

Skin Diseases Classification Using Machine Learning



Me



Hello World !

Hi I'm Waranthorn Chansawang

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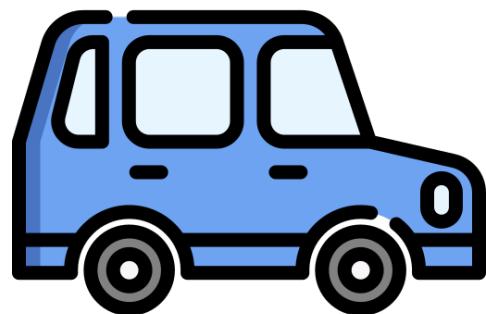
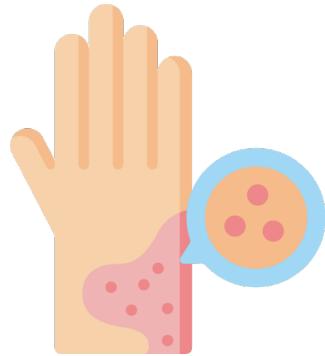


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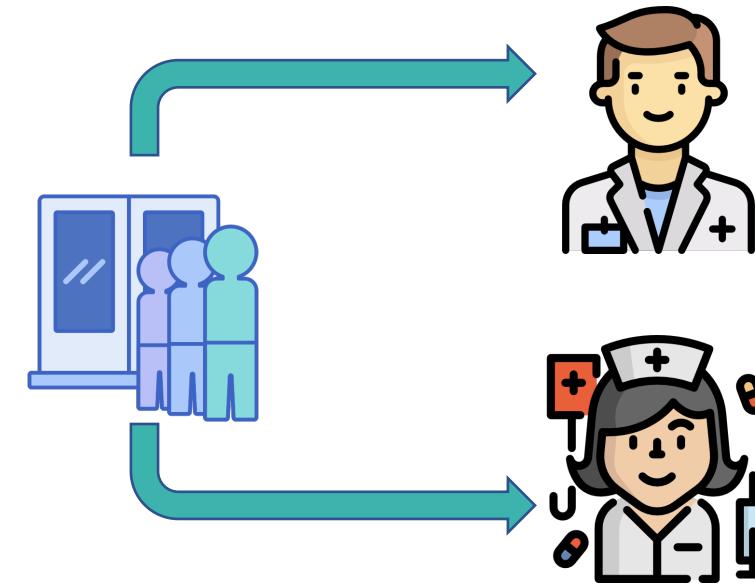
Introduction



	Allergy	Atopic Dermatitis
Children	38%	10-20%
Adult	20%	1-3%



สำนักงานกองทุนสนับสนุน
การสร้างเสริมสุขภาพ

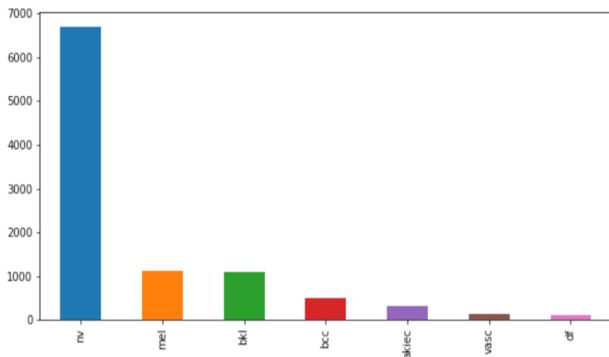
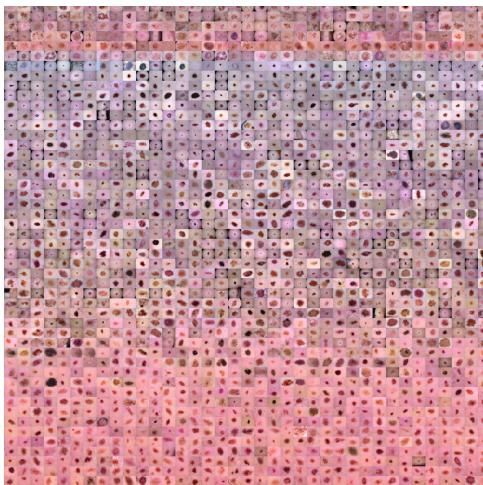


