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Monkeypox Classification based on Skin Images using CNN: EfficientNet-B0

1st Pramudya Eko Niti Taruno
Informatics Engineering
University of Mataram
Mataram, Indonesia
nititaruno@gmail.com

2nd Gibran Satya Nugraha
Informatics Engineering
University of Mataram
Mataram, Indonesia
gibransn@unram.ac.id

3rd Ramaditia Dwiyansaputra
Informatics Engineering
University of Mataram
Mataram, Indonesia
rama@unram.ac.id

Abstract*—Monkeypox is a zoonotic infectious disease caused by a virus of the orthopoxvirus genus. It can infect humans, vertebrates, and arthropods. Transmission to humans occurs through direct contact with infected animal body fluids or consumption of undercooked meat. Monkeypox cases have been reported globally, with thousands of confirmed cases and several deaths. Early symptoms include fever, rash, swollen lymph nodes, back pain, and headache. Diagnosis can be made through physical examination and laboratory tests. Image-based artificial intelligence technology, specifically the EfficientNet-B0 architecture, has been proposed as a solution for the classification of monkeypox based on skin lesion images. The research aims to compare the performance of EfficientNet-B0 with other CNN architectures and contribute to the development of medical image classification technology. Among the models evaluated, the EfficientNet-B0 model emerged as the standout performer, achieving an accuracy of 85.12%, surpassing the accuracy of other models such as MobileNet (63.63%) and InceptionV3 (71.4%). EfficientNet-B0 also demonstrated strong sensitivity (78.46%) and impressive specificity (91.78%), outperforming other models in these metrics. Additionally, despite not surpassing the accuracy of ResNet-50 (87.59%), EfficientNet-B0 achieved its accuracy with approximately four times fewer parameters, highlighting its efficiency in parameter usage and computational resources. These results can help improve models and aid in clinical decision-making.

Keywords*— *Monkeypox, EfficientNet-B0, Images Classification, Convolutional Neural Network, Diagnosis

I. Introduction

Monkeypox (Mpox) is a zoonotic infectious disease caused by virus infection of the genus orthopoxvirus, family Poxviridae, and family Chordopoxvirinae. This virus can infect humans, vertebrates, and arthropods [1]. Monkeypox transmission to humans occurs through direct contact with infected animal body fluids, such as blood, skin lesions, mucosa, or through consumption of meat that is not cooked properly. Monkeypox is transmitted by animals suspected of being primary carriers of the virus [2]. The first case of monkeypox was discovered in 1970 in the Republic of the Congo. The first outbreak outside of Africa occurred in the United States in 2003, causing more than 70 cases of monkeypox. Since early May 2022, monkeypox cases have been reported in various countries, including endemic and non-endemic countries with a total of 71,237 confirmed cases in 107 countries, with 26 deaths [3].

Early symptoms of monkeypox infection include fever, rash that spreads all over the body within 2-3 days, swollen lymph nodes, back pain and headache. The rash usually appears on various parts of the body such as the face, hands, feet, mouth, genital area and eye area [4]. The rash develops into lesions with the stages of macules, papules, vesicles, and pustules [5]. Diagnosis of monkeypox can be made through a physical examination by an expert who sees the typical lesions. However, laboratory diagnosis using PCR tests is also necessary to confirm infection [6], [7].

Several studies have shown the use of image-based artificial intelligence technology and expert systems as a solution for the diagnosis of monkeypox. However, the use of expert systems is less effective because sufferers generally do not know in detail the symptoms that arise. Therefore, another solution using images is more appropriate, because monkeypox causes lesions on the skin that can be recognized through images.

The deep learning Convolutional Neural Network (CNN) technique has shown good performance in image-based research, including in the diagnosis of monkeypox. Several studies have used architectures such as vgg-19 and ResNet50 with accuracy reaching 93.33% and 82.96% respectively [8], [9]. However, ResNet50 has disadvantages in terms of computational resource efficiency due to the large number of parameters and layers, and is prone to overfitting on small datasets [10]. As an alternative, EfficientNet architecture, especially the B0 variant, can improve resource efficiency while still providing good performance in skin image detection and classification tasks [11]–[14].

