AN ANALYSIS OF DEPP LEARNING APPROACHES WITH IMAGE PREPROCESSING TECHNIQUE TO PREDICT MONKEYPOX

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APPROVAL

This Project titled **"An analysis of deep learning approaches with images preprocessing technique to predict monkeypox"**, submitted by Ritu Biswas and Sayma Islam, ID No: 191-15-2684 and 191-15-2610 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 01 February 2023.

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We hereby announced that this project was completed by us under the guidance of **Al Amin Biswas, Senior Lecturer, Department of CSE,** Daffodil International University. Additionally, we certify that no portion of this project or any element of it has been submitted to another institution for the purpose of receiving a degree or certification.

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ABSTRACT

As the world continues to recover from COVID-19, the virus monkeypox provides a new pandemic intimidation. Monkeypox isn't as deadly or as widespread as the virus of COVID-19, but some new cases are reported regularly from the several nations. Without sufficient precautions, it shouldn't come as a fact if another worldwide pandemic occurs. The efficiency of an automated deep-learning algorithm for categorization was evaluated using the monkeypox dataset. The main objective is to create a deep learning model that will understand the different datasets as accurately as appropriate. First, similar image preprocessing techniques are applied to enhance brightness and contrast for this dataset. As the datasets utilized in this experiment contain few images to effectively train a deep learning model, data augmentation is applied. Then, a VGG-16 model with randomly selected hyperparameters and layer numbers is generated. VGG16, VGG19, MobileNetV2, and ResNet50 are evaluated to determine whether the model yielded the highest performance. VGG16 is utilized as the foundational model because it has the best accuracy. In this work, VGG-16 was utilized to assess its robustness and get the highest accuracy level obtainable. Using image preprocessing algorithms with appropriate parameter values, image quality is enhanced. A total of 770 preprocessed images of monkeypox were augmented using seven approaches, yielding a collection of 1991 images. The model was then evaluated for its robustness. Results were compared to those obtained from previous research. Within a training accuracy of 97.29%, a validation accuracy of 95.26%, and a test accuracy of 96.29%, the VGG-16 model performed the best. VGG19 achieved test accuracy of 95.06%, MobileNetV2 of 94.59%, and ResNet50 of 54.32%. Our proposed algorithm, which relies on preprocessing of images, transfer learning, and adjustment, which shown a high level of accuracy in identifying monkeypox based on a small set of intricate photos. After determining appropriate configuration, this model is trained by using remaining of the data set to evaluate overall performance. We generate and evaluate different performance measures for the monkeypox dataset, including accuracy, precision, recall, specificity, and F1-score.

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CHAPTER 1

Introduction

1.1 Introduction

The virus of monkeypox introduces a new threat which is becoming a worldwide pandemic while the effects of the global COVID-19 pandemic are still being not fully recovered. The monkeypox virus is actually not as harmful or infectious as COVID-19 [1], but every day when more people contract the illness, recorded in several countries. Since the initial infection of SARS-CoV-2 epidemic on July 18, in China, 2022 [2], almost 559 million instances of coronavirus diseases (COVID-19) have been recorded. More than 6 million people have perished this pandemic worldwide. Monkeypox is an infectious disease that has been spreading quickly around the world as the world begins to recover from the devastation brought on by Coronavirus disease (COVID-19). There have been reports of monkeypox outbreaks in 75 nations so far this year [3]. Monkeys and rodents are the main providers, despite the fact that human-to-human transmission is likewise quite prevalent [4]. When trained with a large amount of data, those deep networks can evaluate images in multiple layers, automatically recognizing important attributes and learning to determine the best representations for each of these tasks. In that case of scarcity of data, transfer learning [8] is another method that is usually utilized when there is an insufficient amount of information. In order to transfer A CNN model that has already been trained on a big dataset (like ImageNet) is used to transfer its learning to a separate, relatively smaller dataset for context-specific learning. Automated detection algorithms cannot be developed without a dataset of monkeypox skin lesions. When the privacy and legitimacy concerns has been taken into account, difficulties arise. Furthermore, because of the highest prevalence of monkeypox in the undeveloped regions of Africa, the sample may be biased due to the exceptionally high levels of resemblance between classes and intraclass heterogeneity.

In this study, we first take the monkeypox skin image dataset, which is from the Kaggle public dataset. Additionally, we report a preliminary feasibility analysis using transfer learning and DL for VGG19. Monkeypox is classified by experimenting with several image

pre-processing and deep learning approaches to achieve a promising outcome. The dataset comprises four classes of chickenpox, measles, and normal, monkeypox with a total of 770 images. As a result, many image processing and data enhancement techniques used to improve the image quality and increase the quantity of pictures before getting into the classification in order to overcome these issues. We introduce the deep learning model technique for classification. We trained the VGG19 deep learning model. First, five transfer learning models are trained with the pre-processed dataset, from which two models are selected according to the highest accuracy. To evaluate the performance of all the models, a number of performance metrics are introduced, including Test accuracy, Test loss, Recall, Specificity, Precision, Validation accuracy, Validation loss, Training accuracy, training loss and F1 Scores. For this best model, the test accuracy of the individual classes results from observing any bias in the performance. The over-fitting issue and reliability of the proposed model are assessed by showing the accuracy and loss. Finally, to show the statistical difference between the four classes of our dataset.

