A Framework of Deep Learning for Monkeypox Image Classification Based on Particle Swarm Optimization (PSO)

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***Abstract*— Decisions made now will shape the future in which future generations will live. With all of this, people must be aware of the danger that faces every individual living on this earth. Among the dangers to which humanity is exposed are the spread of diseases, natural disasters, wars, and the like. Recently, many diseases have begun to spread, and on top of these diseases are Covid 19, Monkeypox (MPX), and many other diseases. This paper attempts to help many clinicians classify monkeypox by using different models in Artificial Intelligence (AI). Deep learning (DL) as a branch of artificial intelligence has been used as a proposed model to solve this problem. Among the elements used in the proposed model are data augmentation and extraction of various features by means of some VGG16 and Inception models. The Particle Swarm Optimization Algorithm (PSO)was also used to feature selection and optimization of the parameters of the neural network, while the classification process was carried out by Support Vector Machine (SVM). In the final process, the model had to be evaluated by a confusion matrix, which showed that the accuracy of the VGG16 model was 85% but after improved PSO, new accuracy become 94.5%. In the state of Inception model accuracy is 75.2% but when improved PSO is used it becomes 90.2%. These results are useful for the classification and diagnosis of monkeypox. It is no secret that personal hygiene, avoiding touching animal waste, and taking a vaccine to increase immunity are important ways to protect people from diseases.**

Keywords—Monkeypox; Particle Swarm Optimization; Deep learning; Classification; Artificial intelligence

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I. Introduction

There is no doubt that recently, technological applications have been used in various areas of life. Every individual in society has become his own computer, telephone, and even a TV. Therefore, dispensing with these things has become impossible. Due to the diversity of fields, the use of artificial intelligence has increased. This opened the door to many fields that include the industrial field, for example, the field of agriculture and the field Energy, medical field, engineering field, space field, computer vision, and so on. What we are interested in in this research is how to benefit from artificial intelligence in the medical field, because human health is one of the important things through which the life of an individual in society is straightened. Quite simply, the idea of artificial intelligence is based on making the machine how to think like a human being. I used a lot of models that help the machine to think and make some decisions. The existence of the machine does not mean that we cancel the role of the human being. The role of the machine comes in helping the human being in making some decisions such as the initial diagnosis of the diseased condition, performing some complex and quick tasks, and so on. One of the very important branches of artificial intelligence and computer science is machine learning.

IBM is considered a pioneer in the concept of machine learning because this term appeared at the hands of engineer Arthur Samuel (an engineer in the field of computer games and artificial intelligence[1]) in 1959. The idea of machine learning is simply done in two stages. The first stage is to train the machine on the data to be learned from so that knowledge can grow and it is called training data. The second stage is making predictions, decisions and evaluation through test data. In this way the machine has a large amount of knowledge through which the machine is indirectly programmed to do a variety of future actions. For example, supervised learning requires human intervention to label the input data correctly. In contrast, unsupervised learning does not require labeled datasets but groups them according to any distinct characteristics. Reinforcement learning is a process in which a model learns to become more accurate to perform an action in a feedback-based environment. Deep learning is a subset of machine learning.

Deep learning is basically a neural network with three or more layers. These neural networks attempt to mimic the behavior of the human brain where the cell nucleus represents the ganglia, the synapse represents the weights, and the axon represents the output. Each connection, like synapses in a biological brain, can transmit information, a "signal", from one artificial neuron to another. There are different types of neural networks to tackle a lot of problems. For example, convolutional neural networks (CNNs), commonly used fundamental in computer vision applications and image classification, detecting features and patterns within an image. Recurrent neural networks (RNNs) are commonly used in speech recognition and natural language applications because they make use of sequential or time series data.

Since we are dealing with medical images in this research, it is appropriate to use Convolutional Neural Network. CNN has many advantages, for example, simplicity, independence of transformations, involving feeding segments of an image, reduced computation, better performance, great image classification, and finally reduced complexity and saving memory compared to other types. There are several models of deep learning like VGG16, VGG19, ResNet 50, inception v3, etc. Some of the disadvantages of CNNs are that they need a lot of training data, tend to be slow, the training process takes a long time, and finally have an overfitting problem.

