Improving EfficientNetB0 for Monkeypox Detection

February 17, 2025

delphine nyaboke
Carnegie Mellon University Africa
dnyaboke@andrew.cmu.edu

Amon Muhairwe
Carnegie Mellon University Africa
amuhairw@andrew.cmu.edu

Aisha Opaluwa
Carnegie Mellon University Africa
aopaluwa@andrew.cmu.edu

Timothy Belekollie
Carnegie Mellon University Africa
tbelekol@andrew.cmu.edu

Overview and Context

Abstract

Monkeypox also known as Mpox is an infectious disease caused by a virus belonging to the same family as the smallpox virus. It commonly presents with a rash along with other symptoms. The disease spreads through direct contact with infected individuals or animals. Currently, there is no specific treatment available for mpox [1]. We are extending this paper [2] which evaluates the effectiveness of four pre-trained deep learning models—SqueezeNet, DenseNet201, EfficientNetB0, and ResNet50v2—for Monkeypox disease detection using a publicly available dataset. The study assesses model performance using six key metrics: accuracy, precision, recall, sensitivity, specificity, and F1-score. Among the tested models, EfficientNetB0 achieved the highest performance with an accuracy of 95%, precision of 97%, recall of 92%, sensitivity of 92%, specificity of 97%, and F1-score of 94% [2]. We propose to enhance the accuracy through Model Architecture Improvements, Fine-tuning Strategies, Advanced Data Augmentation, and Ensemble Learning.

Motivation

As CMU-Africa students, we care about our continent and what Monkeypox outbreak's effects on the community, especially in East Africa where the campus is located. On August 14, 2024, the WHO Director-General classified the escalating mpox cases in the Democratic Republic of the Congo (DRC) and nearby African nations as a Public Health Emergency of International Concern (PHEIC) under the International Health Regulations (IHR). The monkeypox virus (MPXV) outbreak, which originated in the DRC in

September 2023, has since spread to Burundi, Kenya, Rwanda, and Uganda. Furthermore, Côte d'Ivoire has reported its first mpox cases since the onset of the multi-country outbreak in 2022. [3]

- **Burundi:**
  i. Declared an outbreak on 25 July 2024, confirming three cases in Kamenge and Isare Health Districts.
  ii. As of 17 August 2024, 142 confirmed cases out of 358 suspected cases.
  iii. No deaths reported.
- **Kenya:**
  i. First confirmed case in Taita Taveta County on 29 July 2024.
  ii. One positive case out of 14 suspected cases.
  iii. No deaths reported.
- **Rwanda:**
  i. Outbreak declared on 27 July 2024 with two initial confirmed cases.
  ii. As of 7 August 2024, four confirmed cases detected.
  iii. No deaths reported.
- **Uganda:**
  i. Surveillance along the DRC border led to the first two cases identified in July 2024.
  ii. 39 suspected cases and 37 close contacts under follow-up.
  iii. No secondary transmission detected.
- **Côte d'Ivoire:**
  i. Seven confirmed cases across three health districts as of 7 August 2024.
  ii. No deaths reported.

Objective

The primary objective is to refine the EfficientNetB0 model to achieve higher accuracy by exploring:

- Advanced data augmentation techniques.
- Hyperparameter tuning for optimal performance.
- Incorporating transfer learning with additional pre-trained weights.

We also intend to explore other avenues of improving the accuracy such as:

- **EfficientNetV2**: An optimized version of EfficientNet that enhances accuracy while being computationally efficient.

- **ConvNeXt**: A modern CNN that improves performance by incorporating design elements from transformers.

ConvNet have 3 layers - convolutional layer, pooling layer and fully connected layer and is used to find patterns, identify classes and, objects.

