Penerbit Akademia Baru

Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

Enhanced Detection of the Monkeypox Virus using Pretrained Deep Learning Models and Squeeze Excitation Layers

Muthulakshmi M[1], K. Venkatesan[2], Syarifah Bahiyah Rahayu[3,4,*], Shashank Mahato[1]

[1] Department of Electronics and Communication Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Tamil Nadu 641112, India
[2] Department of Computer Science and Engineering, Amrita School of Computing, Amrita Vishwa Vidyapeetham, Tamil Nadu 641112, India
[3] Faculty of Defence Science and Technology, National Defence University of Malaysia (UPNM), Sungai Besi, 57000 Kuala Lumpur, Malaysia
[4] Cyber Security and Digital Industrial Revolution Centre, National Defence University of Malaysia (UPNM), Sungai Besi, 57000 Kuala Lumpur, Malaysia

ARTICLE INFO

Article history:
Received 11 March 2025
Received in revised form 11 April 2025
Accepted 23 September 2025
Available online 30 September 2025

Keywords:
monkeypox; raw camera images; convolutional neural network; squeeze excitation layer

ABSTRACT

The present study aims to create a model that would help to classify viral skin disease images based on deep learning. The dataset used in the current study included 770 images that were taken with a normal camera, so-called raw camera images. This dataset consisted of four subtypes of diseases such as Normal, Monkeypox, Measles and Chickenpox. It should be mentioned that the current dataset was characterized with a class imbalance since the number of samples in each category was quite different. To address the problem with the class imbalance, the data were augmented by using the library Augmentator, which was then converted back to a dataset. The augmented dataset finally included 1000 images of each class. The parameters of the augmentation included rotate (10° left and 10° right, probability 0.7 each), flip left-right, probability 0.5 and the zoom with the area 0.8 and the probability 0.5. An augmented dataset was used to train convolutional neural network models such as DenseNet121, DenseNet169, DenseNet201 and EfficientNetB0. The generated augmented dataset was used for training and, afterwards, the models were validated based on the accuracy of the results. The validation results indicated that the most accurate model was. while DenseNet201 resulted in validation accuracy overperforming DenseNet169. Improved DenseNet121 had a validation dataset with accuracy equal to 99.08%. Moreover, EfficientNetB0 with a Squeeze Excitation layer was similarly efficient with a validation accuracy estimated to be. Additionally, the network had a validation accuracy of 99.41% without the problem of overfitting. The results imply that data augmentation and certain CNNs are effective in image classification.

1. Introduction

Monkeypox is an illness that falls under the Ortho- poxvirus group, which also includes the variola virus, renowned for inducing smallpox. The term "monkeypox" originated from its identification, in

* *Corresponding author*
E-mail address: syarifahbahiyah@upnm.edu.my

https://doi.org/10.37934/ard.143.1.208221

monkeys back in 1958. However, instances of monkeypox in humans were not documented until in 1970, within the Democratic Republic of the Congo [1].

Monkeypox is attributed to a virus known as the monkeypox virus, which is classified within the Ortho-pox virus family. It is believed that this virus naturally exists in animals, rodents or other small mammals primarily found in West African regions [2]. Humans can contract the infection by encountering the animals or their bodily fluids. There may also be a risk of transmission through consuming their meat. This disease can be transmitted from animals to humans. Transmission can also occur among humans through contact with infected blood or bodily fluids via droplets, as well as through skin-to-skin contact with characteristic lesions or pustules [3]. To curb the transmission of this disease, it is crucial to limit contact with animals maintain hygiene practices and implement quarantine measures during outbreaks. Ongoing research aims to gain an understanding of the reservoirs of this virus and develop effective strategies, for preventing and controlling monkeypox outbreaks. The proposed work also aims towards achievement of better healthy life for world population as an effort for sustainable development goals [4].

Monkeypox usually shows up with a variety of symptoms that typically emerge Within a span of 5 to 21 days after exposure to the virus [5]. At first, you might experience fever, headache, muscle and back pain along with chills and a feeling of fatigue [6]. It is common to have lymph nodes near the infection site. A distinctive symptom of monkeypox is the emergence of a rash on the face, which subsequently extends to other areas of the body. The rash then turns into pustules. Lesions at different stages may be present. While most cases resolve on their severe instances can occur in individuals with weakened systems. The severity of symptoms varies from person to person. Sometimes supportive care is needed for management. Seeking attention is crucial for accurate diagnosis and proper treatment especially, in areas where monkeypox occurs naturally or during outbreaks.

Diagnosing monkeypox requires an approach that starts with a clinical evaluation. Healthcare experts carefully examine symptoms, like fever and different stages of lesions. Laboratory tests play a role in this process. PCR tests are employed for detecting monkeypox virus DNA in blood, skin lesions or respiratory secretions [7]. In cases, imaging studies like chest X-rays may be conducted to evaluate involvement [8]. Given the potential for human-to-human transmission, achieving precise diagnosis is paramount to implementing public health measures such as isolation, contact tracing and vaccination to mitigate further spread of the virus. Healthcare professionals and public health authorities work closely together to manage and contain outbreaks.

The primary way to treat monkeypox is, by providing care since there are currently no antiviral treatments available. Symptomatic relief focuses on managing symptoms such as fever, headaches and muscle aches through the use of pain relievers and medication to reduce body temperature [9]. Individuals with skin lesions need to practice wound care to prevent bacterial infections and antibiotics may be prescribed if there are concerns about such infections. To curb the transmission of monkeypox among individuals, isolation protocols and infection control measures are implemented. While monkeypox has no specific vaccine, during outbreaks the smallpox vaccination effectiveness has been observed among high-risk populations. It is essential to monitor patients in severe cases and ongoing research endeavours strive to deepen our comprehension of the virus while also formulating more specific treatments.

