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Abstract - There are numerous conditions that affect people moment, some of which are delicate to treat and only a small number of which can be cured. Due to its quick spread to further than 40 countries, the rearmost monkeypox outbreak has raised public health enterprises. Monkeypox can be delicate to diagnose clinically in its early stages since it resembles both chickenpox and measles. Computer- supported monkeypox lesion discovery may be useful for monitoring and quick identification of suspected cases when confirmational Polymerase Chain response assays aren't fluently accessible. Under the condition that there are enough training exemplifications available, deep literacy ways have been demonstrated to be useful in the automated identification of skin lesions.

***Keywords* – Deep Learning , Inception v3, MobileNet V2, ResNet Models.**

I.INTRODUCTION

In international societies, the most recent multi-country monkeypox outbreak has raised concerns as the world starts to recover from the COVID-19 pandemic. Although the World Health Organisation (WHO) did not categorise the pandemic as an emergency, it did say that it poses a moderate threat to public health globally. But healthcare institutions like the World Health Network (WHN) expressed a higher degree of anxiety and stressed the necessity for an immediate, all-encompassing global response to the epidemic. The orthopoxvirus is the cause of the zoonotic disease pox. Regarding its clinical features, it resembles chickenpox, measles, and smallpox quite closely. Early diagnosis of this condition has proven to be rather challenging for healthcare professionals due to the relative rarity of the pox and the minor changes in the skin rash associated with these illnesses.

II.LITERATURE REVIEW

The World Health Network [1] The World Health Network issues a statement requesting swift and efficient action from national and international health authorities to stop monkeypox from becoming a catastrophe. To establish a concentrated effort across several nations or the whole world to avert widespread harm, a pandemic must first be declared. A pandemic is defined as an infectious illness that spreads widely, crosses international borders, and typically affects a lot of people. The requirement for declaring a pandemic is met by the epidemic's rapid expansion over several continents and the requirement for coordinated action to halt it. Global cooperation is required.

F. WangL.P. Casalino, et al.[2] Although deep learning is a powerful analytic tool for the complex data contained in electronic inferior in some healthcare applications. In this paper, a brief overview of the limitations of deep learning is illustrated through case studies done over the years aiming to promote the consideration of alternative analytic strategies for healthcare.

K. M. Hosny, et al. [3] Transfer learning has been used to improve the Alex-net in a variety of ways, including as adjusting the architecture's weights, swapping the classification layer with a softmax layer that can recognise two or three different types of skin lesions, and enhancing the dataset with fixed and random rotation angles. The segmented colour picture lesions may be classified by the new softmax layer as either melanoma and nevus or melanoma, seborrheic keratosis, and nevus. The performance of the suggested approach and the current methods are compared using the accuracy, sensitivity, specificity, and precision measurements.

C. Szegedy, et al. [4] In this paper we are exploring ways to scale up networks in ways that aim at utilizing the added computation as efficiently as possible by suitably factorized convolutions and aggressive regularization. We benchmark our methods on the ILSVRC 2012 classification challenge validation set demonstrate substantial gains over the state of the art.

C. Shorten, et al. [5] In this survey, the use of augmentation techniques based on GANs is extensively discussed. This study will briefly cover various aspects of data augmentation, such as test-time augmentation, resolution impact, final dataset size, and curriculum learning, in addition to augmentation approaches. This survey will outline current Data Augmentation techniques, exciting new research, and meta-level choices for using Data Augmentation. The reader will comprehend how Data Augmentation might increase small datasets to take advantage of big data's possibilities and enhance model performance.

III.BLOCK DIAGRAM

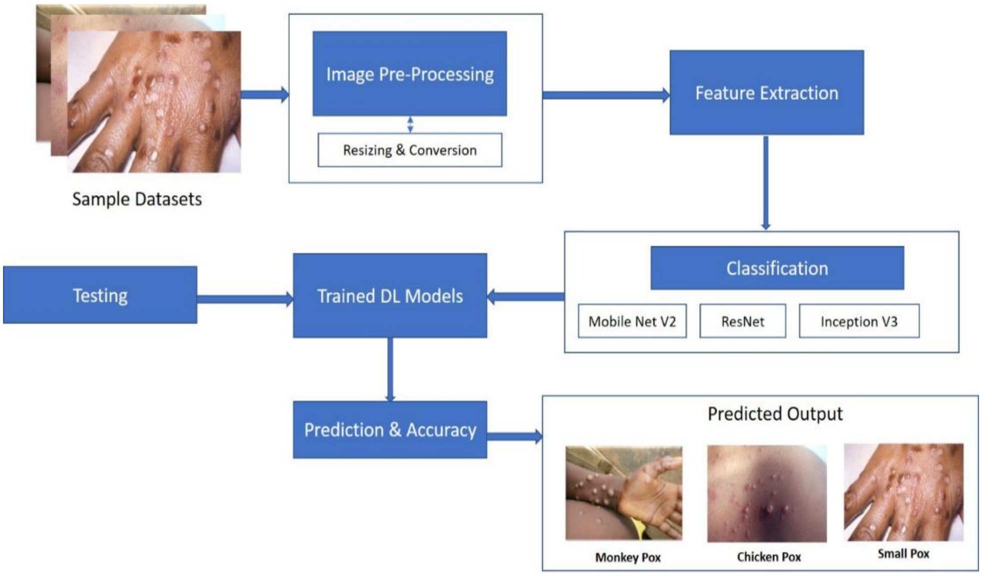


Figure 1: Block Diagram of skin lesion detection using deep learning.

