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Research Article

Utilizing the Ensemble of Deep Learning Approaches to Identify Monkeypox Disease

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ABSTRACT

Recently, the monkeypox disease spreads to many countries rapidly and it becomes a serious health problem. There are several symptoms that decrease the quality of the life. These symptoms must be overcome to detect monkeypox disease in earlier stages. Therefore, it is crucial to decrease the spread rate with the quick determination of the disease. In this study, it is aimed to identify monkeypox disease from images datasets obtained from Kaggle by using Convolutional Neural Network models. These models are named EfficientNetB3, ResNet50, and InceptionV3 respectively. According to the results of the three models, resNet50 is the best model when they compare aspects of performance. The accuracy of resNet50 is %94,00 therefore it has highest accuracy value. There are four parameters to evaluate the performance of the models. They are called as precision, recall, F1-score, and accuracy. These models demonstrate that monkeypox can be classified with high precision. Therefore these models can be used for the future of the work.

Introduction

After Covid-19, the new disease spreads rapidly all over the world. It is called monkeypox. Monkeypox is a disease that given rise to by the monkeypox virus [1]. Monkeypox can be transmitted both from animal to human and human to human [2]. There are numerous symptoms named as headache, fever, muscle aches, and back pain. It is crucial to remove these symptoms for increasing the quality of life [1]. In order to raise the life quality, it is important to detect monkeypox disease in earlier stages before spreading it. Therefore, in this paper, it is aimed by utilizing convolutional neural network techniques to identify monkeypox disease with high efficiency [3].

Monkeypox is an infectious disease caused by the Zoonotic Orthopoxvirus which belongs to the Poxviridae family. The virus was first specified in the body of a monkey in 1958 in a laboratory in Denmark while in humans it is first identified in 1970 in a 9-month-old boy living in the Democratic Republic of Congo. Between 1970 and 1986, the disease was reported in 10 people from the West African countries of Sierra Leone, Nigeria, Liberia, and Ivory Coast, and in 394 people from the Congo Basin countries of Cameroon, the Central African Republic, and the Democratic Republic of Congo. The first monkeypox outbreak outside of Africa in 2003 affected more than 70 people in the United States. The number of cases reported worldwide is increasing every year, with over 6200 and 9400 confirmed and suspected cases reported by the World Health Organization (WHO) in 2020 and 2021, respectively. According to the WHO, from 1 January to 22 June 2022, 3413 laboratory-confirmed cases and one death have been reported [2], [4], [5], [6], [7],[8].

Today, with developing the algorithm and increasing data mount, it is brought a new idea. It is called deep learning. Deep learning method is a subset of machine learning. It has ability to solve complicated problems and it can overcome big datas. Additionally, DL has great advantages in many areas such as speech recognition, computer vision, image processing, etc. Image processing has become a remarkable research topic in the academic field [9]. Image processing has been in the field of Artificial Intelligence and deep learning algorithm has achieved remarkable results in the field of image processing. Traditional image processing models still have some problems. Based on big data processing models, deep learning algorithms have benchmark results [10]. It is well known the importance of detecting monkeypox by utilizing deep-learning models. In this study, three deep-learning models are used. They are named as EfficentNetB3, resNet50 and InceptionV3 respectively. In order to evaluate the performance of the methods, four metrics are used. They are called as accuracy, precision, recall, and F1-score [11].

This paper is divided as follows: section 1 demonstrates the introduction of the study. Section 2 presents the literature survey for analysis of monkeypox disease. Section 3 presents the utilized models. Section 4 shows the results obtained by the classification models. Finally, section 5 concludes the study.

Literature Review

It has been suggested by some researchers that several data collection and classification techniques can be used for monkeypox disease however there are fewer studies in the literature. These studies are demonstrated below.

