Introduction

To build a well-performing machine learning (ML) model, it is essential to train the model on and test it against data that come from the same target distribution. However, sometimes only a limited amount of data from the target distribution can be collected. It may not be sufficient to build the needed train/val/test sets.

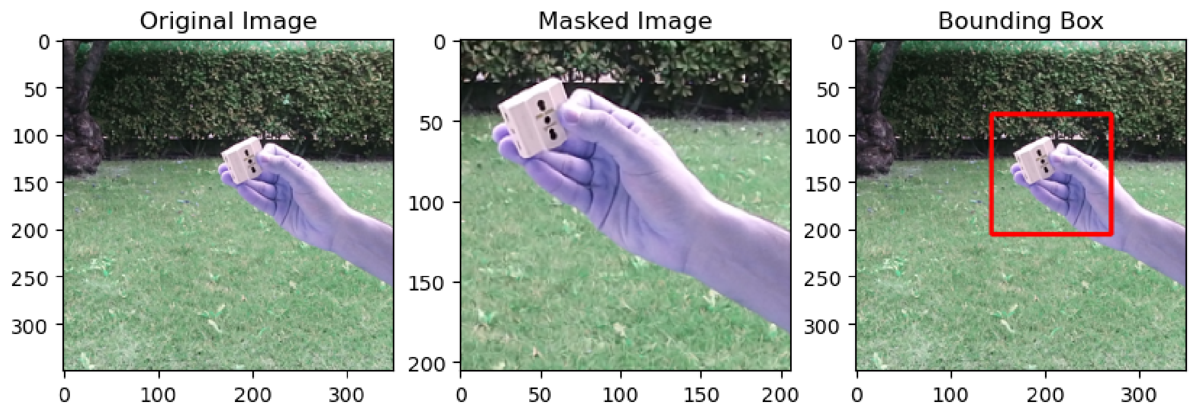
Preprocessing

Cropping the objects using bounding box

Cropping an object using a bounding box can be beneficial when classifying objects because it allows us to isolate the object of interest and remove any extraneous information from the image. By doing this, we can focus solely on the object you want to classify, which can improve the accuracy of our classification model.

When we crop an object using a bounding box, you are essentially creating a new image that contains only the object you want to classify. This can help remove any background noise or distractions that might be present in the original image, which can make it easier for our model to identify the object.

Additionally, cropping an object using a bounding box can help standardise the size and shape of the objects in your dataset. This can be important when training a classification model, as it can help ensure that the model is able to recognize objects of different sizes and shapes.



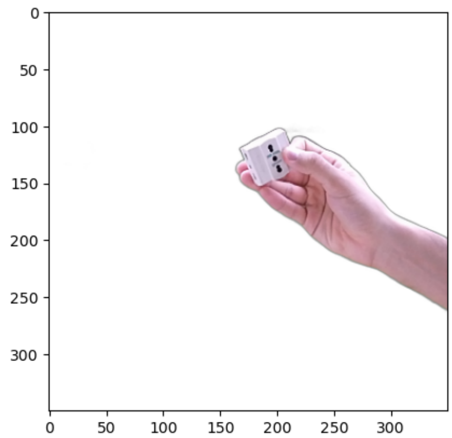
Removing Background

Removing the background from an image can help in several ways when working with object classification. Here are a few reasons why:

Reducing noise: Backgrounds in images can contain a lot of visual noise, such as patterns, textures, or colours that are not relevant to the object we want to classify. By removing the background, we can reduce this noise and make it easier for your model to focus on the object itself.

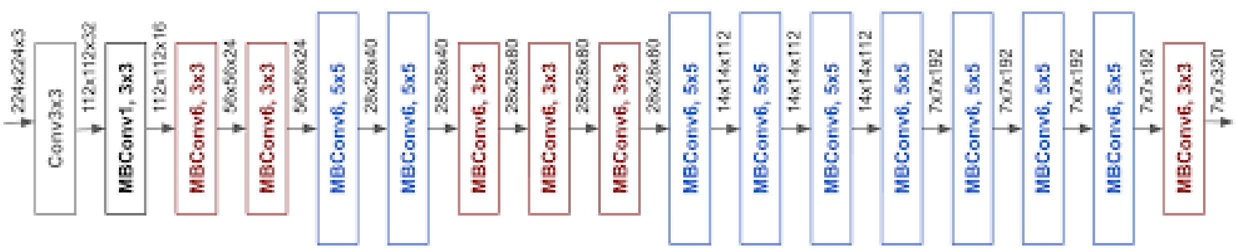
Standardising the appearance: Backgrounds can vary widely between images, which can make it difficult for our model to learn what the object looks like. By removing the background, we can standardise the appearance of the object across all images, which can make it easier for your model to recognize it.

