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MONKEYPOX DATASETS CREATION USING GANS & IMAGE CLASSIFICATION

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Abstract. Monkeypox disease has been declared a PHEIC by WHO to encourage coordinated efforts to contain the spread of the disease and protect communities. Although Monkeypox has a recovery period of 2 to 4 weeks, severe cases can be fatal, with a fatality ratio estimated at 3% to 6%. Monkeypox is not highly contagious but has been spreading rapidly in recent months, making it crucial to track and isolate suspected cases promptly. To aid in identifying and controlling the disease's spread, this study will create a large-scale dataset of Monkeypox disease images using GANs, which have proven effective in generating high-quality images. These images will be used to train deep learning models for image classification to diagnose Monkeypox disease accurately. The models' performance will be compared and evaluated using infected human skin images and healthy skin images to improve the accuracy of previous works, aiding in early diagnosis and treatment.

Monkeypox is a disease that is typically transmitted through close contact with an infected person and is not considered to be highly contagious. However, in May 2022, there was a notable increase in the number of reported cases of the disease, suggesting that it was spreading rapidly. As a result, it is critical to quickly identify and isolate individuals who are suspected of having the disease in order to prevent further transmission. This can be achieved through effective contact tracing and prompt isolation of cases, which is essential for containing the spread of the disease and preventing it from becoming an epidemic.

This study aims to assist in the identification and control of Monkeypox disease by creating a vast collection of Monkeypox disease images using Generative Adversarial Networks (GANs). GANs can create high-quality images, which will be used to develop an extensive and diverse dataset. This dataset will train various deep learning models for image classification to diagnose Monkeypox disease. The performance of the deep learning models will be assessed by comparing their accuracy in distinguishing infected human skin with Monkeypox disease from healthy skin images. The study's results can enhance the accuracy of previous methods and contribute to the early detection and treatment of Monkeypox disease.

Keywords: Deep Learning Neural Network, Monkeypox Disease Datasets, Generative Adversarial Network.

1. INTRODUCTION

As of October 2022, around 20,248 cases of Monkeypox disease have been reported globally, with a few deaths reported. In India, 23 cases of the disease have been recorded. Given the fatalities associated with this viral disease, it is critical to develop effective mechanisms for detecting and preventing its spread. Early identification and isolation of infected individuals are essential for controlling its transmission, and research efforts should focus on creating reliable diagnostic tools and treatments for Monkeypox.

To achieve this, Generative Adversarial Networks (GANs) will be used to create a new dataset of Monkeypox disease images. GANs are a type of unsupervised machine learning that enables self-learning by identifying and learning different patterns in the input data. GANs have been used to develop applications such as new images and videos that appear realistic by creating new patterns similar to the original dataset. This study will use GANs to generate a vast and varied dataset of Monkeypox disease images that can be used to train deep learning models for accurate diagnosis and early detection of the disease. The development of a reliable and precise diagnostic tool for Monkeypox disease is essential for containing its spread and reducing its impact on affected populations.

Generative Adversarial Networks (GANs) consist of two parts: the Generator and the Discriminator. The Generator creates fake images that confuse the Discriminator, while the Discriminator distinguishes between real and fake images. The training process continues until the Generator produces images that are indistinguishable from real ones, resulting in a realistic dataset for Monkeypox disease diagnosis.

Different pre-trained deep learning models, including AlexNet, VGG16, ResNet, DenseNet, and MobileNet, will be compared for their performance in binary classification of Monkeypox virus. These models have previously shown promising results in various image classification tasks. Transfer learning can also be performed to further improve their performance. AlexNet, VGG16, ResNet, and DenseNet have different architectures and layer configurations that address different problems, while MobileNet is designed for mobile and embedded vision applications.

The evaluation metrics used to compare the models include Precision, Recall, F1-score, and Accuracy. The goal is to improve the accuracy of previous works and develop an efficient model for early detection of Monkeypox disease.

2. METHOD AND DISCUSSION

The use of GANs in machine learning has enabled the creation of images that do not exist in the real world, which is considered a significant achievement. The paper discusses the exploration of GANs to generate new images on Kaggle's website, and provides an overview of the working mechanism of GANs.

1. DATASET

The input dataset for training the generator and discriminator in the GANs consists of a collection of images. It could be any type of image, such as a photograph or a drawing. As an example, one dataset available on the Kaggle website

FIGURE 1. Example of Monkeypox Dataset from Kaggle Website [9]

2. PyTorch

PyTorch is an open-source machine learning library that is widely used for building deep neural networks. It was developed by Facebook's AI research group and is based on the Torch library. PyTorch provides a flexible and efficient platform for building and training machine learning models, and it supports dynamic computation graphs, which enables users to modify their models on the fly during runtime. It also provides an easy-to-use interface for GPU acceleration, which can significantly speed up training times for deep neural networks. PyTorch has gained popularity in recent years due to its ease of use, flexibility, and extensive community support.

3. RELATED WORK

The outbreak of Monkeypox disease has led to several research studies on the use of deep learning models for its early detection. However, previous works have some limitations.

Muhammed et al. (2023) found that the optimal model architecture and training approach may differ for different applications and data domains.