This study aims to classify monkeypox based on skin lesion images using the EfficientNet-B0 architecture, a Convolutional Neural Network (CNN). The performance of EfficientNet-B0 will be compared with similar studies using other CNN architectures. It is expected that the results of this study will contribute to the development of medical image classification technology and enhance clinical decision-making.

II. Related Work

A. Selecting a Template (Heading 2)

Implementation of EfficientNet-B0 for a monkeypox diagnosis system based on skin images refers to several related previous studies. The details of several previous studies on the image of smallpox monkeys can be seen in Table 1.

TABLE I. Recent Monkeypox Studies

Paper	Image Type	Classifier (s)	Accuracy
		VGG-16	81.48

(Ali et al., 2022)[9]	Full body, Limbs, Face, Trunk	ResNet50	82.96
		Inception-V3	74.03
		Ensemble	79.26
(Ahsan et al., 2022)[15]	Full body, Limbs, Face, Trunk	VGG-16 (Case 1)	83
		VGG-16 (Case 2)	78
(Muñoz-Saavedra et al., 2022)[8]	Close skin tissue	VGG-16	91.67
		VGG-19	93.33
		ResNet50	95
		MobileNet-V2	88.33
		EfficientNet-B0	90
		Ensemble 1	91.67
		Ensemble 2	91.67
		Ensemble 3	98.33
(Islam et al., 2022)[16]	Full body, Limbs, Face, Trunk	ResNet50	72
		Inception-V3	71
		DenseNet121	78
		MnasNet-A1	77
		MobileNet-V2	77
		ShuffleNet-V2	79
		SqueezeNet	65

In a study by Ali et al., classifiers were performed using VGG-16, ResNet50, Inception-V3, and Ensemble for image classification. The results showed that ResNet50 achieved the highest accuracy, namely 82.96%. Another study by Ahsan et al. divide the data into two cases. In the first case, the VGG-16 classifier achieved an accuracy of 83%, while in the second case, the accuracy achieved was 78%. This shows that the use of VGG-16 can give different results in different situations.

Munoz et al. conducting research related to the classifier of dense skin tissue images. In this study, several classifiers were used, such as VGG-16, VGG-19, ResNet50, MobileNet-V2, and EfficientNet-B0. The results showed that the use of ResNet50 (95%) and EfficientNet-B0 (90%) resulted in the highest accuracy. In addition, the use of ensembles in the form of Ensemble 3 achieves an accuracy of 98.33%. Recent research by Islam et al. deals with the classification of various parts of the human body using several classifiers such as ResNet50, Inception-V3, DenseNet121, MnasNet-A1, MobileNet-V2, ShuffleNet-V2, and SqueezeNet. The results showed that the classifier using ShuffleNet-V2 achieved the highest accuracy, namely 79%.

Based on the research that has been done, in general there are two different types of research. The first research is on close skin tissue, while the second research uses a variety of images showing the full body, limbs, face dan trunk. From the results of the study it can be seen that the classification of close skin tissue produces better accuracy than the various images. Mu˜noz-Saavedra et al. shows the best results using ensemble 3, which combines the ResNet50, EfficientNet-B0, and MobileNet-V2 methods which achieve an accuracy of 98.33%.

The study on images of the entire body, limbs, face, and trunk resulted in an accuracy range of 71% to 82%. This dataset contains more variations and complexities, making it harder to achieve high accuracy. As a result, this dataset provides a more realistic assessment of the model's performance in real-life situations. Therefore, further research on these types of images is necessary to improve the performance of the models created.

