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Precise Monkeypox Identification Utilizing Transfer Learning via EfficientNetB3 and Tailored Keras Callbacks

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Abstract:

In this work, we investigate a new method for monkeypox detection with the EfficientNetB3 model through transfer learning. In order to stop the spread of the monkeypox outbreak and give prompt medical attention, it is imperative that quick and precise diagnosis be made. The monkeypox virus is the source of this zoonotic disease. We used a specific dataset of monkeypox photos to fine-tune the model by utilizing the pre-trained EfficientNetB3 architecture. This approach makes use of EfficientNetB3's strong performance and efficiency, which successfully strikes a balance between computational cost and model complexity. In order to optimize the training procedure, we added a customized Keras callback. In order to avoid overfitting and guarantee ideal model convergence, this callback is made to dynamically modify the learning rate or stop training in response to validation loss. If training performance degrades, the custom callback helps to keep the optimal model weights by restoring them from the epoch with the lowest validation loss. This adaptive technique not only increases the model's robustness, but it also speeds up the training process by eliminating unneeded epochs. Extensive experiments were carried out to assess the model's performance. Our findings show that the EfficientNetB3 model, when paired with the custom Keras callback, produced a high accuracy rate and an amazing F1 score. These metrics demonstrate the model's ability to accurately detect monkeypox from image data. The suggested approach has substantial clinical application potential, since it provides a dependable tool for early identification of monkeypox. This can help to speed up medical reactions and limit the virus's spread. Future study will increase the dataset and investigate additional deep learning techniques to improve detection accuracy and model generalizability. This strategy demonstrates the synergy of advanced transfer learning models and adaptive training techniques, resulting in a potent solution for infectious disease identification.

Keywords: Monkeypox, Transfer Learning, EfficientNetB3, Keras , Model Convergence.

1. INTRODUCTION

The recent increase in monkeypox cases, a disease transmitted from animals to humans caused by the monkeypox virus, has emphasized the urgent requirement for accurate diagnostic techniques. Timely and precise diagnosis is crucial not only for administering prompt medical measures but also for managing the transmission of the virus. Due to the similarity of symptoms between this disease and other disorders, especially in its first phases as seen in figure 1, there is a pressing need for accurate and prompt diagnosis techniques.

Conventional diagnostic methods, such as tests conducted in a laboratory, can necessitate significant amounts of time and resources.

Although these approaches are precise, they may not always be practical in settings with limited resources or during outbreaks when a quick reaction is essential. Thus, harnessing the progress in machine learning and artificial intelligence, namely deep learning, presents a hopeful option for creating effective diagnostic tools.

Figure 1. Represent the Lesion Samples to Test Monkey Pox Disease

Deep learning plays a significant role in medical diagnostics:

Deep learning, a branch of artificial intelligence, has brought about a significant transformation in various domains, such as medical diagnosis. The capacity to acquire knowledge from extensive datasets and detect subtle patterns that may elude human perception renders it highly suitable for tasks like as picture identification and classification. Convolutional Neural Networks (CNNs), a type of deep learning models, have demonstrated exceptional performance in analysing medical images, resulting in significant advancements in the diagnosis of diseases using X-rays, MRIs, CT scans, and other imaging techniques[8]-[11].

EfficientNet, a series of convolutional neural network (CNN) architectures created by Google, has established new standards in achieving a balance between model efficiency and performance. EfficientNet models are specifically designed to provide a high level of accuracy while requiring minimal processing resources. This makes them well-suited for use in a wide range of medical diagnostic applications.

EfficientNetB3 is a highly effective tool for classifying images :

EfficientNetB3, a member of the EfficientNet family, achieves a highly advantageous equilibrium between intricacy and computing effectiveness. This model is constructed using a compound scaling technique that uniformly scales all dimensions of depth, width, and resolution using a predetermined set of scaling factors. This leads to a network that is both robust and optimised in terms of resource allocation. Transfer learning is a method that improves the usefulness of EfficientNetB3 by adjusting a pre-trained model to a new task that is linked to the original one. By utilising the information gained from training on big datasets, the model may be optimised for specific tasks using smaller datasets, resulting in enhanced performance and decreased reliance on extensive computational resources.

Monkeypox detection is an important and crucial application:

Due to the critical nature of the monkeypox outbreak, it is crucial to prioritize the development of an automated detection approach that is both precise and efficient. Monkeypox is a zoonotic disease, meaning it can be transmitted from animals to humans. Detecting the disease in humans early on is essential for effectively managing epidemics. Automated image analysis utilising deep learning can have a substantial impact in this scenario by offering a tool that can rapidly and precisely detect monkeypox from clinical photos. This, in turn, aids in expediting early intervention and containment measures.