Sitaula et all (2022) proposed to compare 13 different deep-learning models in order to identify monkeypox disease. Some models are called as VGG-16, Xception, MobileNet, and ResNet. In the work, fine-tune is used for increasing efficiency. They used well-established measures as they are called precision, recall, accuracy, and F1-score. With these parameters, they aimed to evaluate the performance of the models. The evaluation results demonstrate that the ensemble model provides the highest performance. One of the drawbacks of the study is the dataset size that was comparatively smaller as they explained [3].

Abdelhamid et all (2022) used two algorithms for developing the accuracy of monkeypox disease in the area of image classifications. The first algorithm is named the PSOBER algorithm, which is a hybrid of PSO and BER optimization algorithms and targets to choose the best features that can improve the classification accuracy. The second algorithm is called as SCBER; it aims to optimize the parameters of a neural network to get the best accuracy. A Publicly available dataset was used to assess the proposed algorithms. The assessment of the model was carried out by ten evaluation criteria. Moreover, these parameters were conducted to evaluate the efficiency and robustness of the proposed models [12].

Sahin et all (2022) proposed a new approach to detect automatically monkeypox disease thanks to the mobile system. The authors aimed to use Monkeypox Skin Lesion Dataset (MSLD) which they obtained from the Kaggle platform. For this purpose, MLSD database images were trained by using a deep transfer learning-based system. The authors used several deep learning models such as ResNet18, GoogleNet, EfficientNetb0, and MobileNetv2 and the results of the models were compared. Among the models, MobileNetv2 showed the best performance in terms of accuracy and it was integrated into the mobile applications. Accuracy, jaccard, precision, sensitivity, and F1-score was used to evaluate the performance of the systems [8].

Material and Method

Dataset

In this study, “Monkeypox Skin Lesion Dataset” dataset was used. Dataset composes of monkeypox images and the size of the images is 224x224 pixels. In the data set, there are three number parts. The number of training, the number of validation, number of test images are 2148, 45, and 406 respectively. The type of classification is binary. The images are divided into two parts as monkeypox and normal. For this division, it is aimed to acquire the best accuracy results.

Deep Learning Models

Deep Learning is a subset of the machine learning. In this work, three deep learning algorithms were used. They were efficientNetB3, resNet50 and InceptionV3. These methods are very effective to classify monkeypox accurately and they have specific characteristic and layers. The main differences among these models are the numbers of layer and the structure of the models.

EfficientNetB3

The efficientNetB3 model belongs to a family of models from B0 to B7. It is considered as one of the most highly efficient deep-learning algorithms trained over ImageNet [13]. This model has achieved much better efficiency and accuracy according to other models. Moreover, it has high potential to compute processes and it is faster [14].

In this paper, it is set the learning rate of 0,001 in The efficientNetB3 algorithm. It is also shaped all data images into (224,224,3) sizes. For optimization, it is used adam stochastic gradient algorithm and ‘Relu and Sigmoid Activation’ function was applied in this model. The epoch which is used in this work is 10 and batch size is specified as 32. In addition, there are two dropout layers that is used in the work and the number of dropout is 0,5.

ResNet50

ResNet was proposed by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 research paper titled ‘Deep Residual Learning for Image Recognition’. Many models are based on resNet50 because of its simplicity and practicality. It has been applied in numerous areas such as the detection of disease, identification, and segmentation [15].

It is difficult to solve complex problems with deep CNN networks however ResNet proposes a new opinion. It has the ability to enlighten the complicated task and increase the model's accuracy. ResNet50 has 50 layers of residual networks. ResNet50 includes two structures. They are Identity block and Convolutional block. The curve lines represent the identity blocks and the rest one represent the convolutional block [16].

In this work, it is set the learning rate of 0,001 in resNet50 algorithms. Moreover, it is shaped all data images into (224,224,3) sizes. For optimization, it is used adam stochastic gradient algorithm and 'Relu Activation' function was applied in this algorithm. The epoch which is used in this study is 10 and batch size is specified as 32. In addition, there are two dropout layers that is used in the study and the number of dropout is 0,5.

