SRI LANKA INSTITUTE OF INFORMATION TECHNOLOGY

CODEFEST – DATATHON 2022

Team YNot – DA016

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PROBLEM OVERVIEW

Monkey pox which is declared as a public health emergency by World Health Organization (WHO) has been a source of concern for healthcare professionals. This has created the urge to diagnose the disease at the earliest preventing severity. Through our project solution we have provided necessary approaches aiding the process of early diagnosis in an efficient manner. On this aspect development of an AI based disease diagnosis model is facilitated incorporating some of the advanced concepts of Data science.

EXPLANATORY DATA ANALYSIS

Exploratory data analysis (EDA) is done to study the patterns and insights of the data. It is the first step taken to solve the problem where we could get a closer overview of the dataset provided thus understanding the problem in a more detailed manner.

The five classes of data namely 'Acne', 'Melanoma', 'Monkeypox', 'Normal skin' and 'Cyst, tumor and skin-tags' were first analyzed where we observed the classes Acne had 400 images while Cyst and Melanoma classes had 600 images and the other two classes had 700 images. This clearly showed the presence of an imbalance in the dataset provided. As the next step the pixel concentration of images belonging to each class was examined. It was observed that the images belonging to the Acne class had images in a uniform manner whereas the other classes had images in various different sizes which brings the necessity to resize all images to a uniform context.

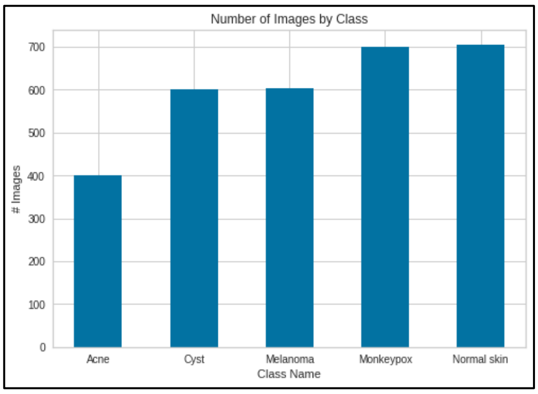

Figure 1 : Number of images in each class

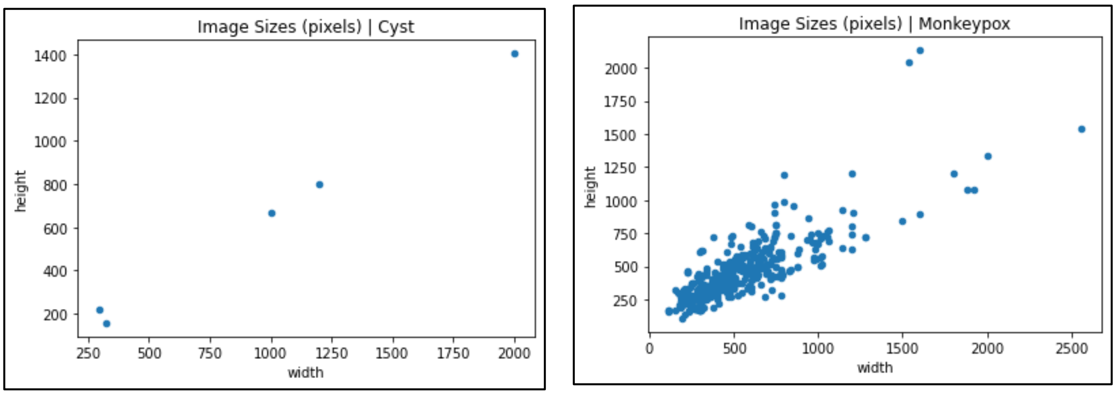

Figure 2 : Image pixel size distribution

DATA AUGMENTATION

As there is an imbalance observed between the images belonging to different classes the application of an oversampling technique was needed. The primary approach used here is data augmentation. Data augmentation is basically a technique used to generate artificial data by making slight modifications to the existing data points. To be more specific; changes such as rotation angles, brightness adjustments, zoom factor and horizontal flipping were done to generate new data points thus oversampling the classes lacking data points. At the end of this step we were able to carry data for training and testing having 4000 data points for each class.

