MONKEY-POX VIRUS DETECTION USING PRE-TRAINED DEEP LEARNING BASED APPROACHES

Ms. KAMALAVALLI M[1], Ms. HAKEEMA M A[2], Mr. PANDIYAN M[3]

[1] *Student, Computer Science and Engineering, Bannari Amman Institute of Technology, Tamilnadu, India*
[2] *Student, Computer Science and Engineering, Bannari Amman Institute of Technology, Tamilnadu, India*
[3] *Assistant Professor-III, Information Science and Engineering, Bannari Amman Institute of Technology, Tamilnadu, India*

ABSTRACT

The monkey-pox virus is slowly spreading around the world. This paper discusses discovering and identifying the monkey-pox virus using pre-trained deep learning-based approaches. The huge epidemic of this sickness has sickened thousands of people and even resulted in deaths. The disease's effects may last up to three or four weeks in a patient. Symptoms include skin rash or mucosal lesions, fever, headache, muscle aches, back discomfort, fatigue, and enlarged lymph nodes. Monkey-pox can spread to humans by personal contact with an infected individual or with contaminated objects. So, detecting the virus early is critical to prevent community transmission. Deep learning-based detection could provide a solution to this problem. Deep learning techniques could help in discovering the disease early and avoiding transmission. The pre-trained model is used in the dataset to reliably identify significant patterns and features. To improve the model's performance, data augmentation is implemented. The experiment is carried out on a dataset containing images of monkey-pox, and accuracy of the model is evaluated. The results indicate that the recommended deep learning approach surpasses previously suggested models, demonstrating its reliability as a efficient tool for detecting the monkey-pox virus. This technique is effective in assisting healthcare workers in making fast and accurate diagnoses.

Keyword *monkey-pox, deep learning, detection, data augmentation, accuracy.*

1. INTRODUCTION

The monkey-pox virus, which belongs to the Poxviridae family, the Chordopoxvirinae subfamily, and the Orthopoxvirus genus, causes the illness known as monkey-pox. Monkey-pox can spread to people by direct contact with diseased animals (such as rodents, monkeys, or other animals) or through contact with infected individuals' fluids or sores. Human-to-human transmission is also possible, usually by respiratory droplets or contact with skin lesions. Monkey-pox symptoms start with fever, headache, muscle aches, back pain, swollen lymph nodes, chills, and tiredness. In humans, this disease often occurs from 5 to 21 days after exposure, and a distinctive rash generally begins on the face and spreads to other areas of the body. The rash may develop into fluid filled blisters that look exactly like pimples. Supportive therapy, such as hydration, pain control, and secondary infection treatment, may be required in severe cases.

Currently, the monkey-pox virus is tested using PCR tests in laboratories. For PCR tests, highly equipped laboratories, highly skilled staff, and safety are needed. Nucleic acid amplification testing (NAAT) validates the PCR test through the use of real-time or traditional polymerase chain reaction (PCR) to identify specific viral DNA sequences. This procedure involves two phases, with the first PCR reaction detecting OPXV. This is then followed by a second step, either PCR based or sequencing-based, to detect the monkey-pox virus specifically. Before testing human clinical specimens in a laboratory, the procedure should be validated and verified by experts. Another important thing in detecting monkey-pox is reagents. Reagents should be stored according to the manufacturer's guidelines. Thus, PCR is time consuming, cost-consuming, and involves manpower. So we need a better solution that saves time, reduces the cost of the patient, reduces manpower, and gives the result instantly. A pre-trained deep learning model will provide a feasible solution. In this model, the convolutional neural network is used to detect monkey-pox.

2. LITERATURE REVIEW

Simrin Fathima et al. [1] proposed "Monkey-pox virus detection using pre-trained deep learning based approaches," which was published in the National Library of Medicine on October 6, 2022. In this work, the virus was detected using deep learning approaches like KNN analysis, Ada Booster classifiers, Naive Bayes classifiers, and decision trees. Here, deep learning techniques like various classification algorithms, how to use them, and how they are used in classification were noted and analyzed.

