Monkeypox Skin Lesion Detection with Deep Learning and Machine Learning

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ABSTRACT
New outbreak diseases are taken under the great consideration of public health due to the frightful experience of COVID-19 in 2020. That is why Monkeypox disease manifestation in 2022 created awareness of all health-conscious. As before the outbreak of Monkeypox disease was known as African regional disease health professionals were lack of information about it. There had been about 79,151 confirmed cases in over 111 countries as of November. Monkeypox disease symptoms are closely resemble to other skin diseases like chicken pox, smallpox skin rashes which made the diagnosis challenging. Polymerase chain reaction (PCR), molecular biology protocols a rare tool to detect monkeypox disease. That's why Computer-based detection models will be helpful, affordable where Polymerase chain reaction in unavailable or expensive. With machine learning and deep learning many diseases even like COVID-19 have been successfully detected. Machine learning and deep learning approach have been performed to classify skin image normal, monkey pox, other class. Different pre-trained models of CNN along with CNN, ML and ensemble technique performed. Among all VGG19 come up with the highest accuracy, 99.52%. With VGG16 accuracy was 98.56%. Applying ResNet-50, DenseNet-121, InceptionV3, MobileNetV2, CNN hyper parameter accuracy reached about 86.06%, 90.86%, 99.04% and 99.04%,98.55% respectively.

Keywords
Monkeypox detection, skin lesion dataset, deep learning, CNN, Hyper parameter tuning, transfer learning, machine learning.

1. INTRODUCTION
Detection of diseases is a prerequisite for cure wherefore surveillance of diseases & rapid identification is very important. AI have been found effective in the automated detection of skin lesions. Considering all these aspects, in this paper. We proposed different deep learning model namely CNN pretrained model (VGG19, VGG16, ResNet-50, Inception V3, MobileNetv2, DenseNet-121) as well as different machine learning model as like – KNN, Random Forest, Decision tree.

2. BACKGROUND
In the Democratic Republic of the Congo, monkeypox was discovered for the first time in people in 1970. An ongoing outbreak, a viral disease confirmed in May 2022.In the past, it was only observed in specific places, and the cases were mostly limited to one family because the transmission from wild animals to humans was restricted and human-to-human transmission required close, prolonged contact. An increase in research on this virus has resulted from the recent appearance of cases with severe symptoms in more than 70 nations unrelated to the African continent, the virus's distribution area. According to the World Health Organization (WHO), this outbreak presents a medium danger to the general public's health (Riazul Islam, B.M. et al., 2022).

Recent years have seen a revolution in various fields, especially the variants of convolutional neural networks (CNNs). However, the use of DL-based frameworks is restricted by the need for substantial amounts of data and time-consuming training with specialized computational resources. Transfer learning is another method that is frequently employed when there is a lack of data (Yağanoğlu, M. et al., 2022).

2.1 Contribution
In this research, we used different preprocessing technique (Grabcut Algorithm, Otsu's method, resizing so on) for detection the Monkeypox skin lesion. Moreover, we applied different Deep learning model such as-CNN (Convolutional Neural Network), pretrained model & machine learning model to detect these infectious diseases. Overall CNN's pretrained model shown the highest accuracy.

3. LITERATURE REVIEW
Javed, R., Rahim, M.S.M., Saba, T. and Rehman, A., 2020. Work on skin lesion detection paper named A comparative study of features selection for skin lesion detection from Dermoscopy images. Here, they used optimal feature set selection for dermoscopic image-based diagnosis of melanoma in skin cancer. Depending on the size of the dataset available to them, different scholars have efficiently approached the feature extraction challenge.

Khan, M.A., Muhammad, K., Sharif, M., Akram, T. and de Albuquerque, V.H.C, 2021.Multi-class skin lesion detection and classification via teledermatology. Firstly, they are mainly used different dataset to detect skin cancer using segmentation technique. After lesion localization used different feature vector & CNN pretrained model for classification.

Khan, M.A., Akram, T., Zhang, Y.D. and Sharif, M., 2021.

Attributes based skin lesion detection and recognition: A mask RCNN and transfer learning-based deep learning framework. In this paper they used to achieve better performance on segmentation & CNN model like DenseNet201 model which is used to generate the features for classification method.

