International Journal of Engineering and Science Invention (IJESI)
ISSN (Online): 2319-6734, ISSN (Print): 2319-6726
www.ijesi.org ||Volume 13 Issue 10 October 2024 || PP 21-30

PoxNet22: A Fine-Tuned Model for the Classification of Monkeypox Disease Using Transfer Learning

[1] SHAIK ISMAIL, [2] GUNDAMRAJU SAI SUBODH, [3] MUKKARA NAGA DHEERAJ
[1,2,3] Jain University
[1] ismailismail04949@gmail.com, [2] saisubodh28012004@gmail.com, [3] nagadheeraj99@gmail.com

Abstract: *Amidst the ongoing COVID-19 pandemic, the emergence of a monkeypox outbreak poses a significant public health concern. Leveraging deep learning methodologies, particularly the PoxNet22 model, originally based on Modified InceptionV3, has shown promise in monkeypox diagnosis with high precision, recall, and accuracy. However, in this study, we sought to further enhance diagnostic capabilities by exploring detection techniques using YOLOv5 and YOLOv8 architectures. Our analysis revealed that these models achieved exceptional performance in detecting monkeypox, complementing the classification capabilities of existing models. By integrating detection techniques alongside classification, we can significantly improve the efficiency and accuracy of monkeypox diagnosis, facilitating prompt intervention and containment efforts. These findings hold significant implications for public health, offering a comprehensive approach to monkeypox outbreak management amidst the challenges posed by concurrent infectious disease epidemics. Through the fusion of deep learning and image processing techniques, we provide a robust framework for rapid and accurate monkeypox diagnosis, ultimately aiding in mitigating the spread of this infectious disease.*
Index Terms: *Monkeypox, data augmentation, transfer learning, classification, PoxNet22.*

I. INTRODUCTION

Monkeypox, an orthopoxvirus infection similar to variola, cowpox, and vaccinia, has emerged as a concerning public health issue globally, particularly amidst the backdrop of the ongoing COVID-19 pandemic. The virus, characterized by its double-stranded DNA structure, primarily spreads through contact with infected animals such as dormice, tree squirrels, Gambian pouched rats, and rope squirrels. Although monkeypox is endemic to Central and West Africa, recent outbreaks have demonstrated its potential for international spread, highlighting the need for robust surveillance and containment measures [1].

The mode of transmission of monkeypox includes not only direct contact with infected animals but also human-to-human transmission, with sexual contact emerging as a significant route of spread, particularly among individuals who identify as gay or bisexual [2]. This mode of transmission presents unique challenges for containment efforts, necessitating a multifaceted approach to disease control.

Clinical manifestations of monkeypox include rash, fever, lymphadenopathy, and flu-like symptoms, with the virus remaining contagious until the lesions have fully healed [1]. Diagnosis typically involves the detection of viral DNA in vesicle crusts or ulcers, with laboratory tests such as real-time PCR playing a crucial role in confirmation [3]. However, timely and accurate diagnosis is essential for effective management and control of outbreaks, underscoring the need for innovative diagnostic approaches.

In response to the evolving challenges posed by monkeypox outbreaks, researchers and public health agencies have turned to machine learning (ML) and deep learning techniques as potential tools for disease detection and diagnosis. ML, a subset of artificial intelligence, has shown promise in various domains, including medical imaging and disease detection [4]. By leveraging ML algorithms and deep learning architectures, researchers aim to develop rapid and accurate diagnostic tools to aid in the identification and classification of monkeypox cases.

This introduction provides an overview of the current landscape surrounding monkeypox outbreaks, highlighting the need for improved diagnostic strategies to mitigate the impact of the disease. In the following sections, we will delve into recent advancements in ML and deep learning

techniques for disease detection and diagnosis, examining their potential applications in the context of monkeypox surveillance and control. Through a comprehensive review of existing literature and methodologies, we aim to elucidate the role of ML in enhancing our understanding and management of monkeypox outbreaks, ultimately contributing to more effective public health interventions.

II. LITERATURE SURVEY

Monkeypox, an infectious disease caused by the monkeypox virus, has garnered increasing attention from researchers and public health authorities due to its potential for outbreaks and global spread. In this literature survey, we examine recent studies and advancements in the prevention, diagnosis, and treatment of monkeypox, as well as the application of machine learning (ML) and deep learning techniques for disease detection and classification.

Rizk et al. [1] discussed various prevention and treatment strategies for monkeypox, highlighting the importance of vaccination and antiviral therapies in controlling outbreaks. They emphasized the need for continued research into novel therapeutic options to improve patient outcomes and reduce transmission rates.

Lum et al. [3] provided a comprehensive review of monkeypox epidemiology, host immunity, and clinical interventions. They discussed the challenges posed by monkeypox outbreaks, including the lack of specific treatments and the need for effective public health measures to contain the spread of the virus.