InceptionV3

Inception is one of the CNN models based on GoogleNet that it is managed in developing the performance of previous algorithms and a smaller error rate. This model is the third version of GoogleNet. The basic idea of the model is to reduce the number of connections. Despite of less connections, the efficiency of the model has high performance [17].

The InceptionV3 model is one of the modified types of the inception family which is generally used for object detection and image processing [18]. According to this model, every filter is added and the best filter is chosen for the particular image instead of selecting the filter size manually for every layer.

In our research study, we have set the learning rate of 0,001 in InceptionV3 algorithms. In addition, it is shaped all data images into (224,224,3) sizes. For optimization, it is used adam stochastic gradient algorithm and 'Relu Activation' function was applied in this work. The epoch which is used in this study is 10 and batch size is specified as 32. Moreover, there are two dropout layers that is used in the work and the number of dropout is 0,5.

The Metrics for The Performance of Models

An evaluation metric is a value to assess the quality of the models like deep learning and machine learning methods. In the evaluation metric, there are four categories that relate the predicted results to the actual results, called as true positive, true negative, false positive, and false negative. There are several evaluation metrics that have been improved to assess the quality of the classification model. In this study, there are four evaluation metrics which are called accuracy, precision, recall, and F1-score to measure the performance of the methods [17].

Accuracy is a metric that calculates total cases that have been successfully identified with reference to the actual value. Equation (1) is the accuracy formula which is showed below.

$$\text{Accuracy} = \frac{\text{True positive} + \text{True negative}}{\text{All cases}} \tag{1}$$

Precision is a metric that calculates the number of cases in the positive that were estimated precisely. Equation (2) is the precision formula which is showed below.

$$Precesion = \frac{\text{True positive}}{\text{True positive} + \text{False positive}} \tag{2}$$

Recall is a metric that measures the number of actual identified positive cases from total positive cases. Equation (3) is the recall formula which is showed below.

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}} \tag{3}$$

F1-score is a metric that presents the average value of precision and recall. Equation (4) is the F1-score formula which is showed below.

$$\text{F1} - \text{Score} = 2 \text{ x } \frac{\text{Precesion x Recall}}{\text{Precesion} + \text{Recall}} \tag{4}$$

Experimental Results

The experiments are conducted on the deep learning algorithms and results are seen in figures and tables. According to this study, three convolutional neural networks were used. They were efficientNetB3, resNet50 and InceptionV3. For the performance of the models, several parameters were used such as accuracy, precision, recall and F1-score. Moreover, ROC curve and confusion matrix were used to support better results of the models. Three models were compared according to their performance.