Chiranjibi Sitaula et al. [2] proposed an idea to detect monkey-pox using pre-trained deep learning based approaches under the title Monkey-pox virus detection using pre-trained deep learning-based approaches, published in the National Library of Medicine on October 6th, 2022. In this method, they initially fine-tune with the addition of universal custom layers and analyze the results under precision, recall, F1 score, and accuracy. In this approach, 13 deep learning models were combined. The best-performing DL model is an ensemble to improve overall performance.

Krishnaraj Chadaga et al. [3] proposed a systematic review under the title "Application of AI techniques for monkey-pox: A Systematic Review," which was published in the National Library of Medicines. In this work, the author reviews recent studies that used AI for monkey-pox detection. He also studied many AI methods that are used in classification.

Othman A. Alrusaini et al. [4], in their recent work, "Deep Learning Models for the Detection of Monkey-pox Skin Lesion on Digital Skin Images," which was published in the International Journal of Advanced Computer Science and Applications in the year 2023. In this paper, he proposes an idea to detect the monkey-pox virus using deep learning models. Overfitting is the main disadvantage of this model.

Shams Nafisa Ali et al. [5], in their recent work, "Monkey-pox Skin Lesion Detection Using Deep Learning Models: A Feasibility Study", published in the Journal of Academia in 2023. They proposed a feasible study about many deep learning models, transfer learning, and how to implement these models to detect monkey-pox. They also discussed ensemble models to increase accuracy.

Manjurul Ahsan et al. [6] suggested a unique model for "Monkey-pox Diagnosis with Interpretable Deep Learning." The idea was published as an IEEE research article on August 9, 2023. In this model, the performance was assessed for six deep learning models, which include VGG16, InceptionResNetV2, ResNet50, ResNet101, MobileNetV2, VGG19, and Vision Transformer (ViT). Among these models, modified versions of the VGG19 and MobileNetV2 models were used in the detection of monkey-pox. This model uses transfer learning.

3. EXISTING SYSTEM

The existing system proposes a solution to detect monkey-pox using deep learning. Here, the algorithm proposed is stratified fivefold cross validation, wherein in each fold, images from 80% of patients were used for training and 20% for validation. The cross-validation was repeated five times. To allow the detection of monkey-pox infection, this model was created using an image based deep convolutional neural network. This model has a dataset of skin lesion photos, using scientific literature, news stories, and social media. The primary limitation of this methodology is the scarcity of monkey-pox images. In this model, a dataset of monkey-pox images was created using monkey-pox images from scholarly papers, encyclopedia articles, news articles, social media, and a prospective cohort rather than using a publicly available dataset. This method, however, is susceptible to bias. This model also provides a mobile application technique to detect monkey-pox; however, this raises concerns and presents major problems. A smartphone app that merely accepts a snapshot of a skin lesion and returns a chance of an MPXV infection is insufficient for user guidance. As the model is lacking in the dataset, many similar skin diseases like chicken pox and measles were wrongly predicted as monkey-pox. Another important drawback of this model is overfitting.

The MPXV-CNN predictions must be evaluated in light of a variety of factors influencing the pre-test probability for an infection, such as additional symptoms reported by users, close contact with infected individuals, and the incidence of infectious cases at the user's location. A system was required that combines the MPXV-CNN prediction with the expert knowledge of healthcare experts, taking into account all of the aforementioned aspects, to create simple suggestions for consumers.

4. PROPOSED METHODOLOGY

The proposed model here is that first the dataset is collected and pre-processed to remove the noise and clean the data. The dataset should be void of missing data, irrelevant data, and noise. The images are then processed using the OpenCV module in Python. Data augmentation is performed to create new data from existing data. The dataset will now contain images along with augmented images. The dataset is split into training and testing (75–25), and the model is trained. The training dataset is used for training purposes, and the remaining 25% is used for validation purposes. The code for image processing, training, testing, and accuracy calculation is implemented in Jupyter Notebook using the Python language. The accuracy is evaluated with the aid of a confusion matrix. If the accuracy is not up to the level, data augmentation is again implemented. The model is finally connected to a GUI developed using Python. The user needs to upload the images, and the model will tell whether the user is affected by monkey-pox or not.

