IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Detection of Monkeypox Disease and Prediction of its Level

[1]Nikunj Shrimali, [2]Dr. Bela Shrimali

[1]Student, [2]Assistant Professor,
[1]Master of Computer Engineering,
[1]LDRP-ITR, Gandhinagar, India

Abstract: As monkeypox spreads quickly around the world, it has become a public health concern since it has been detected in more than 75 countries so far. In an early stage, it is difficult to differentiate monkeypox from Chickenpox, Cowpox, Smallpox, and Measles due to its similarity to these diseases. These similarities make Monkeypox detection challenging for healthcare professionals by examining the visual appearance of lesions and rashes. In the medical sciences, artificial intelligence is now extensively used and machine learning (ML) has demonstrated tremendous potential in image-based diagnostics such as cancer detection, tumor cell identification, and COVID-19 patient detection. As such, the purpose of our research was to develop a deep-learning model to detect monkeypox disease based on images of monkeypox. In this procedure, we use A monkeypox image from the "Monkeypox Skin Lesion Dataset (MSLD)" dataset (publicly available) is used for this study. Modified Mobilenet-v2, VGG-19, and ResNet50 models are used in this paper to detect monkeypox diseases using Convolutional Neural Networks. These classifiers allow automatic classification of healthy, monkeypox, and other skin damages given a close image of them.

***Key words* - Monkeypox disease, Deep Learning, Convolutional Neural Networks, MSLD dataset, Image Processing.**

I.INTRODUCTION

In 1958, monkeypox was first documented in monkey colonies under investigation, when two outbreaks of smallpox-like disease occurred. Even though the disease is known as monkeypox, its origin remains a mystery. Nevertheless, African rodents and non-human primates (such as monkeys) may harbor the virus and transmit it to humans (United Nations, 2022). 1970 marked the first report of monkeypox in humans. Several countries in Central and West Africa had reported monkeypox cases before the 2022 outbreak. International travel to countries where monkeypox occurs frequently or imports of animals had previously been associated with most monkeypox cases outside of Africa (World Health Organization, 2022).

Monkeypox is the second most common disease transmitted to humans from animals and belongs to the genus Ortho-pox virus. There is often a similarity between the symptoms of monkeypox infection and smallpox infection [1].

Globally, more than 23000 cases have been reported since the outbreak started in 2022, according to the most recent CDC report (Centre for Disease Control and Prevention, 2022). Among them, more than 5800 cases have been reported in the United States and more than 4200 in Spain. Furthermore, monkeypox deaths have been reported in Spain and Brazil recently (The Guardian, 2022).

Furthermore, the confirmatory PCR test is not widely available. Despite the recent outbreak's case fatality ratio of 3–6% [2], early detection, contact tracing, and isolation are all important in limiting the spread of monkeypox within communities. AI-powered computer-aided systems could significantly limit the spread of this disease in this scenario.

In this paper, we test the feasibility of using state-of-the-art AI techniques to classify different types of pox from digital skin images of pox lesions and rashes. This work presents the following novelties.

1) We use a database that contains images of skin lesions/rash images from 2 different diseases, namely monkeypox, chickenpox, smallpox, cowpox, and measles, as well as healthy skin images.

2) Our aim is to compare the disease classification power of this type of deep model with that of one and three deep models in, respectively, from digital skin images. In this study, we evaluated the disease classification performance of VGG19, ResNet50, and MobileNet-V2.

II. LITERATURE REVIEW

Ali, Shams Nafisa, et al [3] first develop the “Monkeypox Skin Lesion Dataset (MSLD)” consisting of skin lesion images of monkeypox, chickenpox, and measles. The images are mainly collected from websites, news portals, and publicly accessible case reports. Data augmentation is used to increase the sample size, and a 3-fold cross-validation experiment is set up. we present our preliminary findings of monkeypox skin lesion detection using well-known deep learning architectures (VGG16, ResNet50, InceptionV3) ResNet50 achieves the best overall accuracy of 82.96(±4.57%), while VGG16 and the ensemble system achieved accuracies of 81.48(±6.87%) and 79.26(±1.05%), respectively.

