EAI Endorsed Transactions
on Pervasive Health and Technology

Research Article EAI.EU

An Empirical Study on Classification of Monkeypox Skin Lesion Detection

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Abstract

INTRODUCTION: After the covid-19 outbreak, Monkeypox has become a global pandemic putting people's lives in jeopardy. Monkeypox has become a major concern in 40+ countries apart from Africa as scientists are struggling to clinically diagnose the virus as it looks similar with chickenpox and measles. As a part of our research, we found that to get the clinically tested result of monkey pox through polymerase chain reaction (PCR) test would take 3-4 days which is a lengthy process.
OBJECTIVES: The objective of this paper is to provide a rapid identification solution which can instantly detect monkeypox virus with the help of computer vision architectures. This can be considered for preliminary examination of skin lesions and help the victim isolate themselves so that they would be cautious and can stop the spreading of virus.
METHODS: Many studies have been conducted to identify the monkeypox with the help of Deep Learning models but in this study, we compare the test results obtained by deep learning CNN models AlexNet, GoogLeNet using transfer learning approach and determine the efficient model[2].
RESULTS: Testing the algorithms by changing the batch sizes and number of epochs we have obtained a highest accuracy of 83.61% for AlexNet and 82.64% for GoogLeNet.
CONCLUSION: AlexNet was outperforming GoogLeNet architecture in terms of validation accuracy thus providing better results.

Keywords: Deep learning, Disease diagnosis, Image processing, Monkeypox virus, Machine learning, Transfer learning, CNN models, Computer vision architectures.

Received on 15 February 2023, accepted on 28 April 2023, published on 25 May 2023

doi: 10.4108/eetpht.v8i5.3352

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1. Introduction

While the world is still recovering from the hit of covid-19, another disease named monkeypox emerged in 2022 and declared as a global pandemic by WHO. Apart from Africa from where the virus has emerged, the cases have been registered in more than 40 countries all over the world [1,2]. Monkeypox is a zoonotic disease which shares genus of orthopoxvirus, and it belongs to the poxviridae family. Orthopox virus is the causative agent of monkeypox which results in formation of lumps/lesions on the skin of victim. The skin lesions appear similar with chickenpox, smallpox and measles [1,2]. The minor differences between these are the skin rashes and lump size. The size is much bigger for monkeypox when compared with the rest. The first case of virus was identified in a monkey's body in 1958 which was tested in a lab in Copenhagen, Denmark. Then after the first human case of monkeypox virus was identified in the year 1970 in Democratic Republic of Congo. The virus transmits from a person to person through various ways like physical contact, respiratory droplets, mucus of eye and nose etc... Generally, when the victim gets infected with monkeypox virus, major short-term symptoms identified are fever, body aches, nausea and fatigue and long-term effect shows a red coloured lump on victim skin [1,2,3].

Currently, proper medical treatment for monkeypox virus is unavailable according to the guidelines of centre for disease control [CDC], but it has approved 2 oral medications Bricindofovir and Tecovirimat which are used in the treatment of smallpox virus.

In this paper, the work has been divided into several sections. Section 1 describes about the need of scientific and well-defined approach for this study. The similar, related research by various authors is discussed in section 2. In section 3, the methodology for the same is presented. Experimental evaluation and discussion of results are mentioned in section 4 and 5. Finally, conclusion and future work is mentioned in section 6.

2. Related Work

Machine learning (ML) is a relatively new sub field of artificial intelligence (AI) that is shown significant promise in a variety of applications. These applications range from decision-making tools and industrial sectors to medical imaging and disease diagnosis [1,4]. Clinicians can get imaging solutions that are safe, accurate, and quick because to the special properties that ML has. These imaging solutions have gained universal recognition as a valuable decision-making tool. To diagnosing breast cancer, for instance, Miranda and Felipe (2015) created computer-aided diagnostic (CAD) systems that make use of fuzzy logic. Fuzzy logic has an advantage over traditional machine learning in that it may eliminate time-consuming computational problems while simultaneously imitating the line of thinking and approach used by experienced radiologists. The algorithm will produce a cancer detection result based on the approach that is desired if the user assigns parameters such as contour, density, and shape [1,4,16].

Ardakani etal. (2020) assessed ten distinct deep learning models using a small data set consisting of 108 patients with COVID-19 and 86 patients who did not have COVID-19, and they attained an accuracy of 99 percent. Using 453 CT scan images, Wang etal. (2020) created a modified inception-based model and achieved an accuracy of 73.1 percent20. A low-complexity convolution neural network (CNN) was developed by Sandeep etal [16]. (2022) as a method for identifying skin illnesses such as psoriasis, melanoma, lupus, and chickenpox. They demonstrate that it is feasible to diagnose skin diseases using image analysis with a 71 percent degree of accuracy by utilizing an existing version of VGG Net. In contrast, their suggested approach achieves the highest outcomes, demonstrating superior performance by obtaining an accuracy of around 78%. Using Mobile Net, Velasco etal. (2019) suggested a smartphone-based skin disease diagnosis system and found an accuracy of around 94.4 percent in recognizing individuals with chickenpox symptoms. Acne, candidiasis, cellulitis, chickenpox, and other skin illnesses were among those that Roy etal. (2019) were able to identify using a variety of segmentation techniques.