Overfitting occurs when the model has a high variance, the training data size is not enough, and fails to generalize to unseen examples. Data augmentation techniques consider one of the best solutions that can help accomplish this mission. Data augmentation techniques apply modifications to increase training data samples. This paper proposes a particle swarm optimization-(PSO) based deep-learning approach for medical image classification. The dataset used for this purpose is obtained from Kaggle and contains two classes of monkeypox images, which are maintained and balanced using data augmentation. The pre-trained deep-learning model Google Net is used for feature learning and extraction from the input images. The features are then optimized and reduced using the nature-based optimization algorithm PSO. The derived features from the model are passed on to the classification learner, where different classifiers are implemented. The Support Vector Machine (SVM) classifier outperforms all others with an accuracy of 94.8% while maintaining brisk speed on the given dataset.

Humans are surrounded by many dangers, such as deadly diseases spread all over the world, with Covid-19 and monkeypox coming to the fore. Monkeypox (MPX) virus is a double-stranded DNA virus belonging to the Poxviridae family of the genus Orthopoxvirus with two distinct branches known as the West African and Congo Basin [2]. It is a zoonotic viral infection, which means it can be passed from animals to humans. It was first discovered in 1958 in a monkey during vaccine research [3] in Denmark, hence it is named as Monkeypox virus. MPX endemic disease status updated to worldwide outbreak in 2022. Monkeypox can spread to people when they come into physical contact with an infected animal. However, some symptoms are commonly observed. Clinical signs such as fever, muscle aches, headache, swollen lymph nodes, and rash in specific areas of the body are standard and indicative of the first step in the diagnosis. Following clinical signs, laboratory diagnostic tests such as conventional polymerase chain reaction (PCR) or real-time polymerase chain reaction (RT-PCR) are the most common and accurate diagnostic methods. Antivirals such as tacovirimate, cidofovir, and Brin cidofovir are used to treat symptoms. There is no vaccine for MPX. However, the currently available smallpox vaccines boost the immunization rate.

Due to the seriousness of the spread of this disease, many researchers have been able to diagnose and classify this disease using the concepts of artificial intelligence in an attempt to help doctors. The next section will present some of these important researches.

II.Related Works

We agree that humans cannot live on this planet alone. Humankind is surrounded by many living things, such as plants, animals, and non-living things.

The importance of artificial intelligence is due to the multiplicity of fields. For example, it can be used to know the quality of plants. The proposed approach in [4] classify the maize images into four different categories; three categories representing infected maize leaves and one category representing healthy leaves using an ensemble of pre-trained CNNs. Some of the hyperparameters of every single model in the ensemble model are optimized by the OLPSO optimization algorithm which achieves an accuracy of 98.2%. The experimental results are compared with the performance of other pre-trained CNN models.

[5] chose seven deep models. researcher study found that deep AI models have great potential in the detection of Monkeypox from digital skin images (mean accuracy of 83%). the researcher built and utilized a digital skin database containing skin lesion/rash images of five different diseases.

Paper [6] implements five deep learning models—VGG19, Xception, DenseNet, EfficientNet, and MobileNet along with integrated channel and spatial attention mechanisms and performs a comparative analysis among them. When the Xception model applies to Monkeypox, the accuracy is 83.89%.

Paper [7] used more than ten various deep learning (DL) models as pre-trained for the detection of the Monkeypox virus. For this, we initially fine-tune them with the addition of universal custom layers for all of them and analyzed the results using four well-established measures: Precision, Recall, F1-score, and Accuracy. when the best-performing DL models are determined, we used them to improve the overall performance. We perform our experiments on a publicly available dataset, which results in average Precision, Recall, F1-score, and Accuracy of 85.44%, 85.47%, 85.40%, and 87.13%, respectively with the help of our proposed ensemble approach. These encouraging results, which outperform the state-of-the-art methods, suggest that the proposed approach is applicable to health practitioners for mass screening.

In the study at [8], he used two famous optimization algorithms, a genetic algorithm, and particle swarm optimization to find good features for the fully connected layers of three state-of-the-art CNNs: VGG-16, ResNet-50, and DenseNet. By using optimization proposed algorithms, the F1-score achieved greater than 91% for all used models when compared to previously published studies.

