Skin Classification using Machine Learning

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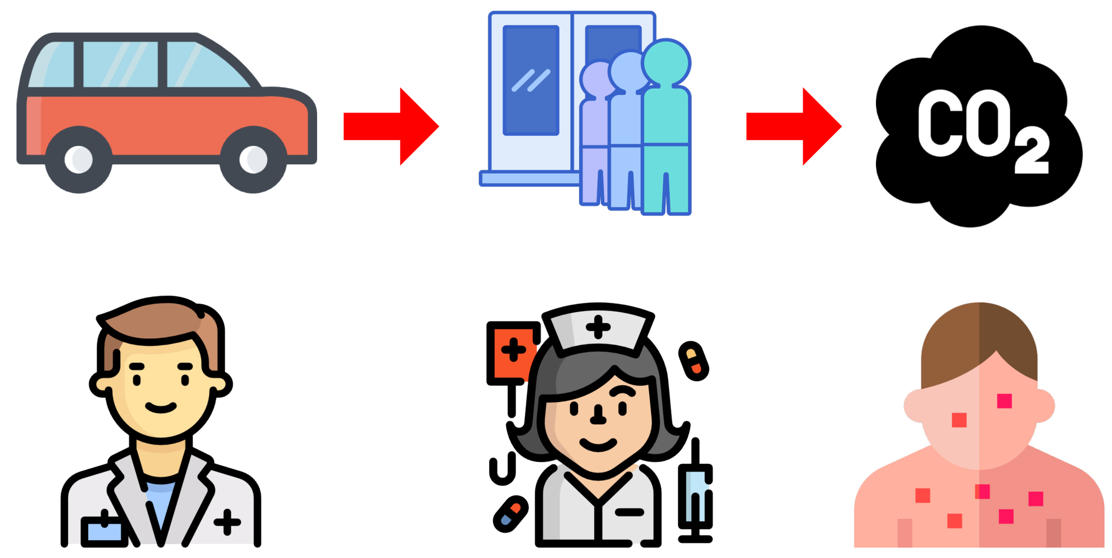
Abstract

Skin diseases are both life-threatening and common kinds, which some kinds don't need direct consultations from the doctor because of self-recovery. While other dangerous kinds could be life-threatening especially ones that occur in children. When taking to see a doctor The lack of screening methods results in congestion in hospitals. Including causing the doctors and nurses to have an excessive amount of work day by day. Therefore, having software that can help in the classification of skin diseases may be beneficial in many cases. From these reasons, therefore interested in developing a model for the classification of skin diseases. By using machine learning The operator has done 9 steps, then applied all the knowledge in the 10th operation, which is the development of a model for the classification of skin diseases in the Skin Cancer MNIST: HAM10000 dataset, using Convolutional Neural Network and the experiment is divided into 3 types such as Oversampling, Class Weights adjustment and using Focal loss. Found that the model with the top 3 F1-score are DenseNet121-Oversampling, DenseNet121-Class weights, and DenseNet121-Focal loss. The F1-score values were 0.80, 0.84 and 0.83 respectively. Weights were then transferred to develop a model for the classification of skin diseases in the PJ61403 dataset. It was found that the model obtained the highest 3 F1-score values. Including PJ61403model-1, PJ61403model-2, and PJ61403model-3 with F1-score 0.92, 0.86, and 0.92, respectively. After that, ensemble these model by using the arithmetic mean the F1-score was 0.97

Introduction

38% CHILDREN + 20% ADULT

There are 3 - 4 times more allergies compared to 10 years ago.



Objective

- To study the use of machine learning to develop models for skin disease classification
- To study the results of the analysis, characterization and classification of different skin diseases
- To study the effects of comparing the use of different machine learning models on the classification of skin diseases