The "Monkeypox Image Lesion Dataset" was produced with the primary goal of separating monkeypox patients from related non-monkeypox cases. As a result, to perform binary classification, we included skin lesion pictures of "chickenpox" and "smallpox" in the "monkeypox" class because of their similarity to the monkeypox rash and initial state pustules. The collection includes a total of 1428 photos that include smallpox, chickenpox, and monkeypox. These are applied to testing and training.

Techniques for pre-processing is One of the data science community's most unexplored issues is image data processing. Every developer approaches the task differently. Python, Pytorch, OpenCV, Keras, Tensor Flow, and Pillow are a few of the platforms and tools used in picture pre-processing. We constantly require data while developing a machine learning or computer vision project. picture information in this scenario. Unfortunately, there are a few issues with picture data, such as complexity, correctness, and sufficiency. To get the intended outcomes, the data must be pre-processed before creating a computer vision model. Before being used for model training and inference, pictures must first undergo image pre-processing.

(a) (b) (c) (d)

Figure 2: Dataset (a) chicken pox (b) monkey pox (c) skin cancer (d) small pox

IV.IMPLEMENTATION

Three well-known CNN architectures, MobileNet V2, ResNet 50, and Inception V3, were chosen for this study and were pre-trained on the ImageNet dataset. These models were chosen because, through transfer learning, they have shown outstanding classification performance across several computer vision domains, including medical pictures. A convolutional neural network (CNN) is a form of artificial neural network that is especially made to analyse pixel input and is used in image recognition and processing.

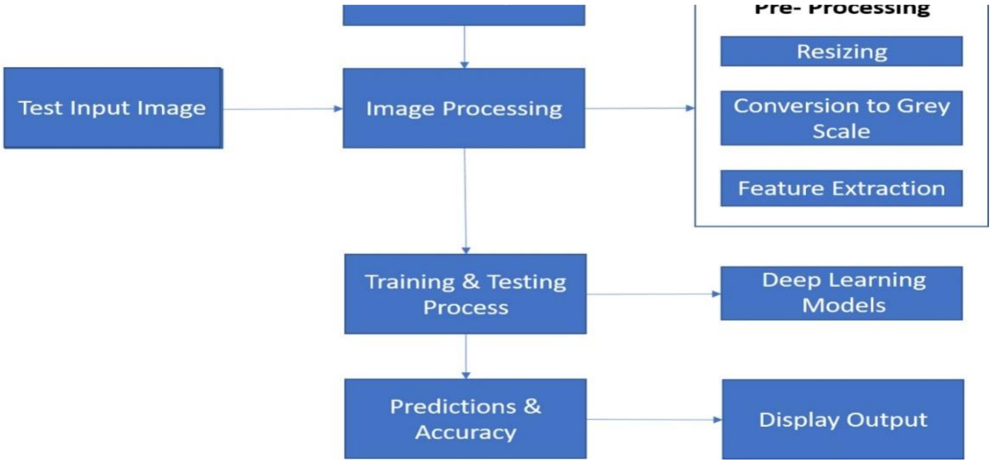


Figure 3: Flowchart

The datasets are trained and ML models for each are created Inception V3, Mobilenet V2 and Resnet. As observed, Resnet has more accuracy when compared with other two. This particular model is used to compare the unknown test images when given as input.

Model Architecture for Inception V3

Convolutional neural networks are the foundation of the deep learning model known as Inception V3 that is used to classify images. The Inception V3 is a better version of the Inception V1, a foundational model that was first released as Google Net in 2014. It was created by a Google team, as the name indicates.

The Inception v3 model, which was introduced in 2015, has 42 layers overall and a lower mistake rate than its forerunners. The use of auxiliary classifiers, factorization into smaller convolutions, spatial factorization into asymmetric convolutions, and efficient grid size reduction are the main changes made to the Inception V3 model.

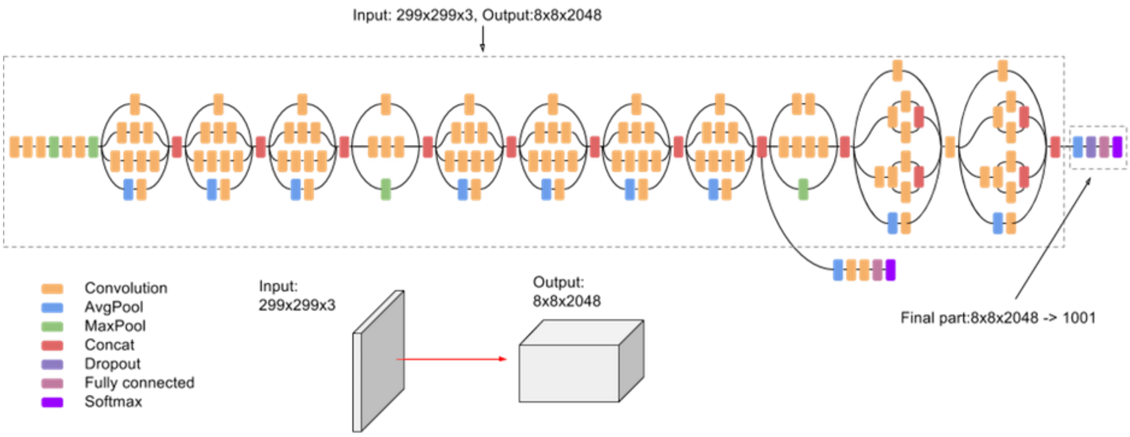


Figure 4: Inception v3 Model

In total, the inception V3 model is made up of 42 layers which is a bit higher than the previous inception V1 and V2 models. But the efficiency of this model is really impressive. We will get to it in a bit, but before it let's just see in detail what are the components the Inception V3 model is made of.

