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Monkeypox Skin Lesion Detection with Deep Learning Models and Development of Its Mobile Application

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Abstract
The COVID-19 pandemic, which left its mark on the 21st century, has spread to large areas all over the world. While COVID-19 has not ended yet, the monkeypox virus began to spread rapidly worldwide. This situation has led to the search for many different methods for the rapid and effective diagnosis of diseases caused by viruses. Scientists who start off from this problem have obtained successful results by using several methods such as image processing, deep learning, and machine learning for diagnosis. With this motivation, this study aims to perform the prediction of skin lesions in the patient via deep learning architectures for the diagnosis of Monkeypox disease. A dataset containing images from cases infected with monkeypox virus and other skin disorders was used. Images were classified separately with VGG16 and VGG19 CNN models and their success performances were compared. Furthermore, it was observed that the success increases with the transfer learning and fine-tuning processes on these architectures. As a result, the VGG19 model exhibited the highest classification accuracy with 97.81%. Fine- tuning VGG19 model, which is the most successful model with Grad-CAM method, focused on the images were analyzed.
Keywords: *Monkeypox, VGG16, VGG19, fine-tuning, disease diagnosis*

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I. INTRODUCTION

Linear alkyl benzene (LAB) is a family of organic compounds with $C_6H_6 - C_nH_{2+1}$ C_nH_{2+1} (n is between 10 and 16). The $C_{12} - C_{15}$, $C_{10} - C_{13}$ LABs are used for detergent production and are produced by the reaction between paraffins and Benzene [5]. LABs are currently being used as a liquid scintillator in neutrino detector due to its good optical transparency, its high yield, low amount of radioactive impurities and high flash points [5]. It is also a suitable material that is being used in a secret Neutrino Interaction Finder (SNIF), it is also used as an antineutrino detector design to detect the presence of nuclear reactor at a distance of 100 – 500KM [5].

Public health officials argue that monkeypox rings the bell of a new pandemic. Monkeypox, a contagious disease, was reported in 75 countries recently. The first monkeypox case was reported in 1970 in the Democratic Republic of the Congo. The disease has symptoms similar to chickenpox, but they are less severe compared to it, and fever and flu-like symptoms [1, 2]. After these symptoms, monkeypox appears as skin rashes on the face area and then spreads to other parts of the body. In some cases, the lesions involve hundreds of exanthema that spread throughout the body, while these exanthemas are fewer in some patients [3]. Monkeypox symptoms usually last between 2 and 4 weeks. The severity of the disease varies according to the degree of exposure to the virus, the patient's health status, and complications. The incubation period of the virus ranges between 5 and 21 days and may appear at different times according to the patients [4].

Currently, unfortunately, there is no registered treatment method specific to monkeypox. However, some drugs used in the treatment of smallpox can be used. For this reason, until proven otherwise, treatment methods used in orthopoxvirus infections are used in the prevention and treatment of monkeypox disease [5].

The World Health Organization (WHO) is taking various initiatives to prevent the further spread of monkeypox. Hence, early diagnosis of the disease is quite significant. Ensuring that patients isolate themselves in case that the symptoms become visible is one of the major initiatives to reduce the spread of the disease [6].

For the diagnosed case, real-time polymerase chain reaction (PCR) tests are used in certain centers to detect non-variola Orthopoxvirus (NVO) in the patient. Unfortunately, the late results due to the high number of tests may increase the contagiousness [7]. For this reason, rapid and reliable alternatives are required for diagnosis.

Although PCR tests have been frequently used in the diagnosis of the COVID-19 pandemic especially, they have many disadvantages that make diagnosis difficult. And, the biggest disadvantage is the difficulty of reaching PCR tests for many countries, as the pandemic has spread to a large extent. Another disadvantage is the necessity of sampling from the nasal and throat mucosa, which makes it difficult to perform the test. Due to the need for a specialist health officer to examine the samples, many patients refuse to give samples in cases where the number of experts is insufficient [8].

In order to meet the requirements in various areas, many new searches have been tried to respond with the development of computer technologies. Artificial intelligence, which is one of these technologies, is used in many areas such as the medicine [9], agriculture [10], finance [11], and science [12]. When examined in more detail in the field of medicine, it is seen that machine learning and deep learning, among sub-branches of artificial intelligence, give successful results in many areas such as skin cancer [13], COVID-19 [14], breast cancer diagnosis [15].

Today, while the development of computer technologies having great impacts in various fields, it also allows applications to be used with more portable and smaller devices. Mobile devices, which can perform many tasks with computers, have become an indispensable part of today. Thanks to phones, tablets, and wearable mobile devices, numerous processes such as personal health monitoring, image processing, and engineering tasks can be performed. In particular, the achievements obtained during the COVID-19 pandemic demonstrate that computer technologies have significant impacts on the health services [16, 17].

This study aims to help reduce the spread of the monkeypox virus by making artificial intelligence technologies available for the early diagnosis of the disease. The purpose is to determine whether the lesions are caused by monkeypox in skin images taken by smart devices by utilizing mobile applications in the use of deep learning models. In this way, it is expected to reduce the workload of healthcare officers in case of a possible monkeypox pandemic and to prevent the spread of the virus by providing self-isolation of infected cases with an application providing possible accurate results within a very short time. Another motivation of the study is that there is no application in the literature for the diagnosis of monkeypox disease at a time when mobile devices, where many processes can be performed, are widely used. It is thought that this software will play a key role in case monkeypox is declared a pandemic in the world.

