AI-Mpox: A Machine Learning-Based Approach for Early Detection and Diagnosis of Monkeypox

Zahraa Bareq ,and Hussain Ali

University of Baghdad, Under supervision of Dr. Heba M. Fadhil

Introduction

The AI-Mpox project aims to develop an AI-powered tool for the accurate identification and classification of six skin conditions: **Chickenpox**, **Cowpox**, **Healthy** skin, **HFMD**, **Measles**, and **Monkeypox**. Using deep learning and computer vision, the system will analyze skin images from standard cameras to help individuals and healthcare professionals quickly identify unknown skin lesions, enabling timely diagnosis and treatment, and contributing to better public health outcomes.

Methods

Dataset:

Used the MSLD v2.0 dataset, containing 755 images from 541 patients, across six categories:

Monkeypox, Chickenpox, Measles, Cowpox, HFMD, and Healthy skin.

Preprocessing:

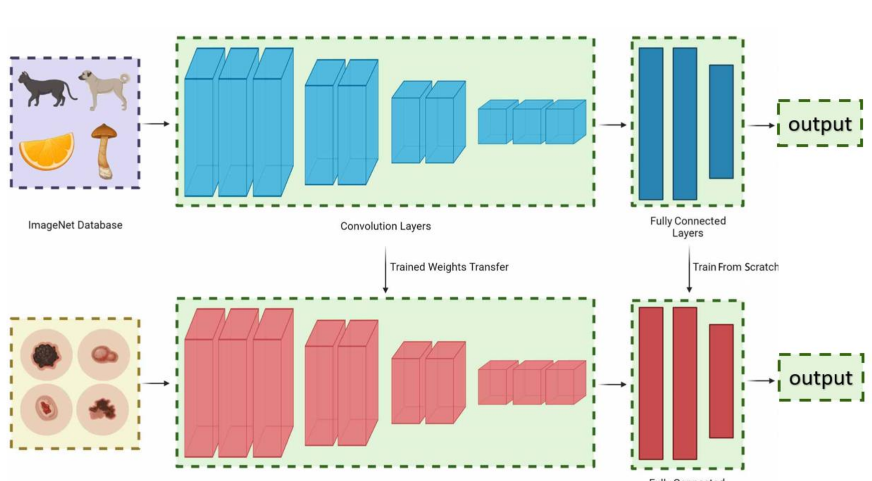
- Resized all images to fit model input dimensions.
- Normalized pixel values for consistent training.
- Applied data augmentation techniques to reduce overfitting.

Data Splitting:

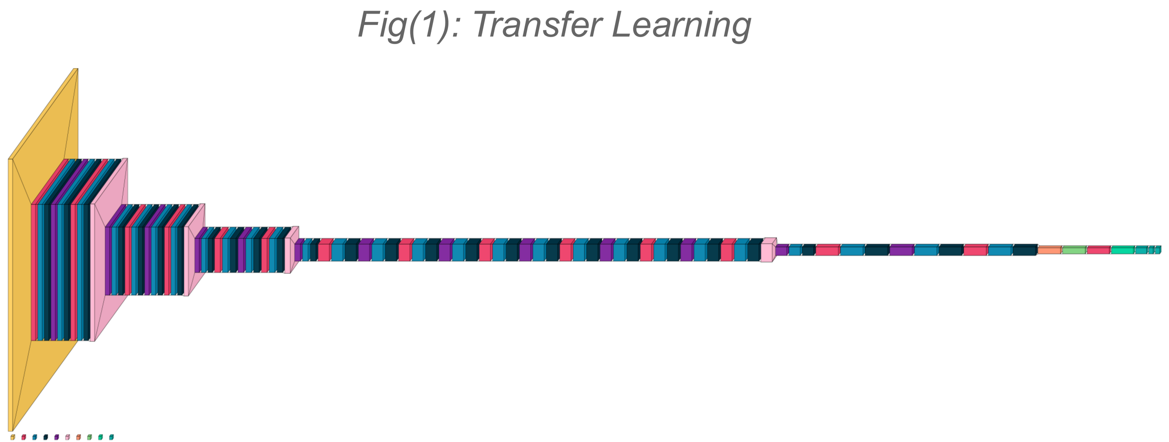
- Split data into 80% training and 20% testing sets.
- Further divided training data into 80% training and 20% validation.

