ORIGINAL ARTICLE

Use of deep learning methods for hand fracture detection from plain hand radiographs

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ABSTRACT

BACKGROUND: Patients with hand trauma are usually examined in emergency departments of hospitals. Hand fractures are frequently observed in patients with hand trauma. Here, we aim to develop a computer-aided diagnosis (CAD) method to assist physicians in the diagnosis of hand fractures using deep learning methods.

METHODS: In this study, Convolutional Neural Networks (CNN) were used and the transfer learning method was applied. There were 275 fractured wrists, 257 fractured phalanx, and 270 normal hand radiographs in the raw dataset. CNN, a deep learning method, were used in this study. In order to increase the performance of the model, transfer learning was applied with the pre-trained VGG-16, GoogLeNet, and ResNet-50 networks.

RESULTS: The accuracy, sensitivity, specificity, and precision results in Group 1 (wrist fracture and normal hand) dataset were 93.3%, 96.8%, 90.3%, and 89.7% , respectively, with VGG-16, were 88.9%, 94.9%, 84.2%, and 82.4%, respectively, with Resnet-50, and were 88.1%, 90.6%, 85.9%, and 85.3%, respectively, with GoogLeNet. The accuracy, sensitivity, specificity, and precision results in Group 2 (phalanx fracture and normal hand) dataset were 84.0%, 84.1%, 83.8%, and 82.8%, respectively, with VGG-16, were 79.4%, 78.5%, 80.3%, and 79.7%, respectively, with Resnet-50, and were 81.7%, 81.3%, 82.1%, and 81.3%, respectively, with GoogLeNet.

CONCLUSION: We achieved promising results in this CAD method, which we developed by applying methods such as transfer learning, data augmentation, which are state-of-the-art practices in deep learning applications. This CAD method can assist physicians working in the emergency departments of small hospitals when interpreting hand radiographs, especially when it is difficult to reach qualified colleagues, such as night shifts and weekends.

Keywords: Computer-aided diagnosis; convolutional neural networks; data augmentation; deep learning; hand fractures; transfer learning.

INTRODUCTION

Distal radius and ulna fractures, carpal-metacarpal bone fractures, and phalanx fractures are commonly seen in patients with hand trauma. Distal radius fractures are the most common fractures of the upper extremity, the most common reason for this type of fractures is a fall on an open hand. Distal ulna fractures are usually associated with distal radius fractures.[1] More than 80% of carpal bone fractures are composed of scaphoid and triquetral fractures. Up to 15–25% of non-displaced fractures may not appear on plain radiographs. Phalanx and metacarpal fractures are among the most common fractures of the skeletal system and constitute 10% of all skeletal system fractures. Phalanx fractures appear as stable and unstable fractures.[2,3] Some complications including nonunion, delayed union, or avascular necrosis might occur

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due to delayed diagnosis and treatment, especially in scaphoid fractures.[3] Patients with hand trauma primarily apply to emergency clinics or emergency departments of hospitals.[1]

The patient with hand trauma should be attentively examined. Some hand fractures such as displaced distal radius fractures can be easily diagnosed by plain radiography, while some others are difficult to evaluate due to their small size, lack of displacement, and location of these fractures.[4] Plain hand radiographs are the first-line imaging modality in emergency departments to evaluate patients with hand trauma. Plain radiography is easily accessible and relatively inexpensive an imaging modality. Furthermore, patients are exposed to low-dose radiation with plain radiographs. However, general practitioners and family physicians working in the emergency department may not have enough experience to evaluate hand radiographs, and there may not be a radiologist or orthopedist at the hospital at that time. Emergency departments of the hospitals are also intensive and stressful working areas. Clinicians may also be exposed to excessive workloads that cause fatigue and sensitivity to interpretation errors. In one study, it is reported that 30% of the hand radiographs were misdiagnosed.[5]

Computer-aided diagnosis (CAD) systems have been used for many years to assist clinicians in interpreting medical images. Nowadays, studies are showing that clinicians' success is improved by the inclusion of deep learning methods in CAD systems.[6] Deep learning method is a sub-class of machine learning and feature extraction is performed automatically. Convolutional neural networks (CNN) is a deep learning method, various filters are applied to the image in the CNN method and feature extraction is done by using various algorithms. CNN's are very successful in feature extraction and image classification, but numerous data are required for CNN training from scratch.[7] Data augmentation and transfer learning can be applied when the number of data is insufficient.