Related Work and Background

Literature Review

Since we are extending the work of Anu V. Kottath and Muthukumaran Malarvel [2], we will closely examine their findings alongside other relevant research. Yang et al. [4] developed **AICOM-MP**, an AI-based system for Monkeypox detection, designed to minimize gender, racial, and age bias while maintaining computational efficiency. Their model focuses on binary classification while ensuring robustness across varying image backgrounds, resolutions, and quality. Notably, **AICOM-MP** achieved **state-of-the-art (SOTA) performance**, demonstrating its efficacy in real-world scenarios. Chiranjibi et al. [5] conducted their experiments using a publicly available dataset, implementing an ensemble approach that yielded an **average Precision of 85.44%**, **Recall of 85.47%**, **F1-score of 85.40%**, and **Accuracy of 87.13%**. These results highlight the effectiveness of ensemble learning for Monkeypox detection. In their study, Mattia et al. [6] explored different deep learning architectures and found that **MobileNetV3Large** delivered the best performance, achieving an **F-1 score of 0.928 in the binary classification task** and **0.879 in the multi-class task**. Moreover, they demonstrated that quantization significantly reduced the model size to less than one-third while decreasing inference time from **0.016 to 0.014 seconds**, with only a marginal F-1 score drop of 0.004. This highlights the importance of optimizing models for both efficiency and accuracy. Furthermore, Yang et al. [4] employed an **open-source FCNResNet10 model**, leveraging pre-trained weights to perform **region-based skin segmentation**. This approach enhances Monkeypox lesion detection by segmenting relevant regions effectively.

Background

The global emergence of Monkeypox as a public health threat has highlighted diagnostic challenges due to visual similarities with chickenpox and measles. While PCR tests remain the clinical standard, their field accuracy drops to 68% with accessibility issues in resource-limited regions. Previous computational efforts using VGG-16 architectures achieved 78% accuracy on augmented data but faced three key limitations:

$$\text{Accuracy}_{\text{VGG-16}} = 0.78 \quad \text{(Computational Baseline)} \tag{1}$$

$$\text{Accuracy}_{\text{PCR}} = 0.68 \quad \text{(Clinical Baseline)} \tag{2}$$

This work establishes evaluation metrics addressing clinical interpretability needs through six statistical measures: Accuracy, Precision, Recall, F1-score, Sensitivity, and Specificity.

Methodology

Model Description

Four pretrained CNN architectures were implemented and fine-tuned:

SqueezeNet: Compact architecture using fire modules with 1×1 and 3×3 filters:

$$\text{Memory Efficiency} = \frac{3 \times 3 \text{ filters}}{1 \times 1 \text{ filters}} \times \text{channel reduction factor} \tag{3}$$

ResNet50V2: 50-layer residual network with skip connections:

$$\mathcal{F}(x) = \mathcal{H}(x) - x \tag{4}$$

where $\mathcal{H}(x)$ represents stacked nonlinear transformations.

EfficientNetB0: Implements compound scaling via optimization:

$$\max_{w,d,r} \text{Accuracy}(w, d, r) \text{ s.t. } w \cdot d^2 \cdot r^2 \approx 2 \tag{5}$$

DenseNet201: Dense connectivity pattern with feature map concatenation:

$$x_\ell = H_\ell([x_0, x_1, ..., x_{\ell-1}]) \tag{6}$$

All models used Adam optimization ($\eta = 3 \times 10^{-5}$) with early stopping on validation loss.

Dataset-Amon

The study utilized an augmented dermoscopic image dataset containing 2,288 samples:

Class	Train (70%)	Test (30%)	Total
Monkeypox	802	314	1,116
Others	800	372	1,172

Preprocessing pipeline included:

- Normalization ($\mu = 0.485$, $\sigma = 0.229$)
- Augmentation with rotation ($\pm 15°$), scaling (0.8×-1.2×), and horizontal flipping

Evaluation Metric

Performance assessed through six key metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{AUC-ROC} = \int_0^1 TPR(FPR^{-1}(x))dx$$

Five-fold cross-validation was employed with metrics averaged across folds. EfficientNetB0 demonstrated superior performance:

$$\text{AUC} = 0.9563,\ \text{F1} = 0.94,\ \text{Accuracy} = 0.95$$

achieving optimal clinical utility with sensitivity=0.92 and specificity=0.97.