Because the monkeypox virus is quickly spreading over a significant number of countries, it is very important currently to identify individuals who are exhibiting signs that they may be infected with it [9]. The strain that has been placed on clinical diagnostics as a direct consequence of the epidemics has led many experts working in the field of medicine to the conclusion that artificial intelligence (AI) technologies would be able to alleviate some of this strain by evaluating visual data. This conclusion was reached as a direct consequence of the burden that has been placed on clinical diagnostics as a direct consequence of the epidemics. It is found that hospitals in China and Italy have used interpreters that were based on AI and image processing to improve the efficiency with which the hospitals handled COVID-19 patients. This was done with the purpose of boosting the degree of medical care that COVID-19 patients can get from the hospitals via the implementation of these changes. On the other hand, as of the time that this article is being written, there is no data set relating to monkeypox that is readily accessible to the public. Because of this, it is difficult to realize the potential advantages of using an AI-based strategy to immediately detect and prevent the monkeypox illness [1,4,8,9,16].

As a direct consequence of this, a substantial number of researchers and practitioners are unable to contribute to the diagnosis of the monkeypox sickness making use of the most cutting-edge AI approaches. Acquiring patient photos that indicate monkeypox was a necessary part of the study that is being described here. Even while our initial data set only has a small number of samples, we do not think that this will be a problem when we carry out the first round of testing. This is supported by the fact that various pieces of referenced research have in the past employed constrained datasets to create AI-based models during the early phases of COVID-19 diseases. This was done in the past. This action was taken while the illness was still in its early stages. On the other hand, the database's material will be continually updated with fresh information that has been donated by many organizations that are situated in a variety of different countries around the world [8,9,14].

3. Methodology

In this section, we discuss the techniques used for collecting the data, develop the transfer learning models of the above mentioned convolutional neural networks and the experimental setup used.

3.1 Data Collection

To perform this experiment, we have collected internal secondary data from google and datasets from Kaggle.

Additional images of normal skin were added to the dataset to increase the size.

Table 1. The size of each image dataset collected for study

DATASET	Total Sample Size
Monkeypox	300
Chickenpox	110
Measles	98
Normal Images	293
TOTAL SAMPLE SIZE	801

Figure 1. Sample set of images from dataset.

3.2 Implementing Transfer Learning for AlexNet and GoogLeNet

Transfer Learning is an approach generally followed in deep learning applications in which we use a pre trained neural network and use it as a starting point to analyse new task. In this study, we have used AlexNet and GoogLeNet for monkeypox image detection. With this transfer learning approach, we can analyse the images faster and easier and with efficiency.

3.2.1 AlexNet

The AlexNet implemented model consists of 25 layers with different filters and Stride values. AlexNet has been trained over a million images and can classify them into 1000 object types. For the input layer images of size [227,227,3] were feeded. The extracted layers were replaced by a fully connected layer, softmax layer and a classification output layer. Values for WeightLearnRateFactor and BiasLearnRateFactor of fully connected layer were initialized which helps the model to learn fast. The batch size, number of epochs and learning rate were constantly monitored to attain maximum validation accuracy and performance [9,10].

Initially a pre-trained network is loaded and final layers of the network are replaced as they were initially trained with other images. Then the network is trained with new dataset of images which we have collected and predict the network accuracy of trained network. Finally, results were deployed and used for further analysis. The data was split in the ratio of 70:30 with the minimum batch size of 10, maximum epochs 35 and learning rate as 0.001.

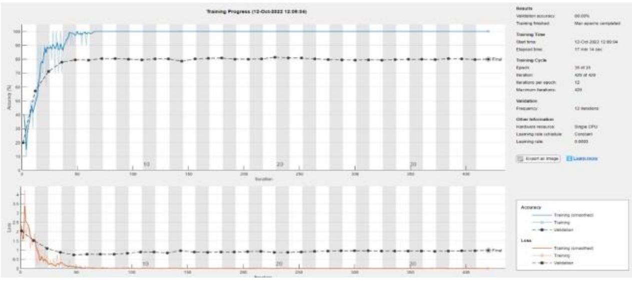

Figure 2. Accuracy vs Epoch Graph

3.2.2 GoogLeNet

GoogLeNet has rich feature representation for a wide range of images. GoogLeNet was trained over 1 million images and can classify them into 1000 different objects. The fully connected layer and classification layer of GoogLeNet have been trained over a million images, so we are replacing these 2 layers with the newly adapted layers to the new dataset. We have replaced the fully connected layer with the new fully connected layer which has number of outputs equal to the number of classes and increased the WeightLearnRate Factor and BiasLearnRateFactor so that the network can learn faster. For the input layer images of size [224,224,3] were feeded. In this case also, we observed the Batch Size, number of epochs and learning rate were monitored to attain maximum validation accuracy and performance [18,19]. Here also the same procedure which was used for training AlexNet was used. Initially a pre-trained network is loaded and final layers of the network are replaced as they were initially trained with other images. Then the network is trained with new dataset of images which we have collected and predict the network accuracy of trained network. Finally, results were deployed and used for further analysis. The data was split in the ratio of 70:30 with minimum batch size of 10, maximum epochs 35 and learning rate as 0.003.

