Medical Image Classification for Monkeypox Case using Deep Learning Algorithms: A Survey

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Abstract

Due to the importance of maintaining public health and preventing the spread of diseases, nowadays, new diseases have spread at a lot of countries called Monkeypox after the world get rid of covid-19.it is crucial to diagnose Monkeypox and stop the spread of this disease. so that we make this review to give a point of view to Monkeypox spread nowadays. We have recently done nine research to overlay it with different artificial intelligence deep learning methods to diagnose Monkeypox from digital skin images due primarily to AI's success in COVID-19 identification. The VGG16, VGG19, ResNet50, ResNet101, DenseNet201, and AlexNet models were used in our proposed method to classify patients with monkeypox symptoms with other diseases of a similar kind (chickenpox, measles, and normal)., Due to the importance of facing this disease and summarizing these researches according to: methodology and results of detection accuracy, precision.

Keywords: artificial intelligence; Monkeypox; deep learning; Data collection; data augmentation.

1. Introduction

In today's world, several synchronized technologies, such as machine learning, deep learning, and artificial intelligence, play an essential part in providing medical assistance and diagnosing illness. We can obtain a massive dataset of diseases thanks to the participation of infected and healthy people worldwide. Because of this, the function of classification in accurately classifying diseases is quite significant. Recently, after the world was prosperous in eradicating the COVID19 virus, a new threat emerged: a skin disease recently appearing in many countries from a rash strain known as Monkeypox. However, the disease only occurred in Africa in the seventies of the previous century [1:8]. This skin disease is a strain of the sporotrichosis virus, related to another skin disease that shares many similarities. The virus that causes Monkeypox is called an orthopoxviral, a zoonotic illness. In most cases, the incubation period for Monkeypox lasts between 6 and 13 days; however, this time frame can range anywhere from 5 to 21 days. There are two time periods during which the infection is noticed. Despite this, the fatality rate has hovered between 3 and 6 percent [9]. It is now quite simple to obtain a complete photo collection of healthy and diseased skin for anyone who can use this collection. The signs of measles, cowpox, chickenpox, smallpox, and Monkeypox can be seen on images of the Monkeypox Skin. Dataset (MSLD), images of skin lesions caused by measles,

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chickenpox, and Monkeypox were collected and assembled. All of these scans originated quickly from readily available sources, such as websites, news portals, and case reports; however, they may contain some noise, blurring, and distortion, which is why we need to improve the image quality by filtering, using adopting size or concentration on the required things of skin Lesion and removing unwanted information from the image [10]. There are lots of pre-trained deep learning models like VGG-16, VGG-19 ResNet50, ResNet101, ResNet201, MobileNetV1and Inception v3. The model's ability to identify and extract effective features gives us more information about the monkeypox virus. The rule deep learning also helps us at covid 19 disaster by classing the disease and correctly diagnosing the covid at first days of symptoms to avoid fatality. It can also diagnose by chest radiograph to classify whether the person is normal or infected with COVID-19. it concerns with the size of lung and its lighting point to classify if it infects. Here the rule of deep learning appears to deal with images [11]. Firstly, the number of images that we have is small to classify images, but we face the overfitting problem which it can be solved by augmentation to increase the number of images and for generalize our model. Secondly, it enhances the photo quality, then it searches for the common thing that repeats in all image called features (size , brightness , …..). Thirdly, applies the pre-trained model and show the performance of classification by performance metrics (accuracy, precision, F1-Score, AUC, …...), or with confusion metrics and ROC curves, and compare results with other results to see if our processes are correct and able to generalize our model for diagnoses disease.

2. Related Work

Paper [12] proposed new model called (PoxNet22) with 100% precision, recall, and accuracy compared with six model (models DenseNet201, Inception -ResNetV2, EfficientNetB7, InceptionV3, ResNet50, and VGG16) according to performance matrices. Then pass through some processes Data collection, Data preprocessing and Data augmentation. Data collection images from various web-scraping sources, including news portals, websites, and publicly available case reports, are gathered and analyzed.

