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RESEARCH ARTICLE

Segmentation of honeycomb cysts, traction bronchiectasis and emphysematous lung parenchyma using the deep learning method

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ABSTRACT

Segmentation of honeycomb cysts, traction bronchiectasis and emphysematous lung parenchyma using the deep learning method

Introduction: This study aimed to perform the segmentation of honeycomb cysts, traction bronchiectasis, and emphysematous lung parenchyma in high-resolution computed tomography (HRCT) examinations using the deep learning method of artificial intelligence.

Materials and Methods: The study included the cross-sectional images of 265 patients diagnosed with usual interstitial pneumonia between 2017 and 2021. Minimum intensity projection (MinIP) was performed on axial sections in the parenchymal window. Emphysema areas, traction bronchiectasis, and honeycomb cysts were segmented and labeled on the axial HRCT images. The dataset was divided into three parts, namely training, validation, and testing, at a ratio of 80, 10, and 10%, respectively. The results were calculated by selecting 50% as the threshold value for the intersection over union (Jaccard index) statistic.

Results: Of the 265 patients included in the study, 184 (69.4%) were male and 81 (30.6%) were female. Mean age of the patients was 73 ± 10 years. In the test group segmented as emphysema, the sensitivity, precision, F1 score, area under the curve (AUC), and accuracy values were calculated as 0.81, 0.90, 0.85, 0.86, and 0.75, respectively. In the test group segmented as traction bronchiectasis, the sensitivity, precision, F1 score, AUC, and accuracy values were found to be 0.95, 0.76, 0.85, 0.80, and 0.75, respectively. In the test group segmented as honeycomb cysts, the sensitivity, precision, F1 score, AUC, and accuracy values were 0.96, 0.92, 0.94, 0.88, and 0.90, respectively.

Conclusion: In this study, we successfully utilized the U-Net architecture, a deep learning technology, to accurately segment honeycomb cysts in MinIP images, one of the parameters that will help classify interstitial lung diseases (ILDs). We anticipate that our study will guide future studies on the classification of ILDs.

Key words: Deep learning; usual interstitial pneumonia; honeycomb cysts; traction bronchiectasis; emphysema

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Data Sharing Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ÖZ

Balpeteği kistleri, traksiyon bronşiektazileri ve amfizemli akciğer parankiminin derin öğrenme yöntemiyle segmentasyonu

Giriş: Bu çalışmanın amacı, yapay zeka derin öğrenme yöntemini kullanarak yüksek çözünürlüklü bilgisayarlı tomografi (HRCT) incelemelerinde bal peteği kistleri, traksiyon bronşiektazisi ve amfizemli akciğer parankiminin segmentasyonunu gerçekleştirmektir.

Materyal ve Metod: Çalışma, 2017-2021 yılları arasında tipik interstisyel pnömoni tanısı alan 265 hastanın kesitsel görüntülerini içermektedir. Parenkimal pencerede aksiyal kesitlerde minimum yoğunluk projeksiyonu (MinIP) gerçekleştirildi. Amfizem alanları, traksiyon bronşiektazisi ve bal peteği kistleri aksiyal HRCT görüntülerinde segmentlere ayrıldı ve etiketlendi. Veri seti, sırasıyla %80, %10 ve %10 oranlarında eğitim, doğrulama ve test olmak üzere üç bölüme ayrıldı. Sonuçlar, birleşim üzerinde kesişim (Jaccard indeksi) istatistiği için eşik değeri olarak %50 seçilerek hesaplandı.

Bulgular: Çalışmaya dahil edilen 265 hastanın 184 (%69.4)'ü erkek, 81 (%30.6)'i kadındı. Hastaların ortalama yaşı 73 ± 10 idi. Amfizem olarak segmentlere ayrılan test grubunda duyarlılık, kesinlik, F1 skoru, eğri altındaki alan (AUC) ve doğruluk değerleri sırasıyla 0.81, 0.90, 0.85, 0.86 ve 0.75 olarak hesaplandı. Traksiyon bronşiektazisi olarak segmentlere ayrılan test grubunda duyarlılık, kesinlik, F1 skoru, AUC ve doğruluk değerleri sırasıyla 0.95, 0.76, 0.85, 0.80 ve 0.75 olarak bulundu. Bal peteği kistleri olarak segmentlere ayrılan test grubunda duyarlılık, kesinlik, F1 skoru, AUC ve doğruluk değerleri sırasıyla 0.96, 0.92, 0.94, 0.88 ve 0.90 olarak hesaplandı.