Objective

- 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

Dataset

HAM10000



nv	6705
mel	1113
bkl	1099
bcc	514
akiec	327
vasc	142
df	115

PJ61403



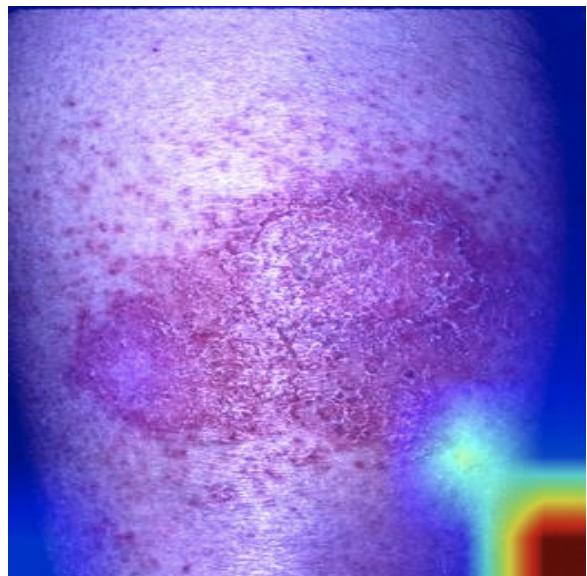
DermNet New Zealand
All about the skin



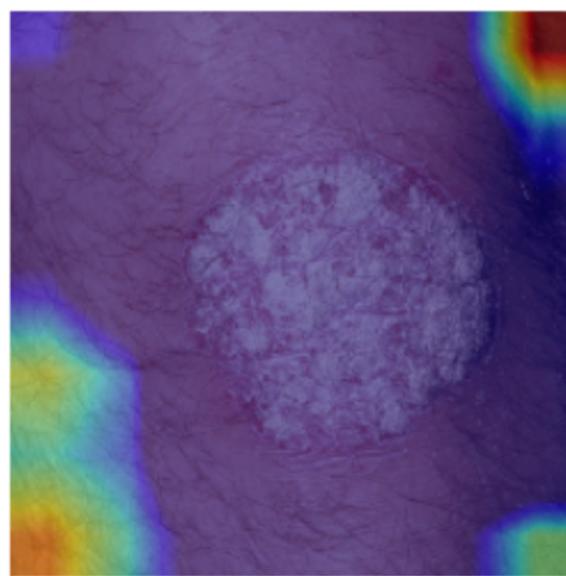
Procedure

1. Learn Python and Practice with MNIST
 - Test accuracy 0.99
2. Atopic Dermatitis VS Contact Dermatitis
 - Test accuracy 0.5013
3. Practice with HAM10000
 - Accuracy 0.72 **but** F1-score 0.36, Imbalanced Data is **IMPORTANT**.
4. Split the model into each organ and SVM VS CNN.
 - Arm, Body skin, Hand, and Leg, CNN is better than SVM.
5. Split the model into 1 and 2 and SVM VS CNN.
 - Test F1-score 0.88 and 0.87
6. Mixed model 1 + 2
 - Test F1-score 0.73