MobileNet V2 model has 53 convolution layers and 1 AvgPool with nearly 350 GFLOP. It has two main components:

- Inverted Residual Block and Bottleneck Residual Block

There are two types of Convolution layers in MobileNet V2 architecture:

- 1x1 Convolution and 3x3 Depthwise Convolution

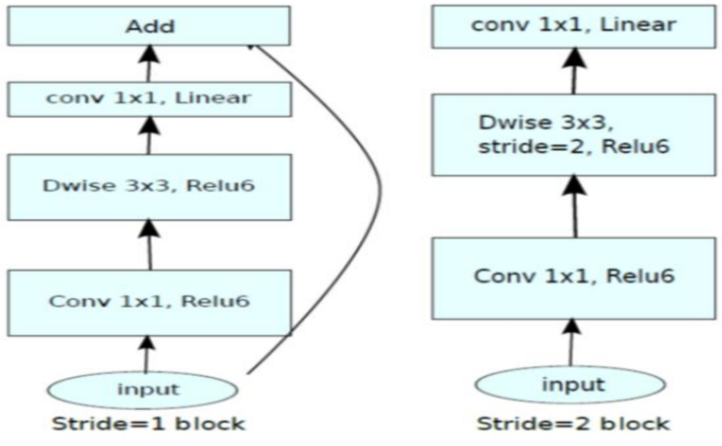


Figure 5: MobileNetV2 architecture

ResNet (Residual Net) Architecture

Every consecutive winning design employs more layers in a deep neural network to lower the error rate, after the first CNN-based architecture (Alex Net) that won the ImageNet 2012 competition. This is effective for smaller numbers of layers, but when we add more layers, a typical deep learning issue known as the "vanishing/exploding gradient arises. This network employs a VGG-19-inspired 34-layer plain network design before adding the shortcut connection. The architecture is subsequently changed into a residual network by these short-cut links.

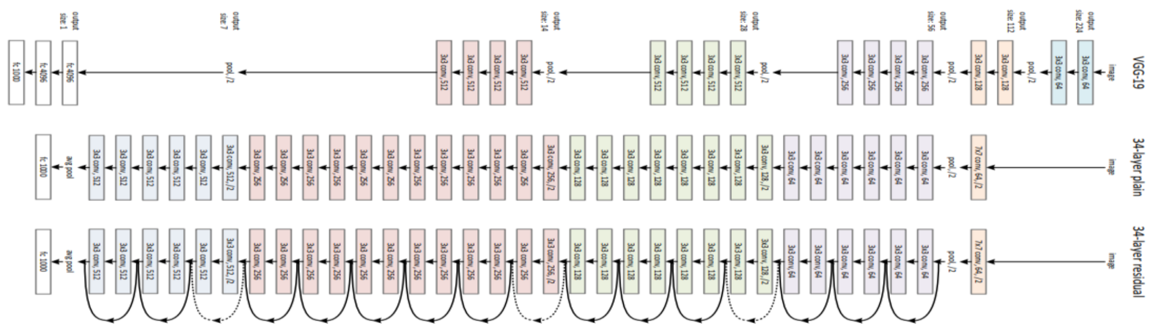


Figure 6: ResNet (Residual Net) Architecture

V.RESULTS AND DISCUSSIONS

The project's front end will include options for testing and training that use a GUI. This paper proposes a way for differentiating various skin disorders using computer vision-related approaches. For feature extraction, we have used a variety of deep learning algorithms, model with the state-of-the-art architecture, the efficiency is increased above 95%.

Testing

No.	Algorithm	Epochs	Accuracy (%)
1	Inception V3	10	20.83
		20	58.33
		60	64.31
		100	77.98
2	MobileNet V2	10	35.41
		20	46.26
		60	66.92
		100	79.63
3	Resnet	10	64.58
		20	68.35
		60	84.68
		100	95.61

The input is an unidentified image that has to be examined. Pre-processing, feature extraction, and segmentation techniques are applied to the picture in order to identify the type of skin lesion present and its symptoms. Since ResNet outperforms other classification models in terms of accuracy, we use it to test an unknown image and anticipate the outcomes, which are presented in the results section.