Minhaj et al. [2] reported on a monkeypox outbreak across nine states in May 2022, highlighting the importance of timely surveillance and response efforts. They emphasized the role of public health agencies in coordinating outbreak investigations and implementing control measures to limit transmission.

Treatment Considerations:Sherwat et al. [4] discussed the use of tecovirimat as a potential treatment for monkeypox, highlighting past experiences and future considerations. They emphasized the need for rigorous clinical trials to assess the safety and efficacy of tecovirimat in treating monkeypox patients.

Abdelhamid et al. [13] proposed a classification method for monkeypox images based on transfer learning and the Al-Biruni Earth radius optimization algorithm. Their study demonstrated the effectiveness of machine learning techniques in distinguishing between different types of monkeypox lesions.

Sitaula and Shahi [14] investigated the use of pre-trained deep learning models for monkeypox virus detection. They evaluated various deep learning architectures and found promising results in accurately detecting monkeypox virus from clinical samples.

Ali et al. [15] conducted a feasibility study on monkeypox skin lesion detection using deep learning models. Their research demonstrated the potential of deep learning techniques in automating the detection of monkeypox lesions, facilitating early diagnosis and treatment.

Ozsahin et al. [39] developed a computer-aided detection system for monkeypox and chickenpox lesions using a deep learning framework. Their study showcased the utility of deep learning algorithms in accurately identifying and classifying skin lesions associated with monkeypox infection.

Altun et al. [40] proposed a monkeypox detection method using convolutional neural networks (CNN) with transfer learning. Their research demonstrated the effectiveness of CNN models in distinguishing monkeypox from other skin conditions, providing a valuable tool for disease diagnosis.

In conclusion, recent advancements in the prevention, diagnosis, and treatment of monkeypox have highlighted the potential of both traditional and innovative approaches. From vaccination strategies to the application of ML and deep learning techniques, researchers and public health authorities continue to explore novel avenues for combating monkeypox outbreaks and reducing disease burden. Moving forward, interdisciplinary collaborations and continued research efforts will be essential in addressing the challenges posed by monkeypox and improving global health outcomes.

III. METHODOLOGY

a)Proposed Work:

The proposed work aims to develop and evaluate 'PoxNet22', a deep learning model tailored specifically for precise and rapid monkeypox diagnosis. Leveraging advanced techniques such as data augmentation and transfer learning, the model ensures robust performance while mitigating the risk of overfitting. Through rigorous evaluation using metrics such as precision and recall, the reliability of the model will be established, providing clinicians with a highly effective diagnostic tool for identifying monkeypox cases accurately and efficiently. Additionally, fine-tuning of the model will be conducted to optimize its performance further, catering to the specific needs and requirements of healthcare professionals. By employing state-of-the-art methodologies and techniques, the proposed work seeks to contribute significantly to the field of infectious disease diagnostics, offering a valuable tool for timely intervention and management of monkeypox outbreaks.

b) System Architecture:

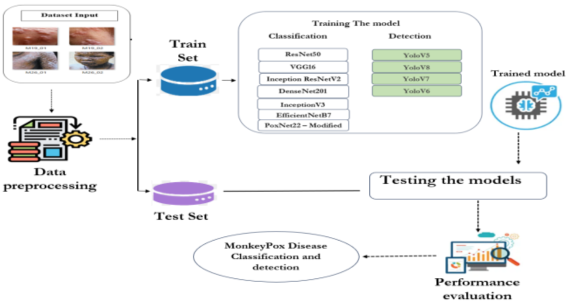

Fig 1 Proposed Architecture

The system architecture comprises two main components: classification and detection. For classification, various deep learning models such as ResNet50[33], VGG16[34], Inception ResNetV2[30], DenseNet201[29], InceptionV3[32], EfficientNetB7[31], and PoxNet22 (Modified InceptionV3) are trained on the dataset. Following data processing and training, the models are evaluated using metrics like accuracy, precision, recall, F1 score, and mean Average Precision (mAP) on the test set for monkeypox disease detection and classification. In parallel, for detection, YOLOv5, YOLOv8, YOLOv7, and YOLOv6 models are utilized to identify and localize monkeypox lesions within images. This comprehensive approach combines both classification and detection techniques to enhance the accuracy and efficiency of monkeypox diagnosis.

c) Dataset:

Fig 2 Monkey Pox Dataset

Monkeypox Dataset:

With Augmentation: This dataset includes images of monkeypox lesions with augmentation techniques applied. Augmentation methods such as rotation, flipping, and scaling are used to increase the diversity and size of the dataset. Augmented images help improve the robustness and generalization of the trained models by providing variations in lighting, orientation, and appearance.