Sonuç: Bu çalışmada, interstisyel akciğer hastalıklarının (ILD) sınıflandırılmasına yardımcı olacak parametrelerden biri olan MinIP görüntülerinde bal peteği kistleri doğru bir şekilde segmente etmek için derin öğrenme teknolojisi olan U-Net mimarisini başarıyla kullandık. Çalışmamızın, ILD'lerin sınıflandırılmasına ilişkin gelecekteki çalışmalara rehberlik edeceğini öngörüyoruz.

Anahtar kelimeler: Derin öğrenme; olağan interstisyel pnömoni; bal peteği kistleri; traksiyon bronşiektazisi; amfizem

INTRODUCTION

Interstitial lung diseases (ILDs) refer to a group of diseases caused by inflammation and fibrosis in the interstitium, for which computed tomography (CT) plays a crucial role in diagnosis (1,2). During the initial stage of diagnosing ILDs, the patients' clinical history is obtained and evaluated together with the results of the physical examination, laboratory test, chest radiography, and respiratory function test. Subsequently, a high-resolution CT (HRCT) examination is requested for suspected cases (3). When categorizing ILDs into subgroups, it is important to identify honeycomb cysts and traction bronchiectasis on CT and distinguish the former from emphysematous changes, as this assists in making an accurate diagnosis. On CT, honeycomb cysts appear as clustered air cysts, usually 3-10 mm in size, and are associated with subpleural, well-circumscribed, irreversible pulmonary fibrosis. They are an important component of usual interstitial pneumonia (UIP) (2,4,5). Traction bronchiectasis is an area of bronchiectasis that is observed as irregular bronchial dilatation and occurs in conjunction with pulmonary fibrosis (6). Emphysematous changes are seen on CT as low-density hypodense areas without walls (7).

HRCT is the imaging method that is primarily used for the diagnosis of ILDs, for which early diagnosis is important due to high mortality and morbidity rates (8,9). In recent years, artificial intelligence-supported software has been utilized in radiology. Effective

characterization of different tissues is one of the most important components of computer-aided diagnosis (CAD) systems. The objective of CAD systems is to shorten the diagnostic time interval and increase diagnostic accuracy. The deep learning component of artificial intelligence, especially convolutional neural networks (CNNs), has demonstrated effective results in many studies, particularly in the field of segmentation in medical image analysis (10,11). Various studies have been conducted to diagnose ILDs using deep learning methods (12,13). In these studies, Anthimopoulos et al. addressed inaccurate classification in the reticulation group with honeycomb cysts among ILD patterns, while Christodoulidis et al. attempted to apply the CAD system to the diagnosis of ILDs by utilizing a CNN and transfer learning in ILD patterns (12,13). ILD patterns, especially traction bronchiectasis and honeycomb cysts, are important for the classification of these diseases, and it is therefore crucial for CAD systems to segment these patterns accurately for classification purposes.

This study aimed to perform the segmentation of honeycomb cysts, traction bronchiectasis, and emphysematous lung parenchyma in HRCT examinations using the deep learning method.

MATERIALS and METHODS

The study commenced after receiving ethics committee approval (date: June 1, 2021, decision number: 16).

Patients

The imaging reports of patients who presented to our hospital with a preliminary diagnosis of ILDs between 2017 and 2021 were screened from the hospital system using the keywords “usual interstitial pneumonia”, “idiopathic pulmonary fibrosis”, and “UIP”. A total of 3.200 images were accessed, and the patients were evaluated according to the UIP criteria and examination quality. Patients diagnosed with typical UIP according to the HRCT examination were included in the study. The examinations of patients aged under 18 years and non-diagnostic HRCT examinations due to respiratory motion artifacts were excluded from the study. Accordingly, five patients who were under 18 years of age and 170 patients with images that had low quality or respiratory motion artifacts were excluded. ILDs were not

detected in 700 patients. Last, 2.060 patients did not meet the UIP criteria. As a result, the cross-sectional images of a total of 265 patients were included in the study (Figure 1).

CT imaging procedure

HRCT examinations were performed on a 128-slice tomography device (GE, Revolution EVO, USA) using the following parameters: Slice thickness= 0.625 mm; matrix size= 514 x 514; zoom= x1.00; WC/WW= -450/1,500; detector coverage= 40 mm; helical thickness= 2.5 mm; pitch and speed= 0.984:1 and 39.37 mm/rot; rotation time= 0.5 s; kV= 120; and mA= 30.