Model Architecture:

- Used MobileNet, a lightweight CNN optimized for mobile and embedded vision applications.
- Used transfer learning technics [see Figure 1].
- [Figure 2] show the architecture of used model



Fig(1): Transfer Learning



Fig(2): The Architecture of MobileNet

Training:

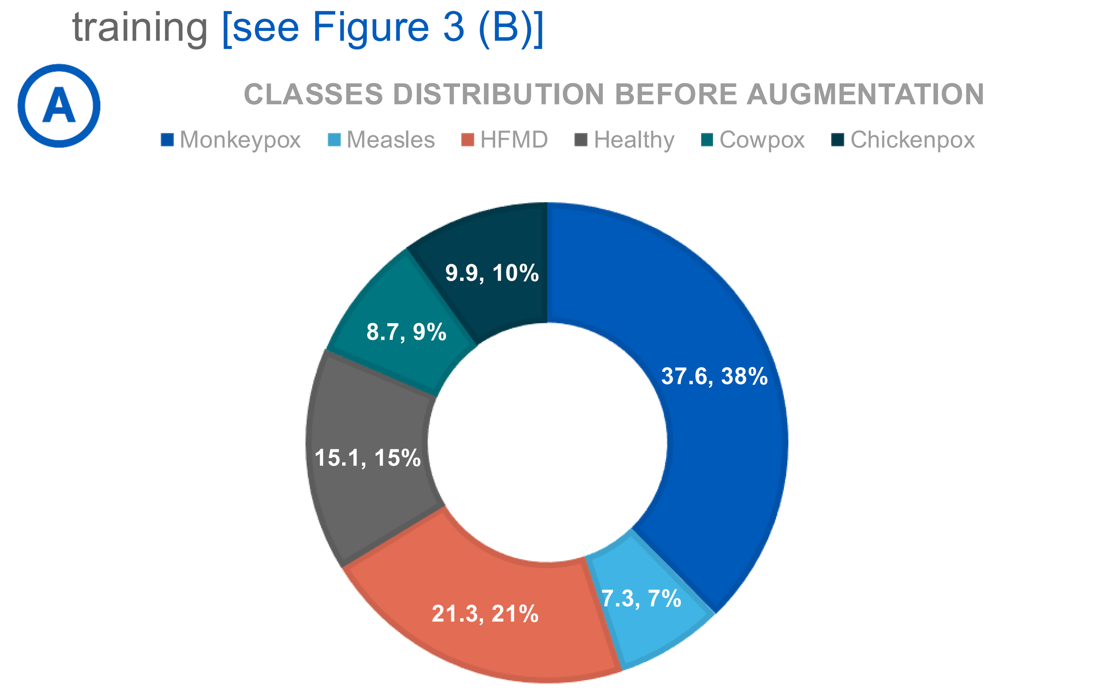
- Trained the model using cross-entropy loss.
- Optimized using the Adam optimizer with tuned hyperparameters.