Md. Enamul Haque; Md. Rayhan Ahmed; Razia Sultana Nila; Salekul Islam 2022.Here, they have undertaken an image-based classification of the human monkeypox disease, concentrate on the area of feature maps .They deployed five deep learning models—VGG19, Xception,DenseNet121, EfficientNetB3, and MobileNetV2 conduct a comparison study among them. With a validation accuracy of 83.89%.

Nafisa Ali et al. mainly compiled a monkeypox skin lesion dataset using case reports, news portals & different sources where they collect 228 images dataset. They Primarily differentiate between similar cases of non-monkeypox such as (chickenpox, measles and other) for binary classification Additionally, for transfer learning, they used the pre-trained weights from the ImageNet dataset, which is devoid of photos of skin lesions.

In computer aided detection methods Irmak et al. used Monkeypox Skin Image Dataset, which was already available. After augmentation they used on different technique on image preprocessing then split the dataset according to train, test & validation. They have used different Transfer learning model where the best accuracy scores achieved on MobileNetV2 of 91.38% accuracy.

The author Kyamelia Roy, Sheli Sinha Chaudhuri, and others use a dataset of skin lesions divided into four categories. Here, they solely concentrated on several segmentation techniques such as K means clustering, morphological operation, and adaptive thresholding method. The result is represented by the SNR (signal-to-noise ratio).

In Computer base monkeypox diagnosis aid system Munoz-Saavedra et al. used publicly available dataset but they surveillance the drawbacks of previous dataset & balance the dataset using different method. In this paper the author mainly builds up CNN model (as ResNet50, VGG16 etc.) & composed those models using ensemble method. For CNN hyper parameter.

Islam et al. instead of Monkeypox Skin Image dataset the author compiled a dataset which consist with five classes. After collecting several lesions image, they used different preprocessing technique & performed different augmentation method. The classifiers proposed seven deep learning method (ResNet50, DenseNet121, InceptionV3, MobileNetV2, SqueezeNet, MnasNet-A1, ShuffleNetV2) composed those models using ensemble method.

The ISIC 2019 skin lesions dataset was used by the author MA Kassem, KM Hosny et al. GoogleNet was used to create the dataset. They altered the architectural layout of the GoogleNet by including additional filters in each layer in order to enhance features and reduce noise. The classification of the images is then done using a bootstrap multi-class support vector machine. Here, the classifier focused mostly on feature construction and fine-tuning the weights of all layers without using any pre-processing techniques.

In computer aided diagnosis purpose Islam et al. used primarily compiled dataset which contains five different diseases & comprehensive images of skin that had the measles, cowpox, chickenpox, monkeypox, and smallpox using web scraping. This database will aid in the development of baseline of ML and DL algorithms for early Monkeypox detection.

4. METHODOLOGY

In this section our primary focus of the research is system architecture. All researchers can understand the methods used in this study. We attempted to keep the system's structure as simple and understandable as possible. Here, firstly focus on different preprocessing method then augmented the dataset. In order to train test spilt is done & using train dataset to apply DL & ML model respectively. At last, using test dataset to evaluate the performance of the model.

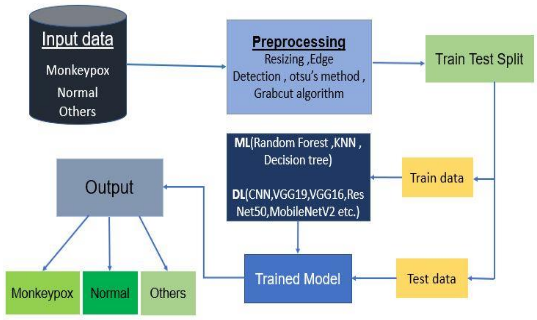

Figure 1: structure of the system

4.1 Dataset collection

We gather image information from several openly accessible environments & kaggle then compiled a dataset which consist with 1040 images of others, normal & monkeypox. For Deep Learning & machine Learning Algorithm Our train-shape & Test-shape contain different ratio of image data for better accuracy. Here, dataset splitting into different ratio of train test part to observe the performance of different model. Using different augmentation technique (Shifting, Horizontal flip, etc.) to enhance the dataset.