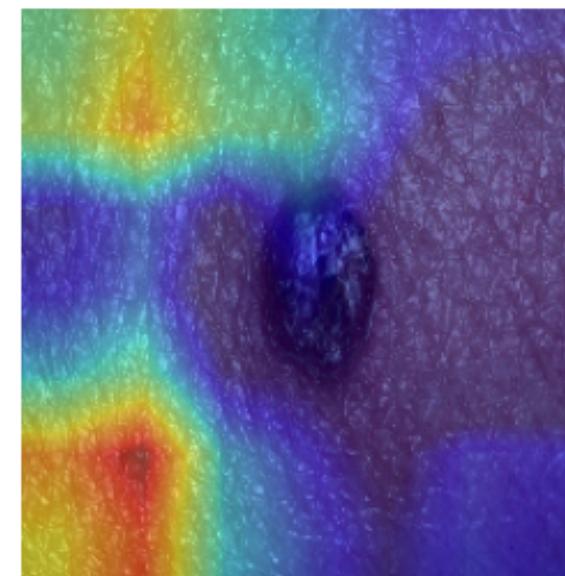
Grad-CAM



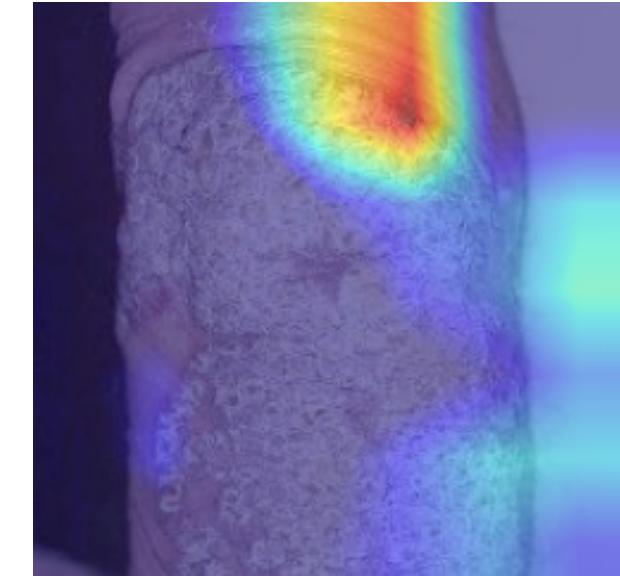
Atopic Dermatitis (AD)



Normal (nm)



Psoriasis (ps)

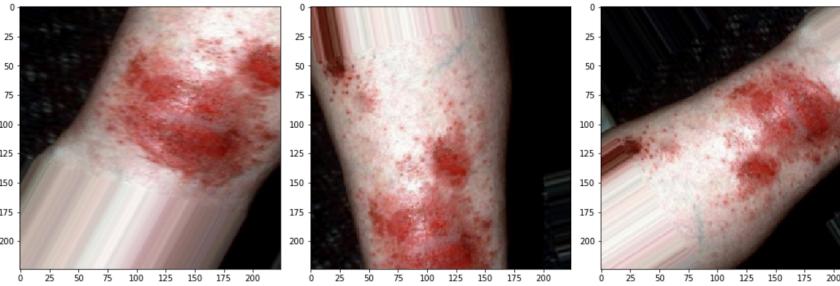


Seborrhoeic Keratosis (sk)

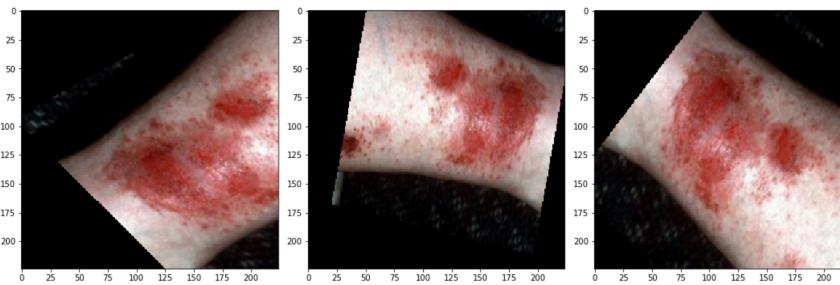
Procedure

7. Practice with Cifar-10
 - Test F1-score 0.86
8. HAM10000 to PJ61403
 - Test F1-score 0.92
9. Ensemble model from 9.
 - Test F1-score 0.89
10. *New Ensemble HAM10000 to PJ61403 using DenseNet121*