Training

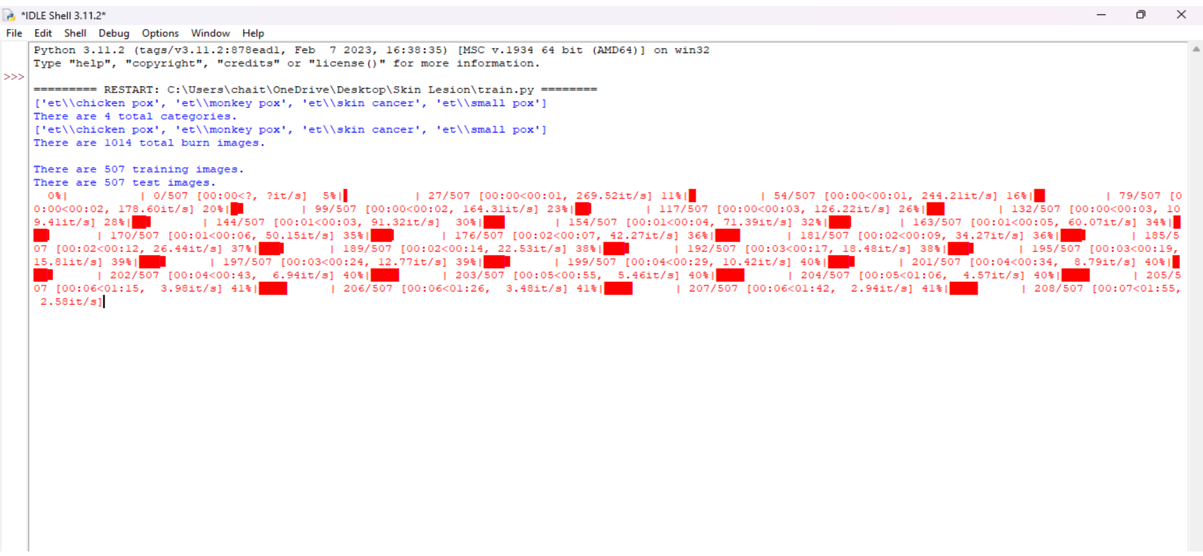


Figure 7: Training dataset

Figure 7 shows the training dataset of chickenpox, monkey pox, skin cancer and small pox.

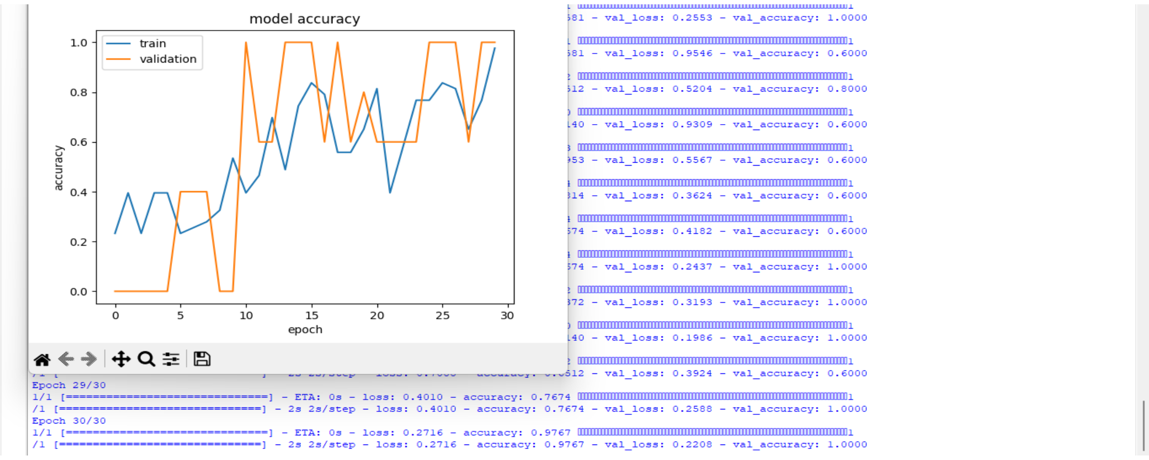


Figure 8: Model Accuracy Graph of MobileNet v2

Figure 8 shows the model accuracy graph of MobileNet v2 ,x-axis indicates the epochs value and y-axis indicates the accuracy of the MobileNet v2.

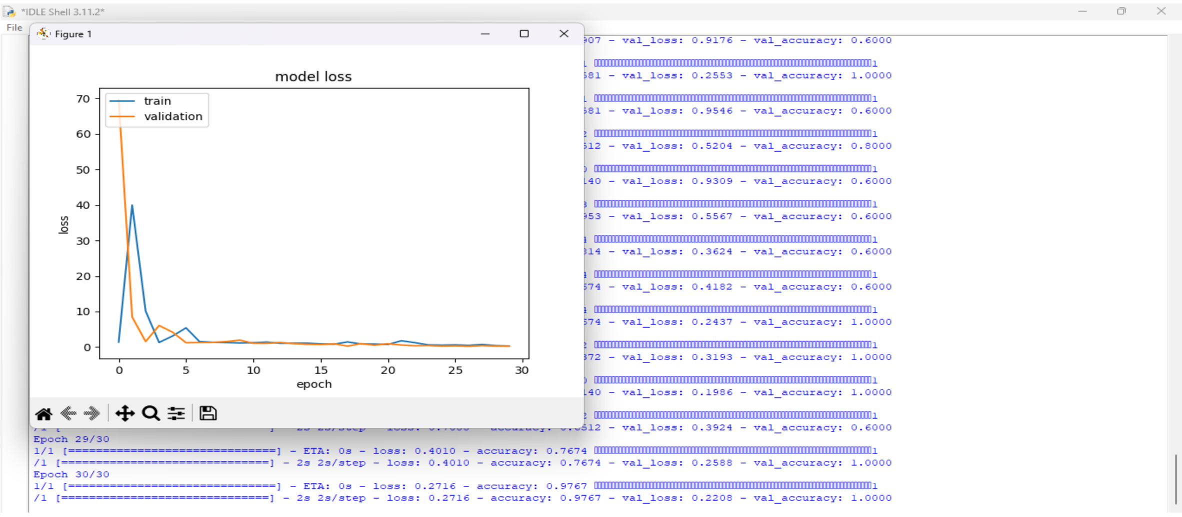


Figure 9: Model Loss Graph of MobileNet v2

Figure 9 shows the model loss graph of Mobilenet v2 ,x-axis indicates the epochs value and y-axis indicates the loss of the MobileNet v2.