The previous studies demonstrated good results for VGG-16, ResNet50, and Inception-V3; however, there is still room for further improvement. In contrast, Mu˜noz-Saavedra et al. achieved good performance with 90% accuracy using EfficientNet-B0 in their study. Nevertheless, there is currently no research that has explored the use of EfficientNet for monkeypox image recognition, particularly in the context of entire body, limbs, face, and trunk images. Consequently, this research aim to employ CNN: EfficientNet-B0 as the chosen approach for the classification of monkeypox. For this reason, it is necessary to know the performance of EfficientNet-B0 for other skin disease classifications as shown in Table II.

TABLE II. EFFICIENTNET-B0 SKIN DISEASE PERFORMANCE

Paper	Images	Accuracy (%)
Hridoy dkk (2021) [17]	Citra penyakit kulit	93.35
Ali et al. (2022) [18]	HAM1000 dataset	83.02
Minarno et al. (2022)[19] .	Breast cancer Histopathological images	98.90
Gunwant et al. (2022) [20].	Eczema, Psoriasis, Lichen Planus, Benign Tumors, Fungal Infections, and Viral Infections	91.36%.

Based on Table 2, there are 4 literature studies that show the performance of EfficientNet-B0. The performance of EfficientNet-B0 showed 91.36% results for the classification of 7 types of skin diseases conducted by Gunwant et al, as well as the research conducted by Hridoy, who was able to achieve 93.35% accuracy for the classification of skin diseases using EfficientNet-B0.

According to Tan et al. [12], EfficientNet-B0 shows good performance on various common datasets. It outperforms other models while requiring fewer parameters. When compared to ResNet-50 and DenseNet-169 using the ImageNet dataset, EfficientNet-B0 achieves superior accuracy at 77.1%, surpassing ResNet-50's accuracy of 76% and DenseNet-169's accuracy of 76.2%, despite having only one-fourth the number of parameters. Additionally, the EfficientNet compound scaling technique enhances accuracy and efficiency compared to other models like MobileNet, which achieves 1.4% higher accuracy on the ImageNet dataset.

CIFAR-10 and CIFAR-100 serve as widely used benchmarks to evaluate the performance of deep learning models in image recognition and classification. In terms of model structure, EfficientNet-B0 outperforms NASNet-A on the CIFAR dataset, delivering higher accuracy with a more streamlined architecture. Therefore, due to its robust scaling adaptability, efficient convolution layers, and ability to recognize intricate image patterns, EfficientNet-B0 emerges as a promising choice for developing deep learning models for the classification of monkeypox images.

EfficientNet-B0 has slightly better performance than other models with less number of parameters. EfficientNet-B0 is compared to ResNet-50 and DenseNet-169 using the ImageNet dataset. The results show that EfficientNet-B0 has a better accuracy, which is 77.1%, compared to ResNet-50 and DenseNet-169 which have an accuracy of 76% and 76.2% respectively, and has fewer parameters by 4 times. In addition, the EfficientNet scaling method improves accuracy and efficiency compared to other models, such as MobileNet which has 1.4% better accuracy on the ImageNet dataset [11].

III. METHODOLOGY

A. *EfficientNet-B0 Architecture*

EfficientNet was first introduced in the research conducted by Tan and Le. The study states that EfficientNet is one of the most efficient models and can achieve the highest accuracy in ImageNet and image classification transfer learning. EfficientNet has several models from B0 to B7. EfficientNet-B0 is the baseline model of the EfficientNet architecture itself [12]. The architecture of the EfficientNet-B0 model can be seen in Fig. 1.

Fig. 1. EfficientNet-B0 Architecture[12]

The basis of this architecture is MBConv (Mobile Inverted Bottleneck), which is also known as an inverted residual block with an additional SE block (Squeeze and Excitation). MBConv (Mobile Inverted Bottleneck Convolution) is the foundational block used in the EfficientNet architecture, which is a computationally efficient Convolutional Neural Network (CNN) model. Here are the MBConv1 and MBConv6 architectures on EfficientNet-B0 as shown in Fig. 2.