This study aims to develop a diagnostic model that assists physicians who work in the emergency departments, especially when it is not possible to reach radiologists or orthopedic specialists, and to provide an objective second opinion to them when interpreting radiographs of patients with hand trauma.

MATERIALS AND METHODS

Dataset

Between March 2012 and December 2018, radiographs of patients with hand fractures in Kırıkkale University, Faculty of Medicine emergency department and between January 2017 and September 2019, radiographs of patients with hand fractures in Nevşehir State Hospital emergency department were included in the study. Hand radiographs of patients over 20-years-old were included in the study. Radiographs with hand fractures were re-evaluated by an orthopedist who was experienced over 5 years and an experienced radiologist over 5 years. This study was performed on 275 wrist fractures, 257 phalanx fractures, and 270 normal hand radiographs.

Data Pre-processing and Splitting

The hand radiographs used in this study were in JPG format, different width, and height pixels. All images were cropped to include the hand. A white color padding was added to the right and left side of each image to prevent data loss and distortion so that the square frame was obtained and the resolution did not change. All of the images were resized to 224×224 pixels. Thus, 224×224×3 (3 means RGB image format) dimension images were obtained. Figure 1 shows some cropped and resized images samples.

When applying machine learning methods, the data is split into training, validation, and test data. During the training of the network, training accuracy and training loss graphics are obtained at every step. And with the validation data set, model performance is evaluated and model hyperparameters are tuned. Before the training of the network, the raw dataset was randomly split into training and test data (75% as training data and 25% as test data) so that test data was not used during training and validation. After that, each image in the training raw dataset was flipped horizontally to increase the training data, and these images were again split into two to be used for training and validation (85% and 15%). Table 1 shows these splittings.

Transfer Learning, Data Augmentation

When there is not enough data for CNN training from

Figure 1. Sample images from the dataset after preprocessing (left 3 images: phalanx fracture images, right 3 images: wrist fracture images).

scratch, data augmentation and transfer learning can be applied. It is difficult to find sufficient data in the medical field due to expert annotation and patient confidentiality, in which case transfer learning can be a solution. Some pre-trained networks trained with natural image data (ImageNet dataset) can be used for transfer learning, their characteristics, depths, and performances are different. Some of these pre-trained networks are AlexNet,[8] GoogLeNet,[9] Inceptionv3,[10] SqueezeNet,[11] Resnet,[12] VGG[13]). In this study, pre-trained VGG-16, ResNet-50, and GoogLeNet networks were used for transfer learning. Transfer learning is the use of a pre-trained model for a new problem. VGG-16 has a sequential network architecture and 16 layers. These layers are convolution layers, max-pooling layers, and fully connected layers. GoogLeNet has an inception network architecture and has 22 layers. The Inception network model consists of modules. Each module consists of different dimensional convolution and max-pooling processes. ResNet has a residual network architecture and is 50 layers, makes shortcut connections between layers, skipping one or more layers. Table 2 shows the properties of these pre-trained networks. Nowadays these pre-trained networks are used successfully for transfer learning. In a few studies, it was observed that the networks initially trained with natural images could be applied to skeletal radiographs with minimal intervention.[14] Previously, the transfer learning method has successfully applied to medical images such as computed tomography (CT) images[15] and X-rays images.[16–18]

Table 1. Number of images after splittings. The raw dataset was first split into training and test data. Flipped training raw dataset was used for training and validation

	Raw Dataset	Training	Validation	Test
Wrist fracture	275	352	62	68
Phalanx fracture	257	328	58	64
Normal	270	345	61	67

Table 2. Properties of pre-trained networks used in this study

Model	VGG-16	GoogLeNet	ResNet-50
	Sequential	Inception modul	Residual network
Depth	16	22	50
Number of filters	64	64	64
Filter size	3×3	7×7	7×7
Stride	1×1	1×1	2×2
Dropout	50%	50%	50%
Activation function	ReLU	ReLU	ReLU

Data augmentation is achieved by making non-exact copies or transformations of each image, such as sharpness, brightness, contrast, and mirror symmetry. Here, data augmentation was applied by the random transformation of images, randomly translating the images up to 3 pixels horizontally and vertically, and rotating the images up to 30° and −30°. In deep learning methods, setting the appropriate hyperparameters during the training of the model improves the performance of the network. Table 2 shows the hyperparameters used in this study. The learning rate and cycle number hyperparameters were iteratively optimized. The learning rate refers to the magnitude of changes made to the model parameters after each iteration. As the training progressed, a learning rate decay was applied, reducing the magnitude of the parameter changes.