Chakraborty, Sovon, et al. [4] develop a new dataset that can be used to train and develop ML models to classify the Monkeypox disease using image analysis techniques. In addition, a modified VGG16 model is developed for the image-based diagnosis of monkeypox-related diseases using machine learning (ML), we present the newly developed "Monkeypox2022" dataset. In this study, there is an AUC of 97.2 (AAUC =97.2) and 88 (AAUC =0.867) for the modified VGG16 model, which can identify monkeypox patients accurately.

Muñoz-Saavedra, Luis, et al. [5] create the Monkeypox Skin dataset, which contains close-up images of the skin where you can see the posthumous formed by the disease. With these images, we design, implement, and evaluate several diagnostic aid systems for monkeypox disease. The results show a system accuracy greater than 93% when using a unique CNN model (VGG-19). The classifiers developed and evaluated are based on Convolutional Neural Networks models and some ensembles composed of a combination of those models, obtaining automatic classification results between healthy, monkeypox, and other skin damages, given a close skin tissue image. The results show a system accuracy greater than 93% when using a unique CNN model (VGG-19 and ResNet50), and greater than 98% when using a CNN ensemble formed by ResNet50, EfficientNet-B0, and MobileNet-V2.

Islam, Towhidul, et al. [6] proposed in this paper, we introduced the Monkeypox Skin Image Dataset 2022, the largest of its kind so far. In addition, in this paper, we utilize this dataset to study the feasibility of using state-of-the-art AI deep models on skin images for Monkeypox detection. Our study found that deep AI models have great potential in the detection of Monkeypox from digital skin images (precision of 85%). However, achieving a more robust detection power requires larger training samples to train those deep models.

III. Methods for Detection of Monkeypox Disease

3.1 VGG-19

VGG-19 is so beneficial and it simply uses 3 × 3 convnet arranged as above to extend the depth. In order to decrease the size, max-pooling layers are applied as a handler. FCN layers are two in number to which have 4096 neurons applied. VGG is trained based on individual lesions and for testing all types of lesions were considered to reduce the number of false positives.

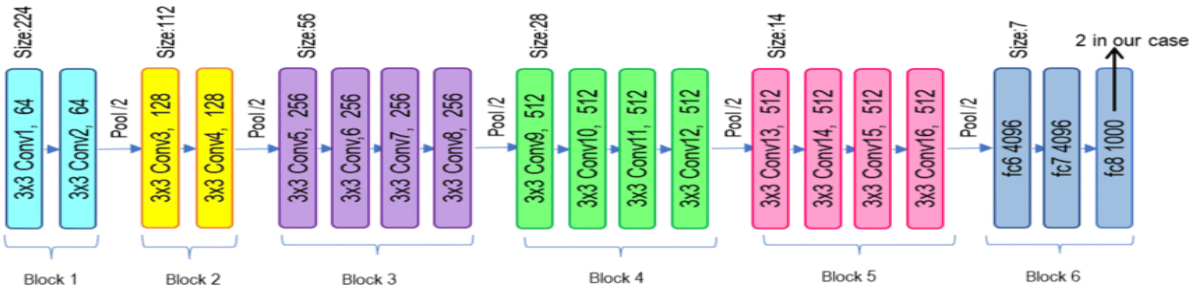

figure1.VGG-19 [7]

Convolution layers perform convolution process over images at every pixel, allowing outcome to pass through the subsequent layer. Filters are used in convolution layer is of 3 × 3 dimension which are trained for feature extraction. Every stacked convolution layer is subsequently added with Rectified Linear Unit (ReLU) layer and max-pooling layer. ReLU is presently the best-known non-linear activation function which allows only the positive portion of the input.

While, comparing the ReLU function with sigmoid function, ReLU is quite effective in computing to indicate the best convergence behaviour that vanish the gradient issue. A down-sampling max-pooling layer is used after ReLU activation function. Generally, the filter of 2 × 2 dimension is considered of same step size. The output will be of maximal value in every sub-region. For dense layer, the activation function must be designed. The dropout layer was abandoned while random activation in the layer to make it zero value. The neurons are eliminated in random process during the training stage to reduce over-fitting issue. This dropout is applied during training.