In the study, the following procedures were carried out in order:

- Images in the dataset are split into train-validation-test (70%-20%-10%).
- Training and testing of VGG16 and VGG19 models were carried out using images.
- Fine-tuning process was applied to VGG16 and VGG19 models in order to increase the classification success.
- Training and testing of fine-tuning VGG16 and VGG19 models were carried out.
- Images were analyzed using the Grad-CAM method to ensure that the most successful model, the fine-tuning VGG19 model, focused on the monkeypox skin lesion area in the images.
- The effectiveness of the models used in the study was compared with other studies in the literature, and an objective result was obtained.

The contributions of the study to the literature are as follows:

- Monkeypox skin lesion detection will be done through images, and the density of health institutions will be reduced.
- Thanks to the mobile application, monkeypox skin lesion can be diagnosed individually.
- The proposed models can be used in the diagnosis of other skin diseases through images.
- CNN models used in the mobile application will be trained for different skin diseases and can be used in the diagnosis of diseases.

The planning of the study is as follows: In the second section, studies related to this study are included in the literature. In the third section, information about the dataset, methods and performance metrics used in the study is given. In the fourth section, information about the training, testing and performance of the models is given. In the fifth section, the results obtained from the study, recommendations and contributions of the study are given.

II. RELATED WORKS

In the literature, the number of studies on the monkeypox virus, which is closely followed by the World Health Organization (WHO), is not yet at a sufficient level. Although limited, both current studies and studies conducted by using images obtained for some diseases in the field of medicine are mentioned below. The motivation of the study ensured the development of the most appropriate system by using images of the monkeypox virus and based on previous studies conducted with images of some other diseases.

Ali et al. created a dataset that included images of skin lesions caused by the monkeypox virus. Images were obtained from websites, news portals, and publicly available case reports. The deep learning architectures in which they performed 3-fold cross-validation, ResNet50, VGG16, and InceptionV3, achieved an overall accuracy of 82.96% (±4.57), 81.48% (±6.87), and 79.26% (±1.05), respectively [18].

Ahsan et al. tested machine learning and deep learning architectures to diagnose the case, with images of monkeypox cases they obtained from the web. The datasets consisted of 1915 images augmented with 161 raw images from monkeypox, chickenpox, measles, and healthy skin. With the VGG16 deep learning architecture, a classification accuracy of 97% (±1.8) (AUC = 97.2) was achieved in the classification performed on the raw data first, while the classification accuracy obtained in the classification performed with the augmented images was 88% (±0.8) (AUC = 0.867) [19].

Islam et al. used a dataset of 39,396 augmented 6-class images of Monkeypox, Chickenpox, Smallpox, Cowpox, Measles, and healthy skin for the diagnosis of the monkeypox virus. Using ResNet50, InceptionV3, DenseNet121, MnasNet-A1, MobileNet-V2, ShuffleNet-V2-1×, and SqueezeNet, among CNN deep learning architectures, for monkeypox diagnosis, an average classification accuracy of 84% was achieved [2].

Due to the low spread of the monkeypox virus, the images obtained and the studies in the literature are not yet at a sufficient level. Studies on some diseases in the literature inspired our study, and their results are as follows.

Benyahia et al., first, used 17 previously trained CNN architectures to classify datasets containing various forms of skin lesions named ISIC 2019 and PH2, which are frequently used in the literature. Then, they classified these datasets with the help of 24 machine learning classifiers. According to the results, the accuracy of image classification in ISIC 2019 and PH2 datasets are 92.34% and 99%, respectively [20].

Qin et al. used generative adversarial networks (GAN)-based data augmentation technique on a small number of image sets for the classification of skin lesions. They evaluated the classification performance of the synthetic data they produced via the GAN with the Inception Score (IS), Fréchet Inception Distance (FID), Precision, and Recall performance metrics. They achieved 95.2% classification performance by augmenting the images in the ISIC 2018 dataset with GAN [21].

In their study, Yap, Yolland, and Tschandl presented a method that combines multiple imaging modalities and patient metadata to improve the performance of automatic skin lesion diagnosis. As a result of the study, they achieved high performance in both dual-class skin cancer and multi-classification, compared to the other studies. It was observed that dermatoscopic images performed better than macroscopic images [22].

In the study conducted by Allugunti, it was tried to classify over 1000 images of more than 150 patients with and without breast cancer, which were obtained from the internet, by using deep learning and machine learning architectures. At the end of the study, 99.67% accuracy was achieved with CNN architecture. Respectively, 89.84% and 90.55% classification accuracies were achieved with the support vector machine architecture and random forest architectures, among the machine learning architectures [23].

One of the main sources of motivation for this study has been the studies on the diagnosis of COVID-19. In the study of Ismael and Şengür, in which x-ray device images of healthy and COVID-19 cases were used, the classification accuracy of up to 94.7% was achieved with the ResNet50 deep learning and SVM machine learning architectures [24].

Sahin et al., have developed an Android mobile application that uses deep learning to detect monkeypox disease in their studies. Video footage collected through the camera of the mobile device, deep convolutional neural network running on the same device tested and sent to the user from the application screen is transmitted to the result as negative or positive. They used the MSLD data as the data set. They conducted experiments on Matlab using different pre-trained networks for model trainings and tests. They stated that they reached the highest classification accuracy of 91.11% with the MobileNetV2 model in the experimental results [25].

