



Related Work for Monkeypox Detection

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(Singh et al., n.d.), et al. proposed a novel Convolutional Neural Network (CNN) model utilizing skin lesion photos to classify and detect monkeypox. The model was created using essential elements such as convolutional layers, max pooling layers, dropout layers, and fully connected layers to extract salient characteristics and raise quality of classification. The model was trained on a dataset of 3,192 images, divided into training (2,297 images) and testing sets (325 images), and obtained a precision of 0.9939 on training data and 0.9148 on testing data. The outcomes showed how well the model distinguished between cases of monkeypox and those that were not., with high precision, recall, and F1-scores, demonstrating its promise as a diagnostic tool in environments with limited resources.

(Pal et al., 2023) proposed an Artificial Intelligence (AI)-based framework for Monkeypox illness prediction utilizing a variety of Convolutional Neural Network (CNN) models. The goal of the study was to categorize pictures of monkeypox using pre-trained CNN models like VGG 19, DenseNet 121, DenseNet 201, Inception V3, Xception, and MobileNet. The optimal outcome was obtained by utilizing Inception V3, with a testing accuracy of 94.99% and an F1 score of 89.97. Two datasets were used by the authors from Kaggle, one containing augmented images of monkeypox and non-monkeypox cases, and the other with a bigger collection of testable enhanced images. Though it also pointed out drawbacks including the paucity of data and the difficulty in differentiating monkeypox from other related illnesses like smallpox, chickenpox, and measles, the study demonstrated the promise of AI in diagnosing monkeypox.

(Shashikala et al., 2024) proposed a deep learning-based strategy for improved skin lesion detection, incorporating monkeypox, smallpox, chickenpox, and skin cancer. The authors utilized pre-trained deep learning models such as VGG-16, ResNet50, and InceptionV3, along with an ensemble method, to categorize skin abnormalities. To expand the sample size, data augmentation techniques were used with pictures from publically accessible sources such as ISIC Archive and MedMNIST. A graphical user interface (GUI) prototype was created to make clinical screening more approachable. The models achieved an average accuracy of 97%.

(Arumugam et al., 2024) proposed a deep learning-based approach for Monkeypox illness detection utilizing three pre-trained models: DenseNet-121, ResNet-50, and EfficientNet-B7. The research made use of the Mpox Skin Lesion Dataset Version 2.0 (MSLD v2.0), which features pictures of monkeypox, chickenpox, measles, cowpox, hand-foot-mouth disease, and healthy skin. Data augmentation techniques, such as rotation, were used to improve the dataset. EfficientNet-B7 outperformed the other models, achieving an accuracy of 97.4%, precision of 92%, recall of 87.3%, and F1-score of 93.2%. The outcomes show how well EfficientNet-B7 can classify photos of skin lesions to identify monkeypox.

(Sehgal & Saini, 2024) proposed a deep learning-based method for detecting monkeypox that uses Generative Adversarial Networks (GAN) for image augmentation and six pre-trained CNN models: EfficientNetB3, VGG16, VGG19, ResNet50, MobileNetV2, and InceptionV3. The research made use of a publicly accessible dataset from Kaggle, which was augmented using GAN to expand the size of the dataset by 10 times. The models were trained and evaluated on the augmented dataset, with EfficientNetB3 achieving the highest accuracy of 98.46%, followed by VGG16 with 96.76%. with VGG16 coming in second with 96.76% accuracy and EfficientNetB3 with the greatest accuracy of 98.46%. The outcomes show how well GAN-based data augmentation works and how EfficientNetB3 is better at classifying pictures of monkeypox.

(Chattopadhyay et al., 2024) proposed an integrative CNN-RF (Convolutional Neural Network - Random Forest) system for evaluating the severity of the human monkeypox virus in a layered manner. The study divided the severity of monkeypox into ten phases, from moderate (1–10%) to severe (91–100%). The CNN was utilized to extract features from photos of skin lesions, and the Random Forest classifier was used to classify the severity of the lesions based on clinical information. The model performed well across all severity levels, with a macro-average accuracy of 94.91%, recall of 94.86%, and F1-score of 94.91%. The accuracy was similar across various class distributions, with a weighted average of 94.75% and a micro average of 94.90%. The model's promise as a prediction tool for early detection and patient management is indicated by its accuracy in classifying monkeypox severity levels.

