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Evaluation of the Pharyngeal Airway with Artificial Intelligence Algorithms Developed by Deep Learning from Lateral Cephalometric Image

Derin Öğrenmeyle Geliştirilen Yapay Zeka Algoritmalariyla Lateral Sefalometrik Görüntüler Üzerinden Faringeal Hava Yolunun Değerlendirilmesi

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ABSTRACT

Objectives: The aim of this study is to investigate the success of pharyngeal airway detection using a special artificial intelligence algorithm on lateral cephalometric images obtained from cone beam computed tomography images.

Materials and Methods: The data set of our study was performed on the lateral cephalometric radiographs was obtained from cone beam computed tomography images of 1040 patients before orthodontic treatment using a special artificial intelligence algorithm and the segmentation method were applied with the free drawing tchnique and the pharyngeal airway was determined. Airway labeling on images was done using CranioCatch annotation software (CranioCatch, Eskişehir, Turkey).

Results: The artificial intelligence model was trained with the Yolov5x model as 500 epochs and 0.01 learning rate**.** Sensitivity, precision and F1 scores in the artifical intelligence model trained in the study were 1, 0.9903 and 0.9951 respectively.

Conclusion: The model in which we evaluated the pharyngeal airway was generally successful. Our study is promising for the development of future CBCT reporting systems. It is thought that these deep learning-based systems will save physicians time as a decision support mechanism in routine clinical practices. It is also anticipated that it will help in minimizing interobserver differences in the evaluation of the pharyngeal airway and inconsistencies that may occur in the evaluations made by observers at different times.

Keywords: *Artificial Intelligence, Pharynx, Tomography.*

ÖZET

Amaç: Bu çalışmanın amacı, konik ışınlı bilgisayarlı tomografi görüntülerinden elde edilen lateral sefalometrik görüntüler üzerinde özel bir yapay zeka algoritması kullanılarak faringeal hava yolu tespitinin başarısını araştırmaktır.

Gereç ve Yöntemler: Çalışmamızın veri seti, özel bir yapay zeka algoritması kullanılarak 1040 hastanın ortodontik tedavi öncesi konik ışınlı bilgisayarlı tomografi görüntülerinden elde edilen lateral sefalometrik radyografiler üzerinde gerçekleştirildi ve serbest çizim tekniği ile segmentasyon yöntemi uygulandı ve faringeal hava yolu belirlendi. Görüntüler üzerindeki hava yolu etiketlemesi CranioCatch yapay zeka yazılımı (CranioCatch, Eskisehir, Türkiye) kullanılarak yapıldı.

Bulgular: Yapay zeka modeli Yolov5x modeli ile 500 epoch ve 0,01 öğrenme oranıyla eğitildi. Çalışmada eğitilen yapay zeka modelinde duyarlılık, kesinlik ve F1 puanları sırasıyla 1, 0,9903 ve 0,9951 olarak gerçekleşti.

Sonuç: Faringeal hava yolunu değerlendirdiğimiz model genel olarak başarılıydı. Çalışmamız gelecekteki KIBT raporlama sistemlerinin geliştirilmesi açısından umut vericidir. Derin öğrenmeye dayalı bu sistemlerin rutin klinik uygulamalarda karar destek mekanizması olarak hekimlere zaman kazandıracağı düşünülmektedir. Ayrıca faringeal hava yolunun değerlendirilmesinde gözlemciler arası farklılıkların ve gözlemcilerin farklı zamanlarda yaptığı değerlendirmelerde oluşabilecek tutarsızlıkların en aza indirilmesine yardımcı olacağı öngörülmektedir.

Anahtar Kelimeler: *Yapay zeka, Farinks, Tomografi.*

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Introduction

It has been noted that there is variation among individuals in terms of the shape and volume of the upper airway. Evaluation of the effects of different orthodontic anomalies on airway volume is important in orthodontic clinical routine. While determining the diagnosis and treatment parameters of the patients, the airway capacity of the patients should be determined and the treatment should be planned accordingly. In a patient with insufficient airway volume, this insufficiency can be reduced with the correct indication and treatment plan. Implementing the right treatment planning the patients' quality of life will be improved and their aesthetic and functional needs will be met.[1]