In the study of Haque et al., they integrated transfer learning-based deep learning architectures together with the convolutional block attention module (CBAM) for the classification of monkeypox disease. They applied VGG19, Xception, DenseNet121, EfficientNetB3 and MobileNetV2 deep learning models with integrated channel and spatial attention mechanisms and presented a comparative analysis between them. Monkeypox used a two-class dataset of 3192 images, 1428 and the others 1764. In this study, the highest classification accuracy was obtained with the Xception-CBAM-Dense model with 83.89% [26].

Sitaula and Shahi compared 13 different pre-trained deep learning models for early detection of monkeypox disease. They have fine-tuned each model by adding custom layers that are universal. The dataset they used consists of 1754 images, 329 for chickenpox, 286 for measles, 578 for monkeypox, and 552 for normal skin. They reported that they achieved 87.13% classification accuracy in their proposed model [27].

Studies on the monkeypox virus in the literature and the characteristics of this study are summarized in Table 1. When compared to other studies, it is seen that the reason for achieving higher accuracy is the fine-tuning performed in CNN architectures, although the same models are used.

Table 1: Summary of studies on monkeypox in the literature

References	Class	Number of images	Augmented Images	Models	Accuracy
Sahin et al. [25]	Monkeypox Other	102 126	1428 1764	MobileNetV2	91.11%
Haque et al. [26]	Monkeypox Other	102 126	1428 1764	Xception-CBAM-Dense	83.89%
Sitaula et al.	Chickenpox Measles Monkeypox Normal	329 286 587 552	-	Ensemble approach	87.13%
Ali et al. [18]	Monkeypox Other	102 126	1428 1764	ResNet50 VGG16 InceptionV3	82.96%(±4.57) 81.48%(±6.87) 79.26%(±1.05)
Ahsan et al. [19]	Monkeypox Chickenpox Measles Normal	43 47 17 54	587 329 286 552	VGG16	97% (±1.8)
Islam et al [2]	Monkeypox Chickenpox Smallpox Cowpox Measles Healthy	117 178 358 54 47 50	5733 8722 17.542 2646 2303 2450	ResNet50 Inception-V3 DenseNet121 MnasNet-A1 MobileNet-V2 ShuffleNet-V SqueezeNet	72% 71% 78% 72% 77% 79% 65%
Our Work	Monkeypox Other	102 106	1428 1764	VGG16 VGG19	96.87% 97.81%

III. MATERIAL AND METHODS

In this chapter, the dataset and methods used in the study are explained. The images in the Monkeypox dataset were classified by four different models. The flowchart of the path followed in the study is shown in Figure 1.

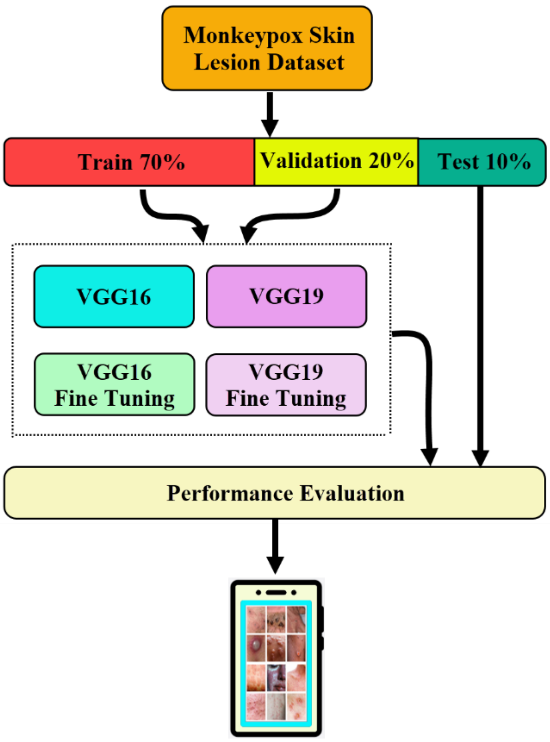

Figure 1: Flow chart of monkeypox classification

3.1 DATASET AND DATA SPLITTING

Monkeypox Skin Lesion Dataset used in the study was taken from kaggle.com [28]. Images were collected manually from news portals and websites. There are 2 classes in the dataset: Monkeypox and Non-Monkeypox skin lesion [18]. Sample images according to the classes in the dataset are shown in Figure 2.

Figure 2: Sample images

Due to the small number of data in the dataset, the augmentation process was applied to the images. Augmentation was performed to obtain 13 different variations of each image. The number of original images and augmented images can be seen in Table 2.

Table 2: Sample images of dataset and number of images

	Original Images	Augmented Images
Monkeypox	102	1428
Non-Monkeypox	126	1764

In order to analyze the classification accuracy of the models used in the study in detail, the dataset was split into 70% training, 20% validation, and 10% test set.

3.2 CONVOLUTIONAL NEURAL NETWORK (CNN)

Computer vision and image recognition are among the most popular applications in the medical field [29, 30]. In order to make sense of the images, their features must be extracted and classified by machine learning methods [31]. However, interpreting images is a quite difficult process. For this reason, CNN deep learning architectures have recently become frequently used in terms of success and usability. There are features that make CNN architectures very advantageous compared to other image processing and classification methods [32]. Due to the pixel density in most images, pixel values may not be given as input to a machine learning method. Pre-processes such as feature extraction and feature reduction may be needed before classification. However, CNN architectures can classify by extracting features from the raw image and reducing features within themselves [33]. This provides advantages in terms of both labor and time. In Figure 3, the general structure of the CNN architecture is shown.

