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พระจอมเกล้าลาดกระบัง

College of Advanced Manufacturing Innovation
KMITL
Foundation for Future Factory

CiRA CORE: Deep learning platform, end-to-end AI solutions for biomedical research

รศ.ดร.ศิริเดช บุญแสง
คณบดี
Assoc. Prof. Dr. Siridech Boonsang
Dean

CiRACORE
รางวัลพระราชทาน
นักเทคโนโลยีดีเด่น
ประจำปี 2562

รางวัลพระราชทาน นักเทคโนโลยีดีเด่น ประจำปี 2562

จาก สมเด็จพระกนิษฐาธิราชเจ้า กรมสมเด็จพระเทพรัตนราชสุดาฯ สยามบรมราชกุมารี

โดยมูลนิธิส่งเสริมวิทยาศาสตร์และเทคโนโลยี ในพระบรมราชูปถัมภ์ เมื่อวันที่ 7 ตุลาคม 2562

ณ หอประชุมสมเด็จย่า มหาวิทยาลัยแม่ฟ้าหลวง


คณะผู้วิจัย


In collaboration with
TMA
55th Anniversary
OUTSTANDING TECHNOLOGIST AWARDS
&
STI FORUM 2019
& Technology in Business"


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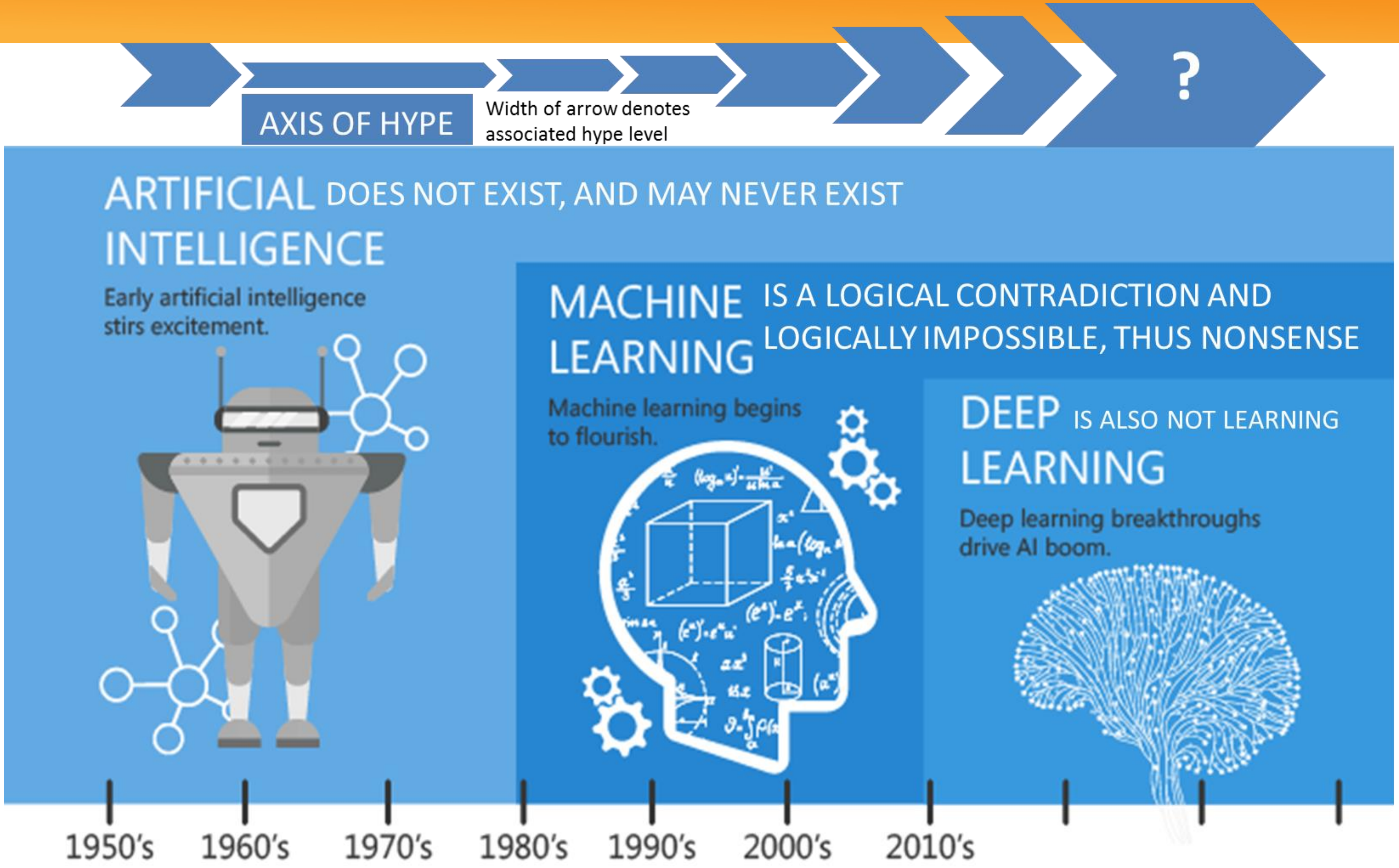
รางวัลพระราชทาน