In data preprocessing, there are various methods were utilized, such as low-contrast pictures, contrast stretching, histogram equalization and adaptive equalization. The dataset is divided into two categories, 'monkeypox' and ‘‘others’’ as mentioned earlier. As a result, the data preparation procedure was applied to each class individually. The contexts in which there is a low contrast between the image and the background make it more difficult for models to decide whether image borders are clear. To increase the range of intensity values that the images can include, contrast stretching was applied to the images. The overall image quality of the dataset has been enhanced using a variety of image preparation methods. Data augmentation has been carried out to reduce the possibility of the model overfitting. This resulted in a considerable rise in the overall number of images inside the collection. Then, the dataset has been divided into:

A train set and a test set in the section titled 'Train Test Split' to run the experiment on both. To ensure that the training dataset contained correct data and information, throughout the whole data augmentation procedure, the rescaled value was kept at 1/255. After that, the rotation's range was modified to 20, which allowed the images to be turned between 0 and 20 degrees in any direction. After this one, the zoom range was increased to 0.2 so that it would allow for a 20% in/out zoom. It was performed in preparation for the next one. It was then carried out to facilitate the adjustment later. Additionally, the shear range was adjusted to 0.2 so that a total of 20% could share the image. Then, different deep learning models then calculate performance matrices:

- DenseNet201 model achieved 92% accuracy, 92% precision, 93% recall, and 19% loss. The model's execution took 7 minutes and 14 seconds.
- InceptionResNetV2 model 96% accuracy, 95% precision, 98% recall, and 9% loss and it took 8 minutes and 49 seconds.
- The EfficientNetB7 model achieved 94% accuracy, 94% precision, 96% recall, and 15% loss. The model’s execution took 9 minutes and 45 seconds. • The InceptionV3 model

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also achieved 99% accuracy, 99% precision, 98% recall, and 7% loss. The model's execution also took 6 minutes and 41 seconds.

- The ResNet50 model additionally achieved 83% accuracy, 81% precision, 89% recall, and 40% loss. The execution of the model took 8 minutes and 23 seconds.

- The VGG16 model obtained 55% accuracy, 55% precision, 100% recall, and 68% loss. The model's execution took 6 minutes and 50 seconds. The model proposed in this research (PoxNet22) is a fine-tuned version of the InceptionV3 model. Then applied SGD known as (stochastic gradient descent) and ADAM optimizer.

- SGD achieved 99% accuracy, 99% precision, 99% recall, and .01% loss. The model's execution took 13 minutes and .04 seconds.

- ADAM achieved 100% accuracy, 100% precision, 100% recall, and 0% loss. The model's execution took 19 minutes and 40 seconds.

Authors in [13] proposed CNN–LSTM hybrid artificial intelligence system, developed and proposed for monkeypox detection, test accuracy was 87% and Cohen's kappa score was 82.22%. The author classifies data with 7 deep learning models (CSPDarkNet, InceptionV4, MnasNet, MobileNetV3, RepVGG, SE-ResNet and Xception). then chose 2model with best performance metrics and combined them with a LSTM encoder network. Data of Monkeypox passes through some processes Data collection, Data preprocessing and Data augmentation.

The dataset consists of normal, Monkeypox, measles and chickenpox classes. It is understood that the distribution in the dataset is unbalanced. Data collection images from various web-scraping sources, including news portals, websites, and publicly available case reports, are gathered and analyzed. Data augmentations are equalized, horizontal flip, random brightness contrast, hue saturation value, shift scale rotate and RGB shift. The parameters and values of the data augmentations. In the new version of the dataset with data augmentation and data preprocessing, the training, validation and test distributions required for network training and classification in deep learning models are 80%. The purpose of the random selection is that the researcher does not have the images in the test and validation dataset relatively easily. Then, different deep learning models then calculate performance matrices:

- CSPDarkNet achieved 80% accuracy, 76% precision, 83% recall, F1 Score 79%, 81.3%, AUC Score 81, 73.33% Cohen's Kappa, 76.64% MCC • InceptionV4 Achieved 74% accuracy, 88% precision, 70% recall, 78 %F1 Score, 80.9% AUC Score, 65.66% Cohen's Kappa ,67.12% MCC

