Efficient Technique for Monkeypox Skin Disease Classification with Clinical Data using Pre-Trained Models

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Abstract

Monkeypox is an infectious zoonotic disease with clinical features similar to those actually observed in victims with smallpox, however being medically less severe. With the control of infectious smallpox diseases in 1980 as well as the termination of smallpox by immunization, monkeypox has become the most significant orthopoxvirus affecting global health. It is very important to prevent and diagnose this disease immediately and efficiently before its spread worldwide. Currently, the traditional system is used for the diagnosis of this infectious disease, in which a medical practitioner identifies monkeypox disease with swabs of fluid from skin rash. This approach has a lot of limitations such as it requires medical expertise, is costly and slow, and its result is not satisfactory. AI-based technologies may assist prevent and identify this infectious disorder. Because of the limitations, this proposed work suggests an AI-based diagnosis system which can detect monkeypox virus efficiently and immediately. Five transfer learning models are applied on image -based dataset with some pre-processing and optimization techniques for monkeypox virus detection. The Inception-Resnet outperformed by achieving 97% accuracy, VGG16 achieved 94% accuracy, Inception achieved 96% accuracy, VGG19 achieved 91% accuracy, and Resnet50 achieved 71% accuracy. The positive results of this investigation suggest that this strategy outperforms the current approaches. The dataset used in this proposed work is obtained from Kaggle online repository

DOI: https://doi.org/10.36548/jiip.2023.2.009
Received: 05.05.2023, received in revised form: 05.06.2023, accepted: 20.06.2023, published: 30.06.2023

and some new patients' data are added from various sources. This suggested strategy can be used by health professionals for screening.

Keywords: Monkeypox disease, Transfer learning, pre-trained models, classification

1. Introduction

Monkeypox disease is among the most dangerous and life-threatening diseases in the world is caused by the monkeypox virus, which mostly originates from monkeys. The monkey pox disease is most frequently found in Asia, the Middle East, and western Africa, but has recently spread to various parts of the world. Monkeypox virus can affect every species, but it transfers to humans via bat or monkey bites. Initial symptoms of monkeypox might include a wide range of discomforts, including aches and pains in the muscles, headaches, feelings of fatigue, and fever, and symptoms may last two to four weeks. The bacterial growth period for monkeypox is normally 6 to 13 days, but this can vary from five to three weeks. The disease occurs in two phases. During the invasion phase, victims have backache, fever, lymphatic gland swelling, a strong headache, muscle pain, and decreased energy. Skin lesions develop in the second phase, after 1–3 days of fever. Typically, the virus spreads from one individual to another after close contact or after touching contaminated objects like mattresses, clothes, etc. [1].

Human monkeypox was discovered in a 9-month-old child in the Democratic Republic of the Congo in 1970, where smallpox had been eradicated in 1968. According to the WHO report, 11 African countries have been infected by monkeypox since 1970. The first monkeypox incident outside of Africa appeared in the US in 2003 and was linked to pet prairie dogs. Due to this epidemic, approximately 70 instances of monkeypox were reported inside the U.S. Nigerian tourists suffered from monkeypox in Israel in August 2018, the UK in October 2018, November 2019, April 2021, and May 2022, and Singapore in May 2019, and the US in August and November 2021 [2]. Furthermore, a new report published by WHO on 15 June 2022 is shown in table 1.

Table 1. WHO Monkeypox Outbreak Report January 2022 to 15 June 2022

Serial	**Country name**	**Cases reported**	**Deaths**
	Canada	159	None
	France	125	
	Germany	163	
	Italy	68	
	Belgium	52	
	Nigeria	36	1
	Portugal	241	None
	Spain	313	1
	United Kingdom	524	None
	Netherland	80	
	Ireland	14	
	Switzerland	28	
	Australia	7	1

Monkeypox was reportedly found in large numbers in non-endemic areas in May 2022. There are now studies being conducted to fully understand the disease's epidemiology, causes, and spreading patterns. Early and accurate diagnosis of monkeypox disease is very essential to overcoming this epidemic. The traditional diagnosis of Monkeypox through conducting swabs tests is not satisfactory because of the unviability of experts, slow and time wasting. Furthermore, the traditional methods of diagnosing monkeypox disease are costly and ineffective. Artificial intelligence is a new and rapidly developing field that provides the foundation for a variety of scientific disciplines. This can be used as a method of learning and discovering patterns and relationships from a large set of sample models to improve the current method for decision-making in a specific domain. Intelligence technologies are used to improve surveillance, disease prevention, and infection control for vector-borne, person-to-person, healthcare-related, and bacterial diseases. As monkeypox diseases influence individual skin, infectious skin images can be employed to construct an AI-based diagnosis system. Machine Learning (ML) has recently shown remarkable achievements in the fields of diagnostic imaging and illness diagnosis [3]. To overcome the drawbacks of current invasive-based strategies, various machine learning and Deep Learning (DL) models were employed to build a smart computer-based system for various diseases' diagnosis.