4.2 Image Preprocessing

With the help of image processing, we can remove undesirable noise and enhance certain attributes that are crucial for the application. Direct application of raw image in training section might make models confused by unwanted pixel value or features. Grabcut operation perform lesion segmentation using a thermoscopic image in four steps: 1. Removal of hairs on the lesion, 2. Detection of the lesion location, 3. Segmentation of the lesion area from the backgroun,4. post-processing with morphological operators. (Halil Murat Ünver et al.,2019).

1.1.1 Resizing image

Images can be resized without being cropped in order to be made smaller or larger. Resizing changes, the image's dimensions, which often has an impact on the image's file size and quality. We have used 224 X 224 resizing image.

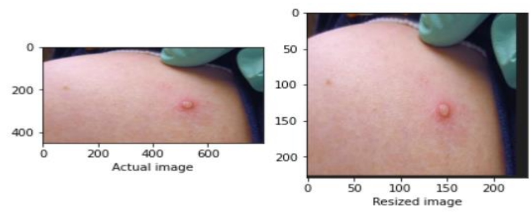

Figure2: Resizing Image

1.1.2 Grabcut Algorithm
GrabCut is a graph-cut-based technique for segmenting images. A user-specified bounding box around the object to be segmented serves as the initial point from which the algorithm estimates the color distribution of the target object and the background using a Gaussian mixture model (Halil Murat Ünver et al.,2019).

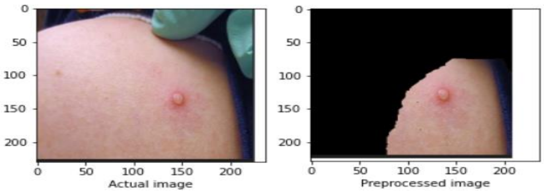

Figure 3: Using grabcut algorithm

1.1.3 Otsu's method
Otsu's method is used in computer vision and image processing to carry out automatic image thresholding. The algorithm returns a single intensity threshold in its most basic form, dividing pixels into the foreground and background classes. (Hoang et al., 2018)

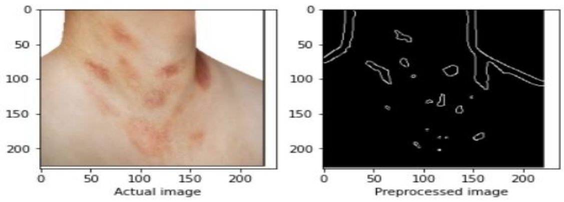

Figure 4: Using Otsu's method

4.3 Deep learning and Machine learning
In this session we have discussed about our applied model. After preprocessing technique, we applied CNN, VGG19, VGG16,ResNet50,InveptionV3,DenseNet121,MobileNet2,Ensemble(VGG16+VGG19+MobileNet+ResNet+DenseNet)from DL & KNN, Decision tree, Random Forest from ML.

4.4 Convolution Layer
To accomplish the convolution operation, a portion of the image is joined to the Convolutional layer as well as determining the dot product between the receptive field and the filter. Due to the fact that characteristics of the images are extracted within this layer, this layer is also known as feature extractor layer. The Result we get from the convolutional operation is single integer of the output volume. Via a Stride, we move the filter over the following receptive area of the identical input picture and repeat the process. Until we have completed the entire image, the same procedure will be repeated (Gogul et al., 2017). The input for the following layer will be the output. Generally, image data are given to the Input layer in CNN. Image data is represented by three-dimensional matrix. (224,224,3) is considered as the standard input shape of CNN where 224 X 224 is the height, width and 3 is the (red, green, blue) color channel. Additionally, the Convolutional layer has ReLU activation to set all negative values to zero.

4.5 Pooling Layer
After convolution, the spatial volume of the input image is reduced using a pooling layer. Between two convolution layers, it is employed. If fully connected layer has applied without applying pooling layer, then it will not be cost efficient which is unwanted. Max pooling, Average pooling are some different kinds of pooling category used for down or up sampling. In Max pooling operation determines the largest or maximum value present in each feature map patch. In average pooling average value is taken from the value present in each feature map patch. Parameter learning does not happen here. That is why we fine no learnable parameter in pooling layer. (Shahi, T.B et al., 2022)

4.6 Fully connected layer
The neural network uses fully connected layers after the application of convolutional and max pooling layers to level-up the analysis. There are neurons, weights, and biases in a fully linked layer (Shahi, T. B et al., 2022). Neurons in one layer are linked to neurons in another layer through this. It is employed to train users to classify photos into several categories.