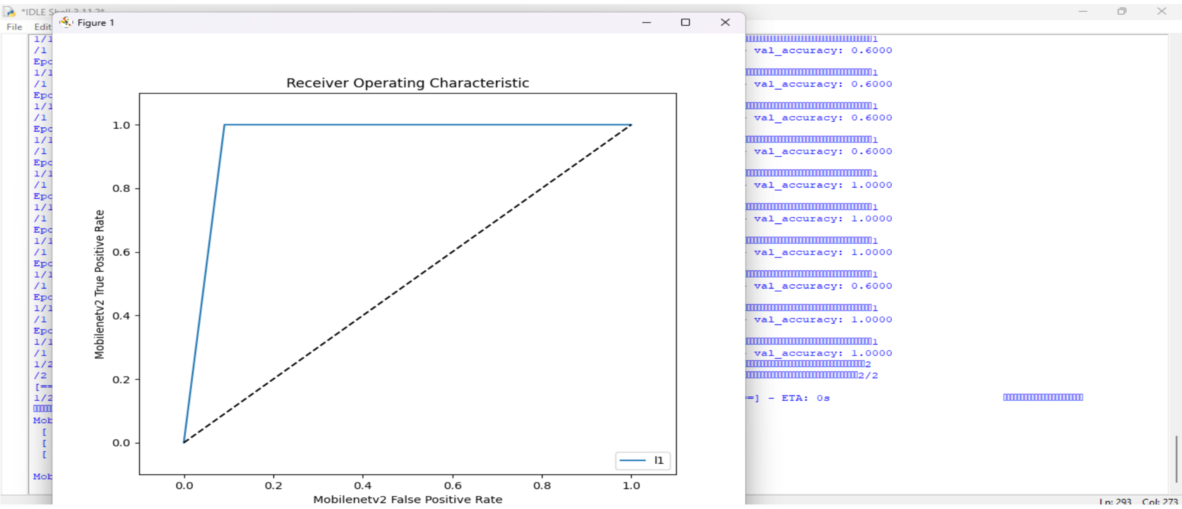


Figure 10: ROC Graph of Mobilenet v2

Figure 10 shows the ROC graph of Mobilenet v2 ,x-axis indicates the MobileNet v2 false positive rate and y-axis indicates MobileNet v2 true positive rate.

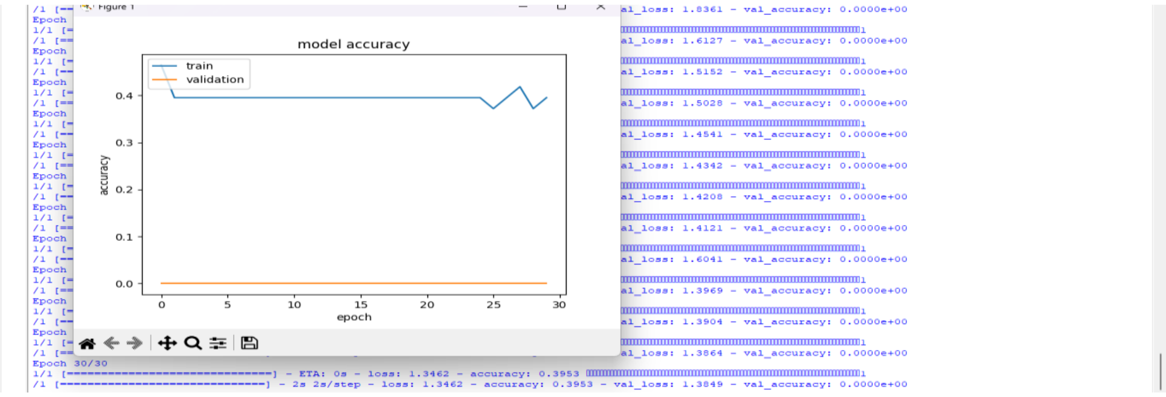


Figure 11: Model Accuracy Graph of Inception v3

Figure 11 shows Model Accuracy Graph of Inception v3,x-axis indicates the epoch value and y-axis indicates the accuracy of the Inception v3.

