# Skin Cancer Classification

## Model Architecture

In this study, the used model is fine-tuned on pre-trained EfficientNet-B0 architecture. Specifically, the adaptation involved replacing the network’s terminal classifier with a custom head comprising a linear layer, a Rectified Linear Unit (ReLU) activation function, a dropout layer, and a fully connected layer designed to output probabilities across the eight target classes.

## Handling Data Imbalance

图表, 直方图

描述已自动生成

In the above figure, the mapping between label and no. is NV – 0, MEL – 1, BCC – 2, BKL – 3, AK – 4, SCC – 5, VASC – 6, and DF – 7. As indicated by the graph, training data is highly imbalanced, which can lead to overfitting. Multiple solutions and techniques are used to mitigate this issue.

The total data in class 0 is more than 12000, which is triple the number of the second largest data class. To reduce the bias toward the majority class, under-sampling is performed to randomly remove data of class 0 and make its total number 8000. Considering the side effects of losing information for class 0, only around 1/4 amount of data is removed.

To further reduce the extent of data imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) is used to generate more data for classes 4, 5, 6, and 7. The data size of classes 4, 5, 6, and 7 are increased to 150%, 150%, 500%, and 500%. As the original sizes of classes 6 and 7 are less than 200, respectively, their data size is extended with the large scale. After applying SMOTE, the class distribution becomes {0: 8000, 1: 4422, 2: 3223, 3: 2524, 4: 1102, 5: 792, 6: 765, 7: 695}.

Apart from adjusting training data, the appropriate loss weights for different classes are adopted. The weight for each class is calculated by N/Nc, where N is the total number of all training data, and Nc is the amount of training data for the class c. The class weights result is [2.6904, 4.8673, 6.6779, 8.5273, 19.5309, 27.1755, 28.1346, 30.9683], where the index of each item corresponds to the class no. This array of class weights is used in cross entropy loss function.

## Data Augmentation

To enhance the model’s generalization ability, various image augmentation techniques are employed. These include random horizontal flipping, rotation, shearing, zooming in and out, conversion to grayscale, color jittering, and Gaussian blurring. Below, the figure presents three sets of images: each set contains an original image alongside its augmented counterparts. The original images look different in color from the corresponding images in the given dataset, since the original images here have undergone the process of standardizing image color channels to a common scale.

形状, 正方形

描述已自动生成

## Evaluation

**图表, 折线图

描述已自动生成**

The model was run for 43 epochs. At the 26th epoch, the model achieves the highest validation accuracy. Therefore, the model at the 26th epoch was saved and used for evaluation. The history plots indicate that the model was not generalized well to the validation set due to overfitting, likely exacerbated by the class imbalance.

|  |  |  |  |
| --- | --- | --- | --- |
| Accuracy | 0.6925 | Recall | 0.6700 |
| Precision | 0.7333 | F1 score | 0.6741 |
| One-vs-One AUC | 0.9450 | One-vs-Rest AUC | 0.9450 |

Above table lists all evaluation indicators. Two types of ROC AUC scores are excellent, suggesting that the model can effectively discriminate between classes. The accuracy, recall, precision, and f1 score are moderately high.

图表, 树状图

描述已自动生成

The above figure of the confusion matrix shows that the model has good classification performance in class 0, class 2, class 3, and class 6. Recall that the sample distribution after resampling is {0: 8000, 1: 4422, 2: 3223, 3: 2524, 4: 1102, 5: 792, 6: 765, 7: 695}, and the dictionary of class weights is {0: 2.6904, 1: 4.8673, 2: 6.6779, 3: 8.5273, 4: 19.5309, 5: 27.1755, 6: 28.1346, 7: 30.9683}. The amount of class 6 training data is the second-fewest, however, the model has a relatively high capability of identifying class 6.