Since the 1800s, researchers have always questioned the relationship between dentofacial morphology and respiratory function. However, due to the inadequacy of medical devices in those years, the research could not go beyond observation.[2] But today, the connections of the airway with the surrounding tissues can be examined comprehensively thanks to the various methods used for airway imaging.[3]

In the era we live in, there are technological developments that bring about significant changes in our quality of life. That has brought about significant changes one of the most important of which is, without doubt, Artificial Intelligence (AI). AI has gained popularity thanks to its mathematical computing power, data storage capacity, and ability to perform different operations.[4] AI is thought to affect the prognosis of treatments by speeding up the diagnosis of diseases. AI includes computer networks (neural networks) that simulate human intelligence. With the inclusion of AI in radiology, it will be easier to detect relevant findings in diagnostic imaging and to separate the detected images into smaller data. AI can deliver data much faster and more reliably than a human brain.[5]

AI shows advances in orthodontics. In the field of AI in orthodontics; it can be used in many areas such as diagnosis and treatment applications, determination of points on lateral and frontal cephalograms, estimation of hard and soft tissue after treatment, classification of malocclusions, determination of skeletal maturation of the patient and orthognathic surgery cases.

Yu et al. aimed to create a robust skeletal diagnostic system with lateral cephalograms. They stated that the presented system showed 90% accuracy, sensitivity and specificity for vertical and sagittal skeletal diagnosis.[6] Aboudara et al. found successful results in determining the need for orthognathic surgery with AI and planning orthognathic surgery.[7] Kök et al. determined the skeletal maturation period by examining the cervical vertebral stages defined in cephalograms with an AI model. They reported that the AI model can be applied for diagnostic purposes in all branches of science where skeletal growth and development need to be determined, as a result of which more objective decisions can be made.[8]

The aim of the machine learning method, which has become widespread recently in this study, is to prevent the evaluation differences between the individuals evaluating. In the evaluation of the pharyngeal airway and the different evaluations that may be seen at other times of the individuals evaluating the pharyngeal airway. We propose an automated system consisting of Deep Convolutional Neural Networks (DCNN) and algorithmic heuristics. This study aims to reveal an alternative way to evaluate the pharyngeal airway in an automated, fast and reliable way using the deep learning method.

Materials and Methods

In this study, cephalograms formed from ultra-low dose CBCT data obtained from patients who applied to Eskişehir Osmangazi University Faculty of Dentistry Department of Orthodontics for orthodontic treatment were used as materials. The dataset consists of CBCT images of 1040 patients without any traumatic facial deformity or craniofacial syndrome, based on the archive of Eskişehir Osmangazi University Faculty of Dentistry, Department of Orthodontics, between January 2013 and March 2022. Radiographs of patients_whose radiographic images have low image quality (artifacts due to position errors during imaging, metal artifacts, etc.) were not included in the study.

The study protocol was approved by the Eskişehir Osmangazi University Non-Interventional Clinical Research Ethics Committee (decision date and number: 26.07.2022/19). The study was carried out according to the principles of the Declaration of Helsinki.

In the study, cephalometric radiographs were created by adjusting the head position so that the Frankfort Horizontal plane was parallel to the ground using the Dolphin Imaging 11.95 software (Dolphin Imaging and Management Solutions, Chatsworth, Calif) from the DICOM files recorded from the CBCT images of 1040 patients. The project was created by uploading the created cephalometric radiographs to

CranioCatch labeling software (Eskisehir, Türkiye). Cephalometric films obtained from cone beam computed tomography images of 1040 patients were loaded into the CranioCatch program to create a project. Labeling of the pharyngeal airway on lateral cephalometric films using CranioCatch (Eskişehir, Turkey) software using Precision 3640 Tower CTO BASE workstation (Intel(R) Xeon(R) W-1250P (6 cores, 12) and a 27", 1920x1080 pixel IPS LCD monitor (Dell, Texas, USA) in Eskişehir Osmangazi University Faculty of Dentistry Dental AI Laboratory. On lateral cephalometric films, the outer borders of the pharyngeal airway were manually labeled by the same researcher using the free drawing technique (polygon method), using the upper point of the pterygomaxillary fissure at the top, the base of the epiglottis at the bottom, and the walls of the pharyngeal airway on the sides as references. (Figure 1)