- MnasNet Achieved 84% accuracy, 84% precision, 87% recall, 85 %F1 Score, 87.3% AUC Score, 78.88% Cohen's Kappa ,79.01% MCC • MobileNetV3 Achieved 79% accuracy, 79% precision, 87% recall, 83 %F1 Score, 87.3% AUC Score, 72.22% Cohen's Kappa ,72.77% MCC

- RepVGG Achieved 85% accuracy, 84% precision, 87% recall, 85 %F1 Score, 96.1% AUC Score, 80% Cohen's Kappa ,80.25% MCC • SE ResNet Achieved 73% accuracy, 67% precision, 87% recall, 75 %F1 Score, 89.2% AUC Score, 64.44% Cohen's Kappa ,65.08% MCC

- Xception Achieved 73% accuracy, 73% precision, 80% recall, 76%F1 Score, 93.9% AUC Score, 64.44% Cohen's Kappa ,65.52% MCC After these results choose the two highest accuracy model MnasNet , RepVGG that the models to be used in the CNN part of the hybrid model should be to improve classification accuracy.

- LSTM The LSTM model is a deep learning model, which is a type of recurrent neural network. Its basic architecture consists of input, recurrent LSTM and output layers,

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respectively. LSTMs actually address the vanishing gradient problem. The recurrent connections in the LSTM layer are cyclic. The proposed CNN–LSTM hybrid deep learning model for monkeypox detection for the following scores on the test dataset: Achieved 87% accuracy, 93% precision, 87% recall, 90 %F1 Score, 93.4% AUC Score, 82.22% Cohen's Kappa ,82.40% MCC.

The author in [21] proposed an Android mobile application that uses deep learning to help with this situation. The application has been developed with Android Studio using Java programming language and Android SDK 12. The system can classify the images with 91.11% accuracy. In addition, the proposed mobile application can be trained for the preliminary diagnosis of other skin diseases. Preprocessing methods. In this stage, we have normalized the pixel values from [0, 255] to [-1, 1]. Then, the system was trained with the transfer learning method using pre-trained networks. Various pre-trained networks have been used, and their performances have been compared in this step. Afterward, the network with the best performance was recreated using TensorFlow. The TensorFlow model has been converted. Deep learning approaches allow automatic learning of complex features needed for visual pattern recognition. Convolutional Neural Networks (CNN) is a type of deep learning approach. CNN has been used for several computer vision tasks.

Different pre-trained netwo1rks have been retrained using the transfer learning approach (ResNet18, GoogleNet, EfcientNetb0, NasnetMobile, ShufeNet, MobileNetv2) and the network results have been compared according to epochs change. The best performances were achieved with MobileNetv2 and EfcientNetb0 in 60 epochs. The EfcientNetb0 and MobileNetv2 networks which show the best performances for the human monkeypox classification task. Then, MobileNetv2 is the best performance in terms of accuracy as 91.11% was adapted into an Android mobile application. It was the best accuracy of the pre-trained model according to the number of epochs =60

- ResNet18: has level of accuracy of 73.33% • GoogleNet,: has level of accuracy of 77.78%
- EfcientNetb0: has level of accuracy of 91.11% • NasnetMobile,: has level of accuracy of 86.67%
- ShufeNet,: has a level of accuracy of 80.00% • MobileNetv2: has a level of accuracy of 91.11% Then choose the best performance of two model MobileNetv2, EfcientNetb0 then calculate the performance of two model:
- EfcientNetb0: has level of accuracy of 91.11%, jaccard 82.61%, precision 86.36%, sensitivity 95.00 %, F1 Score 90.48%.
- MobileNetv2: has level of accuracy of 91.11% jaccard 81.82%, precision 90%, sensitivity 90%, F1 Score90 %.