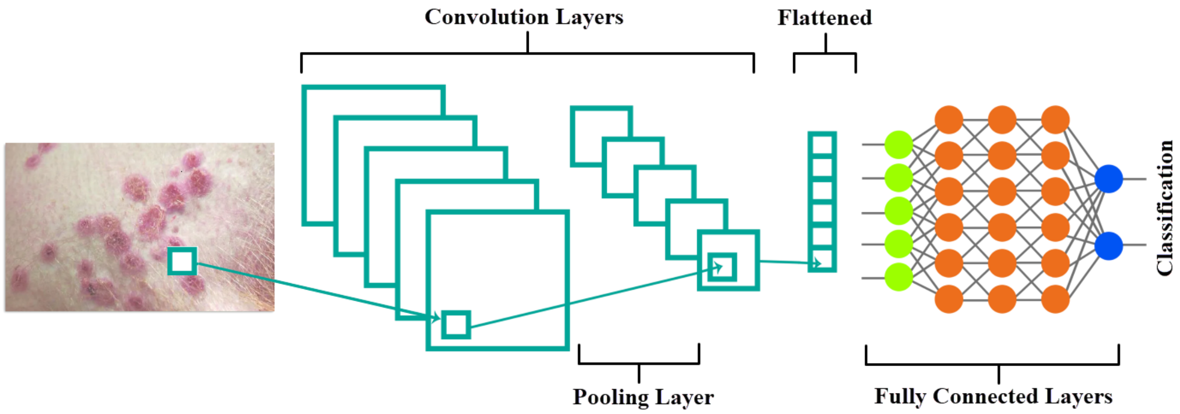

Figure 3: CNN components and general representation

The convolution layer creates feature maps by advancing on the image with the filters it contains. The generated feature maps are matrices containing positive and negative pixel values [34]. The activation layer after this layer, Rectified Linear Unit (ReLU), takes the output from the convolution layer as input and sends the positive inputs as output to the other layer. If the input value is negative, the ReLU output is 0. Thanks to the activation function, the features are simplified and the calculation time of the model is reduced. The data from the ReLU layer is taken as input in the pooling layer. The size of the input is reduced via this layer. In the flatten layer, which is the layer before the last layer, the data is reduced to one dimension and adjusted so that it can be given as input to the next layer. The last layer of the CNN architecture, the fully connected layer, is a kind of neural network and the classification processes are performed in this layer [34].

The Leaky ReLU function used in fine-tuning processes in the study is an activation function. Since ReLU can generate values in the range of 0-1, it can only be used in the hidden layer. Because of this feature, all negative inputs die in the ReLU function and no negative gradient flow occurs. Being called the dying ReLU problem, this problem degrades performance in the case many dead neurons exist in the neural network. The Leaky ReLU function causes a leak, so a small number of negative inputs are transmitted as outputs. Leaky ReLU can contribute to improving performance by expanding the ReLU range [35].

3.3 TRANSFER LEARNING AND FINE-TUNING

In the CNN architecture, the weights are updated after each iteration during the training process. The network may encounter the overfitting problem in training CNN architectures created from scratch with small datasets [36]. Therefore, using pre-trained CNN models that have been previously trained with large datasets is an alternative to avoid this problem. Moreover, in the use of pre-trained models, more successful results are usually obtained since the network has weights belonging to the previous training [37]. Pre-trained models can be used in the training of different datasets with the transfer learning method. Fine-tuning processes are carried out in order to adapt these models to new datasets. In this way, proven models can be easily used in different datasets [38]. Within the scope of this study, VGG16 and VGG19 pre-trained models were used with fine-tuning.

3.4 VGG16 AND VGG19 CNN PRE-TRAINED MODELS

VGG16 CNN architecture has 16 layers. The VGG16 pre-trained model is trained with 14 million images with a total of 1000 classes. The size of the input image is 224x224x3. It includes 2 convolution layers, a max pooling followed by 2 convolution layers and 1 max pooling. After these layers, there are 3 more convolution layers, 1 max pooling layer, 3 convolution layers, and 1 max pooling layer [39]. The data is sent to the fully connected layer after feature extraction and feature reduction in these layers. Convolution filter sizes are 3x3, pooling filter sizes are 2x2, and stride value is 2 [40]. The VGG19 model is similar to the VGG16 model and includes 3 additional convolution layers. The activation function of these architectures is ReLU. In the study, the architectures were trained by using the dataset with the transfer learning method. For this process, the output of the fully connected layer in the last layer was set to 2 according to the number of classes in the dataset of the study [41]. Following this step, all ReLU layers in the models were fine-tuned with Leaky ReLU. In the study, the performances of pre-trained VGG16, VGG19, VGG16 fine-tuning, and VGG19 fine-tuning models were compared.

3.5 CONFUSION MATRIX

A confusion matrix is a table used to measure the performance of algorithms. Performance metrics of classification models can be calculated over the values on the complexity matrix [42]. These matrices make it possible to get insight into what kind of errors the classification model makes. There are (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values on the matrix [42]. One axis of the matrix shows the actual class values, while the other axis shows the predicted class values. A two-class confusion matrix is shown in Figure 4.