Since the outbreak commenced, there have been a cumulative total of 92,182 confirmed cases of monkeypox. reported in 113 countries. The impact of the cases varies across regions. In Africa, there have been 12,873 confirmed cases, which accounts for 14% of the number. The Americas have the prevalence, with 57,128 cases making up around 62% of the count. The Eastern Mediterranean region has reported 3,521 cases (4% of the total) while Europe has reported 13,128 cases

(representing 14%). In the regions of Southeast Asia and the Western Pacific, a total of 2,552 cases have been reported (around 3%) and 2,980 (3%) monkeypox cases [10]. These numbers clearly demonstrate how widespread the monkeypox outbreak is globally with a burden experienced in the Americas specifically. It is important to bear in mind that these statistics are data-driven and subject to updates as the situation evolves. Therefore, it is important to stay informed by referring to health organizations for up-to-date information and insights.

The reported global fatality rate, for monkeypox is 0.18%. This means that out of every 1,000 people who contract monkeypox 2 individuals succumb to the virus [11]. When we break down the fatality rates by region, Africa has experienced a rate of 1.1% while the Americas have a rate of 0.16%. In the Eastern Mediterranean region, the fatality rate stands at 0.28% Europe reports a lower rate of 0.04% and Southeast Asia and the Western Pacific region have rates of 0.20% and 0.23% respectively. It is important to note that these statistics are based on data and may be subject, to updates as the situation progresses.

India recorded its initial case of monkeypox on July 14, 2022, the country has reported a total of 23 confirmed cases [12]. Among these, 10 cases have been confirmed in Delhi, while Kerala has reported 5 confirmed cases. Additionally, there are 8 suspected cases, with 1 each in Delhi and Telangana and 2 in Bihar. Uttar Pradesh has the highest number of cases that are suspected. The scenario is dynamic and since changes occur fast, what will provide a more accurate picture is to watch or keep abreast of developments through reliable health authorities updates. In India, there have not been any reports of deaths by monkeypox002E

2. Latest Related Works

There are several studies that examined advanced algorithms for disease diagnosis. Transfer learning has also been utilized in image-based disease diagnosis [13]. First of all, referring to the work of Saleh *et al.,* [14], it should be noted that he considers the same clinical similarity between monkeypox and smallpox and introducing the Accurate Monkeypox Diagnosing Strategy. In particular, it has a Feature Selection Phase and the Classification Phase, which allows you to apply the Dynamic Recursive Gray Wolf Optimization approach as a modification of the Traditional Gray Wolf Optimization. It can be seen that this modification improves the problem of position sharing in TGWO and makes the pursuit and positioning of prey more accurate. In this case, CP uses classifiers, which are SVM, NB, KNN, as well as DNN. The experiment results show that AMDS significantly increases the recall, accuracy, precision and F- score for monkeypox confirmation, also the information proves that this method is particularly useful in these cases.

Another study, Attention to Monkeypox: An Interpretable Monkeypox Detection Technique Using Attention Mechanism by Raha *et al.,* [15] proposes an attention-based MobileNetV2 model. The model's purpose is the rapid and precise monkeypox diagnosis on edge devices. The spatial and channel attention mechanisms are integrated into the network to boost the precision of such a diagnosis. The study also introduces a new version of the Monkeypox Skin Images Dataset where training data is more diverse as it contains more classes of similar skin diseases. Grad-CAM and LIME are also applied to make the process of monkeypox detection interpretable. Such evaluation metrics as Cohen's Kappa, Matthews Correlation Coefficient, Youden's J Index, accuracy, F1-score, precision, recall, sensitivity and specificity are applied. The model shows more than 92% accuracy on the extended MSID, more than 98% on the original MSID and more than 93% on the (MSLD).

Sitaula *et al.,* [16] compares 13 different pre-trained deep learning models for monkeypox detection. The models were fine-tuned with custom layers and evaluated using precision, recall, F1-score and accuracy metrics. The identified major models with the best performance were further

enhanced by an ensemble learning approach which performed majority voting over the probabilistic output of these models. Experiments were conducted on a publicly available dataset, achieving average precision, recall, F1-score and accuracy of 85.44%, 85.47%, 85.40% and 87.13%, respectively. These results outperform state-of-the-art methods, demonstrating the proposed approach's applicability for mass screening by health practitioners.

Nayak *et al.,* [17] have done investigation to utilize deep learning to diagnose instances of monkeypox from skin lesions images. The experiment used five pre-trained deep neural networks implemented on publicly available datasets: GoogLeNet, Places365-GoogLeNet, SqueezeNet, AlexNet and ResNet-18. The results of the experiment "show that the validation accuracy of ResNet-18 is the greatest" and "equals 99.49%," with the rest of the models also achieving an accuracy greater than 95%.The results indicate that deep leering models, standing especially for the ResNet-18-based model, work well for monkeypox detection.

This research paper of Kumar [18] is about the monkeypox problematic and provides research on deep convolutional neural network features in combination with machine learning classifiers used for monkeypox diagnosis. More specifically, the research combines bottleneck features from AlexNet, GoogLeNet and VGG16Net and fifteen classifiers including SVM, KNN, Naïve Bayes and the like. The obtained outcomes reveal that the combination of VGG16Net features and the last classifier in the list are 91.11% accurate. The article may prove useful for the purpose of the proposed research as it shows how CNN features can be applied with traditional machine learning classifiers given a view through an AI assistant diagnostic system used as an effective and accurate tool in terms of monkeypox with solid propositions made by Florida Gulf Coast University.

According to the results, deep leering models work effectively for monkeypox detection, especially the ResNet-18-based one. At the same time, the developed models can work for their target, which is smartphones. Moreover, the positive aspect of the current research is that it is based on explainable AI technologies, including LIME and GradCAM to visualize the obtained predictions and thereby provide medics with the patterns of why these decisions were made. These aspects prove that deep learning models can successfully be used to combat the monkeypox virus and disease effectively.

The work's main result is comparative analysis of DenseNet121, DenseNet169, DenseNet201 and EfficientNetB0 models, according to their diagnostic accuracy and efficiency to skin disease. The comparison showed that the "EfficientNetB0 with Squeeze-and-Excitation layers" was the best performer. According to the outcome of the comparison, it is recommended for the clinical use in dermatology because of its high accuracy and efficiency in diagnosing viral skin disease, particularly, the monkeypox.