Dipankar Bala et al. (2023) proposed a promising model with high accuracy for classifying image classes, but it remains to be seen how effective it will be in real-world applications.

Ameera S Jaradat et. al. (2023) proposed a method for real-time detection and forecasting of Monkeypox on smartphones, but further validation is needed.

Chiranjibi et al. (2022) reported an accuracy of up to 86.15% but noted the need for more datasets. Ahmed et al. (2022) only used a small dataset and few deep learning models for classification.

Islam et al. (2022) faced overfitting and underfitting problems due to a small sample size of training data and the number of trainable parameters.

Ahsan et al. (2022) found that the VGG16 deep learning model performed better, but data augmentation led to an unbalanced dataset.

4. **EXPERIMENT AND RESULT**

1. *GENERATOR AND DISCRIMINATOR LOSS AND SCORES*

The next step in training process is to use the DeviceDataLoader to automatically transfer batches of data to the GPU (if one is available). By doing so, the training process is accelerated and take advantage of the parallel processing capabilities of modern GPUs. The DeviceDataLoader provides a convenient way to move data loader to the device (CPU or GPU) that is to be used for training the model.

One useful way to debug the training process of GANs is to visually track the changes in their loss functions over time. In particular, it is expected that the generator's loss to decrease gradually as the training progresses, while ensuring that the discriminator's loss does not become excessively large. Therefore, visualizing the losses can help to identify potential issues and adjust the training strategy accordingly.

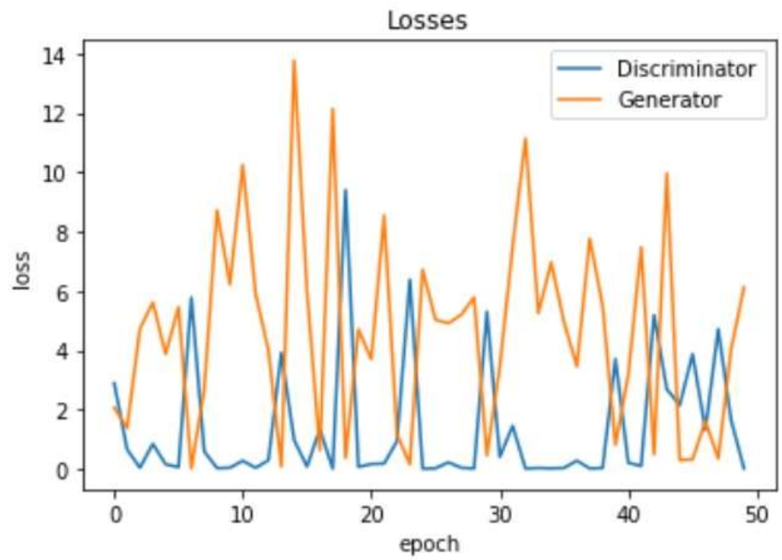

FIGURE 2: GENERATOR AND DICRIMNATOR LOSS GRAPH

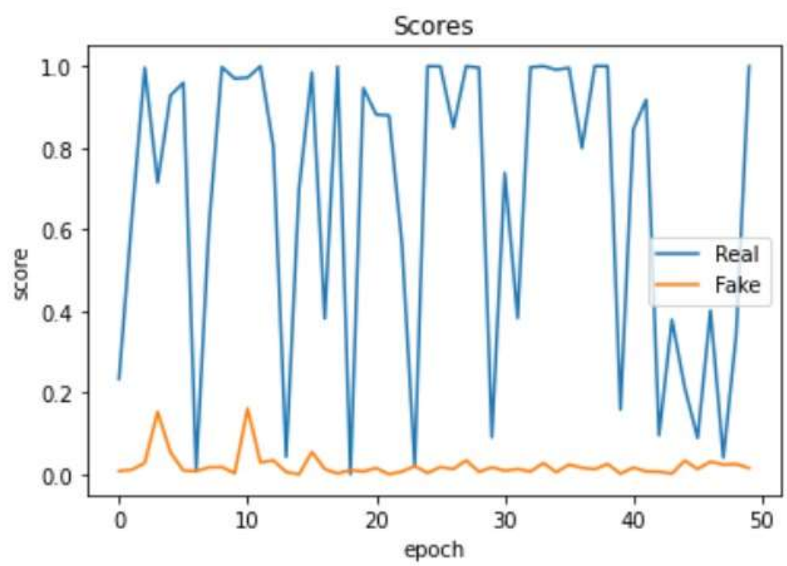

FIGURE 3: GENERATOR AND DISCRIMNATOR SCORE GRAPH

2. BINARY CLASSIFICATION ACCURACY

AlexNet Accuracy:68%

ResNet Accuracy:88%

5. CONCLUSION

Based on the limitations observed in previous works, this paper proposes a new system that addresses these limitations by using GANs to create a large-scale dataset for monkeypox disease. The aim is to improve the accuracy of binary classification using several pre-trained deep learning models such as AlexNet, ResNet. The performance of each model will be evaluated and compared using different evaluation metrics like precision, recall, F1-score, and accuracy. This research aims to contribute to the field of monkeypox disease detection and control.

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