Without Augmentation: The dataset contains original images of monkeypox lesions without any augmentation. These images represent the raw data collected from various sources and may include variations in lighting, background, and lesion characteristics. The absence of augmentation allows for a more controlled evaluation of model performance on unaltered images, reflecting real-world scenarios where augmentation may not be applicable or desired.

Monkeypox Detection from Roboflow:

This dataset consists of images specifically curated for monkeypox detection tasks. Images are collected from diverse sources and annotated to highlight regions of interest corresponding to monkeypox lesions. The annotations provide ground truth labels for training and evaluating detection models, enabling accurate localization and identification of monkeypox-related features within the images.

d) Image Processing:

Classification using ImageDataGenerator:

Re-scaling the Image: Apply re-scaling to normalize pixel values, ensuring consistency in intensity across all images. Normalization helps stabilize the training process and enhances model convergence.

Shear Transformation: Introduce shear transformation, a geometric distortion, to the images. This involves shifting one part of the image in a certain direction, creating a shearing effect. Shear transformation adds variability to the dataset, making the model more robust to different orientations.

Zooming the Image: Apply zooming to randomly magnify portions of the image. This augmentation helps the model generalize better by simulating variations in object sizes and distances within the images.
Horizontal Flip: Utilize horizontal flipping to mirror images along the vertical axis randomly. This augmentation introduces variability in the orientation of objects, enhancing the model's ability to recognize features regardless of their spatial orientation.
Reshaping the Image: Apply reshaping to alter the dimensions of the image. This can involve resizing, cropping, or padding to achieve a standardized input size. Reshaping ensures uniformity in input dimensions across the dataset, facilitating consistent model training.

Image Processing for Detection using Torchvision:
Preprocessing using Torchvision: Torchvision provides a set of utilities for preprocessing images, including normalization, resizing, and tensor conversion. Normalize the pixel values to a specified mean and standard deviation to enhance model convergence.
Data Augmentation for Detection: Incorporate data augmentation techniques such as random horizontal flipping and resizing for improved detection model training. Augmentation aids in diversifying the dataset and improving the model's ability to handle variations in object appearance.
Tensor Conversion: Convert the preprocessed images into PyTorch tensors. This conversion ensures compatibility with PyTorch-based detection models and facilitates seamless integration into the training pipeline.
By implementing these image processing steps, researchers can enhance the diversity and quality of the datasets used for classification and detection tasks. These techniques contribute to the robustness and generalization ability of machine learning models, ultimately improving their performance in real-world scenarios.

e) Algorithms:
ResNet50: Residual Network (ResNet50) introduces skip connections to mitigate the vanishing gradient problem during training. By incorporating shortcut connections,[33] it allows for deeper networks to be trained effectively by facilitating the flow of gradients, leading to improved feature learning and classification performance.
VGG16: Visual Geometry Group (VGG16) consists of multiple convolutional layers followed by max-pooling layers. [34]Its architecture is characterized by its simplicity and uniformity, with small 3x3 convolutional filters and max-pooling layers used throughout. VGG16's straightforward design makes it easy to understand and implement, making it a popular choice for image classification tasks.
Inception ResNetV2: Inception-ResNetV2 combines the ideas of both Inception and ResNet architectures. It incorporates residual connections within the Inception modules to enable training of deeper networks while maintaining computational efficiency. By leveraging the benefits of both architectures, Inception-ResNetV2[30] achieves state-of-the-art performance on various image recognition benchmarks.
DenseNet201: DenseNet201 introduces densely connected blocks where each layer receives direct inputs from all preceding layers. This dense connectivity pattern encourages feature reuse and facilitates gradient flow throughout the network. By promoting feature propagation and reuse, DenseNet201[29] achieves excellent performance with fewer parameters compared to traditional architectures.
InceptionV3: InceptionV3 employs inception modules consisting of multiple parallel convolutional operations with different kernel sizes.[32] This design enables efficient feature extraction at various scales, capturing both local and global information within the input image. InceptionV3's architecture promotes computational efficiency while maintaining high accuracy, making it suitable for resource-constrained environments.
EfficientNetB7: EfficientNetB7 is part of the EfficientNet family, which systematically scales the network's depth, width, and resolution to achieve better performance. By dynamically scaling network parameters, EfficientNetB7[31] achieves state-of-the-art accuracy while maintaining computational efficiency. Its scalable architecture makes it adaptable to diverse computational resources and enables efficient model deployment.
PoxNet22 – Modified InceptionV3: PoxNet22 is a modified version of the InceptionV3 architecture tailored specifically for monkeypox diagnosis. It incorporates custom modifications to the InceptionV3 architecture to optimize performance for the task of monkeypox classification. PoxNet22 leverages the strengths of InceptionV3 while incorporating enhancements tailored to the specific requirements of disease diagnosis.