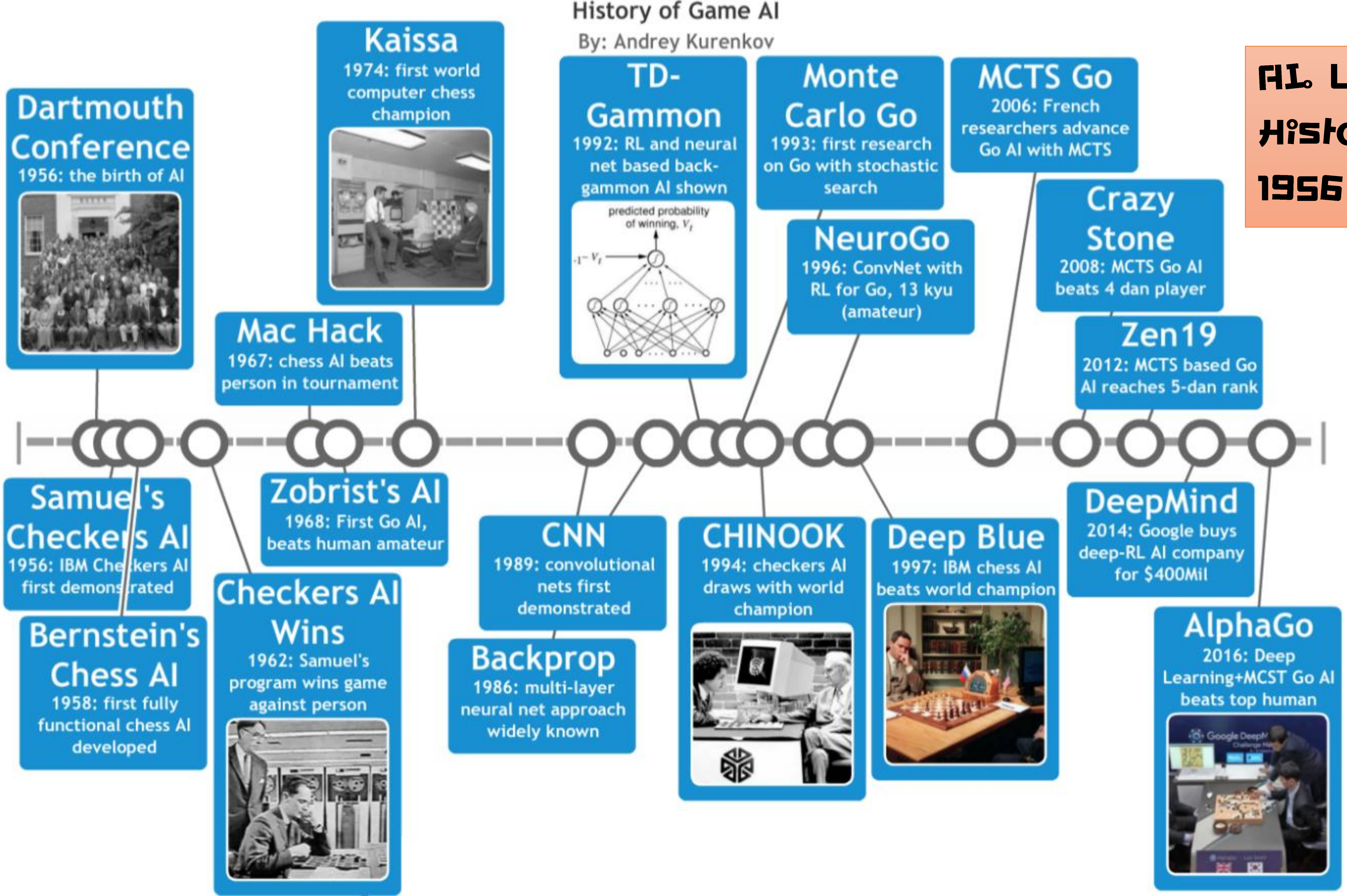
นักเทคโนโลยีดีเด่น

ประจำปี 2562



Since AI has continued to not exist since it was first posited as possible, hype has become the only means of maintaining interest and funding in AI. By creating smaller subsets of something that has continuously failed to materialize we confuse the public and