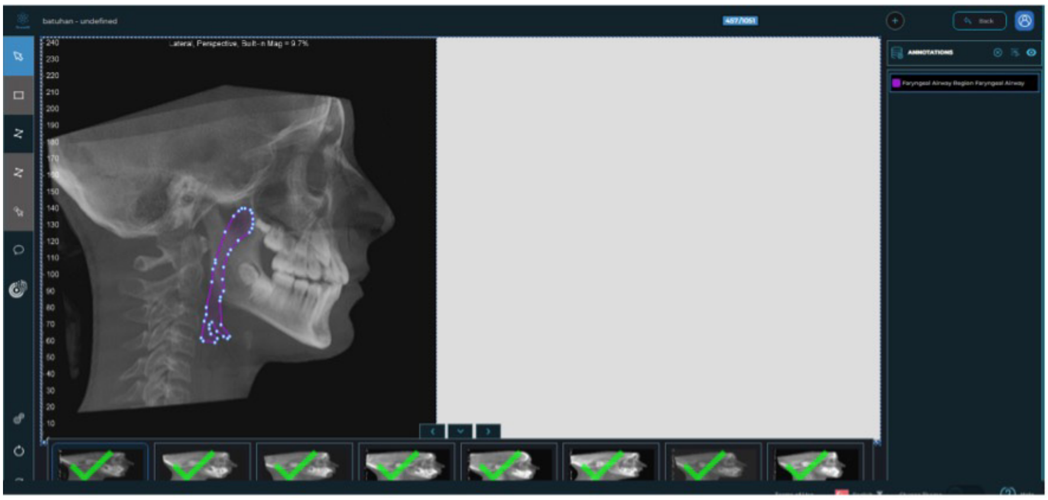

Figure 1. Polygonal labeling of the pharyngeal airway

The architecture was built with the transfer learning methods in the Pytorch library. For the detection of the pharyngeal airway, 500 epochs were trained with the Yolov5x Segmentation model among the Yolov5, You Only Look Once (YOLO) computerized image models with the transfer training technique. 1040 images and 1040 tags were mixed. Images are resized to 640 x 640. The data groups were divided into 3 separate groups training, testing and validation as 80% training, 10% test and 10% validation dataset. Validation and training datasets were used to generate and estimate the CNN algorithm weight factors. The performances of the models were examined using the test data set. Data generated from the test dataset were not reused. The learning rate of the model was determined as 0.01. This process has been implemented on computer material containing Precision 3640 Tower CTO BASE workstation Intel(R) Xeon(R) W-1250P (6 cores, 12M cache), base processor frequency 4.1 GHz, Max Turbo Frequency 4.8 GHz) DDR4-2666, 64 GB DDR4 (4 X16GB) 2666 MHz UDIMM ECC Memory capacity, 256 GB SSD SATA, Nvidia Quadro P620, 2 GB) (Dell, Texas, USA) at Eskişehir Osmangazi University Faculty of Dentistry Dental-AI Laboratory.

Looking at the ROC curve and AUC values, these parameters were calculated for the measurement of success evaluation, and the performances of the models in the detection of the pharyngeal airway were compared. The ROC curve is a performance measure calculated mathematically as the true positive rate (TPR) divided by the false positive rate (FPR). The purpose of the ROC curve is to be located at the point (0,1) in the upper left corner. At this point, the FP value and the FPR value are zero. In general, the accuracy of the test increases as the ROC curve approaches the upper left region. The x-axis on the sensitivity-precision graph and the y-axis on the ROC curve stand for TPR (Recall-Precision). Therefore, the graphs are formed similarly to each other. The Precision-Precision (PR) graph evaluates the performance of the highly important positive group. The target of the PR curve is to be in the upper right corner.

Results

F1 (the harmonic mean of precision and recall score), precision and sensitivity, scores calculated for pharyngeal airway detection of deep learning models are 0.9951, 0.9903 and 1 respectively. According to the general analysis, there were 103 correct and

1 incorrect prediction out of 104 tests. In the tests on the AI program of the Pharyngeal airway. In 1 incorrectly predicted image, the program drew an area much larger than the size of the original label. There were no tags found. The findings are shown in Table 1.