3. Methodology

For the purposes of this study, we have taken a systematic form of methodology as outlined in the Figure 1, to identify the optimal CNN architecture for skin disease classification. The methodology started with the collection of data from the publicly available dermatology databases on a wide variety of skin disease to include category monkeypox. This was followed by pre-processing the images through resizing, normalization and data augmentation to up-scaled and improved the quality of the images. In the third step, the data was split into the training and test set on an 80-20 basis. Four CNN architectures, namely, DenseNet121, DenseNet169, DenseNet201 and EfficientNetB0, were developed for the training. At this stage, the training was fully conducted with optimized hyperparameters. The training process for each model involved using a categorical cross-entropy loss function and an Adam optimizer.

Performance evaluation of these models was conducted using the test dataset, assessing key metrics such as accuracy, F1-score, recall, precision and AUC. Notably, EfficientNetB0 yielded the best initial results, prompting further enhancement by incorporating Squeeze Excitation (SE) layers to improve channel-wise feature response recalibration.

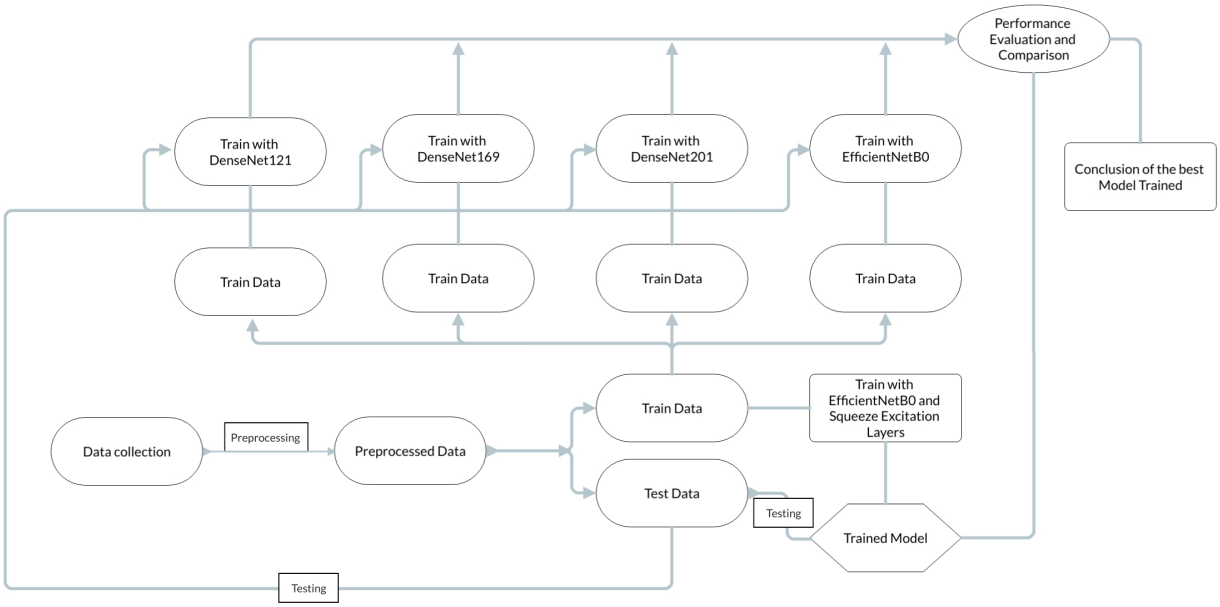
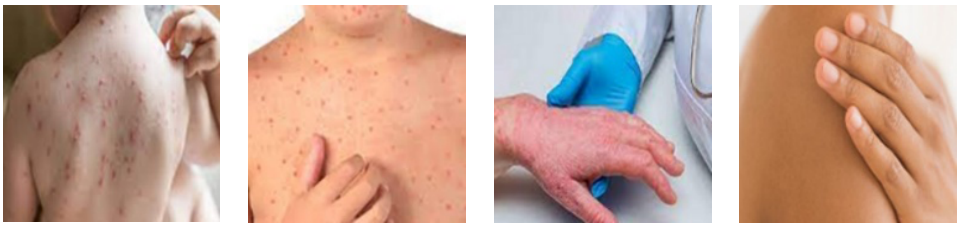


Fig. 1. Proposed flow diagram of the methodology

3.1 Dataset Description and Data Augmentation

A comprehensive dataset Monkeypox Skin Images Dataset (MSID) consisting of 770 skin disease images as shown in Figure 2, was meticulously curated. These images were captured using a standard camera setup and encompassed four distinct subtypes of skin diseases: Normal (293 images), Monkeypox (279 images), Measles (91 images) and Chickenpox (107 images) [19]. However, a notable challenge in the dataset was the presence of class imbalance, whereby certain disease categories had a disproportionately lower number of samples compared to others. To rectify this issue and ensure robust model training, data augmentation techniques were judiciously applied.



(a) (b) (c) (d)

Fig. 2. Augmented dataset (a) Chickenpox (b) Measles (c) Monkeypox (d) Normal

Leveraging the Augmentator library, an augmentation pipeline was crafted to expand the dataset's diversity and balance [20]. The next step comprised of generating augmented images for each disease type to reduce the class imbalanced in the dataset. Multiple augmentation transformations were applied such as rotation (10° left and 10° right with 0.7 probability each), flip left-right with 0.5 probability and zoom with area of 0.8 and 0.5 probability. A total of 1000 images were generated for each disease type through systematic augmentation of the dataset. Through

systematic augmentation, the original set was made diverse in itself and at the same time, the exact number of images of each disease type was made precisely 1000. The resultant data set represented class balanced information and as such, this formed the beginning of subsequent processes of feature extraction and model training to achieve consistent, generalizable performance in classifying skin diseases.