The author in [22] proposed implemented seven DL models that leverage pre-trained capabilities to diagnose Monkeypox disease based on skin lesion images from patients. we employed LIME and Grad-Cam techniques. Data collection and the construction of datasets as an initial step. The dataset of this study consists of 43 Monkeypox, 47 Chickenpox, 27 Measles, and 54 normal images. To standardize the images, we resized them to 128×128 pixels. To enhance the dataset for more robust training, we employed augmentation techniques to increase the number of samples. The augmentation process involved the following parameters: rotation range=45, rescale=1/255, zoom range=0.15, height shift range=0.25, width shift range=0.25, shear range=0.25, channel shift range=25, vertical flip=True, and horizontal flip=True.

For the classification task, 80% of the data was used for training, while the remaining 20% was reserved for testing. seven CNN architectures were implemented, namely InceptionResNetV2, InceptionV3, ResNet152V2, VGG16, VGG19, Xception, and DenseNet201. and compare performance metrics of four and two-class scenario. The results show that our proposed DenseNet201-based architecture has the best performance, with Accuracy=97.63%, F1-Score=90.51%, and Area

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Under Curve (AUC)=94.27% in two-class scenario; and Accuracy=95.18%, F1-Score=89.61%, AUC=92.06% for four-class scenario For four class scenarios:

- InceptionResNetV2: Accuracy 94.48%, F1-Score 88.85%, NPV 96.47%, PPV 89.95%, Specificity 96.27, Sensitivity 88.95%, AUC 84.22%.
- InceptionV3: Accuracy 94.74%, F1-Score 87.93%, NPV 96.64%, PPV 89.98%, Specificity 96.09, Sensitivity 88.9%, AUC 73%
- InceptionResNetV2: Accuracy 94.48%, F1-Score 88.85%, NPV 96.47%, PPV 89.95%, Specificity 96.27, Sensitivity 88.95%, AUC 84.22% • ResNet152V2: Accuracy 94.17%, F1-Score 88.39%, NPV 96.89%, PPV 90.72%, Specificity 95.62, Sensitivity 87.13%, AUC 73.09%
- VGG16: Accuracy 88.78%, F1-Score71.10%, NPV 93.66%, PPV 77.09%, Specificity 91.79%, Sensitivity 75.56%, AUC 72.98%
- VGG19: Accuracy 87.20%, F1-Score 67.21%, NPV 90.86%, PPV 74.19%, Specificity 90.40%, Sensitivity 62.10%, AUC 73.09%
- Xception Accuracy 95.02%, F1-Score 88.41%, NPV 96.78%, PPV 88.94%, Specificity 95.83%, Sensitivity 88.61%, AUC 84.29%.
- DenseNet201: Accuracy 95.18%, F1-Score 89.61%, NPV 97.10%, PPV 90.73%, Specificity 96.50%. Sensitivity 89.82 AUC 92.06%.

For two class scenarios:

- InceptionResNetV2: Accuracy 85.64%, F1-Score 87.05%, NPV 87.59%, PPV 78.40%, Specificity 87.57, Sensitivity 78.02%, AUC 86.52%
- In inceptionV3: Accuracy 85.90%, F1-Score 79.34%, NPV 87.73%, PPV 79.69%, Specificity 87.72, Sensitivity 79.21%, AUC 88.62%
- ResNet152V2: Accuracy 84.26%, F1-Score 70.69%, NPV 86.84%, PPV 71.63%, Specificity 86.81, Sensitivity70.30%, AUC 88.03%
- VGG16: Accuracy 85.11%, F1-Score75.10%, NPV 87.30%, PPV 75.14%, Specificity 87.28%, Sensitivity 75.06%, AUC 88.79% • VGG19: Accuracy 84.85%, F1-Score 73.32%, NPV 87.18%, PPV 75.19%, Specificity 87.13%, Sensitivity 73.25%, AUC 87.66%
- Xception Accuracy 85.99%, F1-Score 79.70%, NPV %, PPV 80.07%, Specificity 87.77%, Sensitivity 79.69%, AUC 90.52%.
- DenseNet201: Accuracy 97.63%, F1-Score 90.51%, NPV 98.89%, PPV 98.47%, Specificity 98.47%. Sensitivity 91.08%, AUC 94.27%. DenseNet201 exhibited the highest performance across all metrics.