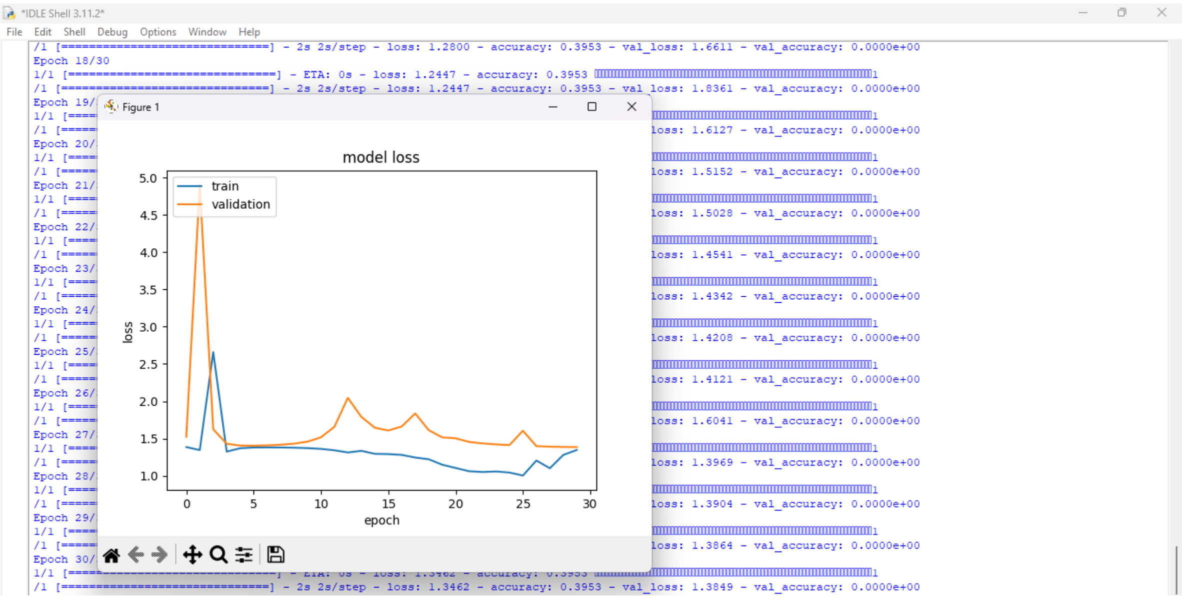


Figure 12: Model Loss Graph of Inception v3

Figure 12 shows Model lossy Graph of Inception v3,x-axis indicates the epoch value and y-axis indicates the loss of the Inception v3.

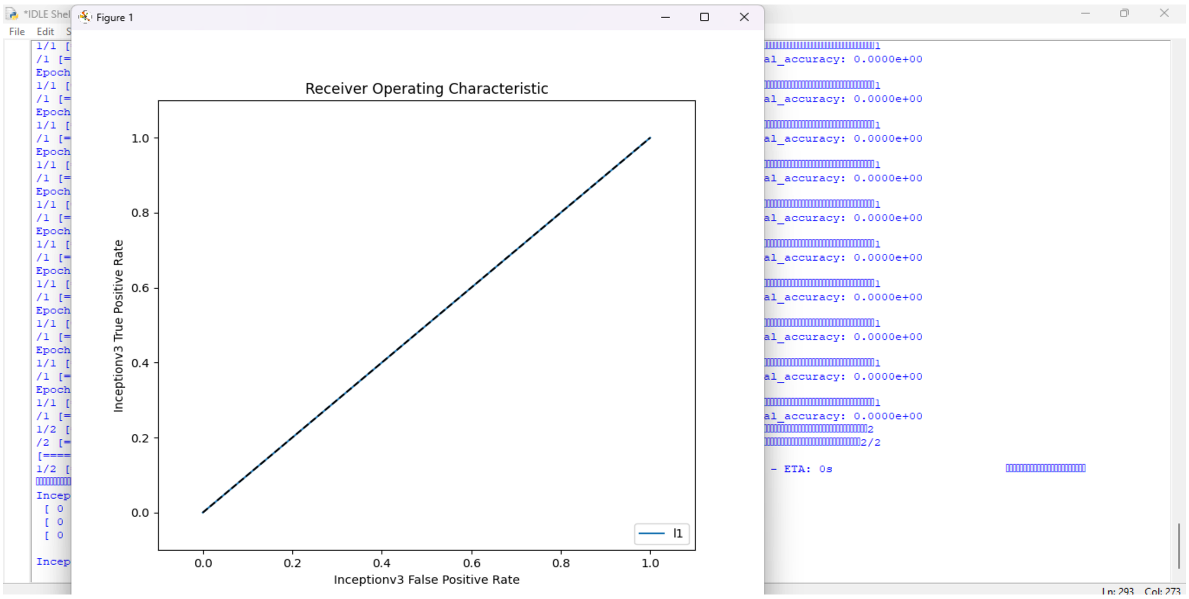


Figure 13: ROC Graph of Inception v3

Figure 13 shows ROC Graph of Inception v3,x-axis indicates the Inceptionv3 true positive rate and y- axis indicates the Inceptionv3 false positive rate.

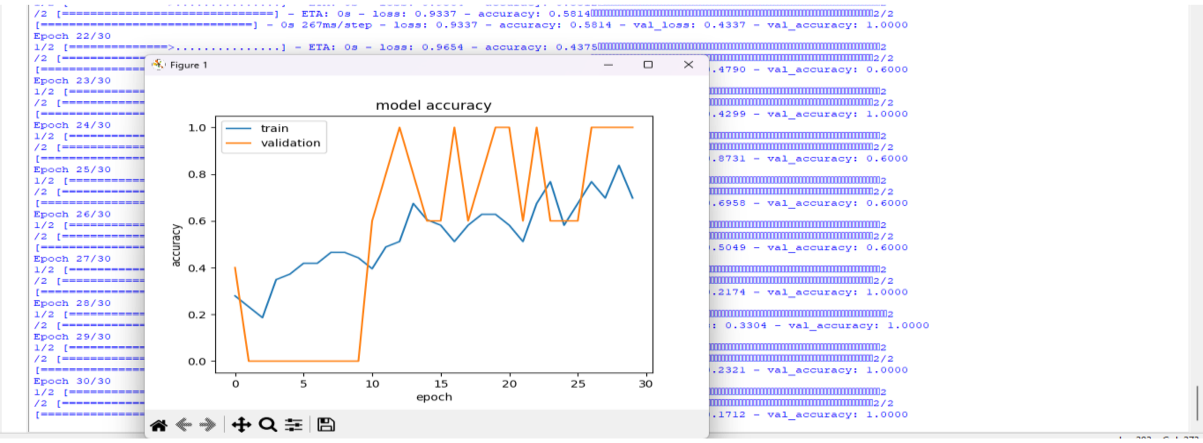


Figure 14: Model Accuracy Graph of ResNet

Figure 14 shows model accuracy Graph of ResNet ,x-axis indicates the epoch values and y-axis indicates the accuracy of the ResNet.