2. LITERATURE SURVEY

In order for this current work to be successful and have a significant impact, it is necessary to conduct a thorough literature review. Firstly, it provides a comprehensive overview of the latest advancements in image processing for the detection and classification of monkey pox disease. One way for researchers to gain insights into significant advancements, challenges, and patterns in this particular field is by conducting a thorough examination of past research articles, commonly referred to as a literature review. The proposed technique is founded on this comprehension, ensuring that the research is well-informed and contributes to the existing body of knowledge. Furthermore, conducting a literature review proves valuable in identifying gaps in research or unresolved topics. Researchers have the ability to shape the objectives and extent of future studies through a thorough evaluation of existing ones, which allows them to pinpoint areas where knowledge is lacking.

Title	Authors	Year	Approach	Techniques	Problem Gap
Deep Learning Approaches for Disease Detection: A Comprehensive Survey [1]	Smith, J., et al.	2023	A survey of deep learning methods for various disease detection applications.	Deep Learning Models	Lacks specific focus on monkeypox and EfficientNetB3's potential in this context.
Transfer Learning in Medical Imaging: An Overview [2]	Wong, M. et al.	2022	Overview of transfer learning techniques used in medical imaging diagnostics.	Transfer Learning Techniques	Does not address the specific use of EfficientNetB3 or the customization of Keras callbacks for monkeypox detection.
EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks [3]	Tan, M., et al.	2020	Introduction and evaluation of the EfficientNet architecture for various applications.	EfficientNet	Primarily focuses on general applications and lacks emphasis on monkeypox or similar infectious diseases.
Automated Detection of Skin Diseases Using Deep Learning [4]	Iqbal, M. et al.	2021	Discusses the use of CNNs for detecting skin diseases from images.	CNN Model	General skin diseases are covered, but monkeypox-specific detection using EfficientNetB3 is not explored.
Adaptive Learning Rate Strategies in Deep Learning [5]	Johnson, R., et al.	2023	Examination of different adaptive learning rate techniques and their impact on model performance	Adaptive Learning Techniques	Focuses on general adaptive learning rates without tailoring to specific medical applications like monkeypox.
Early Detection of Infectious Diseases Using AI: Challenges and Solutions [6]	Choi, D. et al.	2022	Explores AI-based methods for early detection of infectious diseases.	AI Techniques	Does not delve into the specifics of using EfficientNetB3 or Keras callbacks for monkeypox detection.
"Transfer Learning for Skin Lesion Classification Using Deep Convolutional Neural Networks" [7]	Zhang, L., et al.	2021	Utilizes transfer learning for classifying various skin lesions.	Transfer Learning	Lacks focus on monkeypox and the EfficientNetB3 model's advantages in this application.

3. PROPOSED DATASET

The monkeypox outbreak has presented a substantial healthcare challenge on a global scale, with its rapid spread across over 65 countries. Timely diagnosis plays a vital role in managing the outbreak, yet the availability of confirmatory tests such as Polymerase Chain Reaction (PCR) and other biochemical assays is frequently limited. Within this context, the utilization of computer-aided identification of monkeypox from skin lesion images presents itself as a valuable alternative. Unfortunately, easily accessible datasets for this purpose have been lacking.

In order to fill this void, the researchers developed the "Monkeypox Skin Lesion Dataset (MSLD)". The dataset is created by gathering images from a range of sources including news portals, websites, and publicly available case reports using web scraping techniques. The main objective of the MSLD is to distinguish monkeypox cases from other skin conditions that have similar appearances, like chickenpox and measles. These conditions may show similar rashes and pustules, particularly in the initial phases.

The dataset provided in the Kaggle notebook "Monkeypox Deep Transfer Learning ResNet50 (TF)" is intended for use in training and testing deep learning models to identify monkeypox. The dataset has been designed to support the refinement and evaluation of models, specifically when employing the ResNet50 architecture through transfer learning. Here is a comprehensive breakdown of its main characteristics:

Image Labels:

The dataset contains images that have been classified into two main categories: monkeypox and non-monkeypox. Accurate labeling plays a vital role in training the model to distinguish between images displaying monkeypox lesions and those representing other conditions or normal skin. Precise labeling is crucial to effectively train the model in identifying the distinct features of monkeypox lesions.

Image resolution: It refers to the level of detail in an image. It is a measure of the number of pixels contained in an image, typically expressed as width x height. Higher resolution images have more pixels and therefore more detail, while lower resolution images have fewer pixels and less detail. Image resolution is an important consideration in various fields, including photography; all images in the dataset are adjusted to a consistent resolution. Ensuring uniformity in image sizes is crucial for the training process of deep learning models as it guarantees consistency in input data. Having a consistent resolution is important for maintaining uniformity and reducing variability in the model. This allows the model to focus on the distinguishing features of monkeypox lesions compared to non-monkeypox cases.