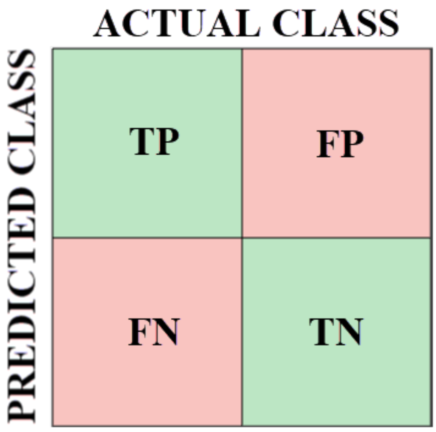

Figure 4: Two-class confusion matrix

3.6 EXPERIMENTAL SETUP

All models used in the study were trained by using 64 GB memory, a 3.61 GHz Intel I7-12700K processor, and NVIDIA RTX 3080 Ti graphics processing unit (GPU). Network training parameters common to all models are given in Table 3.

Table 3: Training parameters for all models

Solver	Initial Learn Rate	Validation Frequency	Max Epochs	Mini Batch Size
sgdm	0.0001	5	8	32

For all models, the parameters of the optimized fully connected (FC) layer where classification is performed are given in Table 4. The scale value for the Leaky ReLU layer used in fine-tuned VGG16 and VGG19 models is set to 0.01.

Table 4. Optimized FC layer parameters for all models

Weight Learn Rate Factor	Weight L2 Factor	Bias Learn Rate Factor	Bias L2 Factor	Weight Initializer	Bias Initializer
1	1	1	0	glorot	zeros

IV. EXPERIMENTAL RESULTS

MATLAB application was utilized to create the models used in the study and perform the calculations. For all models used in the study, the dataset was divided into 70% training, 20% validation, and 10% testing. First of all, classification accuracies were obtained following the transfer learning process with VGG16 and VGG19 models. Figure 5 shows the training and validation charts for these models. Figure 6 gives confusion matrices. After the transfer learning process, fine-tuning was applied to the VGG16 and VGG19 models in order to increase classification accuracy. In addition to the standard transfer learning in fine-tuning, in both models, Leaky ReLU is preferred instead of the ReLU function used as the activation function, since it is thought to be a solution to ignoring the gradients after the use of the ReLU function. Figure 7 gives the training and verification graphics of the models after the fine-tuning process. In Figure 8, the confusion matrices are shown.

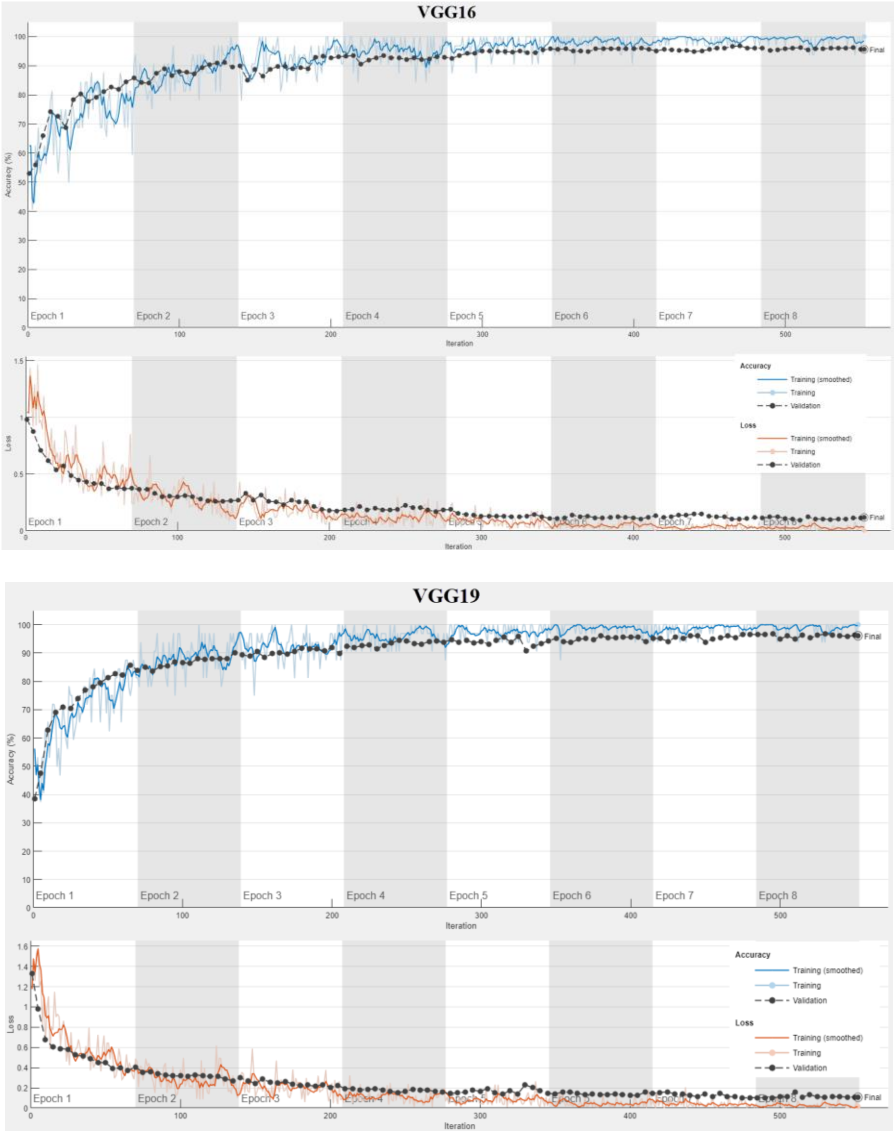

Figure 5: Training and validation charts after transfer learning of the models VGG16 and VGG19