4.7 SoftMax or logistic layer
The last CNN layer is found at the end of the fully connected layer. Binary categorization is performed using a logical function. Multiclass categorization uses the SoftMax function.

4.8 Tuning the hyper-parameter of the Layers
The first hyperparameter to tune is the number of neurons in each hidden layer. In this case, the number of neurons in every layer is set to be the same. It also can be made different. The number of neurons should be adjusted to the solution complexity. Different number of layer and other term. such as- optimizer selection for dense layer, dense number of epochs, activation function selection for each layer, train & validation split, change dropout rate in dense layer, batch size selection, Learning rate selection for different optimizer (Zhang H, Zhang et.al.,2019).

4.9 Optimizer
In order to get the lowest possible loss function, the optimizer must adjust the learning rate and weights of the neurons in the neural network. The best accuracy or least amount of loss is achieved by using an optimizer. Different optimizer that is Adagrad, Adamax, SGD, RMSprop, Adam, and Adadelta used to find out the best accuracy (Hasan, T. et al., 2022).

4.10 Learning rate
The learning rate is one of the optimizer's hyperparameters. We will adjust the learning rate as well. The step size required for a model to achieve the minimal loss function is controlled by learning rate. Although the model learns more quickly with a higher learning rate, it may miss the minimum loss function and merely reach its surroundings. Finding a minimum loss function has a greater chance with a lower learning rate (Hasan, T. et al., 2022). To lower loss function and get the optimal accuracy, different optimizers in different models employed varied learning rates.

4.11 Number of Epochs
The number of times a whole dataset is passed through the neural network model is referred to as epochs. One epoch means that the training dataset is passed forward and backward through the neural network once. A too-small number of epochs results in underfitting because the neural network has not learned enough. On the other hand, too many epochs will lead to overfitting where the model can be used for many different tasks (Galván-Tejada, C.E. et al., 2022).

4.12 Filter selection for each layer
To discover our model feature in our convolutional layer, we used various filters. In every layer we used different size of

filter to find out different feature. overall, our model includes all filter with specific activation function (Van Gool, L. et al., 2017).

4.13 Activation Function

Within each layer, a parameter is called an activation function. The input layer receives input data first, then hidden layers, and finally the output layer. The output value is located in the output layer. The input values constantly change as they transition from one layer to another in accordance with the activation function. How a layer's input values are converted into output values is determined by the activation function (Kligvasser, I. et al., 2018).

4.14 Dropout Layer

Another regularization layer is the Dropout layer. The dropout layer, as its name suggests, randomly drops a certain number of neurons in a layer (Andrianov, S.N. et al., 2014). The dropped neurons are not used anymore. The rate of how much percentage of neurons to drop is set in the dropout rate.

4.15 Train Test Split

The ratio of train test split is another important selection to predict the better accuracy. In our model according our spilt ratio shown the different accuracy for different selection. We did several train test ratios like 70% for training 30% for testing, 75% for training 25% for testing, 80% for training 20% for testing. From them 80% train set and 20 % test set seems to be the best ratio as it giving the highest accuracy in deep learning model and for machine learning we split 70% data as train data ,30 % into test data. We manually tuned the parameter in order to choose the optimum one.

4.16 Performance Analysis

In this section represent the Confusion Matrix which depicts and summarizes a classification algorithm's performance. Separating the number of precise forecasts from the total number of forecasts made allows for the measurement of accuracy. positive predictive value, Precision is the percentage of recovered instances that are relevant. The recall is the proportion of relevant search engine results returned to all relevant search engine results that could have been returned. Recall makes up a very small percentage of the true positive predictions among all the actual certain examples. The F1 Score is the Harmonic Mean between recall and precision. Between 0 and 1 is the F1 Score range. An alternate measurement to the more popular arithmetic mean is the harmonic mean. It frequently comes in handy when calculating an average rate. We calculate the average of precision and recall for the F1 score.