In this article, an innovative strategy for precise and rapid diagnosis of monkeypox sickness has been presented. The suggested approach is based on the pre-trained models and Adam optimization technique. The following are the key contributions of the suggested work.

1. A novel approach proposed based on Adam optimization algorithm with transfer learning models to improve the prediction accuracy of monkeypox disease.
2. The proposed work prevents all possible complexities in healthcare.
3. Using a variety of statistical tools, the strategy suggested is compared to different methods and the results are examined.

The remaining paper is structured as follows: Section 2 describes the related works, section 3 presents the methodology, and section 4 explains the results and discussion, while section 5 presents the conclusion and future work.

2. Related Works

Machine learning and deep learning has shown a remarkable achievement in early and accurate diagnosis of various diseases. The need of artificial intelligence rapidly increases in healthcare industry. Over time, researchers and professionals has showed significant interest in exploring various diseases using ML and DL approaches and developed a number of systems that used to predict various diseases at early stage. However, there is no accurate diagnostic method for monkeypox disease.

Doaa Sami et al., [4] conducted an experiment using various ML and DL algorithms including CNN, KNN, SVM, and DT for detection of monkeypox disease. The proposed work made use of human skin images obtained from an African hospital. Furthermore, in proposed work the performance of various models compared with other approaches. The highest accuracy of 98% achieved with CNN. Marwa M et al., [5] proposed an approach based on LSTM deep network with some optimization techniques. The result with various optimization techniques analyzed using statistical techniques and highest accuracy achieved was 97%.

Korhan Deniz Akin et al., [6] proposed an AI based auxiliary approach for moneybox disease diagnosis using 12 different CNN algorithms. The proposed system achieved 98% accuracy with MobileNet V2. Shams Nafisa Ali et al., [7] carried out an experiment with various pre trained model and developed a web application for monkeypox patient's classification. The proposed approach used skin images collected from various sources and their system was 82.9% accurate. Md Manjurul Ahsan et al., [8] used 6 different transfer learning techniques for early and accurate detection of monkeypox disease and achieved 98% accuracy. Abdelaziz A. Abdelhamid et al., [9] applied transfer learning models on publically available dataset with some optimization and features extraction techniques and achieved 98.8% accuracy.

Veysel Harun Sahin et al., [10] developed an android application for monkeypox disease detection in which video images from a smartphone mobile screen are fed into deep convolutional models and their accuracy was 91%. Furthermore, the study suggested that the proposed mobile app can be used for other skin diseases. Towhidul Islam et al., [11] used a web-scrapping-based Measles, Monkeypox, Smallpox, Cowpox, Chickenpox and healthy skin image dataset to study the efficiency of Deep artificial intelligence models using skin images for the identification of monkeypox disease. The proposed approach achieved 79% accurate result.

Vidit Kumar [12] examined deep Network models with multiple machine classification models for the diagnosis of monkepox disease. The proposed work used AlexNet, GoogleNet, and Vgg16Net in combination with SVM, KNN, Naive Bayes, Decision Tree, and Random Forest. The accuracy of the Naive Bayes classification model was 91.1% with Vgg16Net. Talha Burak Alakus et al., [13] applied deep learning models and examined HPV and MPV DNA sequences in four stages process for warts and monkeypox diseases diagnosis. The proposed work achieved 96% accurate result. Chiranjibi Sitaula et al., [14] applied 13 different transfer learning models on publicly available human skin image dataset and compared their performance. The proposed approach was 87.13% accurate in monekeypox disease detection.

Farhana Yasmin et al., [15] carried out an experiment using the skin image monkeypox dataset by applying nine different models and compared their performance in term of MSE values. Md Manjurul Ahsan et al., [16] collected a new monkeypox dataset from different sources and applied VGG16 pre-trained model for monkeypox disease diagnosis. The collected dataset is now publically available for further study. The proposed model achieved 97% accuracy. Balakrishnama Manohar et al., [17] applied Artificial Neural Network (ANN) with optimization and K-Fold cross validation approaches on skin images dataset for monkeypox disease detection and achieved 98% accuracy. Furthermore, the result was compared with previously used LSTM and GRU models. Saleh Ateeq Almutairi [18] examined three skin diseases namely monkeypox, chicken pox and measles. In the proposed work CNN model is used for features extraction. The extracted features passed to seven different ML algorithms (i.e., Histogram Gradient Boosting, Random Forest Gradient, and AdaBoost). The proposed approach achieved highest accuracy of 96% with Random Forest algorithm.

Table 2 summarizes the previous studies' contribution and their limitations.