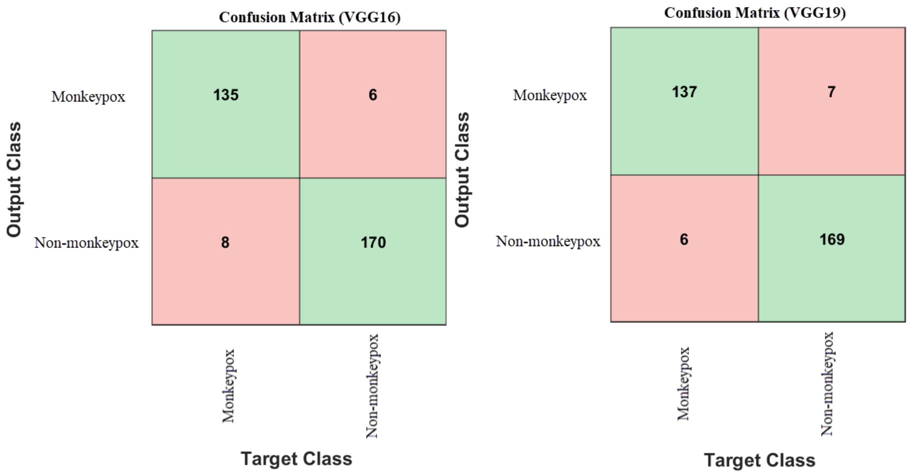

Figure 6: Confusion matrix of VGG16 and VGG19 models after transfer learning

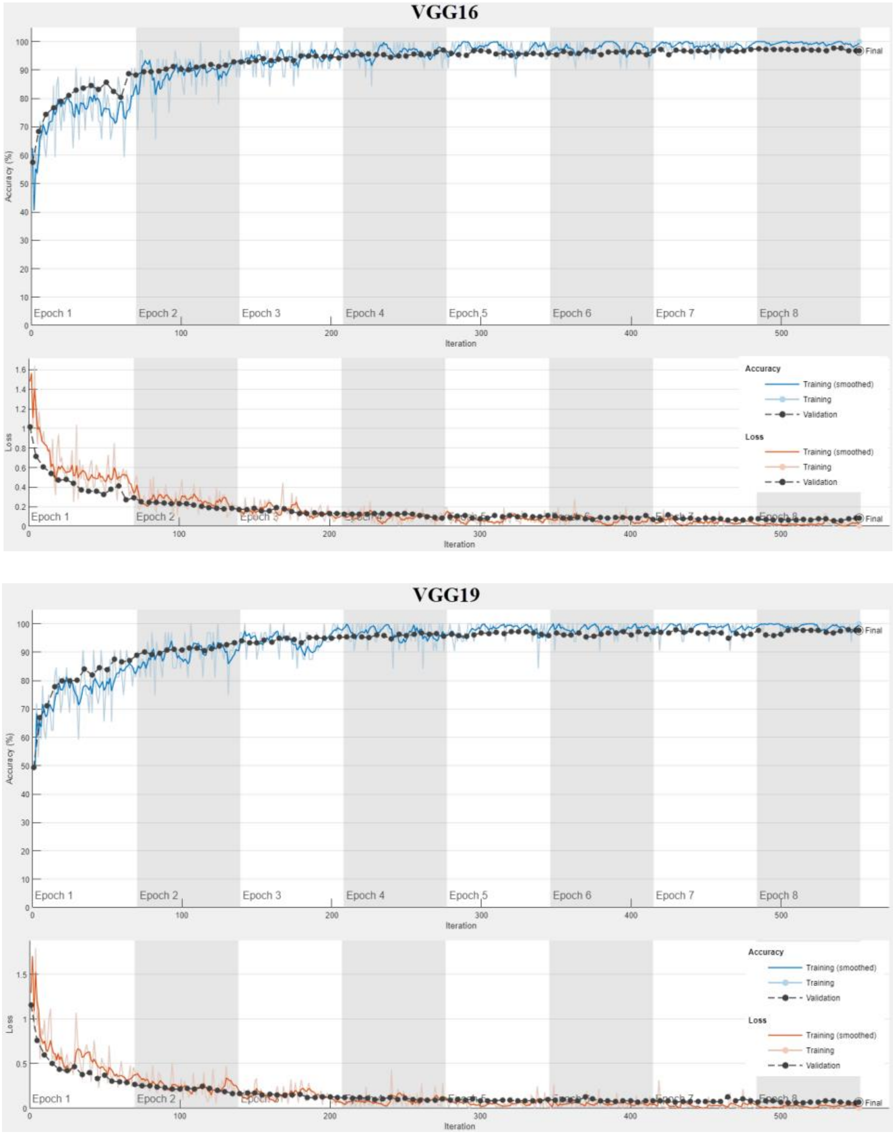

Figure 7: Training and verification graphs after fine-tuning of VGG16 and VGG19 models