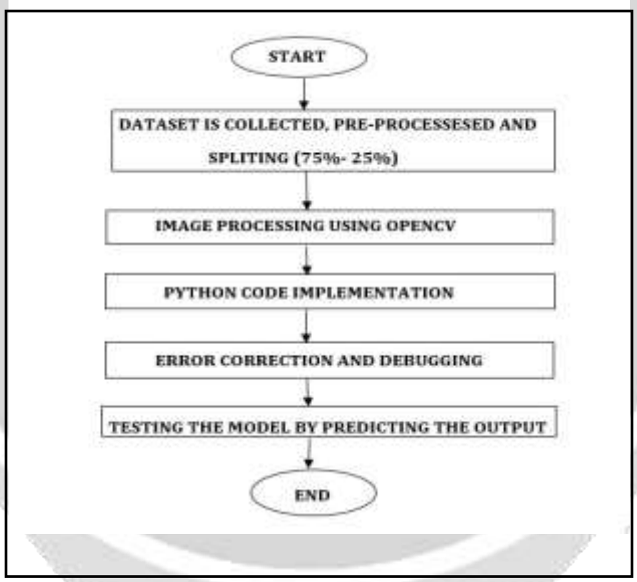

Figure 1: Proposed methodology

4.1 MODEL BUILDING

4.1.1. Dataset collection:

The dataset is collected with various clinical and real-time images of monkey-pox and pre-processed to improve accuracy by reducing the noise and unwanted data in the dataset. The dataset contains 539 images of monkey-pox-affected skin and 54 images of healthy skin. The dataset is uploaded in Jupyter Notebook. The dataset is split into training and testing. 75% of the dataset is used for training, and the remaining 25% is used for testing.

Figure 2: Sample image from the dataset

4.1.2. Image processing:

Image processing aims to improve the quality of the image so that the model can analyze and extract the features in a better way. Through image processing, we can reduce unwanted distortions and boost some features that are required for categorization. For image processing, CV2 is used. CV2 is an important module in OpenCV used for image and video processing in Python. Here, we are using OpenCV to process the images. During the image-processing phase, it is essential to check whether all the images are in the same format to extract some information from the image.

4.1.3. Open CV:

OpenCV is a large open-source Python library primarily used for computer vision, machine learning, and image processing. It is now used extensively in real-time operations in image and video processing. It allows the processing of photos and movies to recognize items, faces, and even human handwriting. In this model, we are using an open CV to process the images in the dataset.

4.1.4. Deep learning-based approaches:

Initially, monkey-pox is detected using a PCR test. This test is not that accurate, and it can provide results only after a day. By this time, there may be a chance of monkey-pox being widespread. So, to avoid this problem, we need a solution that provides instant results to avoid the spread of the monkey-pox virus. Detecting monkey-pox using deep learning provides better and quicker results when compared to traditional PCR methods. In this methodology, monkey-pox is detected using the Resnet-18 CNN methodology.

A convolutional neural network consists of three layers: the convolutional layer, the pooling layer, and the fully connected layer. Each layer is connected to the previous layer, with the input layer receiving data outside. Each neuron's output is determined by applying an activation function to the linear combination of its inputs and weights. The first layer is a convolutional layer, which is the core building block of the CNN. The convolutional layer mainly deals with feature extraction. The next layer is the pooling layer, which replaces the output by calculating a summary statistic of neighboring outputs. In the pooling layer, either max pooling or average pooling is used. This helps to reduce the size of the representation, the amount of computation, and the weights needed. The pooling procedure is applied to each slice of the representation individually. The final layer is a fully connected layer, or dense layer, which maps inputs to output and classifies whether the image is monkey-pox or not.

