Grenze International Journal of Engineering and Technology, January Issue

A Review on AI-based Classification and Staging of MonkeyPox

Ms. A. D. Wadgaonkar[1] and Dr. Ms. A.V. Thalange[2]
[1-2]WIT Solapur/E&TC Department, Solapur, India
Email: Akshatawadgaonkar1998@gmail.com, avthalange@witsolapur.org

***Abstract*— Monkeypox is a viral zoonotic disease, which is caused due to Mpox virus. It has become a serious issue in the world as it spreads quickly. Traditional methods for Mpox diagnosis are very time taking as well as costly.**
Hence, there is a need for an early and accurate detection of this disease as it also progresses through different rash stages. This research mainly focused on Image processing, machine learning and deep learning artificial intelligence method which helps to detect and classify Mpox rashes automatically. The review includes various AI-based algorithms for monkeypox detection and rash stage classification. The main objective of this review paper is to present studies of modern AI techniques over traditional methods for monkeypox detection and rash stage classification. This study will be helpful to new researchers for increasing accuracy of detection of Mpox virus in future.

***Index Terms*— PCR, Vision Transformer, GAN, Monkeypox, Artificial Intelligence (AI).**

I. INTRODUCTION

The monkeypox belong to orthopox virus family. This disease is similar to other pox diseases like chickenpox, cowpox. Even though monkeypox is rare but its cases are increasing day by day. In India most of the cases are found in Kerala. Monkeypox consist of different rash stages like macules, papules, vesicles, pustule and scabs which are shown in below table 1. It is very important to diagnose these diseases accurately with proper detection method.

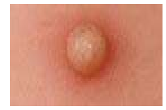
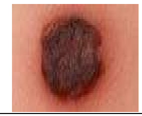
TABLE I. DRAWBACK OF TRADITIONAL METHOD

Cause	Barrier
Time Lag	This process is very time taking
Expensive And Resource- Depleting	Needs health and safety labs, skilled workers, and costly laboratory setups.
Restricted Access	PCR not available in remote or low-resource areas
False Negative Risk	An incorrect diagnosis could result from improper gathering of samples

Traditionally monkeypox was detected by DNA based laboratory tests in the hospital. This method gives correct diagnosis of diseases but it is very time-consuming processes, it needs medical experts and it is available mostly in urban areas where proper hospitality is available [14].
So, there is a need to develop a quick, feasible, automatic system which can early detect and classify rash stages of monkeypox.

Grenze ID: 01.GIJET.12.1.811

TABLE II. RASH STAGE SPECIFICATION

Rash Stage	Stage-I	Stage-II	Stage-III	Stage-IV	Stage-V
Rash type	Macule	Papules	Vesicle	Pustule	Scabs
Rash images					
Specifications	Small bumps without colour	Bumps size increases	Certain fluid secreted in bumps	Bumps containing Pus	Scalps like structure

The review paper is focused on the availability of dataset, existing algorithm and various models design methods used for monkeypox detection and rash stages classification. In this era of artificial intelligence, biomedical image processing is a power weapon. Convolution Neural networks and Vision Transformers (ViT) are the powerful models to understand the deep features from image data and textual data like symptoms, which used to give precise results. By using these AI models, maximum accuracy achieved for Mpox detection and rash classification is near about 75% to 99% till now. Due to these advantages, AI models increase the accuracy of monkeypox detection and rash stage classification over traditional methods.

II. LITERATURE REVIEW

Hossain et. al. [1]: In this research for classification of monkeypox skin lesion transformer learning, pre- trained model is used to increase the accuracy rate. To verify the accuracy of model the researcher used the explainable AI techniques. The highest accuracy achieved by this research is 93.15%. Rahu et.al.[2]: In this paper the researcher used Clinical symptoms dataset for monkeypox detection. The detection was performed by using five different machine learning algorithms amongst which the highest accuracy of 97.7% was achieved by using AdaBoost method. Das et. al. [3]: To increase the accuracy rate the author focused on using hybrid model that combines vision transformer model and Graph Convolutional Networks. The highest accuracy obtained by using this model is 97%.