The main contributions provided by the above paper are as follows:

- Monkeypox Skin Images dataset with four classes is utilized to predict monkeypox
- Gamma correction, image pre-processing technique is used in the dataset for achieving a good prediction.
- MSE, PSNR, SSIM and RMSE value is find which represents the good quality of image after pre-processing.
- Exploring various deep learning techniques VGG16, VGG19, Resnet50, MobileNetV2 is used to effectively detect the presence of monkeypox
- Developed a fine-tuned VGG16 architecture to get the best accuracy.

The following section consists of eight sections. The Literature review is completed in part II, which also includes the limitations of previous studies. Section III, presents the methodology, section IV describes the results, comparison table and section V presents the discussion and conclusion of this study.

1.2 Problem Statement

There were 5000 occurrences in 2020. Previously, it was believed that monkeypox affected people in Africa, however in 2022, Many nations outside of Africa in Europe and the US reported finding cases of the virus. [5]. The genus Oral orthopox virus is the source of the zoonotic disease known as monkeypox. In relation to clinical traits, it mimics smallpox, measles, and chickenpox. It is very challenging for medical professionals to make an early diagnosis of monkeypox due to the slight variations in the skin rash of these diseases and the relative rarity of this ailment. On the other hand, the confirmatory PCR test is likewise not very common [6]. In recent years [7], due to their superior aptitude for Convolutional neural network (CNN) versions are one of the many deep learning (DL) applications that have revolutionized several areas of medical study. That's why, we conducted this study to address these problems.

1.3 Research Objectives

The main objectives of the paper can be summarized as follows:

a) Using the Monkeypox image dataset, which has four classifications and various characteristics, to categorize monkeypox.
b) To use data augmentation techniques to increase the volume of the datasets.
c) To remove challenging artifacts and improve the quality of the image using various image pre-processing techniques.
d) To propose a fine-tuned VGG16 model by modifying the original compact convolutional transformer model for the efficient classification of monkeypox.
e) To solve the problems of lengthy training times and insufficient amount of data with the VGG16 model.

1.4 Research Questions

a) How can the research gaps in the current machine vision-based systems for appropriately categorizing various pox types be investigated??

b) How can we improve the accuracy of classifying monkeypox according to their class by using an attention-based model that makes use of low time complexity and low resolution images?

1.5 Report Layout

Chapter 1 presents the research introduction, objectives, and key research questions.

Chapter 2 summaries the previous study.

Chapter 3 describes the proposed methodology with a detailed description.

Chapter 4 explains the experimental results and discussion.

Chapter 5 concludes the present research along with a direction for future work.

CHAPTER 2

Background

2.1 Related Works

To improve the efficiency of the performance of the diagnostic-aid system, and classification, many specialists and scholars have conducted research in this area. [9] developed a hybrid architecture based on CNN and LSTM to evaluate the accuracy of the prediction model. On the dataset of monkeypox tweets, the accuracy of the proposed approach accuracy was 94%. Several performance measures, including precision, recall, and F1-score, were used to evaluate their models and findings in the most time- and resource-effective approach. The results are being contrasted to many established machine-learning techniques. The results of this study help the general public become more aware of monkeypox infection. Pre-trained models of monkeypox lesions are vital for deep learning as the authors of a recent paper [6] proposed, the sample size is increased with more data in a 3-fold cross-validation experiment. In the second phase, a number of pre-trained deep-learning models, including InceptionV3, ResNet50, and VGG-16, are used to classify diseases such as monkeypox. Additionally, an ensemble of the three models is created. The overall accuracy of ResNet50 is 82.96(4.57%), followed by VGG16 with 81.48(6.87%) and the ensemble system with 79.26 (1.05%). In this recent paper, [10] proposed that AI-based detection may be able to find them early on. They are ensembled by utilizing a simple majority over the probabilistic outputs they generated to enhance overall performance. They conduct their trials using a publicly accessible dataset, and with the aid of their proposed ensemble technique, they achieve the average precision, recall, F1-score, and accuracy are 85.44%, 85.47%, 85.40%, and 87.13%, respectively. [11] proposed two separate experiments, known as Studies One and Two, which are included in the updated VGG16 model. In Studies One and two, their experimental and computational findings suggest that their proposed model can detect monkeypox patients with an accuracy of 97.2% (AUC = 97.2) and an accuracy of 88.8% (AUC = 0.867), respectively. However, [12] evaluated whether such a TensorFlow model has been transformed to the TensorFlow Lite mobile model. In order to identify monkeypox, the

TensorFlow Lite model was further implemented into the mobile application and the TensorFlow Lite library. Three devices have successfully executed the application. During execution, inference times were collected. There have been observations of average inference times of 197 ms, 91 ms, and 138 ms. The provided approach enables individuals with skin lesions to make a fast preliminary evaluation. Thus, monkeypox-infected individuals should attend an expert immediately for a definite diagnosis. The system has a 91.1% accuracy for classifying images, according to the results of the tests. Other authors [13] develop and compare five deep learning models with integrated channel and spatial attention approaches (VGG19, Xception, DenseNet121, EfficientNetB3, and MobileNetV2). With a validation accuracy of 83.89%, an architecture composed of Xception-CBAM-Dense layers outperformed other models in classifying monkeypox and other diseases. The author's [14] evaluated ensemble approach on a publicly available dataset provided average "Precision", "Recall", "F1-score", and "Accuracy" values of 85.44%, 85.47%, 85.40 %, and 87.13 % respectively. [15] Experiments with the ResNet-50 model, trained on widely different and curated skin rash image datasets, demonstrate a classification accuracy of 95.2%, a sensitivity of 81.7%, and a specificity of 97.7%, respectively, for classifying transfer learning to generate deep convolutional neural networks (CNNs) for distinguishing measles rash from other skin conditions. This demonstrates the experiment's effectiveness in providing accurate measles detection, which is crucial for identifying outbreaks. The performance of the smaller CNN model MobileNet-V2 on a collection of image data is also described. The proposed smartphone application should also be used for the early diagnosis of several other skin disorders. Using a web-scraping-based collection of healthy skin images as well as images of monkeypox, chickenpox, smallpox, cowpox, measles, and other viruses, the researcher analyzed the viability of installing reducing AI deep models on skin images for monkeypox identification. They discovered that deep AI models can detect monkeypox with an 85% average accuracy using computerized skin images was evaluated by [16].