Table 2. Summary of Previous Works

Reference	Model applied	Contribution	Accuracy	Dataset Used	Dataset Type	Limitations
Doaa Sami et al. [4]	CNN, SVM, K-NN, DT.	Classification	98%	Kaggle dataset	Image dataset	Used small dataset, High computation time
Marwa M et al. [5]	BER-LSTM, LSTM, BILSTM	Classification	97%	Kaggle dataset		High computation time
Korhan Akin et al. [6]	ResNET-18, ResNet-50, VGG-16,	Classification	98.25%	Kaggle dataset		Used small dataset, High

						computation time
Nafisa Ali et al. [7]	VGG16, ResNet50, InceptionV3	Detection	82.9%	Kaggle dataset		Achieved accuracy is not satisfactory
Md Manjurul et al. [8]	VGG16, InceptionResV2, ResNet50,	Classification	98%	Kaggle dataset		High computation time
Abdelaziz A. et al. [9]	AlexNet, VGG19Net, ResNet-50, G.Net	Classification	93.8%	Kaggle dataset		Achieved accuracy is not satisfactory
Veysel Sahin et al. [10]	VGG-16, VGG19	Diagnosis	91%	Kaggle dataset		Achieved accuracy is not satisfactory
Towhidul Islam et al. [11]	ResNet50, Inception-V3, DenseNet121,MnasNet-A1,	Classification	79%	UCI dataset		Achieved accuracy is not satisfactory
Vidit Kumar [12]	AlexNet, GoogleNet, Vgg16	Classification	91%	Kaggle dataset		Achieved accuracy is not satisfactory, used small dataset
Talha Burak et al. [13]	BiLSTM	Detection	99.51%	Kaggle dataset		Used small dataset, high computation time
Chiranjibi Sitaula et al. [14]	VGG-16, VGG19, RestNet-50	Classification	87.13%	Kaggle dataset		Achieved accuracy is

						not satisfactory
Farhana Yasmin et al. [15]	Polynomial Regression, SVR, Holt's	Diagnosis	49%	Kaggle dataset		Achieved accuracy is not satisfactory
Md Manjurul et al. [16]	VGG16	Classification	78%	Novel dataset		Achieved accuracy is not satisfactory
Balakrishnama et al. [17]	ANN, CNN	Classification	98%	UCI dataset		Used small dataset
Saleh Ateeq [18]	RFG, HGB, AdaBoost	Classification	96%	Kaggle dataset		Used small dataset, high computation time

The current state of investigation for detection of monkeypox disease is not satisfactory. Some approaches have excellent result, but their computation time is high and also good only for small data, while some approaches take less time, but their performance is not efficient. To overcome these limitations, a lot of research work is needed in health care.

3. Materials and Methods

The suggested work aims to classify monkeypox patients and normal people. The transfer learning approaches are used on publically available image dataset. Additionally, some transformation techniques, filters, Histogram equalization, Feature Scaling and Adam optimizer are applied to eliminate noise from images and enhance the quality of images.

3.1 Experimental Setup

The experiment is carried out making use of 8 gigabytes of random-access memory in additional to an 8th Gen Intel core-7073 processors, an Intel Xeon GT 940MX Graphics card and Jupiter Notebook. The proposed model is implemented in Python using Keras open-source library. First, the size of each image is reduced to 120 x 120 pixels, the batch size of Adam optimizer is set to 16 and each model takes 200 epochs. Furthermore, Python modules like pandas, Tensor flow, and Scikit are used to generate classifiers and categorize data.

The proposed work is divided into four phases such as, dataset acquisition, preprocessing, optimization and classification. The complete mechanism of proposed work is explained in figure 1.