Figure 15: Model Loss Graph of ResNet

Figure 15 shows model loss Graph of ResNet ,x-axis indicates the epoch values and y- axis indicates the loss of the ResNet.

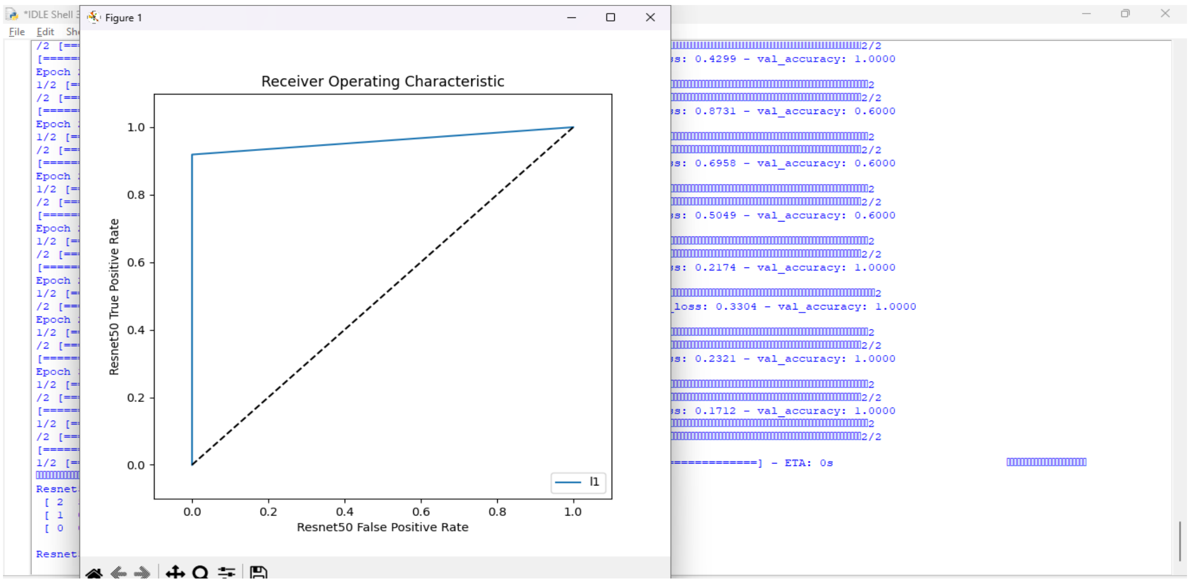


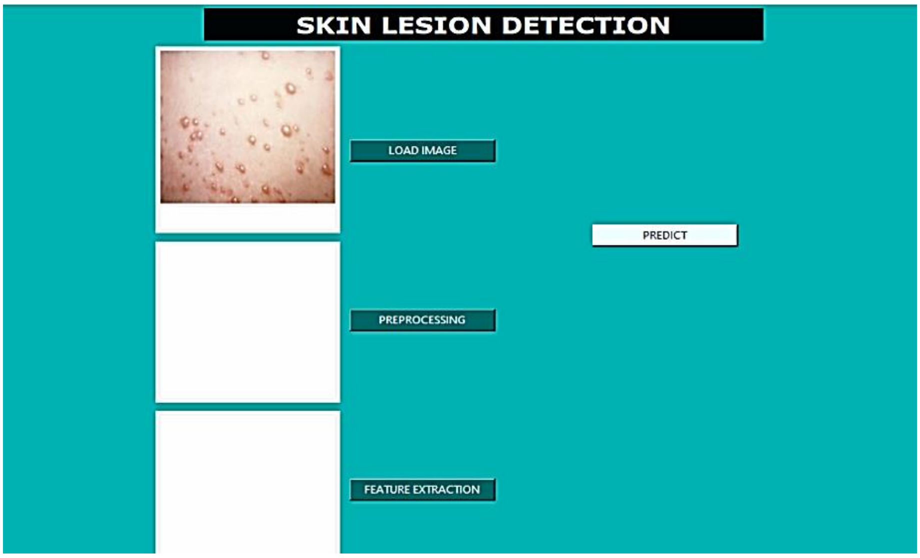
Figure 16: ROC Graph of ResNet

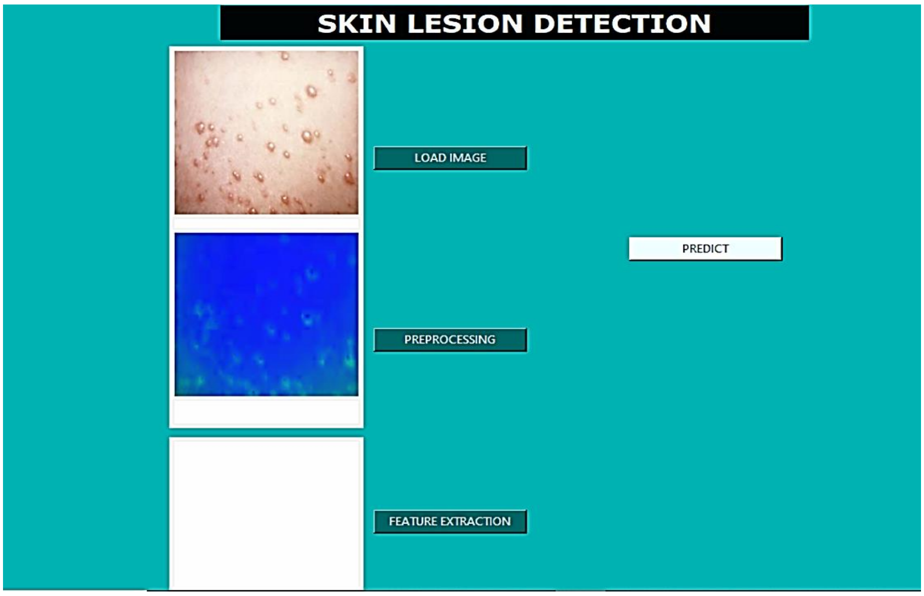
Figure 16 shows ROC graph model of ResNet,x-axis indicates the ResNet false positive rate and y-axis indicates the ResNet true positive rate.