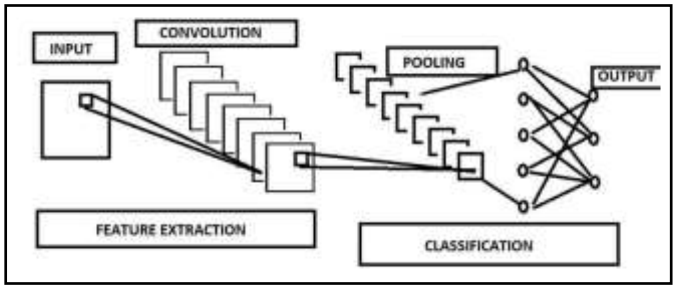

Figure 3: Diagrammatic representation of CNN architecture

4.1.5. Resnetarchitecture:

In Resnet, residual blocks are the primary component. In a traditional neural network, the input is converted by a series of convolutional layers before being given to the activation function. Whereas, in a residual network, the block's input is added to its output, forming a residual link. Another important component in Resnet is the skip connection. The skip connection consists of the residual block's input being bypassed over the convolutional layer and appended to the residual block's output. ResNet structures are created by stacking residual blocks together. These many residual blocks can be combined to create an extremely deep resnet design. Resnet topologies use global average pooling as the final layer preceding the fully connected layer. The diagrammatic representation of the Resnet architecture is shown below.

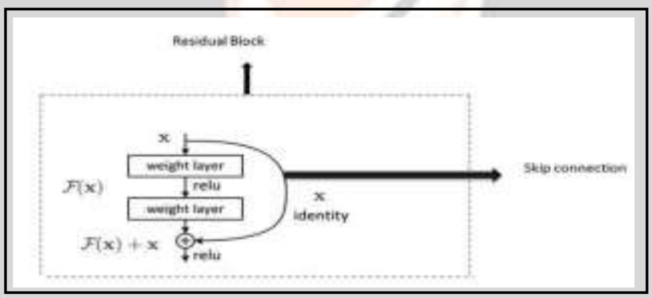

Figure 4: Resnet architecture

4.1.6. Confusion matrix:

A confusion matrix is a method for presenting the number of correct and incorrect instances based on the model's predictions. It is most commonly used in evaluating the performance of classification models.

The matrix shows the number of instances generated by the model using the test data.

- True positives (TP) predicted positive, and it is true.
- True negatives (TN) predicted negatives, and it is true.
- False positives (FP) predicted positive, and it is true (type 1 error).
- False negatives (FN) predicted negative, and it is false (type 2 error).

A confusion matrix is essential for evaluating the performance of a classification model. It provides a comprehensive examination of true positive, true negative, false positive, and false negative predictions, allowing for a more in-depth understanding of a model's recall, accuracy, precision, and overall effectiveness in-class differentiation. From this confusion matrix, the accuracy, precision, F1 score, and recall can be calculated.

4.1.7 Code implementation and debugging:

The code for implementing training, testing, and image processing is implemented using the Python language in Jupyter Notebook. The image is processed using the CV2 module of the OpenCV library. For implementing the code, libraries like NumPy, Pandas, Sys, OS, Sklearn, etc. were used. After implementing the code, the code was debugged, and errors were rectified.

4.1.8 Model evaluation:

After completing the training process for the model, it must be checked and tested. For testing, 132 images of monkeys affected and 15 images of healthy skin were used. The findings, like accuracy, precision, F1 score, and recall, will provide performance measures for our trained model. These performance metrics can be identified by using true positive, true negative, false positive, and false negative values obtained from the confusion matrix. To test the data in our model, we first preprocessed it and reduced it to a suitable size for our model. We then changed our image data to an array type. We used the test prediction approach to evaluate the converted image data in our model. The accuracy is evaluated and compared with the accuracy of existing models. If the accuracy is low, data augmentation is again performed, and the steps are repeated. Finally, accuracy is checked.