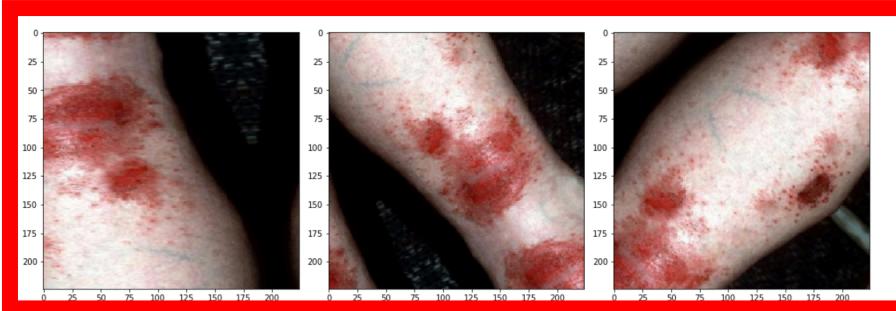
Data Augmentation



aaaaaaaa|abcd|dddddd



kkkkkkkk|abcd|kkkkkkkk



abcddcba|abcd|dcbaabcd

HAM10000

***ตัด NV ออก เหลือ 6 ***
 classes เพื่อแก้ปัญหา
 Imbalanced Dataset

DenseNet121

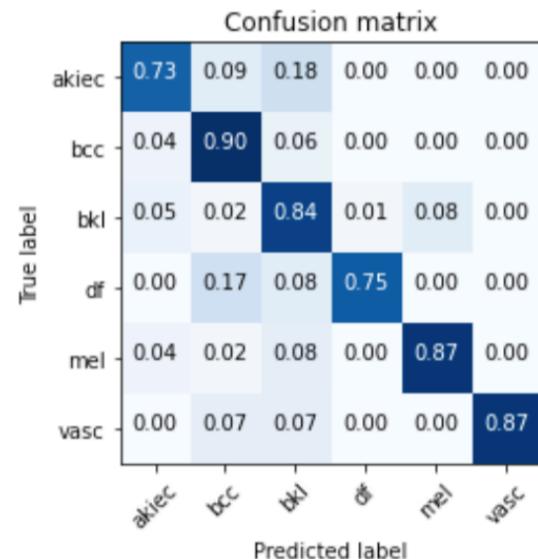
x

HAM10000

Oversampling
 Class Weights
 Focal Loss

HAM10000
 Weights

Model	F1-score	จำนวนประเภทที่มีการแทนค่าตอบ
DenseNet121-Oversampling	0.80	2
DenseNet121-Class weights	0.84	2
DenseNet121-Focal loss	0.83	2

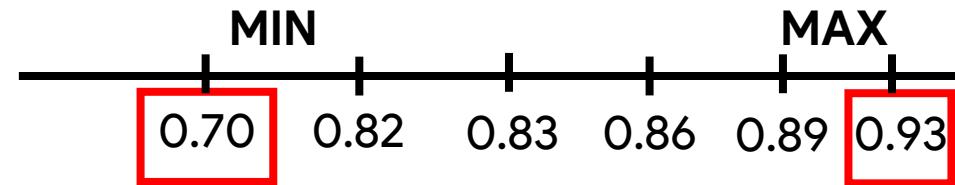


	precision	recall	f1-score	support
akiec	0.67	0.73	0.70	33
bcc	0.82	0.90	0.86	52
bkl	0.82	0.84	0.83	110
df	0.90	0.75	0.82	12
mel	0.92	0.87	0.89	112
vasc	1.00	0.87	0.93	15
accuracy			0.84	334
macro avg	0.85	0.83	0.84	334
weighted avg	0.85	0.84	0.85	334