Table 1. Findings obtained as a result of model training

Model Name	Faryngeal Airway
Number of Education Images	832
Number of Education Images	832
Number of Test Images	104
Number of Test Labels	104
Validation Number of Images	104
Validation Number of tags	104
IoU Thresold: Correct for 50% (TP)	103
IoU Thresold: False Found (FP)	1
IoU Thresold: Not Found (FN)	0
Sensitivity (TP / (TP + FN))	1
Precision (TP / (TP + FP))	0,9903
F1 Score (2TP / (2TP + FP + FN))	0,9951
Epoch	500
Learning Rate	0.01
Model	Yolov5

IoU: Intersection over Union
TP: True positives, FP: False Positives, FN: False Negatives

The real images (manually labeled images) of the pharyngeal airway on the lateral cephalometric radiographs and the AI program prediction images are shown in Figure 2 and Figure 3. The formulas of the FPR and TPR measures are presented in Figure 4. PR graphic reveals that we have grouped all positive values as positive, thus increasing the accuracy (Figure 5)

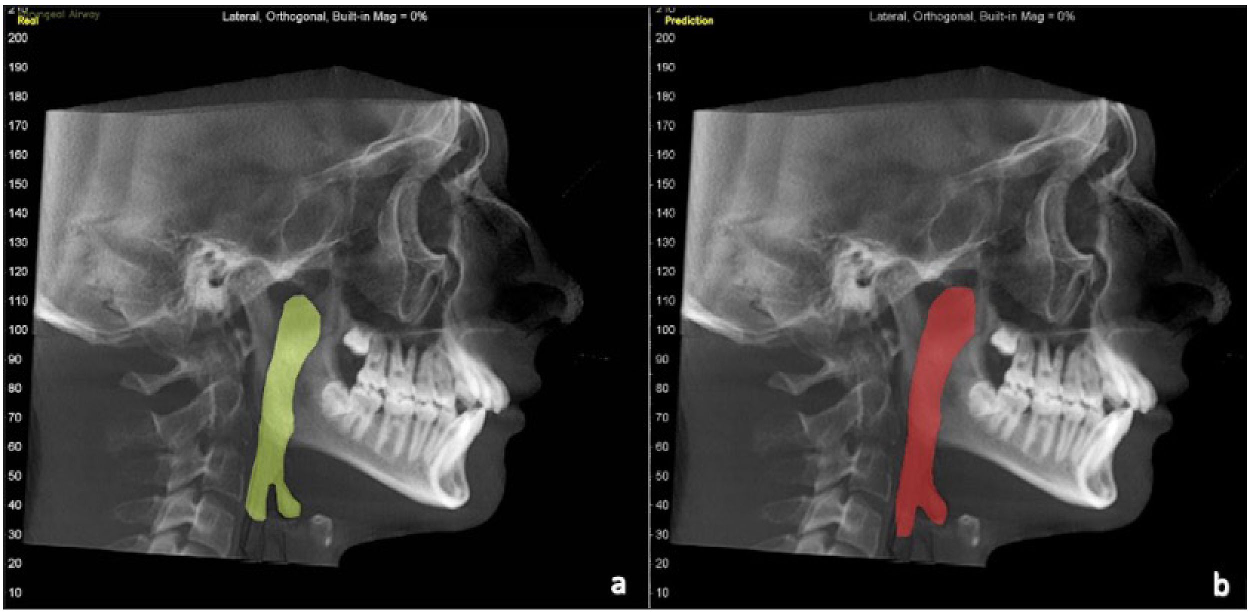

Figure 2. Real image (a) of pharyngeal airway in lateral cephalometry and artificial intelligence program prediction image (b)