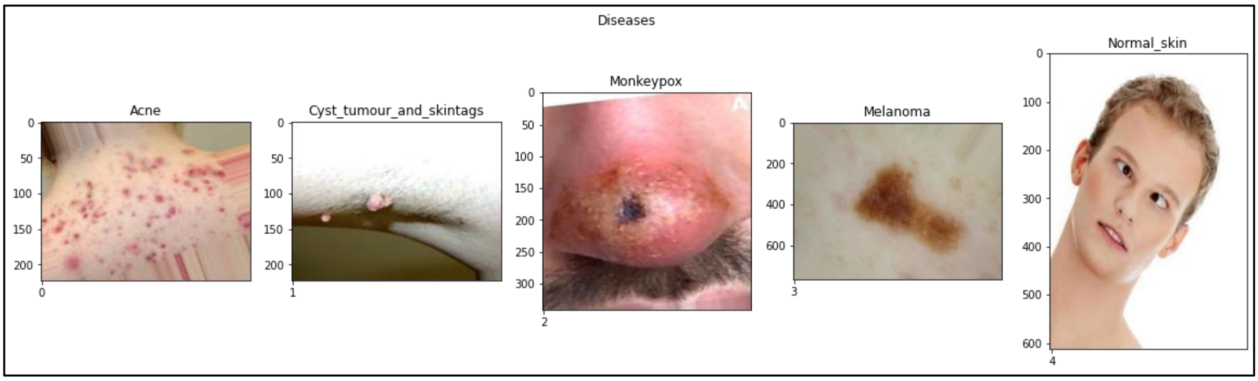

Figure 3 : Images after augmentation

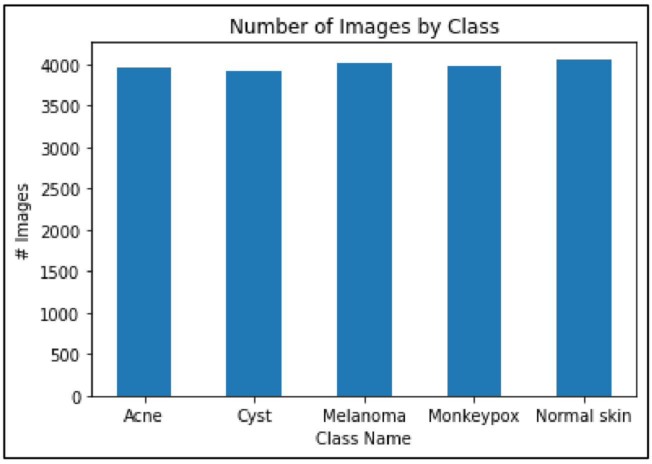

Figure 4 : Data after image augmentation

MODEL APPROACH

Analyzing the problem we realized that the best way to approach towards the solution is to follow a Deep Leaning (DL) approach. The problem is an image recognition problem, and for such a scenario if Machine Learning (ML) approach is used it is required to specify the features to train a model. In case of DL, it has the capability to automatically learn features from images to train model eliminating the need for a manual extraction of features. Thus, we chose DL as the best approach.

To start with we have tried various different models to understand what provides the best performance. Initially we applied transfer learning approaches using VGG19 and VGG16 models. Transfer learning is the approach of using a pretrained model for a problem that is relatable and different. The pretrained model is usually trained using a large number of datasets provides an advantage when dealing with tasks that have less data. Further, there arises no requirement to build a model from scratch. Thus it is much efficient and time saving to use transfer learning approach. Both VGG16 and VGG19 are pretrained models based on Convolutional Neural Networks (CNN).

The trained VGG19 model produced an accuracy of 0.68 while the VGG16 model produced an accuracy of 0.85. Comparatively, VGG16 model performed well.

Additionally an EfficientNetB3 model was trained. It is also based on CNN model architecture which additionally posses a scaling method. The EfficientNetB3 model has the capability to uniformly scale all dimensions using the compound coefficient. Dimensions include depth, width and resolutions. Although the capability of the model is high, in our case the accuracy we obtained was 0.234.

Comparing all trails and experiments, the team decided to go ahead with the VGG16 model.

As the approach, the VGG16 model is loaded and the initial layers were removed to eliminate the classification layers that were trained on ImageNet dataset. Model was then set to non-trainable. Additionally SoftMax activation function too was employed. Initial attempt produced a better accuracy as mentioned above, yet the trial employed the dataset that was not augmented. Thus, the model was retrained after data augmentation as a method of fine tuning.