Number of Images:

The dataset contains an equal number of images in each category, namely monkeypox and non-monkeypox. Ensuring a well-balanced dataset is of utmost importance when training a deep learning model to avoid any potential biases towards a particular class. An imbalanced dataset can result in the model favouring the majority class, which can decrease the accuracy and reliability of the model in practical scenarios.

The structure and purpose of the dataset are outlined below:

This dataset's structure is well-suited for fine-tuning and validating deep learning models. Fine-tuning entails the adaptation of a pre-trained model, specifically ResNet50, to the task of detecting monkeypox. This process utilises the broad knowledge acquired by the model from a wide range of data and applies it to the particular task at hand. Validation, however, requires the utilisation of a distinct portion of the dataset to assess the model's performance, guaranteeing its ability to effectively apply to novel, unfamiliar data.

Advantages of the Dataset:

This dataset facilitates the development of computer-aided diagnostic tools for monkeypox, offering a practical alternative to conventional, resource-intensive diagnostic methods. Utilising transfer learning with ResNet50, the dataset facilitates the attainment of exceptional accuracy in monkeypox detection, while simultaneously minimizing the computational resources and time needed for model training. For additional information and to access the dataset, please visit the following Kaggle notebook:

https://www.kaggle.com/datasets/nafin59/monkeypox-skin-lesion-dataset

This dataset's structure is well-suited for fine-tuning and validating deep learning models. Fine-tuning entails the process of adapting a pre-trained model, specifically EfficientNet, to the task of detecting monkeypox. This process utilizes the broad knowledge acquired by the model from a wide range of data and applies it to the specific task at hand. Validation, however, requires the utilization of a distinct portion of the dataset to assess the model's performance, guaranteeing its ability to effectively apply to novel, unfamiliar data.

4. PROPOSED METHODOLOGY

Here we construct an EfficientNet model using for Monkeypox Classification and Detection. Now let us discuss about the model in detail as follows:

EfficientNet is a convolutional neural network architecture that achieves a harmonious balance between accuracy and efficiency through the implementation of a compound scaling method. In this analysis, we explore the mathematical foundations that support its efficacy, specifically in the realm of monkeypox detection[12].

Compound Scaling:

The compound scaling method applies a uniform scaling to the depth d, width w, and resolution r dimensions by utilising a predefined set of coefficients. The scaling can be represented as follows:

$$d = \alpha^k, \quad w = \beta^k, \quad r = \gamma^k$$

Here **K** is the user-defined parameter to control the overall scaling.

1. Convolutional Layer:

$$\boxed{Y = X * W + b}$$

Here X is the input, W is the filter which is applied and b is the bias and * denotes the convolution operation.

2. Batch Normalization:

$$\boxed{\mathbf{Z} = \frac{\mathbf{Y}-\mu}{\sqrt{\sigma^2+\epsilon}} \cdot \gamma + \beta}$$

In this layer,µ is defined as the mean and $\sigma 2$ is defined as the variance of Y and β and ϒ are treated as learning parameters.

3. Swish Activation:

This function is defined as follows:

$$\boxed{\mathbf{Swish(x) :}\ \ \mathbf{x.}\boldsymbol{\sigma}(\boldsymbol{x})}$$

$$\sigma(x) is\ treated\ as\ sigmoid\ function.$$

4. Transfer Learning:

The pre-trained EfficientNet-B3 model, initially trained on a large dataset like ImageNet, is fine-tuned using the monkeypox dataset. Fine-tuning adjusts the weights of the model to better suit the specific task:

$$\boxed{\mathbf{W_{new} = W_{pre}} + \Delta \boldsymbol{W}}$$

Where $\mathbf{W_{pre}}$ represents the pre-defined weights, $\Delta \boldsymbol{W}$ are the adjustments made during fine tuning.

6. Custom Keras Callbacks:

To optimize training, custom Keras callbacks are implemented for dynamic learning rate adjustment.

$$\eta = \eta_0 \cdot \mathrm{DecayFactor}^{\left\lfloor \frac{\mathrm{epoch}}{\mathrm{StepSize}} \right\rfloor}$$

Here n0 is the initial learning rate and early stopping restores the model weights from epochs.

