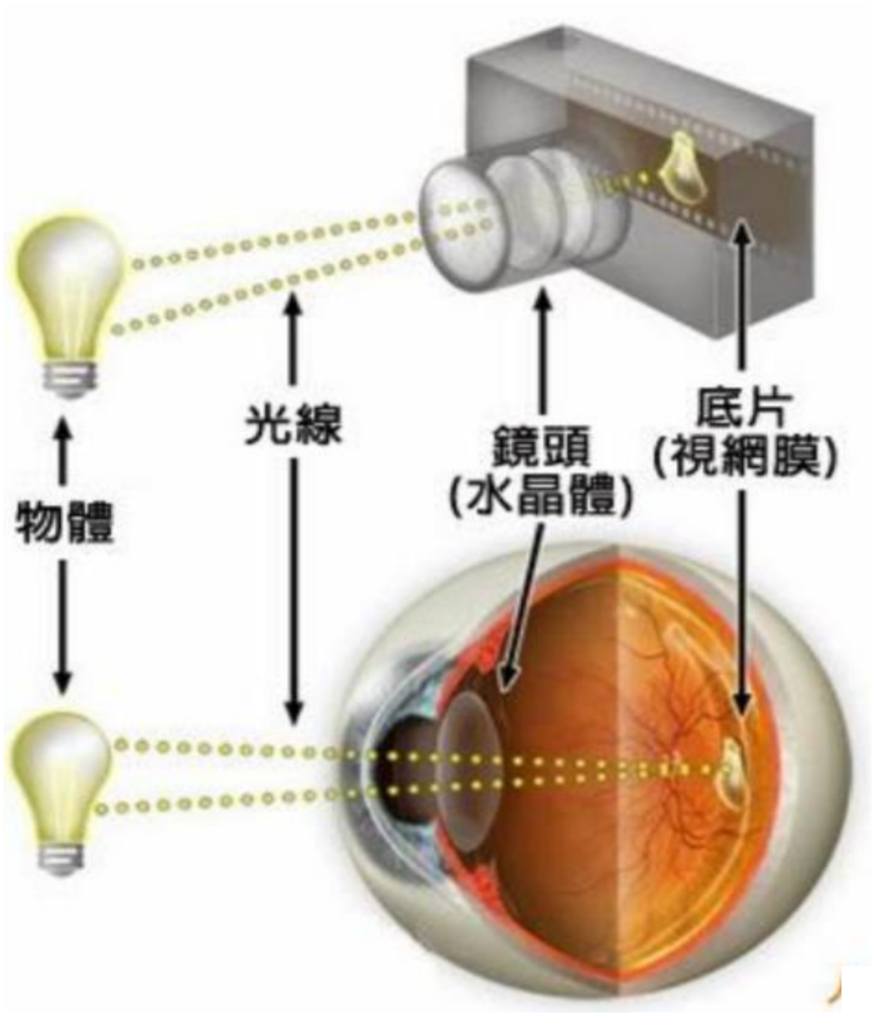
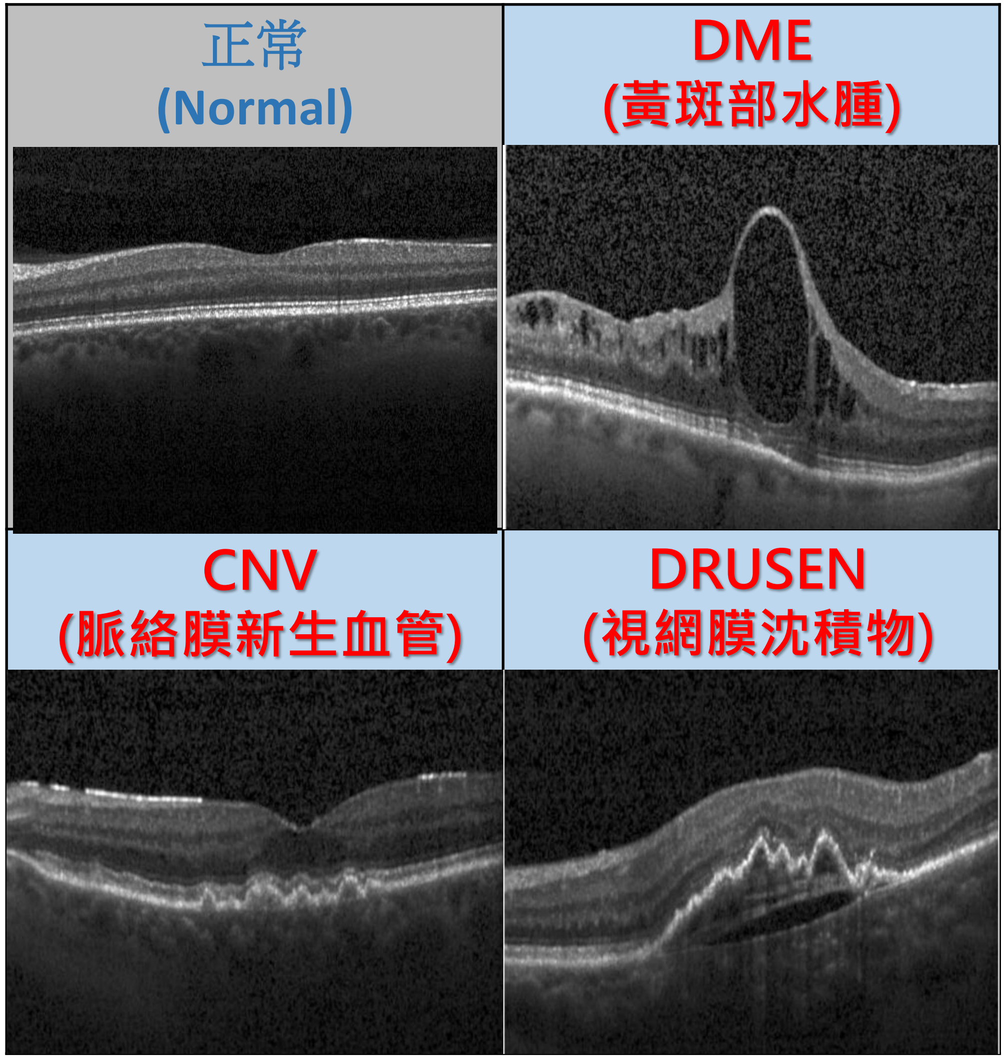
Detecting Retina Symptom
視網膜症狀檢測

視網膜介紹與症狀


光線
鏡頭
(水晶體)
底片
(視網膜)
物體


正常
(Normal)
DME
(黃斑部水腫)
CNV
(脈絡膜新生血管)
DRUSEN
(視網膜沈積物)