5. EXPERIMENTALSETUP AND RESULT

This chapter contains the discussion of the result of the experiment. The model's accuracy, a classification report, the accuracy of the training and validation, loss charting, and a confusion matrix will all be included. We must first understand evaluation metrics in order to comprehend the key concepts of my research. In this session represented the prediction result which are suitable for detection the following are some crucial evaluation metric points.

5.1 Layers and Filters Selection in CNN layer

We have selected different layer with various filter for prediction. In our model, we used three convolutional layers with different filters. We arranged our filter such as 32,64 & 128 are used to assumption the better accuracy.

5.2 Activation Function in CNN Layer

In order to optimize the better accuracy, we utilized various non-linear activation functions such as ReLU, Selu, tanh, and Elu in different layers in our convolution layer.

5.3 Number of Dense Layers

We used various hidden layers in our model to analyze the results. To get the best outcome, we used three hidden layers. Our model predicts with varying degrees of accuracy for different layers.

5.4 Dropout within Dense Layers

We have utilized a predetermined dropout rate with an appropriate optimizer in our fully connected layer. The accuracy score is provided in Table 2.

Table 2 Dropout rate in Dense Layers

Dropout Rate	Accuracy
0.1	0.8990
0.2	0.9087
0.3	0.9038
0.4	0.9081
0.5	0.9038

5.5 Activation Function in Dense Layer

We used different types of non-linear activation functions to the convolutional layer that are-ReLu, Selu, Elu, tanh. In our fully connected layer or dense layer, we use this different non-linear activation function. Given Table 3 shown the accuracy of our models.

Table 3: Performance-based on Activation Function.

Activation Function	Accuracy
ReLu	0.9615
Selu	0.9135
Elu	0.9038
tanh	0.9031

5.6 Performance based on Optimizer

We have used various type of optimizers that is Adagrad, Adamax, SGD, RMSprop, Adam, and Adadelta. Here, the accuracy table which the optimizer gives the highest accuracy.

Table 3: Performance-based on Optimizer.

Optimizer	Accuracy
RMSprop	0.8990
Adam	0.9135
SGD	0.8990

5.7 Final Activation Function in output layer

We used non-linear activation functions like Sigmoid and SoftMax in our output layer to examine the performance. When we used softmax our model represents better accuracy.

5.8 Learning Rate

In our model, we have used several learning rates controls the step size for a model to reach the minimum loss function. In our model, we have used several learning rates controls the step size for a model to reach the minimum loss function. such as (0.01,0.001,0.0001 etc.). In 0.00001 learning rate our model shown the better accuracy.

Table 5: Performance-based on learning rate.

Learning Rate	Accuracy
0.01	0.9231
0.001	0.9135
0.0001	0.9183
0.00001	**0.9615**
0.000001	0.9087

5.9 Batch size

Assigning a batch size will prevent the model from receiving all of the training data at once, which will hasten the learning process. The batch size is the total number of input training data samples.

Table 6: Performance-based on batch size.

Batch size	Accuracy
30	0.9183
20	0.9038
15	**0.9231**

5.10 Performance based on Train-Test Split.

For better assumption we split our dataset in different ratio. We divided the train dataset into several ratios for our model, such as (80%-20%,75%-25%,70%-30%) to analyze the model performance.

Table 7: Performance-based on the split ratio (DL)

Train spilt	Test spilt	Accuracy
80%	20%	**0.9663**
75%	25%	0.9231
70%	30%	0.9135

Table 8: Performance-based on the split ratio (ML)

Train spilt	Test spilt	Accuracy
70%	30%	**0.9294**
75%	25%	0.8923
80%	20%	0.8792

5.11 Comparison of Performance

Here, represents the comparison of the performance of our hyper parameter tuning CNN model with pretrained model & ensemble the model for analyzing the model performance based on accuracy Precision, Recall, and F-score. The given tables shown the comparison among different DL & ML model.