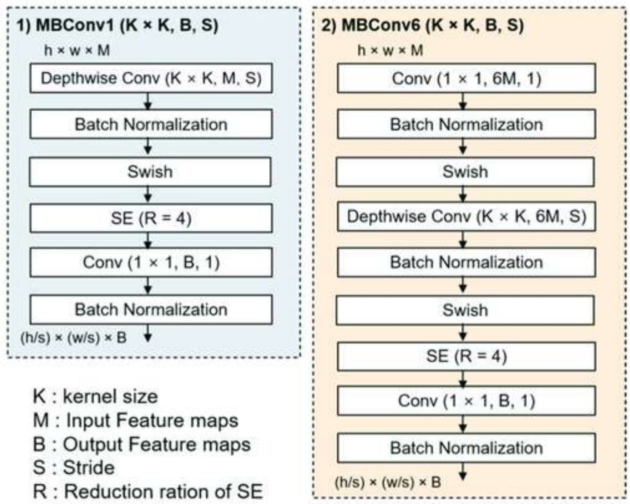

Fig. 2. MBConv Blocks[21]

The MBConv block on EfficientNet-B0 has variations, namely MBConv1, and MBConv6, each of which can have a different convolution kernel in its process. Each MBConv block on EfficientNet-B0 is also equipped with a Squeeze-and-Excitation (SE) block to increase its effectiveness. In addition, EfficientNet-B0 also uses a comprehensive scaling approach called efficient scaling to achieve optimal levels of efficiency and performance. This approach involves increasing the three main dimensions of the CNN architecture, namely width, depth, and image resolution proportionally to achieve the best performance [12], [22].

In the EfficientNet-B0 architecture, MBConv blocks are used at each level or blocks that consist of several MBConv blocks arranged in stages. Each level/block has a different level of depth and width, depending on the overall scale of the CNN architecture. In the overall architecture of EfficientNet-B0, MBConv blocks are used repeatedly in combination with other blocks as shown in Figure 1. The EfficientNet-B0 architecture comprises multiple components that contribute to its overall structure. These components include a 3x3 convolution layer, MBConv1 blocks, and MBConv6 blocks. Each block possesses specific parameters, channels, and layers. Detailed information regarding these parameters can be found in Table 3

TABLE III. EFFICIENTNET-B0 DETAILED INFORMATION.

Stage	Operator	Resolution	Channels	Layers
1	Conv 3x3	224x224	3	1
2	MBConv1 3x3	112 x 112	32	1
3	MBConv6 3x3	112x112	16	2
4	MBConv6 5x5	56x56	24	2
5	MBConv6 3x3	28x28	40	3
6	MBConv6 5x5	28x28	80	3
7	MBConv6 5x5	14x14	112	4
8	MBConv6 3x3	7x7	320	1
9	Conv1x1 & Pooling & FC	224x224	1280	1

B. *Research flow*

This research adopts a systematic and structured research flow to develop and evaluate a Deep Learning model for monkeypox image classification. The key steps involved in this process include dataset collection, data pre-processing, model training, and model testing using sensitivity, specificity, and accuracy evaluation metrics as shown in Fig 3.