視網膜檢測時有以下問題：


誤判


耗時

本專案期望以AI 技術輔助檢測，降低醫生診斷時負擔

解題過程

1.啟動專案 12/25

2.報告大綱確認 1/3

- ✓ 分類
- ✓ 物件偵測
- ✓ Segmentation

3.分類問題完成 1/10

4.物件偵測問題完成 1/17

5. Segmentation 完成 1/22

6.報告完成 2/5

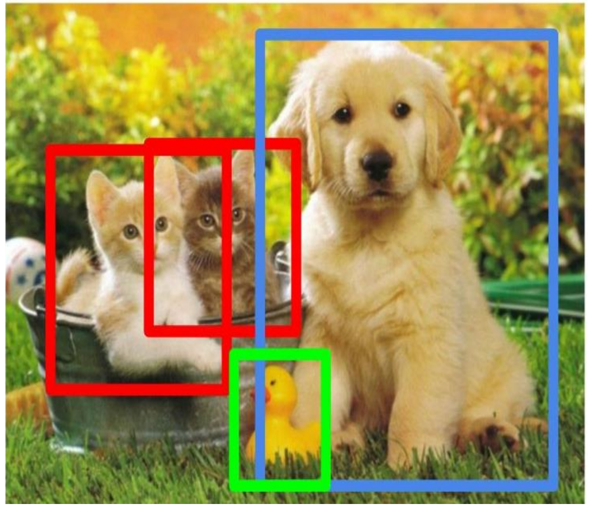
7.結案報告 2/12

視網膜檢測攻堅思維

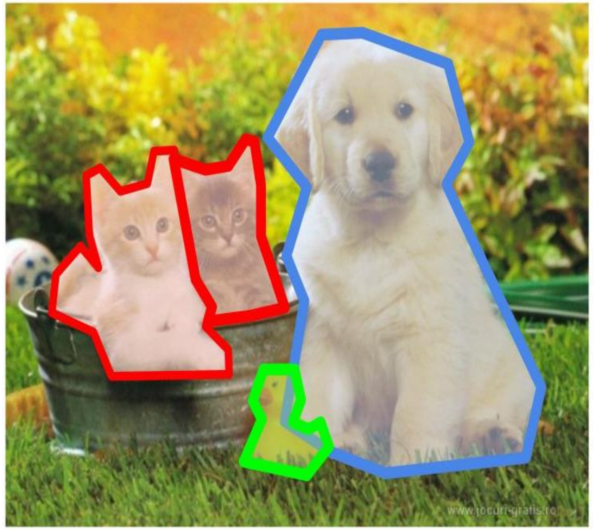
有沒有症狀? → 什麼症狀? → 發生在那/多大?

物件歸類
Classification

物件偵測
Object Detection



語意分析
Instance Segmentation



本專案以電腦視覺三大方法做為主要攻堅計劃

如何順利執行 AI 專案

Tips:

- ✓ 資料拆成 Training / Dev / Test
- ✓ Transfer Learning
- ✓ 注意 High Bias and High Variance
- ✓ 注意 Dev set and Test Set same distribution
- ✓ Error Analysis

✓ 資料拆成 TRAINING / DEV / TEST

Idea #1: Choose hyperparameters that work best on the data

BAD: Easy works perfectly on training data

Your Dataset

Idea #2: Split data into **train** and **test**, choose hyperparameters that work best on test data

BAD: No idea how algorithm will perform on new data

train	test

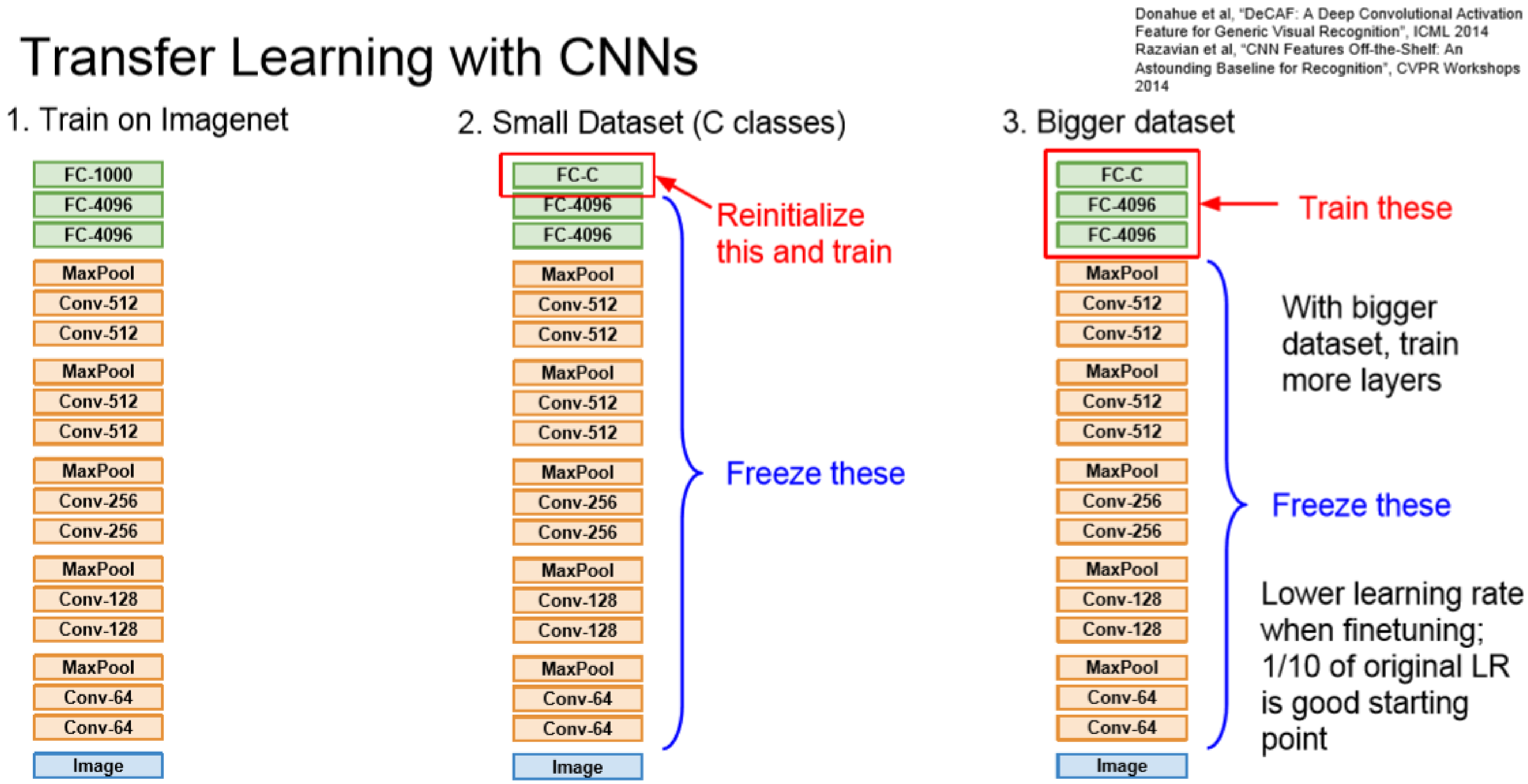
Idea #3: Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