CT imaging analysis and segmentation

HRCT examinations were evaluated by a radiologist with seven years of experience (NA) and a radiology

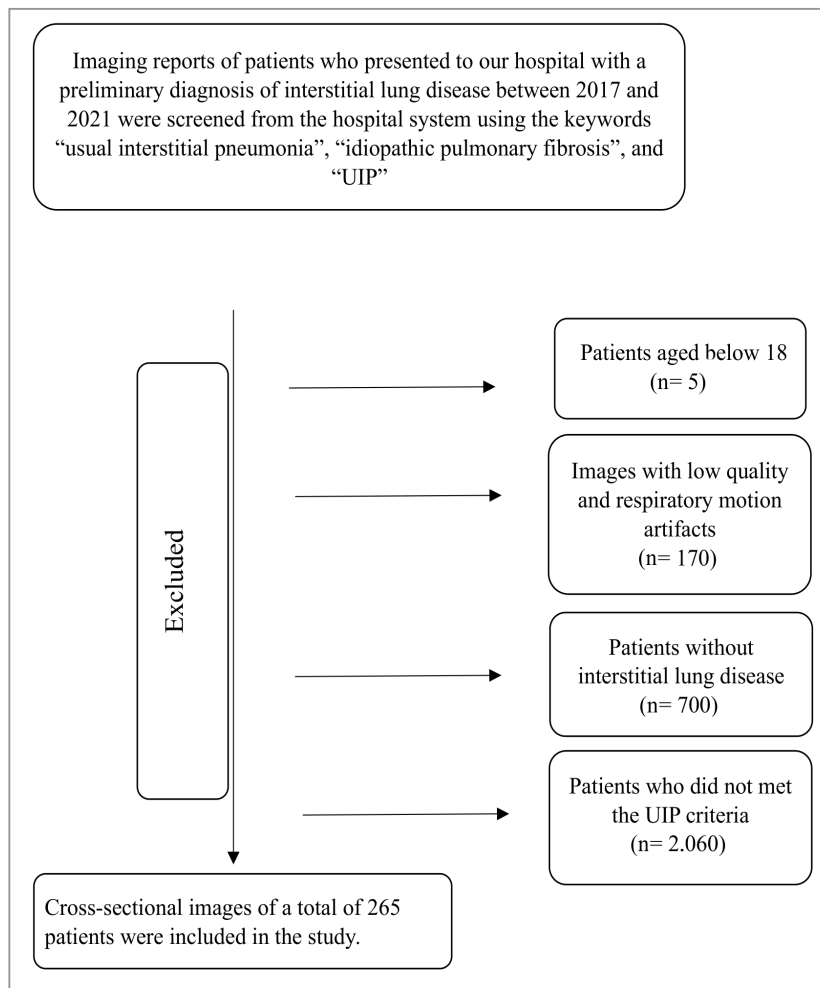


Figure 1. Flow chart showing the selection of patient images.

assistant with five years of experience (BS) based on consensus for segmentation standardization. Patients presenting with an apicobasal gradient of involvement on HRCT, who had honeycomb cysts and traction bronchiectasis and met the UIP criteria were identified. Of these patients, those with centrilobular emphysematous changes above 5% in any lobe were included in the study. The sample included all mild and substantial types of paraseptal emphysematous changes (14). In HRCT examinations, minimum intensity projection (MinIP) was performed on axial sections in the parenchymal window. Then, emphysematous areas, traction bronchiectasis, and honeycomb cysts were segmented and labeled on axial images. The Colabeler 2.0.4.0 (2019) program was used for segmentation. In the computer department of our faculty, mask images of the labeled regions of the images were created and saved using the same names. The dataset obtained was divided into three parts, namely training, validation, and testing, at a ratio of 80, 10, and 10%, respectively. Mixed-size images were resized to 512 x 512. By applying a 50% zoom to the images, the regions to be segmented were enlarged to their maximum capacity inside the image. The Clahe method was employed to increase the clarity of the regions to be segmented. In the emphysema and traction bronchiectasis groups, the number of data points was increased fourfold by applying augmentation (both horizontal and vertical) to the training and validation sets. Epoch training was undertaken using the traditional PyTorch U-Net architecture, extended to handle volumetric input. The utilization of skip connections between the corresponding encoder and decoder layers facilitated the effective training of the deeper sections of the network and allowed for the comparison of the same receptive features with different receptive fields (15).

The results were calculated by selecting 50% as the threshold value for the intersection over union (Jaccard index) statistic, which is defined as the intersection size divided by the size of the union of sample sets and is used to measure the similarity between finite sample sets (16).

Statistical analysis

Continuous data was presented as mean $\pm$ standard deviation, and categorical data as percentages (%). IBM SPSS Statistics v. 21.0 (IBM Corp. Released 2012. IBM SPSS Statistics for Windows, Version 21.0. Armonk, NY: IBM Corp.) was used to perform statisti-

cal analyses. Sensitivity, precision, F1 score, area under the curve, and accuracy values were calculated.

RESULTS

Of the 265 patients included in the study, 184 (69.4%) were male and 81 (30.6%) were female. Mean age of the patients was 73 ± 10 years.