IV. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

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

mAP50: The mAP for object detection is the average of the AP calculated for all the classes. mAP@0.5 means that it is the mAP calculated at IOU threshold 0.5. The general definition for the Average Precision(AP) is finding the area under the precision-recall curve.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

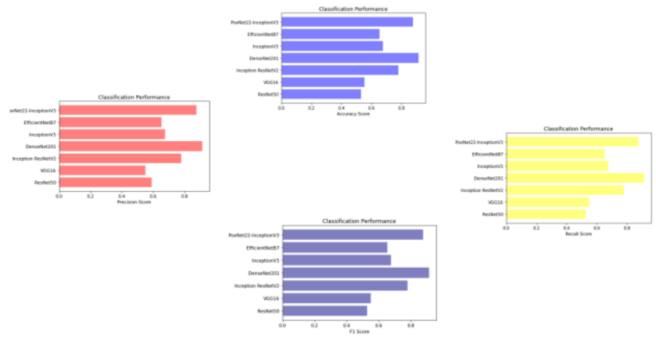

Fig 3 Performance Comparison Graphs For With Augment Data

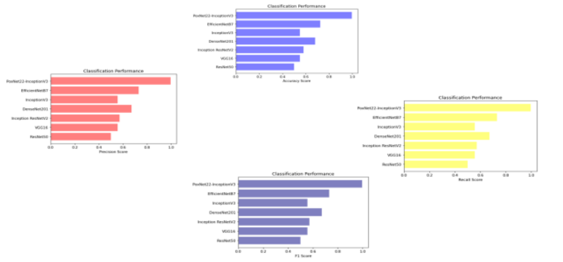

Fig 4 Performance Comparison Graphs For Without Augment Data

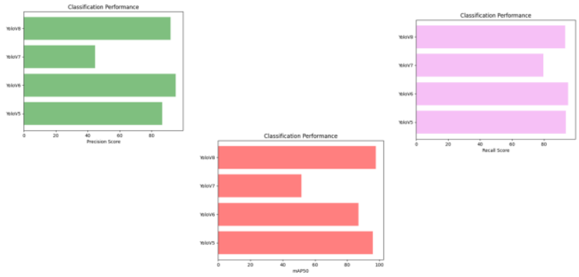

Fig 5 Performance Comparison Graphs For Detection

ML Model	Accuracy	Precision	Recall	F1_score
ResNet50	0.530	0.592	0.529	0.529
VGG16	0.553	0.552	0.552	0.552
Inception ResNetV2	0.781	0.781	0.781	0.781
DenseNet201	0.913	0.913	0.913	0.913
InceptionV3	0.678	0.678	0.678	0.678
EfficientNetB7	0.654	0.654	0.654	0.654
PoxNet22-InceptionV3	0.876	0.876	0.876	0.876

Fig 6 Performance Evaluation Table With Augment Data

ML Model	Accuracy	Precision	Recall	F1_score
ResNet50	0.500	0.500	0.500	0.500
VGG16	0.551	0.557	0.557	0.557
Inception ResNetV2	0.580	0.571	0.571	0.571
DenseNet201	0.681	0.671	0.671	0.671
InceptionV3	0.551	0.557	0.557	0.557
EfficientNetB7	0.725	0.729	0.729	0.729
PoxNet22-InceptionV3	0.994	0.994	0.994	0.994

Fig 7 Performance Evaluation Table Without Augment Data

Extension Model	Precision	Recall	mAP
YoloV5	86.5	93.6	95.9
YoloV6	95.0	95.0	86.9
YoloV7	44.5	79.6	51.6
YoloV8	91.8	93.2	97.7