Table 7: result comparison of different models of DL

Name	Accuracy	Precision	Recall	F1-score
CNN	96.63	96.81	96.31	96.51
CNN (with Hyper parameter)	98.55	98.57	98.56	98.56
ResNet-50	86.05	87.78	86.06	85.67
DenseNet-121	90.86	92.39	90.87	90.80
MobileNetV2	99.04	99.07	99.04	99.04
Inception V3	99.04	99.07	99.04	99.04
VGG16	98.56	98.59	98.56	98.56
VGG19	99.52	99.53	99.52	99.52
Ensemble (VGG19+VGG16+ResNet50+MobileNet+DenseNet)	98.08	96.05	98.65	97.87

Table 8: Comparison of Performance for ML

Name	Accuracy	Precision	Recall	F1-score
KNN	78.52%	80.00%	79.00 %	78.00%
Decision Tree	90.06%	90.00%	90.00 %	90.00%
Random Forest	92.94%	94.00%	93.00 %	93.00%

Graphical representation shown the efficiency of the model. In our model we analyze different accuracy and loss graph. Here we given the best one to ascertain our prediction.

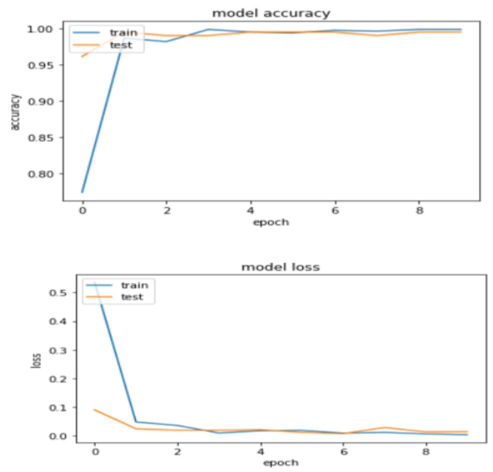

Figure 3: model's Accuracy & loss graph

Table 9 Classification report for Hyper parameter tuning-CNN model.

	precision	recall	f1-score	support
Monkeypox	0.9841	1.0000	0.9920	62
Normal	1.0000	1.0000	1.0000	72
Others	1.0000	0.9865	0.9932	74
accuracy			0.9952	208
macro avg	0.9947	0.9955	0.9951	208
weighted avg	0.9953	0.9952	0.9952	208

6. CONCLUSION

This research's primary objective is to simplify a system for computer aided detection system so that everyone may quickly integrate it. In here, we have detected the Monkeypox diseases using Deep learning model CNN with pretrained model such as VGG19, VGG16, ResNet50, MobileNetV2, AlexNet, InceptionV3, DenseNet121 & also composed different model using ensemble & Machine learning model such as Random Forest (RF), Decision Tree & K-nearest neighbors (KNN). Due of the rarity of the available online, therefore, we have compiled a Monkeypox skin lesion dataset which mainly created by using online source. Then proposed Augmentation method for enhance the size of dataset. Then we used many preprocessing techniques such as resizing, edge detection, Morphological operation, Clustering, Grabcut algorithm etc. Finally, we have achieved 99.52% accuracy using different DL model.

7. REFERENCES

[1] Irmak, M.C., Aydin, T. and Yağanoğlu, M., 2022, October. Monkeypox skin lesion detection with MobileNetV2 and VGGNet models. In *2022 Medical Technologies Congress (TIPTEKNO)* (pp. 1-4). IEEE.

[2] Gogul, I. and Kumar, V.S., 2017, March. Flower species recognition system using convolution neural networks and transfer learning. In *2017 fourth international conference on signal processing, communication and networking (ICSCN)* (pp. 1-6). IEEE.

[3] Sitaula, C. and Shahi, T.B., 2022. Monkeypox virus detection using pre-trained deep learning-based approaches. *Journal of Medical Systems*, *46*(11), p.78.

[4] Wang, Yulong, Zhang H, and Zhang G PSO- CNN: An efficient PSO-based algorithm for fine- tuning hyper-parameters of convolutional neural networks”. In: Swarm and Evolutionary Computation 49, pp. 114–123 (2019). teledermatology. IEEE journal of biomedical and health informatics, 25(12), pp.4267-4275.

[5] teledermatology. IEEE journal of biomedical and health informatics, 25(12), pp.4267-4275.

[6] Smirnov, E.A., Timoshenko, D.M. and Andrianov, S.N., 2014. Comparison of regularization methods for ImageNet classification with deep convolutional neural networks. *Aasri Procedia*, *6*, pp.89-94.

[7] Lettry, L., Perdoch, M., Vanhoey, K. and Van Gool, L., 2017, March. Repeated pattern detection using CNN activations. In *2017 IEEE Winter Conference on Applications of Computer Vision (WACV)* (pp. 47-55). IEEE.

