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Monkeypox Skin Lesion Classification Using Transfer Learning Approach

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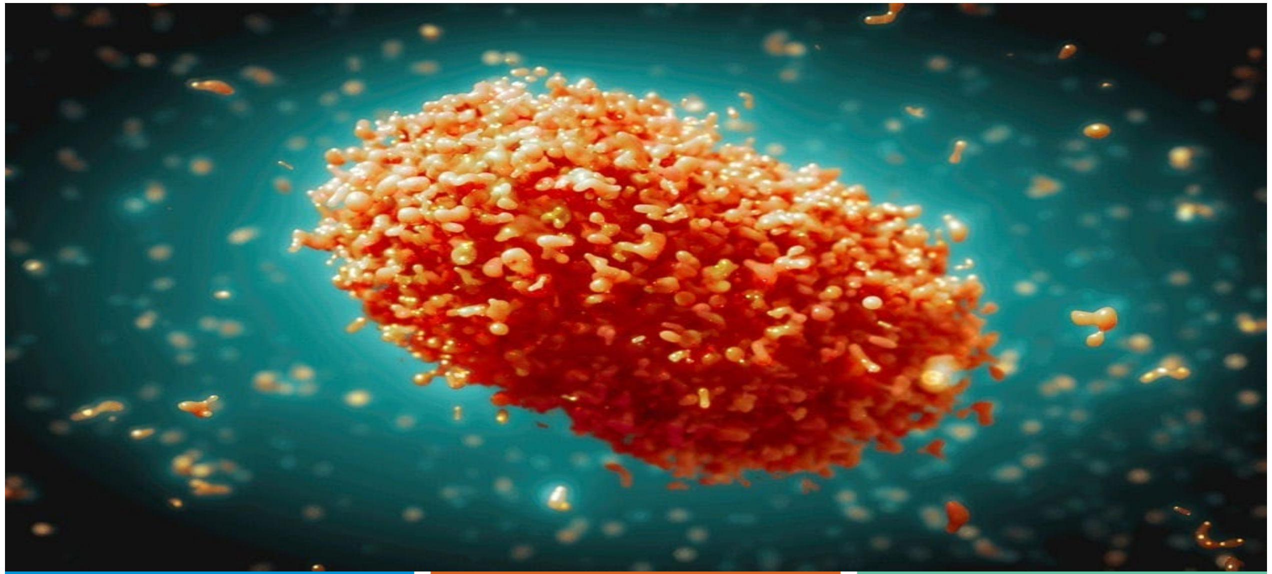
Roadmap

Introduction

- *"Mpox"* is a viral zoonotic disease caused by monkeypox virus, a member of the Orthopoxvirus genus in the family Poxviridae.
- Monkeypox typically presents clinically with fever, rash and swollen lymph nodes and may lead to a range of medical complications.
- Diagnosis done through histopathology, virus isolation and a PCR test.
- Occurs primarily in tropical rainforest areas of central and west Africa and is occasionally exported to other regions.
- Lack of available professionals and diagnosis tools in remote areas with scarcity in resources prevents early diagnosis.



82,088	64	110
Confirmed cases	Deaths	Countries reporting cases

WHO generated Global Trends as of 6th December, 2022

Problem Statement

"To facilitate a computer aided method of early diagnosis of Monkeypox skin lesions using Deep Learning techniques"

Background Of The Research

Image 1

Image 2

Image 1: Monkeypox Skin Lesion
Source: https://www.cidrap.umn.edu/study-monkeypox-outbreak-shows-differing-symptoms
Image 2: Chickenpox Skin Lesion
Source: https://www.cdc.gov/chickenpox/about/photos.html

