Apply Deep Learning to Intelligent Aquaculture

深度學習應用於智慧養殖

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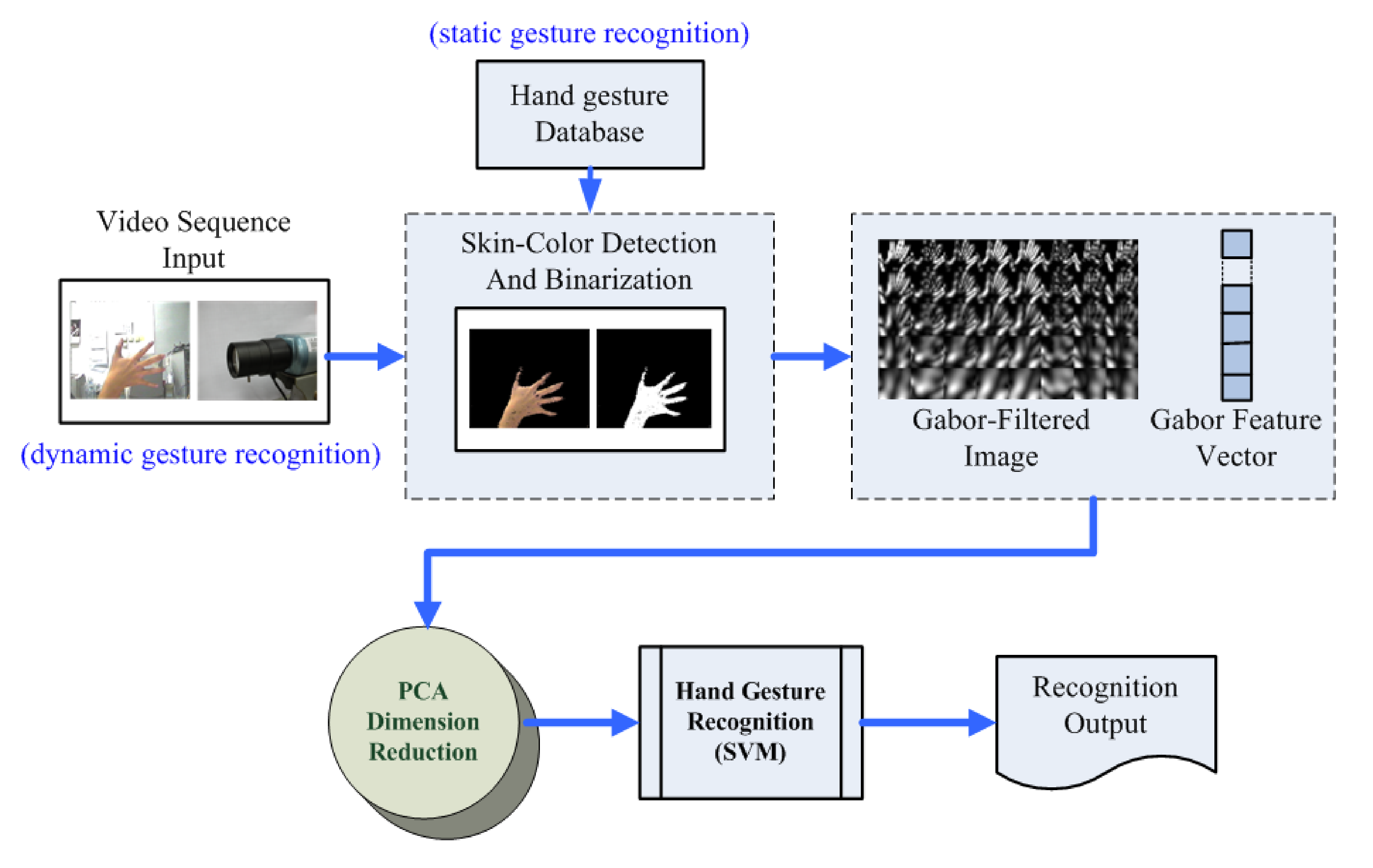
Penghu Fireworks Festival

Machine Learning
VS
Deep Learning

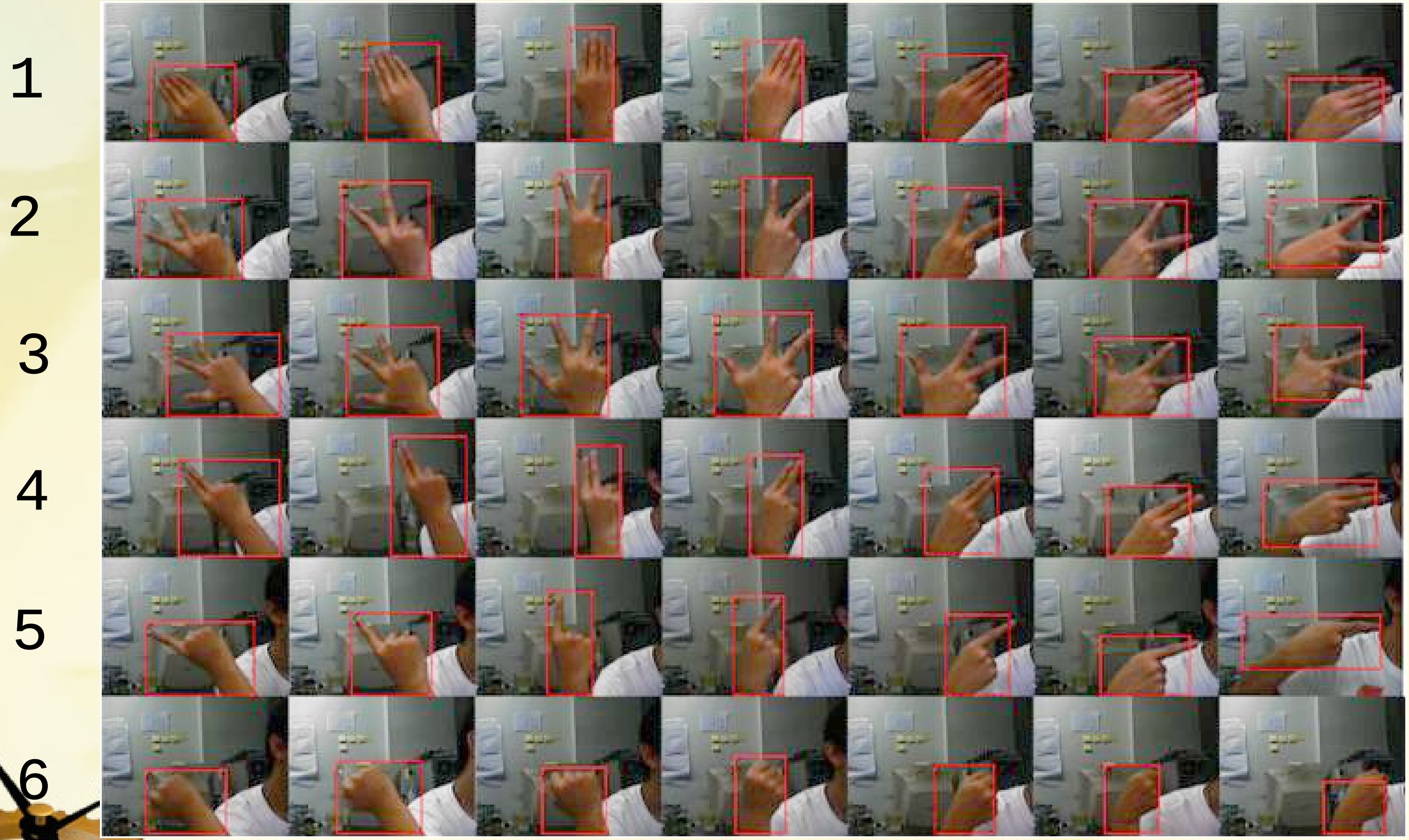
Gesture Recognition



Results of dynamic gesture recognition

- A tested video sequence of 570 (300+270) frames with a size of 320*240 pixels (wearing long-/short-sleeve clothes)
  - Recognition rate is 93.7%

Dynamic gesture detection



Dynamic gesture detection (cont.)

7

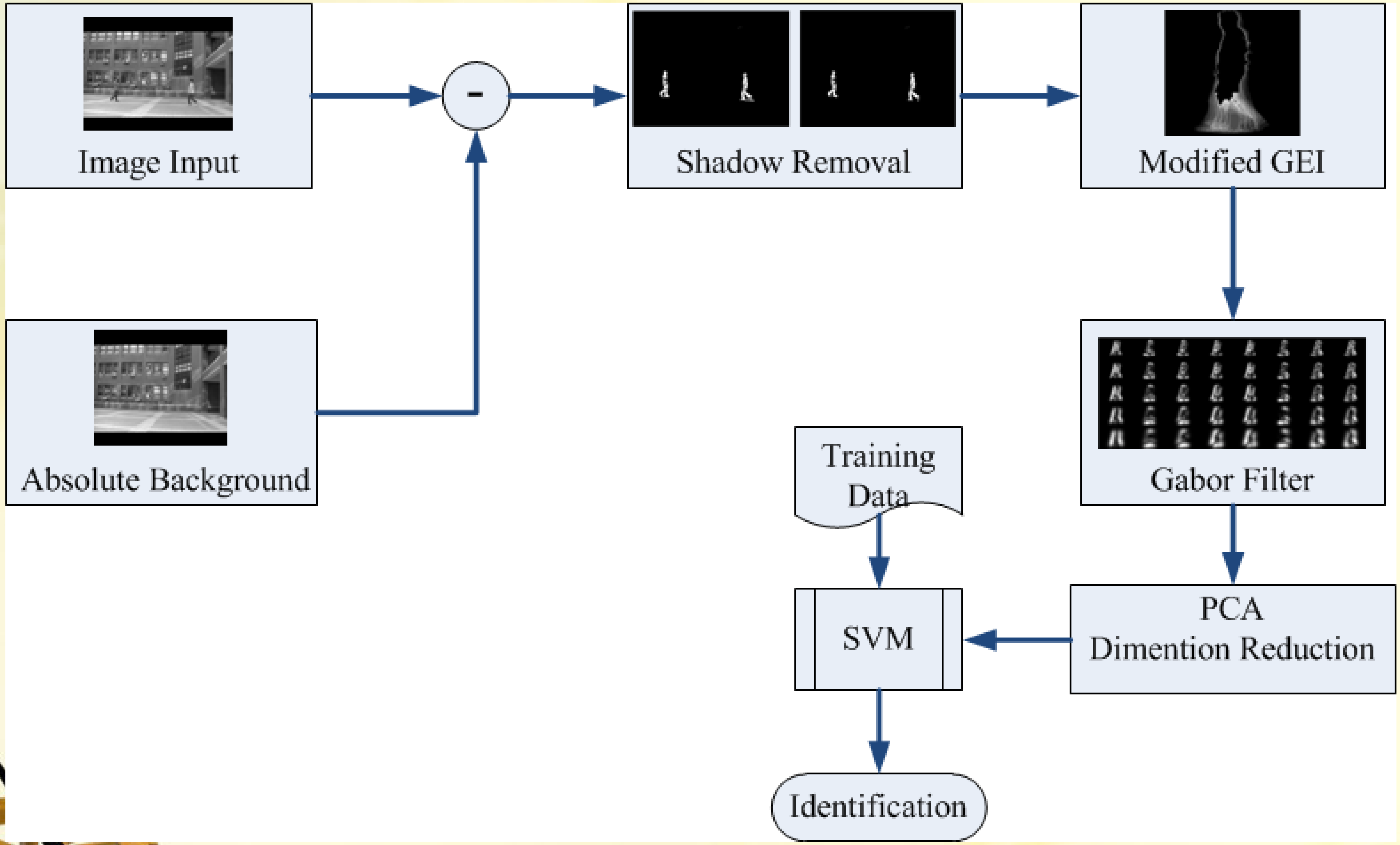
8

9

10

11

Gait Recognition

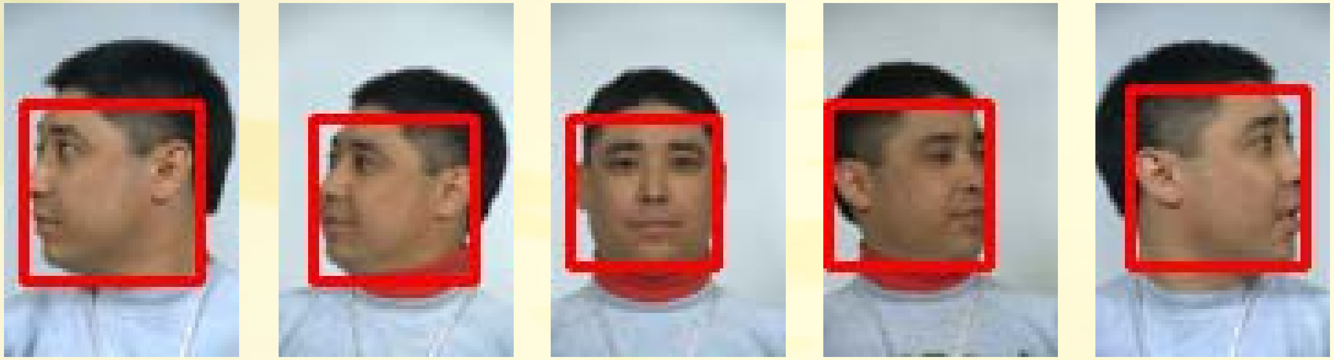


Angle / Classifier	0^o	90^o
	CRR	CRR
SVM	90.0%	88.5%

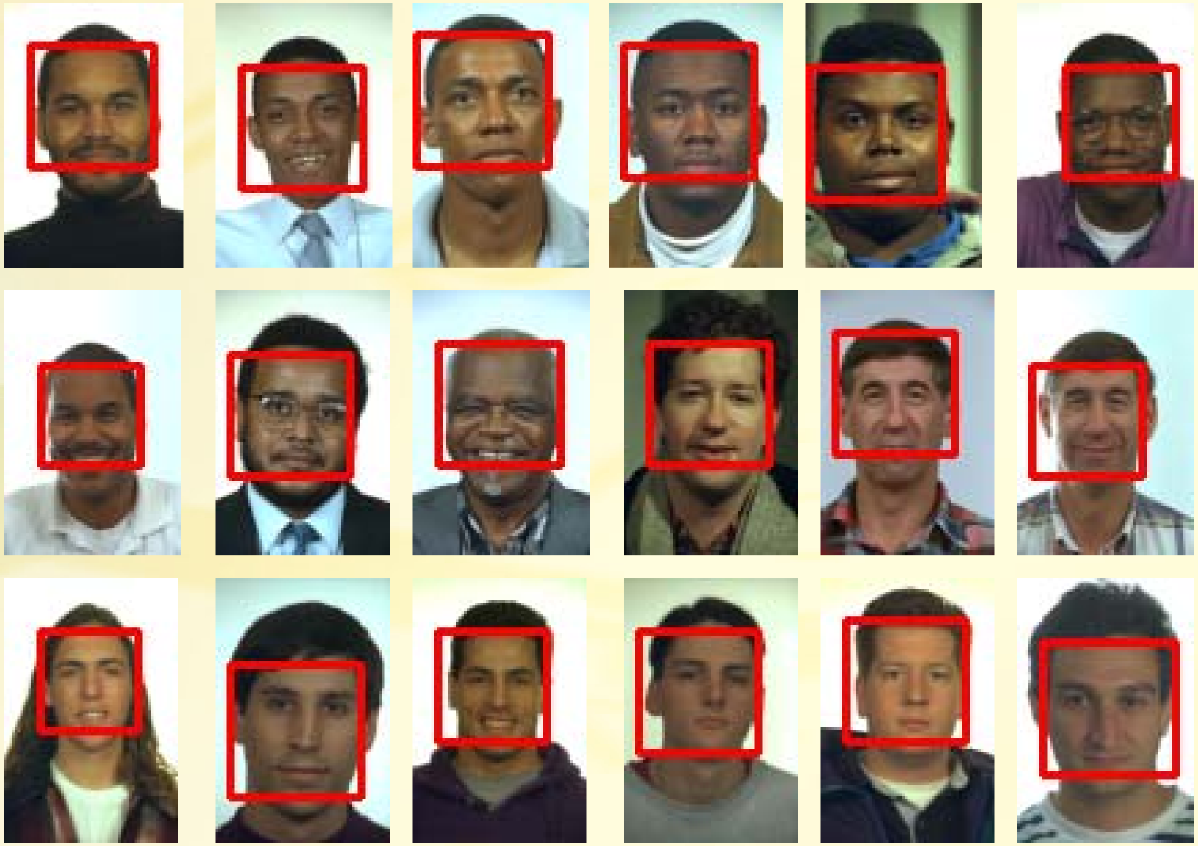
CRR: Correct Recognition Rate

Face Detection

- The detection rate, missing rate, and false alarm rate are about *P*=96.4% , *M*=3.6% , and *FA*=0.7%

