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Research Article

Classification of Monkeypox Skin Lesion using the Explainable Artificial Intelligence Assisted Convolutional Neural Networks

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Abstract

The World Health Organization (WHO) has given people various protective warnings for Monkeypox. If monkeypox spreads rapidly, it becomes a serious public health problem. In this case, it creates a serious congestion in hospitals. Therefore, auxiliary systems can be needed in hospitals. In this study, explainable artificial intelligence (xAI) assisted convolutional neural networks (CNNs) based a decision support system was proposed. The data set was used for this task consists of 572 images in two classes, such as Monkeypox and Normal. 12 different CNN models were used for Monkeypox and Normal skin classification. MobileNet V2 model achieved best performance with the accuracy of 98.25%, sensitivity of 96.55%, specificity of 100.00% and F1-Score of 98.25%. This model was supported by explainable AI methods. As a result, an artificial intelligence (AI) assisted auxiliary diagnosis system has been proposed for Monkeypox skin lesion.

Keywords: Monkeypox, Skin lesion, Deep learning, Convolutional neural networks, Transfer learning.

Açıklanabilir Yapay Zeka Destekli Evrişimsel Sinir Ağları Kullanılarak Maymun Çiçeği Deri Lezyonunun Sınıflandırılması

Öz

Dünya Sağlık Örgütü (DSÖ), insanlara maymun çiçeği için çeşitli koruyucu uyarılar vermiştir. Maymun çiçeği hızla yayılırsa ciddi bir halk sağlığı sorunu haline gelir. Bu durumda hastanelerde ciddi bir yoğunluk oluşturur. Bu nedenle, hastanelerde yardımcı sistemlere ihtiyaç duyulabilir. Bu çalışmada, açıklanabilir yapay zeka (AYZ) destekli evrişimli sinir ağları (ESA) tabanlı bir karar destek sistemi önerilmiştir. Bunun için kullanılan veri seti Monkeypox ve Normal olmak üzere iki sınıfta 572 görüntüden oluşmaktadır. Monkeypox ve Normal ciltlerin sınıflandırılması için 12 farklı ESA modeli kullanılmıştır. MobileNet V2 modeli, %98,25 doğruluk, %96,55 duyarlılık, %100,00 özgüllük ve %98,25 F1-Skoru ile en iyi performansı elde etmiştir. Bu model, AYZ yöntemleriyle desteklenmiştir. Sonuç olarak, maymun çiçeği cilt lezyonu için yapay zeka (YZ) destekli bir yardımcı teşhis sistemi önerilmiştir.

Anahtar Kelimeler: Maymun çiçeği, Deri lezyonu, Derin öğrenme, Evrişimli sinir ağları, Transfer öğrenme.

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1. Introduction

Monkeypox is a disease that is caused by the Monkeypox virus. It can either spread from animals to humans or humans to humans. Fever, headache, muscle aches, back pain, low energy, swollen lymph nodes, and more importantly; a rash found on the face, palms of the hands, soles of the feet, eyes, mouth, throat, groin, and genital and/or anal regions of the body can be examples of the symptoms of Monkeypox (World Health Organization, 2022). In most scenarios, patients recover from the infection with medications to reduce pain and fever. However, newborns, children, and people with weak immunity may experience more severe symptoms than other people and die. There were reports of the disease appearing in the past such as in Cameroon, the Central African Republic, the Republic of the Congo, Côte d'Ivoire, the Democratic Republic of the Congo, Gabon, Liberia, Nigeria, and Sierra Leone (Kumar et al., 2022). However, in 2022 more cases than regularly seen in some parts of Africa have been reported. The outbreak of monkeypox has been seen Europe, the Americas, Africa, the Western Pacific, and countries of the Eastern Mediterranean too in addition to the African continent.

Because of increasing demand, there is a shortage of doctors, especially in rural areas (Al-Shamsi, 2017). Therefore, auxiliary diagnostic systems are needed. For this reason, the use of artificial intelligence (AI) assisted diagnostic systems is increasing day by day. In this context, research studies on computer vision, which is a sub-research are of artificial intelligence are vital. Computer vision researches covers image classification, object detection, and image segmentation. Convolutional neural networks (CNNs) are the basis of these research topics.