This study [9] presents a mobile system to automatically detect human monkeypox skin lesions. The proposed study was also compared with other studies using the same database and produced better results. For this purpose, first, a deep transfer learning-based system has been trained using MSLD database images. In this stage, various pre-trained networks have been retrained using the transfer learning approach, and the network results have been compared. Then, MobileNetv2 which showed one of the best performances in terms of accuracy as 91.11% was adapted into an Android mobile application.

In [10] paper, a combination of pre-trained CNN GoogleNet and a nature-inspired problem optimization scheme, particle swarm optimization (PSO), was employed for autonomous vehicle classification. The model was trained on a vehicle image dataset obtained from Kaggle that has been suitably augmented. The trained model was classified using several classifiers; however, the

Cubic SVM (CSVM) classifier was found to outperform the others in both time consumption and accuracy (94.8%).

Researcher [11] used two CNN models for feature extraction. Principal component analysis (PCA) used as Feature selection. The results showed that all the models performed relatively the same. However, the most effective model was VGG-16 (accuracy = 0.96, F1-score = 0.92). It is an affirmation of the usefulness of artificial intelligence in the detection of Monkeypox disease.

The particle swarm optimization (PSO) algorithm at [12] was used to optimize the network hyperparameters in the convolutional neural network (CNN) in order to enhance the network performance and eliminate the requirement of a manual search. The methodology was tested on computed tomography (CT) with the highest accuracy of 97.62%.

Two algorithms are proposed in [13] 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. To evaluate the proposed algorithms, a publicly available dataset is employed. The assessment of the proposed optimization of feature selection for monkeypox classification was performed in terms of ten evaluation criteria. The results achieved confirm the superiority and effectiveness. The average classification accuracy was 98.8%.

Paper [14] proposes an algorithm to search for the best deep convolutional neural network by using particle swarm optimization (psoCNN). PsoCNN algorithm can quickly optimize any given dataset. With only 20 particles and 10 iterations, the algorithm models are capable of achieving results. From [14] experimental results, we can conclude that psoCNN would be able to and even better architectures if more computational power is available. A novel direct encoding strategy is also proposed in which a CNN architecture is divided into two blocks: one block contains only convolutional and pooling layers, while the other contains only fully connected layers. This encoding strategy allows it to be compared and combined using an almost standard PSO algorithm.

Since then, the phone and the Internet have become an essential part of everyone's life. One of the new areas that will have a great deal in computer science is the connection of artificial intelligence to mobile applications. In this study [15] enhanced version of PSO is proposed called the Improved PSO algorithm aims to enhance the detection of jamming attack sources over randomized mobile networks. To address the Jamming attacks problem, the Particle Swarm Optimization (PSO) algorithm is used to describe and simulate the behavior of a large group of entities, with similar characteristics or attributes, as they progress to achieve an optimal group or swarm.

In [16] all VGG-16, ResNet50, and InceptionV3 are used to classify monkeypox images. Data augmentation is applied to swell the sample size, and a 3-fold cross-validation is already used. It is a good idea to use web applications as a tool for scanning monkeypox. An ensemble of the three models is also developed. ResNet 50 achieves the best accuracy. Enhancing the generalizability of these models needs large and various data.

In light of previous research and studies, it can be said that science will continue to benefit humanity. From the above, we found that a medical image classification model can be made, based on the swarm algorithm. This certainly calls us to answer important questions. What is the proposed model? And what's new? This will become clear in the coming paragraphs.

III.PROPOSED METHODOLOGY

The importance of the previous works referred to is due to the diversity in the use of data and modern methods that can be flexibly modified to serve the required field. So, we thank all of them. When making a comparison with the previous research and our proposed model, we find the following. In [7] compared 13 different pre-trained DL models with the help of transfer learning on the monkeypox dataset. We used data augmentation with improved PSO and CNN models. At [10] used PSO to reduce and optimize obtained features of Vehicle images but our model improves PSO with medical images. At [11] used a monkey data set but used PCA and five augmentation techniques but our proposed model used more than ten data augmentation and PSO. According to [14] used particle swarm optimization (PSO) to search for optimal CNN architectures applied to nine datasets publicly available. Results are chosen to evaluate the proposed algorithm and compare it with other deep learning models. In our paper, PSO is used in every model to do feature selection in monkeypox medical images. Fig.1 shows the pipeline of the proposed model. This paper used two famous models that achieve good results. These models are inception and VGG. The inception-v3 model has two parts. The first part is featuring extraction using a convolutional neural network. The second part, called the classification part, uses fully connected layers and the SoftMax activation function [17]. In the suggested work, the SoftMax layer was not used in the classification process. The features extracted from the CNN model are extracted and optimized using Particle Swarm Optimization (PSO) and then classified using SVM. The model used was a visual geometric group (VGG16). In 2014, the convolutional neural network (CNN) architecture won the ImageNet competition [18]. It is an excellent vision model architecture to date. The most unique feature of the visual geometric group (VGG16) is that instead of having many hyper-parameters, they focused on having convolution layers of 3×3 filters with a stride of 1 and always used the same padding and max -pool layer of a 2×2 filter of stride 2. Follows this arrangement of convolution and max pool layers consistently throughout the [19].