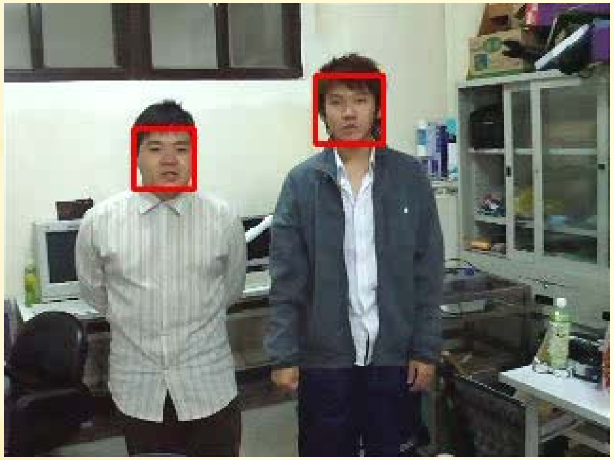


(a)



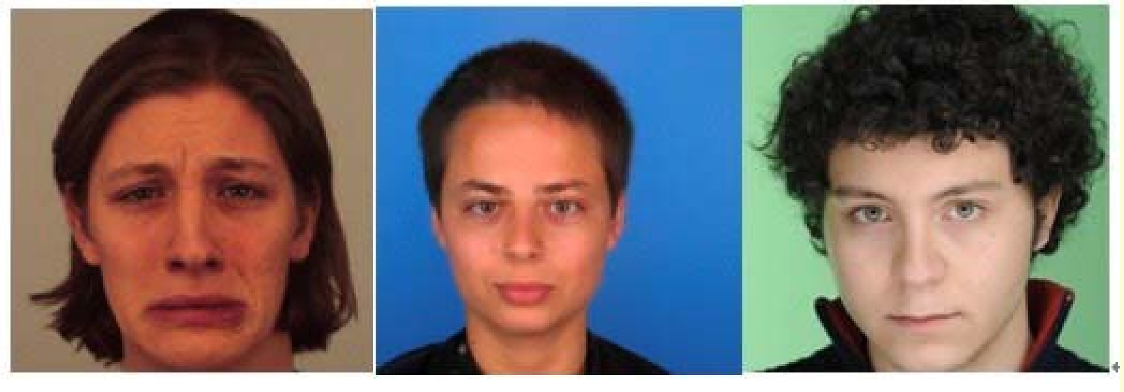

青 青 草 原

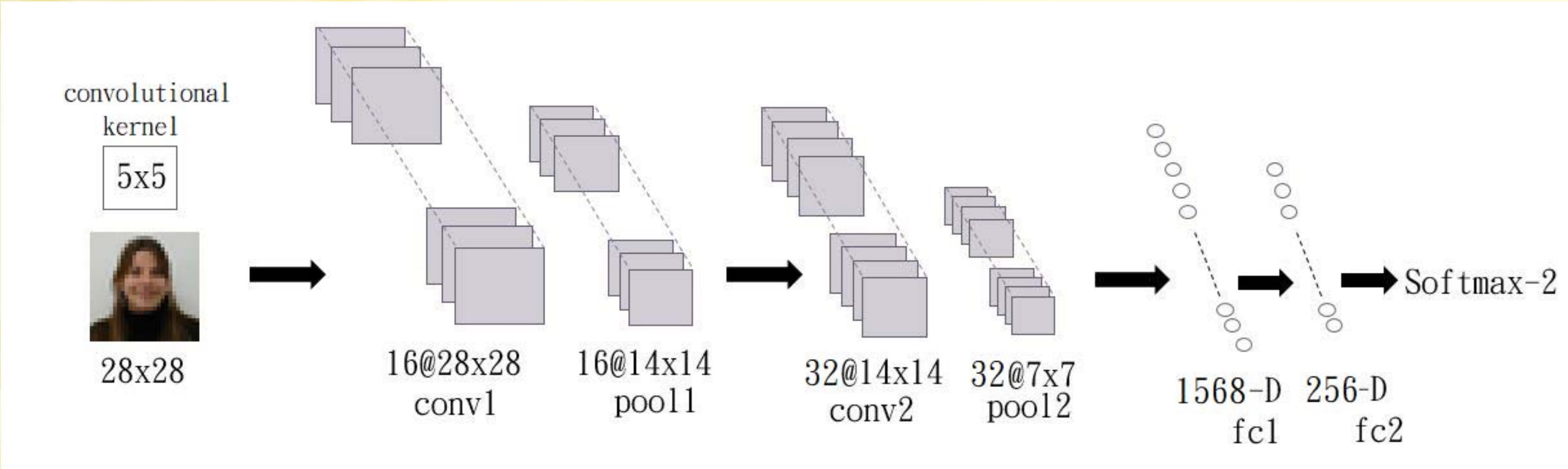
[Face tracking]



[People counting]

Gender Recognition

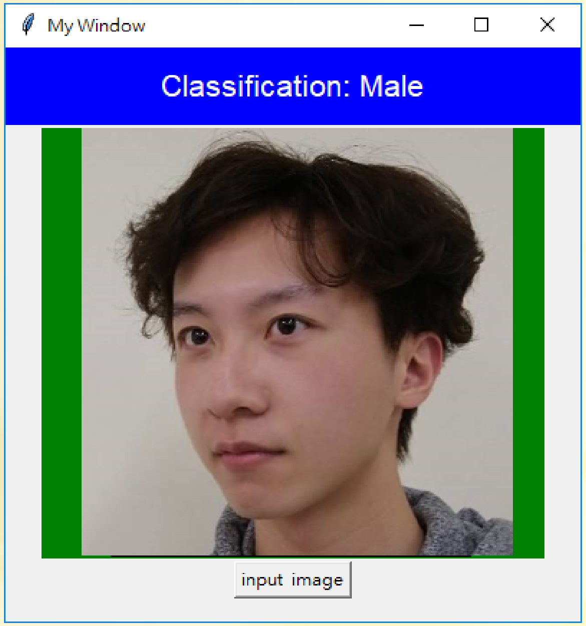


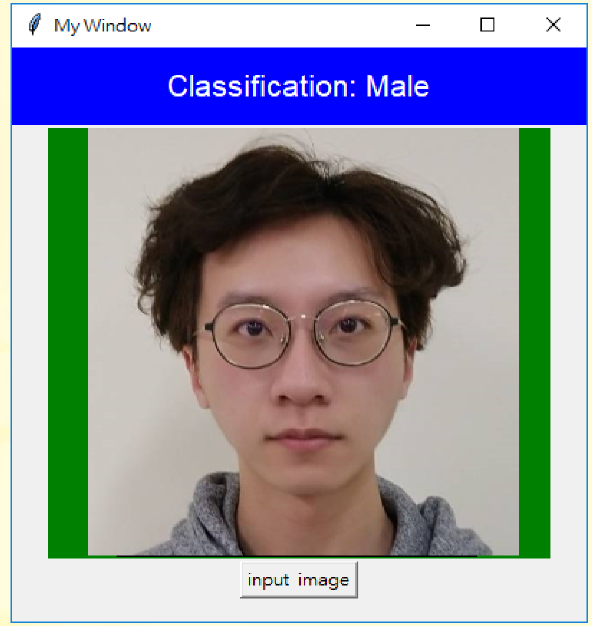


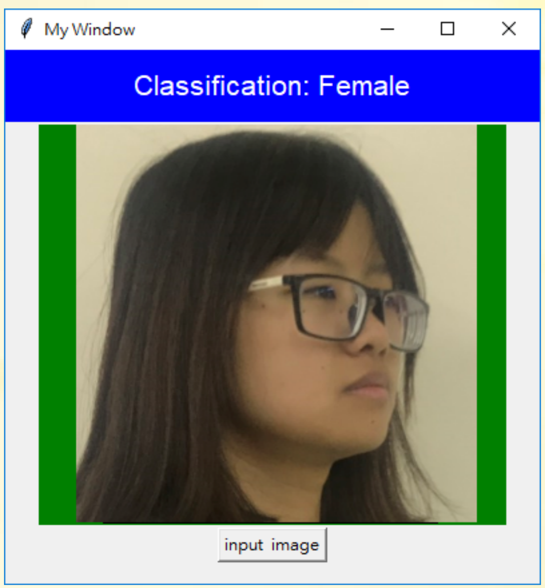
	訓練樣本	測試樣本	樣本總數量
男	1786	446	2232
女	1600	400	2000

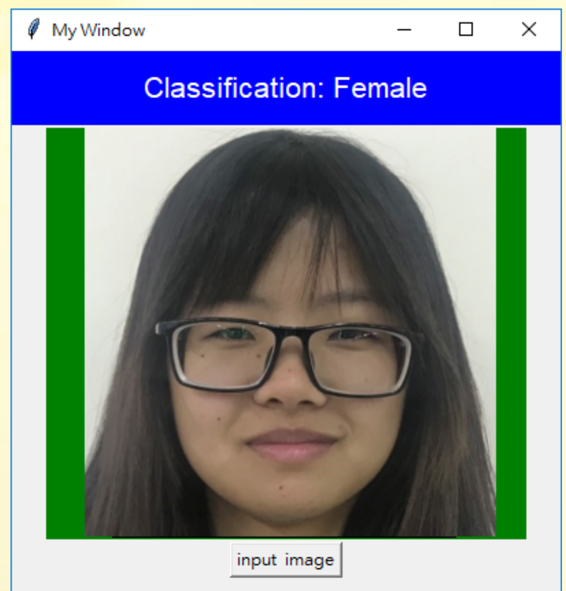
predict	0	1
label		
0	358	42
1	15	431

```
846/846 [==============================] - 0s 250us/step
0.9326241134751773
```