CHAPTER 3

Research Methodology

3.1 Proposed Methodology

The procedure involves five parts, which are elaborated on in the following sections: image processing, data augmentation, model building and robustness assessment. First, a thorough explanation of the datasets is provided. The entire procedure is illustrated in Figure 1 in broad strokes.

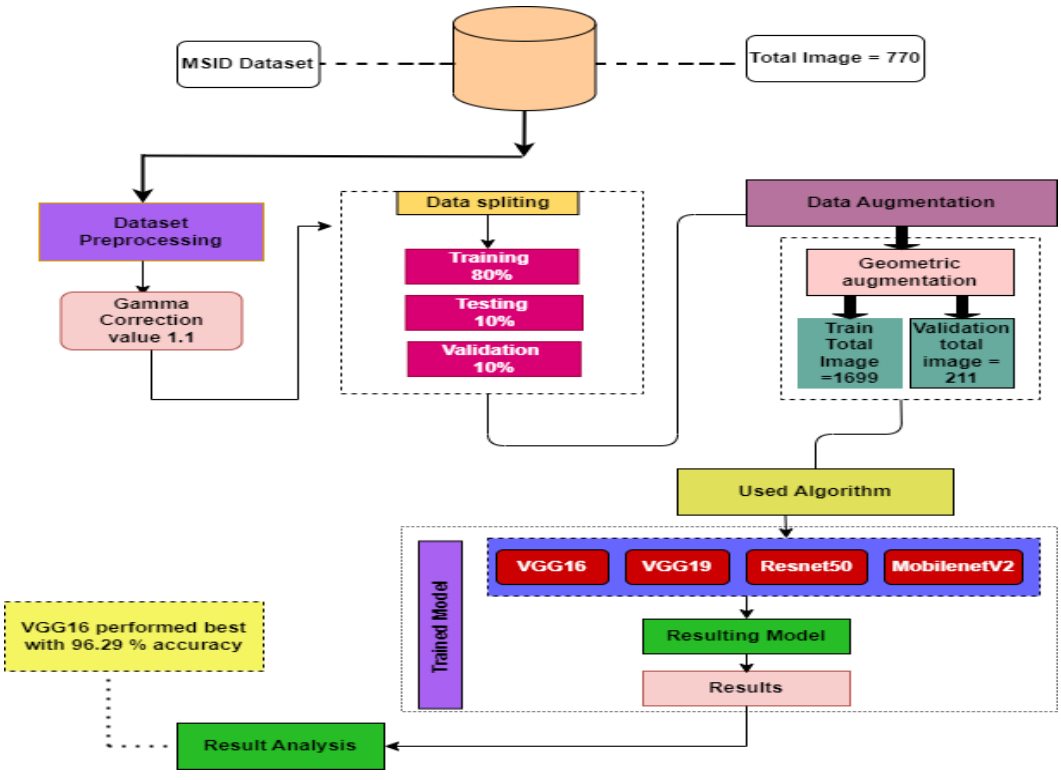

Figure 1: Workflow of entire classification process

As mentioned before, MSID dataset was taken. All images of the dataset are preprocessed. With a value of 1.1, gamma correction is applied. The preprocessed data are statistically analyzed making use of Mean Squared Error (MSE) and Root Mean Square Error (RMSE). Deep learning models often need a lot of training data; however, these data aren't always available, in order to make accurate predictions. Therefore, image augmentation is done in order to expand the dataset volume and create a more generalized model. Geometric augmentation is applied to increase the dataset. Firstly, the dataset is divided into train set, validation set and test set using an 80:10:10 ratio. Augmentation is applied only the train or validation dataset. The model is created with the ideal configuration, and then it is trained on the MSID datasets to see how it performs. The dataset is used to train the transfer learning models VGG16, VGG19, MobilenetV2, and ResNet50. Among these models VGG16 obtained best accuracy. Several performance metrics are used to assess the outcomes of each experiment, including the Mean Absolute Error (MAE), False Positive Rate (FPR), False Negative Rate (FNR), False Discovery Rate (FDR), and Root Mean Square Error (RMSE).

3.2 Dataset Description

This study examines a total of 770 monkeypox skin images from the Kaggle monkeypox skin images (MSID) dataset [17].This monkeypox skin images dataset is divided into four categories: Chickenpox, Measles, Monkeypox and Normal, including 107 Chickenpox images, 91 Measles images, 279 monkeypox images and 293 Normal images. The images have 224 x 224 pixel dimensions and are in the PNG format. Table 1 provides a summary of the dataset's description.