RESULTS

This study was performed on a LENOVO Intel® Core™ i7-9750H/Y540/16G/512 GeForce RTX2060 computer and in MATLAB® environment. Three different dataset groups were created with wrist fractures and normal hand radiographs (Group 1), with phalanx fractures and normal hand radiographs (Group 2), and with wrist fractures, phalanx fractures, and normal hand radiographs datasets (Group 3). The efficiency of the created models was evaluated using performance metrics such as accuracy, sensitivity, specificity, and precision. These performance metrics were calculated using the confusion matrices. The training was repeated five times with each model. The best results obtained with each model can be seen in Table 3. Figure 2 shows the confusion matrixes obtained by training all three datasets with the VGG-16 network. During the training and validation of the Group 3 dataset with the VGG-16 network, samples of validation tests of randomly selected eight images can be seen in Figure 3, Table 4.

The CAD model we developed was tested with images used for neither training nor validation purposes. The test set included 68 wrist fractures, 64 phalanx fractures, and 67 normal hand radiography images. Using pre-trained VGG-16, ResNet-50 and GoogLeNet networks, test accuracy results

Table 3. Hyperparameters used in this study

Optimizer	sgdm
Mini batch size	16
Dropout	0.5
Initial learn rate	1e-4
Learn rate drop factor	0.2
Learn rate drop period	8
L2 regularization	0.004
Validation frequency	16

sgdm: stochastic gradient descent with momentum.

Table 4. Results of performance metrics obtained with validation

		VGG-16	ResNet-50	GoogLeNet
Group 1	Accuracy	93.3	88.9	88.1
	Sensitivity	96.8	94.9	90.6
	Specificity	90.3	84.2	85.9
	Precision	89.7	82.4	85.3
Group 2	Accuracy	84.0	79.4	81.7
	Sensitivity	84.1	78.5	81.3
	Specificity	83.8	80.3	82.1
	Precision	82.8	79.7	81.3
Group 3	Accuracy	83.4	78.4	76.4

Group 1: Wrist fracture & normal hand. Group 2: Phalanx fracture & normal hand. Group 3: Wrist fracture & phalanx fracture & normal hand.

were 85.9, 82.2, and 82.2 for Group 1 dataset respectively, were 84.7, 78.6, and 76.3 for Group 2 dataset respectively, and were 77.3, 67.8, and 71.9 for Group 3 dataset, respectively.

DISCUSSION

Plain radiography is the first-line imaging modality for patients who apply to the emergency departments with hand trauma. General practitioners and family physicians working in emergency departments may not have sufficient experience in evaluating hand radiographs. Besides, it is not always possible to reach an experienced radiologist or orthopedist at emergency departments. Bone fractures may be misinterpreted due to physician fatigue, lack of expertise, and inconsistency between interpreting physicians. Emergency departments of hospitals are also intensive and stressful working areas. Pre-trained VGG-16, ResNet-50, and GoogLeNet networks were used in this preliminary study to develop a CAD system for assisting the physicians who work in the emergency departments in the diagnosis of hand fractures. Model performance was evaluated with performance metrics such as accuracy, sensitivity, specificity, and precision, and promising results were obtained.

Transfer learning can be applied when the number of data is not sufficient for CNN training from scratch. In recent years, there have been several studies showing that pre-trained CNN models trained with the Imagenet dataset have achieved successful results in the training of medical images.[14] Kim and MacKinnon[19] worked on wrist fractures, applied transfer learning with InceptionV3. Their datasets consisted of 695 broken wrist radiographs and 694 normal hand radiographs. According to the ROC curve analysis, 0.954, 0.9 and 0.88 accuracy, sensitivity and specificity were determined, re-