3.2 Model Training and Evaluation

Augmented dataset has been utilized in the process of training and evaluating the model. It is evident that several steps have been undertaken to promote the training and implement to ensure an effective skin disease classification model. First of all, feature extraction on augmented dataset utilizing some pre-trained CNN models, for example, DenseNet121, DenseNet169, DenseNet201 and EfficientNetB0 [21]. The process is aligned with the possibility of these models to capture fine-grained patterns within an image. In addition, these product models have been fine-tuned to extract the meaningful features of the skin diseases images. Afterwards, these features are inputted to fully connected layers that perform the task of classification and, therefore, the developed models are trained to distinguish particular classes of disease [22].

In the paper, various evaluation metrics such as accuracy, precision, recall, F1-score among others were determined to evaluate the performance of the models [23,24]. Based on these metrics, the models were compared and thus, the network with the highest validation accuracy was chosen to be the most effective architecture for skin disease classification.

.

3.3 Model Architecture

DenseNet121 and its illustration, as shown in Figure 3, establishes that it is a type of neural network constructed uniquely. Desnet121 operates through the idea of “dense connectivity,” and as opposed to traditional networks, each layer is connected to every other one that comes before it. The direct communication helps to reuse features effectively and keep the flow of information at a constant level across the network. In addition, the smart idea results in high accuracy of tasks that recognize objects in images while saving the number of parameters to be used.

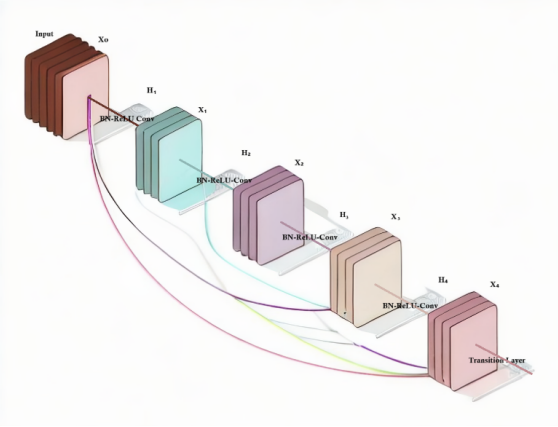


Fig. 3. DenseNet121 architecture

EfficientNet is one of the most famous models that was introduced in 2019. The unique feature of this model is that it strikes a balance of the accuracy of a model and its efficiency. The latter is achieved by the fact that the model uses Squeeze-and-Excitation blocks, as shown in Figure 4. They

are used to increase feature extraction, focusing on important features. Thus, a model is becoming more accurate and resources efficient. To use the powerful feature extraction competences, it is needed to fine-tune the pretrained model on a dataset.

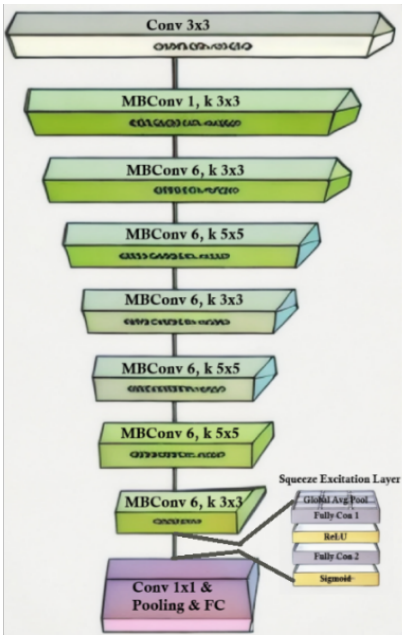


Fig. 4. EfficientNetB0 + Squeeze Excitation Layer architecture

4. Results

4.1 DenseNet121

In the domain of classifying skin disease images, DenseNet121 exhibited good results with an AUC score of 0.9999 and test accuracy of 99.02%. With respect to other models, it was not the best in terms of recall, F1-score and precision. Nevertheless, considering that all these variables reached 99.02% and the model was stable for every disease category, it is an excellent indicator of balanced performance. It was especially impressive that DenseNet121 was flawless in detecting the Measles subtype with 99.99% precision and recall. For that reason, it can be suggested that this model is valuable for assessing dermatological diagnoses due to its high-level performance and dependability, as depicted in Table 1 and Figure 5.

Table 1
DenseNet121 validation report

Class	Precision	Recall	F1-Score	Support
Chickenpox	0.980583	0.990196	0.985366	102
Measles	1	1	1	100
Monkeypox	0.980198	0.980198	0.980198	101
Normal	1	0.990385	0.995169	104
accuracy	0.990172	0.990172	0.990172	407
macro avg	0.990195	0.990195	0.990183	407
weighted avg	0.990172	0.990172	0.990184	407

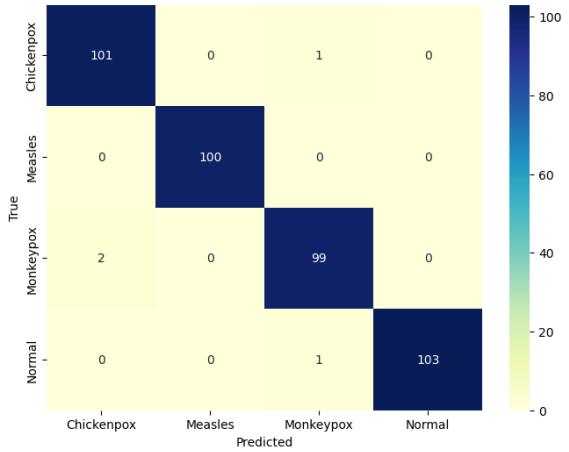


Fig. 5. DenseNet121 validation confusion matrix

4.2 DenseNet169

DenseNet169, as an enlarged variant of the DenseNet structure with 169 layers, proved to attain a high performance for the classification of skin diseases [25]. The model's AUC was 0.9999, its test accuracy was 99.0% and in general, the DenseNet169's performance was not worse than that of other models. At the same time, all the model's precision, recall and F1-score were at the 99.0% level, which indicates the relatively high performance of the developed model and its stability. In addition, the model's precision and recall of the "Measles" subtype were about 99.99% and it means that the model is quite reliable when diagnosing this disease. The data that prove the aforementioned results are presented in Table 2 and Figure 6 below.