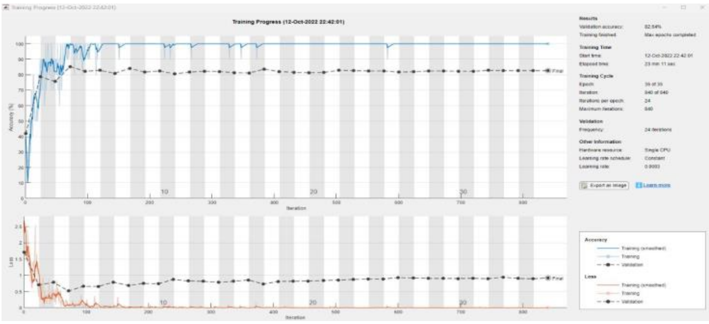

Figure 3. Accuracy vs Epoch Graph

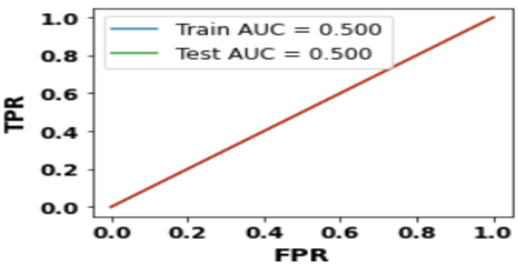

Figure 4. True Positive vs True Negative Graph

4. Experimental Evaluation

4.1 Performance Evaluation

Here we are going to compare the test results obtained from our model. The maximum accuracy achieved with AlexNet is 83.61% and GoogLeNet is 82.64%. Hence, we can conclude AlexNet is a better network to perform the image classification task.

4.2 Experimental Setup

The experiment was carried out on a conventional laptop which consists of Windows 11 operating system, i7 processor, 16GB of RAM. The result displayed in this study was the best result obtained when experiment was carried out[1].

5. Results and Discussion

5.1 Results

Under this section, we are going to investigate the results and have a general discussion on using the neural network architectures. We have conducted the experiment using 2 convolutional neural networks and their results are as follows.

Table 2. Results obtained of the experiment

Pre-Trained Model	Validation Accuracy	Test Number
AlexNet	77.48%	1
AlexNet	83.61%	2
GoogLeNet	80.00%	1
GoogLeNet	82.64%	2

With different values of Batch Sizes and Max Epochs each model is trained for 2 times and their values and implementation was already mentioned in this study before. From the above table we can find that for the above-mentioned values in section 2 of this study, AlexNet gives **83.61%** of accuracy during the training of the dataset and GoogLeNet gives **82.64%**. The performance results of these models are also mentioned in section 2.

5.2 Discussion

In this study, we have used transfer learning approach for detection of skin lesions of monkey pox using pre-trained architecture models of AlexNet and GoogLeNet and our model has achieved an accuracy of 83.61% and 82.64% respectively. Finally, health care professionals can use our model for preliminary detection of monkeypox as it is cost and time efficient and does not require and clinical testing like Polymerase Chain Reaction (PCR) and Microscopy testing, as an effect, our proposed model provides an opportunity to test in real-time screening of the patients with Monkey pox symptoms.

6. Conclusion and Future Scope

The purpose of this research is to develop models of convolutional neural networks using transfer learning approach and pre-trained models of deep learning. Through this we can actually reduce the time taken by clinical methods to detect the monkeypox and in an efficient way using AlexNet and GoogLeNet pre-trained architectures. Despite we have used a smaller dataset when compared to some other studies done on this region using other architectures the promising results reveal the potential use to use AI- assisted early diagnosis of this disease. This study can also be used for preliminary examination and detection of monkeypox suspected victim and control the spread of the virus by warning him at very early stages and medication can also be started upon proper consultation with the doctors[2,6].

In future, we have a scope to present much accurate model using these models and develop a user-interface which is accessible to common people so that they can test themselves using mobile application or web application. We believe that adequate precautions and actions can be taken in early stages of the infection so that the infection rate can be reduced [1,2,4].

Acknowledgements.

Firstly, I would like to thank professors Sujit Kumar Panda and G. Michael for their guidance and support during this research. It was really a great experience working with people who have great knowledge in the subject and dedication towards research. I would specially extend my thanks to Dr. Sachi Nandan Mohanty for his constant support, guidance. His dedication and commitment towards research were my inspiration to complete this research. Finally, I would like to thank all my friends, family and supporters who have supported me directly or indirectly for finishing the research.

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