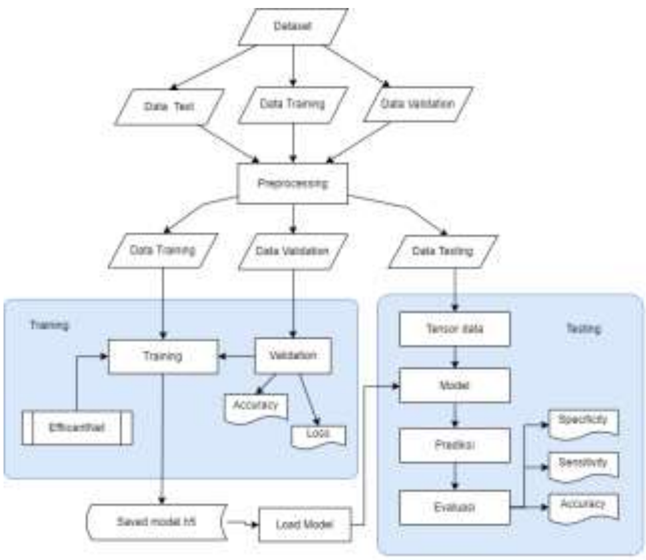

Fig. 3. Research Flow

During the dataset collection stage, we carefully gather a balanced collection of monkeypox images, consisting of 106 samples per class, from reliable and reputable sources. Subsequently, data pre-processing techniques are applied to enrich the dataset by augmenting the samples. Augmentation techniques such as rotation, cropping, and shifting are employed to enhance sample variation.

Following the pre-processing stage, the Deep Learning model is trained using the augmented dataset. After the training phase, the trained model is saved and evaluated using a separate test dataset. Performance evaluation is carried out using sensitivity, specificity, and accuracy metrics. The results obtained can be compared with previous research, contributing to the advancement of improved models and their applications in the future.

C. Dataset Description and Preprocessing

Dataset used in this research consist of a dataset comprising skin lesion images categorized into two classes: monkeypox and non-monkeypox (measles and chickenpox). The dataset, provided by the research team from the University of Dhaka, Bangladesh [9], has undergone augmentation to increase its size to approximately 3192 images, with dimensions of 224 x 224 x 3 RGB. The original dataset consisted of 228 images, which were divided into the monkeypox class (102 images) and the other class (126 images). Considering the context of deep learning, the number of images in this dataset is relatively small. To address this limitation, image augmentation was performed to increase the number of images.

Through the process of image augmentation, the dataset was expanded by a factor of 14. After augmentation, the 'monkeypox' class comprised 1428 images, while the 'others' class contained 1764 images. An imbalance was observed between the number of images in the 'monkeypox' class and the 'others' class. To address this imbalance, additional samples were generated for the 'monkeypox' class using data augmentation techniques. The purpose of introducing these additional samples was to achieve a balanced distribution of classes within the dataset, ensuring 1764 images in each class as show in figure 4.

Fig. 4. Augmented Images

Additionally, to further enhance the robustness of our dataset, we divided it into 7 folds through stratified sampling. This approach ensured that each fold maintained a proportional representation of both the 'monkeypox' class and the 'others' class. The stratified division of the dataset into folds enables more reliable evaluation and validation of the trained model's performance, as it accounts for potential variations in the distribution of classes within the dataset. Each fold is subsequently used for cross-validation, allowing us to assess the model's generalization capabilities across different subsets of the data.

The dataset used in this research has been divided into two subsets: training set and testing set. The training set consists of 1512 augmented images to train the classification model, while the testing set (252 images) is used to test the final model's performance on new data that has never been seen before, providing a more realistic picture of the model's ability to classify monkeypox images. This division of the dataset is important in developing an accurate and reliable classification model.

IV. EXPERIMENTAL RESULTS

In our study, we employed the EfficientNet-B0 architecture from scratch, utilizing 224x224x3 input images for monkeypox classification. The training process involved setting a learning rate of 0.00001 and utilizing the Adam optimizer with a batch size of 16. We trained the model for 150 epochs, implementing an early callback mechanism to prevent overfitting. The primary evaluation metrics for assessing our model's performance were accuracy, sensitivity, and specificity. To ensure robustness, we performed a seven-fold cross-validation and reported the average values of these metrics across the folds. The model development process involved utilizing the RGB color space and an image size of 224x224 as the approach for classifying monkeypox images. After undergoing thorough training and testing procedures, the obtained results are presented in Table 4.

