Skin Lesion Analysis for Monkeypox Detection: A Deep Learning Perspective

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Abstract: **Recent developments have highlighted the escalating global concern surrounding mpox (formerly known as monkeypox). In August 2024, the World Health Organization (WHO) declared the surge of mpox cases in the Democratic Republic of the Congo (DRC) and its spread to neighbouring countries as a public health emergency of international concern. This declaration underscores the critical need for enhanced surveillance and rapid diagnostic methods to curb the virus's transmission.**

The emergence of a new variant, clade Ib, has been particularly alarming. While this strain appears to be less deadly, it is spreading rapidly, with cases reported in diverse locations such as Kenya and Sweden. The rapid transmission of this variant has raised concerns about its potential to become a global health threat.

In response to the escalating situation, the WHO declared mpox a global health emergency in August 2024. This declaration aims to accelerate vaccine access and public health interventions, especially in lower-income regions, to contain the outbreak.

Given the evolving nature of the mpox outbreak and the emergence of new variants, there is an urgent need for effective diagnostic tools. Deep learning techniques have shown promise in the detection of mpox through the analysis of skin images, offering a potential solution for rapid and accurate diagnosis.

In this study, we aim to develop a deep learning model for the detection of mpox using skin image datasets. By leveraging advanced image analysis techniques, we hope to contribute to the timely identification and management of mpox cases, thereby aiding in the global effort to control the spread of this re-emerging infectious disease.

I. INTRODUCTION

Overview of Monkeypox as a Public Health Concern

Monkeypox, caused by the monkeypox virus (MPXV), is a zoonotic disease that has gained global attention due to its increasing incidence and potential for widespread transmission. Initially endemic to Central and West Africa, monkeypox has recently exhibited unprecedented geographical spread, with over 120 countries reporting cases between January 2022 and August 2024. The disease is characterized by fever, lymphadenopathy, and distinctive skin lesions. The re-emergence of the disease in non-endemic regions underscores its global threat, especially as new clades like Clade II spread rapidly.

Importance of Early Detection in Controlling Outbreaks

Early and accurate detection of monkeypox is crucial to implementing timely isolation, treatment, and contact tracing measures. Delayed diagnosis exacerbates community transmission, complicating outbreak management and increasing the burden on healthcare systems. Early detection minimizes morbidity and mortality while enabling health authorities to mitigate the socioeconomic impact of outbreaks.

Limitations of Traditional Diagnostic Methods

Traditional diagnostic methods for monkeypox rely primarily on laboratory techniques such as:

- Polymerase Chain Reaction (PCR): Considered the gold standard but requires specialized equipment and trained personnel, limiting its accessibility in resource-constrained settings.
- Serological Tests: Limited by cross-reactivity with other orthopox viruses, reducing specificity.
- Clinical Diagnosis: Heavily dependent on expert knowledge and prone to errors due to symptom overlap with other dermatological conditions like chickenpox or measles.

  These challenges highlight the need for more accessible and scalable diagnostic solutions.

Role of AI and Datasets in Improving Detection Accuracy

Advancements in artificial intelligence (AI) and deep learning have opened new avenues for disease diagnosis through image-based analysis. AI-powered models can:

- Analyze dermatological images to identify monkeypox-specific lesions with high accuracy.

- Process large datasets rapidly, enabling efficient decision-making in real-time scenarios.
- Enhance diagnostic capabilities in low-resource areas by leveraging mobile and cloud-based solutions.

By integrating AI and well-curated datasets, healthcare providers can overcome the limitations of traditional diagnostics, offering scalable, cost-effective, and timely solutions for monkeypox detection and management. This study focuses on the development of a deep learning-based model to detect monkeypox using skin image datasets, aiming to contribute to global efforts in controlling this re-emerging infectious disease.

II. METHODOLOGY

Dataset Description:

Kaggle Monkeypox Skin Lession Dataset In this dataset along with the 'Monkeypox' class, skin lesion images of 'Chickenpox' and 'Measles' are also included. So it's a binary classification dataset in which one class belongs to Monkeypox whereas another class labelled as 'Others' consists of Chickenpox and Measles images. Further, the dataset has the following 3 folders:

1. Original Images: It contains a total number of 228 images of which 102 belong to the 'Monkeypox' class and the remaining 126 belong to the 'Others' class i.e., (chickenpox and measles) cases.

