Monkeypox Skin Lesion Classification Using Transfer Learning Approach

Arya Shah
Department of Computer Engineering
NMIMS University, MPSTME
Mumbai, India
arya.shah82@nmims.edu.in

***Abstract*—Monkeypox is classified as a viral zoonotic disease which is transmitted to humans from animals. The recent outbreak of the Monkeypox virus has affected more than 40 countries. With the rapid spread and ever-growing challenges of provisioning PCR (Polymerase Chain Reaction) Tests in areas with less availability, computer aided methods incorporating Deep Learning techniques for automated detection of skin lesions proves to be a feasible solution. The paper proposes a Transfer Learning based approach to classify Monkeypox skin lesions from chickenpox and normal skin images. A total of 5 Transfer Learning models namely- MobileNetv2, ResNet50, Inceptionv3, EfficientNetB5 and Xception have been trained on a skin lesion image dataset sourced from News reports, public health websites and case studies. A comparison of the trained models is provided to select the best performing model which can be further utilized in any application for quick, automated detection of monkeypox skin lesions in remote areas. MobileNetv2 provided the best model accuracy of 98.78% for classification of monkeypox skin lesion images.**

Keywords—Skin lesion, Transfer Learning, Deep Learning, Monkeypox, Image Classification, Computer-Aided Diagnosis

I. Introduction

Monkeypox is a clinically less severe zoonotic virus which is transmitted from animals to humans having symptoms similar to the smallpox virus, measles and chickenpox. While the smallpox virus has been eradicated since the 1980s, measles has been declared eradicated in almost 82 countries worldwide as of 2019 [1]. With the origin of Monkeypox virus mainly in central and west Africa, it is an enwrapped double-stranded DNA virus belonging to Orthopoxvirus genus of the Poxviridae family. The first human outbreak was identified in a 9-month boy belonging to the Democratic republic of Congo in 1970 [2]. With the rapid spread of the monkeypox virus globally, the minor differences in the skin between monkeypox and chickenpox virus makes early diagnosis of the disease difficult and challenging for professionals in the healthcare domain. The paper proposes a transfer learning-based approach to classify monkeypox, chickenpox and normal skin images. The dataset is prepared based on a collection of publicly available web-scraped images from various sources such as news reports, public health websites and case studies and hosted on Kaggle. The web-scraped images consist of different body parts including face, neck, legs, hands and arms of patients with monkeypox, chickenpox and healthy cases. The best way to diagnose monkeypox cases at present is through histopathology, virus isolation and a PCR test, however the lack of these diagnostic tools leads to adoption of diagnosis based on clinical examination of the skin lesions. Thus, an AI-based skin lesion detection systems can help diagnose the virus and fill the gap in the healthcare systems making use of ubiquitous computing and availability of smart devices.

II. Literature Review

D. Ravi and et al. [3] highlight the superior learning capability of Convolutional Neural Networks in varied domains of medical science. Automatic medical imaging analysis or computer aided diagnosis has been rapidly being adapted by CNNs which demonstrate outstanding performance in computer vision in terms of extraction of relevant features with the classification procedure. CNNs have been able to learn inherently complex features along with the ability to be parallelized with GPUs.

Shorten and Khoshgoftaar [4] provide an in-depth survey on data augmentation techniques for Deep Learning. Since the Monkeypox dataset originally scrapes only a handful of images from a selected list of sources, in order to train a deep learning model, image data augmentation becomes an important part of the methodology. The authors discuss methods such as geometric transformations, color space augmentations, kernel filters, mixing images, random erasing, feature space augmentation, adversarial training, generative adversarial networks, neural style transfer, and meta-learning to solve dataset-related concerns persistent due to the difficulty of obtaining unbiased, homogeneous medical data.

Pan and Yang [5] conducted a survey on transfer learning to solve the unideal assumption that the training and future data must be in the same feature space and have the same distribution for machine learning applications. Due to the problems faced such as large amounts of data and time-consuming model training even after making use of dedicated resources like GPUs and scarcity of data, the approach of transfer learning makes use of a pre-trained CNN model on a large dataset (e.g., CIFAR10, ImageNet, etc) and transfers context-specific learning of knowledge on another dataset.

Various transfer learning approaches involving VGG16, ResNet50 and InceptionV3 architectures (to name a few) to explore the potential of deep learning models for the early detection of the monkeypox disease have been used based on Simonyan and Zisserman's work on large scale image recognition utilizing very deep convolutional neural networks [6] utilizing the VGG16 model, K. He and et al. [7] work on image resolution using deep residual learning making use of the ResNet50 model and C. Szegedy et al. [8] work on the inception architecture for computer vision.