Literature Review

Paper Title	Authors	Key Takeaways	Results
Deep Learning for Health Informatics	D. Ravi et al. [3]	• Highlight the superior learning capability of Convolutional Neural Networks in varied domains of medical science. • CNNs demonstrate outstanding performance in computer vision in terms of extraction of relevant and complex features with the classification procedure along with the ability to be parallelized with GPUs.	---
A survey on image data augmentation for deep learning	Shorten and Khoshgoftaar [4]	• Aim to solve dataset-related concerns persistent due to the difficulty of obtaining unbiased, homogeneous medical data. • Discuss methods such as geometric transformations, colour space augmentations, kernel filters, mixing images, random erasing, feature space augmentation, adversarial training, generative adversarial networks, neural style transfer, and meta-learning.	---
Very deep convolutional networks for large-scale image recognition	Simonyan and Zisserman [6]	• Explore the potential of deep learning models for work on large scale image recognition utilizing very deep convolutional neural networks for the ImageNet Challenge. • Research showed significant improvement on the prior-art configurations can be achieved by pushing the depth to 16-19 weight layers. Thereby creating the VGG Model.	Accuracy: 93.2%
Measles Rash Identification Using Transfer Learning and Deep Convolutional Neural Networks	K. Glock et al. [9]	• Propose the deep convolution neural network approach to identify measles rash from other skin conditions. • Utilizing the ResNet50 architecture with 5-fold cross validation. • Focused only on the appearance of the rash and did not take into account the body distribution of the rash.	Accuracy: 95.2%
Classification of skin lesions using transfer learning and augmentation with Alex-net	K. M. Hosny et al. [10]	Applied transfer learning to classify skin lesions using Alex-net along with image augmentations. Purpose to present an automatic skin lesions classification system was achieved through fine-tuning weights of Alex-net. Benchmarked various datasets - MED-NODE, Derm (IS & Quest) and ISIC.	Accuracies: MED-NODE: 96.86% Derm: 97.70% ISIC: 95.91%

Novelty Of The Work

- No prior research work or datasets released for the given problem statement
- Ali, S. N. and et al. [11] propose the first ever feasibility study on detection of Monkeypox skin lesions using deep learning models.
- Existing dataset includes chickenpox and measles lesions as “others” class in contrast with Monkeypox class
- This research is an extension to the preliminary study performed by Ali, S. N. and et al by performing work on a novel, extended dataset which includes separate classes for chickenpox, monkeypox and normal skin
- Research done on additional CNN Architectures and benchmarked on newly combined dataset

Dataset	Number of Classes	Total Images in Dataset
MSLD – Monkeypox Skin Lesion Dataset	2	Monkeypox: 1428 Others: 1764 Total: 3192
Current Dataset*	3	Monkeypox: 9068 Chickenpox: 8722 Normal: 3036 Total: 20826

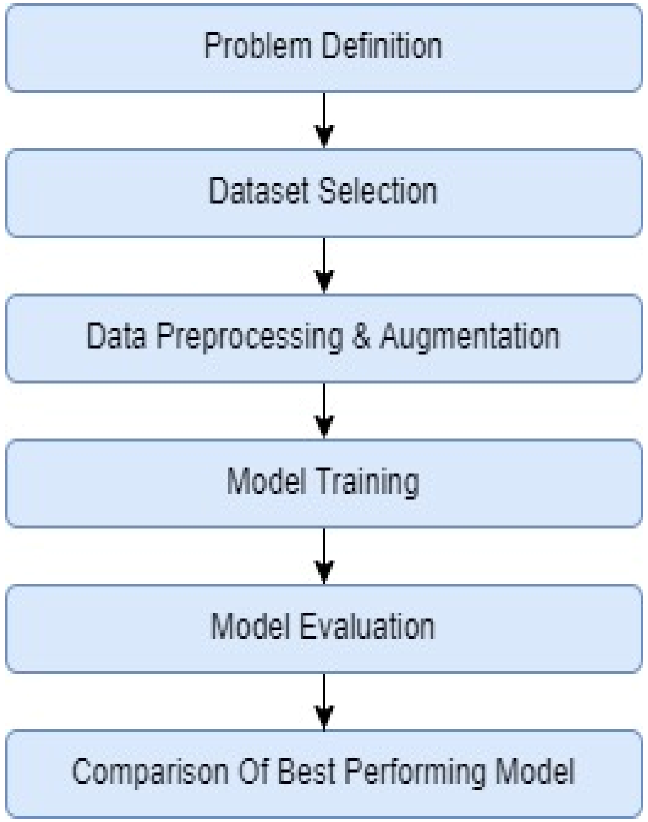
Methodology

Dataset Selection

- 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.