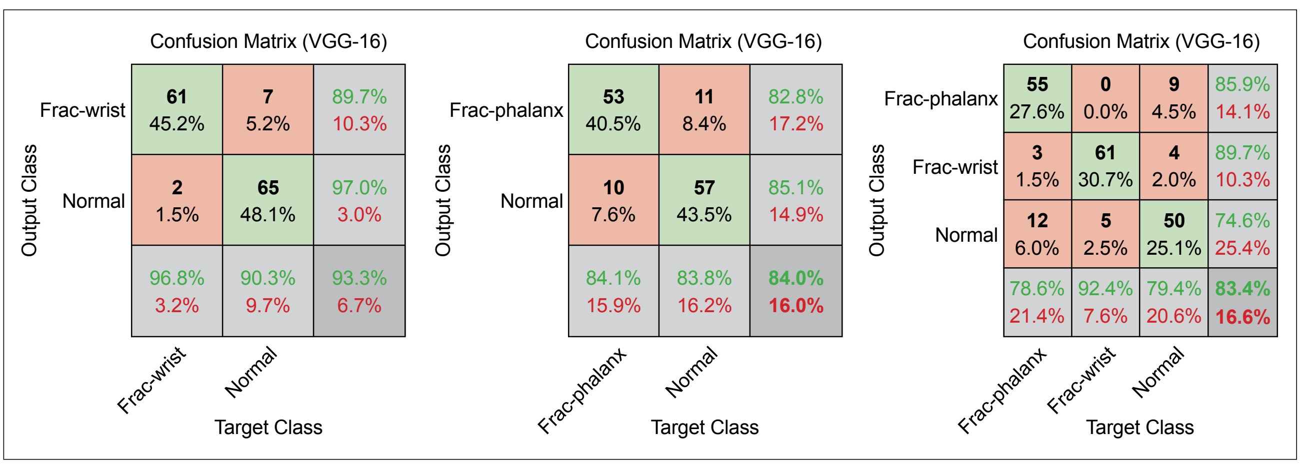

Figure 2. Confusion matrices obtained from training with the pre-trained VGG-16 network.

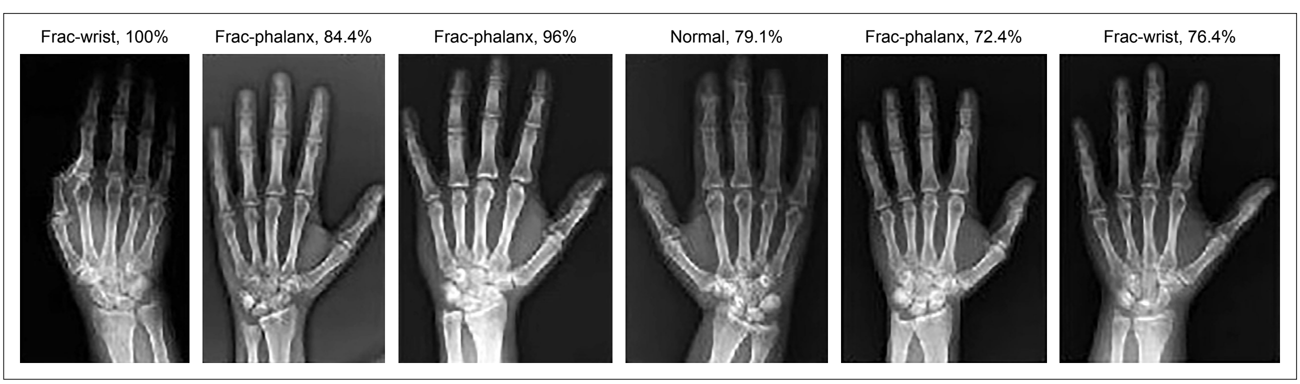

Figure 3. Randomly selected 6 images during testing of the Group 3 dataset with the VGG-16 network.

spectively. Yahalomi et al.[4] performed transfer learning with VGG-16 and studied on distal radius fractures with Faster R-CNN. Their dataset consisted of 55 AP images with distal radius fractures, and 40 AP images without any bone fracture. They achieved 96% accuracy in diagnosing distal radius fractures. In this work, we studied on wrist and phalanx fractures and applied transfer learning methods with pre-trained VGG-16, ResNet-50, and GoogLeNet networks. The VGG-16 performed a bit better than the others. Our models were better in wrist fractures, in our opinion, the reason they performed lower in phalanx fractures depends on the phalanx fractures in different localizations and shapes. For this, the number of images was limited and we think that the models will perform better in phalanx fractures with more images.