(Singla, 2024) proposed a deep learning-based method for classifying monkeypox using the EfficientNetB3 transfer learning model. The project sought to diagnose monkeypox early and accurately by utilizing the skills of convolutional neural networks (CNNs) and transfer learning. The EfficientNetB3 A dataset of 228 photos, comprising both monkeypox and non-monkeypox instances (such as chickenpox and measles), was used to refine the model. With precision, recall, and F1-scores of 0.95 for instances of monkeypox and 0.96 for cases of non-monkeypox, the model's accuracy was 95.5%. The outcomes show how well EfficientNetB3 can categorize photos of monkeypox, indicating that it may be used for early diagnosis and detection in clinical settings.

(Jagani & Degadwala, 2024)suggested a refined Convolutional Neural Network (CNN) model for Classifying Skin Lesions Caused by Monkeypox. A dataset of 228 photos was used in the study, and it was expanded to 3192 photos utilizing methods such noise addition, translation, and rotation. To categorize monkeypox skin lesions, the authors improved pre-trained CNN models, such as AlexNet, VGG16, and ResNet50. With an accuracy of 98.25%, the optimized CNN model outperformed AlexNet (95.61%), VGG16 (96.49%), and ResNet50 (97.36%). The outcomes show how well pre-trained CNN models can be adjusted to accurately and automatically classify monkeypox skin lesions, facilitating early diagnosis and treatment.

Paper	Methods	Advantages	Limitations	datasets	Performance
[1]	CNN model with convolutional layers, max pooling layers, dropout layers, and fully connected layers.	High accuracy (99.39% on training, 91.48% on testing). Effective use of dropout layers to prevent overfitting. Potential for early and accurate Monkeypox diagnosis in	high accuracy (testing at 91.48%, training at 99.39%). Dropout layers are used effectively to avoid overfitting. Possibility of diagnosing	Monkeypox Skin Lesion Dataset: 3,192 images (2,297 training, 325 testing)	Accuracy: 99.39% (training), 91.48% (testing). Precision: 0.95 (Monkeypox), 0.89 (non-Monkeypox). Recall: 0.89 (Monkeypox), 0.96 (non-Monkeypox). F1-score: 0.92 (Monkeypox),

		clinical settings.	monkeypox in clinical settings early and accurately.		0.92 (non-Monkeypox)
[2]	six pre-trained CNN models (VGG19, DenseNet121, DenseNet201, InceptionV3, Xception, and MobileNet) omitting the top fully connected layer and adding custom layers (ReLU and Softmax).	The InceptionV3 model attained a high accuracy of 94.99%. efficient application of data augmentation to enhance model functionality. Possibility of a timely and precise clinical diagnosis of monkeypox.	Reliance on relatively small datasets, which may limit generalization. Potential challenges in distinguishing Monkeypox from other similar diseases (e.g., smallpox, chickenpox).	Dataset 1: 2144 training images, 441 validation images, and 45 testing images. Dataset 2: 5064 augmented Monkeypox images and 4836 non-Monkeypox images	InceptionV3: Accuracy = 94.99%, F1-score = 89.97%. Other models: Lower accuracy compared to InceptionV3.
[3]	pre-trained deep learning models (VGG-16, ResNet50, InceptionV3) and an ensemble method	High accuracy (97%) in classifying skin lesions. User-friendly GUI for clinical use. Ability to detect multiple skin diseases, including monkeypox, smallpox, and chickenpox.	Limited dataset specific to monkeypox. Reliance on publicly available images, which may not cover all clinical variations.	ISIC Archive, MedMNIST, and other publicly available sources.	Average accuracy: 97%. ResNet50 outperformed other models in terms of accuracy.
[4]	DenseNet-121, ResNet-50, and EfficientNet-B7.	High accuracy (97.4%) achieved by EfficientNet-B7.	Limited dataset size, especially for some classes like cowpox and measles.	Mpox Skin Lesion Dataset Version 2.0 (MSLD v2.0),	EfficientNet-B7: Accuracy = 97.4%, Precision = 92%, Recall =