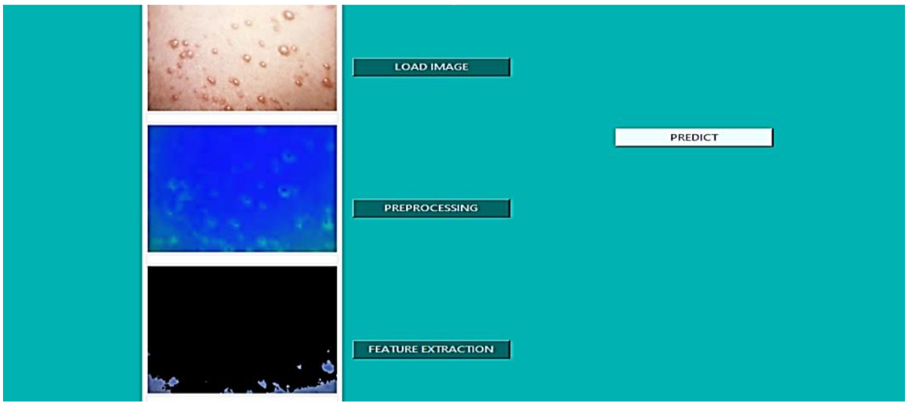
Figure 17: Accuracy Comparison Graph

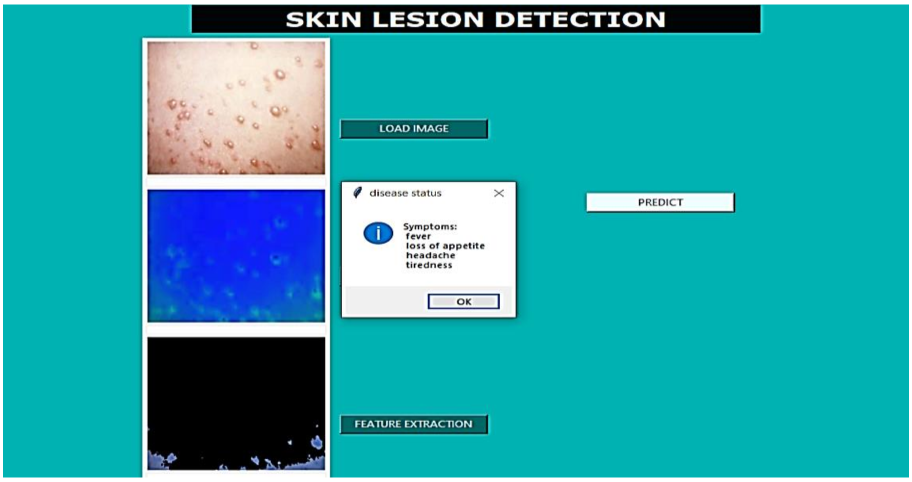
Figure 17 shows the accuracy comparison graph of MobileNetv2, Inceptionv3 and Resnet50.

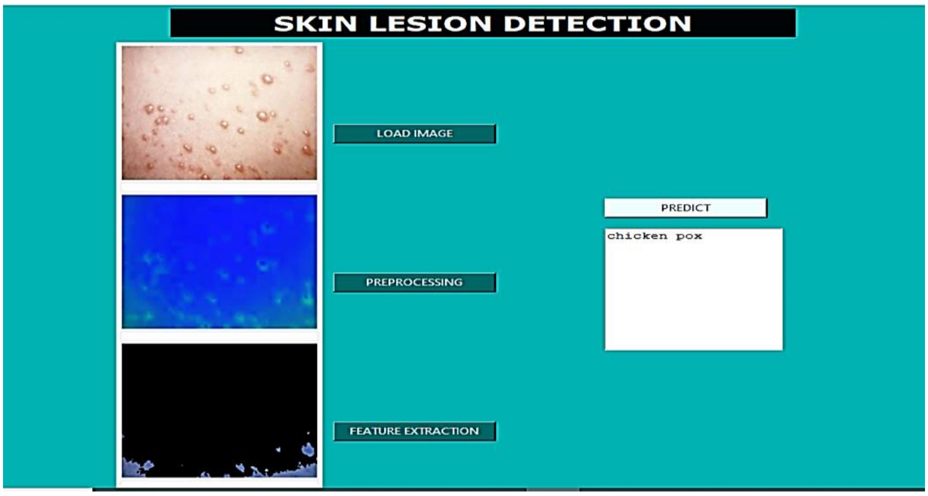
Snapshots Of Testing Results











VI.CONCLUSION

In this study, deep learning methods are used to create a software model for the prediction of skin illnesses. It has been discovered that by utilising ensemble characteristics and deep learning, we can increase accuracy and predict a greater number of illnesses than we could with any other previous model. As the previous models created for this application were only capable of reporting a maximum of four skin conditions with a maximum level of 75% accuracy, With the help of a deep learning system, we can predict up to eight illnesses with a 90% accuracy rate. This demonstrates the enormous potential of deep learning algorithms for diagnosing skin diseases in the real world.

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