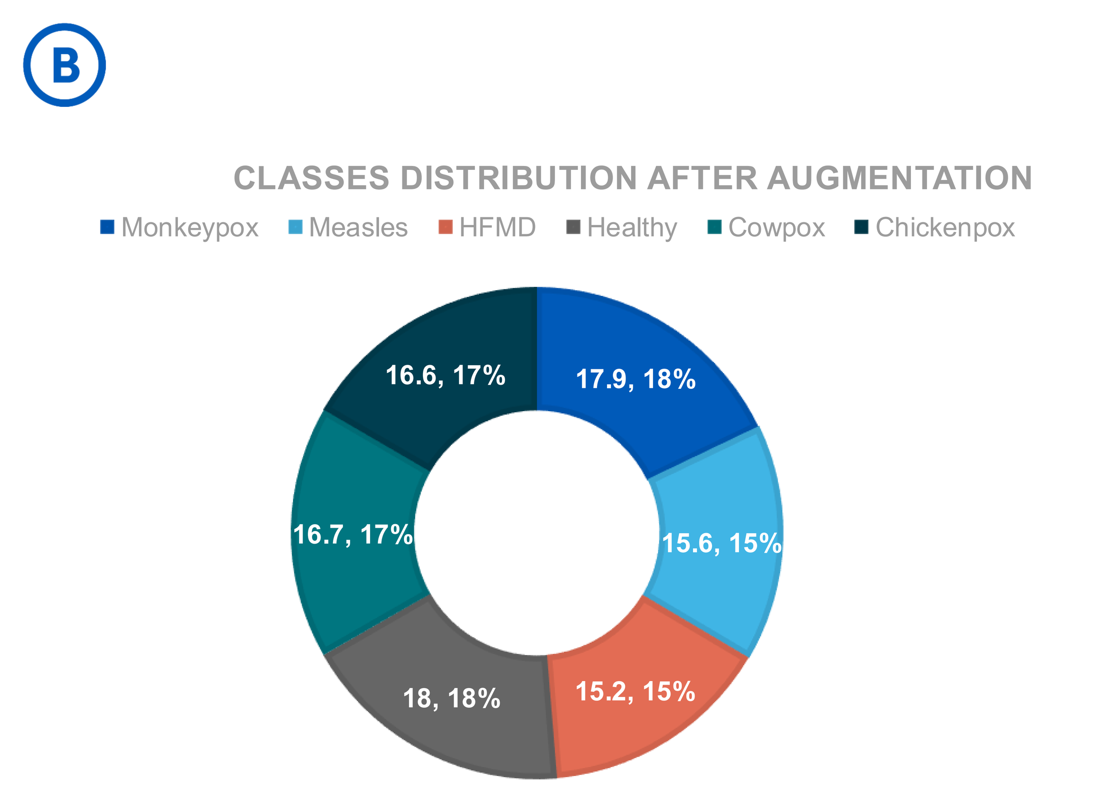
GUI:

- a Graphical User Interface was developed using Gradio to enable easy interaction with the model.

Data Analysis

- The dataset showed clear class imbalance, with some conditions like Mpox having significantly more images than others [see Figure 3 (A)]. This posed a risk of model bias, where the network might favor more frequent classes.
- To address this, we used augmentation techniques (e.g., flipping, rotation, brightness) on the minority classes to increase their representation.
- To fix this, we used a custom augmentation loop base on number of image
- Final distributions were visualized and verified before training [see Figure 3 (B)]

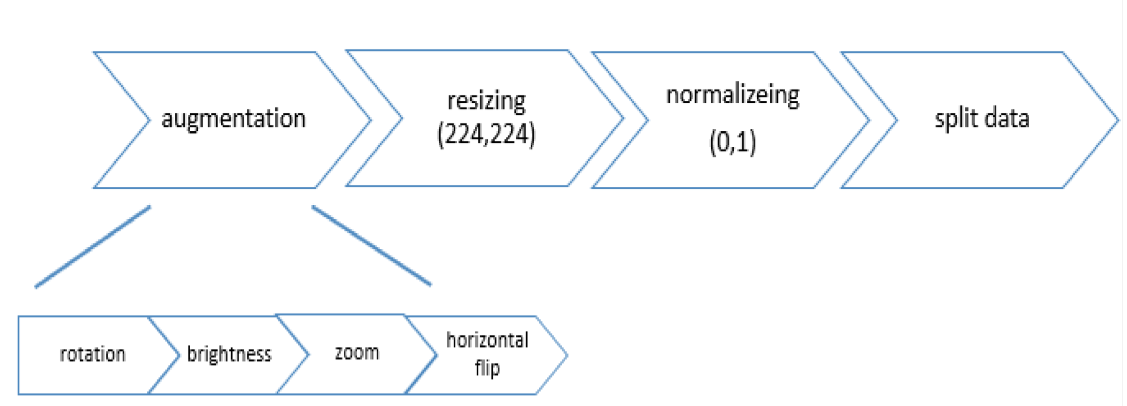




Fig(3): Classes distribution

Preprocessed :