Author in [16] proposed an We propose an ensemble of CNN models for Monkeypox detection using skin lesion images. We first consider three pre-trained base learners, namely Inception V3, Xception and DenseNet169 to fine-tune on a target Monkeypox dataset. we propose a Beta function-based normalization scheme of probabilities to learn an efficient aggregation of complementary information obtained from the base learners followed by the sum rule-based ensemble. The model achieves an average of 93.39%, 88.91%, 96.78% and 92.35% accuracy, precision, recall and F1 scores, respectively.

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We first discuss the dataset we have experimented on followed by introducing the proposed model for identifying Monkeypox from skin lesion images. We first resize the training samples to 224 × 224 pixels. Since we deal with a relatively small-sized dataset, we need to take care of a major challenge while training a CNN model, i.e., the problem of overfitting. To deal with this, we augment all the training images by utilizing augmentation techniques including horizontal and vertical shifting, brightness changing, zooming, channel shifting, horizontal and vertical flipping, rotating, and changing. Additionally, we consider color spaces like YUV and HSV to make sure our framework learns discriminative embeddings. Further, these training images are then fed to these three pre-trained (pre-trained on the ImageNet dataset) CNN models, namely Xception, InceptionV3 and DenseNet169. Before feeding the images, we further augment them using Gaussian noise. These pre-trained CNN models are fine-tuned using this target Monkeypox Skin Lesion dataset including its inner convolutional layers.

Finally, to have a better decision over the predicted probability scores of the individual models, an enhancement scheme is proposed based on the aggregation of Beta- normalized output values of the respective models using the sum rule. The three models give the best results with batch size 16 and learning rate 1e – 4 and the proposed method experiments on a binary-class Monkeypox dataset namely the Monkeypox Skin Lesion dataset. The proposed approach is evaluated using a 5-fold cross-validation setting:

- Xception: Achieved 90.23% accuracy, 84.01% precision, 95.82% recall, 88.91%F1 Score,
- InceptionV3: Achieved 89.45% accuracy, 85.10% precision, 80.15% recall, 86.97 %F1 Score,
- DenseNet169: Achieved 89.47% accuracy, 83.85% precision, 92.31% recall, 87.59 %F1 Score
- Ensemble: Achieved 93.39% accuracy, 88.91% precision, 96.78% recall, 92.35 %F1 Score

Author in [17] proposed an adaptive k-means clustering image segmentation technique that delivers precise segmentation results with straightforward operation. There are six distinct deep CNN models that have been implemented and evaluated to make the diagnosis with the monkeypox viral infection using skin images VGG16, VGG19, ResNet50, ResNet101, DenseNet201, and AlexNet . The best overall accuracy achieved by ResNet101 is 94.25%, with an AUC of 98.59% according to performance matrices.

Then pass through some processes Data collection, Data preprocessing and K-means clustering algorithm. clustering approach that is unsupervised learning, and it is a technique to divide groups of items into homogeneous sub-groups is called data clustering. Each data item is treated as having a position in Euclidean space when using the k-means clustering. It locates divisions so items in each cluster are as close to one another and as far away from one another as feasible. comparison of the ensemble approach's 5-fold cross-validation estimates of the ensemble's mean precision, mean recall, mean F1-score, and mean accuracy for all classes.

- VGG-16 model, which has an accuracy of 92.57% with an AUC of 98.11% and a loss of 0.1005.
- VGG-19 model's accuracy is 90.89%, AUC 96.94%, Loss 0.1411
- The ResNet50 model's performance is categorized in with an AUC of 98.46%, a loss of 0.0813, and an accuracy of 94.05%.
- The ResNet101 model's performance is categorized with an AUC of 98.59%, a loss of 0.0550, and an accuracy of 94.25%.

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- DenseNet201 model, which has an accuracy of 94.05% with an AUC of 98.35% and a loss of 0.0789.

- AlexNet model's accuracy is 87.53%, With an AUC of 94.39% and a loss of 0.1364. We employed the lime to offer correct justification for the values predicted by our LIME to give insights into the monkeypox virus relying on the categorization of different skin images after being motivated by the model's expected performance.