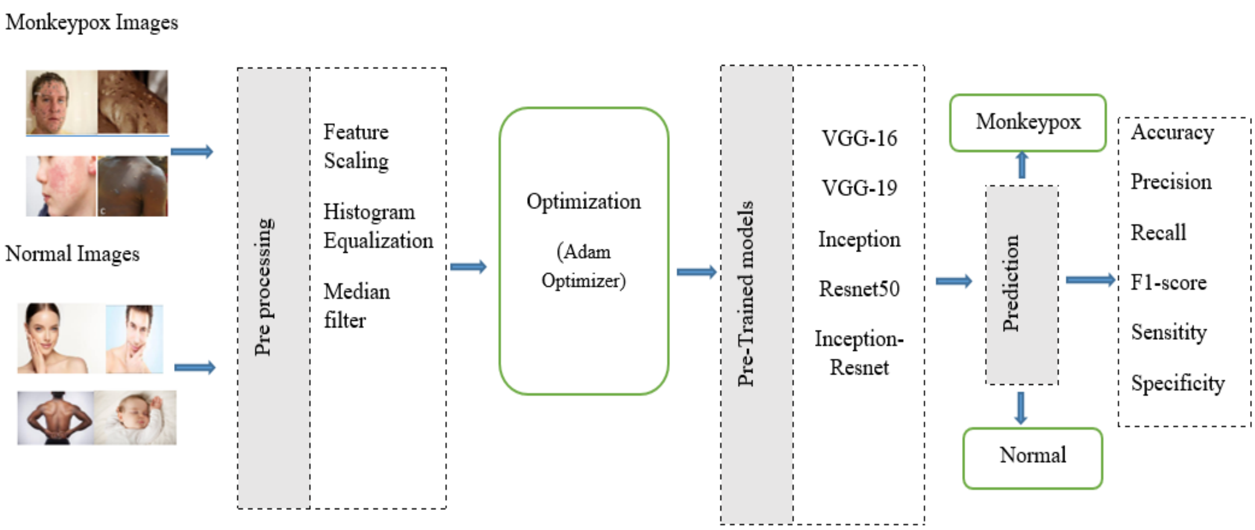

Figure 1. Proposed Methodology

3.2 Dataset Acquisition

The proposed work made use of image dataset. The image dataset is obtained from Kaggle online repository and some new patient data are added from various resources. During collecting images from various sources, various attributes including the symptoms of disease, severity level, age and gender, and disease progression are considered. The final dataset after adding patient’s data contains total 558 images equally divided into binary classes namely:

Monkeypox and normal having images of monkeypox patients and healthy persons. The obtained dataset split into training (70%) and testing (30%). After splitting dataset, 392 images are used for training purposes and 168 images for testing purposes. Figure 2 shows the samples

of data used in the proposed work.

Figure 2. Dataset Samples

3.3 Data Preprocessing

Data preprocessing is the procedure of altering raw data into appropriate data that is suitable for a machine learning model. It is the most important and initial stage in creating a machine learning model. It is impractical to use real-world data directly in ML and DL models because it may contain noise, missing values, or be in an unsuitable format for use in ML models. Data pre-processing is an essential phase for maximizing the performance and effectiveness of a machine learning model. Various data cleaning approaches are applied to assure that every feature of the image must possess the same co-efficient. In addition, at this phase, the image pixels have been normalized. Additionally, standard scalar guarantees that all features have the same means and labeled with 0 and 1, at the end the blur images removed from dataset. The dataset split into 70% for training and 30% for testing.

3.3.1 Feature Scaling

Data normalization, often referred to as "feature scaling" in data preprocessing, is frequently done during the data preparation phase. The aim of feature scaling is to ensure that features have an approximately similar scale, ensuring that each feature has an equivalent amount of significance, and making it easy to understand by machine learning algorithms. The Standard Scaler and MinMax Scaler are used for data standardization. The MinMax Scaler is used to scale all values between 0 and 1. Using the Standard Scaler, the data is scaled so that the mean is 0 and the standard deviation (or variance) is 1. The scaled value of the MinMax Scaler can be calculated using equation (1), and the scaled value of the Standard Scaler can be calculated using equation (2).

$$\boldsymbol{x\_scaled} = \frac{(x - x_{min})}{x_{max} - x_{min}} \tag{1}$$

$$\boldsymbol{x\_scaled} = \frac{(x - x\_mean)}{std\_dew} \tag{2}$$

3.3.2 Histogram Equalization

Image processing is one of the modern technologies that is expanding quickly and has been adopted as a core concept in the fields of computer science and engineering. Among its many techniques, histogram equalization is considered to be one of the most prominent techniques. A histogram is a graph that shows how an image's intensity is distributed. It only indicates how many pixels are involved for each intensity value taken into consideration. Histogram Equalization is used to improve contrast in images. This is achieved by successfully extending the intensity range of the image and spreading out the most common intensity levels. This strategy typically boosts the overall contrast of an image when the useful data is represented by close contrast values. Because of this, regions with less local contrast might acquire more contrast.

3.3.3 Median Filter

A median filter is a non-linear digital filtering method that is frequently used to eliminate noise from an image or signal. Such noise reduction is a common pre-processing procedure to enhance the outcomes of subsequent processing. The median is determined by placing the pixel under consideration with the middle pixel value after placing all the neighboring pixel values in numerical order. The figure below shows the concept of median filtering.

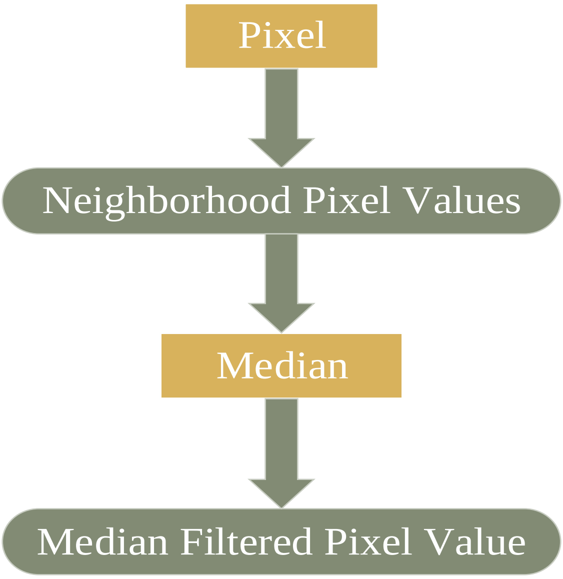

Figure 3. Concept of Median Filter

3.3.4 Adam Optimizer

Adam is an optimization technique that can be applied in place of the traditional stochastic gradient descent technique to modify network weights iteratively based on learning data. This is accomplished by using training information as the basis for Adam's calculations. This optimizer has faster calculation time and fewer tuning parameters than other optimizers. It is the suggested default optimization technique for most systems.