Table 1: Description of the monkeypox skin images (MSID) dataset utilized in this research.

Name	Description
Total Number of images	770
Chickenpox	107
Measles	91
Monkeypox	279
Normal	293
Image ratio	224 X 224
Format	PNG
Image types	monkeypox skin images
Color grading	RGB

In Figure 1 it is showing the percentages of the normal vs disease. 14% people are affected with chickenpox, 12% people are facing measles, 36% people are suffering from monkeypox and 38% people are normal. Sample images of the different classes of monkeypox skin images (MSID) datasets are shown in Figure 2.

Figure 2: Sample images of MSID dataset for each classes.

3.3 Data Preprocessing

Image pre-processing is a crucial step in order to achieve appropriate accuracy and reduce a model's computational complexity. Gamma correction image preprocessing methods are used. Before providing the images to the neural network, image pre-processing is considered to be the most effective process in order to obtain adequate accuracy and reduce computing time.

3.3.1 Gamma Correction

Gamma correction utilizes a nonlinear transformation to adjust an image's overall brightness and contrast in order to improve its resolution [18]. This technique is used to make the monkey pox lesion line up against a dark background. Gamma correction is used to enhance when light and dark regions are distributed [19].

The following equation 1 is used to implement the algorithm:

$$o=g^{(1/g)} \quad (1)$$

where g > 1 indicates that the details are being brightened.

g = 1 indicates there is no effect.

g < 1 indicates a darkness of the details.

Equation 2 represents a power law transformation, where a and b are image coordinates.

$$g(a,b)= [f (a,b)]^{\gamma} \quad (2)$$

We determined an appropriate gamma value of 1.1 by analyzing with various gamma values for the images, as illustrated in Figure 3

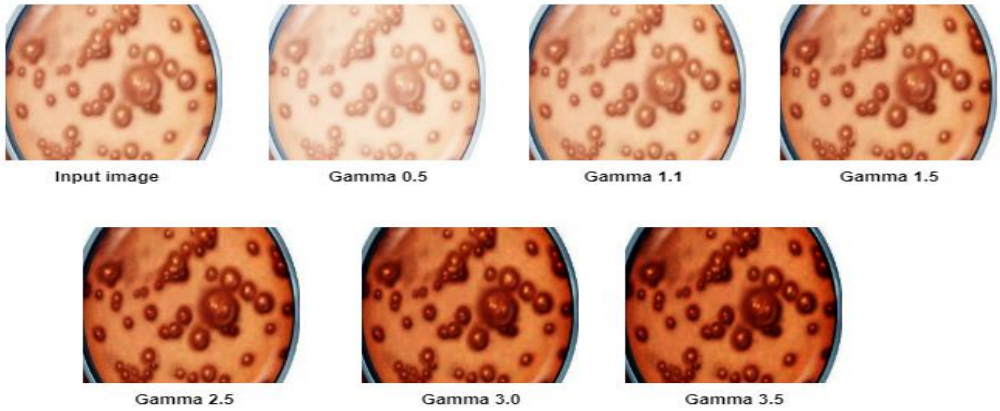

Figure 3: Trying out a variety of gamma values as an experiment

Gamma values greater than two cause the image to darken and cause pixel information to be lost. The image is discovered to be fading for gamma 1. Disease area are less noticeable in both situations, which could affect how well VGG performs. By testing with a few different values, it is possible to choose an appropriate gamma value. For certain datasets, a universal value of 1.1 might not be appropriate, but in this instance it is. The output is then scaled back to its initial range of [0, 255].

3.3.2 Image Quality Measurement

Image quality may be impacted by the image processing procedures. Statistical analysis is carried out to make sure the image quality is not diminished [20]. For each image in the dataset, we have determined the MSE, PSNR, SSIM, and RMSE values.

MSE, or the total squared error, has a value range between 0 and 1 and is used to define the pixel-to-pixel difference between the two pictures that are being compared. For good image quality, the score should be near to 0. Values greater than 0.5 signify a decline in quality

$$MSE = \frac{1}{pq}\sum_{i=0}^{x-1} \quad \sum_{j=0}^{y-1} \quad \big(A(x,y), -B(x,y)\big)^2 \tag{3}$$

where A is the original image and x and y represent the rows and columns of the pixels of A and B, respectively (the "ground truth").

PSNR

The PSNR metric measures the relationship between the highest signal intensity and the amount of noise that impairs the level of an image processing. The value of MSE must first be established. The following formula is then used to compute PSNR.

$$PSNR = 20\left(\frac{(MAX)}{\sqrt{MSE}}\right) \quad (4)$$

The maximum pixel value for the image is MAX (i.e., 255). Typically, a decent 8-bit image's PSNR values fall between 30 and 50 dB.

SSIM

The effectiveness of pre-processing techniques on image quality is measured by the SSIM. It's between the numbers 0 and 1, where 0 means "no similarity" and 1 means "complete structural similarity."

$$SSIM(p,q) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (5)$$

RMSE

The RMSE algorithm determines the quality difference between the original and treated photos. A lower RMSE, especially values almost zero, denotes fewer mistakes and better image quality.

$$RMSE = \left[\sum_{j=1}^{N} \quad \frac{(m_{fi}-m_d)^2}{N}\right]^{\frac{1}{2}} \quad (6)$$

Table 2 denotes the MSE, PSNR, SSIM, RMSE values of 5 images.