3.2 ResNet50

ResNet-50 is a 50-layer convolutional neural network (48 convolutional layers, one MaxPool layer, and one average pool layer). Residual neural networks are a type of artificial neural network (ANN) that forms networks by stacking residual blocks. With the help of ResNets, it is now possible to train ultra-deep neural networks, or networks that can have hundreds or thousands of layers and still perform well.

The ResNets were initially utilized for the image recognition problem, but the framework can also be used for tasks that are not related to computer vision in order to gain more accuracy, as is stated in the study. Many of you may question why residual learning was necessary for training ultra-deep neural networks when merely stacking.

figure2.ResNet50 [8]

A convolution with 64 distinct kernels, each with a stride of size 2, and a kernel size of 7 * 7 gives us 1 layer. Following that, we witness max pooling with a stride size of 2. The following convolution consists of three layers: a 1*1,64 kernel, a 3*3,64 kernel, and finally a 1*1,256 kernel. These three levels are repeated a total of three times, giving us nine layers in this phase.

Following that, we see a kernel of 1 * 1,128 followed by a kernel of 3 * 3,128 and finally a kernel of 1 * 1,512. This phase was done four times for a total of 12 layers.

Following that, we have a kernel of size 1 * 1,256, followed by two more kernels of size 3 * 3,256 and size 1 * 1,1024; this is repeated six times, giving us a total of 18 layers. Finally, a 1 * 1,512 kernel was added, followed by two more kernels of 3 * 3,512 and 1 * 1,2048. This process was done three times, giving us a total of nine layers. Then, we perform an average pool, finish it with a completely linked layer made up of 1000 nodes, and then perform a soft-max function to give us one layer. so, totaling this it gives us a 1 + 9 + 12 + 18 + 9 + 1 = 50 layers Deep Convolutional network.

This architecture can be utilized for computer vision applications like object localization, object identification, and image classification. Additionally, this system can be used to improve non-computer vision tasks by adding depth and lowering their processing costs.

3.3 Mobile Net V2

MobileNet-v2 is a convolutional neural network architecture aimed at improving performance on mobile devices. Residual inversion is used to model the remaining connections between bottlenecks in this structure. There are 155 layers in this model (Sandler et al., 2018). You can load a pre-trained version of the network trained on more than a million images from the ImageNet database.

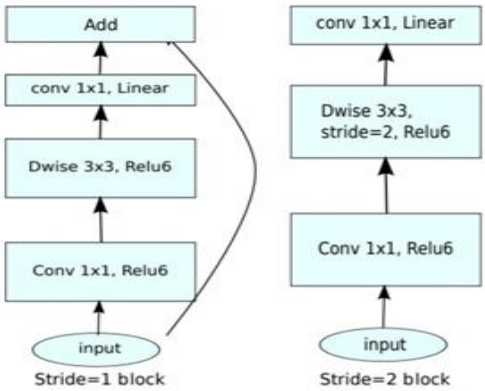

figure3.MobileNet-v2 [9]

• There are two different kinds of blocks in MobileNetV2. One is a shrinking block with a stride of 2, while the other is a residual block with a stride of 1.

• Each of the two types of blocks has three levels. The first layer is an 11-convolution using ReLU6 this time, followed by a depth-wise convolution and a final 11 convolution with no non-linearity. According to this argument, deep networks only have the capability of a linear classifier on the non-zero volume portion of the output domain if ReLU is applied once more [10].

IV. Results and Discussion

4.1 Evaluation metrics

Various and very well measures are frequently used to assess the efficacy of classification systems, including accuracy (the most popular statistic), sensitivity (also known as recall), specificity, precision, and F1score (Sokolova & Lapalme, 2009).

$$Accuracy = \sum_c \frac{TP_c + TN_c}{TP_c + FP_c + TN_c + FN_c}, c \in classes \quad (1)$$

$$Specificity = \sum_c \frac{TN_c}{TN_c + FP_c}, c \in classes \quad (2)$$

$$Precision = \sum_c \frac{TP_c}{TP_c + FP_c}, c \in classes \quad (3)$$

$$Sensitivity = \sum_c \frac{TP_c}{TP_c + FN_c}, c \in classes \quad (4)$$

$$F1_{score} = 2 * \frac{precision * sensitivity}{precision + sensitivity}. \quad (5)$$

About those metrics:

Accuracy:
Compared to all samples, all samples were accurate (see Equation 1).