K. Glock et al. [9] propose the deep convolution neural network approach to identify measles rash using residual deep convolutional neural network that helps differentiate measles rash from other skin conditions. Their image dataset achieved a classification accuracy of 95.2% utilizing the ResNet50 architecture with 5-fold cross validation. Although the authors focused only on the appearance of the rash and did not take into account the body distribution of the rash.

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K. M. Hosny and et al. [10] have applied transfer learning to classify skin lesions using Alex-net along with image augmentations. The purpose to present an automatic skin lesions classification system was achieved through fine-tuning weights of Alex-net, replacing classification layer with a softmax layer and data augmentation through fixed and random rotation angles. Their proposed method could achieve accuracy scores of 96.86%, 97.70%, and 95.91% for the datasets- MED-NODE, Derm (IS & Quest) and ISIC respectively.

Ali, S. N. and et al. [11] propose the first ever feasibility study on detection of Monkeypox skin lesions using deep learning models. The authors identified the lack of datasets to train models for automatic detection of Monkeypox lesions and hence propose the Monkeypox Skin Lesion Dataset (MSLD) consisting skin lesion images of monkeypox, chickenpox, and measles. The authors also perform data augmentation and implement several pre-trained deep learning models, namely, VGG-16, ResNet50, and InceptionV3 along with their ensemble. ResNet50 achieved the best overall accuracy of 82.96(±4.57%), while VGG16 achieved accuracy of 81.48(±6.87%) and the ensemble system scored 79.26(±1.05%).

III. METHODOLOGY

To develop a deep learning-based model for classification of Skin lesion images, a proper methodology needs to be adopted and followed. The pipeline methodology consists of aspects right from the problem definition to dataset collection, augmentation, training and evaluation after a thorough comparison of the various models trained on the dataset. Figure 1 depicts the various steps employed by the author for the topic of skin lesion classification using transfer learning approach.

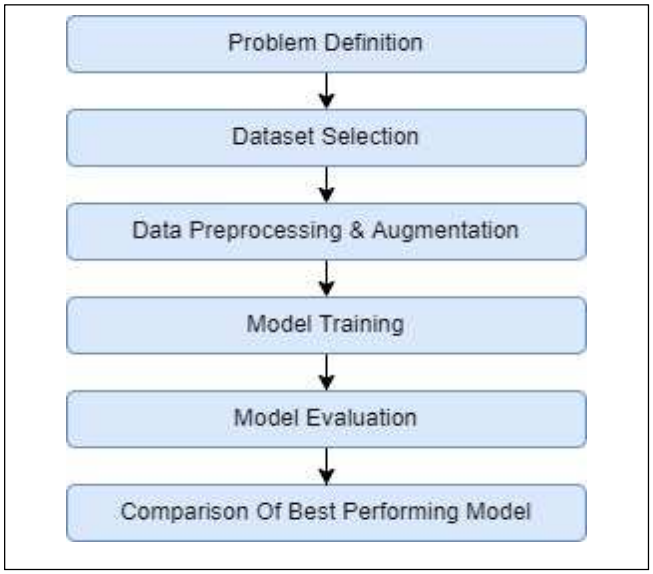

Fig. 1. Workflow for the Deep Learning Based Approach

A. Problem Definition

The first and the most critical stage of any workflow is to define the problem statement. A robust problem statement helps in the later stages of the methodology. The problem statement at present is to develop an AI-based skin lesion detection systems making use of transfer learning based models that can help diagnose the Monkeypox virus and fill the gap in the healthcare systems making use of ubiquitous computing and availability of smart devices.

B. Dataset Selection

In order to prepare a deep learning-based model, there is a need for a good amount of data in order to create a dataset for training and testing the models. For our purpose, the dataset has been selected from a collection of publicly hosted datasets on the platform of Kaggle. The datasets consist of web-scraped images of skin lesions for Monkeypox, Chickenpox and Healthy Skin. The first dataset used is the Monkeypox Skin Lesion Dataset (MSLD) consisting skin lesion images of monkeypox, chickenpox, and measles [11]. The next dataset that has been combined with the previous dataset is the Monkeypox Skin Image Dataset [12] and the Monkeypox 2022 Remastered Dataset [13] on Kaggle.