Better!

train	validation	test

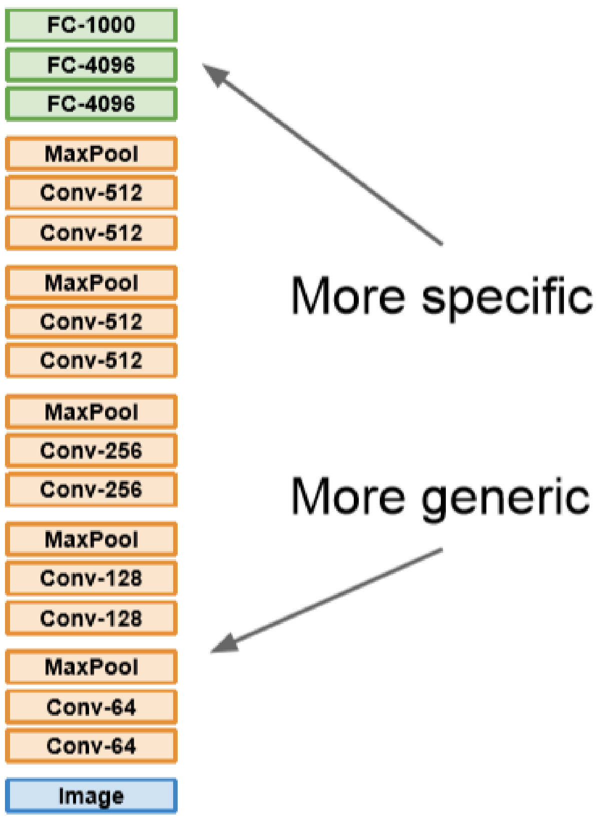
資料來源:
Stanford University CS231n

✓ TRANSFER LEARNING



資料來源:
Stanford University CS231n

✓ TRANSFER LEARNING



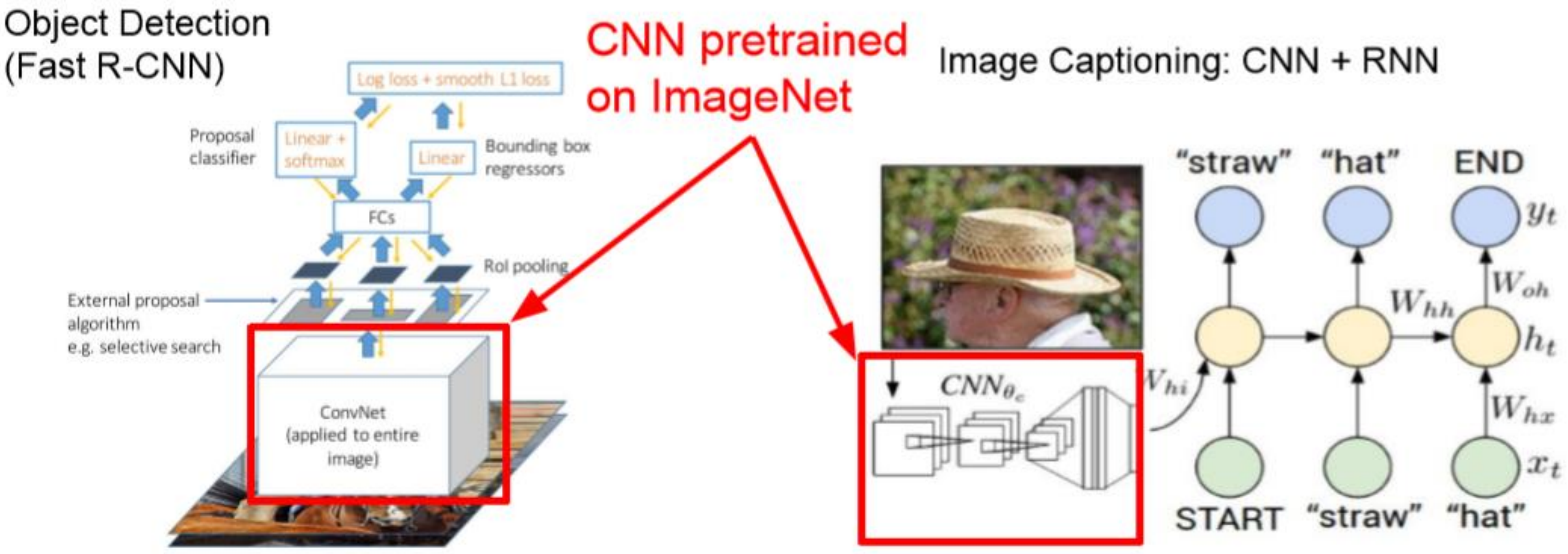
	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

資料來源:
Stanford University CS231n

✓ TRANSFER LEARNING

Transfer learning with CNNs is pervasive…

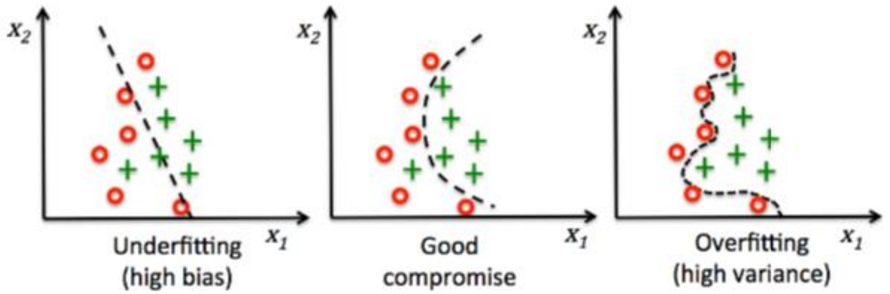
(it’s the norm, not an exception)