Specificity:
Percentage of "true negative" values across all scenarios that don't fall under this category (see Equation 2).

Precision:
Proportion of "true positive" values among all instances that have been given its classification (see Equation 3).

Sensitivity (or **Recall**):
Proportion of values that are "truly positive" in all occurrences and fall within this class (see Equation 4).

F1score:

When calculating the score, the test's sensitivity (recall) and precision are both taken into account. Both parameters' harmonic means make up this value. (see Equation 5)

Confusion matrix:

The confusion matrix is a matrix used to determine the performance of the classification models for a given set of test data. It can only be determined if the true values for test data are known. The matrix itself can be easily understood, but the related terminologies may be confusing. Since it shows the errors in the model performance in the form of a matrix, hence also known as an error matrix.

The results of the training process for each of the 3 models are shown in this section. The confusion matrices and the most widely used metrics (already mentioned) demonstrate these conclusions. The results of the mobilenet-v2 model are described in detail. It assesses the MobileNet-V2 model. It provides more information on the outcomes of this model. The global accuracy in this instance falls below 88.33%, making it the lowest evaluated model to date.

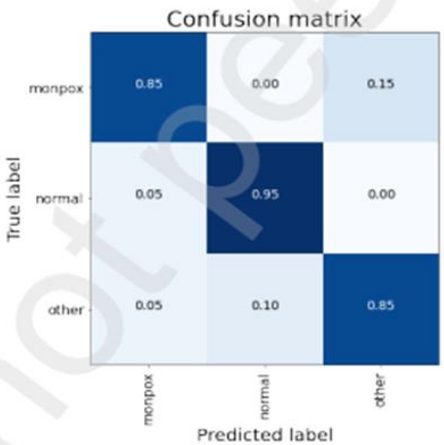

figure4.Confusion matrix for MobileNet-V2 classification [11]

Figure 4's confusion matrix can be used to confirm these findings. 15% of samples in the monkeypox class are labelled as "other skin damages" (false negatives), while 5% of samples in the other two classes are labelled as monkeypox (false positives). According to the information provided above, this model yields the lowest results, primarily because of the false negatives (described by the low value of sensitivity).

VGG-19 is the second model. It provides more information on the outcomes for this model. As can be seen, overall accuracy is more than 93%. These results outperform those from theVGG-16 model, but only the "other skin damages" class.

Figure 5 makes it easy to see these outcomes. Although false negative instances are decreased to 5% (designating them as "other skin damages") in this scenario, there are false positive cases for the "monkeypox" class (5% of the "healthy" class).

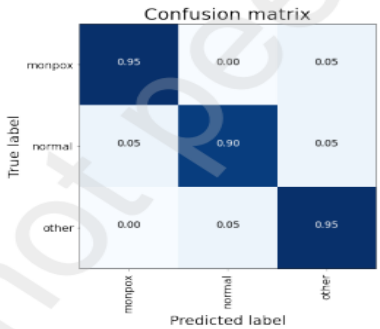

figure5.Confusion matrix for VGG-19 classification [12]

ResNet50 is the next model. It provides more information on the outcomes for this model. As may be seen, the average global accuracy is 95%. These outcomes are the best ones to date (better than those obtained for the VGG-19 model).

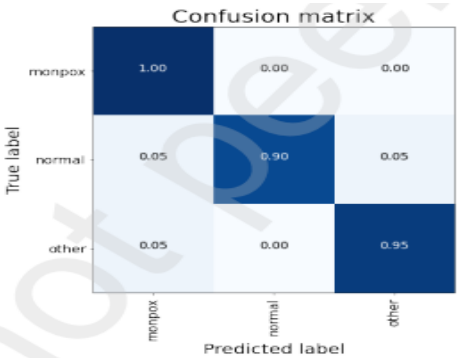

figure6.Confusion matrix for ResNet50 classification [13]

Additionally, as seen in Figure 6, there is a significant distinction between the ResNet50 and VGG-19 values. This distinction is based on the absence of false negatives for the monkeypox class. In this instance, the decrease in false negative cases is changed to an increase in false positive instances. This model is the most effective for diagnostic purposes because of its accuracy and lack of false negatives.