Table 2
DenseNet169 validation report

Class	Precision	Recall	F1-Score	Support
Chickenpox	0.97	1	0.99	102
Measles	1	1	1	100
Monkeypox	1	0.98	0.99	101
Normal	1	0.99	1	104
accuracy	0.99	0.99	0.99	407
macro avg	0.99	0.99	0.99	407
weighted avg	0.99	0.99	0.99	407

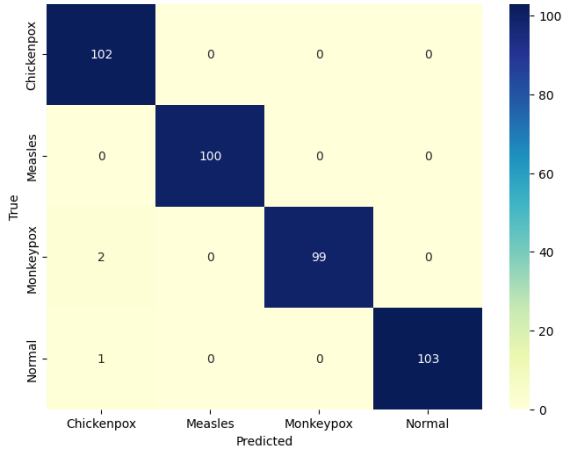


Fig. 6. DenseNet169 validation confusion matrix

4.3 DenseNet201

In classifying skin disease images, DenseNet201 found to be robust and demonstrated good performance [26]. Even though the AUC of DenseNet201 is 0.9992, which is slightly lower than other models, it delivered competitive results with the testing accuracies of 98.78%. In addition, the precision, recall and F1-score of 98.78% for all disease categories show that the performance of DenseNet201 is very reliable, which is illustrated in Table 3 and Figure 7. In addition, the model presented % precision and recall for the "Normal" disease type and this implies that the DenseNet201 is an effective model in correctly classifying this disease.

Table 3
DenseNet201 validation report

Class	Precision	Recall	F1-Score	Support
Chickenpox	0.98	1	0.99	102
Measles	0.99	1	1	100
Monkeypox	1	0.97	0.98	101
Normal	1	1	1	104
accuracy	0.99	0.98	0.99	407
macro avg	0.99	0.99	0.99	407
weighted avg	0.99	0.98	0.99	407

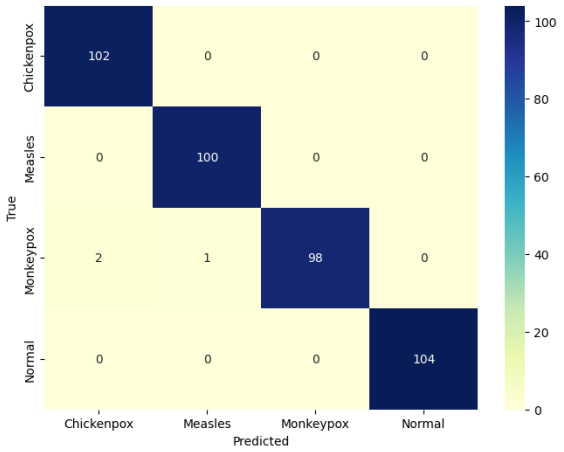


Fig. 7. DenseNet201 validation confusion matrix

4.4 EfficientNetB0

One of the models that showed the high level of performance in skin disease classification is EfficientNetB0, which is one of the most balanced models of the EfficientNet family in terms of performance and efficiency [27]. The model demonstrated clear superiority with an AUC score of 1.00 and a test accuracy of 99.46%. The model also had highly valuable discriminative ability. Moreover, in comparison with other models analysed, it was the only one that had precision, recall and F1-score values of 99.99% across all categories of the disease, which indicates the model's high level of reliability. In general, the fact that it showed exceptional performance 99.41%, as presented in Table 4 and Figure 8, explains why EfficientNetB0 is the strongest model in achieving accurate reliable skin disease classification.

Table 4
EfficientNetB0 validation report

Class	Precision	Recall	F1-score	Support
Chickenpox	1	1	1	102
Measles	0.99	1	1	100
Monkeypox	1	0.98	0.99	101
Normal	0.99	1	1	104
Accuracy	1	1	1	407
Macro avg	1	1	1	407
Weighted avg	1	1	1	407

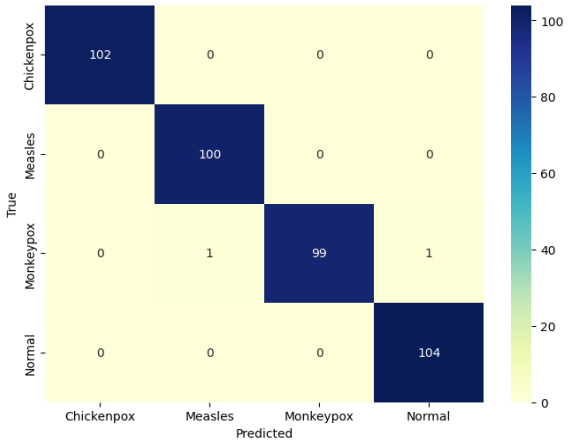


Fig. 8. EfficientNetB0 validation confusion matrix

4.5 EfficientNetB0 + Squeeze Excitation Layer

We proposed an addition of a Squeeze Excitation layer to a pretrained EfficientNetB0 model to enhance the accuracy of skin disease classification. The discriminative ability of an obtained model can be considered outstanding as it was evaluated at an AUC level of 1.00 across disease subtypes. During evaluation, it also achieved an accuracy of 100.0% on the test, while several high results were observed for precision, recall and F1-scores of 99.99%, as recorded in Table 5 and Figure 9. According to class-wise analysis, the model demonstrated a consistently high level of precision and recall in the diagnosis of all disease classes. It is remarkable that the addition of this layer to the EfficientNetB0 model has also had a positive effect on the F1-scores of the Chickenpox and Monkeypox subtypes in comparison to the original results.