Overfitting is an important problem when the number of data is insufficient. When there is not enough data, transfer learning and data augmentation are applied. Image data augmentation is a way to prevent overfitting, as well as improve network performance. Overfitting occurs when a model learns detail and noise in training data. When new images are introduced to the network, the model cannot interpret them correctly and accuracy decreases. In addition to data augmentation, methods such as drop out, early stopping, L2 regularization, learning rate decay are applied to prevent overfitting.[20,21] In this study, these methods were also applied to prevent overfitting. In addition, the image of the hand was cropped from the entire image during preprocessing so that the artifact pixels will not interfere with the training process, and symmetric mirror images of hand radiographs were added to the data sets thereby increasing the number of data for training. During the training of the models, we did not observe any signs of overfitting.

The performance of the CNN improves as the number of data increases. In addition to the low number of images, the asymmetric position of the radiographs, inappropriate X-ray dose, and presence of artifacts adversely affect the success of the CNN model. This preliminary study was conducted on the hand radiography images of two distinct centers. If multicenter studies can be conducted in the future, both the number of images will be higher and the radiographs interpreted by many experts will be included. Thus, the generalization and reliability of the method are achieved.

Conclusion

Despite the limited number of data, we achieved promising results in this CAD method, which we developed by applying appropriate preprocessing processes and applying state-of-the-art methods in deep learning practices during the training of models. This method can assist physicians working in the emergency rooms of small hospitals when interpreting hand radiographs, especially when it is difficult to reach qualified colleagues such as night shifts and weekends. In addition, this method can help physicians in preventing undesired consequences that may arise due to intensity, fatigue, stress, and carelessness.

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Ethics Committee Approval: This study was approved by the Kirikkale University Faculty of Medicine Non-interventional Clinical Researches Ethics Committee (Date: 07.08.2019, Decision No: 2019.07.08).

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REFERENCES

1. Chung KC, Spilson SV. The frequency and epidemiology of hand and forearm fractures in the United States. J Hand Surg 2001;26:908–15.
2. Christie BM, Michelotti BF. Fractures of the carpal bones. Clin Plast Surg 2019;46:469–77. [CrossRef]
3. Bernstein ML, Chung KC. Hand fractures and their management: An international view. Injury 2006;37:1043–8. [CrossRef]
4. Yahalomi E, Chernofsky M, Werman M. Detection of distal radius fractures trained by a small set of X-ray images and faster R-CNN. In: Advances in Intelligent Systems and Computing. Berlin, Heidelberg: Springer Verlag; 2019. p. 971–81. [CrossRef]
5. Er E, Kara PH, Oyar O, Ünlüer EE. Overlooked extremity fractures in the emergency. Ulus Travma Acil Cerrahi Derg 2013;19:25–8. [CrossRef]
6. Lindsey R, Daluiski A, Chopra S, Lachapelle A, Mozer M, Sicular S, et al. Deep neural network improves fracture detection by clinicians. Proc Natl Acad Sci U S A 2018;115:11591–6. [CrossRef]
7. Rawat W, Wang Z. Deep convolutional neural networks for image classification: A comprehensive review. Neural Comput 2017;29:2352–449.
8. Krizhevsky A, Sutskever I, Hinton GE. ImageNet Classification with Deep Convolutional Neural Networks. In: Advances in Neural Information Processing Systems; 2012.
9. Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, et al. Going deeper with convolutions. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE Computer Society; 2015. p. 1–9. [CrossRef]
10. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the Inception Architecture for Computer Vision. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE Computer Society; 2016. p. 2818–26. [CrossRef]
11. Iandola FN, Han S, Moskewicz MW, Ashraf K, Dally WJ, Keutzer K. SqueezeNet: AlexNet-level Accuracy with 50x Fewer Parameters and <0.5MB Model Size; 2016. p. 1–13. Available from: http://arxiv.org/