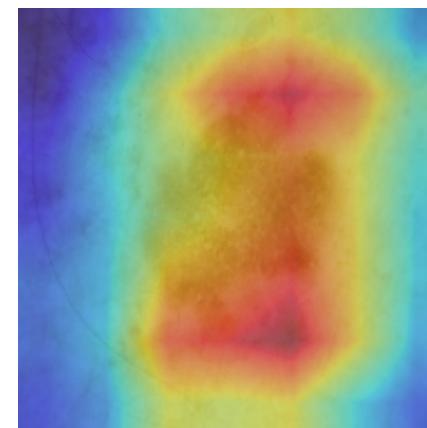
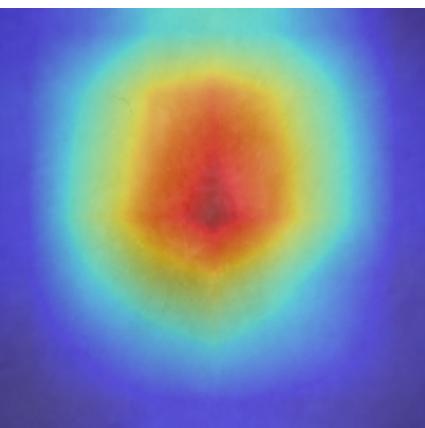
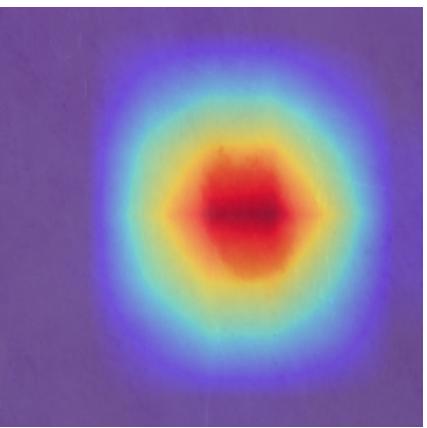
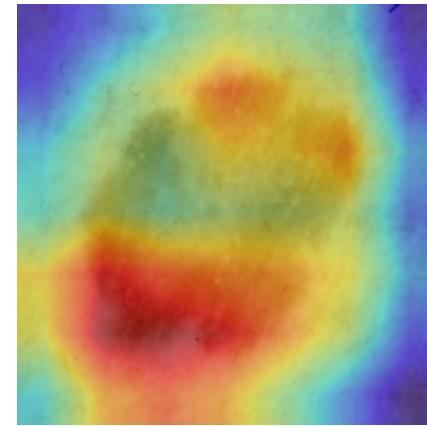
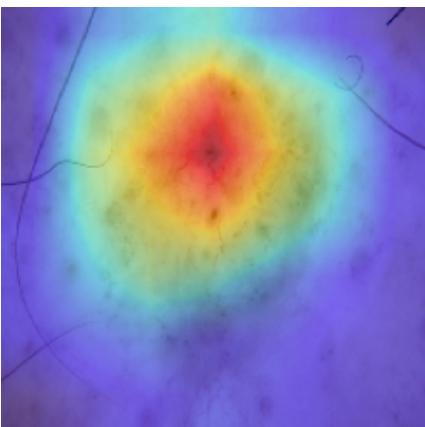
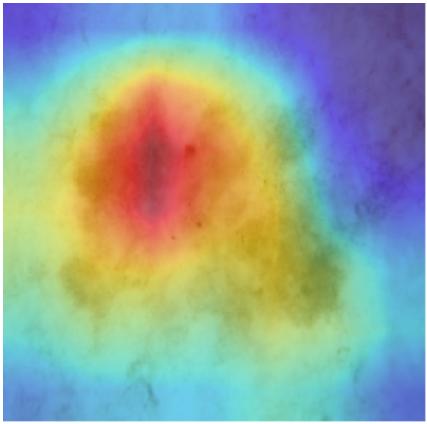
$$M.D. = \frac{\sum_{i=1}^N |X_i - \bar{X}|}{N} = 0.06$$