Parinda L.et. al. [4]: Authors develops a mobile application that utilizes deep learning techniques for self-screening and identifying the progression of monkeypox rashes. Researcher used Convolutional neural networks (CNNs) techniques to classify different stages of monkeypox lesions and rashes. Kundu. et.al [5]: Authors focused on a federated deep learning method. Data augmentation is done by using Cycle generative adversarial network (CycleGAN), classification done by using deep learning models including ResNet50, MobileNetV2 and Vision Transformer (ViT). For data privacy and security, a Flower-based federated learning environment is used. The highest accuracy achieved by this model was 97.90% using Vision Transformer model. Manjurul et. al. [6]: In this paper author check the performance of transfer learning and vision transformer method for classification of Mpox. The maximum accuracy achieved by this model is 88% using Vision transfer model.

Getu M. Setegn et al. [7]: Author focused on extracting feature from clinical symptoms data especially like fever, rash, lymphadenopathy. The extracted features are encoded into numerical format which used is as an input feature for machine learning model. Researcher utilized explainable AI method for identifying importance of extracted feature. The highest accuracy achieved by this model was 89.3% by using

LightGBM classifier. D.K. Saha et.al.[8]: The authors used SwinViT, Xception, DenseNet201, and EfficientNetB7 method for extracting image feature. Then researcher combines the entire extracted feature to increase the accuracy. Explainable AI model like global average pooling and Grad-CAM methods is used to validate the performance of extracted feature. The maximum accuracy obtained by this model is 98.70%. Kundu et.al.[9]: Researcher developed a Vision Transformer-based deep learning model for Monkeypox detection. The model was trained on 1,300 skin lesion images, leveraging the transformer's self-attention mechanism to capture intricate patterns and features in the images. The model demonstrated a high accuracy of 93%, reinforcing the potential of transformer models in medical image analysis. Rashid Iqbal et.al.[10]: Study presented a comprehensive survey of deep learning methods for automatic Monkeypox detection. The paper categorized existing approaches into deep CNNs, ensemble methods, hybrid learning models, and Vision Transformers. The study focused more on methodologies rather than experimental results.

Ameera S. Jaradat et. al. [11]: This paper focused on detection of Monkeypox virus using five deep learning pretrained models ResNet50, MobileNetV2, VGG19, VGG16, and EfficientNetB3 to recognize the more efficient model for precisely classification of Monkeypox. The highest accuracy achieved by the model was 98.16% using MobileNetV2. Amir Sorayaie Azar et. al. [12]: This study aimed to detect Monkeypox virus using

Deep Neural Networks (DNNs), inspired by their success in identifying COVID-19. The dataset included skin images of Monkeypox, Chickenpox, Measles, and Normal cases. The authors developed seven DNN models, implementing both two-class (Monkeypox vs. others) and four-class (all diseases separately) classification scenarios. The maximum accuracy achieved by this model was 97.63% using DenseNet201. Author used an explainable AI method for validation of predicted result.

Ajay Krishan Gairola et al. [13]: This paper mentioned the limitations for an early detection of monkeypox. To overcome this, author used a machine learning based method to analyse RGB images for detection of monkeypox symptoms. Author used freely available dataset and develops pre-trained CNN model with six machine learning classifiers. Saznila Islam et al. [14]: Authors aims to develop a low-cost system for monkeypox detection and rash stage classification, for the area where laboratory-based test method is not available. The dataset used by researcher consist three types of images like Normal, Monkeypox, and other classes. This dataset is given to various pre-trained CNN model like MobileNetV2, ResNet-50, DenseNet- 121, VGG19, and VGG16. The maximum accuracy achieved by this model was 99.52% using VGG19 model.

H. Bhosale et. al. [15]: Authors focus is on detection of monkeypox virus using machine learning algorithm. The researchers used elasticNet, linear regression, ARIMA, decision tree, and random forest, models for detection of monkeypox. The highest accuracy achieved by model is 92.67% using ARIMA model. Hamdan et. ai.[16]: The main aim of the researcher is to predict Mpox using clinical symptoms. Author used neural network model based on adaptive artificial bee colony for Mpox detection. These networks enhance the detection rate. But this method totally depends on proper labelled clinical data. Saleh et al. [17]: Authors used multimodal dataset contains images plus text data for increasing accuracy of monkeypox detection. Support vector machine is used for classification of monkeypox.