Improving accuracy: By focusing solely on the object you want to classify, you can improve the accuracy of your model. This is because the model doesn't have to spend time and resources trying to distinguish between the object and the background.



Model Architecture

EfficientNetB0 is a convolutional neural network architecture that was introduced in 2019 by researchers at Google. It is part of the EfficientNet family of models, which are designed to be highly efficient in terms of computational resources while still achieving state-of-the-art performance on image classification tasks. EfficientNetB0 is based on a compound scaling method that involves scaling the network's depth, width, and resolution simultaneously. This allows the model to achieve high accuracy while using fewer parameters and less computation than other models of similar accuracy.It has achieved state-of-the-art performance on several image classification benchmarks, including ImageNet, which is a large-scale dataset of images used for training and evaluating computer vision models. It has also been used as a base model for transfer learning in a variety of computer vision tasks, such as object detection and segmentation.



Transfer Learning

Transfer learning is a powerful technique in machine learning and deep learning that involves using a pre-trained model as a starting point for a new task. Here are a few ways that transfer learning can help:

Reduced training time: By starting with a pre-trained model, you can significantly reduce the amount of time and computational resources required to train a new model from scratch. This is because the pre-trained model has already learned a lot of useful features that can be applied to the new task.

Improved accuracy: Transfer learning can often lead to better accuracy on a new task than training a model from scratch. This is because the pre-trained model has already learned useful features that can be applied to the new task, which can improve the model's ability to generalize and make accurate predictions.

Smaller training set: Transfer learning can be particularly useful when you have a small training set for the new task. This is because the pre-trained model has already learned useful features from a large dataset, which can help compensate for the smaller training set.

Train/Validation/Test Split

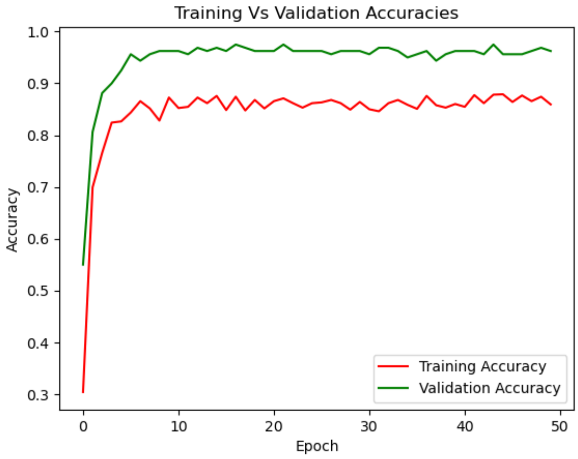
This is a common technique used in machine learning to evaluate the performance of a model. The basic idea is to split the available data into three sets: a training set, a validation set, and a test set.

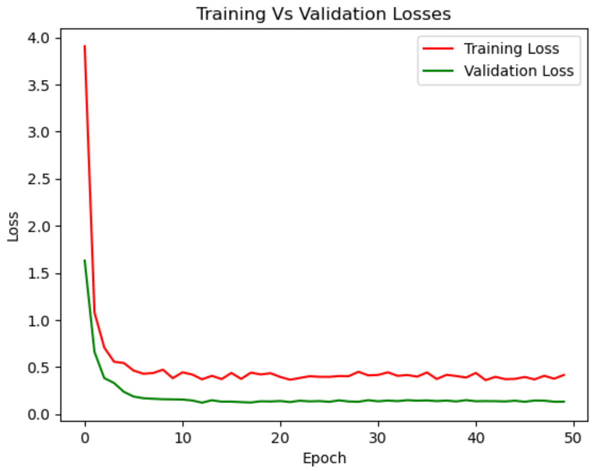
The training set is used to train the model, i.e., to adjust the model's parameters based on the available data. The validation set is used to evaluate the model's performance during training, i.e., to check if the model is overfitting or underfitting. The test set is used to evaluate the final performance of the model, i.e., to check how well the model generalises to new, unseen data.

The split ratio is 70/10/10 in our cas, meaning that 70% of the data is used for training, 10% for validation, and 10% for testing. However, the exact split ratio may vary depending on the size and complexity of the dataset.

Results

We calculated confusion matrices, accuracy and f1 score measures for each lesion category in order to determine the classifier performance.





Accuracy of the network on the test images: 96 %

Accuracy of 00 : 100 %

Accuracy of 01 : 90 %

Accuracy of 02 : 100 %

Accuracy of 03 : 95 %

Accuracy of 04 : 100 %

Accuracy of 05 : 90 %

Accuracy of 06 : 100 %

Accuracy of 07 : 100 %