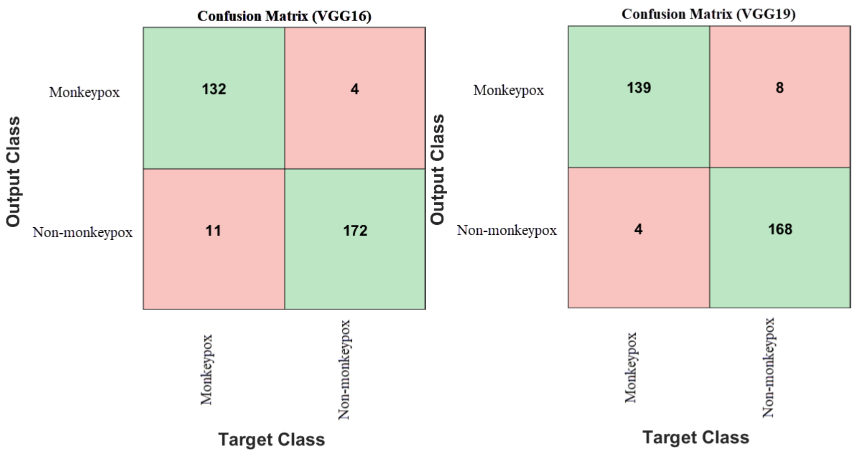

Figure 8: Confusion matrix of VGG16 and VGG19 models after fine tuning

Classification accuracies of the trained models are calculated according to Equation 1. The classification accuracies and training times obtained from these models are given in Table 5.

$$Accuracy = \frac{Number\ of\ correctly\ detected}{Total\ number\ of\ samples} \tag{1}$$

Table 5. Classification accuracies and training times of the models

	Model	Accuracy (%)	Training time
Transfer Learning	VGG16	95.61	15 min 11 sec
	VGG19	96.08	20 min 46 sec
Fine-Tunning	VGG16	96.87	6 min 42 sec
	VGG19	97.81	8 min 38 sec

According to Table 5, the highest classification accuracy belongs to the VGG19 model among the models in which both transfer learning and fine-tuning are performed. Also, validation accuracy was obtained as 100% for all models. It is seen that preferring the Leaky ReLU activation function together with the fine-tuning process applied to the models provides another positive gain, besides increasing the classification accuracies in both models. When the training times are examined, it is seen the training of the models was performed in a much shorter time with the applied fine-tuning. Although the training times performed in this study seem short due to the number of images in the dataset, it is inevitable to gain from training times for much larger data sets. As a result, the proposed models can detect monkeypox skin lesions in a quite short time with high accuracy of 97.81%.

Grad-CAM (Gradient-weighted Class Activation Mapping) is a deep learning visualization technique learned by a Convolutional Neural Network (CNN) model to understand the visual features that contribute most to the prediction of a given class. It provides a heatmap that highlights regions of an input image that the model considers important when making its estimation. The heatmap is produced by calculating the gradient of the target class against the feature maps in the final convolution layer and then taking a weighted average over all feature maps. Grad-CAM is useful for debugging, model interpretation, and improving model performance. Grad-CAM images of the VGG19 model are shown in Figure 9.

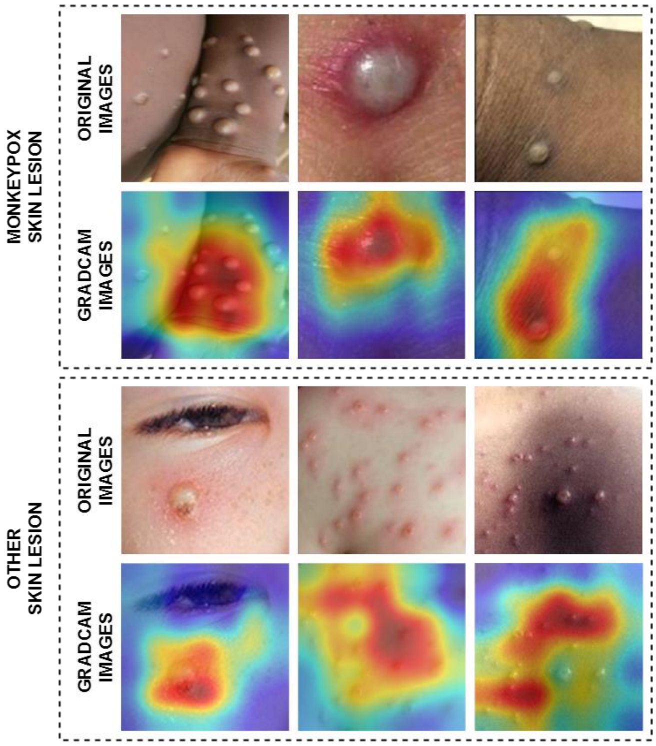

Figure 9: Grad-CAM images from model VGG19

According to Figure 9, it is seen that the VGG19 model focuses on the diseased areas on the skin while performing the classification processes. In the heat maps obtained, the red regions represent the regions where the model focused. The blue color shows the regions that it does not take into account. Grad-CAM images show that classification processes are performed by focusing on diseased areas in the skin.

With the created mobile application, users can perform the classification process by sending the snapshots taken from the camera or the images in the gallery of their mobile device to the server. The result of the sent image is transmitted from the server and information is presented to the user as “monkeypox” or “others” on the mobile app's screen. In Figure 10, images of the application are given.