III. METHODOLOGY

Methodology for detection of monkeypox and rash stage classification are divided into different steps. First one is data collection. It involves collection of image or clinical data from various sources. Next step is Data pre-processing which is used to enhance the data quality and remove noise from the data. Next step is to extract the meaningful features from pre-processed data. The extracted feature is given to the model which will develop using prepared trained data. Last stage is evaluating the performance of model using different parameter, all these steps are mentioned in by authers Rashid Iqbal et.al.[10]. The workflow for monkeypox detection and rash stage classification is given in below figure.1

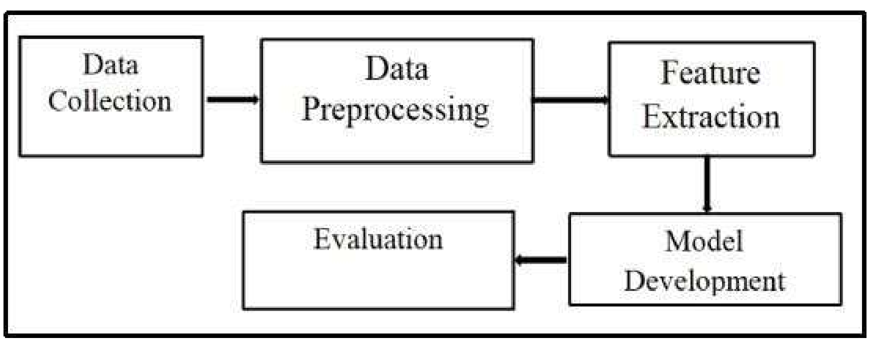


Figure 1. Monkeypox Detection and Rash Stage Classification Framework

A. Data Collections Methods

The selection of proper and correct data is very important for training and evaluating the model. This section gives the information about the publicly available datasets or synthetically generated dataset for monkeypox detection and rash stage classification.

Publically Available Dataset

There are many datasets that are freely available on website like WHO, Kaggle, GitHub for Mpox detection. The different datasets are available for image data and clinical data. For image data Monkeypox Skin Lesion Dataset is used by author Kundu et al. [5] and D.K. Saha et.al.[8]. For textual data, clinical datasets including symptoms (like fever, swelling in lymph node and muscle ache) are available which is used by author Raha et.al.[2], Getu M. Setegn et al. [7]. The author Hamdan et. ai.[16] used clinical data available from medical colleges or hospitals.

Synthetic Dataset

Due to lack of availability of labelled rash stage classification dataset there is a need to generate synthetic dataset.

There are different methods available for synthetic data creation like generative adversarial network (GAN), Variational Autoencoder, and statistical method. The author Parinda L.et. al. [4] develops a synthetic data by using generative advisal network (GAN), to overcome the drawback of limited dataset.

Multimodal Datasets

In literature review it is observed that to increase the accuracy rate there is a need to used multimodal data that combines clinical data i.e. symptoms and images data of the same patient. The author Saleh et al. [16] used this multimodal dataset to enhance the performance of model.

B. Pre-processing Methods

Pre-processing is the important step to make both the skin lesion images and clinical data noise free and prepare it for input to the proposed modal.

The main goal of pre-processing technique is to improve the data quality. The steps involved in pre-processing are given below.

Image Preprocessing Techniques for Image Data

- Resizing: The image data is available in various resolutions. There is a need to convert all images into standardized resolution size i.e. 224x224 pixels or 512x512 pixels. The step is mostly used in deep learning method by the authors Saleh et al. [16].
- Normalization: This step is used to scale image pixel value into standard pixel intensity range. The authors H. Bhosale et. al. [15] used general range for pixel value i.e. [0,1]. The step keeps the constant brightness and intensity for all the image.
- Noise Removal: Noise removal is necessary to remove unwanted information from the image due to variation of brightness, compression parameter and camera quality. The various filtering technique is used to remove noise in image [6].
- Image Enhancement: The authors Kundu. et.al [5] used image enhancement technique to improve image contrast, which helps model to differentiate image features for rash stages.
- Data Augmentation: To rotate, to zoom and to flip the data, data augmentation technique is used by the authors Parinda L.et. al. [4] Kundu. et.al [5].