Original Image	MSE	PSNR	SSIM	RMSE
1	0.02	44.22	0.992	0.2
2	0.70	29.66	0.989	0.8
3	0.56	30.57	0.994	0.7
4	0.66	29.88	0.994	0.8
5	0.68	29.78	0.995	0.8

3.4 Dataset Split and Augmentation

Data is initially divided into validation, train, test and with a ratio of 80:10:10, respectively, before data augmentation is performed. In the training set there are 1699 images, 211 images for the validation set, and 81 images for the test set are obtained after splitting. In addition to the number of images in each class, Table 3 showing the number of images in the training, validation, and test sets.

Table 3: Distribution of images from each class throughout the train, validation and test set.

Dataset after splitting	Total image	Chickenpox	Measles	Monkeypox	Normal
Train	1699	171	145	446	937
Validation	211	21	18	55	117
Test	81	12	10	29	30

In regard to data augmentation, the test set is left excluded and only the training and validation sets are enhanced. There were insufficient images in the initial dataset for each class, which might cause overfitting issues and decreased classification accuracy. A common technique is data augmentation, where various methods can enhance the number of images. In this approach, the information included in the original images is not altered,

and because the amount of the dataset has expanded, deep learning performance has a propensity to improve. In order to increase the quantity of pictures by eight times, the preprocessed dataset in this study is applied to seven geometrical augmentation techniques, including vertical flipping, horizontal flipping, horizontal-vertical flipping, custom rotation ang - rotating 30°, custom rotation ang - rotating 30°-horizontal flip, custom rotation ang - rotating 30°, and custom rotation ang - rotating 30°. Table 4 showing the number of images after and before augmentation.

Table 4 shows the number of images after and before augmentation

SL No.	Dataset Split	Before Augmentation	After Augmentation
1.	Test	81	81
2.	Train	614	1699
3.	Val	75	211
		Total=770	Total=1991

3.5 Proposed Model

Obtaining a prospective classification accuracy is rather challenging since monkeypox has concealed and complicated lesion and features in an image. To select the most appropriate deep learning model with the best performance, experiment transfer learning model selection and model are conducted accordingly. However, the hypermeter and training method used to train the models are the same.

Training Strategy

Table-5 shows the training parameter for VGG 16 model. Each model is initially trained for 30 epochs and a batch size of 32 using the optimizer Adam and a learning rate of 0.001 before performing experiments. Additionally, the loss function is also categorical cross-entropy. In the case of research, the best model configuration is obtained after testing

methods. As a result, the previously chosen hyper-parameters are modified, and the ideal model configuration is discovered.

Table-5 Training Parameter for fine-tuned VGG16 model

Parameters	**Description**
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Loss Function	Categorical Cross-entropy
Epochs	30
Activation Function (Hidden layer)	Relu
Activation Function (Output Layer)	Softmax

Transfer Learning Model Selection

To evaluate their effectiveness in terms of the highest test accuracy, four transfer learning models—named VGG19, VGG16, ResNet50, and MobileNetV2—were trained using the preprocessed dataset. These models are often utilized in several image classification tasks, especially in the area of medical imaging. With regard to monkeypox categorization, several research has been carried out throughout time utilizing these models, and in the majority of cases, a promising result has been obtained. The networks from VGG19, VGG16, ResNet50, and mobilenetV2 had the highest accuracy levels after being trained with our dataset. As a result, these models are chosen for the exploration of further techniques.

Transfer Learning Model

To identify which model performs the best, four pre-trained models—MobileNetV2, ResNet50, VGG16, and VGG19—are trained on training data and assessed on testing data.

MobilenetV2

The Google community proposes MobileNetV2. Each block consists of three levels and two distinct sorts of blocks. The second layer in both blocks is a depthwise convolutional layer, while the first and third layers in each consist of 11 layers of convolutional filters total 32. A rectified linear activation function is used in each layer (ReLU). Longitudinal bottlenecks between layers are crucial to avoid non-linearity from corrupting a significant amount of data. [21]. Block 1 has a one-step stride, whereas Block 2 has a two-step stride, making this distinction between the two blocks.

ResNet50

To address the CNN models' deterioration problem and the training time issue brought on by deep structure, the ResNet50 design combines convolution filters of varying sizes. In addition to a maxpool layer and an average pool layer, ResNet50 has 48 convolutional layers. This framework has about 23 million trainable parameters.

VGG16

DCNN model VGG16 was proposed by Simonyan and Zisserman [22]. After obtaining top-five test accuracy using the ImageNet dataset, the model was declared the winner of the Large-Scale Visual Recognition Challenge (ILSVRC) contest held by the Oxford Visual Geometry Group. [23]. The VGG model's greater depth can help the kernel understand more intricate features. It was discovered in studies on the efficiency of transfer learning [24] revealed a pre-trained and fine-tuned VGG16 delivered a much greater accuracy compared to a fully trained network.

VGG19

The VGG model comes in a variety called VGG19, which has a total of 19 layers. At the summary of Three more FC layers with a combined total of 4096, 4096, and 1000 neurons

are present in the VGG16 model. A Softmax layer and five Maxpool layers are also included. ReLU activation functionality is built into the convolutional layers.