maintain our positions of influence in academia and technology. Who knows what made up term we will think of next. My money is on systems of intelligence although data science has gotten off to a really strong start.

AI Long History since 1956

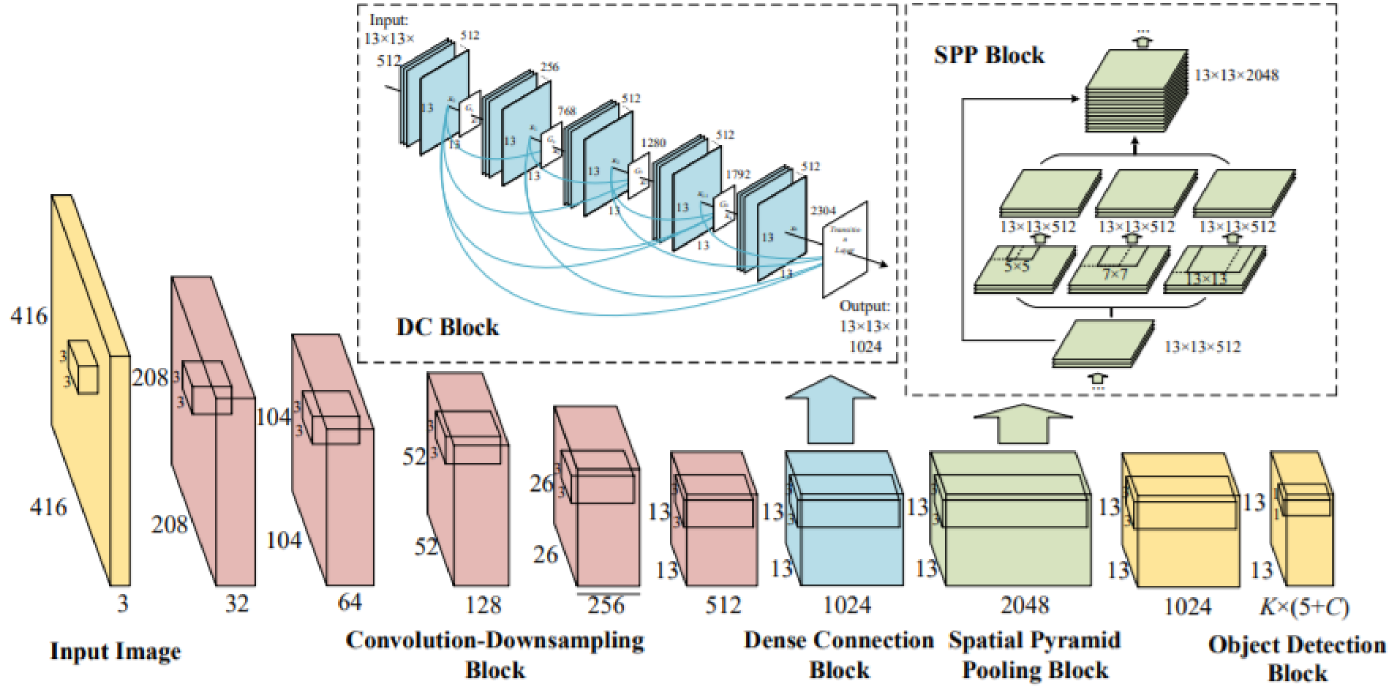


Deep learning is a trending topic worldwide.