Authors in [18] proposed transfer learning models such as residual networks and SqueezeNet to diagnose Monkeypox from measles, chickenpox, and healthy patients. An average accuracy of 91.19% and an F1-score of 92.55% were obtained for the Monkeypox class compared to four deep-learning model. The four models used were ResNet-18, ResNet-50, ResNet-101, and SqueezeNet. The findings show that the models can detect the contagious virus. Since the classifiers are easily deployable, they can be used on camera-ready devices such as phones and laptops. For four class scenarios:

- ResNet-18 Among all, the validation accuracy was the highest for 91.19%. The validation loss was 0.45. The batch size used and the learning rate were 16 and 0.001, F1-score 92.54%, Recall 90.43%.

- ResNet-50 was the next best-performing model. It was able to obtain an accuracy of 91.01% and a validation loss of 0.47. The batch size and the learning rate used were 16 and 0.001, F1-score 90.62%, Recall 88.06%.

- The ResNet-101 obtained a good accuracy and validation loss of 90.08% and 0.56, F1-score 90.43%, Recall 87.72%.

- SqueezeNet model. It was able to obtain an accuracy of 86.87% and a validation loss of 0.64. The batch size and the learning rate used were 16 and 0.001, F1-score 89.7%, Recall 88.5%.

Author in [19] proposed and evaluated a modified DenseNet-201 deep learning-based CNN model named MonkeyNet. Using the original and augmented datasets, this study suggested a deep convolutional neural network that was able to correctly identify monkeypox disease with an accuracy of 93.19% and 98.91%, respectively. The proposed model will also help doctors make accurate early diagnoses of monkeypox disease and protect against the spread of the disease. The data preprocessing step includes feature scaling, data resizing, splitting, and augmentation. These are illustrated in the following: Feature Scaling: The procedure initially started by exporting the dataset so that we could work with it and modify the data so that it could be used by multiple classifiers to accurately forecast monkeypox disease detection. the skin images in the dataset are transformed to RGB and then downsized to 224 × 224 pixels. The standard image size is in the range [0,255], with 255 being the largest image size allowed by the system.

Data splitting: As a result of the feature rescaling, all of the images in the dataset are resized into the range (224,224), where the image’s height and width are both 224 pixels. The dataset must now be divided into two parts: a training portion and a testing portion. Specifically, in this study, we divided the dataset into two parts: 80% for training and 20% for testing our proposed model, respectively. From the training dataset, 20%. Data Augmentation: Data augmentation is a process that is used to expand the size of a dataset by applying random transformations to the original data. ImageDataGenerator is a class in the Keras deep learning framework that allows us to fit the model using image data. Comparison of the ensemble approach's 5-fold cross-validation estimates of the ensemble's mean precision mean recall, mean F1-score, and represent accuracy for all classes:

- VGG16: Precision 94.48%, Recall 94.43%, F-1 score 94.44%, Test accuracy 94.43%, AUC 99.31%.

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- ResNet50: Precision 95.89%, Recall 95.86%, F-1 score 95.87%, Test accuracy 95.86%, AUC 99.62%. • MobileNetV1: Precision 96.48%, Recall 96.44%, F-1 score 96.44%, Test accuracy 96.44%, AUC 99.79%.

- Inception V3: Precision 97.71%, Recall 97.70%, F-1 score 97.70%, Test accuracy 97.70%, AUC 99.89%.

- Xception: Precision 96.53 %, Recall 96.49, %F-1 score 96.50%, Test accuracy 96.49%, AUC 99.89%.

- Proposed model: Precision 98.92%, Recall 98.91%, F1 score 98.91%, Test accuracy 98.91%, AUC 99.97%.