Clinical Data Preprocessing Technique

- Cleaning: To remove the unwanted value form text data and to add missing value in clinical data, cleaning process is used. The author Raha et.al.[2] used cleaning process to improve the quality of clinical data. This method used to give complete clinical data.
- Tokenization: The authors Hamdan et. ai.[16] used tokenization method to break down the word into small part from textual data.
- Embedding: To convert the text data into numerical vector and to give input for machine learning model, the authors Getu M. Setegn et al. [7] used Embedding method. For example, whether patient is having fever - Yes/No.

C. Feature Extraction Methods

Feature Extraction method is used for understanding pattern and structure from both image and clinical symptoms for accurately detection of Mpox and rash stage classification.

Techniques Based on Texture

To differentiate Monkeypox from other skin disorders, texture-based methods, examine patterns and variations in pixel intensity within lesion imaged is used by researchers Hossain et. al. [1].

Methods Based on Shape

The authors Parinda L.et. al. [4] used this method to extract feature based on shape. In order to stage the evolution of a rash, shape-based approaches concentrate on obtaining the structural features of lesions.

Methods of Statistics

To extract useful features from lesion images, statistical methods examine the distributions and correlations of pixel intensity which is mentioned by author Rashid Iqbal et.al.[10].

Methods based on Transformation

The author Hossain et. al. [1] and Kundu et.al.[9] used transform-based algorithms method in order to uncover significant patterns from skin lesions images for monkeypox detection.

Feature Extraction Based on Deep Learning

The authors Ameera S. Jaradat et. al. [11] and Saznila Islam et al. [14] used deep learning automated feature extraction method like CNNs (convolutional neural networks). CNNs assist in detecting visual patterns that distinguish monkeypox from other skin disorders such as lesion size, shape, colour, and texture. CNNs learn abstract patterns in the deeper layers after identifying fundamental visual elements like edges and gradients in the first level. Because of its excellent accuracy, little preprocessing needs, and efficiency in obtaining significant visual features, CNNs are preferred.

D. Model Design Approaches

For monkeypox detection, Machine learning and deep learning techniques are used to increase the accuracy of diagnosis. For better understanding of the data related to monkeypox images, Machine learning is a powerful tool. It divides into two part i.e. supervised learning and unsupervised learning. When proper labelled data is presented then supervised learning model is used, which helps for classification of images, such as whether it is monkeypox or other pox disease and it also classifies rash stages of monkeypox. On the other hand, when unlabelled data is presented then unsupervised learning model is used. It helps to learn hidden patterns in data which classifies similar rashes and to track disease progress over time.

Machine learning Model

- Support Vector Machines (SVM): The author Saleh et al. [17] used support vector machine (SVM) which is supervised learning method used to classify binary issues, such as whether it is monkeypox (Mpox) case or not. In SVM different kernels are used to deal with complex high dimensional data hence it gives better result. But accuracy SVM can be affected by noisy data and by using multiple features selected at one time. Because of this all parameters need to be adjusted properly to increase accuracy of result.
- Random Forest (RF): Random Forest (RF), a supervised learning technique, used by author H. Bhosale et. al. [15] as it handles high-dimensional datasets with a variety of data sources so it classifies Mpox rash phases using both visual and non-visual characteristics. The important feature selected by model is to find medical significance for diagnosis of Mpox and it avoid overfitting.
- K-Nearest Neighbors (KNN): The authors Jaradat et al. [11] used KNN method for monkeypox detection by analysing skin texture and colour from image data. It also distinguishes monkeypox skin lesion and healthy skin. KNN sorts the data by searching equality in nearest data point. The main advantage of KNN method is that it works on small datasets that contains only few labelled data. But the disadvantage of KNN is that its prediction speed is minimal, especially for expanded dataset and it don't give proper result for complex and high-dimensional data.
- Auto-encoders: The authors Rashid Iqbal et.al.[10] mentioned Autoencoder method, to learn compressed representations of lesion images for monkeypox detection. Autoencoder used to identify Mpox rashes with other rashes.