	Applied data augmentation techniques, including rotation, to enhance the dataset. Evaluated models using precision, recall, F1-score, and accuracy metrics.	Effective use of data augmentation to improve model performance. Potential for clinical application in early detection of monkeypox.	Reliance on publicly available images, which may not cover all clinical variations.	containing images of monkeypox, chickenpox, measles, cowpox, hand-foot-mouth disease, and healthy skin.	87.3%, F1-score = 93.2%. ResNet-50: Accuracy = 85%, Precision = 82%, Recall = 83%, F1-score = 82.5%. DenseNet-121: Accuracy = 71%, Precision = 75.3%, Recall = 69%, F1-score = 70.8%.
[5]	Utilized GAN for data augmentation to increase the dataset size by 10 times. Trained six pre-trained CNN models: EfficientNetB3, VGG16, VGG19, ResNet50, MobileNetV2, and InceptionV3. Evaluated models using accuracy, precision, recall, and F1-score metrics.	High accuracy (98.46%) achieved by EfficientNetB3 . Effective use of GAN for data augmentation to improve model performance. Potential for clinical application in early detection of monkeypox	Reliance on publicly available images, which may not cover all clinical variations. Limited dataset size before augmentation.	Publicly available dataset from Kaggle, augmented using GAN to increase the dataset size.	EfficientNetB3 : Accuracy = 98.46%, Precision = 98%, Recall = 96%, F1-score = 98%. VGG16: Accuracy = 96.76%, Precision = 93%, Recall = 94%, F1-score = 93%. VGG19: Accuracy = 93.78%, Precision = 92%, Recall = 94%, F1-score = 93%. ResNet50: Accuracy = 69.01%, Precision = 37%, Recall = 90%, F1-score = 50%. MobileNetV2: Accuracy =

					75.25%, Precision = 49%, Recall = 72%, F1-score = 58%. InceptionV3: Accuracy = 85.68%, Precision = 86%, Recall = 83%, F1-score = 85%
[6]	Utilized CNN for image feature extraction from monkeypox skin lesion images. Employed Random Forest (RF) for severity classification based on clinical data. Combined CNN and RF to create an integrative framework for severity assessment.	High accuracy (94.91%) in classifying monkeypox severity across ten stages. Effective integration of image and clinical data for comprehensive severity assessment. Potential for early detection and improved patient management in clinical settings.	Reliance on a specific dataset of monkeypox skin lesion images and clinical data. Potential challenges in generalizing the model to other infectious diseases.	Dataset of monkeypox skin lesion images and clinical data, classified by medical specialists into ten severity levels.	Macro-average: Accuracy = 94.91%, Recall = 94.86%, F1-score = 94.91%. Weighted average: Accuracy = 94.75%, Recall = 94.75%, F1-score = 94.75%. Micro average: Accuracy = 94.90%, Recall = 94.90%, F1-score = 94.90%. Overall accuracy: 79.62%, with true positives ranging from 568 (Class 1) to 1658 (Class 10).
[7]	Utilized the EfficientNetB3 pre-trained	High accuracy (95.5%) in classifying	Reliance on a relatively	Dataset of 228 images, including	Accuracy: 95.5%.

	model for transfer learning. Fine-tuned the model on a dataset of 228 images (102 monkeypox and 126 non-monkeypox). Trained the model using the Adam optimizer with a batch size of 32 for 20 epochs.	monkeypox and non-monkeypox cases. Effective use of transfer learning to improve model performance with limited data. Potential for early detection and diagnosis of monkeypox in clinical settings.	small dataset of 228 images. Potential challenges in generalizing the model to other infectious diseases.	102 monkeypox and 126 non-monkeypox cases (e.g., chickenpox and measles).	Precision: 0.95 (monkeypox), 0.96 (non-monkeypox). Recall: 0.95 (monkeypox), 0.96 (non-monkeypox). F1-score: 0.95 (monkeypox), 0.96 (non-monkeypox).
[8]	Utilized fine-tuned pre-trained CNN models (AlexNet, VGG16, ResNet50) for Monkeypox skin lesion classification. Augmented the dataset from 228 to 3192 images using techniques like rotation, translation, and noise addition. Trained and evaluated the models using accuracy, precision, recall, and F1-score metrics.	High accuracy (98.25%) achieved by the fine-tuned CNN model. Effective use of data augmentation to improve model performance. Potential for early and accurate diagnosis of Monkeypox in clinical settings.	Reliance on a relatively small initial dataset of 228 images. Potential challenges in generalizing the model to other infectious diseases.	Dataset of 228 images (102 Monkeypox and 126 non-Monkeypox), augmented to 3192 images	Fine-tuned CNN: Accuracy = 98.25%, Precision = 98.25%, Recall = 98.25%, F1-score = 98.25%. ResNet50: Accuracy = 97.36%, Precision = 97.36%, Recall = 97.36%, F1-score = 97.36%. VGG16: Accuracy = 96.49%, Precision = 96.49%, Recall = 96.49%, F1-score = 96.49%. AlexNet: Accuracy = 95.61%,

					Precision = 95.61%, Recall = 95.61%, F1- score = 95.61%.
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