$$\text{MIN} = 0.84 - M.D. = 0.78$$

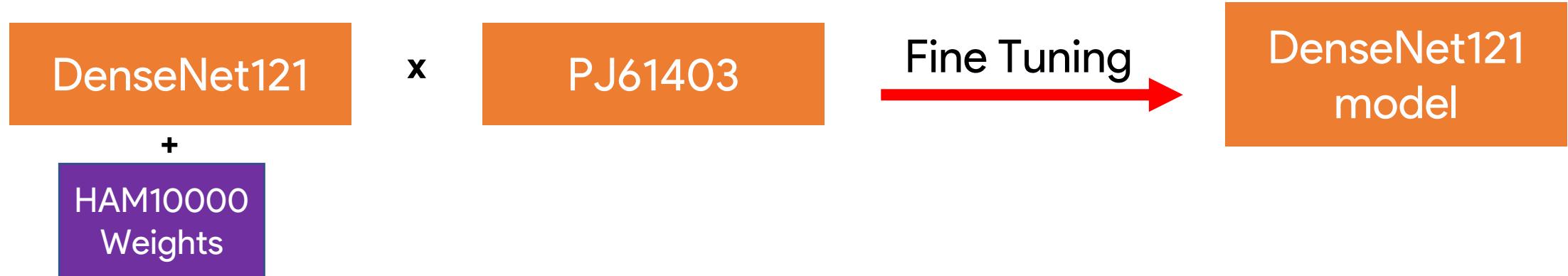
$$\text{MAX} = 0.84 + M.D. = 0.90$$



HAM10000 Grad-CAM

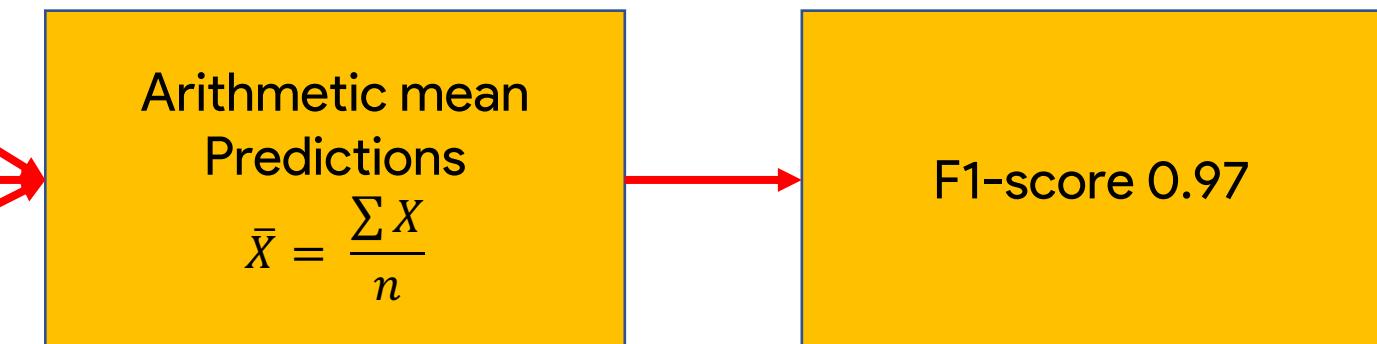


Ensemble HAM10000 to PJ61403

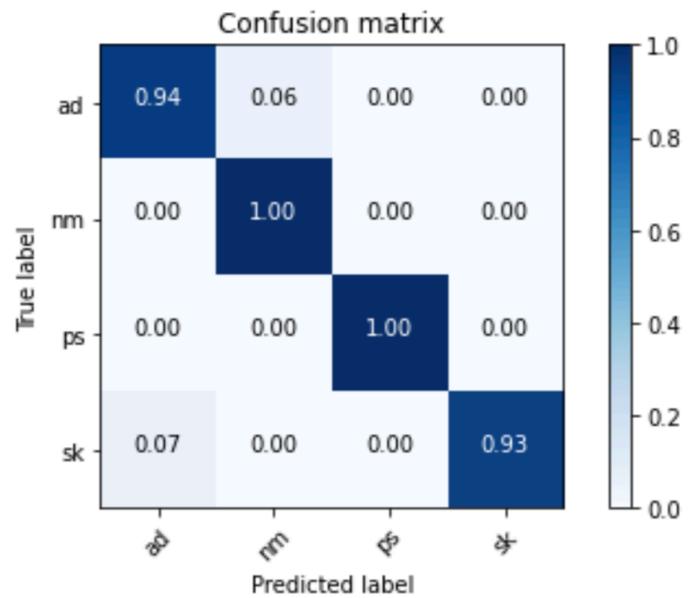


Model	F1-score
DenseNet121-Oversampling	0.92
DenseNet121-Class weights	0.86
DenseNet121-Focal loss	0.92