Deep Learning Method

- CNNs (convolutional neural networks): The author Parinda L.et. al. [4] and Saznila Islam et al. [14] used Convolution neural networks model. CNNs is core of image-based deep learning model. Convolution, pooling and non-linear activation function layers are used automatically to extract hierarchical characteristics from input image. The CNNs design VGG16, ResNet50, DenseNet, and MobileNet are frequently utilized.
- Transformers of Vision (ViTs): The authors Hossain et. al. [1], Das et. al. [3] and Kundu. et.al [5] used Vision transformer model which used in difficult visual tasks like monkeypox classifying rash stages or determining lesion development. This enables the model to grasp long-range dependencies across the image. ViTs are able to comprehend textural differences in a picture or simulates the spatial link between several lesions in cases of monkeypox detection.
- Generative Adversarial Networks (GANs): The Author Jaradat et al. [11] used Generative Adversarial Networks (GANs) for monkeypox detection. GANs can produce realistic lesion images to fill in the gaps in monkeypox image collections, which are generally tiny and uneven (for example, having more pictures of one stage of the rash than another). Training more strong and balanced classifiers is aided by this synthetic data.

TABLE II. COMPARISON OF MACHINE LEARNING & DEEP LEARNING METHODS FOR MONKEYPOX DETECTION

Method	Type	Accuracy	Advantage	Disadvantage
Support Vector Machine (SVM)	Supervised	85-90%	Effective with tiny dataset; capable of handling high-dimensional data	Requires careful adjustment and sensitive to scale and noise
Random Forest (RF)	Supervised	80-90%	Strong against overfitting; significance of interpretable features	More trees mean more complexity and slower inference
K-Nearest Neighbors (KNN)	Supervised	80-85 %	Easy to use; suitable for small datasets	Predictive computation is costly; high dimensions are poor
Autoencoders	Unsupervised (DL)	88-93%	Rebuilds input and learns succinct representations	Need meticulous instruction; not necessarily comprehensible
Convolutional Neural Networks (CNNs)	Deep Learning - Supervised	90-98%	High precision; automated feature extraction	Requires tagged data and has trouble understanding the global context
Vision Transformers (ViTs)	Deep Learning - Supervised	88-98%	Great for spatial problems; captures global features	Needs a lot of data and costly computation
Generative Adversarial Networks (GANs)	Deep Learning - Unsupervised	92–98%	Closes data gaps and produces artificial lesion pictures	Unrealistic sample risk and unstable training.

E. Evaluation

The authors Rashid Iqbal et.al.[10] mentioned the various techniques to evaluate the performance of trained model for classification of monkeypox rash staging. It involves values like True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). By using these values standard mathematical equations is designed for evaluating the performance in terms of accuracy, precision, F1-Score, recall, MCC, sensitivity and, AUC.

IV. SUMMARY AND RESEARCH GAP

From the above survey it has been observed that some challenges and gaps are still present, that points towards future research in this area. The most important gaps are as follows:

- Rash Stage Classification is ignored: From above review it is noted that most of the work has been done only for monkeypox detection and very less work is done for rash stage classification of monkeypox.
- Lack of Labelled skin lesion dataset: Unavailability of a validated monkeypox skin stage classification dataset is the main problem for Mpox rash stage classification.
- Multimodal Data Integration is underutilized: Integration of images with clinical data is underutilized, lowering the diagnostic accuracy.
- Transformer Models have not been exclusively used for both Monkeypox rash stage classification, limiting their capabilities to make accurate classifications.

V. CONCLUSION

This review paper mentioned the overall review of machine learning and deep learning methods used for the detection of monkeypox. Most of the work is done using supervised learning, unsupervised learning and deep learning methods, there is still a gap in the classification of skin rash stages, which is essential for monitoring the progression of the disease. In future, researcher can use multimodal datasets that combines skin lesion images with relevant clinical symptoms data for monkeypox detection and classification of rash staging using advanced architectures like transformers model. This will help in the creation of even better, more reliable and clinically applicable AI-assisted systems for monkeypox detection and rash stage classification.

REFERENCES

[1] M. Z. Hossain, M. R. Islam, and M. Samu, “Explainable AI-Driven Detection of Human Monkeypox Using Deep Learning and Vision Transformers: A Comprehensive Analysis,” arXiv preprint arXiv:2505.01429, 2025.

[2] M. U. R. Rahu, Q. Liu, and A. G. Rahu, “Accurate prediction of Monkeypox Disease Cases by Analyzing Symptoms with Ensemble learning Boosting Methods and using ML Techniques,” SSRN Preprint, no. 4978187.