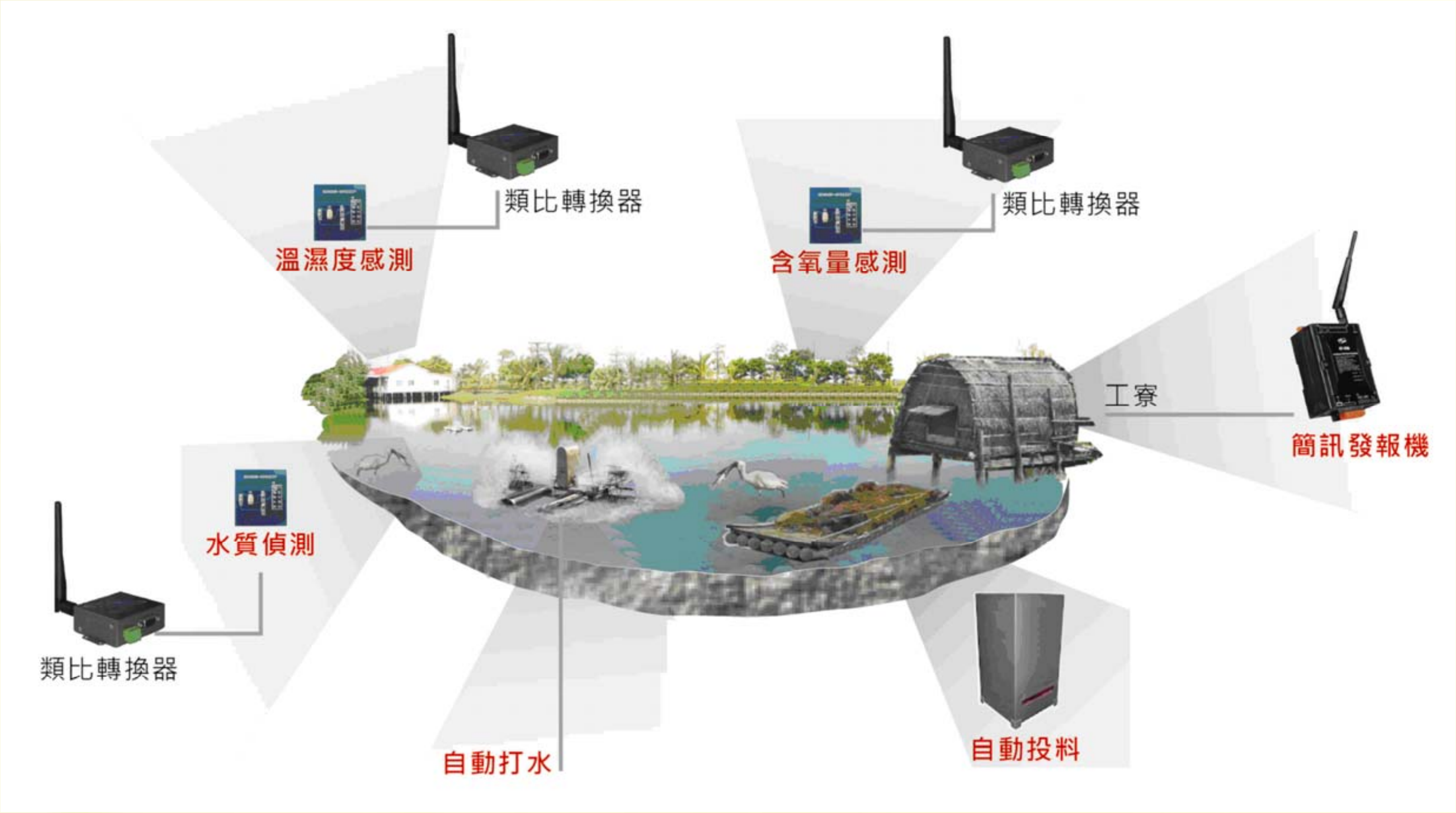

My Window
Classification: Male
input image


My Window
Classification: Male
input image


My Window
Classification: Female
input image


My Window
Classification: Female
input image

Automatic Surveillance of Aquaculture

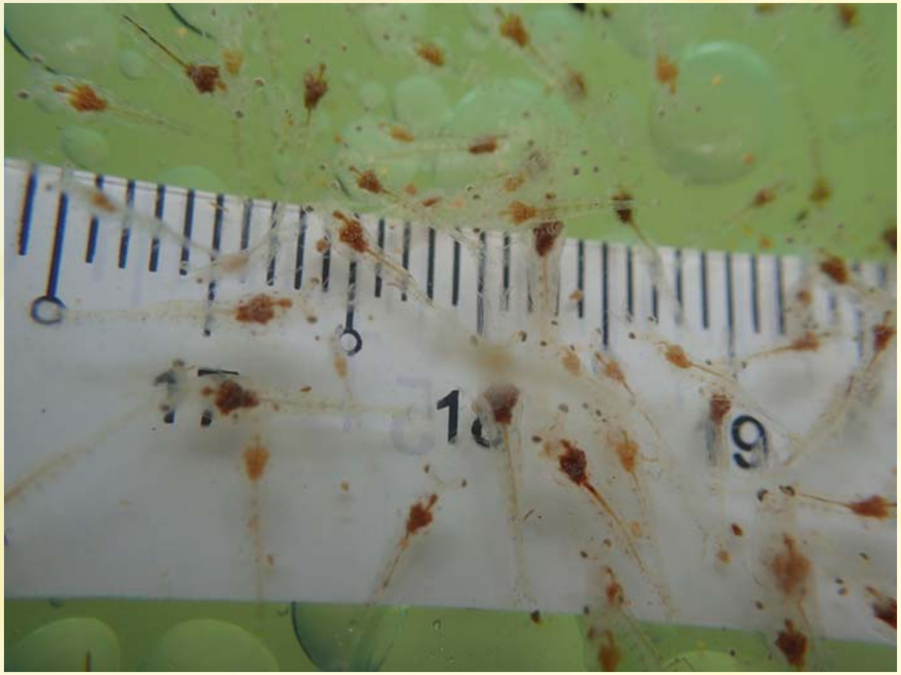


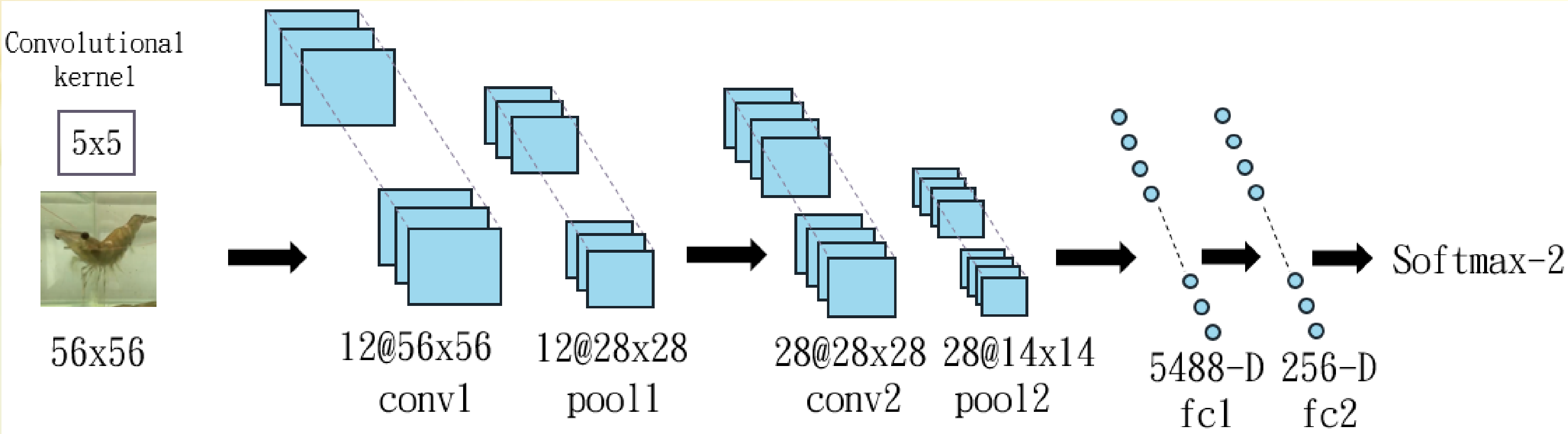
Intelligent Aquaculture

- Fish is an island country’s important source of income.
- Fish is also another main source of animalistic protein.
- Shrimp is the world's most important trade goods.
- Annual trade volume of shrimp is about tens of billions of dollars.

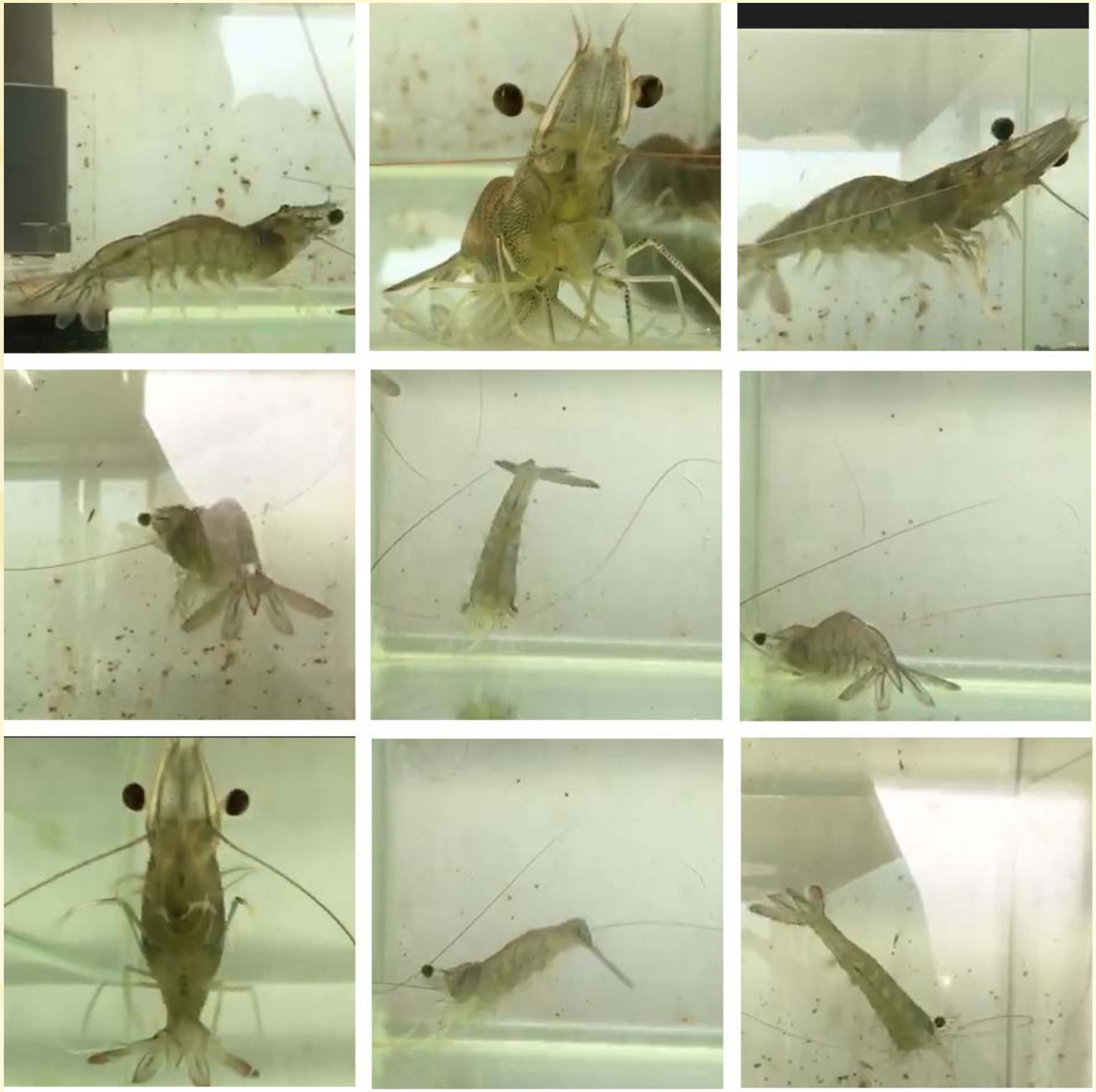
- **The output value of white shrimp is about 1.5 billion per year in Taiwan.**
- **The domestic demand for white shrimp is roughly estimated about 4.5 billion per year.**
- **About 2/3 of the total demand gap of white shrimp needs to be covered by imports.**

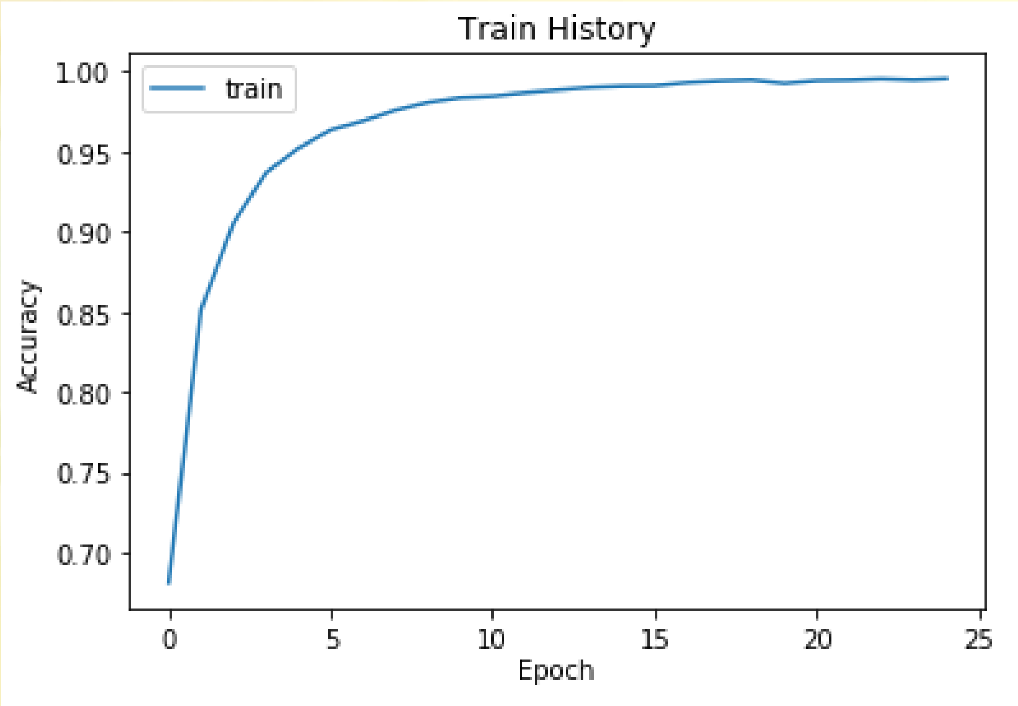
White Shrimp Recognition




Convolutional
kernel
5x5
56x56
12@56x56
conv1
12@28x28
pool1
28@28x28
conv2
28@14x14
pool2
5488-D
fc1
256-D
fc2
Softmax-2

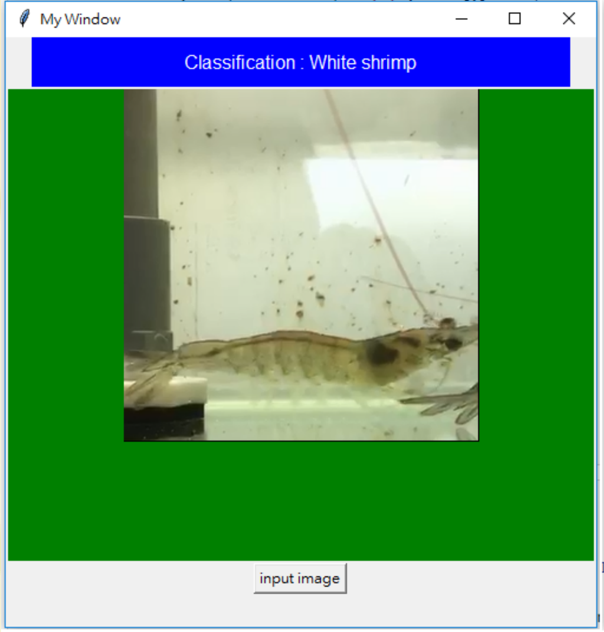
Category of shrimp	Samples
White shrimp (白蝦)	7539
Giant river shrimp (螳螂蝦)	3185
Marsupenaeus japonicus (斑節蝦)	1992
Procambarus clarkia (螯蝦)	1034
Peacock mantis shrimp (泰國蝦)	1305
Panulirus ornatus (龍蝦)	1083
Total	16138

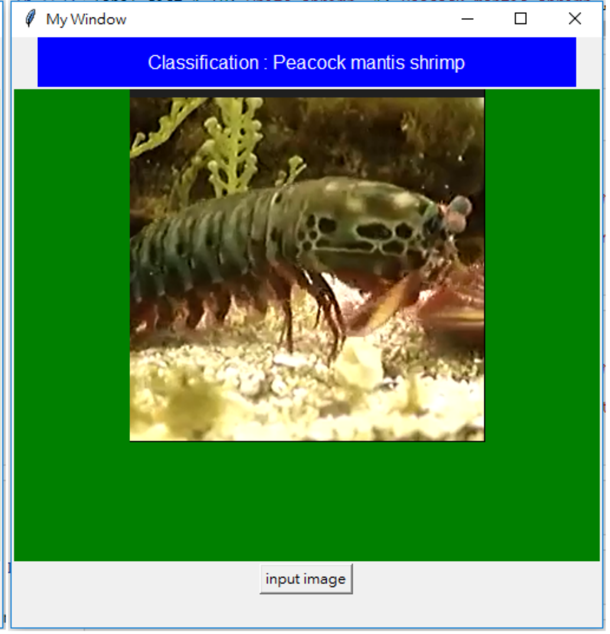


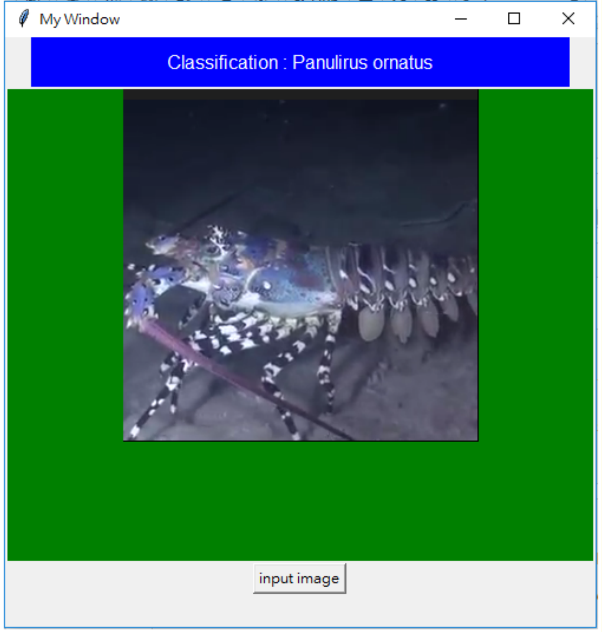


predict	0	1
label		
0	1493	20
1	41	1679

Accuracy of two categories: 98.14%
Accuracy of six categories: 95.48%

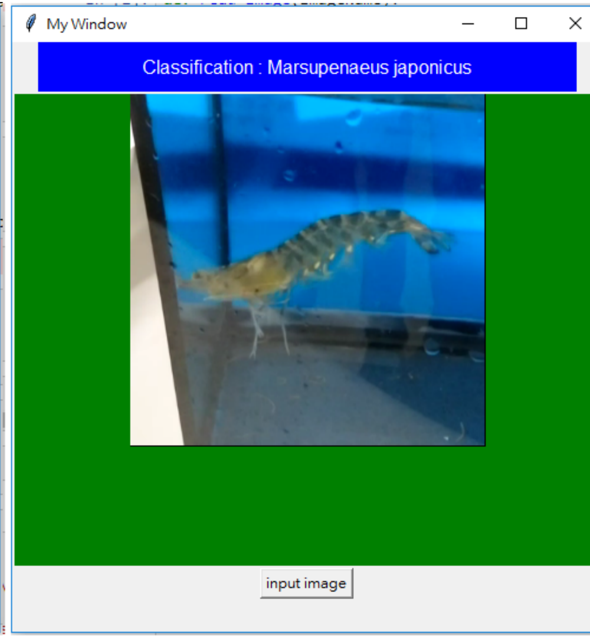

My Window
Classification : White shrimp
input image


My Window
Classification : Peacock mantis shrimp
input image


My Window
Classification : Panulirus ornatus
input image


My Window
Classification : Giant river shrimp
input image


My Window
Classification : Procambarus clarkii
input image


My Window
Classification : Marsupenaeus japonicus
input image

APP for edible shrimp and crab in Penghu

- Using GooLeNet Inception V3 network architecture to obtain recognition of shrimp and crab.
- Edible shrimp in Penghu has 11 categories.
- Edible crab in Penghu has 11 categories.