A total of 150 axial sections taken from the HRCT examinations of 52 patients were labeled for emphysema. The labeled emphysema area was divided into training (80%), validation (10%), and test (10%) sets. Augmentation was applied to the training and validation groups (both horizontal and vertical flips). All images were resized to 512 x 512. Using PyTorch U-net, 300 epochs were trained. After augmentation, the number of images was 480, and the number of labels was 1,084 in the emphysema training group, and the number of images was 60 and the number of labels was 96 in the emphysema validation group. In the emphysema test group, the number of images was 15, and the number of labels was 24. In the group segmented as emphysema, the results of the test set were as follows: 18 true positives, two false positives, and two undetected. For the emphysema group, the sensitivity, precision, F1 score, area under curve (AUC), and accuracy values were calculated as 0.81, 0.90, 0.85, 0.86, and 0.75, respectively (Figure 2).

All patients had traction bronchiectasis. Traction bronchiectasis areas labeled on 584 axial sections obtained from the HRCT examinations of 265 patients were grouped into the training (80%), validation (10%), and test (10%) sets. Augmentation was applied to the training and validation images (both horizontal and vertical flips). All images were resized to 512 x 512. PyTorch U-net was used to train 300 epochs. After augmentation, the traction bronchiectasis training set contained 1.872 images and 6.088 labels. In the validation set, there were 232 images and 752 labels. In the test set, the number of images was 58, and the number of labels was 179. In the group segmented as traction bronchiectasis, the results of the test group were as follows: 43 true positives, 13 false positives, and two undetected. For the traction bronchiectasis group, the sensitivity, precision, F1 score, AUC, and accuracy values were determined to be 0.95, 0.76, 0.85, 0.80, and 0.75, respectively (Figure 3).

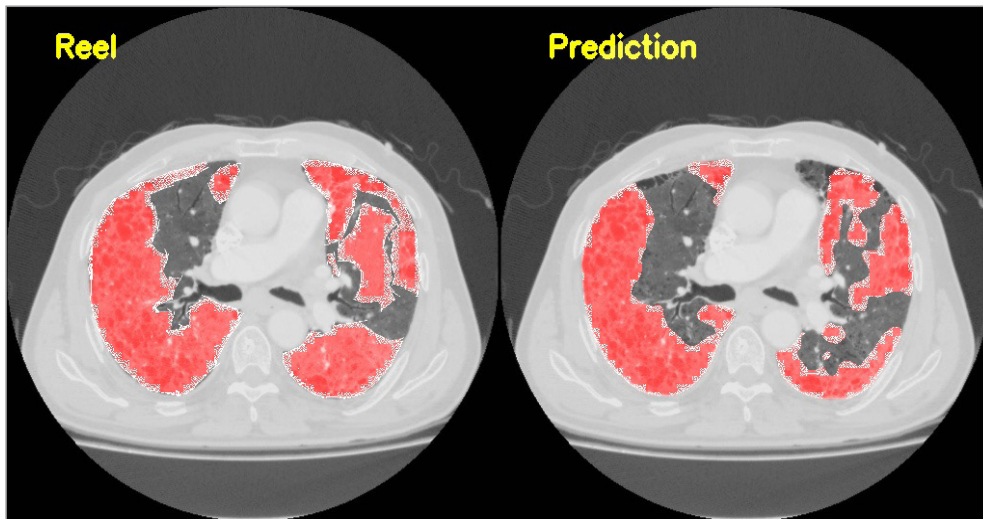


Figure 2. Real and deep learning-based cross-sectional images of a patient in the emphysema test group.