MODEL EVALUATION

Any models trained using ML or DL approaches could be evaluated in multiple ways. As a method of evaluation we have employed performance metrices like accuracy and classification reports and confusion matrix.

Accuracy is the ratio of number of predictions that were correct and total number of predictions.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ Predictions}$$

Accordingly, the fine-tuned InceptionV3 model produced 0.90 and 0.85 training and test accuracies respectively. The below figures represent the accuracy and loss plots. Analyzing the plots it is clear that the model performance is efficient and does not have any overfitting or underfitting.

In order the evaluate the model further, the classification report was obtained and using it the confusion matrix was developed. The classification report provides the report of model performance metrices in a tabular format. It provides the details required to understand the efficiency and quality of model. Below image represents the classification report obtained for the trained model.

	precision	recall	f1-score	support
Acne	0.85	0.88	0.86	40
Cyst_tumour	0.93	0.70	0.80	60
Melanoma	0.88	1.00	0.94	61
Monkeypox	0.87	0.94	0.91	71
Normal_skin	0.96	0.96	0.96	71
accuracy			0.90	303
macro avg	0.90	0.90	0.89	303
weighted avg	0.90	0.90	0.90	303

Figure 5 : classification report of InceptionV3

Analyzing the above image, we can observe that there are four other metrices namely precision, recall, f1-score and support that helps to evaluate the model performance further. Accordingly we can observe all classes available do show better precision, recall and f1 scores. Thus, this inferences the model performs really well.

The confusion matrix is an easy way of visualizing the model outcomes in a tabular format. The image shown below represents the confusion matrix obtained for the trained model.

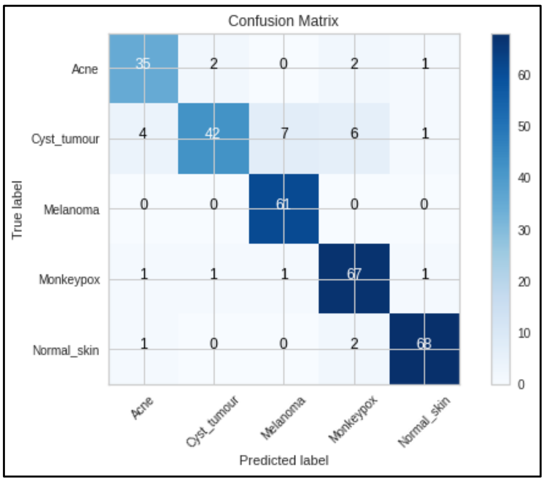

Figure 6 : Confusion matrix of InceptionV3

Observing the confusion matrix we can clearly analyze that the model performs well generally when considering all classes as the rate of misclassification is considerably low. When analyzing deeper it is observed compared to all classes the ‘Melanoma’ performs the best while classes ‘Monkeypox’ and ‘Cyst tumor’ comparatively shows a less performance.

Analyzing all the methods, we further evaluated the predictions by passing the images belonging to specific classes and obtained the model predictions. The below image represents the predictions we tested for all five classes which again proves that the model performs well as all five tests are successful.