資料來源:
Stanford University CS231n

✓ 注意 HIGH BIAS AND HIGH VARIANCE

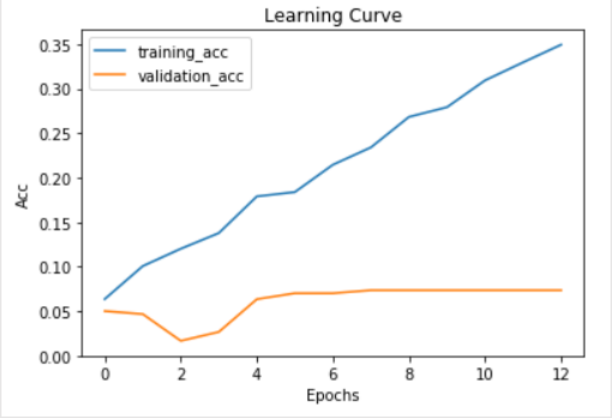
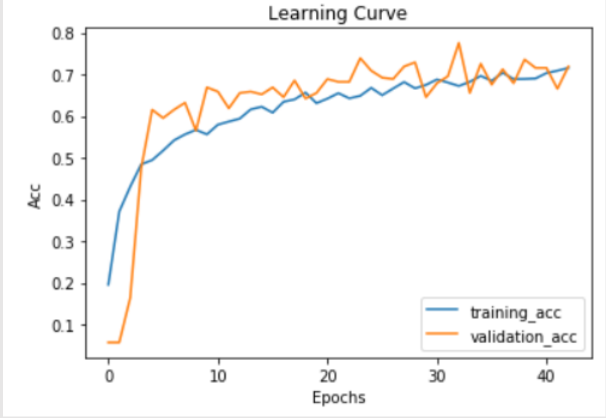
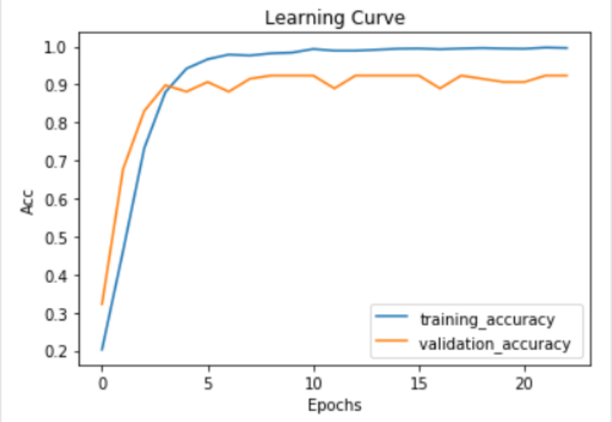
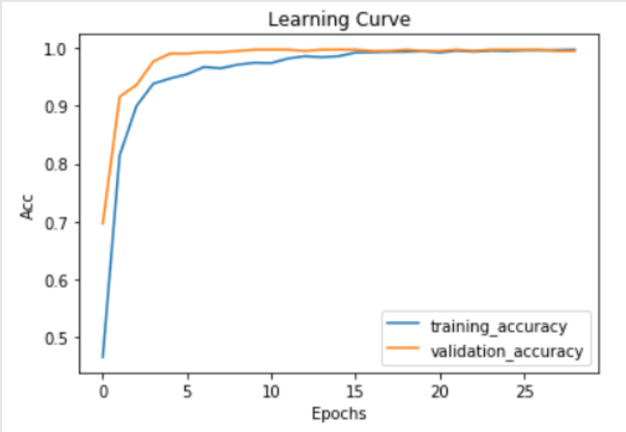
➢ 何謂 High Bias , High Variance



➢ Action of High Bias , High Variance Problems

High Bias	High Variance
1. Train bigger model 2. Train longer/better optimization algorithms 3. NN architecture / hyperparameters search	1. More data 2. Regularization 3. NN architecture / hyperparameters search

本例 human-level performance ≈ 1

High Bias & High Variance	High Bias
	
High Variance	**Perfect**
	

參考資料:
Coursera , Deep Learning, Structuring Machine Learning Projects, Andrew Ng

✓ 注意 DEV SET AND TEST SET SAME DISTRIBUTION

Regions:

- US
- UK
- Other Europe
- South America
- India
- China
- Other Asia
- Australia

$\boxed{\text{Dev}}$ ←

$\boxed{\text{Test}}$ ←

Randomly shuffle into dev/test

Guideline:

Choose a dev set and test set to reflect data you expect to get in the future and consider important to do well on.

Same Distribution

資料來源:
Coursera , Deep Learning, Structuring Machine Learning Projects, Andrew Ng

✓ ERROR ANALYSIS

➢ 製作表格，針對分類錯誤的 Image 下 Comments

Image	Dog	Great Cat	Blurry	Incorrectly labeled	Comments
1				✓	Labeler missed cat in background
2		✓			
3				✓	Drawing of a cat; Not a real cat.
…					

資料來源:
Coursera , Deep Learning, Structuring Machine Learning Projects,   Andrew Ng

- ✓ 有了 AI Project Knowledge 後，開始實作

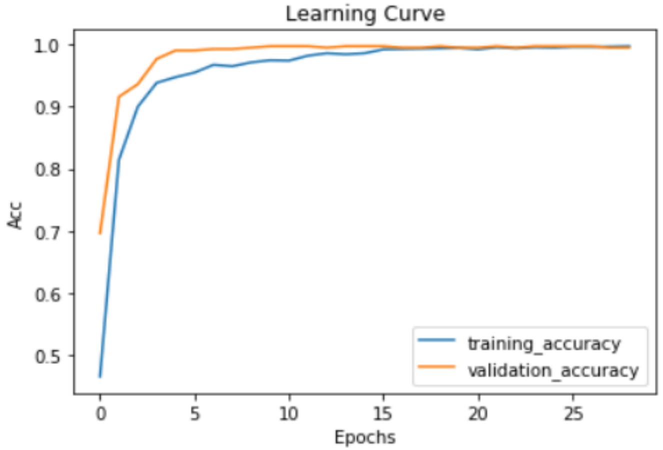
攻堅計劃一：影像分類判定症狀

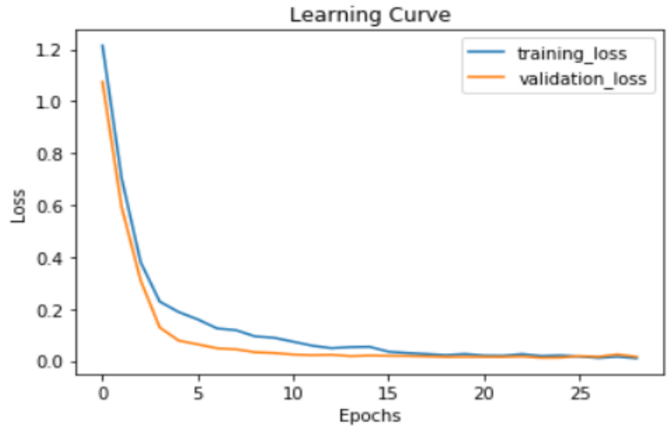
- Basic Information

Method		Transfer Learning
Model		Xception
Hyperparameter	optimizer	Adam(lr=10e-6)
	epochs	100
ImageDataGenerator		rotation_range=10, width_shift_range=0.1, height_shift_range=0.1, shear_range=0.1, zoom_range=0.1, horizontal_flip=True, fill_mode='nearest')
Earlystop		val_loss 連續 5 epoch 無下降
Data		CNV 605 DME 501 DRUSEN 580 Normal 517
Train_Test_Split		0.8/0.2