3.6 VGG16 Architecture

The optimized VGG16 architecture produces the best classification accuracy out of the four architectures mentioned above. As a result, we suggest the model, which is based on a tuned VGG16 architecture and has been tested on our dataset in a number of ways to assess its performance. Figure 5 depicts the model's architecture

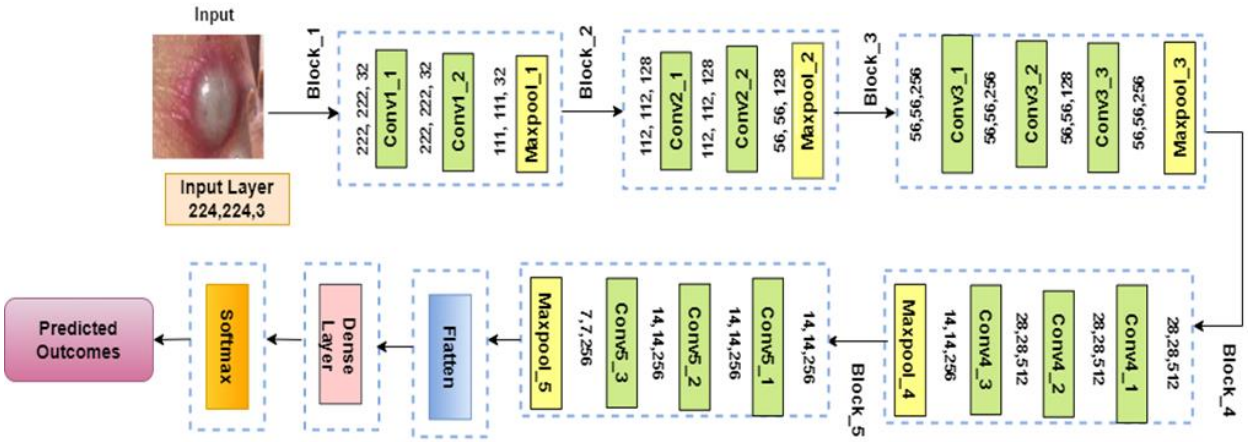

Figure 4: Fine-tuned VGG16 architecture

The original VGG16 has a depth of 23 and 16 layers, as indicated by its name. There are two to three convolution layers and a Maxpooling layer in each of its five blocks. An array of input data is multiplied by a two-dimensional array of weights, which is frequently referred to as a filter or kernel, to perform a convolution layer's function.

$$(x * y)\{n\} = m \sum k=1\ y(k) \cdot x(n - k + m/2) \qquad (7)$$

In this case, the input function is denoted by y(), the kernel function by x(), and the dot product of y() and x() across the set of variables denoted by (x * y) is denoted by (x * y). Once the feature matrix has been obtained By using filters or kernels, the Maxpooling layer compacts the maps created by the convolution layer. Following the application of the filter on the input matrix with an input image size of (m x m) and a filter size of ((x * x)), the output size is as follows:

$$(m \times m) * (x \times x) = (m - x + 1) \times (m - x + 1) \quad (8)$$

After the sixth block of VGG16, a thick, flat layer is added to create this model. We use 224 x 224 x 3 as the input dimension for the first convolutional layer because the architecture's input layer needs the RGB image's size to be 224 224 x 3. In this case, the first block consists of the same padding, two convolutional layers, each with 64 channels, a 3 by 3 kernel size. The layer after that is a Maxpooling layer with a stride of 2 by 2. In the second block, which comes after the first, there are two convolution layers with a total of 128 channels and a kernel size of 3 x 3.

CHAPTER 4

Experimental Results and Discussion

4.1 Result and Discussion

This section describes the results of this research are explained, including the outcomes of numerous ablation experiments and model validation metrics. This part also includes a description of the accuracy loss curves and confusion matrix to further examine the efficacy of the transfer learning models.

Evaluation Metrics

A range of performance indicators, such as train accuracy, training loss, validation accuracy, validation loss, test accuracy, test loss, recall, specificity, and precision, as well as F1 scores, are analyzed to assess the effectiveness of each technique. The outcome (FN) is determined by the confusion matrix created from the values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Additionally calculated are the Matthews correlation coefficient, the positive predicted value (PPV), the negative predicted value (NPV), and the true positive rate (TPR), as well as the true negative rate (TNR) (MCC). The confusion matrix scores for true positive (TP), true negative (TN), false positive (FP), and false negative determine the categorization outcomes (FN). The formula for the performance metrics can be specified as follows:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{9}$$

$$\text{RecaIl} = \frac{\text{TP}}{\text{TP+FN}} \tag{10}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{11}$$

$$\text{F}_1 = 2\,\frac{\text{precision}*\text{recall}}{\text{precision+recall}} \tag{12}$$

After the training procedure is completed, confusion matrices are developed to detect whether or not there is any bias present. The values in the sections indicate the labels that were actually applied to the test images, although the values in the columns represent the labels that the model generated and applied to the test set images. The confusion matrix shows horizontal values based on whether frequently the model correctly predicted the test images. Figure 6 shows the reader the confusion matrices generated by the VGG16 model.