In this paper, explainable AI assisted CNN based a decision support system was proposed to detection of Monkeypox skin lesion. Another main goal is to prevent the density that may occur in hospitals with the proposed system. For this purpose, state-of-the-arts image classification networks, such as ResNet-18, ResNet-50, VGG-16, Densenet-161, EfficientNet B7, EfficientNet V2, GoogLeNet, MobileNet V2, MobileNet V3, ResNeXt-50, ShuffleNet V2, and ConvNeXt were used in the experimental analysis. MobileNet V2 model achieved best performance with the accuracy of 98.25%, sensitivity of 96.55%, specificity of 100.00% and F1-Score of 98.25%. Therefore, the MobileNet V2 model was supported by explainable AI features.

The rest of this paper is organised as: Section 2 presents the literature survey for analysis of Monkeypox disease. Section 3 presents the utilized methodologies. Section 4 presents the results obtained by the classification models. Section 5 presents concluding remarks.

2. Related Works

It has been suggested by many researchers that several data collection and classification techniques can be used for Monkeypox disease.

Islam et al. (Islam et al., 2022a) proposed a Web-scraping-based data collection system for monkeypox skin lesion. After, researchers applied several preprocessing methods such as resizing and data augmentation to the data set. As a result, researchers shared the data set as open source with other scientists. Islam et al. (Islam et al., 2022b) aimed to perform Monkeypox classification. The used data set consists of 804 original images and 39,396 augmented images. In the classification task, ResNet50, Inception-V3, DenseNet121, MnasNet-A1, MobileNet-V2, ShuffleNet-V2-1×, and SqueezeNet models were used. In the study, ShuffleNet-V2-1× model achieved the best performance with the accuracy of 0.79. Ahsan et al. (Ahsan, Uddin, & Luna, 2022) created a new data set for Monkeypox classification. The data set consists of 43 Monkeypox, 47 Chickenpox, 17 Measles, and 54 Normal images. Ahsan et al. (Ahsan, Uddin, Farjana, et al., 2022) aimed to perform Monkeypox classification. The used data set consists of 1915 augmented images. In the classification task, VGG16 model was implemented using transfer learning. In the study, VGG16 model achieved accuracy of 0.97, precision of 0.97, recall of 0.97, F1-score of 0.97, sensitivity of 0.973, and specificity of 0.97. Ali et al. (Ali et al., 2022) aimed to perform Monkeypox classification. The used data set consists of 228 original images and 3192 augmented images. In the classification task, VGG16, ResNet50, Inception-V3, and ensemble of these models were implemented using transfer learning. In the study, ResNet50 model achieved the best performance with the accuracy of 82.96%, precision of 87%, recall of 83%, and F1-score of 84%.

3. Methodology

The utilized methodologies in the paper are presented under the subtitles of experimental setup and performance evaluation metrics.

3.1. Experimental Setup

Data set includes two classes namely, Monkeypox and Normal. The data set consists of total of 572 images (*Monkeypox Skin Images Dataset (MSID) | Kaggle*, n.d.). Training part of data set includes 224 and 235 images for Monkeypox and Normal classes, respectively. Validation part of data set includes 28 and 29 images for Monkeypox and Normal classes, respectively. Test part of data set includes 28 and 28 images for Monkeypox and Normal classes, respectively. All images in the data set were resized to 224 by 224 pixels.

Models trained on the ImageNet data set were used in the transfer learning method. ResNet-18, ResNet-50, VGG-16, Densenet-161, EfficientNet B7, EfficientNet V2, GoogLeNet, MobileNet V2, MobileNet V3, ResNeXt-50, ShuffleNet V2, and ConvNeXt models were used for Monkeypox disease classification. In the training phase of image classification models; cross entropy was used as loss function, stochastic gradient descent (SGD) was used as optimizer, momentum value was set as 0.9, batch size was set as 32, and epoch was set as 50. 1e-2 was set as the initial learning rate. If classification performance of models is not improvement for throughout the 7 epochs, the learning rate was multiplied by 0.1. PyTorch framework in Python programming language on the Google Colab integrated development environment (IDE) was used in the experiments. NVIDIA Tesla T4 graphics card was used in the experimental phase.