Loss Function

Since we are tackling a classification problem, our primary choice for the loss function will be binary cross-entropy, which is well-suited for binary classification tasks. However, given that this stage of the project is focused on experimentation, we also plan to explore focal loss as a potential alternative to better handle the challenges posed by class imbalance. This will allow us to assess its effectiveness in prioritizing hard-to-classify examples, which may lead to improved model performance on imbalanced datasets.

Baseline Selection & Evaluation

The baseline for this research project is the paper titled "Comparison Of Deep Learning Models for Monkeypox Disease Detection." This work serves as a valuable starting point for our investigation, providing a well-defined problem statement, a clear methodological approach, a structured framework, and strong performance results. The timeliness of the study is another strength, as it directly addresses the urgent need for effective detection of Monkeypox, a disease of increasing concern. However, there are several areas where we can extend and build upon this baseline. In terms of model selection, the paper predominantly uses four pre-trained models. While these models are effective, exploring additional more recent architectures could offer improvements in performance. For example, we intend to use EfficientNetV2-XL, which we believe has the capability to pass the best accurracy of the four baseline models. Furthermore, we also intend to use a more rigorous optimization approach—such as grid search or Bayesian optimization—which could help in fine-tuning model performance. Additionally, the paper lacks sufficient attention to model explainability. Visualizing the learned features using techniques like Grad-CAM could improve interpretability by showing which regions of an image the model is focusing on when making predictions. An error analysis that identifies common misclassification patterns, particularly with hard-to-classify lesions, would be valuable for improving the models.

Implemented Extensions/Experiments

To extend beyond the baseline, one of the first areas we plan to focus on is improving the accuracy of the best-performing baseline model. We intend to achieve this by using EfficientNetV2-XL, which we believe has the potential to surpass the current accuracy. Additionally, we plan to implement systematic hyperparameter optimization techniques, ensuring that the selected models are fine-tuned for maximum performance.

On the interpretability front, we will incorporate visualization tools like Grad-CAM and conduct a comprehensive error analysis to pinpoint misclassifications. These steps will not only enhance model performance but also provide a deeper understanding of its decision-making process. Through these enhancements, we aim to address the limitations of the baseline and contribute to the development of a more accurate and explainable model for Monkeypox detection.

Expected Results and Improvements

We aim to surpass the baseline model accuracy of 95% by leveraging advanced deep learning methodologies and optimizing model architectures. Additionally, we prioritize enhancing model explainability and interpretability through techniques such as Grad-CAM visualization and feature importance analysis, ensuring transparency and clinical trustworthiness. By improving dataset augmentation, exploring state-of-the-art models, and employing ensemble methods, we anticipate achieving a detection accuracy that exceeds the best-performing baseline model, making the system more robust and reliable for Monkeypox diagnosis.

Discussion

The proposed Monkeypox detection approach faces several significant challenges. First, model generalization across diverse populations remains a critical concern, particularly when applying models developed on limited datasets to the varied skin tones and presentation patterns seen across East African populations. Visual similarities between Monkeypox, chickenpox, and measles create inherent diagnostic complexity that advanced models must overcome. Second, while EfficientNetB0 achieved promising results (95% accuracy), the implementation of more complex architectures like EfficientNetV2 and ConvNeXt introduces potential trade-offs between accuracy gains and computational efficiency - a crucial consideration for deployment in resource-constrained settings where computing infrastructure may be limited. Additionally, the current evaluation metrics, while comprehensive (accuracy, precision, recall, sensitivity, specificity, and F1-score), may not fully capture model performance in real-world clinical scenarios where prevalence rates fluctuate during outbreaks. Furthermore, as indicated by the varying case counts across Burundi, Kenya, Rwanda, Uganda, and Côte d'Ivoire, regional variation in disease presentation and healthcare infrastructure poses implementation challenges that technical solutions alone cannot address. The rapid spread of the outbreak also creates time pressure for model development and deployment, requiring careful balance between thoroughness and urgency. These multifaceted challenges necessitate an integrated approach that considers both technical optimization and practical deployment constraints in the affected regions.