Ensemble



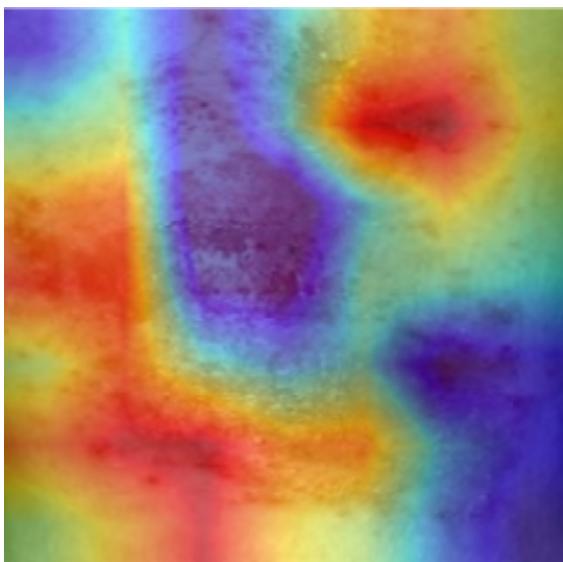
Ensemble HAM10000 to PJ61403



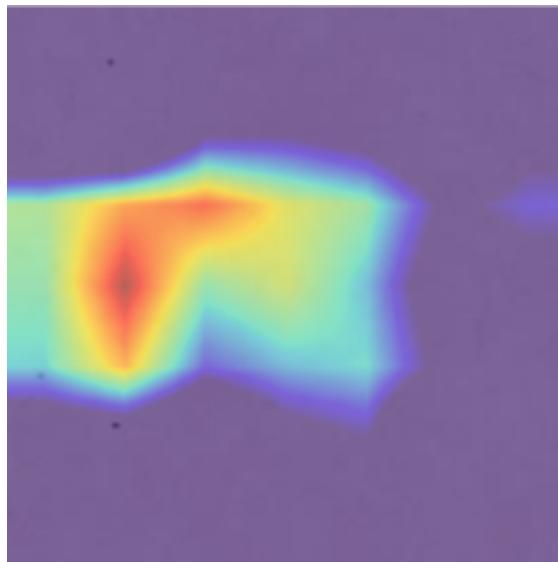
Classification Report

	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

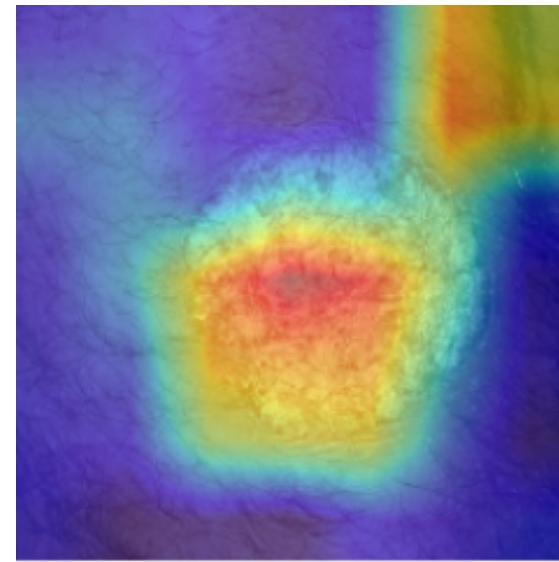
PJ61403 Grad-CAM



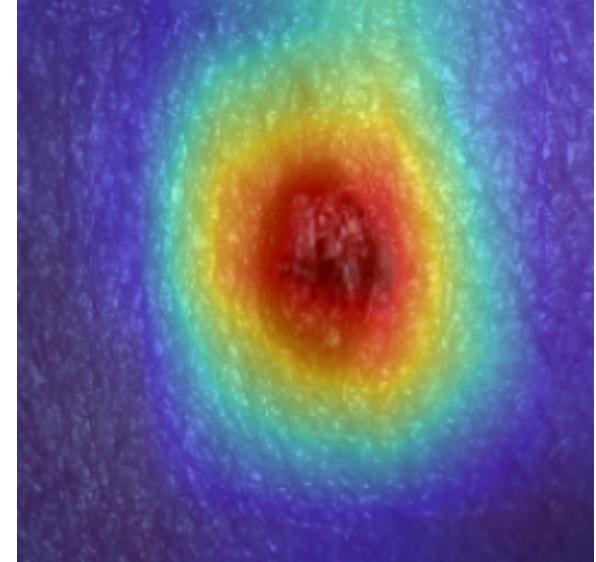
Atopic Dermatitis (AD)



Normal (nm)



Psoriasis (ps)



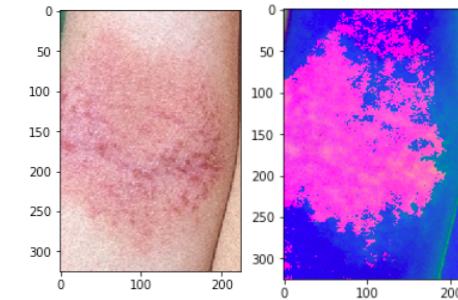
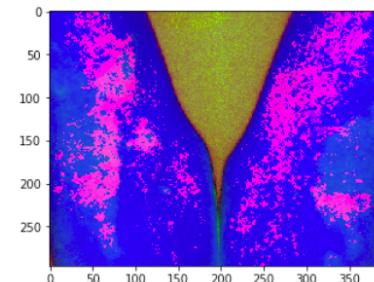
Seborrhoeic Keratosis (sk)

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.

Future Plan

- Data synthetic using GAN
- ต่อยอดการทำ Data Augmentation โดยใช้ PCA Color Augmentation เป็นพื้นฐานเพื่อให้ชุดข้อมูลมีความหลากหลายมากยิ่งขึ้น
- เปลี่ยนจากการเทรนโมเดลด้วยภาพ RGB เป็น HSV



- เพิ่มการคัดแยกโรคผิวหนังด้วยการใช้การตอบค่าตามชักประวัติ
- ใช้เทคนิค One Shot Learning เนื่องจากหมายเหตุกับชุดข้อมูลที่มีจำนวนน้อย

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สมาคมแพทย์ผิวหนังแห่งประเทศไทย สมาคมโรคภูมิแพ้และวิทยาภูมิคุ้มกันแห่งประเทศไทย ชมรมแพทย์ผิวหนัง เด็กแห่งประเทศไทย .ม.ป.ป .(แนวทางการดูแลรักษาโรคผื่นภูมิแพ้ผิวหนัง) .ออนไลน์ .(สืบค้นได้จาก :http://www.dst.or.th/files_news/Atopic_Dermatitis_2010.pdf). [17 พฤษภาคม 2562].

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Extra



THANK YOU

Q&A