3.2. Performance Evaluation Metrics

Accuracy, sensitivity, specificity, and F1-score were used for the performance comparison of the classification models. Accuracy, precision, sensitivity, specificity, and F1-score formulas are shown from equation 1 to equation 5. True Positive (TP) refers to number of correctly classified positive class. True Negative (TN) refers number of correctly classified negative class. False Positive (FP) refers incorrectly classified positive class. False Negative (FN) refers number of the incorrectly classified negative class.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (4)$$

$$\text{F1} - \text{Score} = \frac{2 \text{ x Precision x Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (5)$$

4. Results and Discussion

From Table 1, ResNet-18 model achieved accuracy of 98.25%, sensitivity of 96.55%, specificity of 100.00% and F1-Score of 98.25%. The training time of ResNet-18 model is 3 minutes 32 seconds. Size of weight file of ResNet-18 model is 42.7 Megabyte. ResNet-50 model achieved accuracy of 96.49%, sensitivity of 93.10%, specificity of 100.00% and F1-Score of 96.43%. The training time of ResNet-50 model is 4 minutes 33 seconds. Size of weight file of ResNet-50 model is 90.0 Megabyte. VGG-16 model achieved accuracy of 92.98%, sensitivity of 89.66%, specificity of 96.43% and F1-Score of 92.86%. The training time of VGG-16 model is 5 minutes 39 seconds. Size of weight file of VGG-16 model is 512 Megabyte. Densenet-161 model achieved accuracy of 96.49%, sensitivity of 96.55%, specificity of 96.43% and F1-Score of 96.55%. The training time of Densenet-161 model is 6 minutes 52 seconds. Size of weight file of Densenet-161 model is 102 Megabyte. EfficientNet B7 model achieved accuracy of 94.74%, sensitivity of 100.00%, specificity of 89.29% and F1-Score of 95.08%. The training time of EfficientNet B7 model is 8 minutes 27 seconds. Size of weight file of EfficientNet B7 model is 245 Megabyte. EfficientNet V2 model achieved accuracy of 96.49%, sensitivity of 100.00%, specificity of 92.86% and F1-Score of 96.67%. The training time of EfficientNet V2 model is 8 minutes 57 seconds. Size of weight file of EfficientNet V2 model is 449 Megabyte. GoogLeNet model achieved accuracy of 96.49%, sensitivity of 96.55%, specificity of 96.43% and F1-Score of 96.55%. The training time of GoogLeNet model is 5 minutes 35 seconds. Size of weight file of GoogLeNet model is 512 Megabyte. MobileNet V2 model achieved accuracy of 98.25%, sensitivity of 96.55%, specificity of 100.00% and F1-Score of 98.25%. The training time of MobileNet V2 model is 3 minutes 42 seconds. Size of weight file of MobileNet V2 model is 8.75 Megabyte. MobileNet V3 model achieved accuracy of 75.44%, sensitivity of 62.07%, specificity of 89.29% and F1-Score of 72.00%. The training time of MobileNet V3 model is 3 minutes 10 seconds. Size of weight file of MobileNet V3 model is 5.94 Megabyte. ResNeXt-50 model achieved accuracy of 92.98%, sensitivity of 100.00%, specificity of 85.71% and F1-Score of 93.55%. The training time of ResNeXt-50 model is 5 minutes 15 seconds. Size of weight file of ResNeXt-50 model is 88.0 Megabyte. ShuffleNet V2 model achieved accuracy of 78.95%, sensitivity of 65.52%, specificity of 92.86% and F1-Score of 76.00%. The training time of ShuffleNet V2 model is 3 minutes 37 seconds. Size of weight file of ShuffleNet V2 model is 20.6 Megabyte. ConvNeXt model achieved accuracy of 96.49%, sensitivity of 100.00%, specificity of 92.86% and F1-Score of 96.67%. The training time of ConvNeXt model is 23 minutes 25 seconds. Size of weight file of ConvNeXt model is 748 Megabyte.