GooLeNet Inception V3

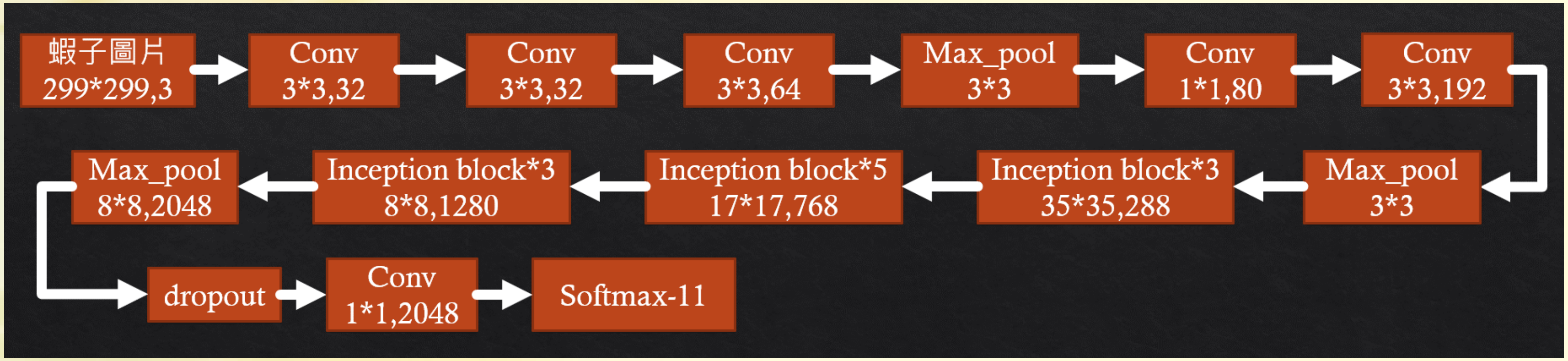
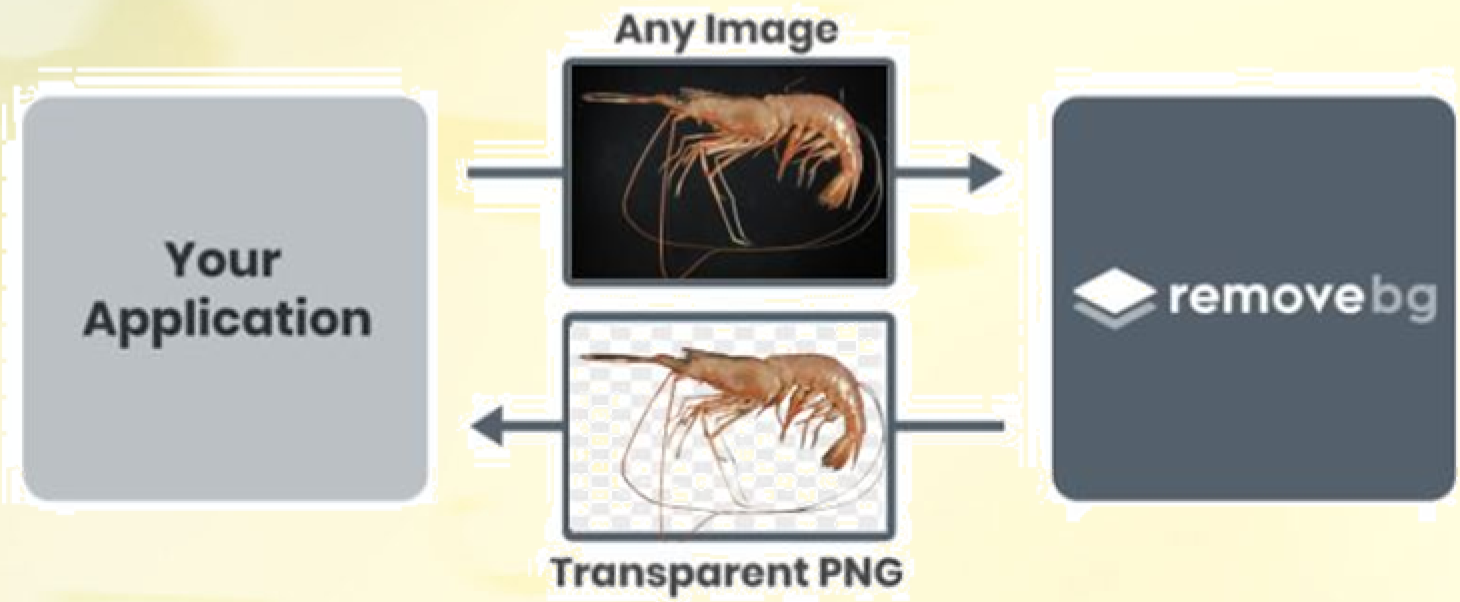
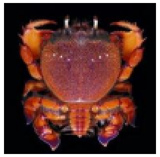
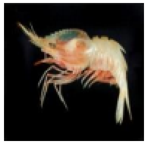
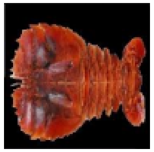
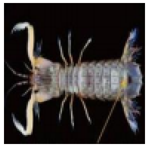
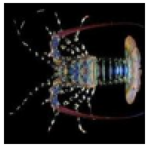
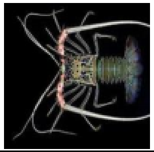
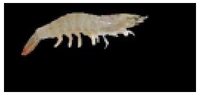


Image Matting: remove.bg API (https://www.remove.bg/zh)

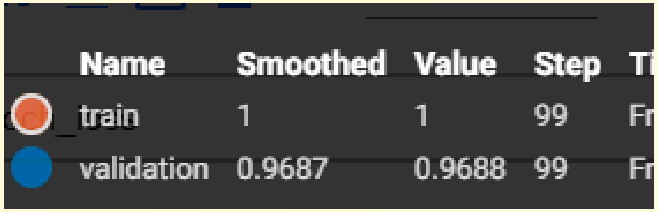


螃蟹名稱	訓練樣本	測試樣本	總量
捲折饅頭蟹	11	3	14
銹斑蟳	16	4	20
武士蟳	11	3	14
白紋方蟹	13	3	16
細紋方蟹	17	5	22
勝利黎明蟹	16	4	20
遠海梭子蟹	17	4	21
三點蟹	17	4	21
旭蟹	17	4	21
底棲短槳蟹	16	4	20
毛足圓盤蟹	21	5	26

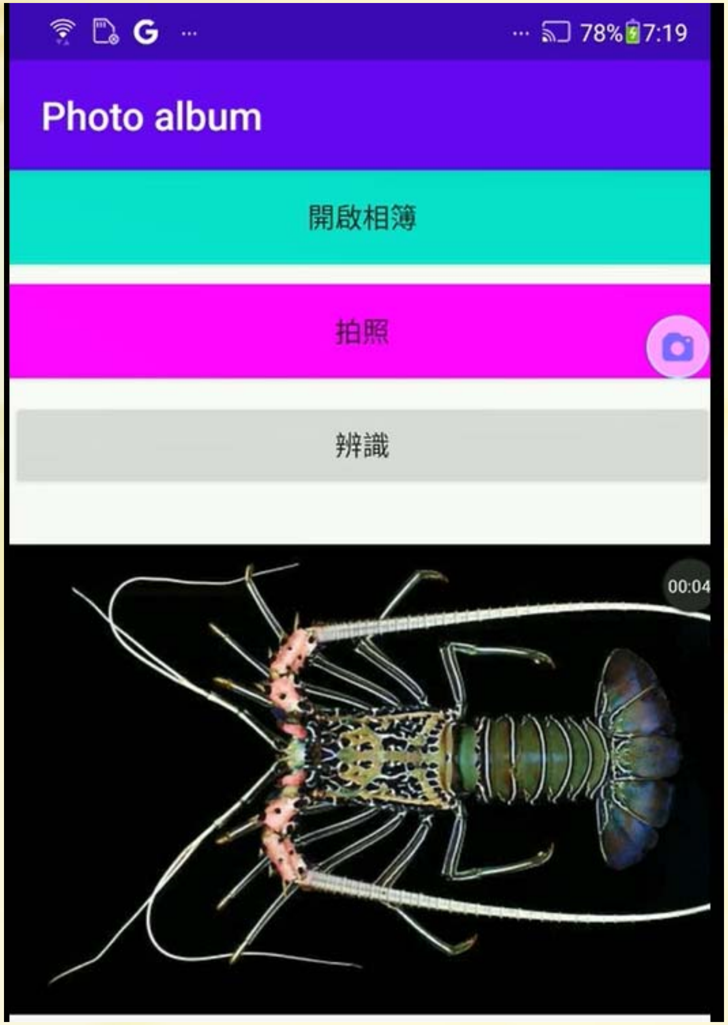
蝦類名稱	訓練樣本	測試樣本	總量
雄壯鬚蝦	24	6	30
東方異腕蝦	32	8	40
九齒扇蝦	51	13	64
臺灣後海螯蝦	17	5	22
鬚赤蝦	29	7	36
刀額新對蝦	19	5	24
斷脊小蝦蛄	21	6	27
錦繡龍蝦	14	5	19
雜色龍蝦	24	6	30
草對蝦	50	12	62
白蝦	48	12	60

捲折饅頭蟹	銹斑蟳	武士蟳	白紋方蟹	細紋方蟹
				
勝利黎明蟹	遠海梭子蟹	三點蟹	蛙形蟹	底棲短槳蟹
				
毛足圓盤蟹	雄壯鬚蝦	東方異腕蝦	九齒扇蝦	臺灣後海螯蝦
				
鬚赤蝦	刀額新對蝦	斷脊小蝦蛄	錦繡龍蝦	雜色龍蝦
				
草對蝦	白蝦			
				

Name	Smoothed	Value	Step
train	1	1	99
validation	0.9968	0.9969	99



Name	Smoothed	Value	Step	Ti
train	1	1	99	Fr
validation	0.9687	0.9688	99	Fr


78% 7:19
Photo album
開啟相簿
拍照
辨識
00:04


78% 7:19
Photo album
確定
00:09
雜色龍蝦
學名:Panulirus versicolor
俗稱:青龍，青殼仔
辨識成功

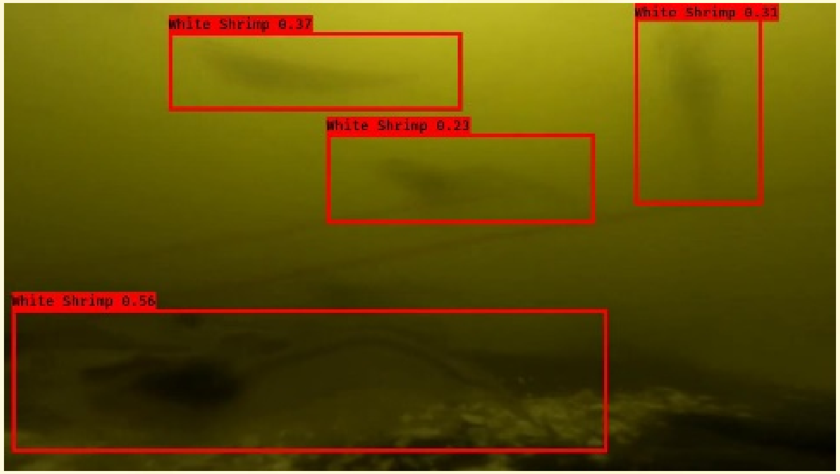
White Shrimp Tracking

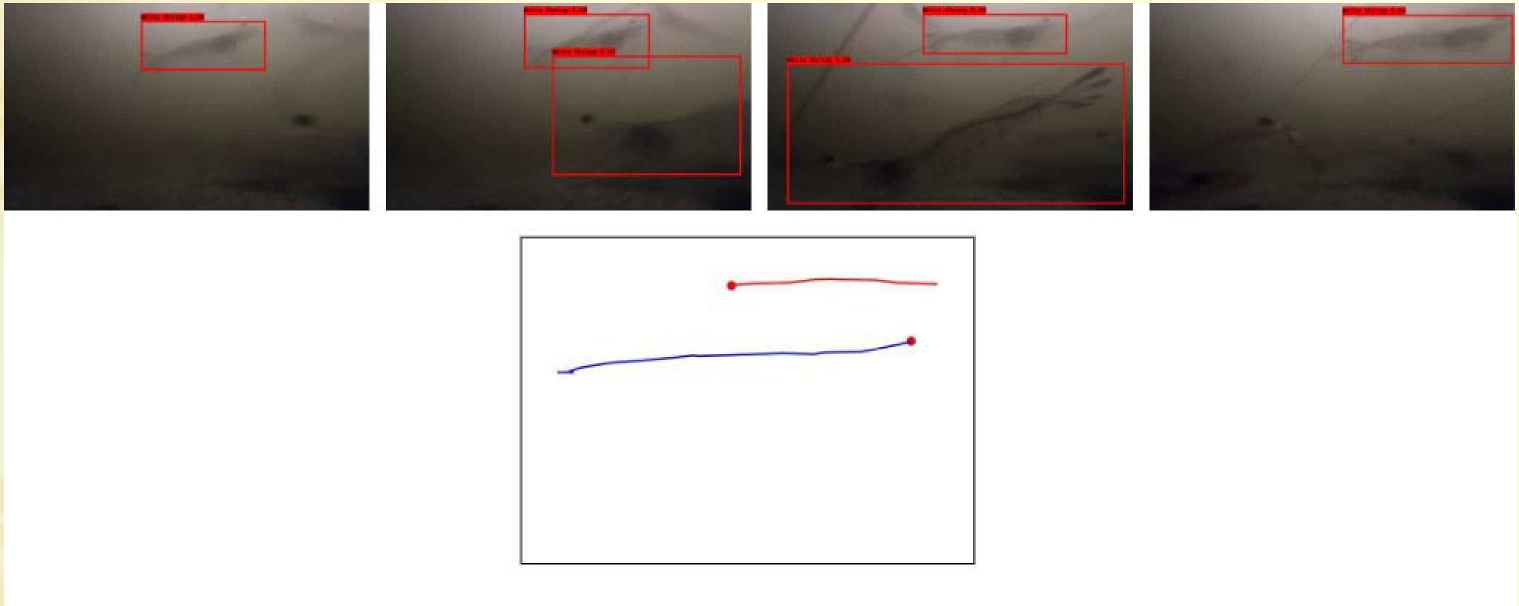
- **Using YOLO v3 network architecture**
- **Condition: low light transmission, turbidity, high impurities.**
- **Samples: 3766**
- **Training Set: 90.52% (Accuracy)**
- **Validation Set: 89.65% (Accuracy)**