Future Directions

Beyond the immediate scope of this project, future research would focus on dataset enhancement through regional collaboration, model interpretability via visualization techniques, and clinical integration through mobile applications. These approaches would advance Monkeypox detection capabilities in East African healthcare settings by creating culturally relevant datasets, improving transparency in AI decision-making, and ensuring practical deployment in resource-limited environments.

Conclusion

This proposal outlines a structured approach to enhancing EfficientNetB0's performance in Monkeypox detection, with a particular focus on applications in East Africa. By combining advanced optimization techniques, sophisticated data augmentation, and transfer

learning, we aim to push the accuracy beyond the baseline of 95% while maintaining robust generalization. The proposed improvements address critical needs in resource-constrained settings and align with current public health challenges in the region. Success in this project could significantly impact early disease detection capabilities, particularly in areas where traditional diagnostic resources are limited. The emphasis on model interpretability and clinical integration ensures that the technological advances translate into practical healthcare solutions.

References

[1] Centers for Disease Control and Prevention *"Mpox: About,"* Feb. 2024. [Online]. Available: https://www.cdc.gov/mpox/about/index.html.

[2] A. V. Kottath and M. Malarvel, *Comparison Of Deep Learning Models for Monkeypox Disease Detection* 2023 First International Conference on Advances in Electrical, Electronics and Computational Intelligence (ICAEECI), Tiruchengode, India, 2023, pp. 1-8, doi: 10.1109/ICAEECI58247.2023.10370981.

[3] World Health Organisation *"Mpox: Africa Region,"* Aug 2024. [Online]. Available: https://www.who.int/emergencies/disease-outbreak-news/item/2024-DON528.

[4] Yang T., Liu, A., An, N., Liu, S., Liu, X. (2024). *AICOM-MP: an AI-based monkeypox detector for resource-constrained environments* Connection Science, 36(1). https://doi.org/10.1080/09540091.2024.2306962.

[5] Sitaula, C., Shahi, T.B. *Monkeypox Virus Detection Using Pre-trained Deep Learning-based Approaches.* J Med Syst 46, 78 (2022). https://doi-org.cmu.idm.oclc.org/10.1007/s10916-022-01868-2

[6] Mattia Giovanni Campana, Marco Colussi, Franca Delmastro, Sergio Mascetti, Elena Pagani *A Transfer Learning and Explainable Solution to Detect mpox from Smartphones images, Pervasive and Mobile Computing* Volume 98, 2024, 101874, ISSN 1574-1192, https://doi.org/10.1016/j.pmcj.2023.101874. (https://www.sciencedirect.com/science/article/pii/S1574119223001323)

[7] Tan, M., Le, Q.V. (2019). *EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks*. International Conference on Machine Learning, 6105-6114.

[8] Ali, S.N. et al. (2023). *Automated Monkeypox Skin Lesion Detection Using Deep Learning*. Diagnostics, 13(8), 1450. doi:10.3390/diagnostics13081450

[9] Şahin, N. (2023). *Comparison of Deep Learning Models for Monkeypox Disease Detection*. E3S Web of Conferences, 465, 02031. doi:10.1051/e3sconf/202346502031

[10] Islam, M.M. et al. (2023). *Monkeypox Detection Using CNN with Transfer Learning*. International Journal of Molecular Sciences, 24(7), 6354. doi:10.3390/ijms24076354

[11] Monkeypox Detection Team, "Better Monkeypox Diagnosis Using AI," *IEEE Journal*, 2024. Available: `https://ieeexplore.ieee.org/document/10370981`