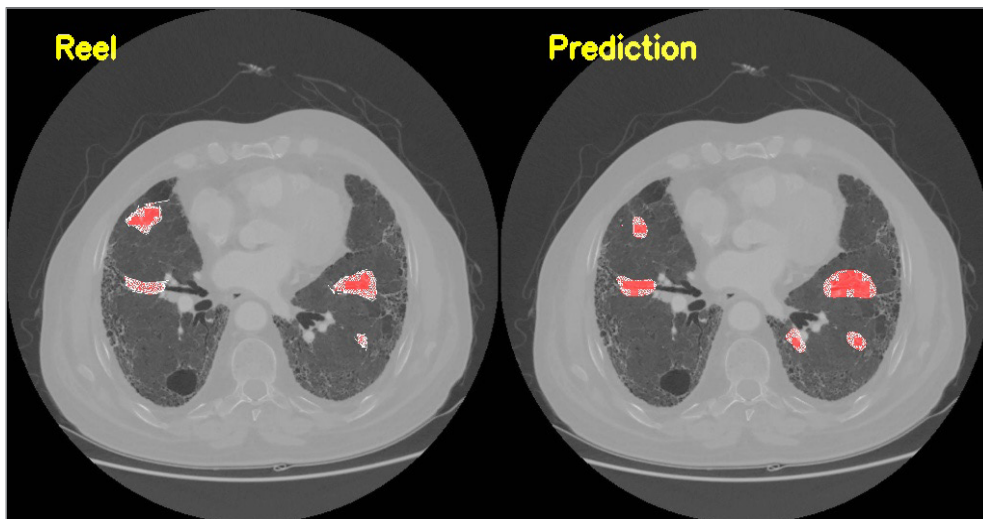


Figure 3. Real and deep learning-based cross-sectional images of a patient in the traction bronchiectasis test group.

All the patients had honeycomb cysts. The honeycomb cyst areas labeled in 1.039 axial sections obtained from the HRCT examinations of 265 patients were divided into training (80%), validation (10%), and test (10%) sets. All images were resized to 512 x 512. Using PyTorch U-net, 750 epochs were trained. After the first 25 epochs were completed, the learning rate was reduced by 10 times, and the training was completed. The numbers of images and labels were 839 and 2.562, respectively, in the training set; 100 and 291, respectively, in the validation set; and 100 and 194, respectively, in the test set. In the group segmented as honeycomb cysts, the results of the test set were as follows: 173 true positives, 14 false posi-

tives, and seven undetected. For the honeycomb cyst group, the sensitivity, precision, F1 score, AUC, and accuracy values were found to be 0.96, 0.92, 0.94, 0.88, and 0.90, respectively (Table 1) (Figure 4).

DISCUSSION

This study employed the deep learning component of artificial intelligence with the aim of performing segmentation on ILDs based on the HRCT sections of patients diagnosed with UIP. The components of fibrosis, honeycomb cysts, and traction bronchiectasis, which are important findings in the diagnosis phase of the disease, were segmented using the deep learning method. Although emphysematous changes

Table 1. Results of the emphysema, traction bronchiectasis, and honeycomb cyst test groups					
	Sensitivity	Precision	F1 score	AUC*	Accuracy
Emphysema	0.81	0.90	0.85	0.86	0.75
Traction bronchiectasis	0.95	0.76	0.85	0.80	0.75
Honeycomb cysts	0.96	0.92	0.94	0.88	0.90

*AUC: Area under the curve.

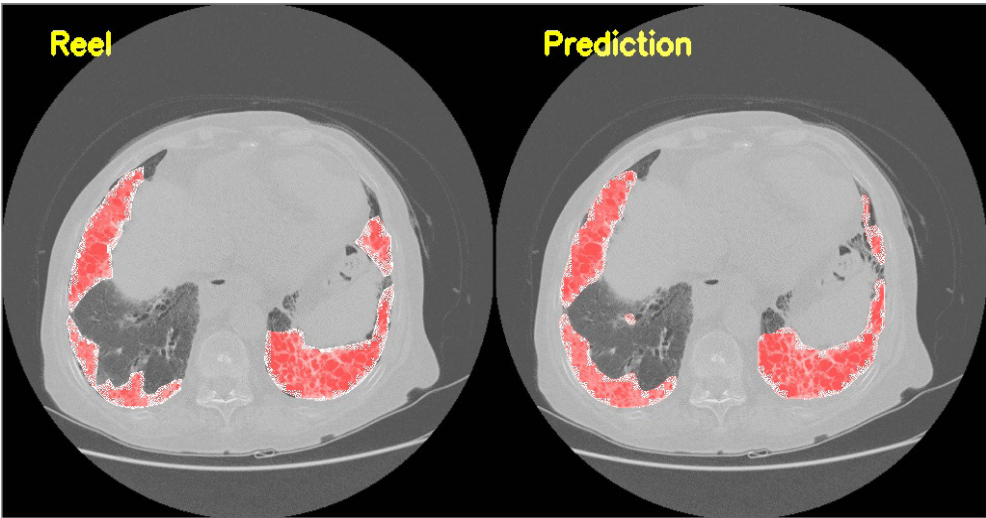


Figure 4. Real and deep learning-based cross-sectional images of a patient in the honeycomb cyst test group.

are distinguished from honeycomb cysts based on findings such as the absence of wall structure and fibrosis, as well as their distribution, they can still cause confusion in clinical practice at the diagnosis stage. Therefore, we also segmented paraseptal and centrilobular emphysematous changes detected in the examinations of some patients using the deep learning method. In our study, honeycomb cysts demonstrated the highest level of success in segmentation, which was followed by the emphysema group and, last, the traction bronchiectasis group, according to the AUC values. In our study, unlike previous research, we attempted segmentation after performing MinIP on the HRCT images of the patients. MinIP images are multiplanar slab images that facilitate the evaluation of airways. These images are particularly useful for differentiating traction bronchiectasis from honeycomb borders (17,18).