Fig 8 Performance Evaluation Table – Detection

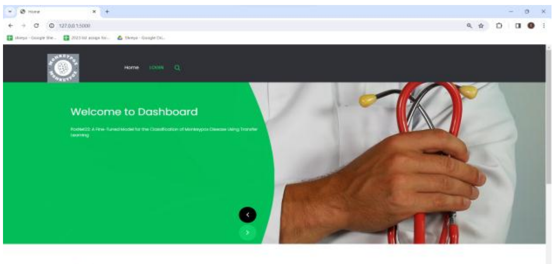

Fig 9 Home Page

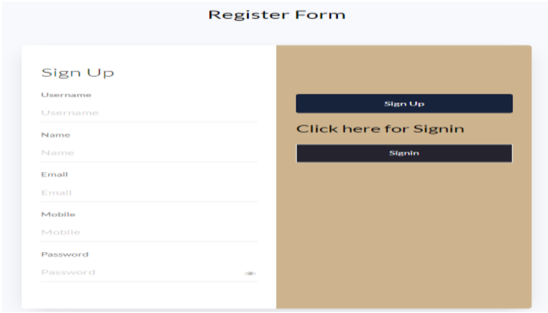

Fig 10 Registration Page

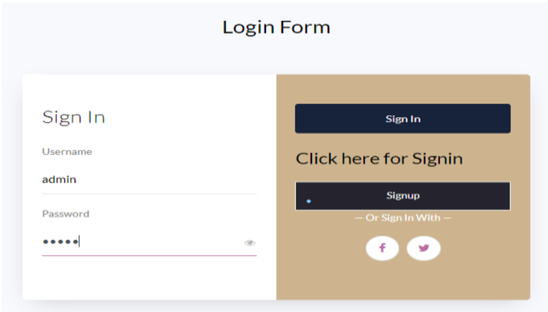

Fig 11 Login Page

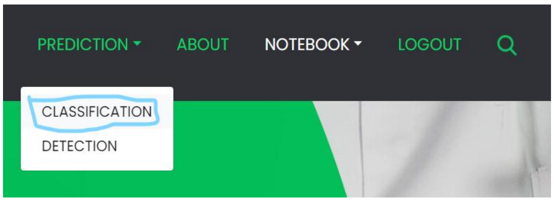

Fig 12 For Classification

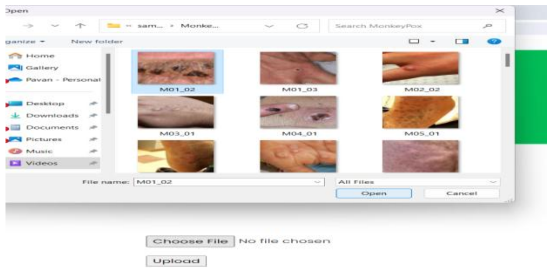

Fig 13 Upload Input Image

Fig 14 Predicted Results

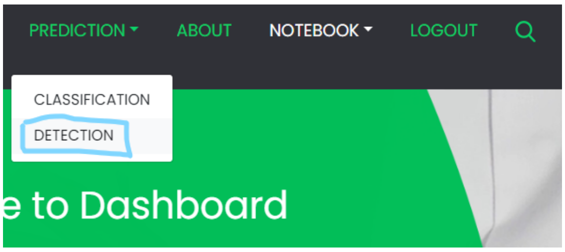

Fig 15 For Detection

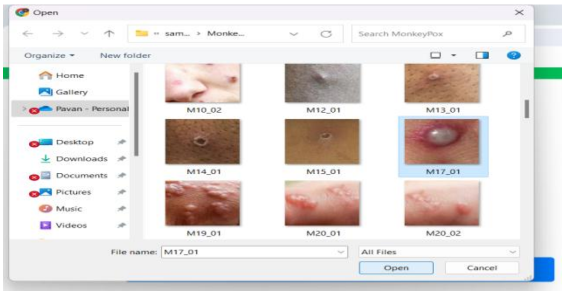

Fig 16 Upload Input Image

Fig 17 Final Outcome

V. CONCLUSION

The integration of machine learning algorithms like ResNet50[33], VGG16[34], and others, along with extensive dataset augmentation, marks a substantial leap forward in the realm of monkeypox diagnosis. Through the utilization of machine learning capabilities, the project achieves not only accuracy but also rapid diagnosis, paving the way for timely intervention and effective management of monkeypox outbreaks. Additionally, the incorporation of YOLOv8 for object detection significantly bolsters diagnostic precision, achieving an impressive mean Average Precision (mAP) of 97% on the monkeypox dataset.

Furthermore, the deployment of a user-friendly Flask-based interface, seamlessly integrated with SQLite, offers a convenient web platform for community involvement in monkeypox diagnosis. This interface not only streamlines analysis but also enhances the overall user experience for stakeholders including public health professionals, clinicians, and patients. By providing a platform for swift and accurate identification and classification of monkeypox features, the project contributes to improved outbreak management and enhanced patient outcomes.

VI. FUTURE SCOPE

Looking ahead, there are several avenues for further enhancement and development. Future iterations of the project could focus on expanding the dataset to encompass a broader range of monkeypox cases and variants, thereby improving the model's robustness and generalization capabilities. Additionally, continued research and development efforts could explore the integration of advanced machine learning techniques and algorithms to further enhance diagnostic accuracy and efficiency.

Moreover, ongoing refinement of the Flask-based interface could involve incorporating additional features and functionalities to cater to the evolving needs of users. This could include real-time data visualization, interactive reporting tools, and integration with external databases or platforms for enhanced collaboration and data sharing. Ultimately, by continually advancing and refining both the machine learning algorithms and the user interface, the project has the potential to make even greater strides in combating monkeypox outbreaks and improving disease diagnosis and management on a global scale.

