a learning process of 1000 epochs with the DetectNet model. They tested the training model obtained separately with test1 and test2 data and evaluated them mutually. They stated that the model they proposed showed 1.0 accuracy for inflamed and healthy sinuses, while it showed 0.98 and 0.89 accuracy in cyst detection. In the proposed study, in addition to only incorporating deep learning methods into the process, machine learning

Table 1. Performance metrics obtained as a result of the study

Model	Accuracy	Precision	Sensitivity	Specificity	F1 Score
EfficientNetB0	0.7879	0.8125	0.7647	0.8125	0.7879
EfficientNetB1	0.8182	0.8667	0.7647	0.8750	0.8125
EfficientNetB2	0.8182	0.9231	0.7059	0.9375	0.8000
EfficientNetB3	0.8182	0.8462	0.7333	0.8889	0.7857
EfficientNetB4	0.7879	0.7857	0.7333	0.8333	0.7586
EfficientNetB5	0.8485	0.8125	0.8667	0.8333	0.8387
EfficientNetB6	**0.8788**	**0.7857**	**0.9167**	**0.8571**	**0.8462**
EfficientNetB7	0.8485	0.8235	0.8750	0.8235	0.8485

methods are also included in the study by presenting a hybrid approach. Compared to their study, accuracy was approximately 0.02 lower. The reasons for this situation include factors such as the number of data and the deep network model. It is seen that if data is expanded and the number of models is diversified, the performance will increase accordingly.

Another study aimed to create effective models for the detection of maxillary sinuses in panoramic radiographs and diagnosis of sinusitis by transferring the deep learning source model from one institution to another. 350 panoramic radiographs from source A and 25, 50, 100, 150, or 225 panoramic radiographs from source B were included in the study, and target models named T25, T50, T100, T150, and T225 were created. The study showed that the maxillary sinus detection performance of the source model was high when test data from source A was used, but its performance was low when test data from source B was used. B's test data proves that the T25 model has better detection performance. In addition, the T50 model is highly sensitive for the maxillary sinusitis diagnosis (26). In the present study, a versatile hybrid method is proposed, as opposed to using only a deep model. However, an approach is being considered in which various models can be tried to achieve higher performance and diversity.

Another study investigated the maxillary sinusitis diagnosis performance of the model with a large panoramic radiography data set in source A, using the transfer learning method with a limited number of Waters' radiography in source B. The model was created with VGG-16 using a data set consisting of 800 training and 60 validation data for 200 training rounds. Also tested with 180 Waters' and 180 panoramic images from source B. The target model was used for transfer learning over several 200 training rounds on training and validation sets of Waters' radiographs. By applying test Waters' images to the source and target models, the performance of both models was evaluated. When Waters' images are used as the test set, the target model works better than the source model, showing that transfer learning is used effectively by using a limited number of data to increase maxillary sinusitis diagnostic performance (27). In parallel with this study, significant results were obtained with a limited number of data in this proposed study. This is an indication that the problem of limited data can be minimized when correct model selection and parameter setting are performed.

When the limitations and main contributions of the study are evaluated, the restricted number of studies in the literature constitutes the main contribution of the proposed study to the literature. The studies in the literature are carried out using only deep network models rather than hybrid methods. In the proposed study, a hybrid method is presented by combining deep learning and machine learning models. The small number of data used in the study is one of the limitations affecting the performance of the study. Another limitation is that we can not create our deep architecture due to a lack of hardware. It is thought that the operating performance will improve when the number of data increases, the necessary hardware is provided and the architectural design is carried out manually which is specific to the problem.

CONCLUSION

This study has shown that MRC in the maxillary sinuses can be detected and safely identified using an AI-based hybrid method. In line with the obtained results, it can be stated that if the specified limitations are improved in the following stages, there will be an increase in operating performance.

Ethics Committee Approval: The study was approved by the non-interventional clinical research ethics committee of Fırat University (23.02.2023, 03-15).

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