Diagnosis of Monkeypox Disease Using Deep Learning

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The virus that causes monkeypox has been observed in Africa for several years, and it has been linked to the development of skin lesions. Public panic and anxiety have resulted from the deadly repercussions of virus infections following the COVID-19 pandemic. Rapid detection approaches are crucial since COVID-19 has reached a pandemic level.

biological mechanism | monkeypox detection | deep learning | transfer learning | feature selection

1. Introduction

Early detection is essential to treat and prevent the spread of monkeypox effectively. Deep learning is a kind of machine learning that employs convolutional neural networks to study and learn from large datasets. The diagnosis of infections like monkeypox has been greatly aided by this method. Deep learning algorithms can sift through mountains of data from medical imaging, laboratory testing, and patient records to better diagnose disease. The interactions between the monkeypox virus and the host cells are fundamental to the disease's complicated molecular mechanisms. A virus infects a host cell and then replicates inside of it, causing the host cell to die and the virus to spread to neighboring cells and tissues. When the immune system detects a virus or infected cells, it responds by making antibodies and immune cells to destroy them. Hopefully, by delving into the molecular workings of monkeypox, more effective therapies and vaccinations might be created. Deep learning can be applied to massive amounts of molecular and genetic data to find promising areas to focus on when designing treatments or vaccines. Researchers can benefit from deep learning's ability to zero in on specific disease-related chemicals and pathways to create more precise and tailored treatments. It is crucial to understand the basic underpinnings of monkeypox to understand how deep learning can detect the disease. Effective therapies and vaccinations for monkeypox require an understanding of the disease's basic mechanisms, which the use of deep learning algorithms for detection and diagnosis can aid. These strategies can potentially enhance the control of monkeypox and other viral infections [1][2][3].

The monkeypox virus, responsible for this illness, is a member of the Poxviridae family and the orthopoxviral genus. Similarly, smallpox is caused by the Variola virus, a Poxviridae family member. The cowpox virus causes bovine smallpox, and vaccines are made with the Vaccinia virus. While it is commonly referred to as "monkeypox", the virus that causes it actually originated in rodents. The virus known as monkeypox was first identified in 1958 after two outbreaks with symptoms identical to those of smallpox occurred in monkey colonies housed for scientific purposes. In 1970, the monkeypox virus was recognized for the first time in a human host. Since those times, monkeypox incidence has been extremely low throughout Africa. Transmission of monkeypox, which has been observed for a considerable amount of time in West and Central Africa due to the region's high concentration of tropical rainforests, has rarely occurred due to animals shipped from the region. The disease has recently spread and been identified in a wider variety of people and geographic locations than ever before. Because of the terrible impacts of the COVID-19 pandemic, monkeypox cases have begun to be closely monitored, even though they are not yet at the pandemic stage, and indicate an epidemic spread [4][5][6][7].

Monkeypox is characterized by a rash lasting anywhere from one to five days. Rash symptoms frequently manifest themselves initially on the face before spreading elsewhere. Lesions in the vaginal area, eyes, and intraoral mucosa have been reported in certain patients. The rashes of this illness often seem like those of chickenpox, leading to misdiagnoses. These rashes start as water-filled blisters but eventually heal into crusty areas. Lesions can manifest in a wide variety of ways; for some people, it is a widespread rash of small blisters, while for others it is more extensive. Lesions may join together to form widespread rashes on the skin's surface in severe situations. Depending on the severity of the sickness, the rashes typically vanish entirely in two to four weeks, and the disease heals.

Convolutional neural networks (CNNs) are widely employed in academic studies in deep learning, as is evident when examining the most cutting-edge technologies in image processing and classification. When gathering insights, images are a common input for CNN, a type of deep learning model. It records the results of several processes on the image to categorize the future inferences that might be drawn from it. In 1988, the authors of [8] presented the first CNN structure using the LeNet design, which was refined until 1998. CNN algorithms find use in various areas, including NLP (natural language processing) and biomedicine (particularly in processing images and sounds). The best outcomes have been achieved, particularly in image processing. Using CNN, the authors of a recent paper [9][10][11] were able to bring the error rate on the MNIST dataset down to 0.23%.

2. Categorize Monkeypox Using Deep Learning

Previous research was reviewed to use deep learning to categorize monkeypox. Researchers generated skin lesion images from open-source websites to boost the amount of data for use in deep learning to classify monkeypox skin lesions. They used data augmentation techniques, including k-fold cross-validation. Pre-trained versions of the VGG-16, ResNet50, and InceptionV3 models were tested to categorize monkeypox and other diseases. The highest rate of accuracy was found in ResNet50; hence, that model was utilized. A 0.82 F1 Score was calculated for the ResNet50. The Grad-Cam and LIME methods have been implemented into the Xception transfer learning model [12][13][14]. The Xception and DenseNet models have developed a community-based strategy; it is based on cooperation. The investigation was conducted using the proposed ensemble approach, with average precision, recall, F1 score, and accuracy of 85.44%, 85.47%, and 87.13%, respectively, based on the performance scores acquired from trials on a publicly available dataset.