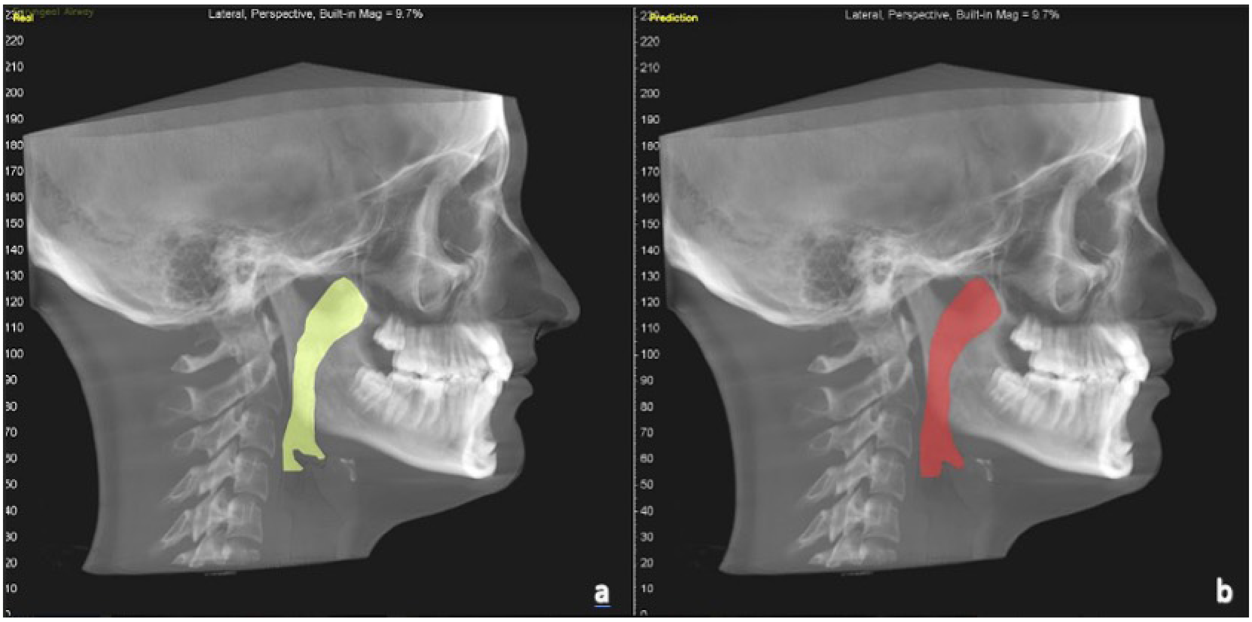

Figure 3. Real image (a) of pharyngeal airway in lateral cephalometry and artificial intelligence program prediction image (b)