4. Results and Discussion

The numerous classification algorithms and related statistical evaluations are presented in this section. The results of several models applied to the Kaggle monkeypox dataset are first assessed and compared. Second, the suggested models are compared with earlier studies. Table 3 displays a summary of several models’ performances.

Table 3. Performance of Various Models

Model	Training accuracy (%)	Testing accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Sensitivity (%)	Specificity (%)	Time complexity (sec)
VGG 16	99.5	94	94	95	97	97.46	85.7	18
Inception	99.7	96	96	98	99	98.7	87.7	9
ResNet50	89	71	73	91	93	92.7	54.7	13
Inception-Resnet	99.7	97	97	97	97	97.6	95.4	21
VGG19	99.8	91	92	98	88	98.6	79.6	14

Table 3 shows that the inception-Resnet achieved high accuracy then VGG16, Resnet50, VGG19 and inception model. The overall performance of proposed classifier is shown in Figure 4.

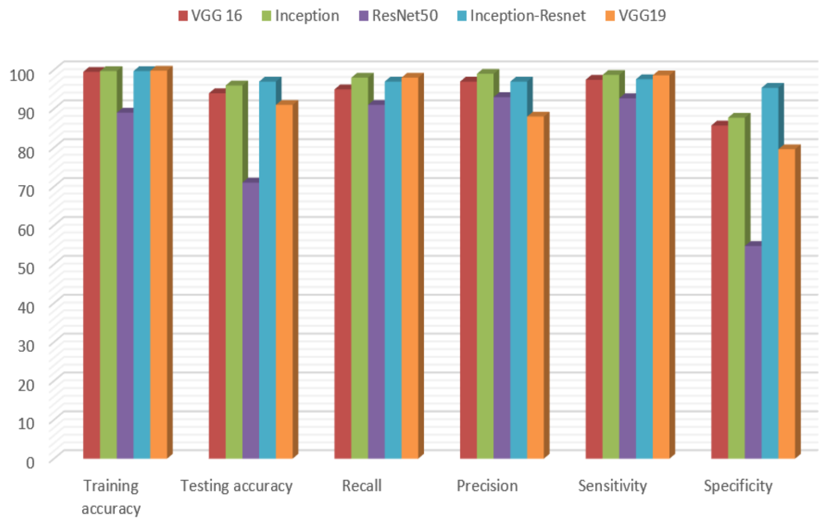

Figure 4. Result of the Various Models

In table 3 and figure 4, the inception-Resnet classifier shows good performance with 97% testing accuracy, 97% F1-score, 97% recall, and 97% precision, 97.6% sensitivity and 95.4% specificity.

4.1 Experimental Result of VGG16 Classifier

To examine the performance of applied models, various evaluation matrices are used. VGG16 achieved 99.5% training accuracy, 94% testing accuracy, 95% Recall, 97% precision, 97.4% sensitivity, and 85.7% specificity in 18 sec computation time. Additionally, a table known as the confusion matrix is often utilized to evaluate the effectiveness of classifiers. It shows an overview of the classifier effectiveness and a visual depiction of it. Figure 5 displays the suggested model's confusion matrix.

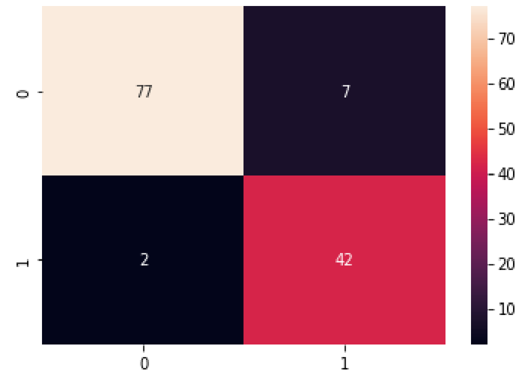

Figure 5. Confusion Matrix of VGG16 Model

Training accuracy, testing accuracy, training loss and validation loss of the proposed model is shown in the figure 6.