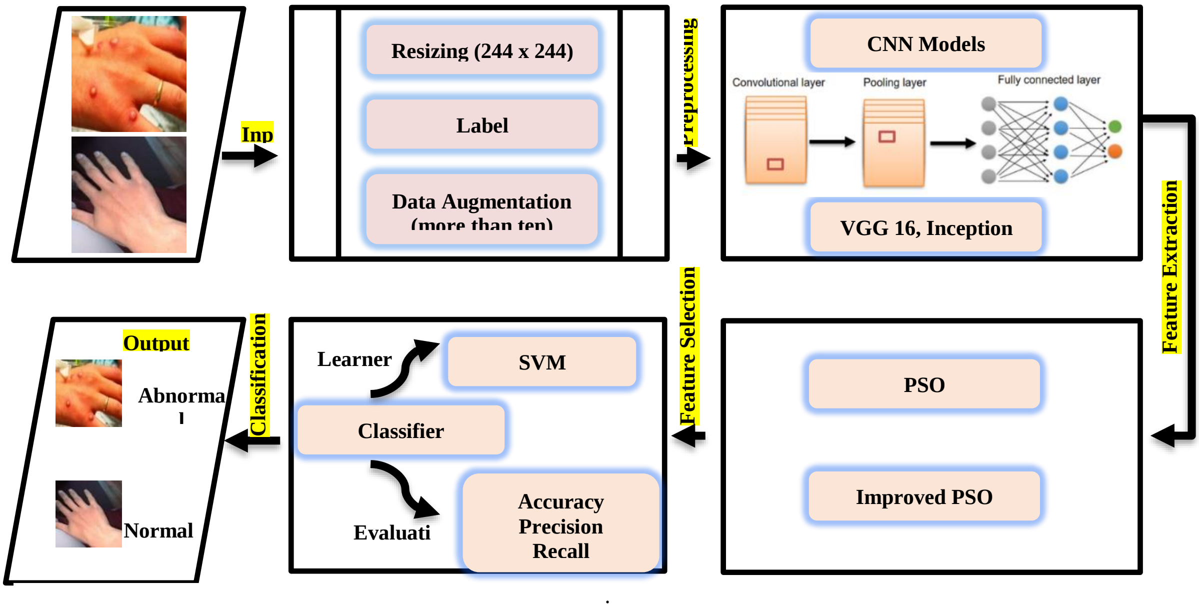


Fig. 1. Proposed method for classification

A. Data preprocessing

The Kaggle dataset used in the proposed model, which originally contained monkeypox images (279 Abnormal, 290 normal). The entire dataset has been developed by the Department of Computer Science and Engineering, Islamic University, Kushtia-7003, Bangladesh [20]. The reason for resizing the image is to reduce the calculations used in the following layers and standardize the different dimensions. The overfitting problem is overcome by rearranging and balancing them using image augmentation techniques. Data augmentation is essential because it prevents models from overfitting, when the initial training set is too small, and the benefits include improved model accuracy, and reduced operational cost of labeling and cleaning up the initial dataset. Samples of data augmentation images are in Fig. 2.

Fig. 2. Samples of data augmentation

B. Feature Extraction

The most important CNN concepts used in the current process.

1) Input layer: It was used to perform a set of pixels that belong to the input data of the image.

2) *Convolutional layer:*The convolution process uses the image input to the filter and passes toon the image pixels to extract the features to create the output function as a feature map for this image, thus reducing the storage space in which each image is stored. The convolution layer performs convolution operations with the output of the previous layer as the input to the current layer.The convolutional layer is the core building block. Used to reduce complexity. There are three hyper parameters: depth, stride, and setting zero padding. Overview of these important parameters.