5. RESULTS AND DISCUSSION

The primary goal of this project is to detect monkey-pox using pre-trained deep learning-based methods. As a result, the disease can be detected early and prevented from spreading. This technology aims for speedy prediction, making it more effective than the classic PCR method. This method detects the monkey-pox virus using pre-trained deep-learning models. The dataset is collected, and the model is trained using the photos from the dataset. The Resnet-18 model in CNN technology has the potential to improve accuracy, scalability, and early detection capabilities and save money and time in the medical industry. This model contributes to increased response efficiency by automating the detection process and producing reliable and consistent results. This includes the need for a high-quality pre-processed training dataset. Overall, while pre-trained deep learning based algorithms have enormous potential for increasing monkey-pox virus detection capabilities, their successful implementation requires a thorough understanding of both the technical parts and the broader socio-ethical factors involved. 75% of the dataset is set aside for training purposes, with the remaining 25% for testing. Performance is evaluated using a variety of measuring criteria. The confusion matrix displays true positive (TP), true negatives (TN), false positives (FP), and false negatives (FN) instances produced by the model on the test data. These values are used to identify the accuracy of the model and help evaluate it. The calculation for the accuracy value is presented below.

ACC=TP+TNTP+TN+FP+FN

Recall is the inverse of confidence; it compares false negatives with true positives.

Recall=TPTP+FN

Precision is a positive analytical value. It determines how dependable the measurements are, even if they deviate from the recognized value.

Precision=TPTP+FP

The F1 score is used to assess the trade-off between recall and precision measurements. The harmonic mean is utilized instead of the arithmetic mean based on the F1 score. The procedure for determining the score is shown below. **F1 (Score) =2.Precisionx Recall Precision + Recall** Accuracy has a value between 0 and 1. The closer the score gets to one, the more successful it is. When we tested our model, we achieved an accuracy score of 0.9997 on the training data. The verification results yielded a score of 0.9654. When the graph was evaluated, there were no overfitting or under fitting circumstances in which the curves progressed steadily.

The recall value is a statistic that tells how many of the transactions we need to forecast as positive are anticipated as positive. It's also called sensitivity. The sensitivity value should be high.

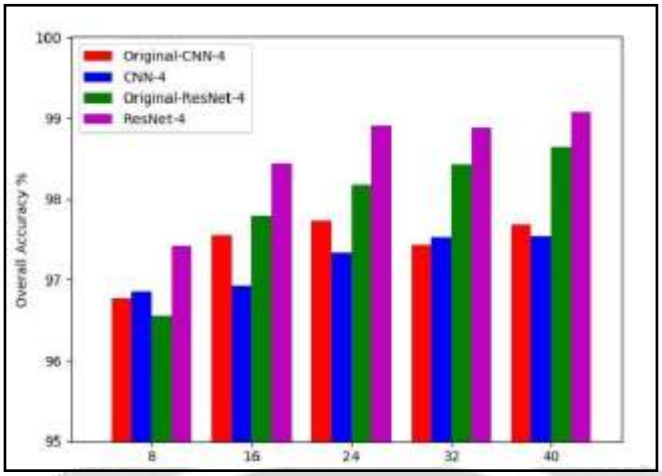

Figure 5: Comparison graph

6. CONCLUSION

Monkey-pox is an emerging threat all over the world. So it is important to identify and treat this virus at an early stage to save the lives of people and to avoid community transmission. The proposed algorithm provides an effective solution to detect the monkey-pox virus at an early stage and also saves time and money for the users. This algorithm uses pre-trained deep learning models to detect the monkey-pox virus, thus providing instant results. The dataset is collected, and the model is trained with the images of the dataset. The potential benefits of using CNN technology include increased accuracy, scalability, early detection capabilities, and cost and time savings in healthcare. This model helps in increasing response efficiency by automating the detection process and providing reliable and uniform findings. However, various challenges must be overcome to optimize the effectiveness and accuracy of this strategy, which include the requirement for a high-quality pre-processed training dataset, careful model validation, continuous maintenance and updates, and addressing ethical issues if any. Overall, while pre-trained deep learning-based techniques have tremendous potential for improving monkey-pox virus detection capabilities, successful application necessitates a thorough grasp of both the technical elements and the broader socio-ethical factors involved.