To improve the accuracy of monkeypox detection, scientists [15] standardized the transfer learning approach. Using GitHub, they distributed their image database to the public. The data used to build the dataset were culled from various sources on the web. After utilizing the VGG16 model to achieve the area under the curve (AUC) values between 0.88 and 0.97, they presented a modified model version incorporating data from two studies. Another study focused on human–monkey disease classification from skin lesion images using pre-trained deep mesh on mobile application [16][17][18]. It is possible to classify some image data using the help of an Android app for mobile devices and some transfer learning techniques. No improvements were made to the authors' original version of the MobileNetv2 model. A dataset was accessed through a public Kaggle competition. Researchers utilized models such as ResNet18, GoogleNet, EfficientNetb0, NasnetMobile, ShuffleNet, and MobileNetv2. An accuracy of 0.91 and an F1-score of 0.90 were attained on the MobileNetv2 model.

Classification studies of skin lesion images significantly benefit from combining convolutional neural networks (CNNs) with transfer learning approaches. Convolutional neural networks trained using transfer learning were investigated in another study [19][20][21] to detect Lyme disease from images of skin lesions; the results showed an AUC of 0.91, a sensitivity of 0.83, an accuracy of 0.87, and a specificity of 0.80. Automatic detection of erythema migrans and other skin lesions using deep learning algorithms in detecting Lyme disease was studied in another study by [22][23] within the context of skin lesion classification. Hence, with deep learning, an accuracy of 0.86 and an AUC score of 0.95 were attained.

Increased classification precision is one potential outcome of applying ML methods. The two algorithms were evaluated on a publicly available monkeypox dataset, where they were found to classify monkeypox with an average accuracy of 98.8 percent, outperforming the best-competing algorithms. Medical imaging has recently benefited from applying DL methods to improve disease diagnostic accuracy. Many studies have employed CNNs to accurately categorize skin lesions as benign or malignant. To classify skin cancer, for instance, in [24][25][26][27], a CNN was trained using a dataset of images of skin lesions, and an accuracy level of 96.3% was reached. While deep learning (DL) is promising for monkeypox image analysis detection and classification, knowledge gaps must still be filled. To begin, comprehensive data sets are scarce. Past research has often relied on sample sizes that are too small to portray the whole spectrum of monkeypox variation accurately. Because of this, it is possible that overfitting took place, resulting in less accurate results overall [28][29][30]. In addition, much of the earlier research did not employ a validation set to ensure the models were not overfitted to the training data, which could reduce their accuracy when applied to new data. Some categorization methods have restrictions that make their usage undesirable. However, other classification methods, including support vector machines (SVM), naive Bayes, decision tree (DT), k-nearest neighbors (KNN), and random forest, may also be useful for monkeypox classification, even though CNNs have been utilized exclusively in prior studies. Fewer still are real-world data applications that can make use of this information. However, there has been no previous work on employing DL to detect monkeypox by image analysis. Authors in [31] suggested a deep learning strategy for detecting monkeypox from skin lesion images, which stands out among the rest of the literature. But they could only utilize it on a tiny dataset and did not employ transfer learning. **Table 1** presents a review of the relevant works related to the problem of monkeypox diagnosis.

Table 1. Review of related works.

Paper	Model	Method	Purpose
[32]	VGG-16, ResNet50, and InceptionV3 models	Monkeypox skin lesion detection using deep learning models	Monkeypox skin lesion detection
[33]	Xception, DenseNet	Detection of monkeypox virus by transfer learning methods	Monkeypox virus detection
[34]	They propose and evaluate the VGG16 model with D curve	Image data collection and implementation of a deep-learning-based model in detecting monkeypox disease	Detecting monkeypox disease
[35]	GoogleNet, EfficientNetb0, NasnetMobile, ShuffleNet, MobileNetv2 models	Human monkeypox classification from skin lesion images with deep pre-trained network	Human monkeypox classification from skin lesion images
[36]	ResNet50	Convolutional neural networks with transfer learning to diagnose Lyme disease from skin lesion	Lyme disease from skin lesion images
[37]	Resnet50	Automated detection of erythema migrans and other confounding skin lesions via deep learning	Automated detection of erythema migrans
[38]	EfficientNetV2s, MobileNetV3, VGG19, ResNet50, DenseNet	Monkeypox detection using CNN with transfer learning	Monkeypox detection
[39]	GoogleNet and Metaheuristic Optimization	Monkeypox detection using CNN with transfer learning	Monkeypox detection

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