There are studies in the literature using the deep learning method in fibrotic lung diseases. In a study by Walsh et., fibrotic lung diseases were grouped, and these groups were tested with a deep learning-based algorithm (19). The authors used the 2011 ATS/ERS/JRS/ALAT guidelines and Fleischner Society

guidelines for classification. Experienced radiologists and a deep learning algorithm produced similar results in distinguishing between the UIP and non-UIP groups (20,21). In the current study, rather than grouping fibrotic lung diseases, we assessed the success of the segmentation of honeycomb cysts and traction bronchiectasis, which are important imaging criteria in the diagnosis of UIP, using deep learning. Our results revealed that this method was especially successful in the segmentation of honeycomb cysts. The higher success rate of segmentation in honeycomb cysts may be related to the more distinct contours and wall structure of these cysts compared to emphysema.

Anthimopoulos et al. used the CNN algorithm for the classification of ILD patterns and achieved a success rate of 85.5% (12). However, the authors noted that misclassifications occurred in the grouping of honeycomb, reticulation, and ground glass components and their combinations. Therefore, it is important to be able to accurately segment components such as honeycomb cysts and traction bronchiectasis, which will assist in the classification of ILDs. For successful classification, such algorithms should be able to

accurately identify and group these findings. To this end, in our study, we segmented traction bronchiectasis and honeycomb cysts, considering that this would contribute to future artificial intelligence-based ILD classification studies. However, our analysis did not include components such as reticulation and ground glass opacity due to their indistinct borders and contours and frequent coexistence.

In another ILD study, shallow (support vector machine) and deep learning methods were compared in the classification of ILDs, and the CNN-based deep learning algorithm was reported to be more successful. The authors stated that the CNN algorithm contributed to the decrease in the rate of misclassifications arising from the ambiguity between normal emphysema cases and between honeycombing and reticulation cases (22).

Agarwala et al. classified ILD patterns in HRCT images using the deep learning and transfer learning methods (23). They evaluated consolidation, emphysema, and fibrosis groups among ILD patterns by utilizing the MedGIFT ILD database and the PASCAL VOC database, along with their own cases (24,25). In our study, we exclusively used the data of our original cases, although this limited our sample size. Since our dataset was limited, we could have used transfer learning; however, due to our images being MiniP images, the lack of similar studies in this area, and the absence of an appropriate database, we decided not to apply transfer learning, as it would have hindered the model training process.

Park et al. conducted a study where they utilized deep learning to perform lung segmentation in HRCT and volumetric CT for diffuse ILD (26). Similar to our study, the authors employed the U-Net architecture, which is the most commonly used segmentation network of CNN architecture in medical images (15). They classified the patients into cryptogenic organizing pneumonia, UIP, and non-specific interstitial pneumonia groups. Despite the inclusion of volumetric CT image data, the authors utilized the two-dimensional U-Net architecture, which is a characteristic that aligns with our study.

In another study, Koh et al. employed the deep learning method to measure progression in ILDs. They accepted increased honeycombing and reticulation as indicative of fibrosis and included ground glass and fibrosis areas in the study. In contrast to our

work, the authors evaluated clinical parameters together with CT findings and reported that decreases in absolute force vital capacity by $\geq 5\%$ and $\geq 10\%$ were significantly associated with the progression of fibrosis findings and an increase in the prevalence of fibrosis (27).

In a multicenter study on ILDs, the classifications made for UIP with a deep learning-based method (CNN algorithm) were compared with the visual evaluation of radiologists. The results demonstrated good test performance for the artificial intelligence-based classification system (28).

Among the major limitations of this study are its single-center and retrospective design. In addition, the number of segmented images was relatively lower in the emphysema group compared to the other groups. Furthermore, we did not include ground glass areas or increased reticulation in segmentation since these findings are clearly distinguishable from each other. We believe that this situation did not affect the classification capacity of the model, since MiniP images reduce the detectability of high-density areas such as ground-glass opacities (29). For this reason, separate segmentation categories for reticulation and ground-glass areas were not created.

In conclusion, in our study, we used the U-Net architecture based on the CNN algorithm, one of the deep learning methods, to test a segmentation model in honeycomb cysts, traction bronchiectasis, and emphysematous lung parenchyma, which are parameters that will help classify ILDs. We achieved success with this deep learning method, especially in the segmentation of honeycomb cysts. The segmentation model we developed can play an important and effective role in the clinical differentiation of ILD and COPD, in distinguishing emphysema from honeycomb cysts, and in the follow-up and treatment decision processes of ILD. We consider that these findings will be important for future ILD classifications.