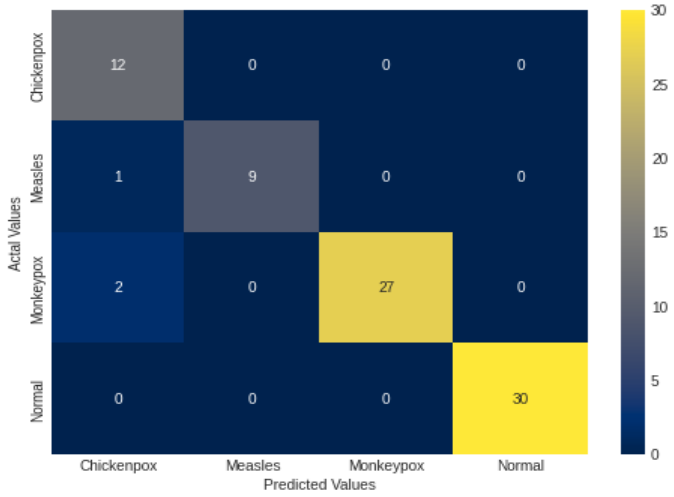

Figure 5: Confusion matrices for VGG16

The model does not favor any particular class over another, nor does it forecast any particular class more accurately than the others. The model's robustness is demonstrated by the nearly same proportions of accurate predictions it makes for each class. Figure 7 shows the confusion matrices for ResNet50, MobileNetV2, and VGG19.

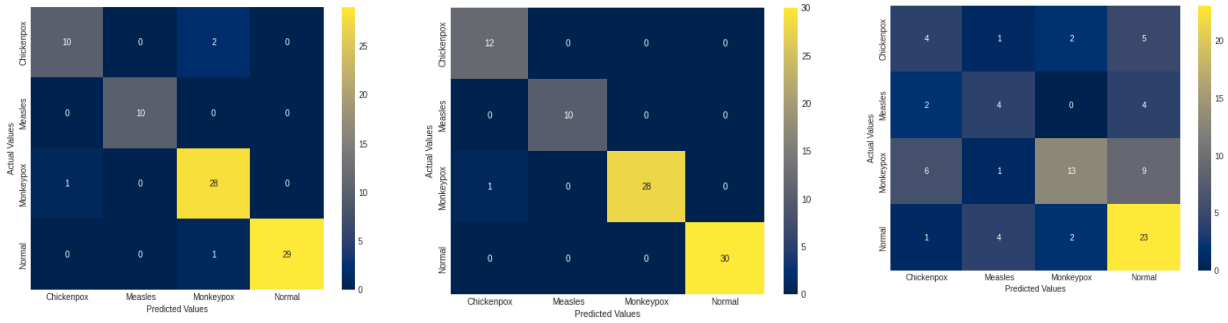

Figure 6: confusion matrices of VGG19, MobileNetV2, ResNet50.

Accuracy and loss curves for the monkeypox dataset were created during the training process to evaluate overfitting concerns. The accuracy curve and loss curve for the monkeypox dataset are shown in the figure 7

Figure 7: Accuracy curve and loss curve for VGG16

Figure 7 demonstrates the proposed VGG16 model's accuracy and loss curves for the dataset. It is visible that the accuracy and loss curves approach in a highly organized sequence from the beginning to the completion of the experiment, with no significant breaks in consistency mostly along approach. This indicates that the training procedure did not cause overfitting.

The loss and accuracy curves for the following three transfer learning models. These models have no overfitting issues. Figure 8 depicts the loss and accuracy curves for VGG19, MobileNetV2, and ResNet50

a) Accuracy and loss curve of VGG19

b) Accuracy and loss curve of MobileNetV2

c) Accuracy and loss curve of ResNet50

Figure 8. accuracy and loss curve of VGG19, MobileNetV2, ResNet50

The results of each of the four models are shown in Table 5. With a result of 96.29% and a test loss of 0.1221, it appears that the VGG16 model had the highest test accuracy. Additionally, VGG16 achieved 95% precision, 95.76% recall, 98.91% of specificity and 95.39% F1 score. For VGG19, the relative testing accuracy value is 95.06% which is near to the VGG16 model. In addition, the precision, recall, specificity and F1-score of VGG19 model are respectively 95.30%, 94.34%, 98.19% and 94.72%. 94.59% of MobileNetV2's test findings were accurate. The precision, recall, specificity and F1-score of MobileNetV2 model are relatively 94.30%, 93.57%, 95.63% and 96.60 %. With an accuracy of 54.32 %, ResNet50 performed badly. These outcomes (Table 4) show that VGG16 performed consistently well on our dataset and is capable of performing classification tasks. In order to create a more reliable model for this classification problem, we choose VGG16 as our model. All transfer learning models' results are shown in Table 6

Table 6: Showing all the result of transfer learning models

Classifier Name	Precision (%)	Recall (%)	Specificity (%)	F1-score (%)	Test_Accuracy (%)
VGG-16	**95.0**	**95.76**	**98.91**	**95.39**	**96.29**
VGG-19	95.30	94.34	98.19	94.72	95.06
MobileNetV2	94.30	93.57	95.63	96.60	94.59
ResNet50	50.83	48.71	83.88	49.75	54.32

4.3 Comparison with Previous Literature

Ali et al. [6] based on the Adam optimizer, batch sizes of 16, and learning rate of 0.00005, obtained an accuracy of about 82.96%. Sitaula et al. [10] obtained an accuracy of 87.13%, a precision of 85.44%, a recall of 85.47%, and an F1-score of 85.40% based on Ensemble models for VGG-16, VGG-19, ResNet-50, ResNet-101, IncepResNetv2, MobileNetV2, InceptionV3, Xception, EfficientNet-B0, EfficientNet-B1, EfficientNet-B2, DenseNet-121, and Adam as optimizer with. As described, Haque et al. [13] achieved 83.89% accuracy a binary crossentropy that computes the loss in cross-entropy between true labels and predicted labels, with the accuracy measures, using the Adam optimizer, batch sizes of 32, and a learning rate of 0.001%. Other researchers Sahin et al. [12] and Mohbey et al. [9] obtained an accuracy of 91.11% and 94% respectively.