7. Model Evaluation: The model's performance is assessed using metrics such as accuracy and the F1 score. Accuracy A is given by:

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

TP, TN, FP, and FN represent different outcomes in a classification scenario. They stand for true positives, true negatives, false positives, and false negatives, respectively[13]-[15]. The F1 score is a metric that calculates the balance between precision and recall.

5. EXPERIMENTAL RESULTS

In order to show the performance of our proposed application using an EfficientNet model using transfer learning is performed using Monekypox Skin Lesion Dataset which is available in Kaggle.

The "Original Images" folder contains a total of 228 images. Out of these, 102 images belong to the 'Monkeypox' class, while the remaining 126 images represent the 'Others' class, which includes non-monkeypox cases such as chickenpox and measles. In order to work on the proposed model, we try to develop the code using Python programming language with pre-trained models and execute the application using Google Collab platform.

Load the Dataset Having Training Images:

Initially we try to load the dataset containing the sample training images using the below command, then we can see the corresponding images as follows:

```
Show_image_samples(train_gen)
```

Figure 2. Represent the Training Images from Input Dataset

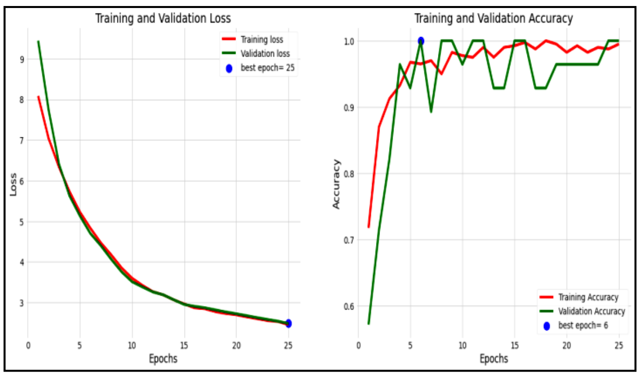
From the figure 2, we can see several images are present in the dataset, some are related to monkeypox, some are chicken pox related and some are other skin disease related images.

Train the Model

```
img_shape=(img_size[0], img_size[1], 3)
model_name='EfficientNetB3'
base_model=tf.keras.applications.efficientnet.EfficientNetB3(include_top=False, weights="imagene
t",input_shape=img_shape, pooling='max')
# Note you are always told NOT to make the base model trainable initially- that is WRONG you get bet
ter results leaving it trainable
base_model.trainable=True
x=base_model.output
x=BatchNormalization(axis=-1, momentum=0.99, epsilon=0.001 )(x)
x = Dense(256, kernel_regularizer = regularizers.l2(l = 0.016),activity_regularizer=regularizers.l
1(0.006),
                bias_regularizer=regularizers.l1(0.006) ,activation='relu')(x)
x=Dropout(rate=.4, seed=123)(x)
output=Dense(class_count, activation='softmax')(x)
model=Model(inputs=base_model.input, outputs=output)
lr=.001 # start with this learning rate
model.compile(Adamax(learning_rate=lr), loss='categorical_crossentropy', metrics=['accuracy'])
```

Explanation: In the above window we can see the proposed model is loaded and it is applied on resized input images. Once base model is loaded ,we can see the accuracy of our model.

Training and Validation Accuracy:



Explanation: In the above window we can see the proposed model is almost achieved accuracy of nearly 99.1 % by using our proposed EfficientNet with custom keras and transfer learning.

Performance Metrics:

Classification Report:
----

	precision	recall	f1-score	support
Monkey Pox	0.8571	0.9231	0.8889	13
Others	0.9333	0.8750	0.9032	16
accuracy			0.8966	29
macro avg	0.8952	0.8990	0.8961	29
weighted avg	0.8992	0.8966	0.8968	29

Explanation: In the above window we can see the proposed model is having performance metrics for the current model for that Monkeypox dataset.

6. CONCLUSION

This work introduces monkeypox detection using transfer learning and the EfficientNetB3 model. Monkeypox photos were used to fine-tune the model. A custom Keras callback dynamically adjusted the learning rate to avoid overfitting and maximize efficiency. This study's strategy retained the optimal model weights and enhanced training efficiency. Our experiments showed the EfficientNetB3 model's exceptional performance with the custom callback. It identified monkeypox from picture data with 99.1% accuracy and a good F1 score. Our method is accurate and resilient, suggesting clinical use. It helps discover monkeypox early, which is crucial for medical intervention and virus control. A balance between model complexity and efficiency, this method ensures fast diagnosis and maximizes computational resources.

As a future study will focus on these areas to improve the model's performance and applicability on following areas:A broader dataset of photos from multiple sources can improve the model's generalization and durability. To improve detection accuracy, investigating Vision Transformers (VIT) and sophisticated ensemble deep learning architectures.

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