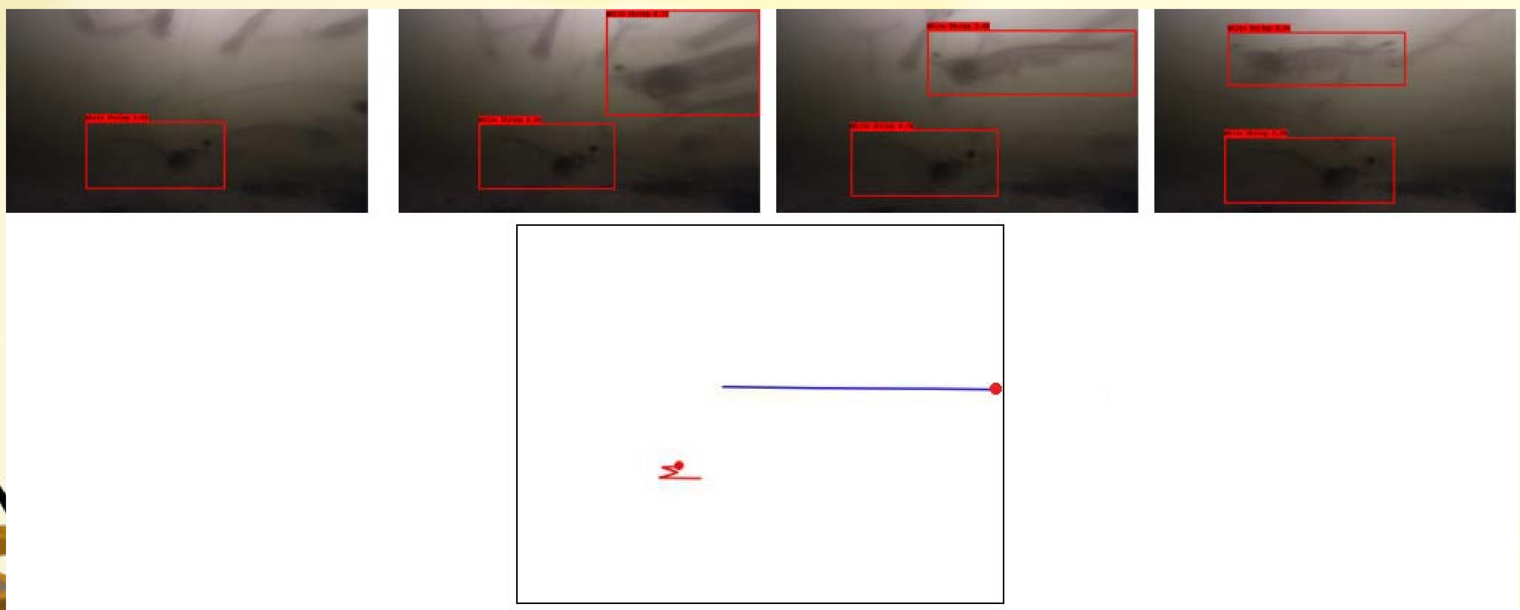
```
Epoch 86/100
337/337 [==============================] - 170s 505ms/step - loss: 10.4204 - val_loss: 10.6027
Epoch 87/100
337/337 [==============================] - 170s 505ms/step - loss: 10.5408 - val_loss: 10.8974
Epoch 88/100
337/337 [==============================] - 170s 504ms/step - loss: 10.3058 - val_loss: 10.3096
Epoch 89/100
337/337 [==============================] - 170s 504ms/step - loss: 10.1982 - val_loss: 10.6953
Epoch 90/100
337/337 [==============================] - 170s 504ms/step - loss: 10.0509 - val_loss: 10.5568
Epoch 91/100
337/337 [==============================] - 170s 505ms/step - loss: 10.1654 - val_loss: 10.3364
Epoch 92/100
337/337 [==============================] - 170s 504ms/step - loss: 10.0255 - val_loss: 10.0437
Epoch 93/100
337/337 [==============================] - 170s 505ms/step - loss: 9.9140 - val_loss: 9.7392
Epoch 94/100
337/337 [==============================] - 170s 505ms/step - loss: 9.8323 - val_loss: 10.5573
Epoch 95/100
337/337 [==============================] - 170s 504ms/step - loss: 9.8567 - val_loss: 9.7695
Epoch 96/100
337/337 [==============================] - 170s 505ms/step - loss: 9.7183 - val_loss: 10.4855
Epoch 97/100
337/337 [==============================] - 170s 505ms/step - loss: 9.5550 - val_loss: 9.7015
Epoch 98/100
337/337 [==============================] - 170s 504ms/step - loss: 9.7115 - val_loss: 9.6717
Epoch 99/100
337/337 [==============================] - 170s 504ms/step - loss: 9.5858 - val_loss: 10.1433
Epoch 100/100
337/337 [==============================] - 170s 504ms/step - loss: 9.4823 - val_loss: 10.3509
```


White Shrimp 0.21
White Shrimp 0.06
White Shrimp 0.28


White Shrimp 0.13
White Shrimp 0.68

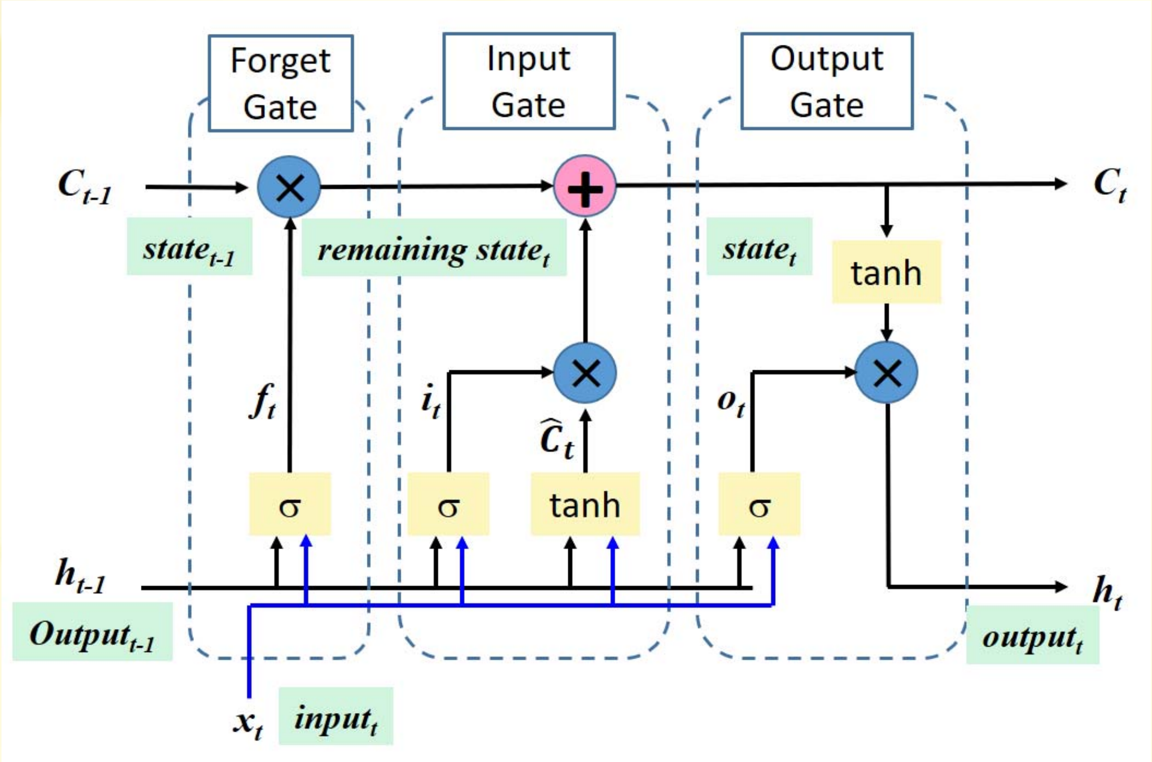

White Shrimp 0.37
White Shrimp 0.31
White Shrimp 0.23
White Shrimp 0.56

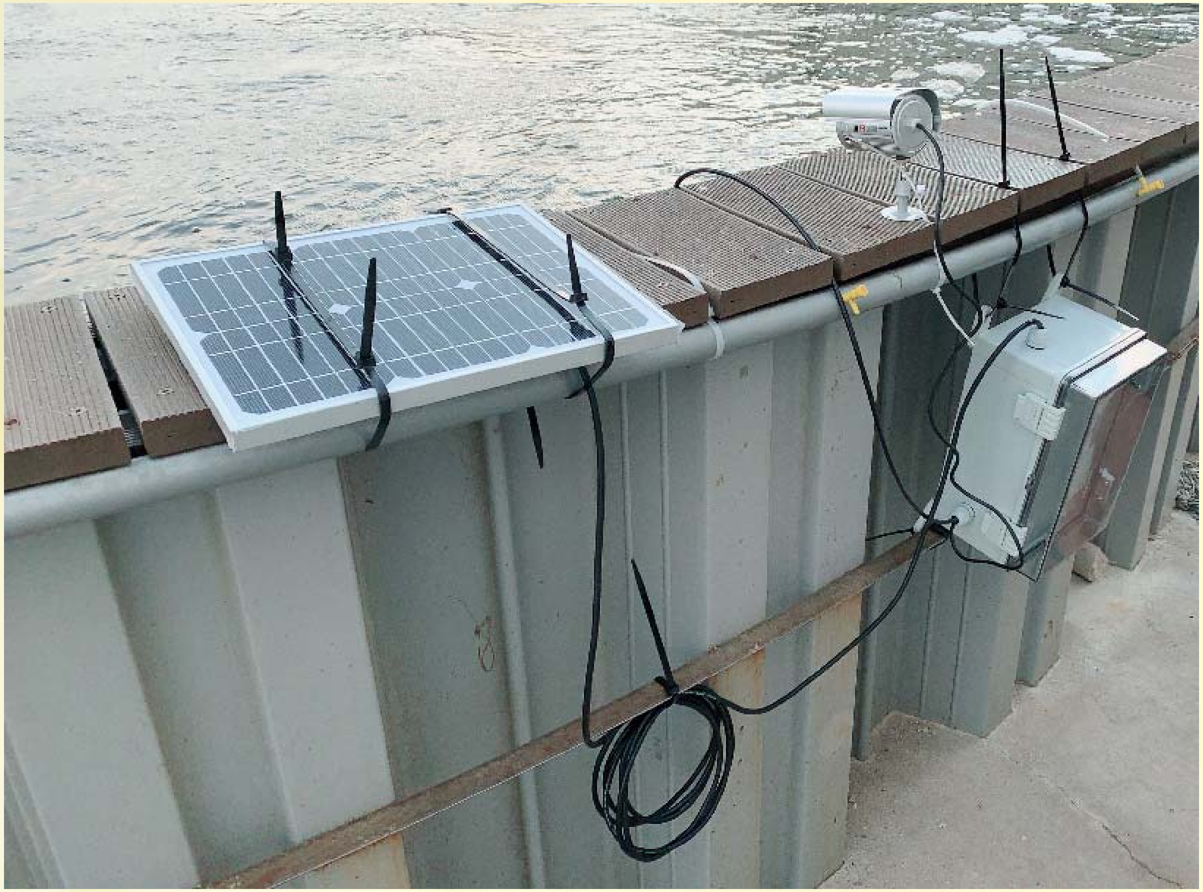




Water Quality Prediction

- Sensors: Ph, Do, Salt, T, ORP
- Using LSTM model to obtain prediction of water quality





```
dataset = read_csv('data.csv', header=0, index_col=0)
```

檔案 常用 插入 版面配置 公式 資料 校閱 檢視

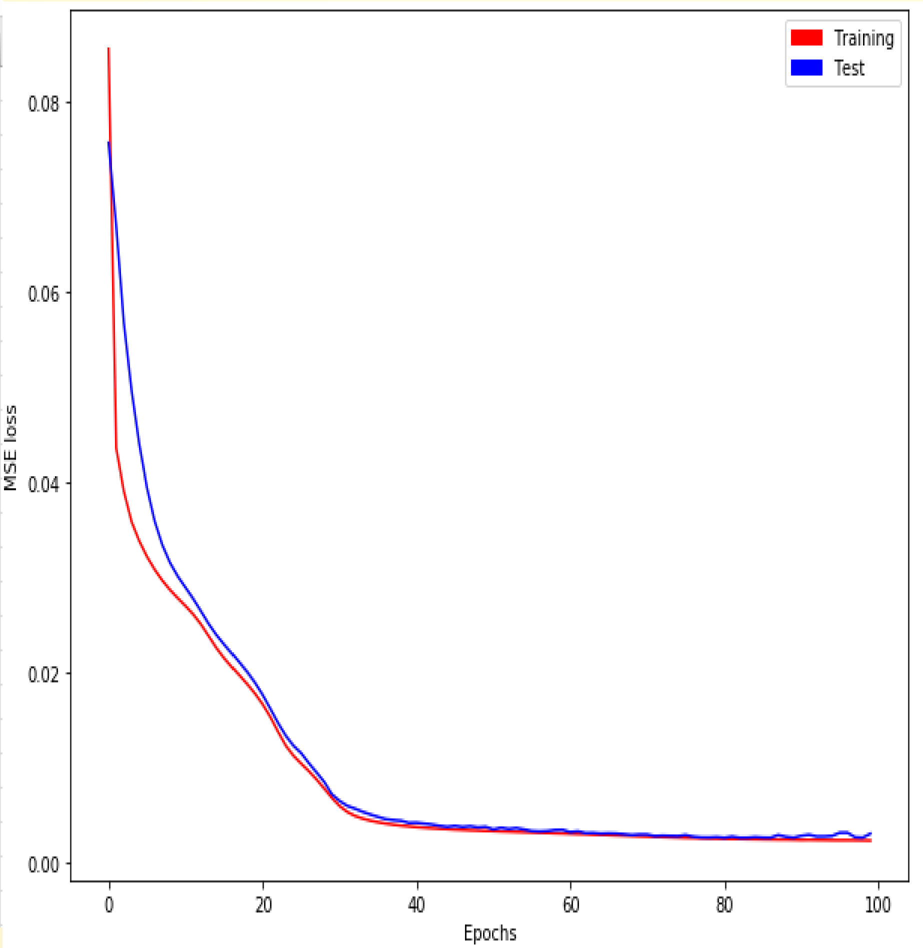
A1 0

	A	B	C	D	E	F
1	0	data-ORP	data-Do	data-Salt	data-T	data-pH
2		168	14.7	35.99	22.5	8.01
3		167	14.68	35.98	22.8	7.76
4		167	14.65	35.97	22.1	8.5
5		167	14.61	35.96	22.9	8.13
6		167	14.61	35.95	22.8	8.3
7		167	14.6	35.94	22.1	8.41
8		178	16.85	35.93	22.2	7.87
9		178	16.93	35.92	22.1	7.64
10		179	16.99	35.91	22.4	7.58
11		178	17.15	35.9	22.8	8.06
12		200	17.4	35.89	22.4	7.78
13		179	17.53	35.88	22.6	8
14		180	17.59	35.87	22.7	8.36
15		201	17.65	35.86	23	8.45
16		181	17.71	35.85	23	8.23
17		180	17.74	35.84	22.6	8.15
18		184	17.77	35.83	22.8	8.06

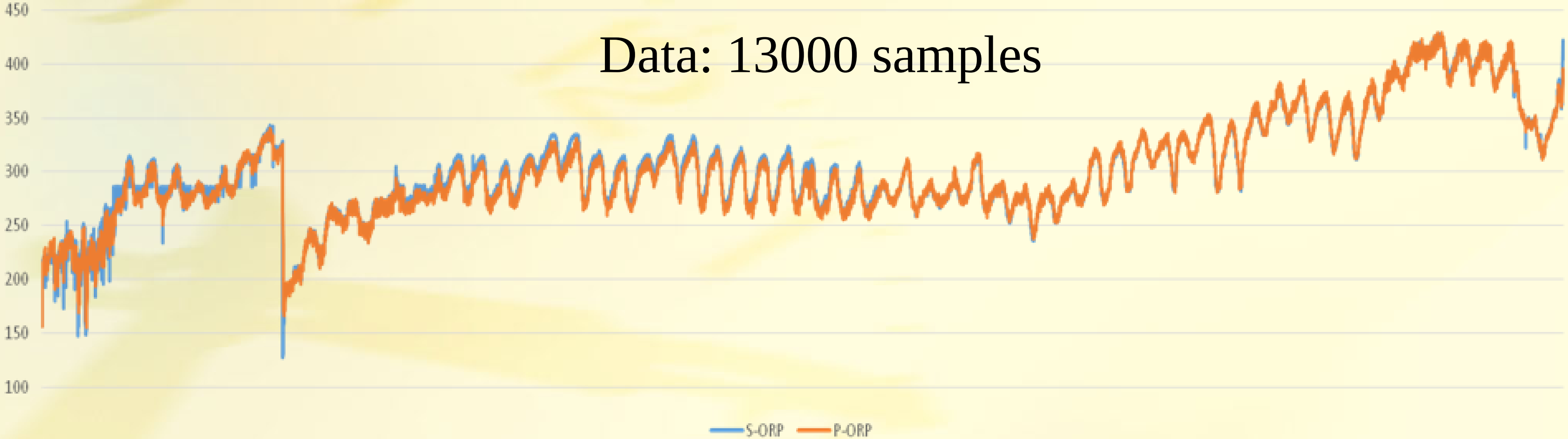
```
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (50, None, 10)            640
_________________________________________________________________
time_distributed_1 (TimeDist (50, None, 5)             55
=================================================================
```