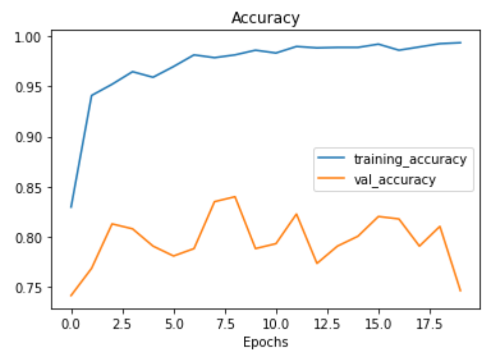

Figure 1. Accuracy of the efficientNetB3

Figure 2. Loss of the efficientNetB3

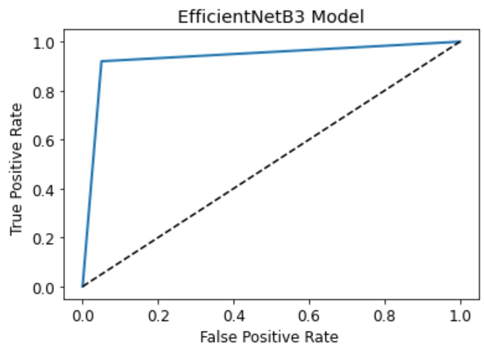

Figure 3. ROC curve of the efficientNetB3

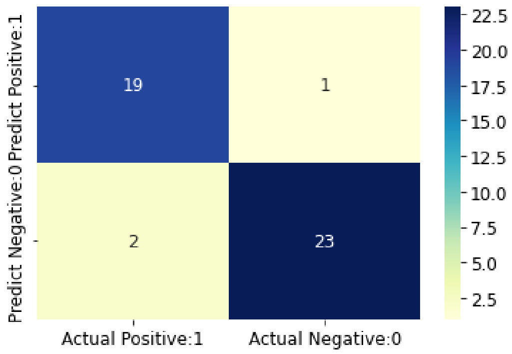

Figure 4. Confusion matrix of the efficientNetB3

The accuracy, loss, ROC curve and confusion matrix of the efficientNetB3 are shown above to observe the performance of the model. With regard to these parameters, this model has high efficiency. The ROC curve value of the efficentNetB3 model is 0.93 and it is considered a great score. The confusion matrix parts can be set as below.

- True Positives(TP) = 19
- True Negatives(TN) = 23
- False Positives(FP) = 1
- False Negatives(FN) = 2

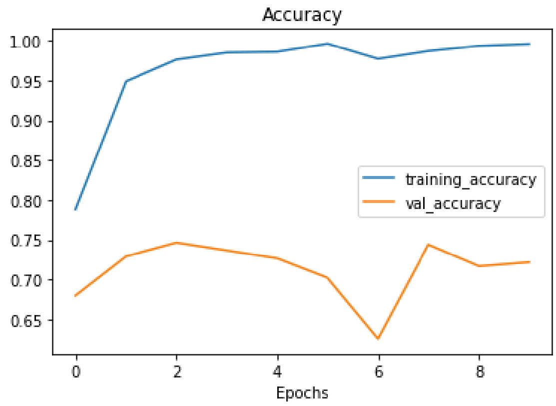

Figure 5. Accuracy of the resnet50

Figure 6. Loss of the resNet50

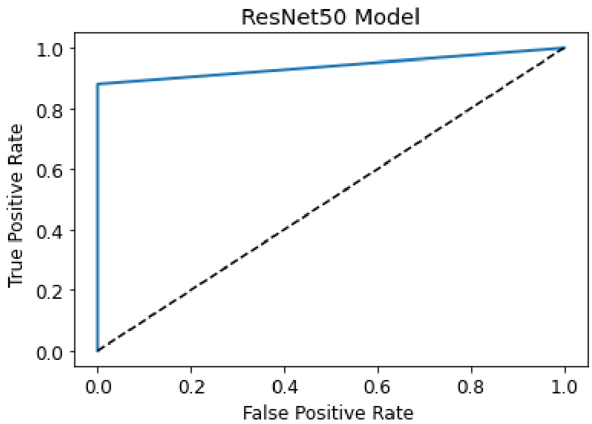

Figure 7. ROC curve of the resNet50

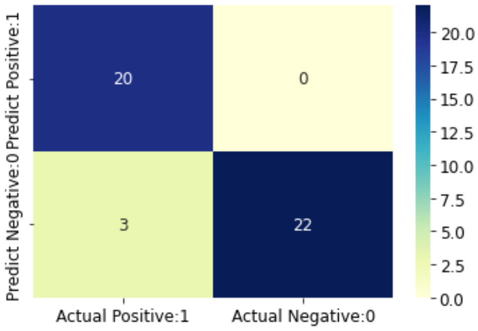

Figure 8. Confusion matrix of the resNet50

Figure 5,6,7,8 are parameter results of the resNet50 model. This model demonstrates that it has the best results according to values of the models. The ROC curve value of the resNet50 model is 0.94 and it is considered a high score. The confusion matrix parts can be set as below.