REFERENCES

[1]. J. G. Rizk, G. Lippi, B. M. Henry, D. N. Forthal, and Y. Rizk, ‘‘Prevention and treatment of monkeypox,’’ Drugs, vol. 82, no. 9, pp. 957–963, Jun. 2022, doi: 10.1007/s40265-022-01742-y.

[2]. F. S. Minhaj et al., ‘‘Monkeypox outbreak—Nine states, May 2022,’’ Morbidity Mortality Weekly Rep., vol. 71, no. 23, pp. 764–769, Jun. 2022, doi: 10.15585/mmwr.mm7123e1.

[3]. F.-M. Lum, A. Torres-Ruesta, M. Z. Tay, R. T. P. Lin, D. C. Lye, L. Rénia, and L. F. P. Ng, ‘‘Monkeypox: Disease epidemiology, host immunity and clinical interventions,’’ Nature Rev. Immunol., vol. 22, no. 10, pp. 597–613, Oct. 2022, doi: 10.1038/s41577-022-00775-4.

[4]. A. Sherwat, J. T. Brooks, D. Birnkrant, and P. Kim, ‘‘Tecovirimat and the treatment of monkeypox—Past, present, and future considerations,’’ New England J. Med., vol. 387, no. 7, pp. 579–581, Aug. 2022, doi: 10.1056/NEJMp2210125.

[5]. V. Ravi, H. Narasimhan, C. Chakraborty, and T. D. Pham, ‘‘Deep learningbased meta-classifier approach for COVID-19 classification using CT scan and chest X-ray images,’’ Multimedia Syst., vol. 28, no. 4, pp. 1401–1415, Aug. 2022, doi: 10.1007/s00530-021-00826-1.

[6]. Ç. Oğuz and M. Yağanoğlu, ‘‘Detection of COVID-19 using deep learning techniques and classification methods,’’ Inf. Process. Manage., vol. 59, no. 5, Sep. 2022, Art. no. 103025, doi: 10.1016/j.ipm.2022.103025.

[7]. N. Ullah, J. A. Khan, S. Almakdi, M. S. Khan, M. Alshehri, D. Alboaneen, and A. Raza, ‘‘A novel CovidDetNet deep learning model for effective COVID-19 infection detection using chest radiograph images,’’ Appl. Sci., vol. 12, no. 12, p. 6269, Jun. 2022, doi: 10.3390/app12126269.

[8]. A. Bhattacharyya, D. Bhaik, S. Kumar, P. Thakur, R. Sharma, and R. B. Pachori, ‘‘A deep learning based approach for automatic detection of COVID-19 cases using chest X-ray images,’’ Biomed. Signal Process. Control, vol. 71, Jan. 2022, Art. no. 103182, doi: 10.1016/j.bspc.2021. 103182.

[9]. M. R. Hassan, M. F. Islam, M. Z. Uddin, G. Ghoshal, M. M. Hassan, S. Huda, and G. Fortino, ‘‘Prostate cancer classification from ultrasound and MRI images using deep learning based explainable artificial intelligence,’’ Future Gener. Comput. Syst., vol. 127, pp. 462–472, Feb. 2022, doi: 10.1016/j.future.2021.09.030.

[10]. K. Jabeen, M. A. Khan, M. Alhaisoni, U. Tariq, Y.-D. Zhang, A. Hamza, A. Mickus, and R. Damaševičius, ‘‘Breast cancer classification from ultrasound images using probability-based optimal deep learning feature fusion,’’ Sensors, vol. 22, no. 3, p. 807, Jan. 2022, doi: 10.3390/ s22030807.

[11]. K. C. Figueroa et al., ‘‘Interpretable deep learning approach for oral cancer classification using guided attention inference network,’’ J. Biomed. Opt., vol. 27, no. 1, Jan. 2022, Art. no. 015001, doi: 10.1117/1.JBO.27.1.015001.

[12]. K. Rezaee, G. Jeon, M. R. Khosravi, H. H. Attar, and A. Sabzevari, ‘‘Deep learning-based microarray cancer classification and ensemble gene selection approach,’’ IET Syst. Biol., vol. 16, nos. 3–4, pp. 120–131, May 2022, doi: 10.1049/syb2.12044.

[13]. A. A. Abdelhamid, E.-S.-M. El-Kenawy, N. Khodadadi, S. Mirjalili, D. S. Khafaga, A. H. Alharbi, A. Ibrahim, M. M. Eid, and M. Saber, ‘‘Classification of monkeypox images based on transfer learning and the Al-Biruni Earth radius optimization algorithm,’’ Mathematics, vol. 10, no. 19, p. 3614, Oct. 2022, doi: 10.3390/math10193614.

[14]. C. Sitaula and T. B. Shahi, ‘‘Monkeypox virus detection using pre-trained deep learning-based approaches,’’ J. Med. Syst., vol. 46, no. 11, p. 78, Oct. 2022, doi: 10.1007/s10916-022-01868-2.