TABLE I. COMBINED DATASET DETAILS

Class	No. of Images
Monkeypox	9068
Chickenpox	8722
Healthy	3036
Total	20826

The following figure (Figure 2) shows a sample image from each of the three classes:

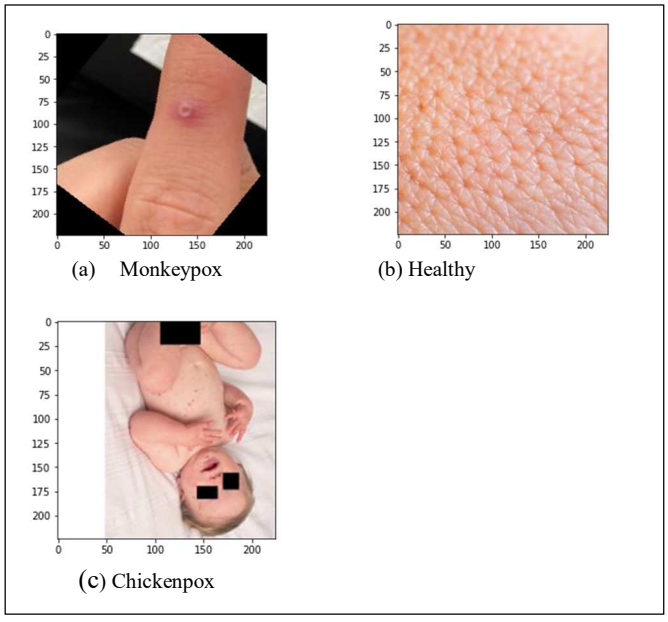

Fig. 2. Sample images for each class from the dataset

C. Data preprocessing and Augmentation

The dataset once selected is subjected to pre-processing and augmentation. For pre-processing, the images within the dataset were subjected to normalization and conversion to

fixed size. All images were converted to standard 224x224x3 dimensions for the model training purpose.

Under Data Augmentation the images collected over the web through scraping different sources were subjected to different augmentation techniques in order to increase the size of the dataset. Techniques such as horizontal flipping, vertical flipping, mirroring, blurring and fixed rotation were applied.

After applying augmentation, the final combined number of images for each class were 21026.

D. Model Training

After the final dataset is prepared using pre-processing and augmentation techniques, the dataset is ready to be sent to deep learning models for training. For the purpose of training the dataset for classification sing transfer learning, libraries used were Keras and TensorFlow. TensorFlow library has a variety of pre-trained transfer learning models including Inceptionv3, Xception, ResNet-50, VGG16, VGG19, MobileNetv2 and many more.

Out of the 21026 images for 3 classes finally present in the dataset, 16821 images were used for training and 4205 images were used for testing.

In order to maintain the uniformity in comparison of various models, all the models were subjected to the same number of epochs, batch size, train-test splits, learning rates and additional layer architectures built on top of the pretrained models. In addition, all the pretrained models utilized the weights derived from ImageNet.

The parameters utilized for all the transfer learning models can be summarised as follows:

TABLE II. MODEL TRAINING PARAMETERS

Parameter	Set value for all models
Image Size	224x224x3
Batch Size	32
Validation Split	0.2
Weights	ImageNet
Optimizer	Adam
Loss Function	Categorical_cross entropy
Epochs	10

Coming to the additional layers defined on top of the pre-trained model as mentioned above, the additional hidden layers were added in the sequence of 1024, 512, 128 and 64. In addition the hidden layers were added with batch normalization and dropout.

The activation function for the output was set to softmax and the dropout rate was added to the last two layers which was kept at 0.15 and 0.3 respectively.

The following layers were added for all the pre-trained models:

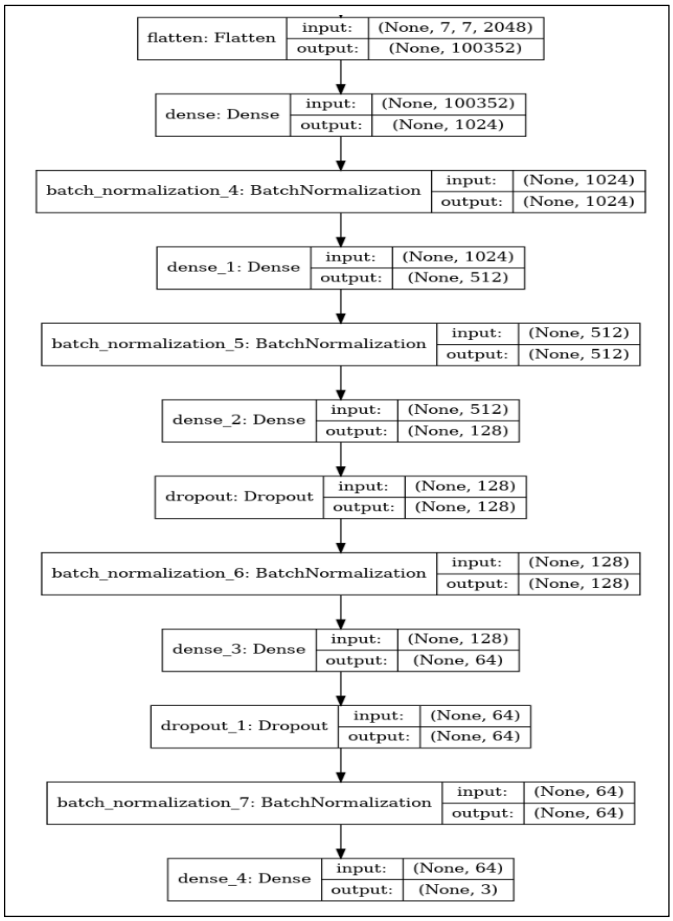

Fig. 3. Additional layers on pre-trained models

IV. DISCUSSION AND RESULTS

A total of 21026 images were collected for 3 classes namely Monkeypox, Chickenpox and Healthy skin. Based on the techniques of data augmentation to increase the dataset in terms of size and diversity, the dataset was enhanced to be trained on a set of 55 transfer learning models namely- Inceptionv3, Xception, ResNet-50, EfficientNetB5 and MobileNetv2.

Based on the training performance and testing on the 20% of the validation set, the following results were obtained:

TABLE III. MODEL RESULTS

No.	Model	Accuracy
1.	MobileNetv2	0.9878
2.	ResNet-50	0.9841
3.	EfficientNetB5	0.9769
4.	Inceptionv3	0.9526
5.	Xception	0.9791

Thus, from the above table it has been observed that MobileNetv2 performs the best among all the models trained on the dataset. The following figure (Figure 3) depicts the bar

chart of accuracies for each of the models for better visualization.

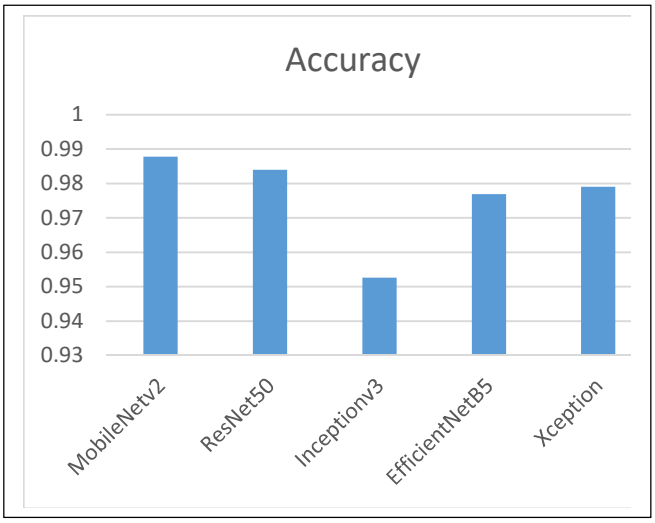

Fig. 4. Model Comparison Bar Chart

The following table shows the Accuracy and loss plots for each of the models.