2. Augmented Images: This folder consists of augmented images in both classes. In this images are augmented using different augmentation techniques: rotation, translation, reflection, shear, hue, saturation, contrast and brightness jitter, noise, scaling, etc.

3.Fold1: This folder is one of the three-fold cross-validation datasets. The original images were split into training, validation, and test set(s) with the approximate proportion of 70: 10: 20. In this only the training and validation images are augmented while the test set consists of original images. In this project, we have used the Fold1 dataset for training our computer vision models. The distribution of images in Train, Val, and Test under the Fold 1 folder is given below:

- Train: Monkeypox–980 and Others-1,162
- Val: Monkeypox–168 and Others-252
- Test: Monkeypox–20 and Others-25Model Selection

III. TYPE OF MODEL USED

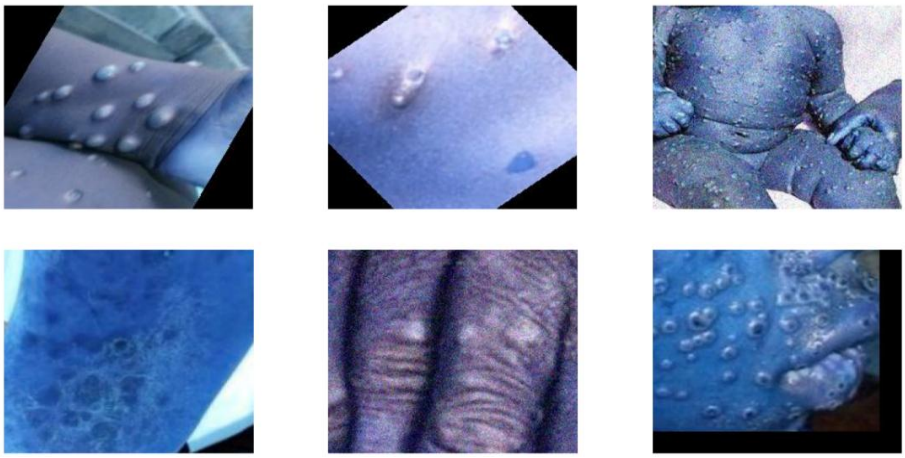
The model primarily used in this study is a Convolutional Neural Network (CNN), known for its ability to automatically learn spatial hierarchies of features.

Justification for CNN Architecture: CNNs are highly effective in analyzing visual data due to their convolutional layers that preserve spatial information between neighboring pixels. The key advantage is their ability to capture local patterns, which is crucial for recognizing skin lesions in medical images. By applying filters and pooling operations, CNNs can detect intricate details that aid in distinguishing between healthy and infected skin.

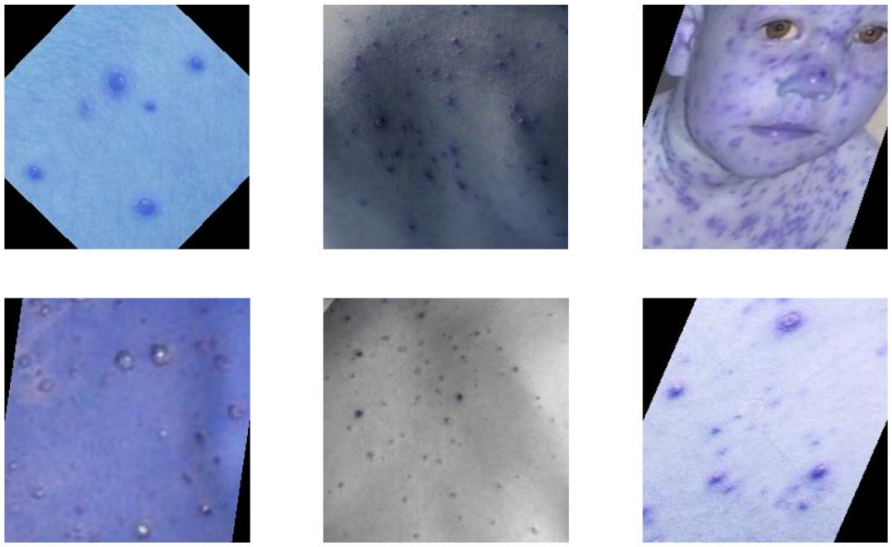
Transfer Learning: Models like ResNet and EfficientNet have also been explored for comparison, particularly for fine-tuning on smaller datasets, utilizing pre-trained weights to enhance feature extraction capabilities. However, CNN remains the core architecture due to its straightforward and robust design for lesion detection.