[15]. S. N. Ali, M. T. Ahmed, J. Paul, T. Jahan, S. M. S. Sani, N. Noor, and T. Hasan, ‘‘Monkeypox skin lesion detection using deep learning models: A feasibility study,’’ Jul. 2022, arXiv:2207.03342.

[16]. M. Bhandari, T. B. Shahi, B. Siku, and A. Neupane, ‘‘Explanatory classification of CXR images into COVID-19, pneumonia and tuberculosis using deep learning and XAI,’’ Comput. Biol. Med., vol. 150, Nov. 2022, Art. no. 106156, doi: 10.1016/j.compbiomed.2022.106156.

[17]. M. Loey, S. El-Sappagh, and S. Mirjalili, ‘‘Bayesian-based optimized deep learning model to detect COVID-19 patients using chest X-ray image data,’’ Comput. Biol. Med., vol. 142, Mar. 2022, Art. no. 105213, doi: 10.1016/j.compbiomed.2022.105213.

[18]. E. Khan, M. Z. U. Rehman, F. Ahmed, F. A. Alfouzan, N. M. Alzahrani, and J. Ahmad, ‘‘Chest X-ray classification for the detection of COVID-19 using deep learning techniques,’’ Sensors, vol. 22, no. 3, p. 1211, Feb. 2022, doi: 10.3390/s22031211.

[19]. A. H. Barshooi and A. Amirkhani, ‘‘A novel data augmentation based on Gabor filter and convolutional deep learning for improving the classification of COVID-19 chest X-ray images,’’ Biomed. Signal Process. Control, vol. 72, Feb. 2022, Art. no. 103326, doi: 10.1016/j.bspc.2021. 103326.

[20]. S. V. Kogilavani, J. Prabhu, R. Sandhiya, M. S. Kumar, U. Subramaniam, A. Karthick, M. Muhibbullah, and S. B. S. Imam, ‘‘COVID-19 detection based on lung CT scan using deep learning techniques,’’ Comput. Math. Methods Med., vol. 2022, pp. 1–13, Feb. 2022, doi: 10.1155/2022/7672196.

[21]. K. Purohit, A. Kesarwani, D. R. Kisku, and M. Dalui, ‘‘COVID-19 detection on chest X-ray and CT scan images using multi-image augmented deep learning model,’’ in Proc. 7th Int. Conf. Math. Comput., Singapore, 2022, pp. 395–413, doi: 10.1007/978-981-16-6890-6_30.

[22]. C. Ieracitano, N. Mammone, M. Versaci, G. Varone, A.-R. Ali, A. Armentano, G. Calabrese, A. Ferrarelli, L. Turano, C. Tebala, Z. Hussain, Z. Sheikh, A. Sheikh, G. Sceni, A. Hussain, and F. C. Morabito, ‘‘A fuzzy-enhanced deep learning approach for early detection of COVID-19 pneumonia from portable chest X-ray images,’’ Neurocomputing, vol. 481, pp. 202–215, Apr. 2022, doi: 10.1016/j.neucom.2022.01.055.

[23]. G. Latif, G. Ben Brahim, D. N. F. A. Iskandar, A. Bashar, and J. Alghazo, ‘‘Glioma tumors’ classification using deep-neural-network-based features with SVM classifier,’’ Diagnostics, vol. 12, no. 4, p. 1018, Apr. 2022, doi: 10.3390/diagnostics12041018.

[24]. S. Rinesh, K. Maheswari, B. Arthi, P. Sherubha, A. Vijay, S. Sridhar, T. Rajendran, and Y. A. Waji, ‘‘Investigations on brain tumor classification using hybrid machine learning algorithms,’’ J. Healthcare Eng., vol. 2022, pp. 1–9, Feb. 2022, doi: 10.1155/2022/2761847.

[25]. U. Zahid, I. Ashraf, M. A. Khan, M. Alhaisoni, K. M. Yahya, H. S. Hussein, and H. Alshazly, ‘‘BrainNet: Optimal deep learning feature fusion for brain tumor classification,’’ Comput. Intell. Neurosci., vol. 2022, pp. 1–13, Aug. 2022, doi: 10.1155/2022/1465173.

[26]. K. Wei, T. Li, F. Huang, J. Chen, and Z. He, ‘‘Cancer classification with data augmentation based on generative adversarial networks,’’ Frontiers Comput. Sci., vol. 16, no. 2, Sep. 2021, Art. no. 162601, doi: 10.1007/s11704-020-0025-x.

[27]. T. R. Mahesh, V. V. Kumar, V. Vivek, K. M. K. Raghunath, and G. S. Madhuri, ‘‘Early predictive model for breast cancer classification using blended ensemble learning,’’ Int. J. Syst. Assurance Eng. Manage., vol. 3, pp. 1–10, Jun. 2022, doi: 10.1007/s13198-022-01696-0.