The future scope includes a dataset with images based on age, country, and gender, which improves accuracy. Collaboration with researchers, healthcare practitioners, and technology developers to maximize the benefits of new emerging technologies. It is compatible with other technologies, such as microscopes with digital imaging capabilities or mobile diagnostic devices. This integration has the potential to produce useful tools for on-site detection of the monkey-pox virus in remote or resource-constrained settings. Deep learning models facilitate data sharing and collaboration among researchers and healthcare facilities. Another future goal is to provide annotated datasets and the number of affected persons with symptoms, as well as model designs, with government health care, hospitals, and researchers to speed up monkey-pox virus detection, resulting in more effective disease control and preventative measures. Block chain technology can improve the security, transparency, and integrity of the data used to create and deploy deep-learning models to detect monkey-pox. Block chain integration can increase trust in model results by creating tamper-resistant records of data provenance and outputs, which can then be used in clinical practice and public health decisions.

7. REFERENCES

[1]. Krishnaraj Chadaga, Tushar Nayak, Niranjana Sampathila, and Hilda Mayrose, "DDeep learningbased detection of monkeypox virus using skin lesion images," Medicine in Novel Technology and Devices, Volume 18, June 2023, 100243

[2] Othman A. Alrusaini," Deep Learning Models for the Detection of Monkeypox Skin Lesion on Digital Skin Images," International Journal of Advanced Computer Science and Applications 2023

[3] Hams Nafisa Ali, Md. Tazuddin Ahmed, Joydip Paul, Tasnim Jahan, S. M. Sakeef Sani, and Nawsabah Noor TTauqHasan," Monkeypox Skin Lesion Detection Using DeepLearning Models: A Feasibility Study," Journal of Academia 2023.

[4] Manjurul Ahsan, Shahin Ali, Mehedi Hassan,
Tareque Abu Abdullah, Kishor Datta Gupta, Ulas Bagci, Chetna Kaushal, and Naglaa F. Soliman," Monkeypox Diagnosis With Interpretable Deep Learning," IEEE Research Article on August 9, 2023

[5] K. Chadaga, S. Prabhu, N. Sampathila, S. Nireshwalya, S.S. Katta, R.S. Tan, and U.R. Acharya, "Application of artificial intelligence techniques for monkeypox: a systematic review," in Diagnostics on February 21, 2023.

[6] C. Sitaula, T.B. Shahi, "Monkey-pox virus detection using pre-trained deep learning-based approaches," Journal of Medical Sciences, published on October 6, 2022, Volume 46, article number 78 (2022).

[7]V.H. Sahin, I. Oztel, and G. Yolcu Oztel, "Human monkey-pox classification from skin lesion images with a deep pre-trained network using a mobile application," published in the Journal of Medical Sciences on October 9, 2022, volume 46.

[8]A.A. Abdelhamid, E.S. ElKenawy, N. Khodadadi, S. Mirjalili, D.S. Khafaga, A.H. Alharbi, A. Ibrahim, M.M. Eid, and M. Saber, "Classification of monkey-pox images based on transfer learning and the Al-Biruni Earth Radius Optimization algorithm," published in the journal of mathematics on October 2, 2022, volume 10.

[9] K.D. Akin, C. Gurkan, A. Budak, and H. Karataş, "Classification of monkey-pox skin lesions using explainable artificial intelligence assisted convolutional neural networks," published in 2022 in the Journal of Alevism-Bektashism Studies

[10] Murat Altun Hüseyin Gürüler Osman Özkaraca Faheem Khan Jawad Khan and Youngmoon Lee, "Monkey-pox Detection Using CNN with Transfer Learning," on February 5, 2023, on Sensor Data Fusion Based on Deep Learning for Computer Vision and Medical Applications II.