IV. IMPLEMENTATION

Monkey pox sample images



Other Diseases



Hyper parameters: Epoch size 8,Batch size 32

#making layers:

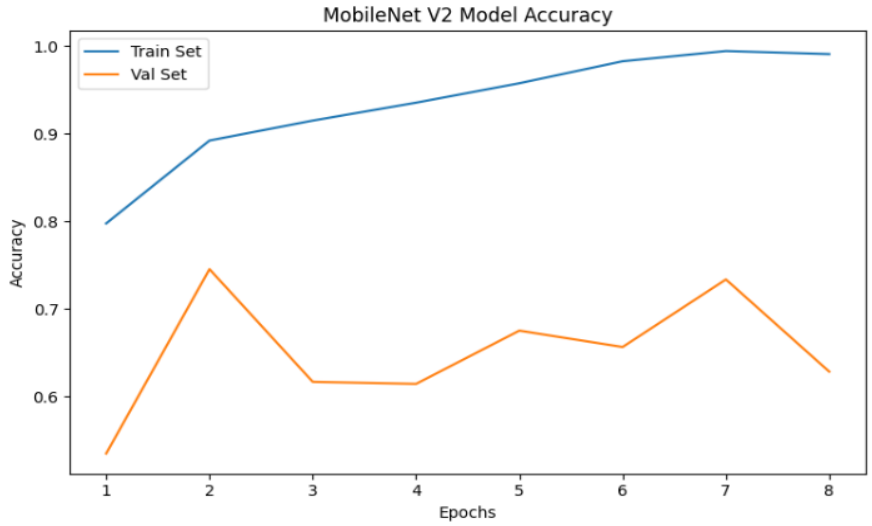
```
x = conv_base.output
x = layers.GlobalAveragePooling2D()(x)
x = layers.Dense(128, activation='relu')(x)
x = layers.Dropout(0.2)(x)
x = layers.Dense(64, activation='relu')(x)
predictions = layers.Dense(2, activation='softmax')(x)
model = Model(conv_base.input, predictions)
```

```
# Define the optimizer
#optimizer = Adam(lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0, amsgrad=False)
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
model.summary()
```

Model training

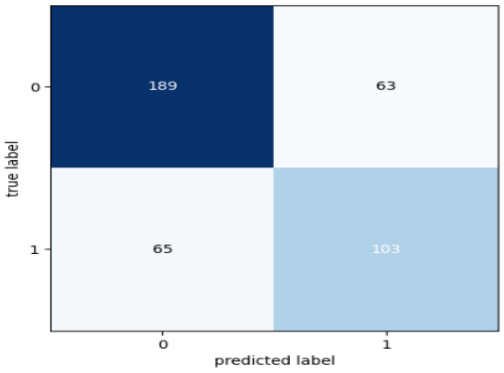
```
history = model.fit(x_train,y_train,batch_size=batch_size,callbacks=callbacks, validation_data=(x_test,y_test),epochs=epochs,verbose=1)
```

V. RESULTS



ROC CURVE

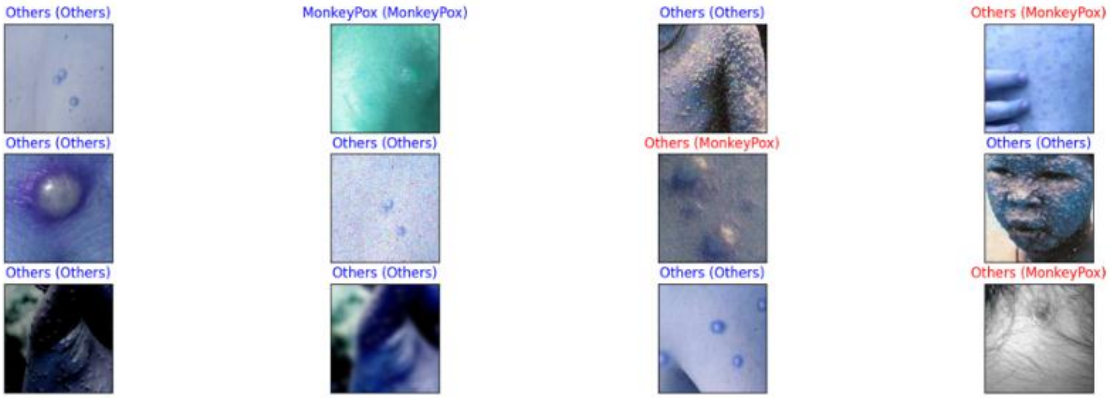
Confusion Matrix:



Classification Report

	precision	recall	f1-score	support
0	0.74	0.75	0.75	252
1	0.62	0.61	0.62	168
accuracy			0.70	420
macro avg	0.68	0.68	0.68	420
weighted avg	0.69	0.70	0.69	420

Output:



VI. CHALLENGES FACED

1. Dataset Quality and Imbalance:

One of the primary challenges faced during this study was the imbalance in the dataset. While there were a sufficient number of monkeypox lesion images, the distribution of classes (e.g., monkeypox lesions vs. normal skin vs. other skin conditions) was uneven. This imbalance led to issues such as the model being biased towards predicting the majority class, affecting the performance on the minority classes. To address this, techniques like oversampling, under sampling, and adjusting class weights in the loss function were implemented, but it remained a key challenge throughout the project.

2. Limited Dataset Size:

The relatively small size of available datasets for monkeypox lesions posed another challenge. Training deep learning models with a limited dataset often leads to overfitting and poor generalization to unseen data. To mitigate this, data augmentation techniques were applied to artificially increase the size and diversity of the dataset, but it still required careful fine-tuning of the model to achieve satisfactory performance.

3. Model Bias and Generalization:

Despite the application of preprocessing and augmentation techniques, the model was occasionally biased toward certain classes due to inherent patterns in the data (e.g., skin tone variations, lesion shapes, etc.). This bias could affect the generalizability of the model across diverse populations and lesion types. Extensive evaluation on a diverse validation set and cross-validation helped address some of these biases, but it was an ongoing challenge to ensure fairness and accuracy.

4. Hardware Limitations - Google Colab Usage:

Since the project was initially developed using Google Colab, there were limitations in terms of hardware resources, such as limited access to GPU capabilities (e.g., T4 GPUs) and restricted runtime sessions. While Google Colab provided a free platform, the session timeouts and occasional resource restrictions hindered longer training sessions. To manage this, models were frequently saved, and training was done in stages, but these interruptions slowed down the process.

5. Model Convergence:

CNN models, especially deep ones, require careful tuning of hyperparameters, including learning rates, batch sizes, and filter sizes. Fine-tuning to ensure that the model converged efficiently without overfitting or underfitting posed a significant challenge, requiring multiple iterations and experiments with different hyperparameters.

VII. SUGGESTIONS FOR FUTURE RESEARCH

- Larger and More Diverse Datasets: One of the key limitations in this study was the limited size and imbalance of the dataset. Future research should focus on creating and curating larger, more diverse datasets that include a wider range of lesion types, skin tones, and clinical stages of monkeypox to improve the model's robustness and generalizability.
- Inclusion of Other Imaging Modalities: To improve detection accuracy, future studies could integrate other imaging modalities, such as dermoscopy or ultrasound, alongside standard photographs of skin lesions. Combining different imaging types could enhance the model's ability to recognize subtle lesions and provide a more comprehensive diagnostic tool.
- Incorporating Advanced Model Architectures: Future work can explore more advanced neural network architectures, such as attention mechanisms or transformer-based models, which could improve the model's ability to focus on important regions of the lesion and better handle complex cases.
- Cross-Disease Classification: In addition to monkeypox, the model could be expanded to detect other dermatological conditions, such as chickenpox, measles, or bacterial infections, creating a multi-condition diagnostic tool. This would broaden the applicability of the model in public health monitoring.
- Real-World Validation: Finally, future work should involve real-world validation of the model in clinical settings with diverse patient populations. This would help in understanding the practical challenges of implementing such a tool in everyday healthcare systems, as well as refining the model's performance in various real-world conditions.

VIII. REFERENCES

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