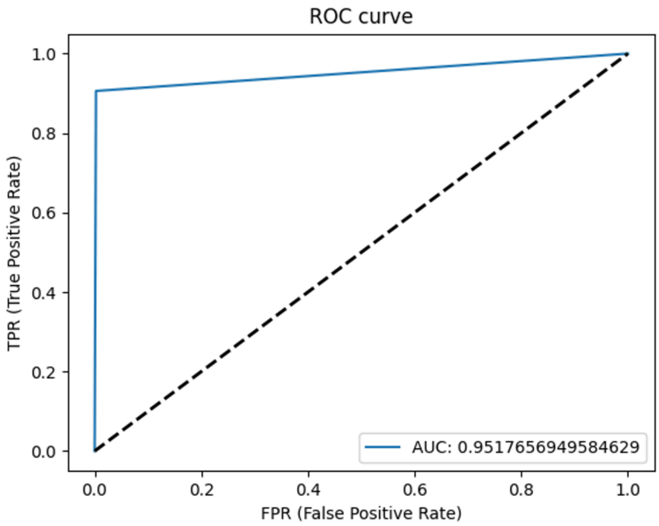

Figure 4. ROC curve for pharyngeal airway detection

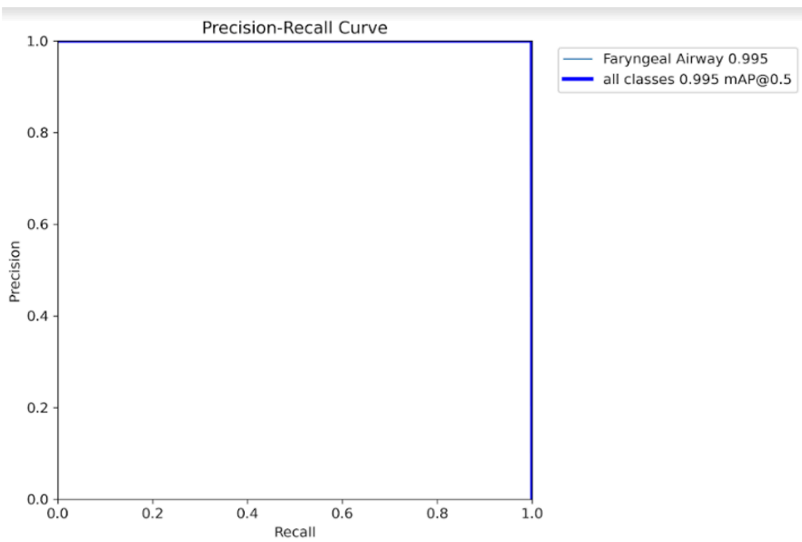

Figure 5. Precision-Recall curve for pharyngeal airway detection

Discussion

Different techniques are used in the imaging and evaluation of pharyngeal expectations. In this study, lateral cephalometric images obtained from cone beam computed tomography images were studied. Although the use of lateral cephalometric images for pharyngeal airway detection and evaluation has been criticized for evaluating a three-dimensional structure using two dimensions and not fully presenting soft tissue detail, it is preferred by orthodontists due to its ease of use in their clinical practice.[12]

Cephalometric imaging may be preferred for various reasons such as ease of application, low cost, and easier comparison with other studies.[13-15] It has been reported that lateral cephalometric images, which are not sufficient for horizontal plane examinations, are still successful in the evaluation of pharyngeal tissues.[16]

Moon J et al. investigated the amount of learning data required for adequate training in AI deep learning systems. They noted that AI's finding errors were highly correlated not only with the number of training data, but also with the amount of objectives set for each image. The probability of detection errors is inversely proportional to the increase in the number of data in AI training. They stated that at least 2300 data are needed to develop AI in terms of prediction applications. There are 1040 data in our research.[17]

Sin et al. used CBCT images of 306 patients to determine the pharyngeal airway and created an AI algorithm. In this study, in which U-Net architecture was used, the algorithm was found to be successful when the measurements made with manual methods were compared with the measurements resulting from automatic segmentation.[18] In our study, pharyngeal airway detection was also performed, but we developed the AI algorithm using the Yolov5x-seg model on 1040 lateral cephalometric images. We used lateral cephalometric images obtained from CBCT data in our research to reduce layered and bilateral structures. However layered structures still appeared in the images. The lateral borders of the pharyngeal airway could not be clearly detected in some images. To solve this problem, it may be recommended to use MIP images similar to those of Kim M et al.[19]

Leonardi et al. conducted a study to test the success of deep learning supported models of automatic segmentation of the pharyngeal airway and sinonasal cavity. It has been reported that deep learning supported models of automatic segmentation show successful performance.[20] In our study, the AI algorithm we developed for pharyngeal airway detection, which supports this research, was found to be successful in general. While the amount of research dealing with DL for the identification of anatomical structures in 2D and 3D radiographs is increasing rapidly, we can never be completely sure of the results. Moreover, it is not known how much research on DL has developed and whether there is a difference in accuracy between 2D and 3D images. Our aim in this research is to support the removal of this suspicion by examining the success of DL on 2D cephalometric images created from CBCT images. Another limitation of ours is that the respiratory phase of the airway, which is a dynamic area affected by respiratory changes, could not be standardized during extraction. Since the study was retrospective, the patients' swallowing and therefore their epiglottis positions during imaging could not be standardized.

Conclusion

If we look at the F1 score, sensitivity and precision values in our research for the pharyngeal airway, the F1 score was 99%, the precision value was 99%, and the sensitivity value was 100%. In the AI model we developed, which we applied to the lateral cephalometric images obtained from 1040 patients, there were no tags that could not be found, and the model was generally successful.

The results we obtained in the detection of the pharyngeal airway labeled with the segmentation method on the lateral cephalometric images produced from the CBCT data with the algorithm we developed are promising. Thanks to the data we reach of AI-based systems, we think that it will create the potential to save time for orthodontists time in cases where we need pharyngeal airway measurement such as orthognathic surgery planning and functional jaw orthopedics in orthodontic routine.

Conflict of interest

None of the authors of this article has any relationship, connection or financial interest in the subject matter or material discussed in the article.

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Authorship Contributions

Idea/Concept: B.K, M.U Design: B.K, M.U Control/ Supervision: B.K, M.U Literature Review: B.K, M.U Data Collection and/or Processing: B.K, M.U Analysis and/or Interpretation: B.K, M.U Writing the Article: B.K, M.U Critical Review: B.K, M.U

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