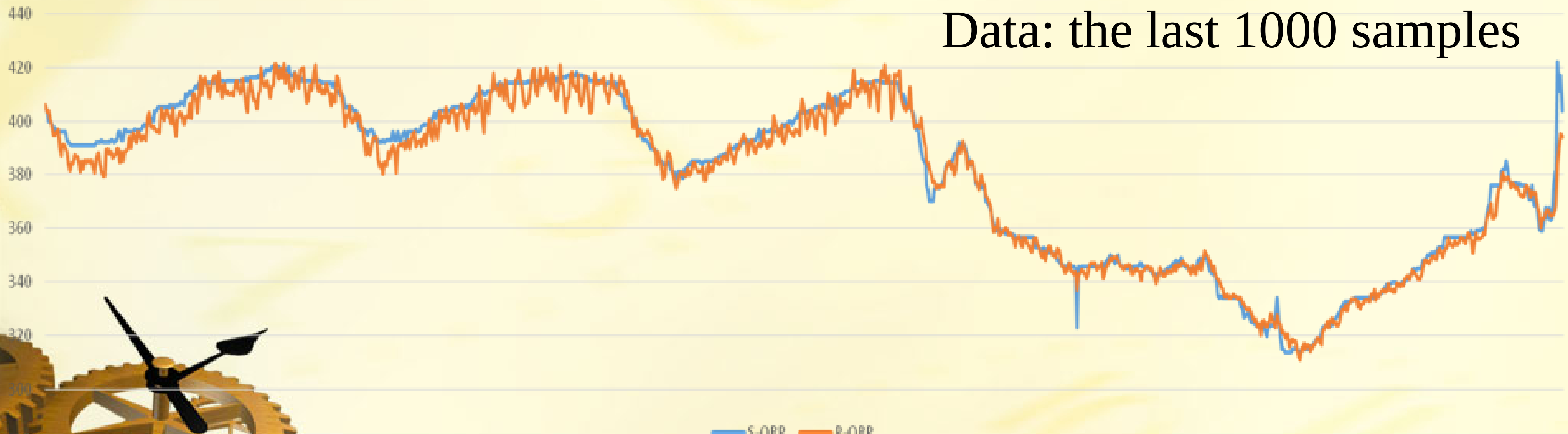
```
Epoch 96/100
7000/7000 [==============================] - 6s 884us/step - loss: 0.0015 - val_loss: 0.0016
Epoch 97/100
7000/7000 [==============================] - 6s 889us/step - loss: 0.0015 - val_loss: 0.0016
Epoch 98/100
7000/7000 [==============================] - 6s 881us/step - loss: 0.0015 - val_loss: 0.0016
Epoch 99/100
7000/7000 [==============================] - 6s 886us/step - loss: 0.0015 - val_loss: 0.0016
Epoch 100/100
7000/7000 [==============================] - 6s 888us/step - loss: 0.0015 - val_loss: 0.0016
```

	S-ORP	S-Do	S-Salt	S-T	S-pH	P-ORP	P-Do	P-Salt	P-T	P-pH
2	168	14.7	35.99	22.5	8.01	167.4701	5.623731	33.45408	19.30233	7.70999
3	167	14.68	35.98	22.8	7.76	194.251	7.903296	33.84658	22.90895	7.715435
4	167	14.65	35.97	22.1	8.5	202.1625	9.020904	34.53415	23.7742	7.834112
5	167	14.61	35.96	22.9	8.13	193.7639	9.920977	34.8942	23.61285	7.706228
6	167	14.61	35.95	22.8	8.3	190.0474	10.70706	35.17765	23.36772	8.354321
7	167	14.6	35.94	22.1	8.41	188.0059	11.14744	35.38359	23.33293	8.028434
8	178	16.85	35.93	22.2	7.87	191.9519	12.09424	35.47575	23.0656	8.229623
9	178	16.93	35.92	22.1	7.64	203.2044	12.65169	35.56309	22.49122	8.380111
10	179	16.99	35.91	22.4	7.58	212.2343	12.70086	35.54268	22.10835	7.796977
11	178	17.15	35.9	22.8	8.06	198.6275	12.43277	35.52947	21.88572	7.560342
12	200	17.4	35.89	22.4	7.78	211.302	12.79192	35.57704	22.11442	7.508049
13	179	17.53	35.88	22.6	8	205.6201	13.09984	35.58604	22.5836	7.998814
14	180	17.59	35.87	22.7	8.36	193.458	12.7504	35.6324	22.34005	7.669884
15	201	17.65	35.86	23	8.45	191.2448	12.99109	35.62965	22.22048	7.889915
16	181	17.71	35.85	23	8.23	192.9485	13.35275	35.6124	22.66217	8.231968
17	180	17.74	35.84	22.6	8.15	196.2834	13.48955	35.6518	22.76852	8.343572
18	184	17.77	35.83	22.8	8.06	197.015	13.43861	35.63114	22.63882	8.134267
19	181	17.77	35.82	23	8.41	186.4842	13.20398	35.6004	22.35571	8.03384
20	180	17.81	35.81	22.8	8.09	192.3747	13.49094	35.58185	22.48436	7.935283
21	180	17.83	35.8	22.6	7.97	197.0956	13.80949	35.59527	22.68174	8.33418
22	180	17.85	35.79	23	7.64	206.1135	13.63218	35.55171	22.49181	7.999357
23	180	17.86	35.78	22.3	7.86	209.6108	13.56661	35.59096	22.14288	7.881775
24	182	17.88	35.77	22.7	8.05	200.1995	13.31811	35.5325	22.39995	7.549439
25	181	17.89	35.76	22.6	7.53	208.3533	13.69005	35.54646	22.05287	7.770587



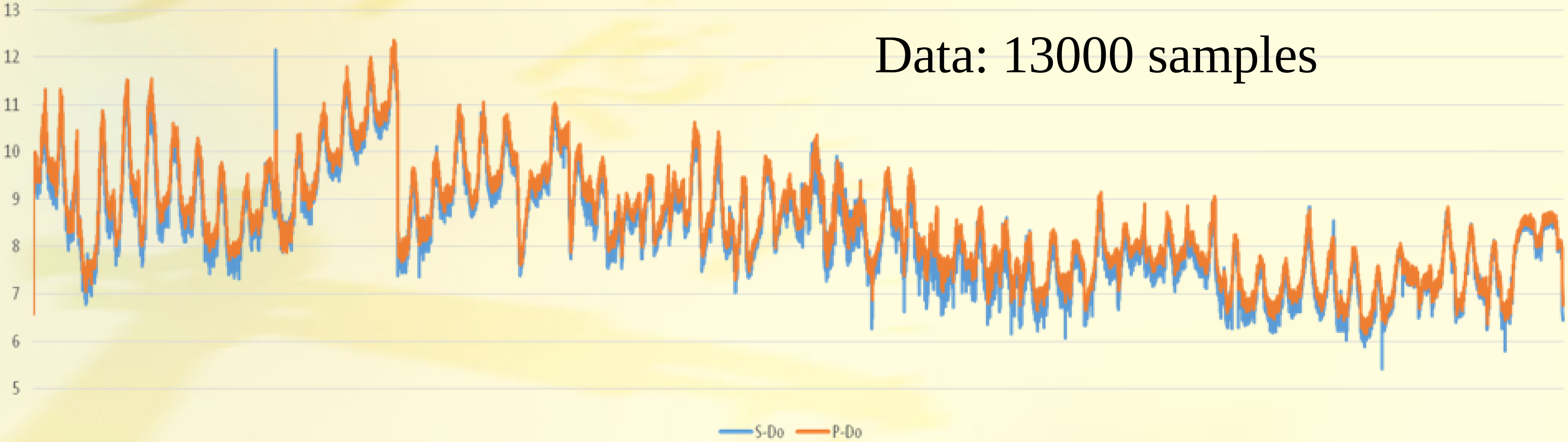
Prediction Result of ORP



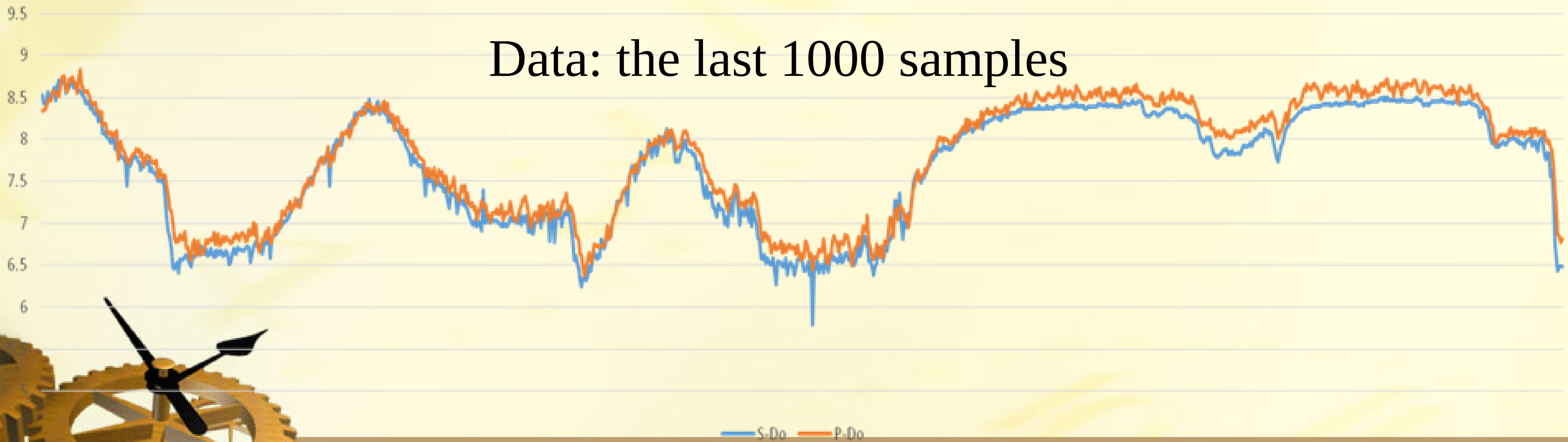


Prediction Result of Do

Data: 13000 samples



Data: the last 1000 samples



Performance

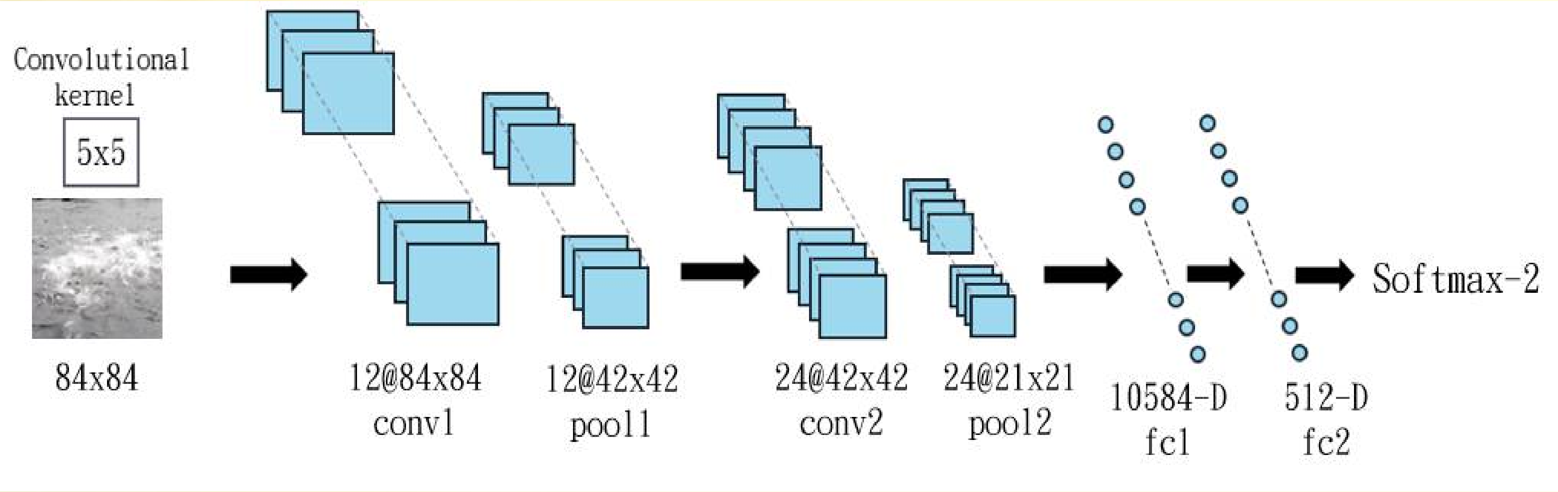
	T	Do	pH	ORP	SALT
MAE	0.62	0.22	0.34	4.49	0.28
	C	ppm		mV	ppt

	T	Do	pH	ORP	SALT
Original	16 ~ 20.5	5.41 ~ 12.26	7.5 ~ 8.5	128 ~ 428	34.7 ~ 35.7
Prediction	15.36 ~ 20.58	6.15 ~ 12.34	7.29 ~ 8.51	155.87 ~ 428.74	34.64 ~ 35.74

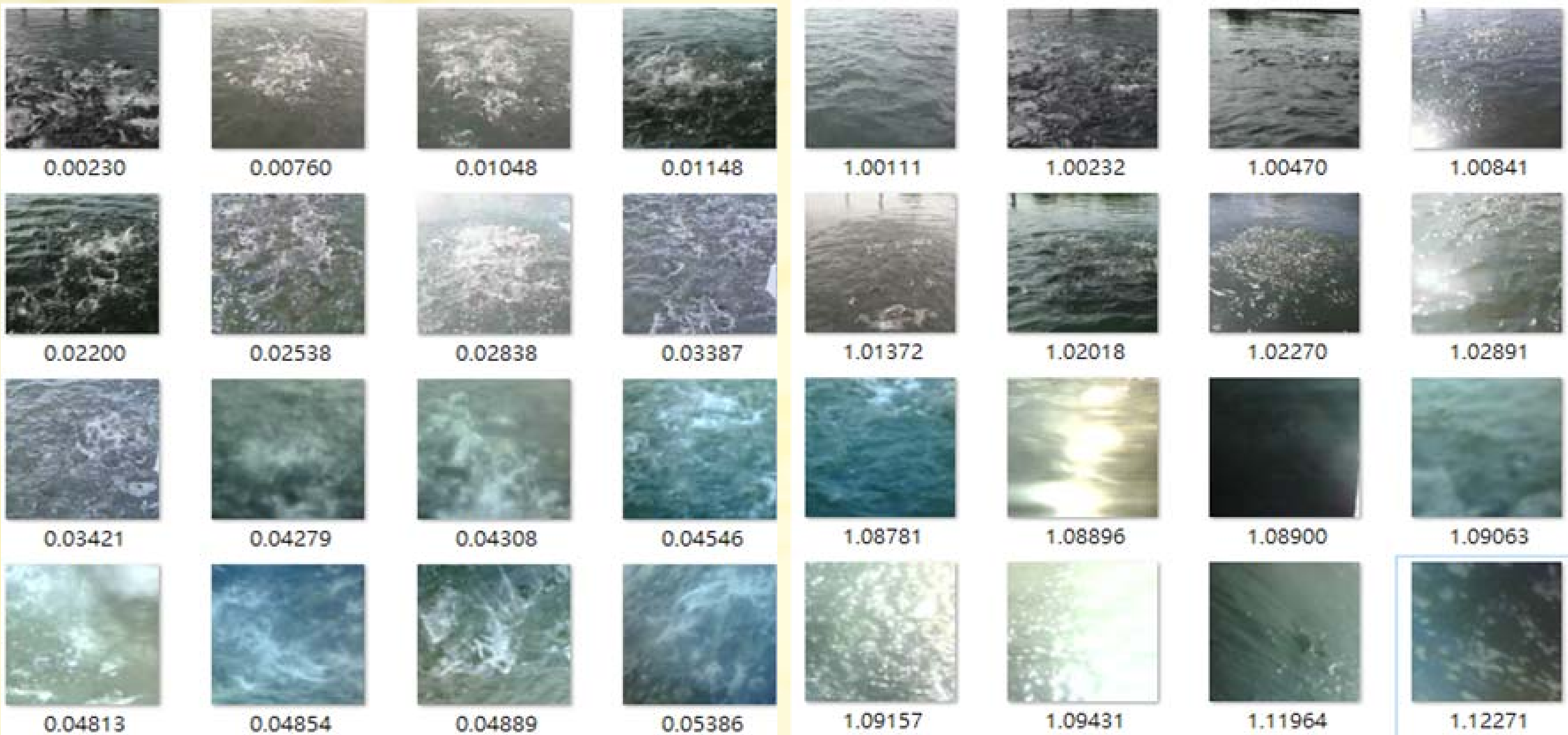
Seawater: Corrosion, Moss, Barnacles,…

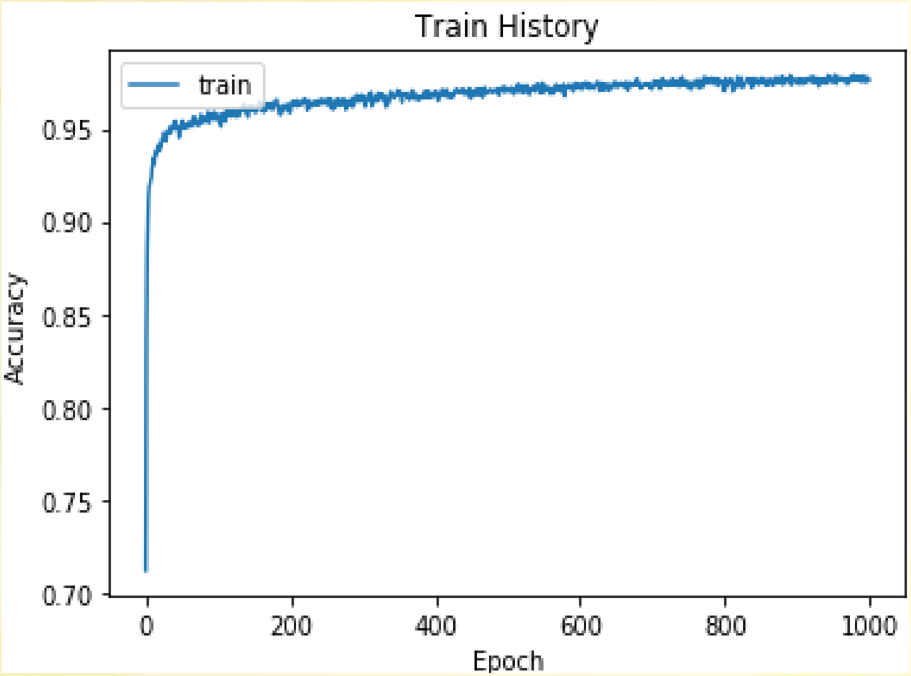
Intelligent fish feeding


DEEP LEARNING



- ❖ **Data Set: 25054 samples**
  - ❖ **Training data: 20043 samples**
  - ❖ **Testing data: 5011 samples**