The findings discussed above can be analysed collectively to draw broad generalizations.

Table1.Results

Algorithm	Overall Accuracy
VGG-19	93%
ResNet50	95%
MobileNet-V2	88.33%

V. Conclusion

This paper discusses four different CNN models for detecting monkeypox disease from a database image. Based on monkeypox images, VGG-19 (an updated version of VGG-16) and RestNet50 and MobileNetV2 are also used to detect monkeypox disease. Based on database testing, we concluded that ResNet50 is more accurate than VGG-19 with an overall accuracy of 95%, and MobileNetV2 is slightly more accurate with an overall accuracy of 93% and 88.33%. The MobileNetV2 has high accuracy when used in conjunction with a single dataset and mobile to identify a disease. Mobile Net is 32 times smaller than VGG16, but has the same level of accuracy, suggesting it is more efficient both at capturing knowledge and at capturing it.

References

[1] S. B. S. W. J. P. Thornhill, "Monkeypox virus infection in humans across 16 countries," New England Journal of Medicine, 2022.

[2] WHO, "WHO — Monkeypox Fact Sheet," 2022. [Online]. Available: HTTPS: //www.who.int/news-room/fact-sheets/detail/monkeypox..

[3] S. N. e. a. Ali, "Monkeypox skin lesion detection using deep learning models: A feasibility study," IEEE, p. 4, 2022.

[4] S. e. a. Chakraborty, "Implementation of deep learning methods to identify rotten fruits," IEEE, 2021.

[5] L. e. a. Muñoz-Saavedra, "Monkeypox Diagnostic-Aid System with Skin Images Using Convolutional Neural Networks.," SSRN, p. 31, 2022.

[6] T. e. a. Islam, "Can artificial intelligence detect Monkeypox from digital skin images?," JOURNAL OF LATEX CLASS FILES, p. 7, 2022.

[7] A. Q. S. Khattar, "Generalization of convolutional network to domain adaptation network for classification of disaster images on twitter".

[8] "resnet50-architecture," [Online]. Available: https://iq.opengenus.org/resnet50-architecture/.

[9] "mobilenetv2-architecture," [Online]. Available: https://iq.opengenus.org/mobilenetv2-architecture/.

[10] "review-mobilenetv2-light-weight-model-image-classification-,"[Online].Available: https://towardsdatascience.com/review-mobilenetv2-light-weight-model-image-classification-8febb490e61c.

[1] S. B. S. W. J. P. Thornhill, "Monkeypox virus infection in humans across 16 countries," *New England Journal of Medicine,* 2022.

[2] WHO, "WHO — Monkeypox Fact Sheet," 2022. [Online]. Available: HTTPS: //www.who.int/news-room/fact-sheets/detail/monkeypox..

[3] S. N. e. a. Ali, "Monkeypox skin lesion detection using deep learning models: A feasibility study," *IEEE*, p. 4, 2022.

[4] S. e. a. Chakraborty, "Implementation of deep learning methods to identify rotten fruits," *IEEE*, 2021.

[5] L. e. a. Muñoz-Saavedra, "Monkeypox Diagnostic-Aid System with Skin Images Using Convolutional Neural Networks.," *SSRN*, p. 31, 2022.

[6] T. e. a. Islam, "Can artificial intelligence detect Monkeypox from digital skin images?," *JOURNAL OF LATEX CLASS FILES*, p. 7, 2022.

[7] A. Q. S. Khattar, "Generalization of convolutional network to domain adaptation network for classification of disaster images on twitter".

[8] "resnet50-architecture," [Online]. Available: https://iq.opengenus.org/resnet50-architecture/.

[9] "mobilenetv2-architecture," [Online]. Available: https://iq.opengenus.org/mobilenetv2-architecture/.

[10] "review-mobilenetv2-light-weight-model-image-classification-," [Online]. Available: https://towardsdatascience.com/review-mobilenetv2-light-weight-model-image-classification-8febb490e61c.