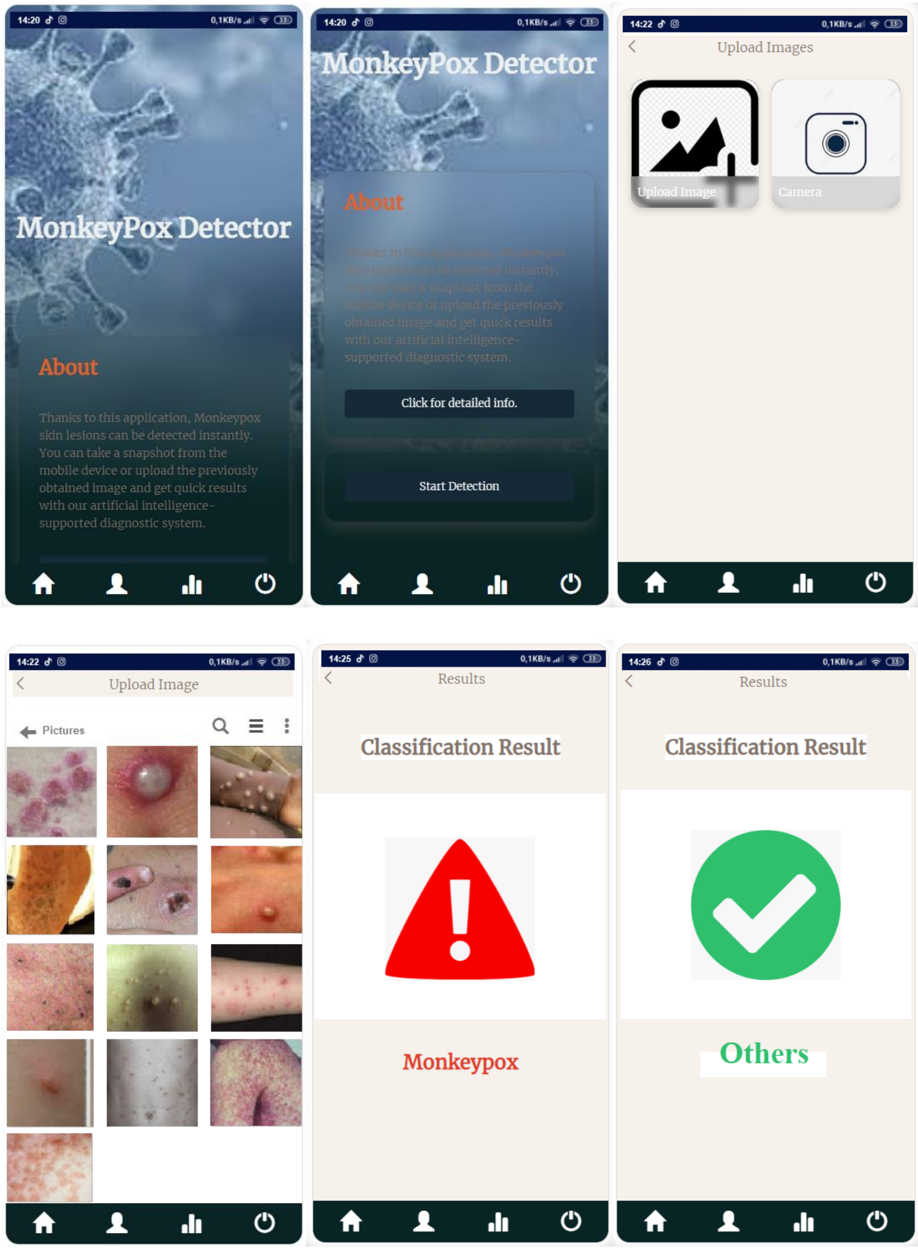

Figure 10: Monkeypox mobile application

V. CONCLUSION AND DISCUSSION

Within the scope of this study, two different CNN models were used in order to detect monkeypox skin lesion disease via images and the performance of the classification results obtained as a result of using these models in four different ways was evaluated. In the research, first, the deep features of the images were extracted via the pre-trained VGG16 and VGG19 deep learning models, and then classification processes were performed. In both of the models, 4096 features were extracted from the images. However, the highest classification accuracy belongs to the model VGG19 with more layers. In order to increase the classification performance of the models, fine-tuning was applied to the pre-trained models used in the study. The obtained results showed that the classification performance of both models increased after the fine-tuning process, while the training times decreased. After the fine-tuning process, the highest classification accuracy belongs to the VGG19 model again. Looking at the whole study, it can be stated that the highest classification accuracies were obtained from the fine-tuned models.

The fine-tuning VGG19 model proposed in the study showed higher performance than the models in other studies using the same dataset in the literature. Sahin et al. [25] and Ali et al. [18] they achieved the highest classification accuracy of 91% and 82.96%, respectively. In this study, the highest classification accuracy was 97.81%. The model has been shown to effectively classify the monkeypox skin lesion. The same model has been tried with images of different skin diseases and its effectiveness has been proven.

In the field of medicine, very small variations in classification accuracies in disease detection and diagnosis performed by machine learning and image processing methods are of great importance. With this study, decision support systems can be created that can help medical experts in the detection of a monkeypox skin lesion or another skin lesion disease. Moreover, via the adaptation of the classification models created to reduce the workload of paramedics to the mobile environment, systems that help people make preliminary self-diagnoses can be developed.

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