Table 5
EfficientNetB0 + Squeeze excitation validation report

Class	Precision	Recall	F1-Score	Support
Chickenpox	1	1	0.99	102
Measles	0.99	1	1	100
Monkeypox	1	0.98	0.98	101
Normal	1	1	1	104
accuracy	1	1	1	407
macro avg	1	1	1	407
weighted avg	1	1	1	407

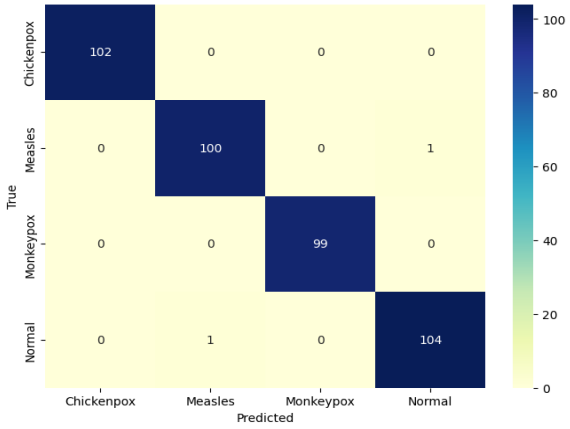


Fig. 9. EfficientNetB0 + squeeze excitation layer validation confusion matrix

Models including DenseNet121, DenseNet169, DenseNet201 and EfficientNetB0 were rigorously evaluated using separate datasets for validation and testing. The model DenseNet169 and DenseNet201 produced the highest test accuracy of 98.9% followed closely by the model DenseNet121 of 98.7%. In addition to that, the model EfficientNetB0 also provided comparable performance as it had a test accuracy of 99.1%. The training accuracy of the model ranged between 98.29% and 99.51% with EfficientNetB0 leading with 99.41%. The outcomes of the validation were similar to those of the test, with the models DenseNet169 as well as DenseNet201 providing the best performance at 99.26% with EfficientNetB0-Depthwise, Squeeze Excitation having the test accuracy of 99.51%. Other classification performance metrics that were evaluated included precision, recall and F1-score. Besides, the knowledge gained from misclassified images was used to assist with deciding on the best architecture to use for diagnosing dermatological conditions. In general, the purpose of this evaluation was to analyse various CNN models and MAC architecture.

5. Discussions

The primary purpose of the current comparative analysis focused on choosing the most efficient CNN architecture that can be used for classifying skin disease, which is monkeypox. After extensive testing and validation, it was determined that EfficientNetB0 with a Squeeze Excitation layer had the best performance, as shown in Table 6. This architecture had excellent results, boasting a test accuracy of 99.1% and a validation accuracy of 99.51%. This model performed the best because of its large capacity and low computational cost. It can be reliably used for clinical purposes. The inclusion of a Squeeze Excitation layer allowed the model to reanalyse channel-wise feature responses socially and to recalibrate them adaptively. Such a model will have a higher accuracy at telling different skin diseases apart.

It can also be said about derm grades. There exists some peculiarity. Here, the maximum achieved test result will be applicable. It was reached in the present case. Since the cut-off was set in the same way, most of the values below this limit are also relevant. In this aspect, the linear weighted kappa value, which was recorded against the test results, will be beneficial in the present context. That is why the reliability coefficient that was calculated and given based on the test results can be trusted, as it has high accuracy. As a result, there is the possibility that the value will also be the same. In conclusion, it is rational to infer that efficient netb0 is a reliable and precise model that is beneficial in both high-resource and extremely low-resource conditions for differentiating between 11 types of skin diseases.

Compared with the existing studies, our work has greatly improved the accuracy of monkeypox image classification. Although the previous work has achieved satisfactory accuracy in the classification of monkeypox. For example, the average accuracy was 97.9% by the algorithms based on the vision transformer architecture and federated learning [26]. According to Table 3, the EfficientNetB0 Model with Squeeze Excitation Layer established in this study achieved the accuracy of 99.51%. In the meantime, the use of the most updated CNN architecture and new methods has also greatly improved the performance of the monkeypox diagnosis as illustrated in Figure 10. Additionally, while the MonkeyNet CNN model and the MSID dataset achieved accuracies of 93.19% and 98.91% respectively [28] and a Deep Convolutional Neural Network-based model using ResNet101 attained 94.25% accuracy, the utilization of EfficientNetB0 with Squeeze Excitation Layer in the current study demonstrates superior performance. This advancement not only contributes to the field by providing highly accurate classification results but also holds significant promise for facilitating early diagnoses and aiding clinicians in effectively managing and mitigating the spread of monkeypox.

Table 6
Comparative analysis of various models

CNN Architecture	Test Accuracy	Validation Accuracy
DenseNet121	98.29%	99.02%
DenseNet169	98.29%	99.26%
DenseNet201	98.29%	99.26%
EfficientNetB0	99.46%	99.41%
EfficientNetB0 + Squeeze Excitation	99.76%	99.51%

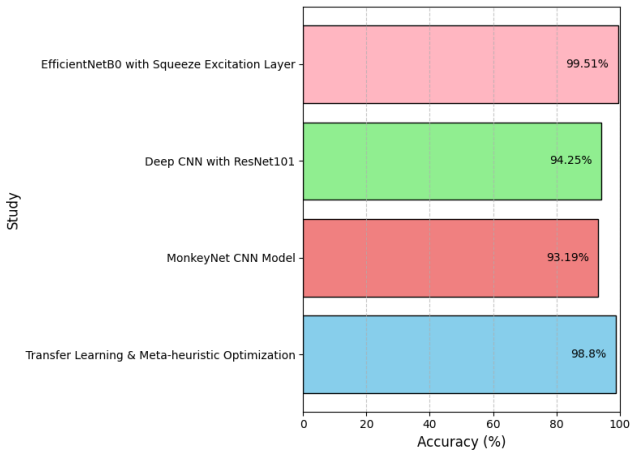


Fig. 10. Performance comparison of other existing models with proposed model

6. Conclusions

Thus, this comprehensive study enabled the identification of the most effective CNN architecture for viral skin disease classification tasks. We have concluded that DenseNet169 and DenseNet201 were the best-performing models. They demonstrated the highest accuracy, which constituted 98.9% on the test dataset and 99.26% of the validation dataset. DenseNet121 was an extremely close competitor with the values of 98.7% for the test and 99.02% for the validation accuracy. Besides, EfficientNetB0 with a Squeeze Excitation layer was also strong in terms of performance, displaying 99.1% for the test and 99.51% for the validation accuracy, which was the highest across all models.