0.00230
0.00760
0.01048
0.01148
1.00111
1.00232
1.00470
1.00841
0.02200
0.02538
0.02838
0.03387
1.01372
1.02018
1.02270
1.02891
0.03421
0.04279
0.04308
0.04546
1.08781
1.08896
1.08900
1.09063
0.04813
0.04854
0.04889
0.05386
1.09157
1.09431
1.11964
1.12271



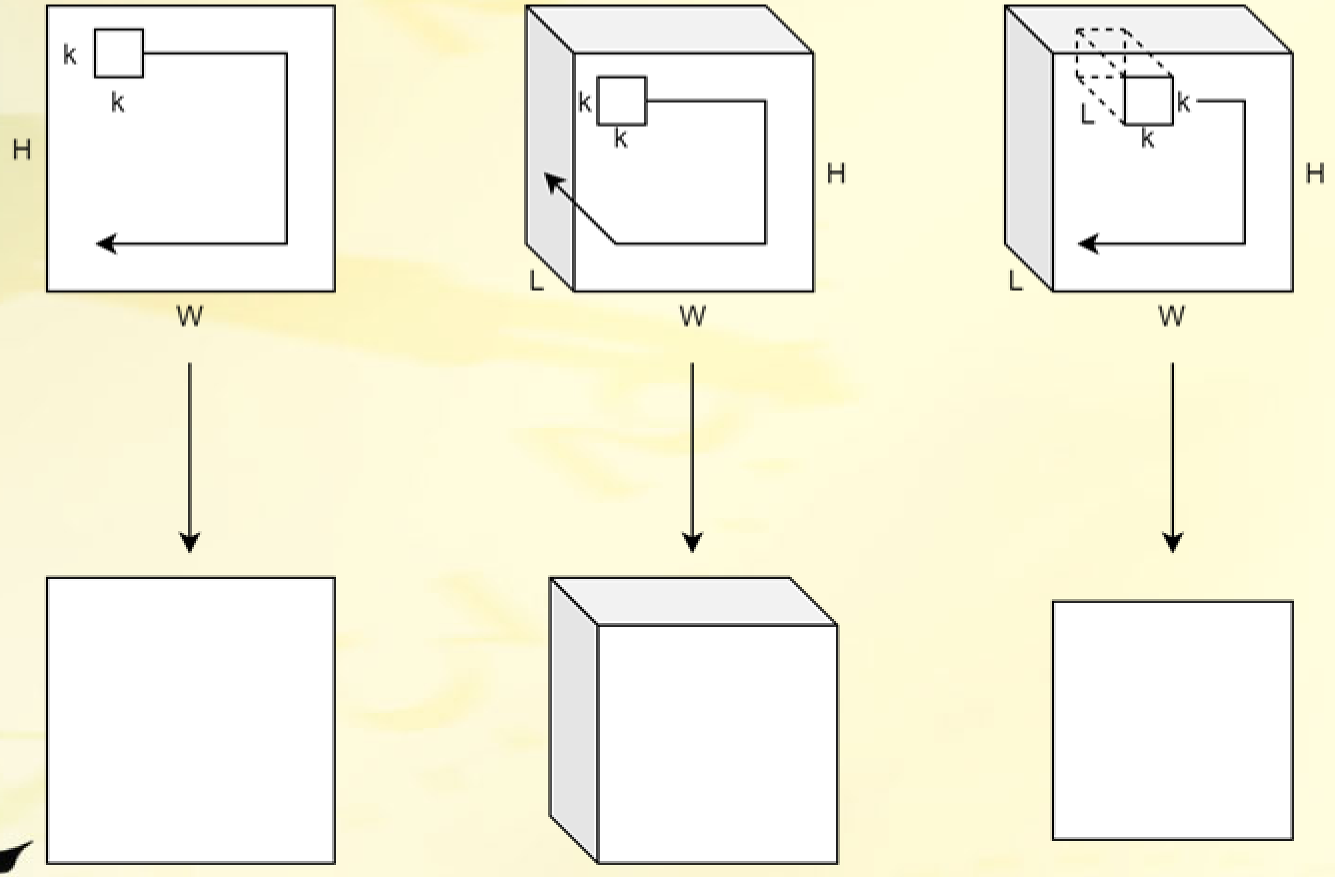
predict label	0	1
0	1646	104
1	22	3239

```
5011/5011 [==============================] - 8s 2ms/step
0.9748553037643433
```

Abnormal behavior recognition

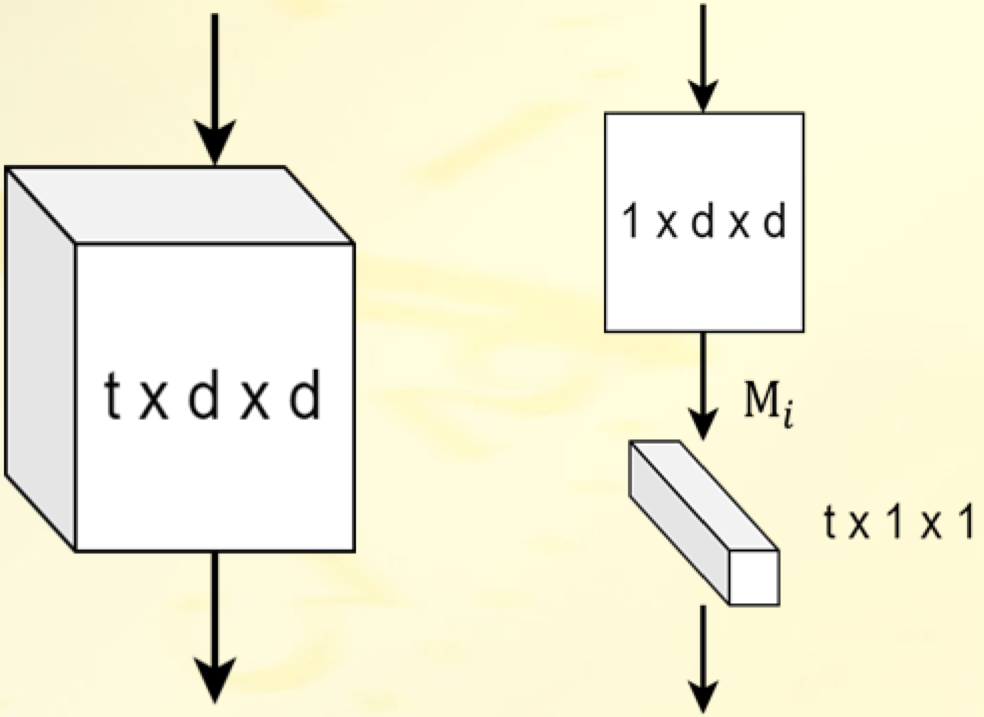
- **Abnormal behavior recognition of aquaculture field**
- **Using modified R(2+1)D network architecture**
- **Using continuous 16 frames randomly extracted from sample of video sequences.**

2D and 3D convolution operations



[6]

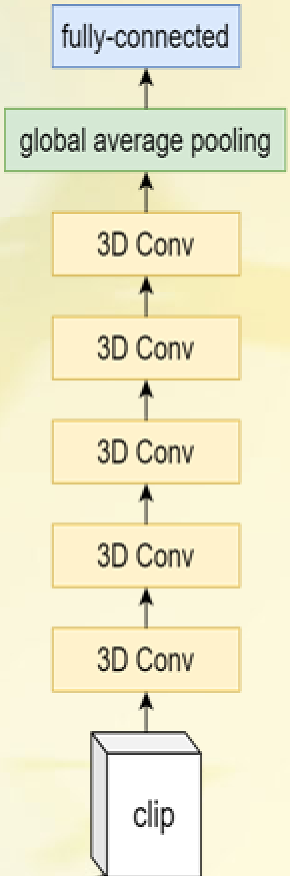
3D vs (2+1)D convolution



3D Conv

(2+1)D Conv

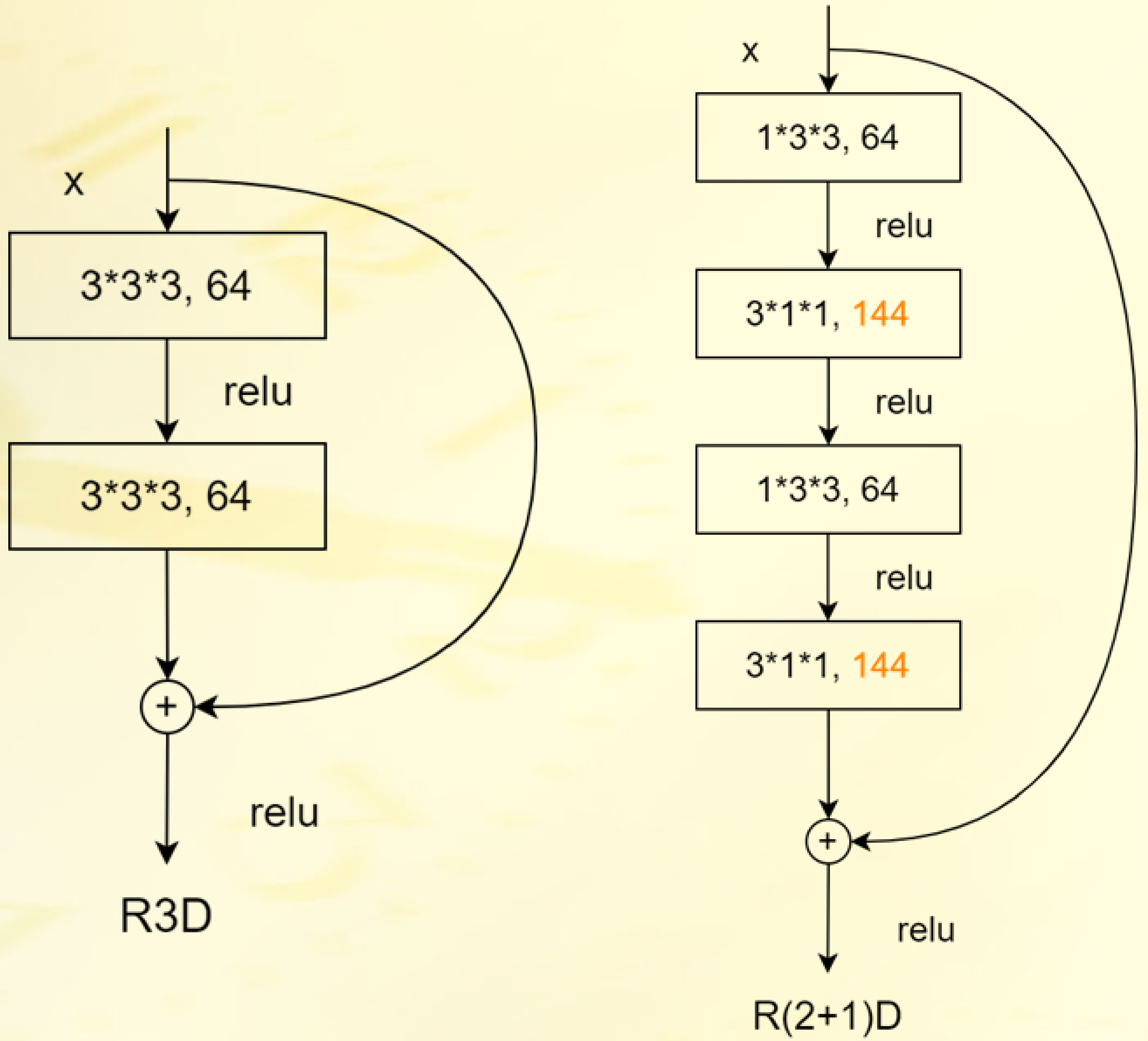
Residual network architectures for video classification