- True Positives(TP) = 20
- True Negatives(TN) = 22
- False Positives(FP) = 0
- False Negatives(FN) = 3

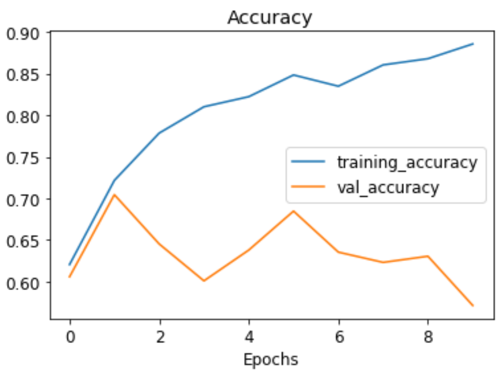

Figure 9. Accuracy of the inceptionV3

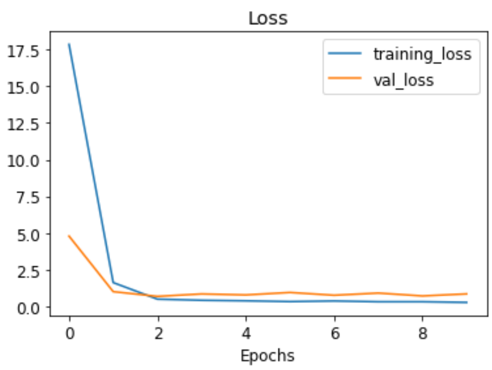

Figure 10. Loss of the inceptionV3

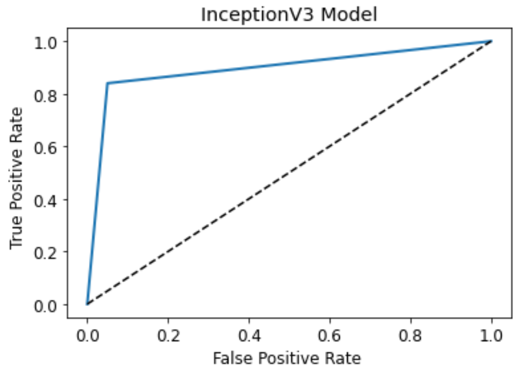

Figure 11. ROC curve of the InceptionV3

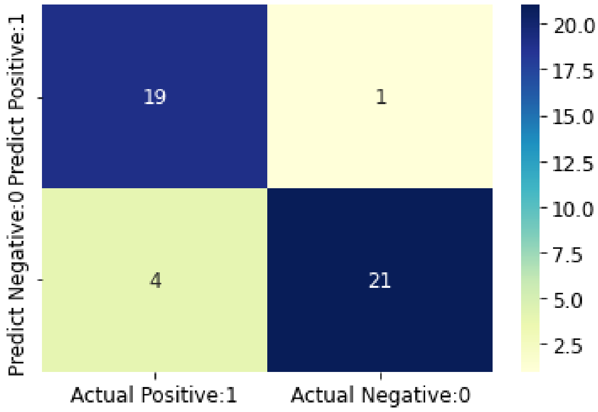

Figure 12. Confusion matrix of the inceptionV3

Figure 9,10,11,12 are results of the InceptionV3 algorithm. According to these results, This model is not considered a good score because the accuracy is set as 0.73 and it is lowest value among the models results. However, the ROC curve value of the InceptionV3 model is 0.89 and it is considered a satisfactory score. The confusion matrix parts can be set as below.

- True Positives(TP) = 19
- True Negatives(TN) = 21
- False Positives(FP) = 1
- False Negatives(FN) = 4

Result and Discussion

In this work, it is aimed to identify monkeypox disease from image datasets obtained from Kaggle website by using Convolutional Neural Network models. It was used three different deep-learning algorithms to detect monkeypox disease. There are a number of characteristics and specific features associated with each model. All models were compared according to their performance and these performances were evaluated by some parameters such as accuracy, precision, recall and F1-score. Among the models, resNet50 is the best method in terms of performance. Three tables are demonstrated below to compare the performances of the models.