Furthermore, the results were enhanced by analysis considering other essential performance measures such as precision, recall and F1-score. It allowed developing a nuanced understanding of how each model performed in terms of identifying different disease subcategories.

Along with comparing the behaviour and the performance of the five models, the comparative analysis included the comparison of the training accuracies at which the best training accuracy was obtained by the EfficientNetB0 model and accounted for 99.27%. The DenseNet121, DenseNet169 and DenseNet201 models all had the same training accuracy of 98.29%. However, the EfficientNetB0 with the Squeeze Excitation layer demonstrated the best training accuracy of 99.51%. In addition, the qualitative FMs analysis of the misclassified images may provide valuable hypotheses and conclusions about the presence of some malfunction or inefficiency patterns in models, as for each type of disease subcategories. As a result, the output of the performed comparative analysis provides the recommendation for choosing the most appropriate variant of the CNN model architecture for the purpose of dermatological diagnosis in real-world clinical applications [29].

Acknowledgement
This research was not funded by any grant.

References

[1] Rahimi, Fatemeh Sadat, Siamak Afaghi, Farzad Esmaeili Tarki, Kasra Moeinabadi-Bidgoli, Maryam Golmohammadi, Nasser Malekpour Alamdari and Sara Besharat. "The Historical Epidemiology of Human Monkeypox: A Review of Evidence from the 1970 Emergence to the 2022 Outbreak." *The Tohoku journal of experimental medicine* 258, no. 4 (2022): 243-255. https://doi.org/10.1620/tjem.2022.J081

[2] Karagoz, Aysel, Huseyin Tombuloglu, Moneerah Alsaeed, Guzin Tombuloglu, Abdullah A. AlRubaish, Amal Mahmoud, Samira Smajlović, Sabahudin Ćordić, Ali A. Rabaan and Ebtesam Alsuhaimi. "Monkeypox (mpox) virus: Classification origin, transmission, genome organization, antiviral drugs and molecular diagnosis." *Journal of infection and public health* 16, no. 4 (2023): 531-541. https://doi.org/10.1016/j.jiph.2023.02.003

[3] Lai, Chih-Cheng, Chi-Kuei Hsu, Muh-Yong Yen, Ping-Ing Lee, Wen-Chien Ko and Po-Ren Hsueh. "Monkeypox: An emerging global threat during the COVID-19 pandemic." *Journal of Microbiology, Immunology and Infection* 55, no. 5 (2022): 787-794. https://doi.org/10.1016/j.jmii.2022.07.004

[4] In, Jenny. "Suggesting Priorities of Sustainable Development Goals Considering the Lingering Impacts of COVID-19." *Journal of Health and Quality of Life* 3, no. 1 (2024): 1-12. https://doi.org/10.37934/jhqol.3.1.112

[5] Chandran, Deepak, P. Hridya, Diya Prasanth, D. Abernaa, A. V. Kaaviya, P. S. Menon, D. Vinodhini *et al.,* "Changing Patterns in the Spread of Human Monkeypox: A Dangerous New Development in Disease Epidemiology." *Journal of Pure & Applied Microbiology* 16 (2022). https://doi.org/10.22207/JPAM.16.SPL1.11

[6] Ahmed, Sirwan K., Rabab GA El-Kader, Salar O. Abdulqadir, Ardalan J. Abdullah, Nahed A. El-Shall, Deepak Chandran, Abhijit Dey, Talha B. Emran and Kuldeep Dhama. "Monkeypox clinical symptoms, pathology and advances in management and treatment options: An update." *International Journal of Surgery* 109, no. 9 (2023): 2837-2840. https://doi.org/10.1097/JS9.0000000000000091

[7] Nakhaie, Mohsen, Nasir Arefinia, Javad Charostad, Davood Bashash, Mohadeseh Haji Abdolvahab and Mohammad Zarei. "Monkeypox virus diagnosis and laboratory testing." *Reviews in medical virology* 33, no. 1 (2023): e2404. https://doi.org/10.1002/rmv.2404

[8] Ciepłucha, Hubert Dawid, Mateusz Bożejko, Paweł Piesiak, Sylwia Serafińska and Bartosz Szetela. "Bacterial Pneumonia and Cryptogenic Pleuritis after Probable Monkeypox Virus Infection: A Case Report." *Infectious Disease Reports* 15, no. 6 (2023): 795-805. https://doi.org/10.3390/idr15060071

[9] Dubey, Tanishq, Swarupa Chakole, Suyash Agrawal, Anannya Gupta, Pratiksha K. Munjewar, Ranjana Sharma, Seema Yelne and Pratiksha Munjewar. "Enhancing nursing care in monkeypox (Mpox) patients: differential diagnoses, prevention measures and therapeutic interventions." *Cureus* 15, no. 9 (2023). https://doi.org/10.7759/cureus.44687

[10] Evans, Alfred S. *Viral infections of humans: epidemiology and control*. Springer Science & Business Media, 2013.