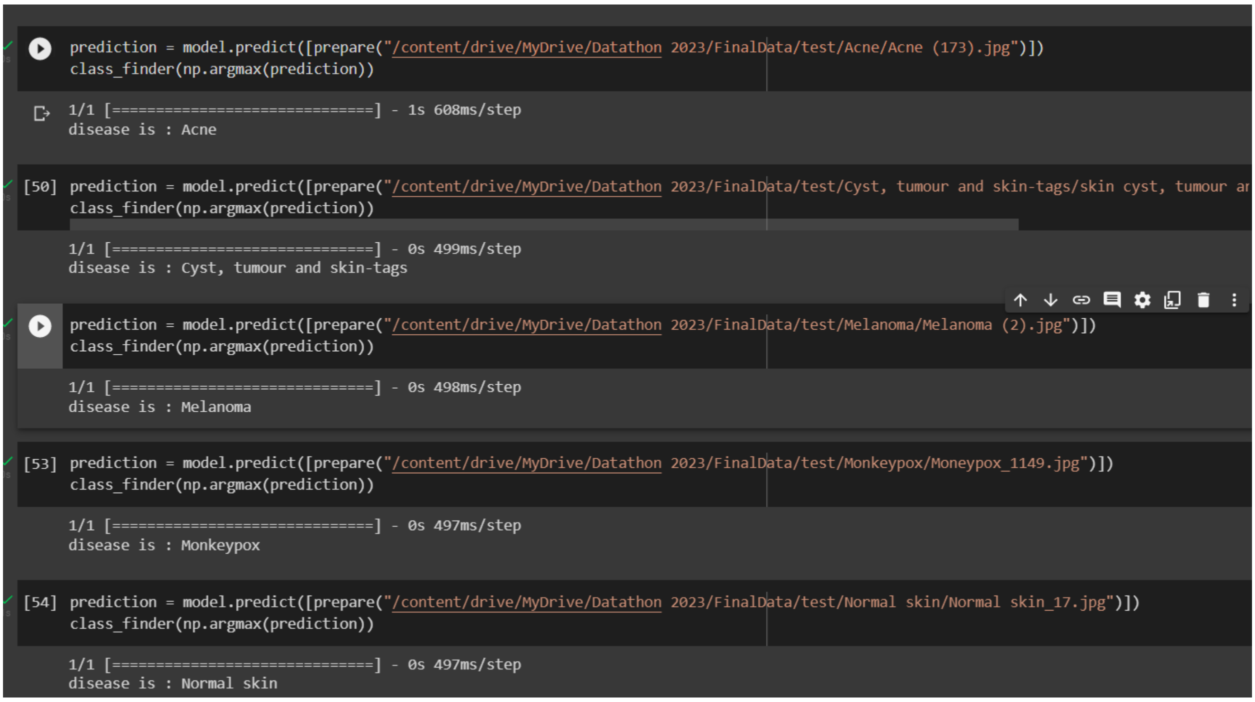

Figure 7 : Predictions

Overall, considering all methods of model evaluation, it is clear that the trained model shows a very good and acceptable rate of performance with improved accuracies, other performance metrices like precision, recall and f1 score additionally supported by confusion matrix and classification report.

MODEL INTERPRETATION USING SALIENCY MAPPING

Model interpretation deals with the process to understand our model better so that it will pave way for a better decision making. Understanding the model provides model fairness and ensures that the model is free from any biasness so that the model becomes applicable to real world scenarios. There are various methods to interpret a model such as using available explainable libraries like SHAP, LIME, employing techniques like dimensionality reduction or analyzing the model using its performance metrices. In our approach we have used Saliency mapping as a mean of model interpretation.

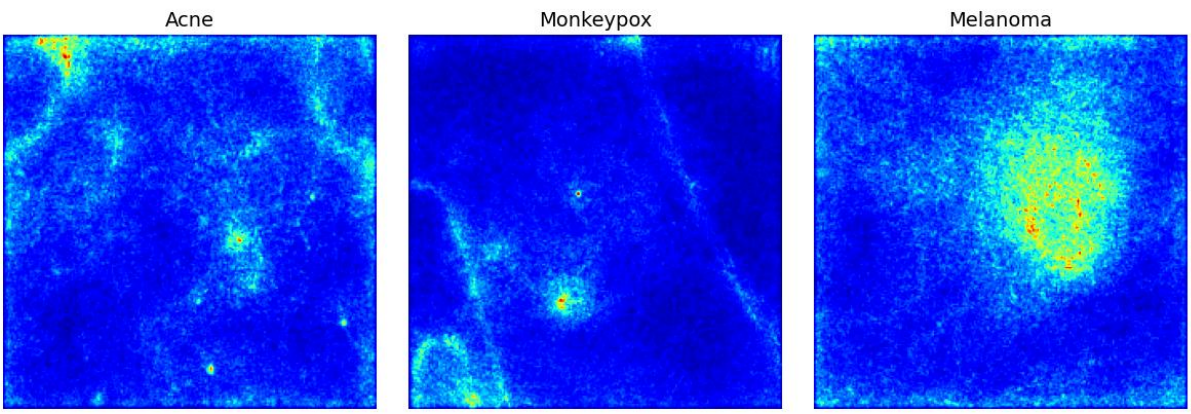

Figure 8 : Saliency map