Considering the results of all performance evaluation metrics, the training times of the models, and the size of model weight file, the three best classification performances were achieved by MobileNet V2, ResNet-18, and Densenet-161. The reason why the performance evaluation metrics results are the same is because the models cannot achieve the more classification performance. Figure 1 shows the randomly choose number of 25 input images, and the classes of output images obtained by the MobileNet V2 model. Figure 2 shows the randomly choose number of 6 input images, and the heatmaps of output images obtained by the MobileNet V2 model. SmoothGradCAMpp method was used for heatmaps.

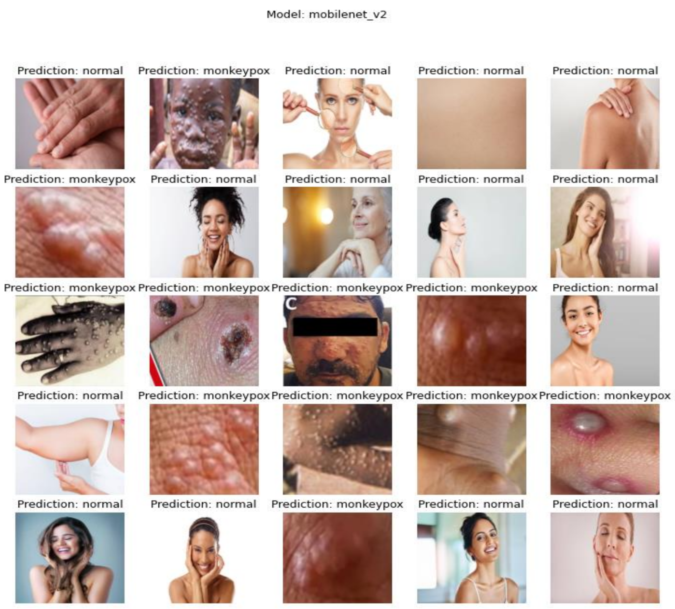

Figure 1. Predictions obtained by MobileNet V2

Table 1. Results obtained by CNN models

Models	Accuracy	Sensitivity	Specificity	F1 Score	Training Time	Size of Model Weight File
ResNet-18	98.25%	96.55%	100.00%	98.25%	3 minutes 32 seconds	42.7 Megabyte
ResNet-50	96.49%	93.10%	100.00%	96.43%	4 minutes 33 seconds	90.0 Megabyte
VGG-16	92.98%	89.66%	96.43%	92.86%	5 minutes 39 seconds	512 Megabyte
Densenet-161	96.49%	96.55%	96.43%	96.55%	6 minutes 52 seconds	102 Megabyte
EfficientNet B7	94.74%	100.00%	89.29%	95.08%	8 minutes 27 seconds	245 Megabyte
EfficientNet V2	96.49%	100.00%	92.86%	96.67%	8 minutes 57 seconds	449 Megabyte
GoogLeNet	96.49%	96.55%	96.43%	96.55%	5 minutes 35 seconds	512 Megabyte
MobileNet V2	98.25%	96.55%	100.00%	98.25%	3 minutes 42 seconds	8.75 Megabyte
MobileNet V3	75.44%	62.07%	89.29%	72.00%	3 minutes 10 seconds	5.94 Megabyte
ResNeXt-50	92.98%	100.00%	85.71%	93.55%	5 minutes 15 seconds	88.0 Megabyte
ShuffleNet V2	78.95%	65.52%	92.86%	76.00%	3 minutes 37 seconds	20.6 Megabyte
ConvNeXt	96.49%	100.00%	92.86%	96.67%	23 minutes 25 seconds	748 Megabyte

Images | **Heatmaps and Predicted Classes** | **Images** | **Heatmaps and Predicted Classes**