- Training/Validation Accuracy/Loss

-Model 無 bias，variance 問題





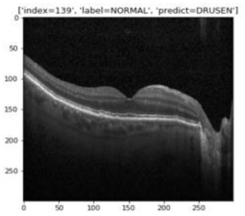
- 錯誤分析: 模型預測 Validation Set 結果

正常照片 recall 0.99/異常照片 recall 1
=> Model 無漏篩問題

predict label	CNV	DME	DRUSEN	NORMAL
CNV	117	0	0	0
DME	0	87	0	0
DRUSEN	0	0	112	0
NORMAL	0	0	1	124

```
Validation loss: 0.011931998532713135
Validation accuracy: 0.9977324
```

	precision	recall	f1-score	support
CNV	1.00	1.00	1.00	
DME	1.00	1.00	1.00	
DRUSEN	0.99	1.00	1.00	
NORMAL	1.00	$\boxed{0.99}$	1.00	
accuracy			1.00	441
macro avg	1.00	1.00	1.00	441
weighted avg	1.00	1.00	1.00	441

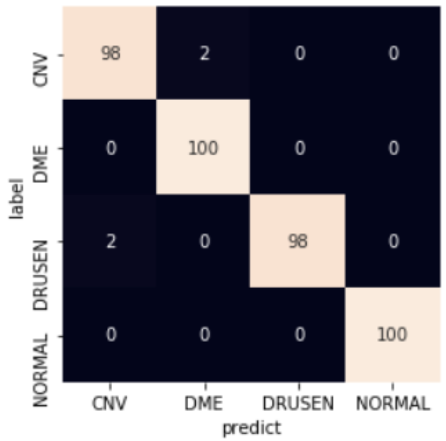


攻堅計劃一：影像分類成效驗證

- 新資料預測 (每類各 100 張)

  正常照片 recall 為 1 (100/100)
  異常照片 recall 為 0.987 (4/300)
  => Model 無漏篩問題

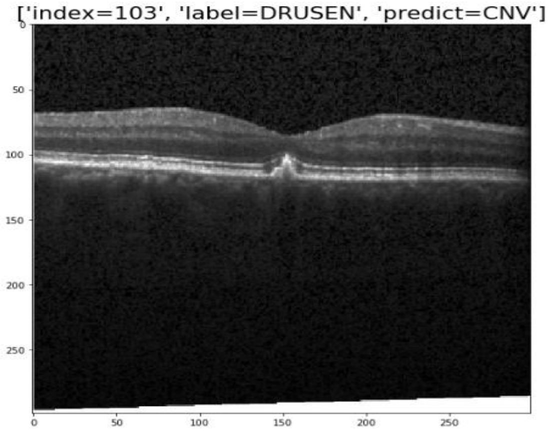
predict	CNV	DME	DRUSEN	NORMAL
label				
CNV	98	2	0	0
DME	0	100	0	0
DRUSEN	2	0	98	0
NORMAL	0	0	0	100

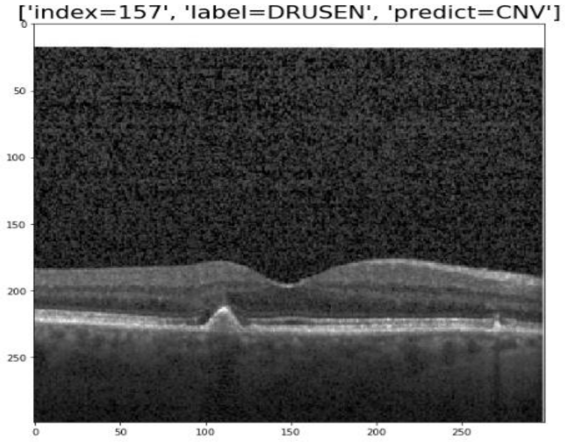


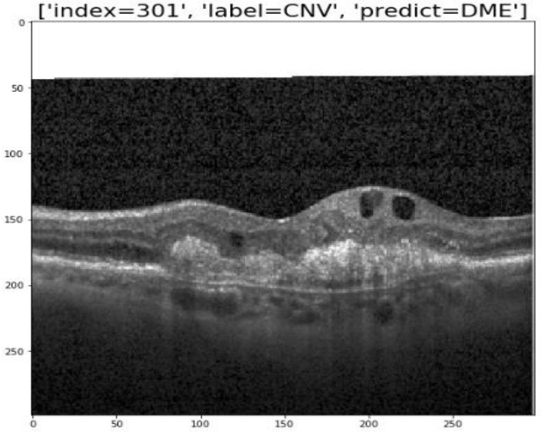
	precision	recall	f1-score	support
CNV	0.98	0.98	0.98	100
DME	0.98	1.00	0.99	100
DRUSEN	1.00	0.98	0.99	100
NORMAL	1.00	1.00	1.00	100
accuracy			0.99	400
macro avg	0.99	0.99	0.99	400
weighted avg	0.99	0.99	0.99	400

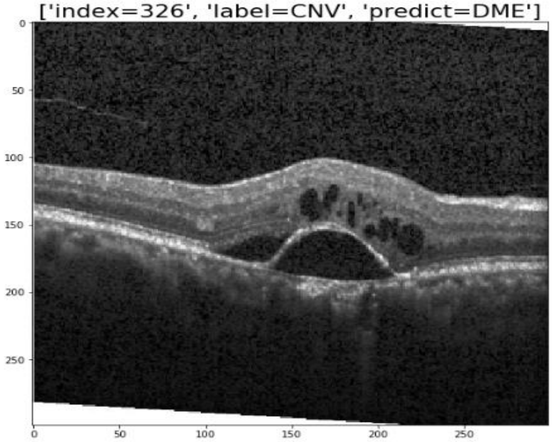
- 失效影像驗證:

  複合型異常，導致分類錯誤。解法: Object Detection





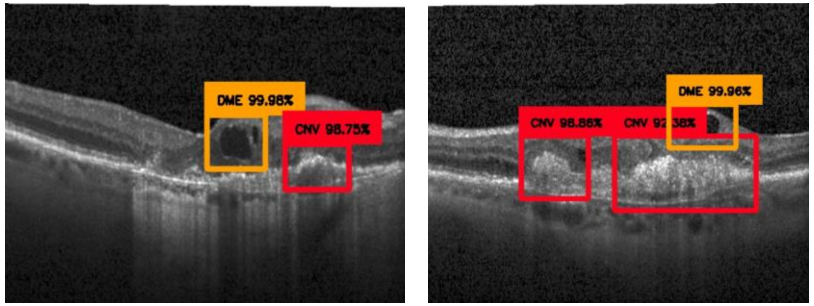




攻堅計劃二：物件偵測解決複合型異常

- Basic Information

Method		YOLOv3
Hyperparameter	epochs	30
Number of label		CNV 252 DME 146 DRUSEN 183



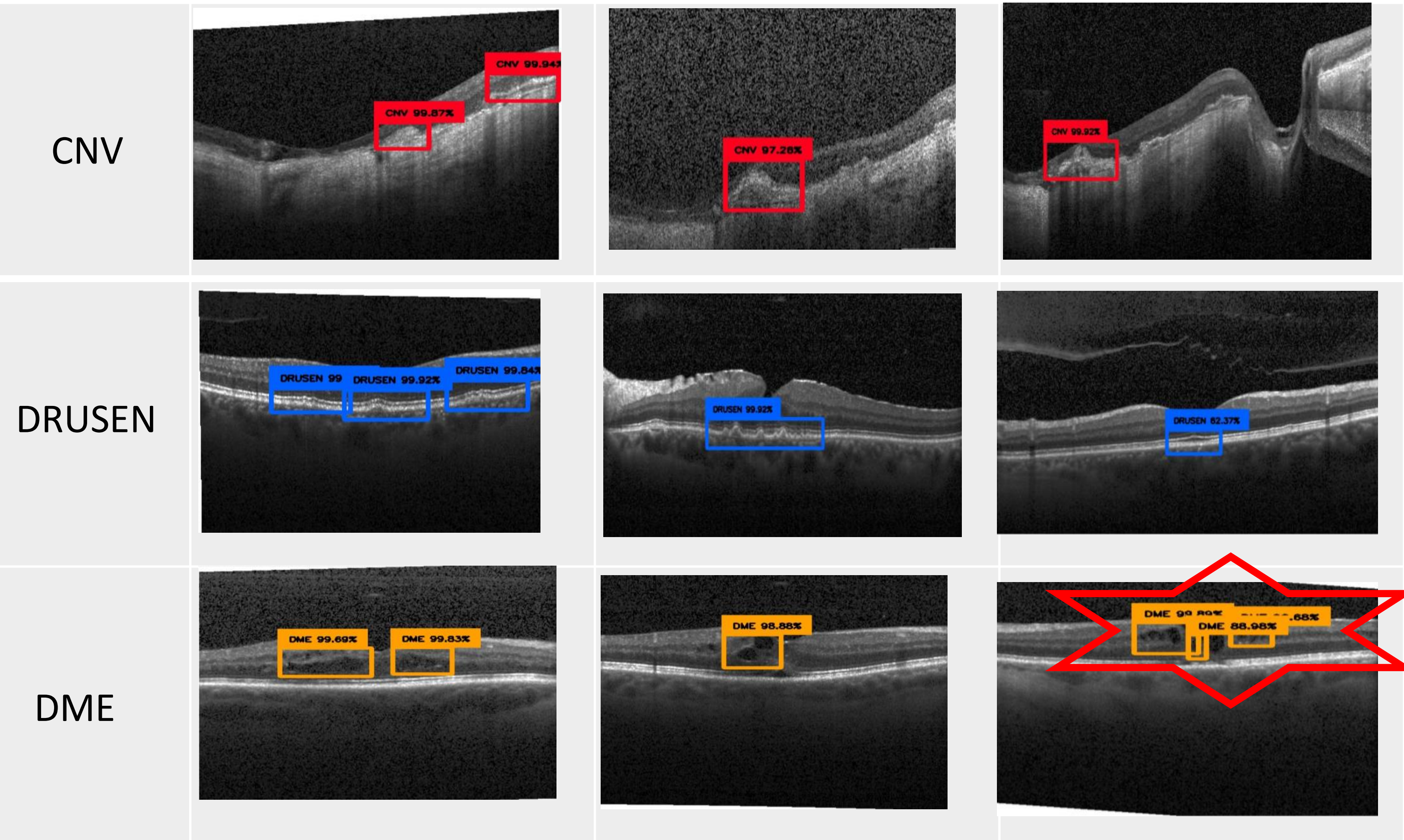
準確度

```
CNV: 0.9020
DME: 0.9540
DRUSEN: 0.9279
mAP: 0.9280
```

平均準確度

結果: mAP: 0.928

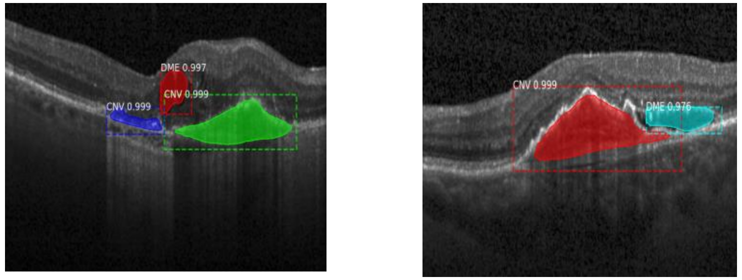
- 成效驗證：平均準確度mAP 達92.8%
- 後續問題：偵測的 Box 集中不美觀。解法: Segmentation