3) *Pooling layer:* The pooling layer is another building block of CNN. It is executed after each convolutional layer. The aggregation process involves moving a 2D filter over each channel in the feature map as it summarizes the features within the area covered by the filter to reduce the dimensions of the feature map. This reduces the number of tasks that have to be learned and the number of operations performed in the network. Pooling layer types are max pooling and average pooling.

4) *Fully connected layer:* A fully connected layer can be called an assembler, and it can connect and connect all the features in the layers together so that the classification operation can be performed. The fully connected layer is the last layer and takes a long time, the reason is that it collects the data from the previous layers and gives it to the final layer (the output layer). It should be borne in mind, that batch normalization is used to standardize the inputs to the convolutions by calculating the mean and standard deviation across the minimum batch, dropout can also help reduce overfitting.

C. Feature Selection

Particle swarm optimization (PSO) comes from the common action of birds, insects, and also fish. Particles fly around the space to discover a potentially most favorable solution. At first, the particles are placed indiscriminately in the search space [21]. At any iteration, each particle considers its local best-known location ($lbest$) as well as the global best-known position of the particle swarm ($gbest$) to explore the search space. Let assume that v_i^t indicates to the particle velocity χ_i at iteration t , χ_i^t indicates the current location of particle χ_i at iteration t , P_i^t shows to the best solution that particle i th has obtained so far, g^t is the superior solution of the particles population has obtained so far and $\mathcal{W}$ refers to the inertia weight, C_1 and C_2 are cognitive social parameters, r_1 and r_2 are indiscriminate numbers among 0 and 1. Equation (1) shows updating of velocity and new position of particle χ_i is found by equation (2) as the following:

$$v_i^{t+1} = \mathcal{W}.v_i^t + C_1.r_1.(\mathrm{P}_i^t - \chi_i^t) + C_2.r_2.(g^t - \chi_i^t) \quad (1)$$

$$\chi_i^{t+1} = \chi_i^t + v_i^{t+1} \quad (2)$$

The velocity update equation in (1) has three main parts:

- The first part appears as momentum and practice.
- The second part is a linear attractiveness towards the most excellent position ever discovered by the given particle by an indiscriminate weight, referred to as self-knowledge memory.
- The third part is a linear attraction towards the most excellent position discovered by any particle by another indiscriminate weight, indicated to as group knowledge, cooperation, shared information, and social knowledge.

Fig.3 gives a particle update in swarm at the next time where g^t is the most excellent value of the particle fitness.

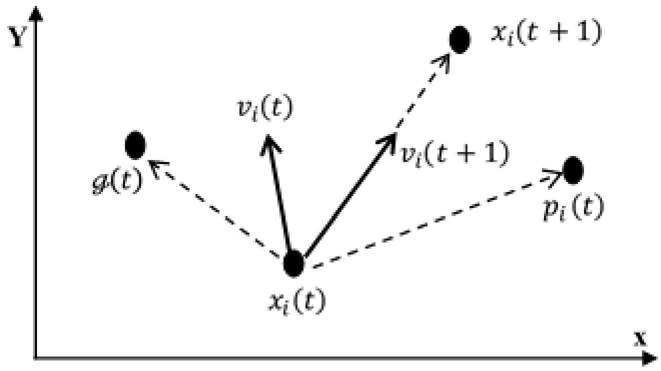


Fig. 1. A particle update in swarm.

The advantage of PSO algorithm is that PSO Particles update themselves with the internal velocity. They also have memory, which is important to the algorithm and does not have genetic operators like crossover and mutation like Genetic Algorithm (GA). The pseudo-code of PSO is detailed as Algorithm 1:

Algorithm 1. Particle Swarm Optimization (PSO)	
Input	put parameters: $\mathcal{W} = 0.99$, $C_1 = C_2 = 2$, $t = 0$,
Step 1	Generate initial population's positions χ_i and velocities ν_i^t
Step 2	Evaluate all χ_i
Step 3	Initialize P_i^t and g^t according to the evaluation results;
Step 4	While (not meet the stop conditions)
Step 5	For $i = 1$: N all N particles
Step 6	Update ν_i^t and χ_i according to Eqs. (2) and (3), respectively
Step 7	If $\mathrm{fit}(\chi_i) < \mathrm{fit}(P_i^t)$
Step 8	$P_i^t = \chi_i$; $\mathrm{fit}(P_i^t) = \mathrm{fit}(\chi_i)$;
Step 9	If $\mathrm{fit}(\chi_i) < \mathrm{fit}(g^t)$
Step 10	$g^t = \chi_i$; $\mathrm{fit}(g^t) = \mathrm{fit}(\chi_i)$;
Step 11	End If

Step 12	End If
Step 13	End For
Step 14	$t = t + 1$
Step 15	End While
Step 16	Post process results
Step 17	End
Output	New optimization for global location

* fit (χ_i) is the fitness of individual χ_i.

The improved PSO algorithm aims at reducing the number of iterations required to reach the optimal fitness value. Improved PSO updated positions according to equation (3) and equation (4).

$$v_i^{t+1} = \mathcal{W}.v_i^t + sin(\mathrm{P}_i^t - \chi_i^t) + sin(g^t - \chi_i^t) \quad (3)$$

$$\chi_i^{t+1} = \chi_i^t + v_i^{t+1} \quad (4)$$

The importance of the benchmark functions is to evaluate of the suggestion algorithms and their characteristics such as accuracy, convergence rate and overall performance [22].

D. Classification

Support Vector Machine (SVM) is used for classification and regression processes. The goal of the SVM algorithm is to discover a hyperplane in an N-dimensional space. Features number responsible for hyperplane dimension. When the number of input features takes two, then the hyperplane is a line. If the number of input features is three, then the hyperplane becomes a 2-D plane. The SVM has a kernel called a function that takes low-dimensional input space and transforms it into higher-dimensional space. After features appear from CNN, they will pass through the SVM classifier [23].

Five evaluation metrics were applied to assess the performance of the proposed method. These metrics were sensitivity (tell us about the percentage of total results which had been truly classified by model), specificity (SPE), accuracy (proportion of correct predication among the total number of cases), precision (tell us about the proportion of input data that are true), and F-score (is the harmonic average of precision and recall). Mathematic representations are:

$$\text{Accuracy} = \text{ACC} = \frac{\text{TP+TN}}{\text{TP+TN+FN+FP}} \text{ X } 100 \quad (5)$$

$$\text{Sensitivity} = \text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \text{ X } 100 \quad (6)$$

$$\text{Specificity} = \text{SPE} = \frac{\text{TN}}{\text{TN+FP}} \text{ X } 100 \quad (7)$$

$$\text{Precision} = \text{PPV} = \frac{\text{TP}}{\text{TP+FP}} \text{ X } 100 \quad (8)$$

$$\mathrm{F-score} = \frac{2TP}{2TP+FP+FN} \times 100 \qquad (9)$$

Where these metrics are evaluated in the terms:

TP=True Positive=both actual data and predicated data are true.

FP=False Positive=actual data is false but class predicated data is true.

FN=False Negative= actual data is true but class predicated data is false.

TN=True Negative= both actual and predicated data are false.

IV. REULTS

The operations belong to proposed model are performed on Intel Core i7 with 16 GB RAM running on Windows 11 OS. Our model uses Keras and TensorFlow libraries. Keras is a deep learning API written in Python that runs on top of the machine learning platform Tensor Flow [24]. It was developed with a focus on enabling rapid experimentation. Being able to go from an idea to results as fast as possible is the key to doing good research. TensorFlow is an open-source software library developed by the Google Brain team. Computing using tensor flow can be executed on a variety of systems[25].

Now, the statistics for the data used will be displayed, as shown in TABLE I. The next step is to present the models and results before and after using the optimized algorithm.

TABLE I. DATA AFTER USING AUGMENTATION.

Data	Images		
	Tasted	*Trained*	*After augmentation*
Monkeypox	55	224	$4256 \ (= 224 \times 19)$
Normal	58	232	$4408 \ (= 323 \times 19)$
Total	113	456	8664

1) *VGG experiments result:*

Fig. 4 shows how the result of the VGG is updated. it started with an accuracy of 85% in part (a) and when we used PSO with VGG get a good result and new accuracy of 91.1%. Part (c) has proposed model VGG and improved PSO with a fantastic result with a result of 94.5%.