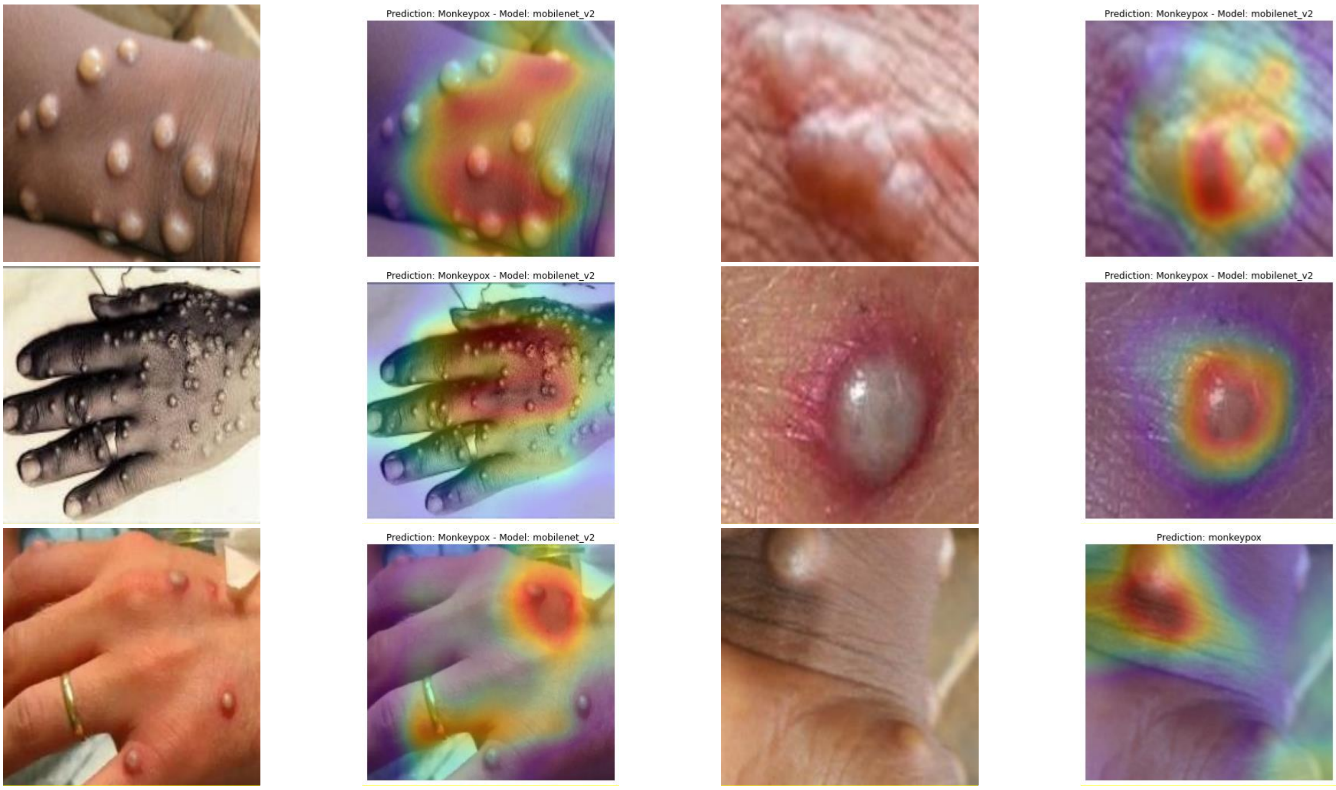

Figure 2. Heatmaps and predicted classes obtained by MobileNet V2

5. Conclusion

In this study, ResNet-18, ResNet-50, VGG-16, Densenet-161, EfficientNet B7, EfficientNet V2, GoogLeNet, MobileNet V2, MobileNet V3, ResNeXt-50, ShuffleNet V2, and ConvNeXt models were used to perform classification of Monkeypox skin lesion. In comparative analysis, MobileNet V2 model achieved best performance with the accuracy of 98.25%, sensitivity of 96.55%, specificity of 100.00% and F1-Score of 98.25%. This model was used for explainable artificial intelligence. Thus, the classification decision of the classification model was explained. Also, this model can be used on mobile devices as the size of weight file of MobileNet V2 is small. Thus, if monkeypox turns into a pandemic, patients can test themselves at home. As a result, a caused by the pandemic workload on health employees can be avoided.

6. Acknowledge

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