R3D

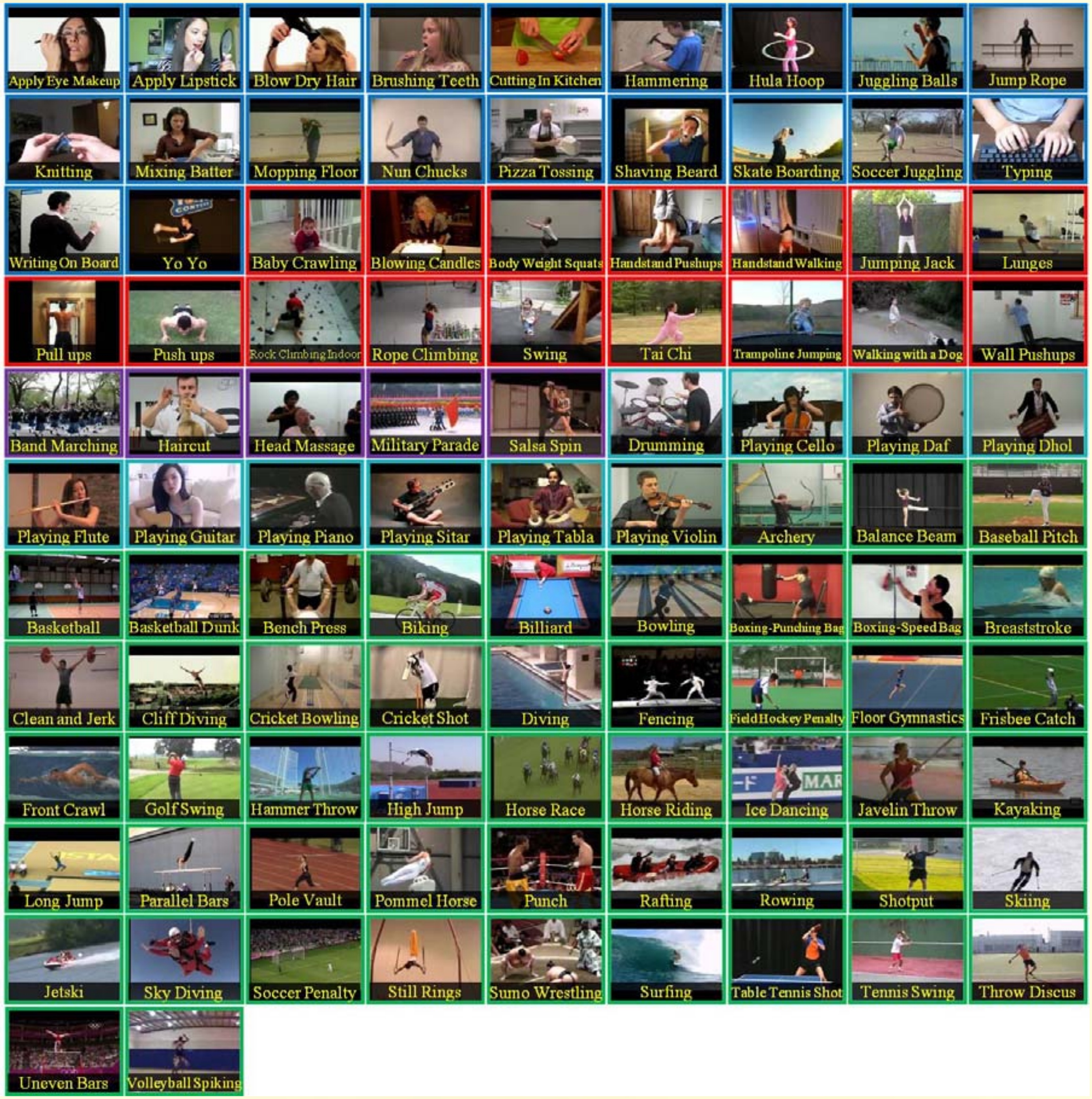
Layer name	Output size	Stride	R3D-18	R3D-34
Conv 1	$L*56*56$	$1*2*2$	$3*7*7, 64$	
Conv 2_x	$L*56*56$	$1*1*1$	$\begin{bmatrix} 3*3*3, 64 \\ 3*3*3, 64 \end{bmatrix} * 2$	$\begin{bmatrix} 3*3*3, 64 \\ 3*3*3, 64 \end{bmatrix} * 3$
Conv 3_x	$\frac{L}{2}*28*28$	$2*2*2$	$\begin{bmatrix} 3*3*3, 128 \\ 3*3*3, 128 \end{bmatrix} * 2$	$\begin{bmatrix} 3*3*3, 128 \\ 3*3*3, 128 \end{bmatrix} * 4$
Conv 4_x	$\frac{L}{4}*14*14$	$2*2*2$	$\begin{bmatrix} 3*3*3, 256 \\ 3*3*3, 256 \end{bmatrix} * 2$	$\begin{bmatrix} 3*3*3, 256 \\ 3*3*3, 256 \end{bmatrix} * 6$
Conv 5_x	$\frac{L}{8}*7*7$	$2*2*2$	$\begin{bmatrix} 3*3*3, 512 \\ 3*3*3, 512 \end{bmatrix} * 2$	$\begin{bmatrix} 3*3*3, 512 \\ 3*3*3, 512 \end{bmatrix} * 3$
	$1*1*1$		global average pooling, fully-connected with softmax	

[7]

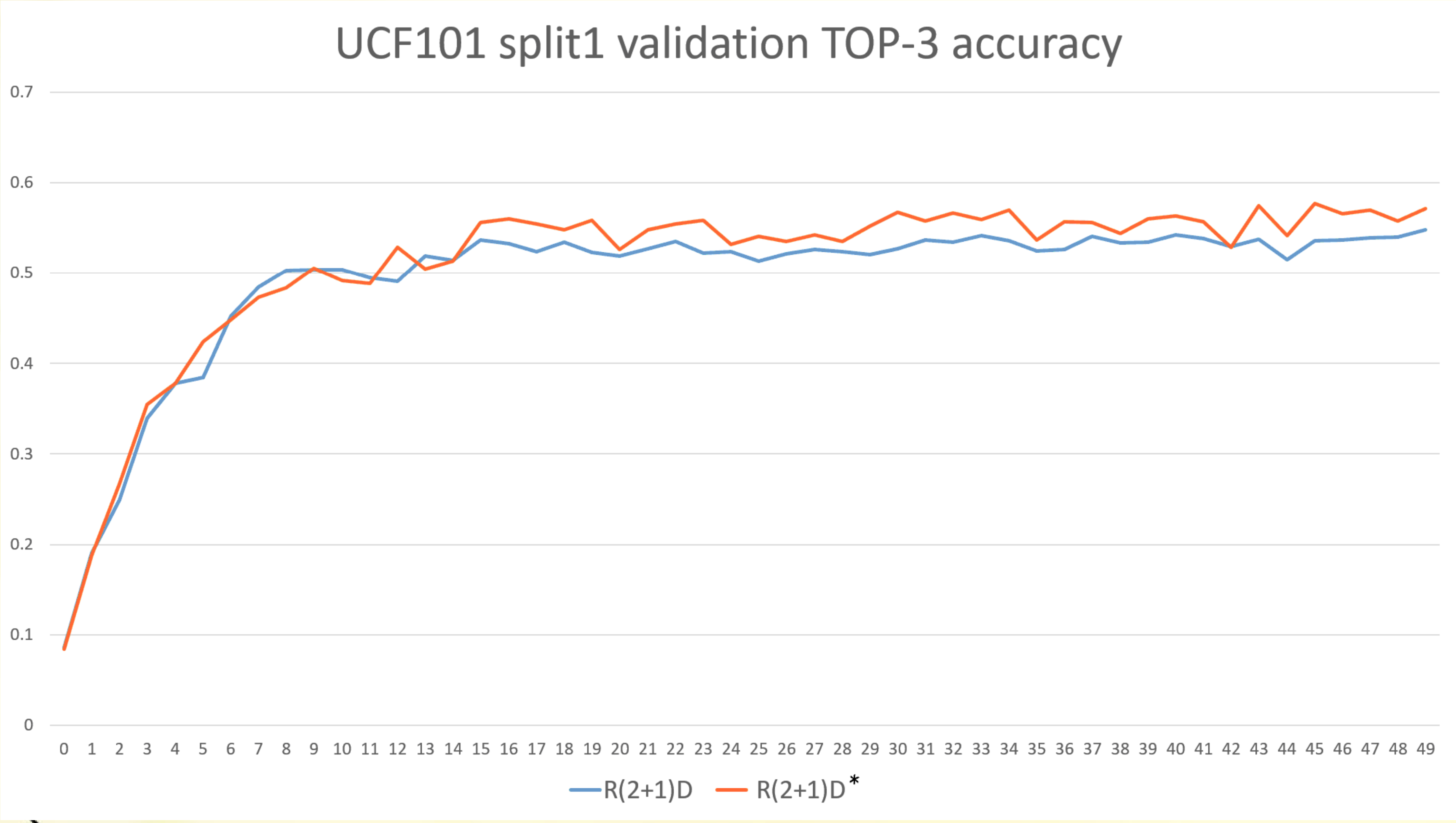


x
3*3*3, 64
relu
3*3*3, 64
+
relu
R3D
x
1*3*3, 64
relu
3*1*1, 144
relu
1*3*3, 64
relu
3*1*1, 144
+
relu
R(2+1)D

Layer name	Output size	R(2+1)D	Stride
Conv_1	$L*56*56$	$1*7*7$ $3*1*1$	$1*2*2$
Conv_2	$L*56*56$	$\begin{bmatrix} 1*3*3 \\ 3*1*1 \\ 1*3*3 \\ 3*1*1 \end{bmatrix}*3$	$1*1*1$
Conv_3	$\frac{L}{2}*28*28$	$\begin{bmatrix} 1*3*3 \\ 3*1*1 \\ 1*3*3 \\ 3*1*1 \end{bmatrix}*4$	$2*2*2$
Conv_4	$\frac{L}{4}*14*14$	$\begin{bmatrix} 1*3*3 \\ 3*1*1 \\ 1*3*3 \\ 3*1*1 \end{bmatrix}*6$	$2*2*2$
Conv_5	$\frac{L}{8}*7*7$	$\begin{bmatrix} 1*3*3 \\ 3*1*1 \\ 1*3*3 \\ 3*1*1 \end{bmatrix}*3$	$2*2*2$
	$1*1*1$	spatiotemporal pooling, fc layer with softmax	



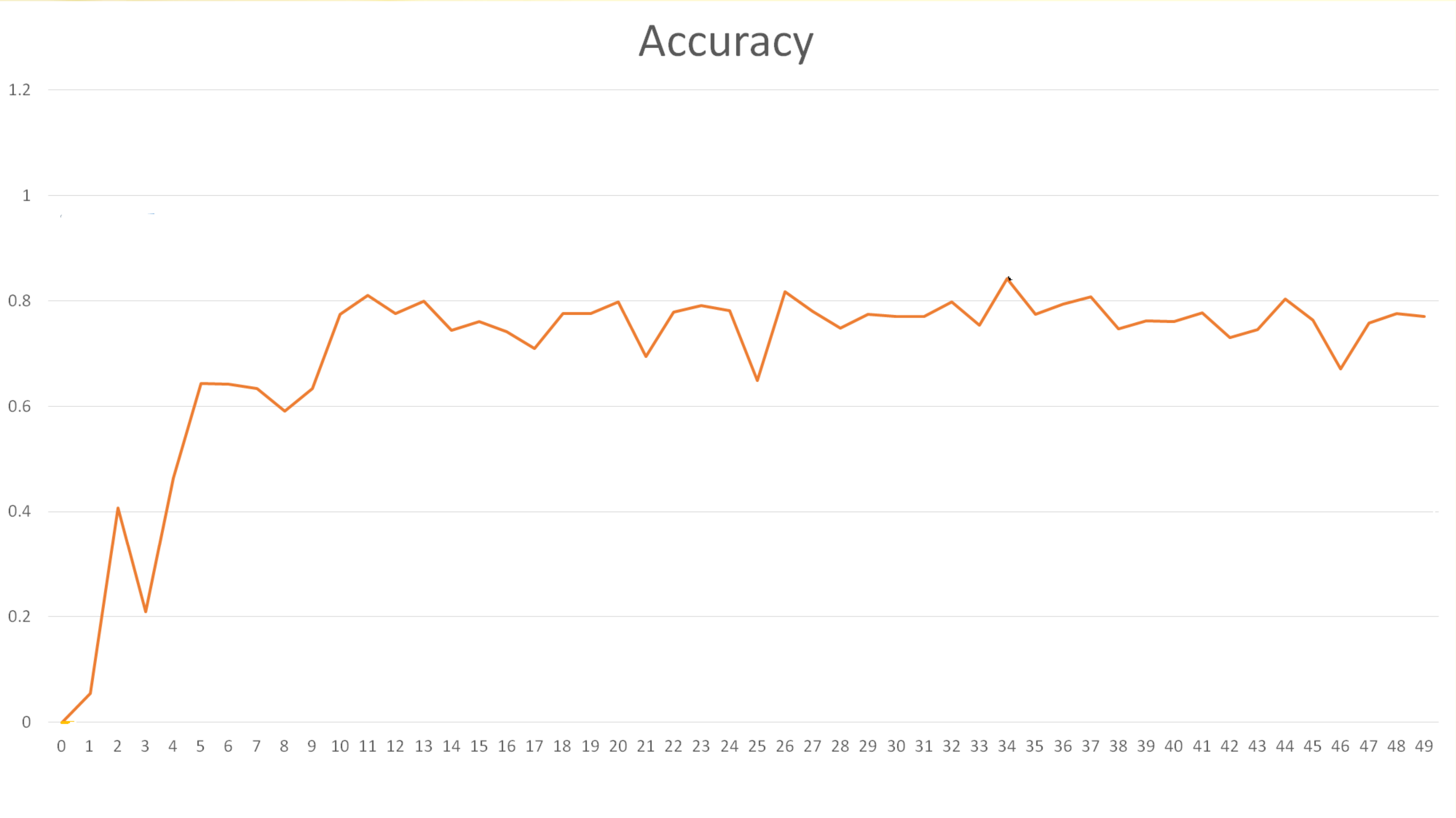
UCF101 data set: 101 behaviors, 13320 video sequences.


UCF101 split1 validation TOP-3 accuracy
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49
R(2+1)D
R(2+1)D*

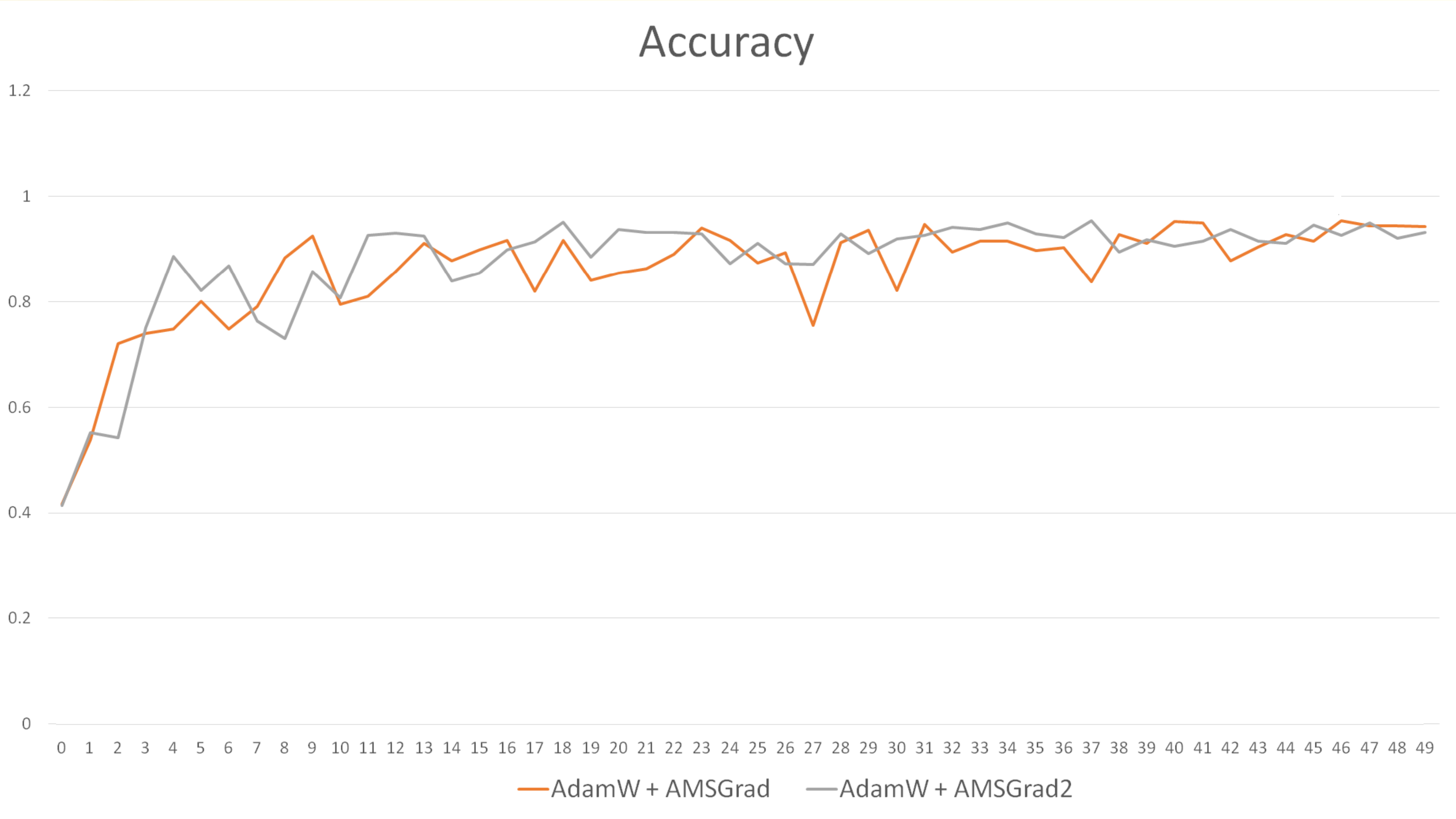
Video sequences of aquaculture field

	normal	abnormal
Train	16,473	667
Validation	0	667

	Normal events	Abnormal events
Detecton of normal events	TP	FN
Detection of abnormal events	FP	TN



Accuracy=0.842



Accuracy=0.954

Abnormal behavior recognition of aquaculture field

↓

Abnormal behavior recognition of shrimp or fish under seawater

Thanks for Your Attention !!