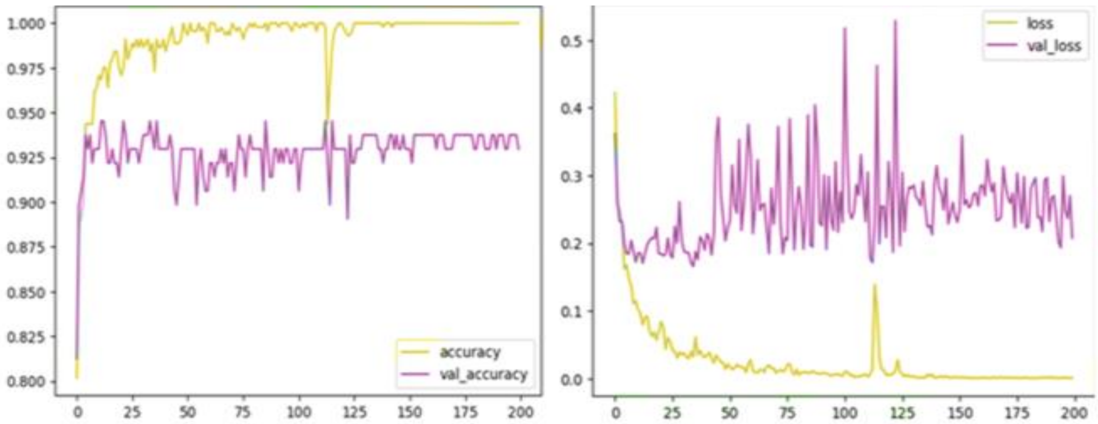

Figure 6. Accuracy and Loss of VGG16 Model

4.2 Experimental Result of Inception Classifier

The inception model worked well in the intended experiment. The Inception model achieved 99.7% accuracy during training, 96% accuracy during testing, 98% recall, 99% precision, 98.7% sensitivity, and 87.7% specificity in 9 seconds of computation time. The confusion matrix for the Inception classification model is shown in Figure 7.

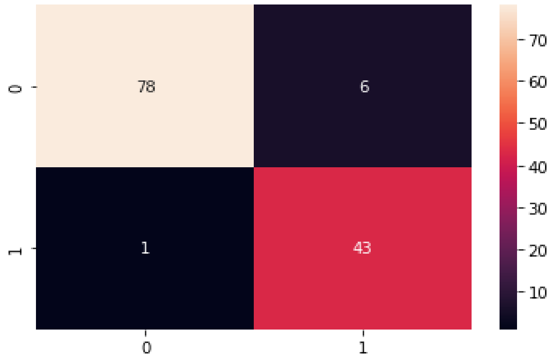

Figure 7. Confusion Matrix of Inception Model

Figure 8 depicts the inception model training accuracy, testing accuracy, training loss, and validation loss respectively.

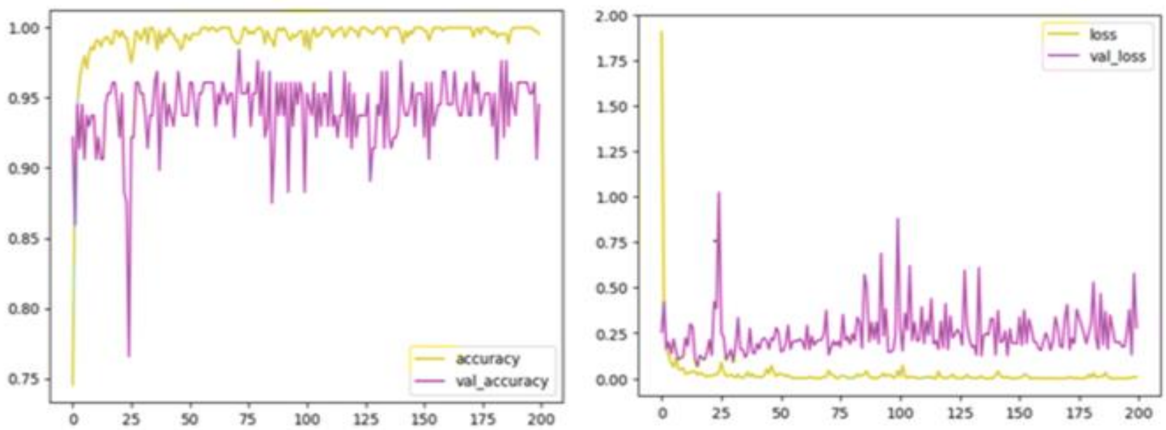

Figure 8. Accuracy and Loss of Inception Model

4.3 Experimental Result of Resnet50 Classifier

Resnet50 model achieved lowest accuracy then other classifiers applied in suggested experiment. Resnet50 model achieved 89% accuracy during training, 71% accuracy during training, 91% Recall, 93% precision, 92.7% sensitivity, and 54.7% specificity and its computation time was 13 sec. Figure 9 displays the confusion matrix of Resnet50 model.

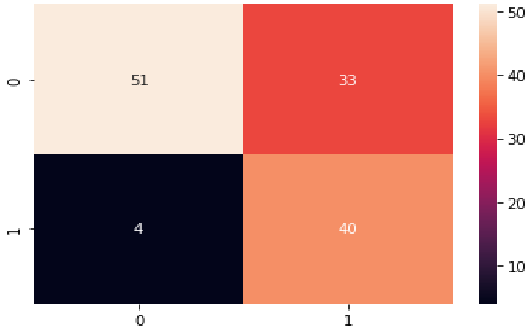

Figure 9. Confusion Matrix of the Resnet50 Model

The training accuracy, testing accuracy, training loss, and validation loss of the Resnet50 model is shown in figure 10.