Ethical Committee Approval: This study was approved by Eskişehir Osmangazi University Non-interventional Clinical Research Ethics Committee (Decision no: 16, Date: 16.04.2021).

Peer-review: Externally peer-reviewed.

CONFLICT of INTEREST

The authors declare that they have no conflict of interest.

AUTHORSHIP CONTRIBUTIONS

Concept/Design: NA, BM

Analysis/Interpretation: ÖÇ, AFA, AO

Data acquisition: NA, HY, FA, SD

Writing: NA, BM, BS

Clinical Revision: NA, BM

Final Approval: NA

REFERENCES

1. Trusculescu AA, Manolescu D, Tudorache E, Oancea C. Deep learning in interstitial lung disease-how long until daily practice. *Eur Radiol* 2020; 30(11): 6285-92. <https://doi.org/10.1007/s00330-020-06986-4>
2. Lynch DA, Godwin JD, Safrin S, Starko KM, Hormel P, Brown KK, et al. High-resolution computed tomography in idiopathic pulmonary fibrosis: diagnosis and prognosis. *Am J Respir Crit Care Med* 2005; 172: 488-93. <https://doi.org/10.1164/rccm.200412-1756OC>
3. Meyer KC. Diagnosis and management of interstitial lung disease. *Transl Respir Med*. 2014; 2: 4. <https://doi.org/10.1186/2213-0802-2-4>
4. Primack SL, Hartman TE, Hansell DM, Müller NL. End-stage lung disease: CT findings in 61 patients. *Radiology* 1993; 189: 681-6. <https://doi.org/10.1148/radiology.189.3.8234691>
5. American Thoracic Society/European Respiratory Society International Multidisciplinary Consensus Classification of the Idiopathic Interstitial Pneumonias. This joint statement of the American Thoracic Society (ATS), and the European Respiratory Society (ERS) was adopted by the ATS board of directors, June 2001 and by the ERS executive committee, June 2001. *Am J Respir Crit Care Med* 2002; 165: 277-304. [Published correction appears in *Am J Respir Crit Care Med* 2002; 166(3): 426]. <https://doi.org/10.1164/ajrccm.165.2.ats01>
6. Hogg JC, Macklem PT, Thurlbeck WM. Site and nature of airway obstruction in chronic obstructive lung disease. *N Engl J Med* 1968; 278: 1355-60. <https://doi.org/10.1056/NEJM196806202782501>
7. Foster WL Jr, Gimenez EI, Roubidoux MA, Sherrier RH, Shannon RH, Roggli VL, et al. The emphysemas: radiologic-pathologic correlations. *RadioGraphics* 1993; 13: 311-28. <https://doi.org/10.1148/radiographics.13.2.8460222>
8. Nishimura K, Kitaichi M, Izumi T, Nagai S, Kanaoka M, Itoh H. Usual interstitial pneumonia: histologic correlation with high-resolution CT. *Radiology* 1992; 182(2): 337-42. <https://doi.org/10.1148/radiology.182.2.1732946>
9. Johansson KA, Chaudhuri N, Adegunsaye A, Wolters PJ. Treatment of fibrotic interstitial lung disease: current approaches and future directions. *Lancet* 2021; 398(10309): 1450-60. [https://doi.org/10.1016/S0140-6736\(21\)01826-2](https://doi.org/10.1016/S0140-6736(21)01826-2)
10. Chen G, Zhang J, Zhuo D, Pan Y, Pang C. Identification of pulmonary nodules via CT images with hierarchical fully convolutional networks. *Med Biol Eng Comput* 2019; 57: 1567-80. <https://doi.org/10.1007/s11517-019-01976-1>
11. Takahashi R, Kajikawa Y. Computer-aided diagnosis: a survey with bibliometric analysis. *Int J Med Inform* 2017; 101: 58-67. <https://doi.org/10.1016/j.ijmedinf.2017.02.004>
12. Anthimopoulos M, Christodoulidis S, Ebner L, Christe A, Mougiakakou S, et al. Lung pattern classification for interstitial lung diseases using a deep convolutional neural network. *IEEE Trans Med Imaging* 2016; 35(5): 1207-16. <https://doi.org/10.1109/TMI.2016.2535865>
13. Christodoulidis S, Anthimopoulos M, Ebner L, Christe A, Mougiakakou S, et al. Multisource transfer learning with convolutional neural networks for lung pattern analysis. *IEEE J Biomed Health Inform* 2017; 21(1): 76-84. <https://doi.org/10.1109/JBHI.2016.2636929>
14. Lynch DA, Austin JH, Hogg JC, Grenier PA, Kauczor HU, Bankier AA, et al. CT-definable subtypes of chronic obstructive pulmonary disease: a statement of the Fleischner Society. *Radiology* 2015; 277(1): 192-205. <https://doi.org/10.1148/radiol.2015141579>
15. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional networks for biomedical image segmentation. *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2015* vol 9351. pp 234-241 Springer, Online ISBN: 978-3-319-24574-4.
16. Tan PN, Steinbach M, Kumar V. *Introduction to Data Mining*. (2005). ISBN 0-321- 32136-7.
17. Ghonge NP, Chowdhury V. Minimum-intensity projection images in high-resolution computed tomography lung: Technology update. *Lung India* 2018; 35(5): 439-40. https://doi.org/10.4103/lungindia.lungindia_489_17
18. Fotheringham T, Chabat F, Hansell DM, Wells AU, Desai SR, Gückel C, et al. A comparison of methods for enhancing the detection of areas of decreased attenuation on CT caused by airways disease. *J Comput Assist Tomogr* 1999; 23: 385-9. <https://doi.org/10.1097/00004728-199905000-00012>
19. Walsh SLF, Calandriello L, Silva M, Sverzellati N. Deep learning for classifying fibrotic lung disease on high-resolution computed tomography: a case-cohort study. *Lancet Respir Med*. 2018; 6(11): 837-45. [https://doi.org/10.1016/S2213-2600\(18\)30286-8](https://doi.org/10.1016/S2213-2600(18)30286-8)
20. Raghu G, Collard HR, Egan JJ, Martinez FJ, Behr J, Brown KK, et al. An official ATS/ERS/JRS/ALAT statement: idiopathic pulmonary fibrosis: evidence-based guidelines for diagnosis and management. *Am J Respir Crit Care Med* 2011; 183: 788-824. <https://doi.org/10.1164/rccm.2009-040GL>
21. Lynch DA, Sverzellati N, Travis WD, Brown KK, Colby TV, Galvin JR, et al. Diagnostic criteria for idiopathic pulmonary fibrosis: a Fleischner Society White Paper. *Lancet Respir Med* 2018; 6: 138-53. [https://doi.org/10.1016/S2213-2600\(17\)30433-2](https://doi.org/10.1016/S2213-2600(17)30433-2)