[3] B. Das, H. A. Dagdogen, M. O. Kaya, and R. Das, "A novel hybrid model combining Vision Transformers and Graph Convolutional Networks for monkeypox disease effective diagnosis," Information Fusion, vol. 117, p. 102858, 2025.

[4] P. Labcharoenwongs, D. Noolek, and O. Chunhapran, "Monkeypox Lesion and Rash Stage Classification for Self-screening on Mobile Application Using Deep Learning Technique," Current Applied Science and Technology, pp. e0257989–e0257989,2025.

[5] D. Kundu, M. M. Rahman, A. Rahman, D. Das, U. R. Siddiqi, M. G. R. Alam, S. K. Dey, G. Muhammad, and Z. Ali, "Federated deep learning for monkeypox disease detection on GAN-augmented dataset," 2025.

[6] M. Ahsan, T. E. Alam, M. A. Haque, M. S. Ali, R. H. Rifat, A. A. N. Nafi, M. M. Hossain, and M. K. Islam, "Enhancing monkeypox diagnosis and explanation through modified transfer learning, vision transformers, and federated learning," Informatics in Medicine Unlocked, vol. 45, p. 101449, 2024.

[7] G. M. Setegn and B. E. Dejene, "Explainable AI for Symptom-Based Detection of Monkeypox: a machine learning approach," BMC Infectious Diseases, vol. 25, no. 1, p. 419, 2024,

[8] N. A. Asif, Y. Sarker, R. K. Chakrabortty, M. J. Ryan, M. H. Ahamed, D. K. Saha, and Z. Tasneem, "Graph neural network: A comprehensive review on non-euclidean space," IEEE Access, vol. 9, pp. 60588–60606, 2024.

[9] D. Kundu, M. M. Rahman, A. Rahman, D. Das, U. R. Siddiqi, M. G. R. Alam, S. K. Dey, G. Muhammad, and Z. Ali, "Federated deep learning for monkeypox disease detection on GAN-augmented dataset,",2023.

[10] S. H. Khan, R. Iqbal, and S. Naz, "A recent survey of the advancements in deep learning techniques for monkeypox disease detection," arXiv preprint arXiv:2311.10754, 2023.

[11] A. S. Jaradat, R. E. A. Mamlook, N. Almakayeel, N. Alharbe, A. S. Almuflih, A. Nasayreh, H. Gharaibeh, M. Gharaibeh, A. Gharaibeh, and H. Bzizi, "Automated monkeypox skin lesion detection using deep learning and transfer learning techniques," Int. J. Environ. Res. Public Health, vol. 20, no. 5, p. 4422, 2023.

[12] A. Sorayaie Azar, A. Naemi, S. B. Rikan, J. B. Mohasefi, H. Pirnejad, and U. K. Wiil, "Monkeypox detection using deep neural networks," BMC Infectious Diseases, vol. 23, no. 1, p. 438, 2023.

[13] A. K. Gairola and V. Kumar, "Monkeypox disease diagnosis using machine learning approach," in Proc. 8th Int. Conf. Signal Process. Commun. (ICSC), 2022, pp. 423–427, 2023.

[14] S. Islam, F. A. Nishi, T. Akter, and M. A. Azim, "Monkeypox Skin Lesion Detection with Deep Learning and Machine Learning," Int. J. Comput. Appl., vol. 185, no. 23, pp. 39–45, 2023.

[15] Y. H. Bhosale, S. R. Zanwar, A. T. Jadhav, Z. Ahmed, V. S. Gaikwad, and K. S. Gandle, "Human Monkeypox 2022 Virus: Machine Learning Prediction Model, Outbreak Forecasting, Visualization with Time-Series Exploratory Data Analysis," in Proc. 13th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT), 2022.

[16] A. M. K. Hamdan and D. Ekmekci, "Prediction of monkeypox infection from clinical symptoms with adaptive artificial bee colony-based artificial neural network," Neural Comput. Appl., vol. 36, no. 22, pp. 13715–13730, doi: 10.1007/s00521-024-09782-z,2022.

[17] H. Saleh, S. Mostafa, A. H. Ismail, S. Srivastava, and S. H. Alsamhi, "Swin-PSO-SVM: A Novel Hybrid Model for Monkeypox Early Detection," IEEE Access, vol. 12, pp. 187367–187385, doi: 10.1109/ACCESS.2024.3513818,2022.