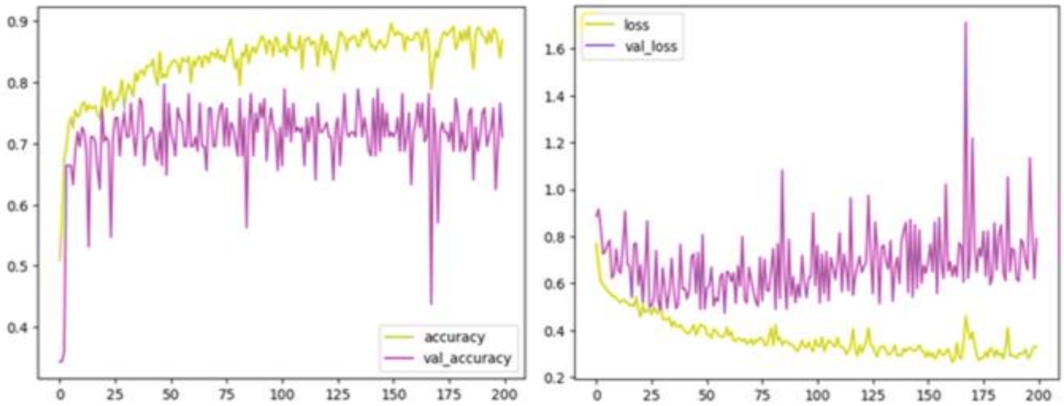

Figure 10. Accuracy and Loss of Resnet50 Model

4.4 Experimental Outcome of Inception-Resnet Model

The inception-Resnet outperformed in suggested experiment. Proposed model achieved 99.7% training accuracy, 97% testing accuracy, 97% Recall, 97% precision, 97.6% sensitivity, and 95.4% specificity and its computation time was 21 sec. Figure 11 displays the confusion matrix of Inception-Resnet classifier.

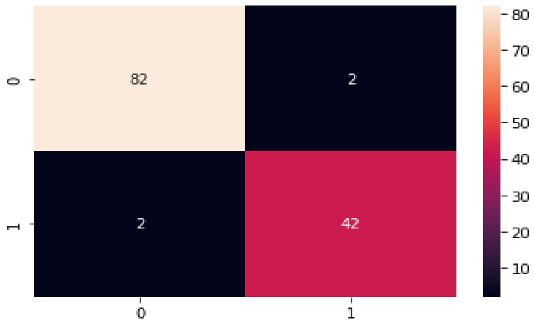

Figure 11. Confusion Matrix of Inception- Resnet Model

Figure 12 depicts the inception-Resnet model training accuracy, testing accuracy, training loss, and validation loss respectively.

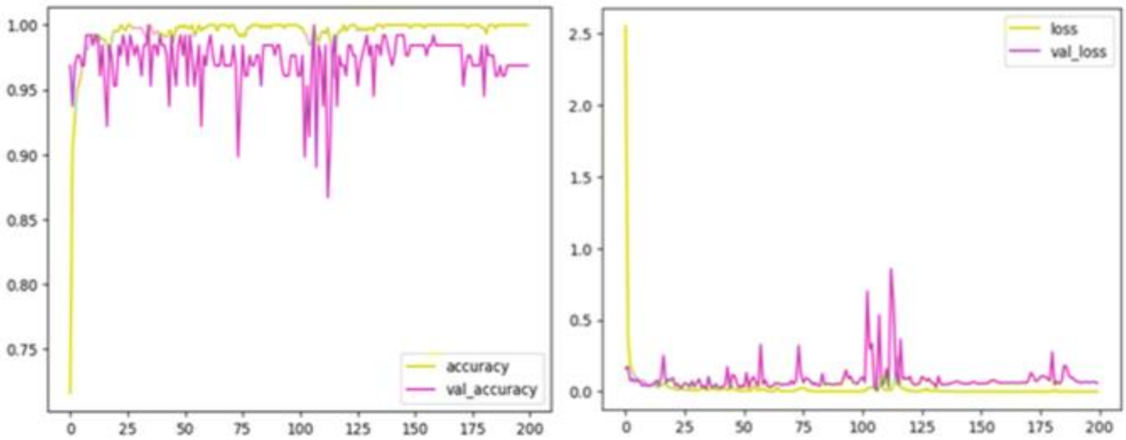

Figure 12. Accuracy and Loss of Inception-Resnet Model

4.5 Experimental Outcome of VGG19 Model

The performance of VGG19 was low as compared to VGG16, Inception, and Inception-Resnet although its performance was satisfactory compared to Resnet50. VGG19 classifier achieved 99.8% training accuracy, 91% testing accuracy, 98% Recall, 88% precision, 98.6% sensitivity, and 79.6% specificity and its computation time was 14 sec. Figure 13 depicts the confusion matrix of VGG19 model.