[28]. R. Kaur, H. GholamHosseini, R. Sinha, and M. Lindén, ‘‘Melanoma classification using a novel deep convolutional neural network with dermoscopic images,’’ Sensors, vol. 22, no. 3, p. 1134, Feb. 2022, doi: 10.3390/s22031134.

[29]. K. V. Hong, T. T. Minh, H. L. Duc, N. T. Nhat, and H. L. Hoang, ''104 fruits classification using transfer learning and DenseNet201 fine-tuning,'' in Complex, Intelligent and Software Intensive Systems. Cham, Switzerland: Springer, 2022, pp. 160–170, doi: 10.1007/978-3-031-08812-4_16.

[30]. N. Ullah, J. A. Khan, M. S. Khan, W. Khan, I. Hassan, M. Obayya, N. Negm, and A. S. Salama, ''An effective approach to detect and identify brain tumors using transfer learning,'' Appl. Sci., vol. 12, no. 11, p. 5645, Jun. 2022, doi: 10.3390/app12115645.

[31]. D. Attota, D. N. Tadikonda, S. Pethe, and M. A. A. H. Khan, ''An ensembled method for diabetic retinopathy classification using transfer learning,'' in Proc. IEEE 46th Annu. Comput., Softw., Appl. Conf. (COMPSAC), Jun. 2022, pp. 1444–1449, doi: 10.1109/COMPSAC54236.2022.00229.

[32]. P. Młodzianowski, ''Weather classification with transfer learning— InceptionV3, MobileNetV2 and ResNet50,'' in Digital Interaction and Machine Intelligence. Cham, Switzerland: Springer, 2022, pp. 3–11, doi: 10.1007/978-3-031-11432-8_1.

[33]. X. Zhao, K. Li, Y. Li, J. Ma, and L. Zhang, ''Identification method of vegetable diseases based on transfer learning and attention mechanism,'' Comput. Electron. Agricult., vol. 193, Feb. 2022, Art. no. 106703, doi: 10.1016/j.compag.2022.106703.

[34]. D. Purkayastha and D. Malathi, ''Leveraging transfer learning for effective recognition of emotions from images: A review,'' in Cyber Security, Privacy and Networking. Singapore: Springer, 2022, pp. 13–24, doi: 10.1007/978-981-16-8664-1_2.

[35]. U. K. Lilhore, S. Simaiya, A. Kaur, D. Prasad, M. Khurana, D. K. Verma, and A. Hassan, ''Impact of deep learning and machine learning in industry 4.0: Impact of deep learning,'' in Cyber-Physical, IoT, and Autonomous Systems in Industry 4.0. Boca Raton, FL, USA: CRC Press, 2021, pp. 179–197.

[36]. C. Kaushal, D. Koundal, and A. Singla, ''Comparative analysis of segmentation techniques using histopathological images of breast cancer,'' in Proc. 3rd Int. Conf. Comput. Methodol. Commun. (ICCMC), Mar. 2019, pp. 261–266.

[37]. A. Kaur, M. Khurana, P. Kaur, and M. Kaur, ''Classification and analysis of water quality using machine learning algorithms,'' in Proc. Int. Conf. Commun., Circuits, Syst. Singapore: Springer, 2021, pp. 389–398.

[38]. C. Kaushal, S. Bhat, D. Koundal, and A. Singla, ''Recent trends in computer assisted diagnosis (CAD) system for breast cancer diagnosis using histopathological images,'' IRBM, vol. 40, no. 4, pp. 211–227, Aug. 2019.

[39]. D. U. Ozsahin, M. T. Mustapha, B. Uzun, B. Duwa, and I. Ozsahin, ''Computer-aided detection and classification of monkeypox and chickenpox lesion in human subjects using deep learning framework,'' Diagnostics, vol. 13, no. 2, p. 292, Jan. 2023, doi: 10.3390/diagnostics13020292.

[40]. M. Altun, H. Gürüler, O. Özkaraca, F. Khan, J. Khan, and Y. Lee, ''Monkeypox detection using CNN with transfer learning,'' Sensors, vol. 23, no. 4, p. 1783, Feb. 2023, doi: 10.3390/s23041783.

[41]. D. Powers, ''Evaluation: From precision, recall, and F-factor to ROC, informedness, markedness & correlation,'' Mach. Learn. Technol., vol. 2, pp. 1–19, Jan. 2008.

Dataset Link:
Classification : https://www.kaggle.com/datasets/nafin59/monkeypox-skin-lesion-dataset
Detection:
https://roboflow.com/convert/labelbox-json-to-yolov5-pytorch-txt