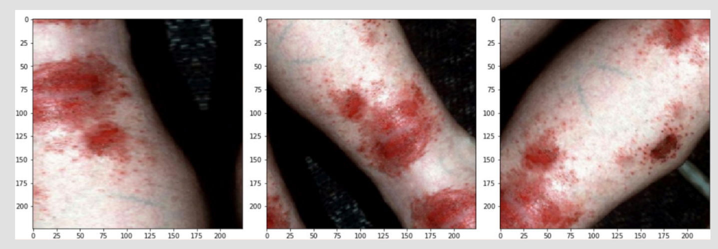
Procedure

- Oversampling
- Class Weights
- Focal Loss

DenseNet121 X HAM10000 → Fine Tuning → HAM10000 weights

DenseNet121 + HAM10000 weights X PJ61403 → Fine Tuning → PJ61403 model

Data Augmentation → Reflect → abcddcba | abcd | dcbaabcd →



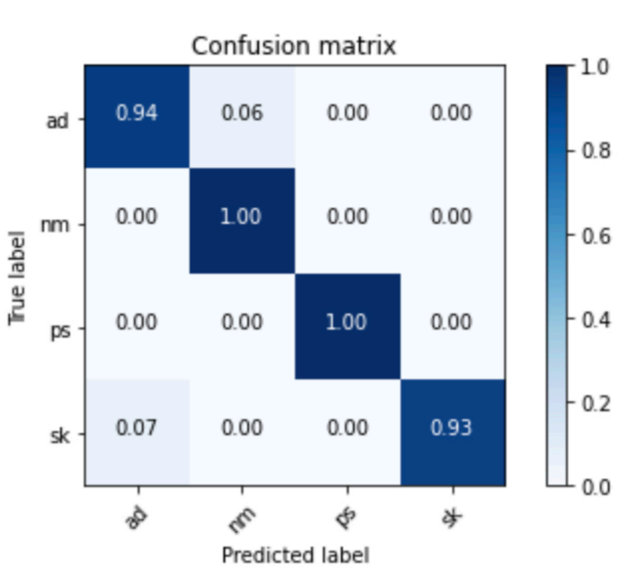
Ensemble → PJ61403 model-1, PJ61403 model-2, PJ61403 model-3 → Arithmetic mean Predictions

$$\bar{X} = \frac{\sum X}{n}$$

Result

Solution	Accuracy	Precision	Recall	F1-score
Oversampling	0.83	0.81	0.80	0.80
Class Weights	0.84	0.85	0.83	0.84
Focal Loss	0.83	0.86	0.81	0.83

Solution	Accuracy	Precision	Recall	F1-score
PJ61403-1	0.92	0.93	0.92	0.92
PJ61403-2	0.86	0.88	0.86	0.86
PJ61403-3	0.92	0.93	0.92	0.92

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Classification Report
              precision    recall  f1-score   support

          ad       0.94      0.94      0.94        17
          nm       0.94      1.00      0.97        15
          ps       1.00      1.00      1.00        16
          sk       1.00      0.93      0.97        15

    accuracy                           0.97        63
   macro avg       0.97      0.97      0.97        63
weighted avg       0.97      0.97      0.97        63
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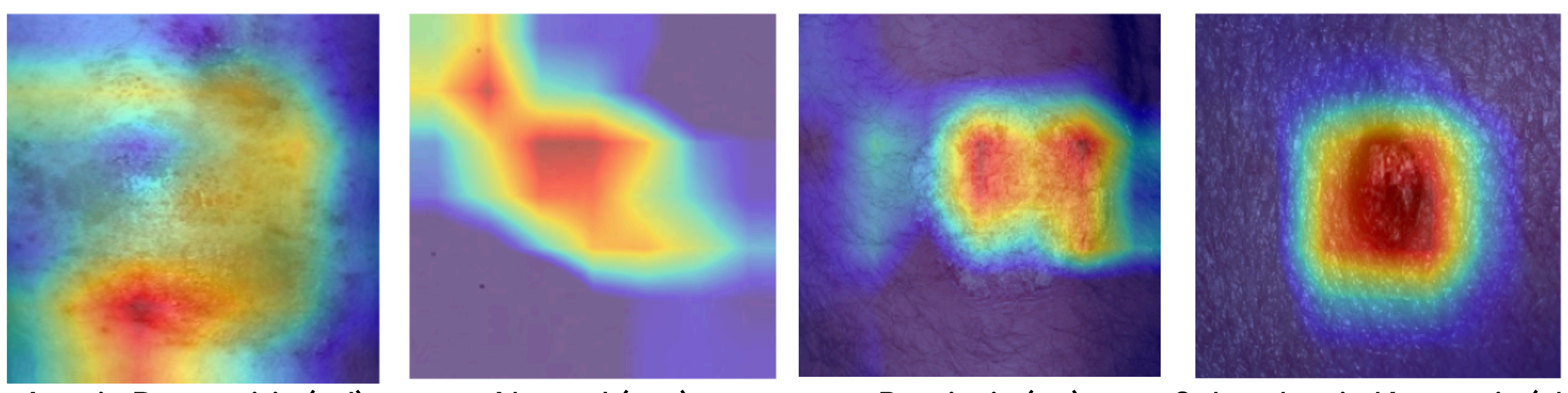
Conclusion

From the 10 experiments, found that when weights obtained from the development of the HAM10000 model using DenseNet121 with Oversampling, Class Weights adjustment, and using Focal Loss for solving the imbalanced dataset problem, then use transfer Learning with the PJ61403 dataset, metrics are higher than all previous experiments. Due to the feature being transferred to the network and when ensemble learning using the arithmetic mean, the metrics are higher and Grad-CAM is more accurate.

Image



Atopic Dermatitis (ad) Normal (nm) Psoriasis (ps) Seborrhoeic Keratosis (sk)

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