Dataset Pre-processing & Augmentation

- All images were converted to standard 224x224x3.
- Techniques such as horizontal flipping, vertical flipping, mirroring, blurring, noise insertion, fixed rotation and zooming in were applied.



Methodology

Model Training

- Usage of open-source library Tensorflow with Keras as backend for modelling CNN.
- Trained on a set of 5 models namely- Inceptionv3, Xception, ResNet-50, EfficientNetB5 and MobileNetv2.
- Model training done with Train-Test split of 80:20
- Additional layers defined on top of the pre-trained model 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.

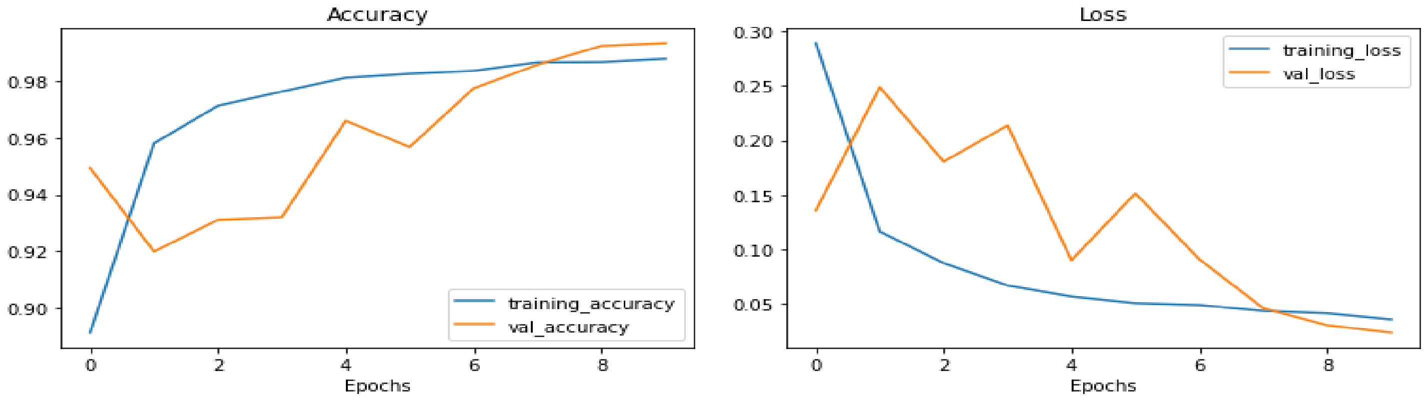
Parameter	Set value for all models
Image Size	224x224x3
Batch Size	32
Validation Split	0.2
Weights	ImageNet
Optimizer	Adam
Loss Function	Categorical_crossentropy
Epochs	10

Results

- A total of 21026 images were collected for 3 classes namely Monkeypox, Chickenpox and Healthy skin.

- Based on the training performance and testing on the 20% of the validation set, the following results were obtained as shown on the right half of the slide.

- Thus, from the above table it has been observed that MobileNetv2 performs the best among all the models trained on the dataset.



Accuracy and Loss Plots of best performing model-MobileNet-v2

Model	Ali, S. N. and et al. [11]	Current Work*
ResNet-50	82.96	**98.41**
Inceptionv3	---	**95.26**
Ensemble	79.26	---
VGG-16	81.48	---
MobileNetv2	----	**98.78**
EfficientNetB5	---	**97.69**
Xception	----	**97.91**

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