Authors in [20] proposed two algorithms are proposed for improving the classification accuracy of monkeypox images. The proposed algorithms are based on transfer learning for feature extraction and meta-heuristic optimization for feature selection and optimization of the parameters of a multilayer neural network. The GoogleNet deep network is adopted for feature extraction, and the utilized meta-heuristic optimization algorithms are the Al-Biruni Earth radius algorithm, the sine cosine algorithm, and the particle swarm optimization algorithm. Based on these algorithms, a new binary hybrid algorithm is proposed for feature selection, along with a new hybrid algorithm for optimizing the parameters of the neural network. The results achieved confirm the superiority and effectiveness of the proposed methods compared to other optimization methods. The average classification accuracy was 98.8%. First stage is data processing, which includes image resizing, data augmentation, and feature extraction. This stage focuses on preparing the input images and increasing the number of images, and then extracting the relevant features using GoogleNet.

The second stage, on the other hand, is the feature selection, which involved the proposed feature selection algorithm. The target of this stage is to select the most effective features that can accuracy classify the input images. The third stage is the optimization of the neural network’s parameters using the proposed optimization algorithm. The target of this step is to choose the best set of parameters for classification.

Data Augmentation The term "data augmentation" refers to the method of changing the size and orientation of the dataset images to generate new image that can enrich the existing dataset. Data augmentation is used on both training and validation sets to boost the generalization capacity of deep learning-based image classification models. Various data augmentation techniques, such as geometric modification, kernel filters, picture mixing, random erasure, and transformations, were applied to increase the size of the dataset. Evaluation of the features extracted using four deep neural networks and the developed multilayer neural network compared 4 models.

- AlexNet has Accuracy 84%, Sensitivity 63%, Specificity 90%, Pvalue 66%, F-score 64%

- VGG19Net: has Accuracy 86%, Sensitivity 63%, Specificity 93%, Pvalue 73%, F-score 67%

- ResNet-50: has Accuracy 88%, Sensitivity 63%, Specificity 96%, Pvalue 85%, F-score 72%

- GoogLeNet: has Accuracy 89%, Sensitivity 63%, Specificity 98%, Pvalue 91%, F-score 94%

- bPSOBER : has Accuracy 93.802%, Sensitivity 62.5%, Specificity 99.8%, Pvalue 98.36%, F-score 76.43%

Table 1 summarizes the different researches proposed to classify moneybox images.

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6. Conclusion

According to summarization of these research we notice that the importance of data classification to have high performance of detection the disease. The data is the most important to classify the disease, it is separated into two classes (Monkeypox, normal) people or in four classes normal, Monkeypox, measles and chickenpox. Data augmentation is also important to avoid overfitting, it increases the number of images which helps classifier to have accurate detection of disease. There were numerous of pre-trained deep learning model (VGG16, VGG19, ResNet50, ResNet101, MobileNetv2, EfcientNetb0, DenseNet201, and AlexNet). It helps us to diagnose the disease at first appearance and avoid spreading. The results were excellent for detection of disease it reaches 100% because of help of optimization algorithms.

Table 1: Summary of different works in monkey box classification

Work	Model used	Dataset	Accuracy	Optimization model	No. class approach
	PoxNet22	MSLD [22]	100%	ADAM	2-class approach
	Proposed CNN–LSTM hybrid model	MSID [21]	87%	hybrid	4-class approach
	MobileNetv2	MSLD [22]	91.11%	-	2-class approach
	DenseNet20	Own dataset	97.63%	LIME and Grad-Cam	2-class approach
	Beta function-based normalization scheme	MSLD [22]	93.39%	Grad-Cam	2-class approach
	ResNet101	Kaggle	94.25%	LIME	4-class approach
	ResNet18	MSID [21]	91.11%	Explainable artificial intelligence (XAI)	4-class approach
	modified DenseNet-201	MSID [21]	93.19%	ADAM	4-class approach
	optimization of NN using SCBER	MSID [21]	98.8%	PSO, BER and SCA	2-class approach

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Train/validation / test split (%)	No. cross validation
80 – 0- 20	-
80-10-10	-
70-20-10	-
80-0-20	5-fold cross validation
80-0-20	5-fold cross validation
80-0-20	5-fold cross validation
-	-
80-0-20	5-fold cross validation
70-0-30	5-fold cross validation

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