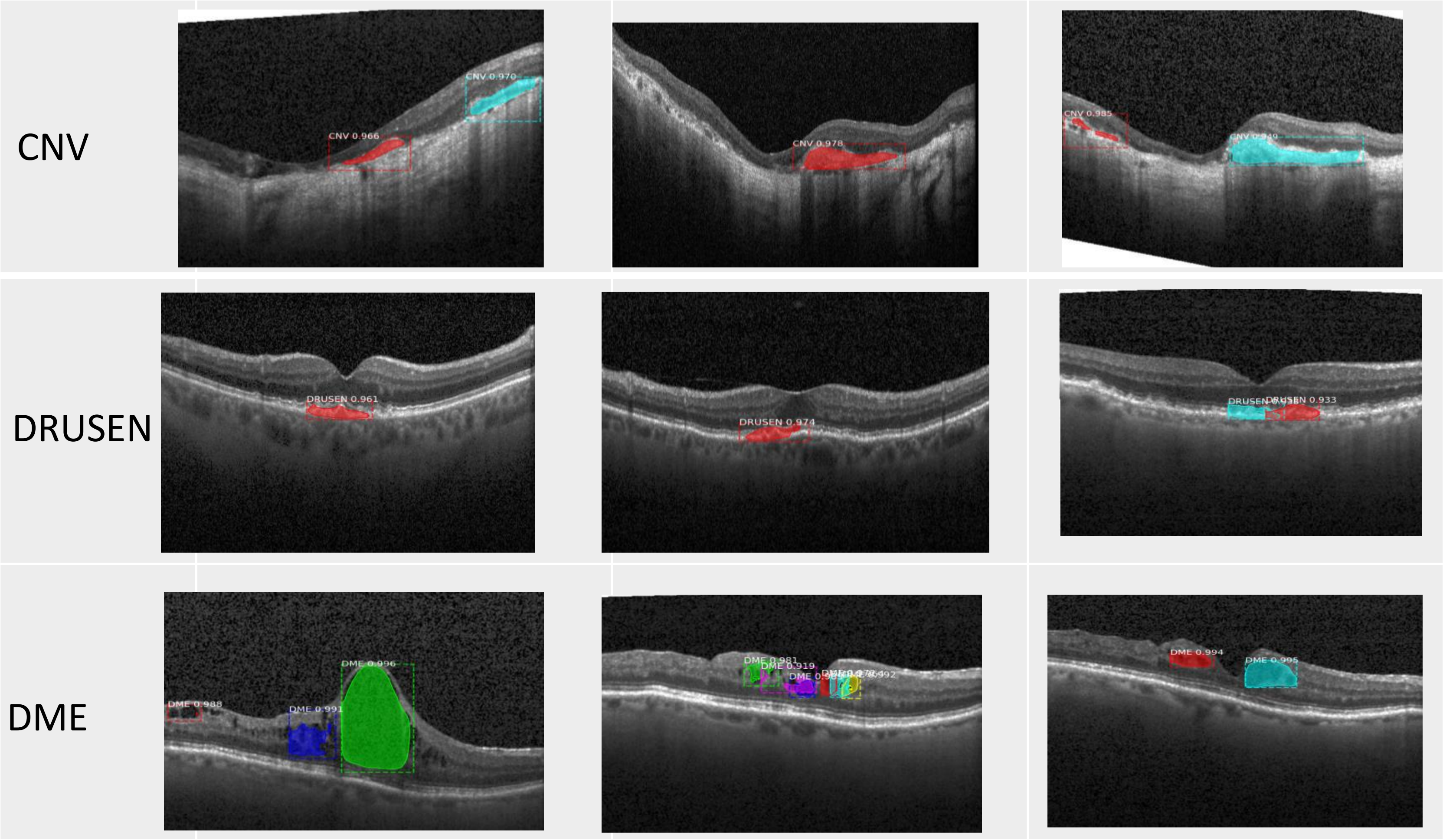
攻堅計劃三：語意分析解決偵測BOC 集中問題

- Basic Information

Method		Mask R-CNN
Hyperparameter	epochs	10
STEPS_PER_EPOCH		100
Detection min confidence		0.9
Number of label		CNV 30 DME 30 DRUSEN 30