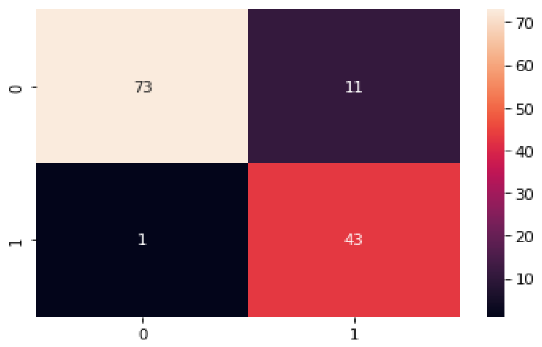

Figure 13. Confusion Matrix of VGG19 Model

Training accuracy, testing accuracy, training loss and validation loss of the proposed model is shown in the figure 14.

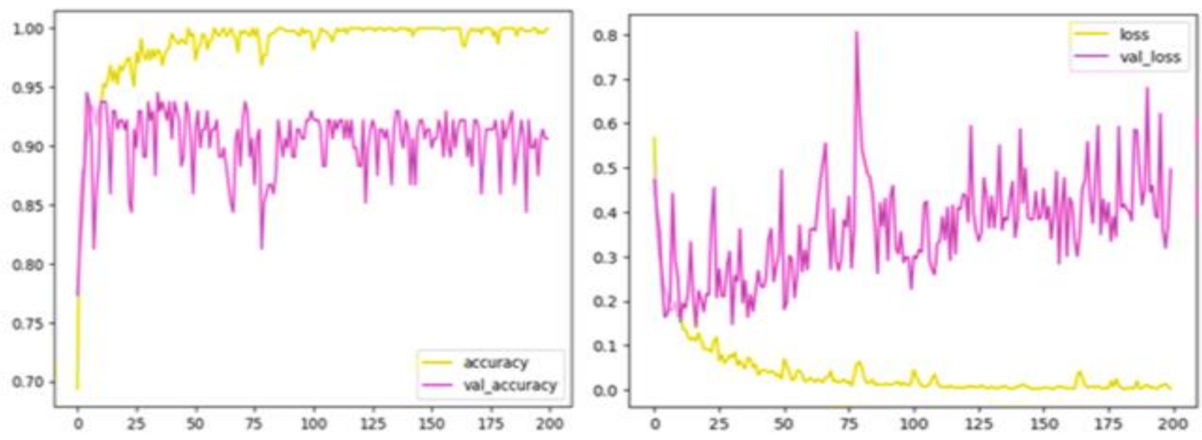

Figure 14. Accuracy and Loss of VGG19 Model

Inception-Resnet model achieved maximum accuracy compared to other models while the Resnet-50 achieved minimum accuracy then all other models used in the proposed work.

4.6 Comparative Analysis

Outcomes showed that, for each of the performance matrices, the suggested method produced efficient outcomes with the least amount of computing time. Finally, based on the results of statistical analyses, it can be concluded that the proposed models are more efficient, as illustrated in Table 4.

✓

Table 4. Comparison of Proposed Approach with Previous Studies

Reference	**Model applied**	**Accuracy**	**Dataset used**
Nafisa Ali et al. [7]	VGG16, ResNet50, InceptionV3	82.9%	Kaggle dataset
Abdelaziz et al. [9]	AlexNet, VGG19Net, ResNet-50, G.Net	93.8%	✓
Veysel Harun et al. [10]	VGG-16, VGG19	91%	✓
Towhidul Islam et al. [11]	ResNet50, InceptionV3, DenseNet121, MnasNet-A1	79%	UCI dataset
Farhana Yasmin et al. [15]	Polynomial Regression, SVR, Holt's	49%	Kaggle dataset
Chiranjibi Sitaula et al. [14]	VGG-16, VGG19, RestNet-50	87.13%	✓
Manjurul Ahsan et al. [16]	VGG16	78%	Novel dataset
Proposed approach	VGG-16, VGG19, RestNet-50, Inception, Inception-Resnet	97%	Novel dataset

5. Conclusion

This study presents a diagnosis system for monkeypox diseases based on pre-trained model. Four different pre-trained models are applied on monkeypox image dataset and then the performance of these models is compared. Also, some optimization techniques are applied with the pre-trained models. The inception model achieved the highest accuracy of 96%, F1-score 96%, Recall 98%, and precision 99%. VGG16 achieved the second highest accuracy of 94%, F1-score 94%, Recall 95%, and precision 99%. Inception_Resnet achieved the third highest accuracy of 93%, F1-score 93%, Recall 95%, and precision 94%, while the Inception-Resnet achieved lowest accuracy of 71%, F1-score 73%, Recall 91%, and precision 93%. There are two limitations in the proposed research work; first, the dataset used is comparatively small and second, only 4 pre-trained models are applied. In future, work will be carried out on large dataset and more machine learning and deep learning algorithms will be applied. Furthermore, in future, various skin diseases such as chickenpox, smallpox, lumpy skin disease etc., will be targeted.

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