The drawbacks of earlier studies can be overcome by our approach. The picture preparation procedures and parameter settings used in this study were selected after thorough testing with our dataset. The number of images has raised from 770 to 1991 by utilizing geometrical augmentation in place of it. We propose a VGG16 model by optimizing its performance for improved accuracy. Maximum accuracy of 96.29 % is achieved with a batch size of 32, 30 iterations, and a learning rate of 0.001 using the Adam optimizer. Table 7 shows a comparison of our model with existing work.

Table 7 shows a comparison of our model with existing work.

Reference	**Year**	**Model**	**Dataset**	**Batch size**	**Epochs**	**Optimizer**	**Learning Rate**	**Best performance**
Ali et al. [6]	2022	ensemble of the 3 models-there are: VGG16 , ResNet50, InceptionV3	Monkeypox Skin Lesion Dataset (MSLD)	16	-	Adam	0.00005	Highest accuracy 82.96(±4.57%)
Sitaula et al. [10]	2022	ResNet-50, ResNet-101, IncepResNetv2, MobileNetV2, InceptionV3, Xception, EfficientNet-B0, EfficientNet-B1, EfficientNet-B2, DenseNet-121, and DenseNet-169 are ensemble models.	monkeypox dataset	16	-	Adam	0.0001	87.13%
Haque et al. [13]	2022	Xception-CBAM-Dense	Monkeypox skin lesion	32	-	Adam	0.001	83.89%
Sahin et al. [12]	2022	Convolutional Neural Networks (CNN)	monkeypox dataset	-	60	-	-	91.11%
Mohbey et al. [9]	2022	CNN	monkeypox dataset	-	-	-	-	94%
Our work		**VGG16**	**Monkeypox Skin Lesion Dataset (MSLD)**	**32**	**30**	**Adam**	**0.001**	**96.29%**

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Smallpox is a highly contagious and sometimes deadly disease that has been eradicated globally through a coordinated effort by the World Health Organization (WHO). However, the threat of Monkeypox as a biological weapon still exists, making the development of a Monkeypox prediction system important for public health and national security.

A Monkeypox prediction system would use advanced data analysis and machine learning techniques to monitor for potential outbreaks of Monkeypox and provide early warning to public health officials. This would enable them to take prompt action to contain the spread of the disease, vaccinate those at risk, and implement other measures to prevent an outbreak.

The impact of a Monkeypox prediction system on society would be significant, as it would provide an added layer of protection against the spread of this dangerous disease. It could also help to reduce the social and economic costs associated with Monkeypox outbreaks, by enabling public health officials to respond quickly and effectively to contain and control the spread of the disease.

5.2 Impact on Environment

As smallpox is a human disease and does not affect the environment directly, the impact of a Monkeypox prediction system on the environment would likely be minimal. However, the implementation of a Monkeypox prediction system could potentially have indirect effects on the environment, such as the use of resources for the development and maintenance of the system, or the potential release of pollutants during its production or operation.

It's also important to consider the potential environmental impact of any response to a Monkeypox outbreak, such as the mass vaccination of populations or the use of insecticides to control the spread of the disease. These interventions could potentially have negative impacts on the environment, such as the release of pollutants or the disruption of ecosystems.

Overall, the impact of a Monkeypox prediction system on the environment would likely be minimal, but it's important to consider both the direct and indirect effects of such a system and to minimize its impact on the environment where possible.

5.3 Sustainability Plan

Here are some potential components of a sustainability plan for using computer vision for the early detection of Monkeypox:

Energy efficiency: Ensuring that the computer systems and other equipment used for the diagnostic process are energy efficient can help to reduce the environmental impact of the process.

Use of renewable energy: Using renewable energy sources, such as solar or wind power, to power the computer systems and equipment used for the diagnostic process can further reduce the environmental impact.

CHAPTER 6

Conclusion and Future Work

6.1 Conclusion

Without early diagnosis and treatment, monkeypox can rapidly progress and be fatal. Using datasets, the purpose of this study is to develop a system capable of identifying and classifying monkeypox lesions. Analyzing several variables was the main goal of this study. four distinct types of data using a single computer vision and deep learning framework. This challenge is effectively created by adding image preprocessing methods and studies on data augmentation. The approach begins with the development of a base model, followed by an evaluation of the model using the monkeypox dataset, which is usually considered as the most challenging dataset available. The suggested VGG-16 model is created and afterwards trained on the datasets. No indication of overfitting is found for any dataset which is demonstrated by the accuracy, loss curves. A test accuracy of 98.29% for the Monkeypox Skin Images Dataset (MSID) dataset was achieved.

6.2 Limitation and Future Work

Despite a positive outcome, the dataset is not big enough for the model. Absence of actual data. A model that is more accurate and reliable might be included in future suggestions. To aid the model beneath the ROI, a variety of image preprocessing and augmentation approaches can be used. Work on segmentation might take many different forms. The model can be used to research further diseases. A comparable smartphone app will eventually be created to identify skin cancer and show people skin data.

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