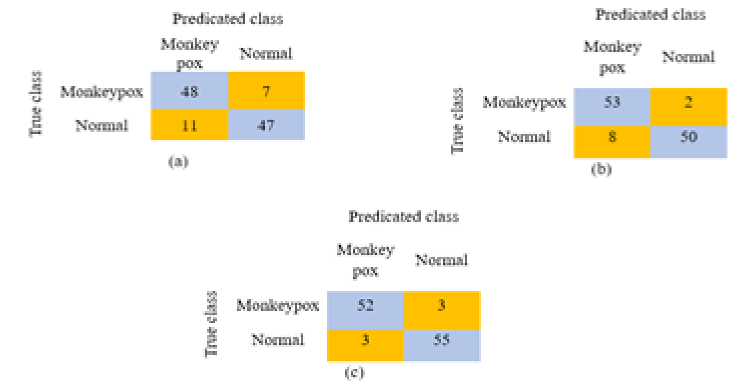


Fig. 1. VGG 16 models result in (a)VGG16 (b)VGG16 and PSO (c)VGG16 and improved PSO.

Now when we express the result, we get from the data given in Fig. 4. We find, in order, in Fig. 5 part (a) a plot of the result of VGG but the plot (b) shows the result of VGG with PSO. Part (c) Plot result for the new VGG and PSO

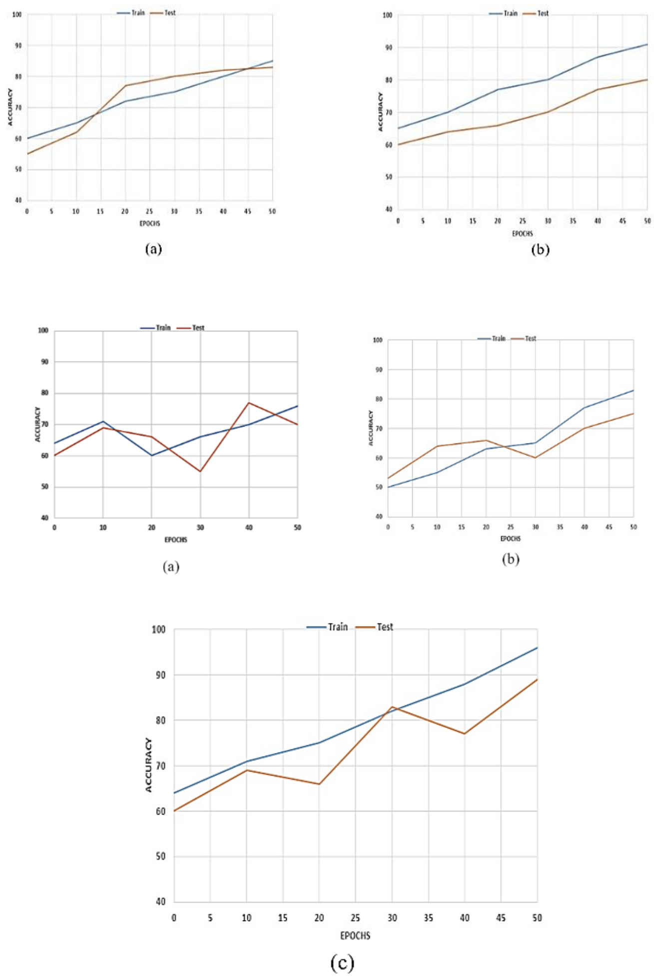


Fig. 5. Samples of train/test plot (a) result of VGG (b) result of VGG and PSO (c) result of VGG and new PSO.

After using the proposed new model, which shows good results, we find in Figure 6 a presentation of some of the details when using the matrix of evaluation.

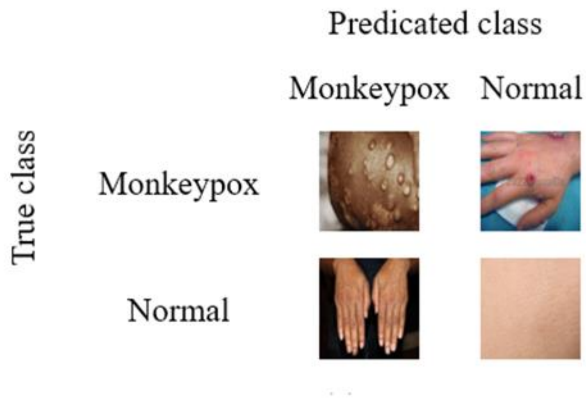


Fig. 3 Samples of visual results for VGG and improved PSO.