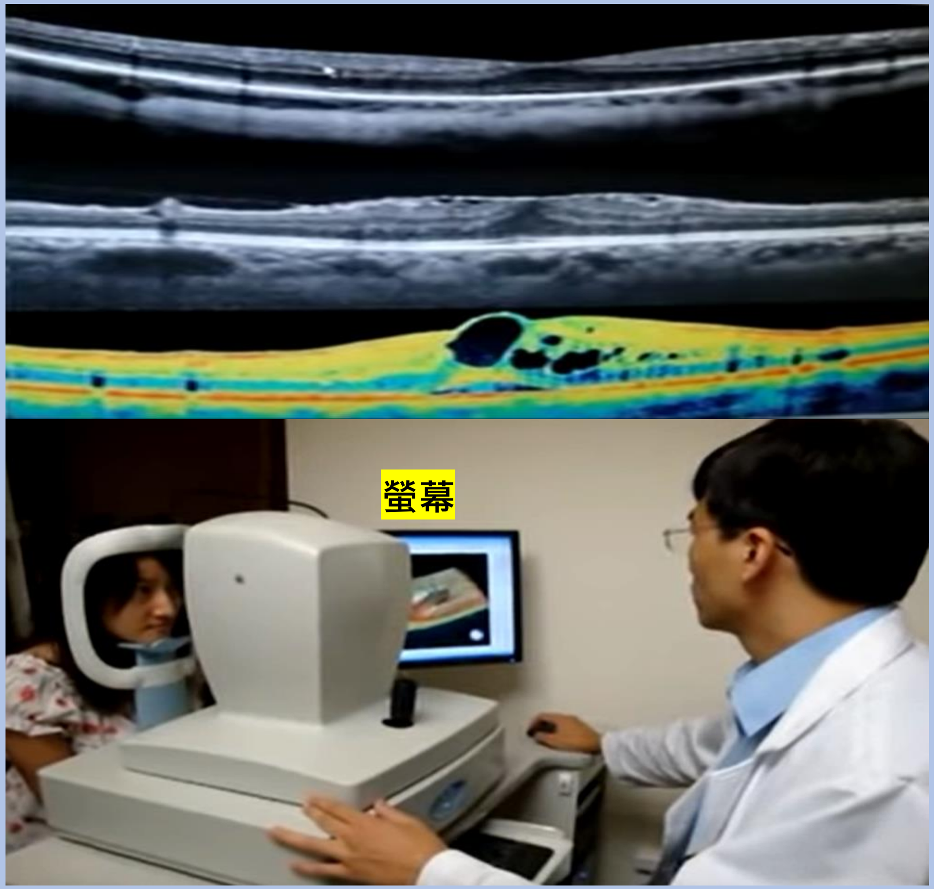


- 成效驗證：有效解決物件偵測BOS 集中，不美觀問題
  並與物件偵測手法比較



AI 導入前

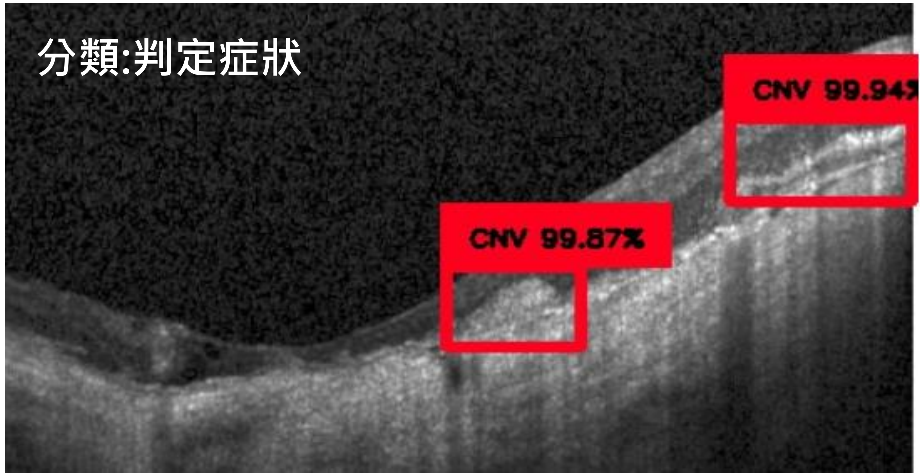
醫生盯著螢幕看症狀

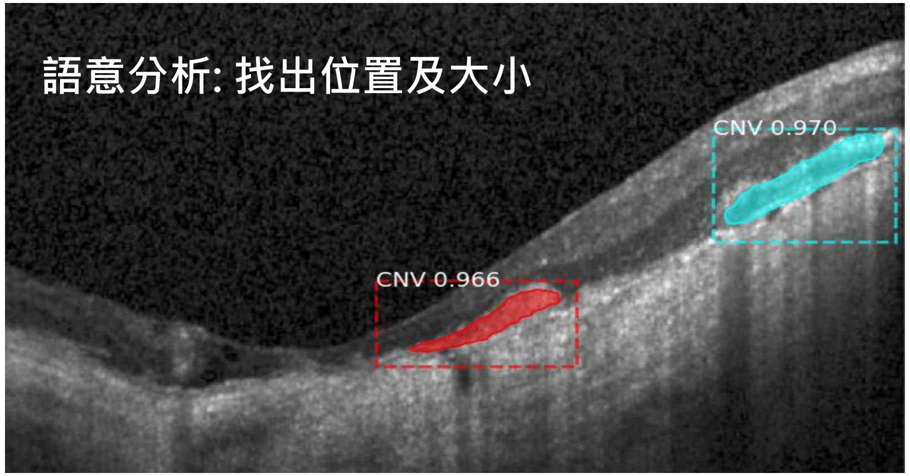


資料來源:
高雄榮總台南分院眼科李尹暘醫師

AI 導入後

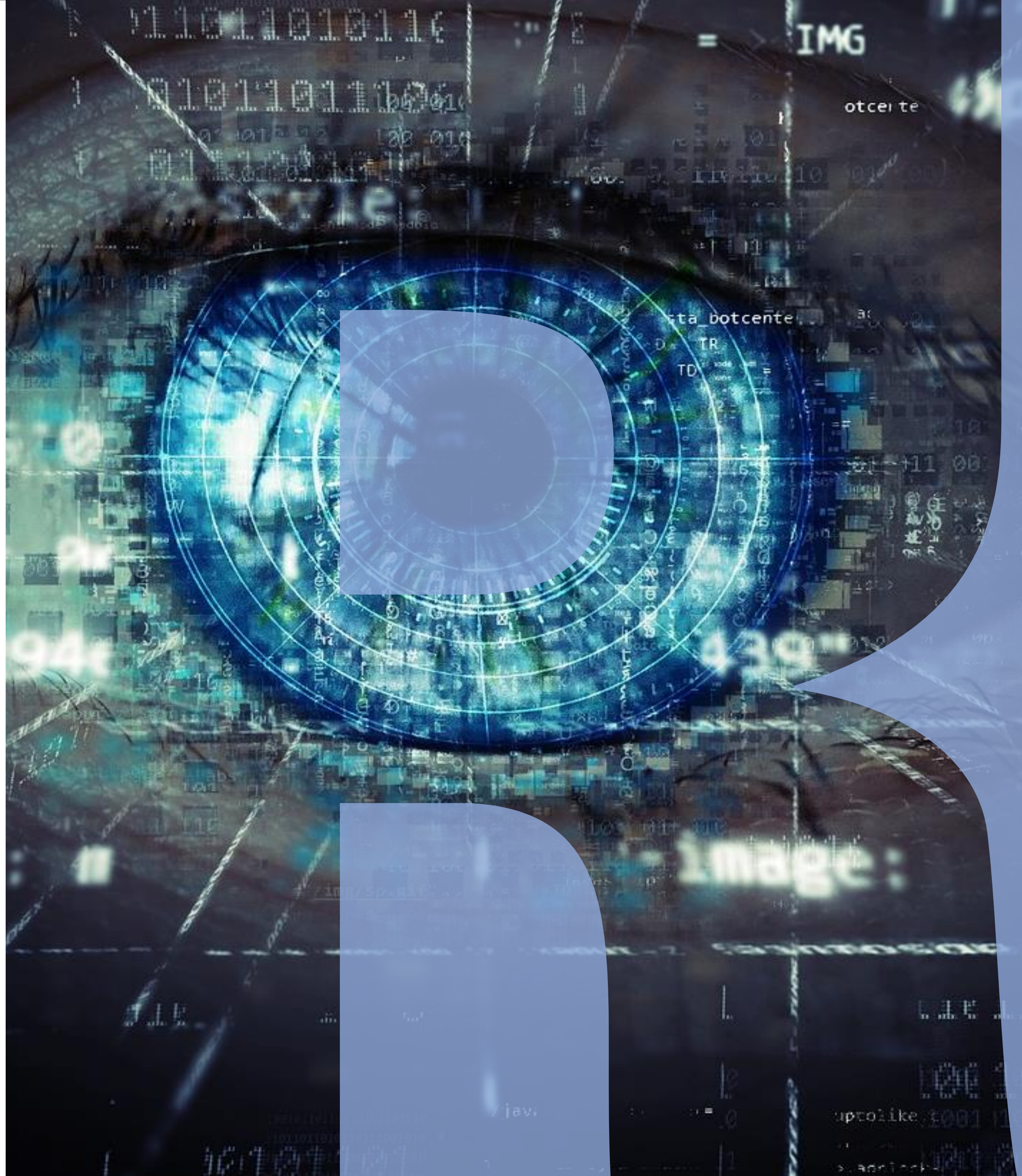
分類與偵測顯示螢幕輔助判斷





對企業/產業的IMPACT

AI 時代
一個打十個已
經不流行了



本報告 Demo

異常檢測的 AI 專案應有的流程與技術，供各企業參考!!

參考資料

- Coursera , Deep Learning, Structuring Machine Learning Projects,   Andrew Ng
- Stanford University CS231n
- AI 學校技術班 YOLOv3 教材
- ORAI Mask R-CNN
- 高雄榮總台南分院眼科李尹暘醫師:視網膜眼斷層掃描 Retina OCT
  https://www.youtube.com/watch?v=T2kuA5ZfKL4