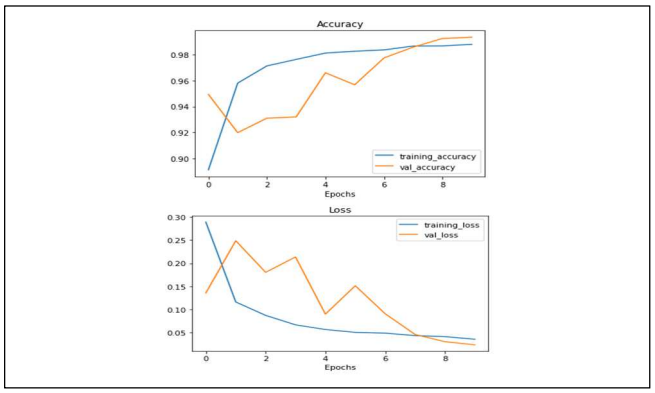

Fig. 5. MobileNetv2 Accuracy and Loss Plots

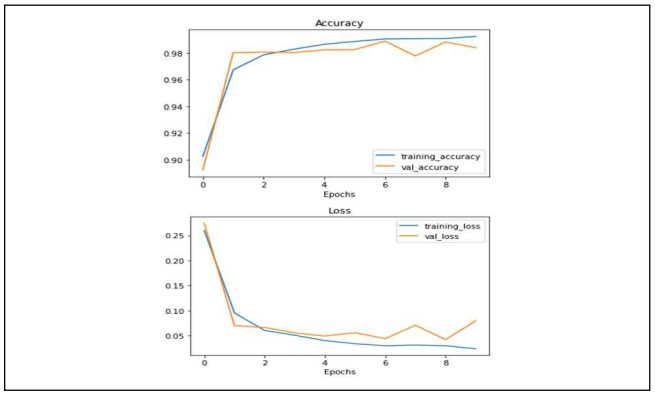

Fig. 6. ResNet-50 Accuracy and Loss Plots

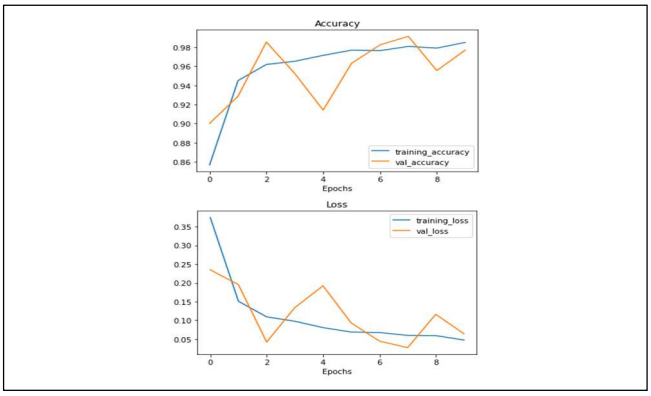

Fig. 7. EfficientNetB5 Accuracy and Loss Plots

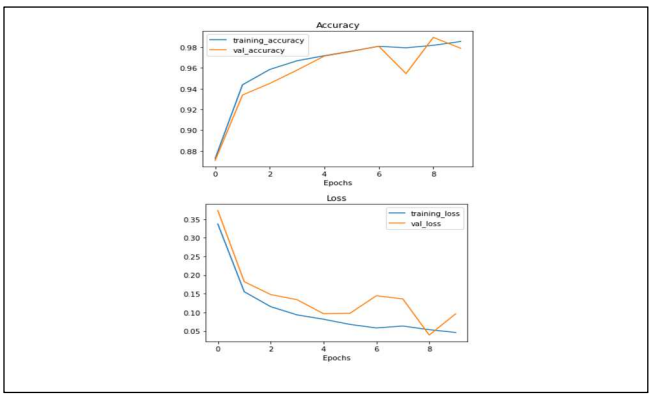

Fig. 8. Xception Accuracy and Loss Plots

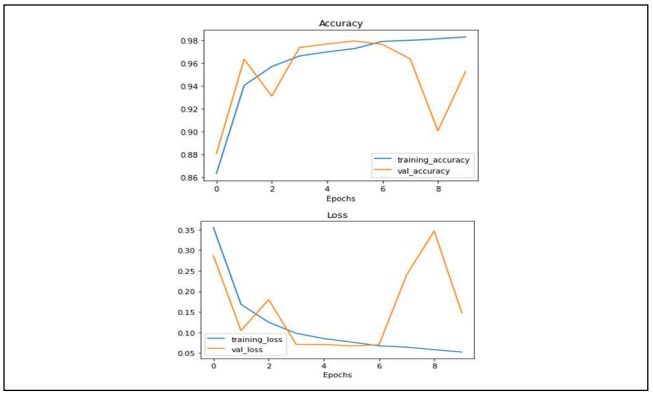

Fig. 9. Inceptionv3 Accuracy and Loss Plots

V. CONCLUSION AND FUTURE WORK

The paper proposed the Transfer Learning approach to classify Monkeypox skin lesion images on publicly available data and it has been observed that each of the deep learning models used has significantly performed well on the image dataset. Thus, it can be concluded that given the effort to collect good amount of quality data that is not just scraped from the internet but instead collected in a systematic manner in presence of medical professionals, the problem statement of building an AI-based skin lesion detection systems can help diagnose the virus and fill the gap in the healthcare systems can be solved.

In terms of future work, it is important to put the trained models to use and collect more quality data from the medical environment that can make the models more robust and result

in higher precision and recall too. With the advent of edge computing, ubiquitous computing, integrating an AI model in devices such as computer systems, handheld mobile devices is feasible and can help in early diagnosis of Monkeypox skin lesions quickly and effectively thereby easing the burden of the medical workforce.

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