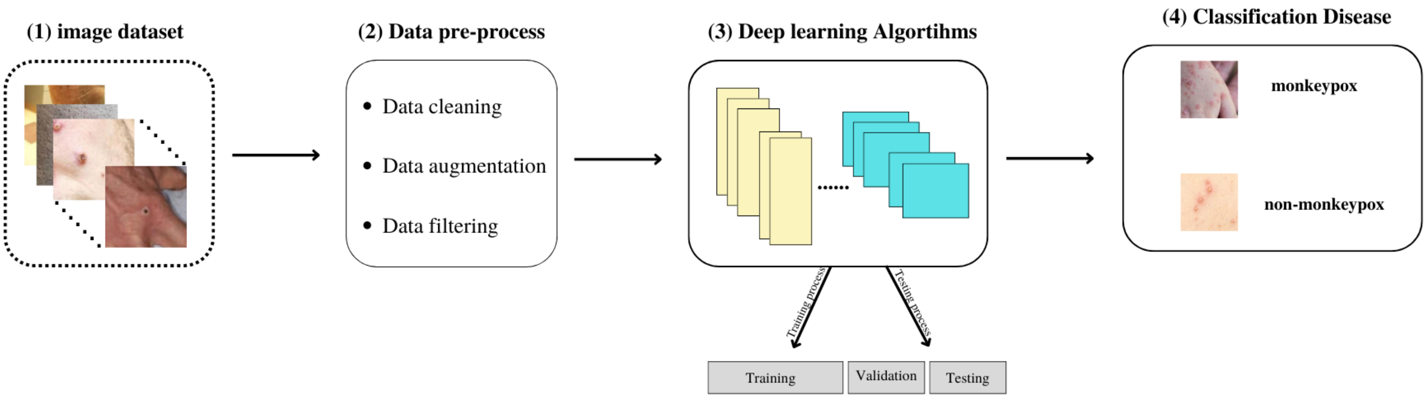

Figure 13. The work flow of the proposed models

The figure 13. demonstrates the processes of the proposed models. At the beginning, the images are acquired from Kaggle website. Datasets can be public or original. Before using training and test processes, images must be exposed to several steps such as data cleaning, data augmentation and data filtering. The basic target of all these steps are to have high-efficiency results. After these processes, models are designed and training/test steps are used. Finally, it is aimed to classify monkeypox disease [19].

Table 1. shows the evaluation metric of the methods. Using these metrics, we can figure out how well the models are performing. According to these parameters, it can be seen as easily that resNet50 has the best performance. InceptionV3 model has lower values with respect to performance because of the structure of the algorithm.

Table 2. demonstrates the speed of the models. Depending on the computer's performance, these values can be changed. Among the models, inceptionV3 seems the fastest model however resNet50 has the best parameter in terms of training and test accuracy.

Table 3. indicates the accuracy of the training and test processes. The results demonstrate that training and test processes carried out with high efficient performance. EfficientNetB3 and resNet50 are better than inceptionV3 with regard to parameters. Therefore, both models strongly provide training and test processes.

In general, it is seen that resNet50 and efficientNetB3 models are very close each other in regard to their performance however resNet50 is better than other models.

Table 1. The performance of the models

Models	Accuracy	Precision	Recall	F1-score
EfficientNetB3	0,93	0,9	0,95	0,93
ResNet50	0,93	0,87	1	0,93
InceptionV3	0,73	0,67	0,8	0,8

Table 2. The time comparison of the models

Models	Training accuracy	Time used	loss
EfficientNetB3	0.9832	11s 153ms/step	0.0061
ResNet50	0.9953	24s 345ms/step	0.0158
InceptionV3	0.8855	7s 102ms/step	0.2708

Table 3. Training and test accuracy of the models

Experiments	Model	Traning accuracy	Test Accuracy
1	EfficientNet B3	0.9832	0.9933
2	ResNet50	0.9958	0.9933
3	InceptionV3	0.8855	0.7333

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