22. Kim GB, Jung KH, Lee Y, Kim HJ, Kim N, Jun S, et al. Comparison of shallow and deep learning methods on classifying the regional pattern of diffuse lung disease. *J Digit Imaging* 2018; 31(4): 415-24. <https://doi.org/10.1007/s10278-017-0028-9>
23. Agarwala S, Kale M, Kumar D, Swaroop R, Kumar A, Kumar Dhara A, et al. Deep learning for screening of interstitial lung disease patterns in high-resolution CT images. *Clin Radiol* 2020; 75(6): 481.e1-481.e8. <https://doi.org/10.1016/j.crad.2020.01.010>
24. Depeursinge A, Vargas A, Platon A, Geissbuhler A, Poletti PA, Müller H. Building a reference multimedia database for interstitial lung diseases. *Comput Med Imaging Graph* 2012; 36(3): 227-38. <https://doi.org/10.1016/j.comp-medimag.2011.07.003>
25. Everingham M, Eslami SMA, Gool LV, Williams CKI, W John, Zisserman A. PASCAL visual object classes challenge: a retrospective. *Int J Comput Vis* 2015; 111: 98-136. <https://doi.org/10.1007/s11263-014-0733-5>
26. Park B, Park H, Lee SM, Seo JB, Kim N. Lung segmentation on HRCT and volumetric CT for diffuse interstitial lung disease using deep convolutional neural networks. *J Digit Imaging* 2019; 32(6): 1019-26. <https://doi.org/10.1007/s10278-019-00254-8>
27. Koh SY, Lee JH, Park H, Goo JM. Value of CT quantification in progressive fibrosing interstitial lung disease: a deep learning approach. *Eur Radiol* 2024; 34(7): 4195-205. <https://doi.org/10.1007/s00330-023-10483-9>
28. Chung JH, Chelala L, Pugashetti JV, Wang JM, Adegunsoye A, Matyga AW, et al. A deep learning-based radiomic classifier for usual interstitial pneumonia. *Chest* 2024; 165(2): 371-80. <https://doi.org/10.1016/j.chest.2023.10.012>
29. Beigelman-Aubry C, Hill C, Guibal A, Savatovsky J, Grenier PA. Multi-detector row CT and postprocessing techniques in the assessment of diffuse lung disease. *Radiographics* 2005; 25: 1639-52. <https://doi.org/10.1148/rg.256055037>