[11] Song, Haifeng, Nicole Josleyn, Krisztina Janosko, Jeff Skinner, R. Keith Reeves, Melanie Cohen, Catherine Jett *et al.,* "Monkeypox virus infection of rhesus macaques induces massive expansion of natural killer cells but suppresses natural killer cell functions." *PloS one* 8, no. 10 (2013): e77804. https://doi.org/10.1371/journal.pone.0077804

[12] Relhan, Vineet, Rima R. Sahay, Anita M. Shete, Pragya D. Yadav, Bijaylaxmi Sahoo, Deepak Y. Patil, Suresh Kumar *et al.,* "Clinical presentation, viral kinetics and management of human monkeypox cases from New Delhi, India 2022." *Journal of Medical Virology* 95, no. 1 (2023): e28249. https://doi.org/10.1002/jmv.28249
[13] Khaw, Li Wen and Shahrum Shah Abdullah. "Mri Brain Image Classification Using Convolutional Neural Networks and Transfer Learning." *Journal of Advanced Research in Computing and Applications* 31, no. 1 (2023): 20-26. https://doi.org/10.37934/arca.31.1.2026
[14] Saleh, Ahmed I. and Shaimaa A. Hussien. "Monkeypox diagnosis based on Dynamic Recursive Gray wolf (DRGW) optimization." *Biomedical Signal Processing and Control* 87 (2024): 105483. https://doi.org/10.1016/j.bspc.2023.105483
[15] Raha, Avi Deb, Mrityunjoy Gain, Rameswar Debnath, Apurba Adhikary, Yu Qiao, Md Mehedi Hassan, Anupam Kumar Bairagi and Sheikh Mohammed Shariful Islam. "Attention to monkeypox: An interpretable monkeypox detection technique using attention mechanism." *IEEE Access* (2024). https://doi.org/10.1109/ACCESS.2024.3385099
[16] Sitaula, Chiranjibi and Tej Bahadur Shahi. "Monkeypox virus detection using pre-trained deep learning-based approaches." *Journal of Medical Systems* 46, no. 11 (2022): 78. https://doi.org/10.1007/s10916-022-01868-2
[17] Nayak, Tushar, Krishnaraj Chadaga, Niranjana Sampathila, Hilda Mayrose, Nitila Gokulkrishnan, Srikanth Prabhu and Shashikiran Umakanth. "Deep learning based detection of monkeypox virus using skin lesion images." *Medicine in Novel Technology and Devices* 18 (2023): 100243. https://doi.org/10.1016/j.medntd.2023.100243
[18] Kumar, Vidit. "Analysis of CNN features with multiple machine learning classifiers in diagnosis of monkeypox from digital skin images." *MedRxiv* (2022): 2022-09. https://doi.org/10.1101/2022.09.11.22278797
[19] Bala, Diponkor and Md S. Hossain. "Monkeypox skin images dataset (msid)." *Mendeley Data 6* (2022): 2023. https://doi.org/10.34740/KAGGLE/DSV/3971903
[20] Bloice, Marcus D., Christof Stocker and Andreas Holzinger. "Augmentor: an image augmentation library for machine learning." *arXiv preprint arXiv:1708.04680* (2017). https://doi.org/10.21105/joss.00432
[21] Palaniappan, S., S. Varshaa Sai Sripriya, Amalladinna Rama Lalitha Pranathi and M. Muthulakshmi. "Diagnosis of acute respiratory syndromes from x-rays using customised CNN architecture." In *2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, pp. 1-5. IEEE, 2022. https://doi.org/10.1109/IICAIET55139.2022.9936750
[22] Muthulakshmi, M., G. Kavitha and N. Aishwarya. "Multi-Objective Butterfly Optimization for Feature and classifier parameter's selection in Diagnosis of Heart Failure types Using CMR images." In *2022 IEEE Global Conference on Computing, Power and Communication Technologies (GlobConPT)*, pp. 01-06. IEEE, 2022. https://doi.org/10.1109/GlobConPT57482.2022.9938325
[23] Elmrabit, Nebrase, Feixiang Zhou, Fengyin Li and Huiyu Zhou. "Evaluation of machine learning algorithms for anomaly detection." In *2020 international conference on cyber security and protection of digital services (cyber security)*, pp. 1-8. IEEE, 2020. https://doi.org/10.1109/CyberSecurity49315.2020.9138871
[24] Milton, Md Ashraful Alam. "Automated skin lesion classification using ensemble of deep neural networks in isic 2018: Skin lesion analysis towards melanoma detection challenge." *arXiv preprint arXiv:1901.10802* (2019).
[25] Asif, Sohaib, Ming Zhao, Fengxiao Tang, Yusen Zhu and Baokang Zhao. "Metaheuristics optimization-based ensemble of deep neural networks for Mpox disease detection." *Neural Networks* 167 (2023): 342-359. https://doi.org/10.1016/j.neunet.2023.08.035
[26] Adegun, Adekanmi A. and Serestina Viriri. "FCN-based DenseNet framework for automated detection and classification of skin lesions in dermoscopy images." *IEEE Access* 8 (2020): 150377-150396. https://doi.org/10.1109/ACCESS.2020.3016651
[27] Abdelhamid, Abdelaziz A., El-Sayed M. El-Kenawy, Nima Khodadadi, Seyedali Mirjalili, Doaa Sami Khafaga, Amal H. Alharbi, Abdelhameed Ibrahim, Marwa M. Eid and Mohamed Saber. "Classification of monkeypox images based on transfer learning and the Al-Biruni Earth Radius Optimization algorithm." *Mathematics* 10, no. 19 (2022): 3614. https://doi.org/10.3390/math10193614
[28] Kundu, Dipanjali, Md Mahbubur Rahman, Anichur Rahman, Diganta Das, Umme Raihan Siddiqi, Md Golam Rabiul Alam, Samrat Kumar Dey, Ghulam Muhammad and Zulfiqar Ali. "Federated deep learning for monkeypox disease detection on gan-augmented dataset." *IEEE Access* (2024). https://doi.org/10.1109/ACCESS.2024.3370838
[29] Bala, Diponkor, Md Shamim Hossain, Mohammad Alamgir Hossain, Md Ibrahim Abdullah, Md Mizanur Rahman, Balachandran Manavalan, Naijie Gu, Mohammad S. Islam and Zhangjin Huang. "MonkeyNet: A robust deep convolutional neural network for monkeypox disease detection and classification." *Neural Networks* 161 (2023): 757-775. https://doi.org/10.1016/j.neunet.2023.02.022