[8] Irmak, M.C., Aydin, T. and Yağanoğlu, M., 2022, October. Monkeypox skin lesion detection with MobileNetV2 and VGGNet models. In *2022 Medical Technologies Congress (TIPTEKNO)* (pp. 1-4). IEEE.

[9] teledermatology. IEEE journal of biomedical and health informatics, 25(12), pp.4267-4275.

[10] Hussain, M.A., Islam, T., Chowdhury, F.U.H. and Islam, B.R., 2022. Can artificial intelligence detect monkeypox from digital skin images? *BioRxiv*, pp.2022-08.

[11] Sahin, V.H., Oztel, I. and Yolcu Oztel, G., 2022. Human monkeypox classification from skin lesion images with deep pre-trained network using mobile application. *Journal of Medical Systems*, *46*(11), p.79.

[12] Ünver, H.M. and Ayan, E., 2019. Skin lesion segmentation in dermoscopic images with combination of YOLO and grabcut algorithm. *Diagnostics*, *9*(3), p.72.

[13] Sahin, V.H., Oztel, I. and Yolcu Oztel, G., 2022. Human monkeypox classification from skin lesion images with deep pre-trained network using mobile application. *Journal of Medical Systems*, *46*(11), p.79.

[14] Alcalá-Rmz, V., Villagrana-Bañuelos, K.E., Celaya-Padilla, J.M., Galván-Tejada, J.I., Gamboa-Rosales, H. and Galván-Tejada, C.E., 2022, November. Convolutional neural network for monkeypox detection. In *Proceedings of the International Conference on Ubiquitous Computing & Ambient Intelligence (UCAmI 2022)* (pp. 89-100). Cham: Springer International Publishing.

[15] Bibaeva, V., 2018, September. Using metaheuristics for hyper-parameter optimization of convolutional neural networks. In 2018 IEEE 28Th international workshop on machine learning for signal processing (MLSP) (pp. 1-6). IEEE.

[16] Haque, M.E., Ahmed, M.R., Nila, R.S. and Islam, S., 2022, December. Human Monkeypox Disease Detection Using Deep Learning and Attention Mechanisms. In *2022 25th International Conference on Computer and Information Technology (ICCIT)* (pp. 1069-1073). IEEE.

[17] Muñoz-Saavedra, L., Escobar-Linero, E., Civit-Masot, J., Luna-Perejón, F., Civit, A. and Domínguez-Morales, M., Monkeypox Diagnostic-Aid System with Skin Images Using Convolutional Neural Networks. *Available at SSRN 4186534*.

[18] assem, M.A., Hosny, K.M. and Fouad, M.M., 2020. Skin lesions classification into eight classes for ISIC 2019 using deep convolutional neural network and transfer learning. *IEEE Access*, *8*, pp.114822-114832.

[19] Islam, T., Hussain, M.A., Chowdhury, F.U.H. and Riazul Islam, B.M., 2022. A web-scraped skin image database of monkeypox, chickenpox, smallpox, cowpox, and measles. *bioRxiv*, pp.2022-08.

[20] Wang, Y., Zhang, H. and Zhang, G., 2019. cPSO- CNN: An efficient PSO-based algorithm for fine-tuning hyper-parameters of convolutional neural networks. *Swarm and Evolutionary Computation*, *49*, pp.114-123.

[21] Hoang, N.D., 2018. Detection of surface crack in building structures using image processing technique with an improved Otsu method for image thresholding. *Advances in Civil Engineering*, *2018*.

[22] Javed, R., Rahim, M.S.M., Saba, T. and Rehman, A., 2020. A comparative study of features selection for skin lesion detection from dermoscopic images. *Network*

Modeling Analysis in Health Informatics and Bioinformatics, *9*, pp.1-13.

[23] Kligvasser, I., Shaham, T.R. and Michaeli, T., 2018. xunit: Learning a spatial activation function for efficient image restoration. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 2433-2442).

[24] Khan, M.A., Akram, T., Zhang, Y.D. and Sharif, M., 2021. Attributes based skin lesion detection and recognition: A mask RCNN and transfer learning-based deep learning framework. Pattern Recognition Letters, 143, pp.58-66.