TABLE IV. EFFICIENTNET-B0 PERFORMANCE RESULT

Fold	TP	FN	TN	FP	Acc (%)	Sensitivity (%)	Spesifisity (%)
1	198	54	232	20	85,32	78,57	92,06
2	200	52	234	18	86,11	79,37	92,86
3	198	54	234	18	85,71	78,57	92,86
4	193	59	231	21	84,13	76,59	91,67
5	201	51	234	18	86,31	79,76	92,86
6	199	53	223	29	83,73	78,97	88,49
Average					85,12	78,46	91,78

In the 7-fold experiment conducted on EfficientNet-B0, the average accuracy, sensitivity, and specificity results were 85,12%, 78,46%, and 91,78%, respectively. These results show the model's performance in classifying monkeypox images using EfficientNet-B0. These results indicate that EfficientNet-B0 architecture provides good performance in classifying monkeypox images. In the test results, it the models converge slowly. This is caused by the small learning rate value. A small learning rate value results in very small changes in the weight and bias of the model each time an update is carried out, so the model learns at a slower speed.

The variation in accuracy observed across different folds can be attributed to several factors. Differences in data distribution and representation within each fold can significantly impact the performance of the model. For instance, one-fold may exhibit imbalanced class representation or contain outliers, leading to lower accuracy. Additionally, variations in data characteristics among folds can also influence model performance, as the variability in data may pose challenges for the model to identify patterns and generalize effectively.

It is essential to emphasize that variations in accuracy across folds do not necessarily imply the superiority or inferiority of any fold. These differences are, to some extent, a result of randomization in data distribution and can be mitigated by employing more extensive and consistent evaluation techniques, such as employing more complex cross-validation methods. In this study, the observed accuracy variation across different folds highlights the importance of utilizing a cross-validation approach with a higher number of folds to obtain more representative and reliable outcomes. In addition, this study also compares the performance of the EfficientNet-B0 architecture with other popular architectures as follows:

TABLE V. MODEL PERFORMANCE

Model	Acc	Sensitivity	Spesificity
EfficientNet-B0	85,12	78,46	91,78
MobileNet	63,63	57,99	69,27
ResNet-50	87,59	82,77	92,4
InceptionV3	71,4	63,21	79,59

Table 6 showcases the results of our research, presenting the average accuracy achieved through a six-fold cross-validation process. Among the models evaluated, the EfficientNet-B0 model stood out with accuracy of 85.12%, surpassing the accuracy of other models such as MobileNet (63.63%) and InceptionV3 (71.4%). Notably, the EfficientNet-B0 model also exhibited strong sensitivity with a value of 78.46%, outperforming MobileNet's sensitivity of 57.99%. In terms of specificity, EfficientNet-B0 showcased impressive performance with a specificity value of 91.78%, surpassing the specificity values of MobileNet (82.77%) and InceptionV3.

EfficientNet-B0 model demonstrated competitive performance, achieving an accuracy of 85,12%. While it did not surpass the accuracy of ResNet-50, which achieved 87.59%, it is noteworthy that the EfficientNet-B0 model achieved this level of accuracy with approximately four times fewer parameters. This highlights the efficiency of the EfficientNet-B0 architecture in terms of parameter usage and computational resources. These findings underscore the potential of EfficientNet-B0 as an effective and resource-efficient model for image classification tasks, providing a promising avenue for optimizing deep learning architectures in terms of both performance and computational cost. The results also emphasize the potential impact of EfficientNet-B0 in improving clinical decision-making processes and advancing the field of medical image analysis.

V. CONCLUSION

In conclusion, this study highlights the superior performance of the EfficientNet-B0 model in classifying monkeypox images compared to other architectures. The EfficientNet-B0 model exhibits higher accuracy and demonstrates its effectiveness in extracting image features, leading to improved classification results. Therefore, it is recommended to consider EfficientNet-B0 as a potential architecture for the classification of monkeypox images, serving as a valuable guide for the development of more efficient and accurate models in the future. Additionally, expanding the dataset by incorporating diverse image samples and encompassing various variations of monkeypox is recommended to enhance the representativeness of the dataset and further improve the accuracy and reliability of the classification outcomes.

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