abs/1602.07360
12. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE Computer Society; 2016. p. 770–8. [CrossRef]
13. Simonyan K, Zisserman A. Very deep Convolutional Networks for Large-scale Image Recognition. 3rd International Conference on Learning Representations, ICLR 2015-Conference Track Proceedings; 2015. p. 1–14.
14. Anwar SM, Majid M, Qayyum A, Awais M, Alnowami M, Khan MK. Medical image analysis using convolutional neural networks: A review. J Med Syst 2018;42:226. [CrossRef]
15. Setio AA, Ciompi F, Litjens G, Gerke P, Jacobs C, Van Riel SJ, et al. Pulmonary nodule detection in CT images: False positive reduction using multi-view convolutional networks. IEEE Trans Med Imaging 2016;35:1160–9. [CrossRef]
16. Üreten K, Erbay H, Maraş HH. Detection of hand osteoarthritis from hand radiographs using convolutional neural networks with transfer learning. Turkish J Electr Eng Comput Sci 2020;28:2968–78. [CrossRef]
17. Shen D, Wu G, Suk HI. Deep learning in medical image analysis. Annu Rev Biomed Eng 2017;19:221–48. [CrossRef]
18. Üreten K, Arslan T, Gültekin KE, Demir AN, Özer HF, Bilgili Y. Detection of hip osteoarthritis by using plain pelvic radiographs with deep learning methods. Skeletal Radiol 2020;49:1369–74. [CrossRef]
19. Kim DH, MacKinnon T. Artificial intelligence in fracture detection: Transfer learning from deep convolutional neural networks. Clin Radiol 2018;73:439–45. [CrossRef]
20. Srivastava N, Hinton G, Krizhevsky A, Salakhutdinov R. Dropout: A simple way to prevent neural networks from overfitting. J Mach Learn Res 2014;15:1929–58.
21. Wong SC, Gatt A, Stamatescu V, McDonnell MD. Understanding Data Augmentation for Classification: When to Warp? In: 2016 International Conference on Digital Image Computing: Techniques and Applications, DICTA 2016. Institute of Electrical and Electronics Engineers Inc.; 2016.

ORİJİNAL ÇALIŞMA - *ÖZ*

Düz el radyografilerinden el kırıklarının tespiti için derin öğrenme yöntemlerinin kullanılması

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AMAÇ: El travması olan hastalar genellikle hastanelerin acil servislerinde muayene edilir. El travmalarında el kemik kırıkları sıklıkla görülür. Bu çalışmada, derin öğrenme yöntemlerini kullanarak el kırıklarının tanısında hekimlere yardımcı olmak için bilgisayar destekli bir yöntem geliştirmeyi hedefledik.
GEREÇ VE YÖNTEM: Bu çalışmada, konvolüsyonel sinir ağları kullanılmış ve öğrenme transferi yöntemi uygulanmıştır. Veri kümesinde 275 el bilek kırığı, 257 falanks kırığı ve 270 normal el radyografisi vardı. Bu çalışmada derin öğrenme yöntemi olan konvolüsyonel sinir ağları kullanılmıştır. Modelin performansını artırmak için önceden eğitilmiş VGG-16, GoogLeNet ve ResNet-50 ağları ile öğrenme transferi uygulanmıştır.
BULGULAR: Grup 1 (el bilek kırığı ve normal el) veri setindeki doğruluk, duyarlılık, özgüllük ve kesinlik sonuçları VGG-16 ile sırasıyla %93.3, %96.8, %90.3 ve %89.7, ResNet-50 ile sırasıyla %88.9, %94.9, %84.2 ve %82.4 ve GoogLeNet ile sırasıyla %88.1, %90.6, %85.9 ve %85.3 idi. Grup 2 (falanks kırığı & normal el) veri setindeki doğruluk, duyarlılık, özgüllük ve kesinlik sonuçları, VGG-16 ile sırasıyla %84.0, %84.1, %83.8 ve %82.8, Resnet-50 ile sırasıyla %79.4, %78.5, %80.3 ve %79.7 ve GoogLeNet ile sırasıyla %81.7, %81.3, %82.1 ve %81.3 idi.
TARTIŞMA: Derin öğrenme uygulamalarında son teknoloji uygulamalar olan transfer öğrenme, veri artırma gibi yöntemler uygulayarak geliştirdiğimiz bu bilgisayar destekli tanı yönteminde umut verici sonuçlar elde ettik. Bu bilgisayar destekli tanı yöntemi, el radyografilerini yorumlarken, özellikle gece vardiyaları ve hafta sonları gibi uzman meslektaşlara ulaşmak zor olduğunda, küçük hastanelerin acil servislerinde çalışan hekimlere yardımcı olabilir.
Anahtar sözcükler: Bilgisayar destekli tanı; derin öğrenme; el kırıkları; konvolüsyonel sinir ağları; öğrenme transferi; veri artırma.

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