Preprocessing involved resizing all images to 224×224 and normalizing pixel values to [0, 1].To handle class imbalance, data augmentation was applied using rotation, brightness shift, zoom, and horizontal flipping. The final dataset was then split into training, validation, and testing sets. [see Figure 4]




```
datagen = ImageDataGenerator(
    rotation_range=20,
    brightness_range=[0.2, 1.4],
    zoom_range=0.2,
    horizontal_flip=True,
```

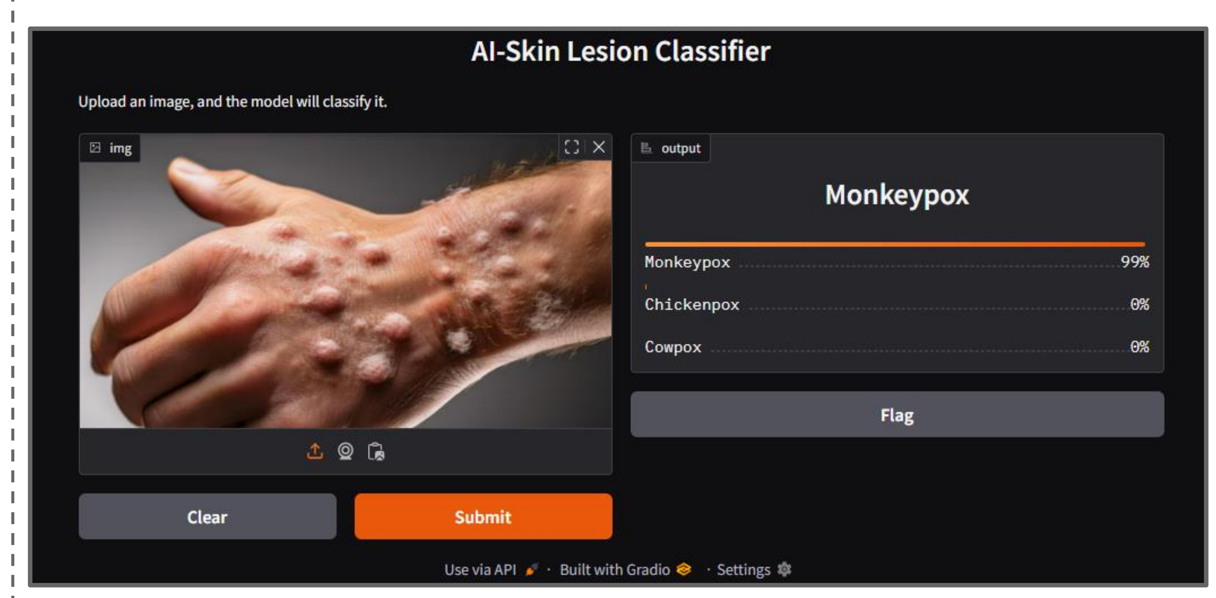
Fig(4): Preprocessing steps

Results

The model achieved an overall accuracy of 93%, with strong classification performance across most diseases. Cowpox and Healthy classes showed the highest precision and recall, while Monkeypox had a lower recall, as show in table below. GUI was developed using Gradio to facilitate user interaction. It allows users to upload images and receive disease classifications, providing a simple interface for testing and deployment [see Figure 5]

Classification Report

Label	Precision	Recall	F1-Score
Chickenpox	0.88	0.99	0.93
Cowpox	1.00	0.96	0.98
Healthy	0.91	0.99	0.95
HFMD	0.88	0.92	0.90
Measles	0.92	0.94	0.93
Monkeypox	0.97	0.78	0.86
Accuracy			0.93



Fig(5): GUI

Conclusion

The AI-Mpox system leverages machine learning and deep learning techniques to accurately detect and diagnose Monkeypox and five other skin conditions. Achieving an impressive 93% classification accuracy, the system uses advanced data augmentation to improve model performance. Designed with a user-friendly graphical interface (GUI), AI-Mpox provides a practical and accessible solution for rapid, reliable skin disease diagnosis, ultimately supporting more efficient and accurate healthcare delivery.

References

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