2) Inception model experiments result:

Fig. 7 shows how the result of the Inception model is updated. it started with an accuracy of 75.2% in part (a) and when we used PSO with Inception model get a good result and new accuracy of 83%. Part (c) has proposed model VGG and improved PSO with a fantastic result with a result of 90.2%.

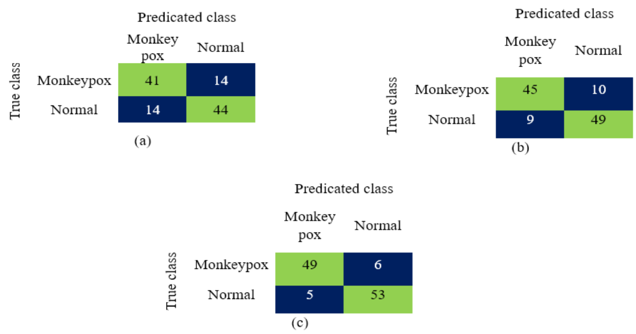
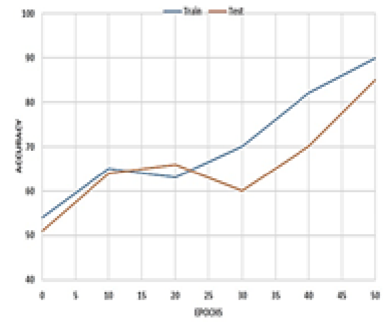


Fig. 1. Inception model result in (a) Inception (b) Inception and PSO (c) Inception and improved PSO.

Now when we express the result, we get from the data given in Fig. 7. We find, in order, in Fig. 8 part (a) a plot of the result of Inception but the plot (b) shows the result of Inception with PSO. Part (c) Plot result for the new Inception and PSO



(c)

Fig. 4. Samples of train/test plot (a)result of Inception (b) result of Inception and PSO (c) result of Inception and new PSO.

After using the proposed new Inception model, which shows good results, we find in Figure 9 a demonstration of some pictures when using the confusion matrix.

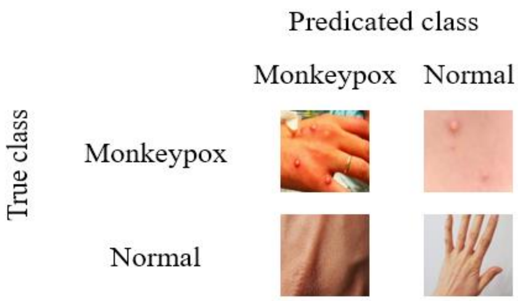


Fig. 1. Samples of visual results for Inception and improved PSO.

After presenting the previous results, it becomes clear to us the importance of VGG Model, which displays an accuracy of 94%, but the Inception model displays an accuracy of 90%. This is not considered a defect in Inception Model, as the beginning before the modification was 75%, and after improvement, the results were raised to 90%, and this in itself is a positive thing.

V.CONCLUSION

The technology can be used to help detect the disease faster and more conveniently. The classification of medical images is a complex matter and is characterized by difficulty, due to the fact that the field of image classification is multiple and very branched. But modern methods and scientific and technological development can help solve problems. The proposed classification system is based on optimizing PSO to classify different images. The steps of data augmentation and filtering are implemented before passing the images to the CNN network, which used the two most famous and best models, VGG and Inception. The ultimate goal of this step was to learn the features and extract them. The most important step is to improve and reduce the features using the optimized algorithm PSO. The final step is to test the selected features and finally classify them using SVM. The reason for choosing SVM in the classification process is accuracy, speed and time consumption.

Now comes the question, what are the possible future actions? To make an improvement on this proposal, it is possible to use the combination of fire fly and PSO algorithms. As a popular idea, it is now possible to use mobile applications with deep learning models in improving and diagnosing medical images. A new fuzzy algorithm can be derived using new medical or other scientific data. We hope that the proposed model will be an auxiliary tool in the classification of medical images.

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