This wasn't the case 7 years ago; back then, nobody was talking about it and nobody cared.

So How to implement then?

$$i_t = \sigma(W_i x_t + R_i h_{t-1} + b_i)$$
$$f_t = \sigma(W_f x_t + R_f h_{t-1} + b_f)$$
$$o_t = \sigma(W_o x_t + R_o h_{t-1} + b_o)$$
$$c'_t = \tanh(W_c x_t + R_c h_{t-1} + b_c)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ c'_t$$
$$h_t = o_t \circ \tanh(c_t)$$



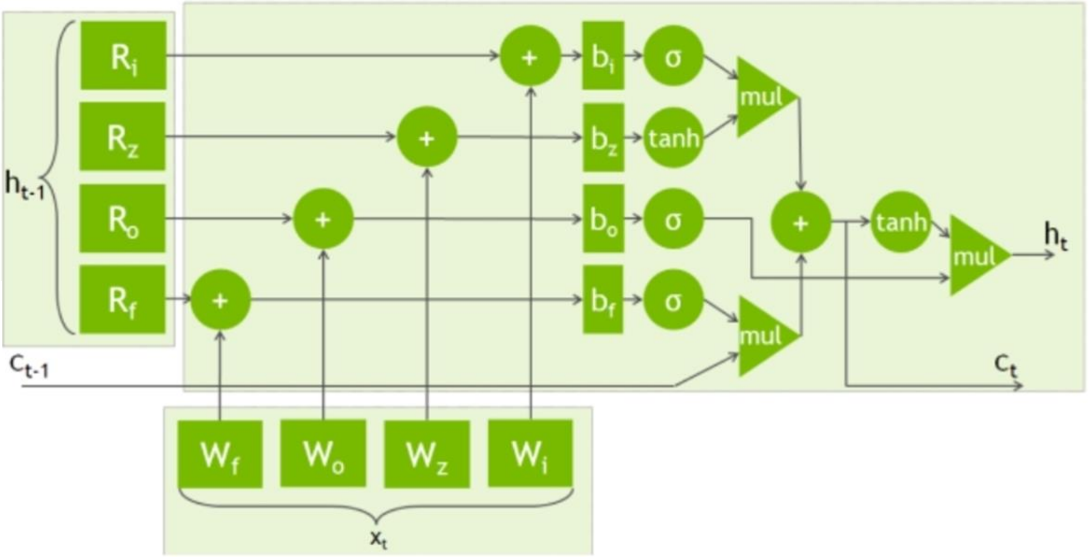
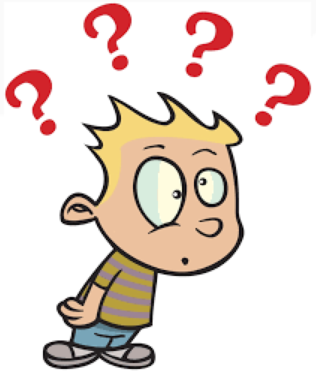


Figure 2: A diagram of an LSTM unit



Deep Learning Frameworks

Azure AWS Google Cloud

Service	GCP	Azure	AWS
Image Recognition	Cloud Vision API	Compute Vision API	Amazon Rekognition
Video Recognition	Cloud Video Intelligence API	Video Indexer	Amazon Rekognition Video
Speech Recognition	Cloud Speech API	Speech Recognition API	Amazon Transcribe*
Text Analysis	Cloud Natural Language API	Text Analytics API	Amazon Comprehend
Language Translation	Cloud Translation API	Translator Text API	Amazon Translate*

Amazon offers "pay as you go" approach which means a user will pay only for the individual services s/he uses without any long term licensing.
Microsoft Azure is less expensive than AWS and charges on a minute basis.
GCP too charges on a minute basis and there are no up-front costs or termination fees.

400K USD
12 ล้านบาท

500K USD project for 3 years

33K USD
7.5 แสนบาท

33K USD
7.5 แสนบาท

33K USD
7.5 แสนบาท

CiRA CORE consortium

Permanent Members

Licensing managed by

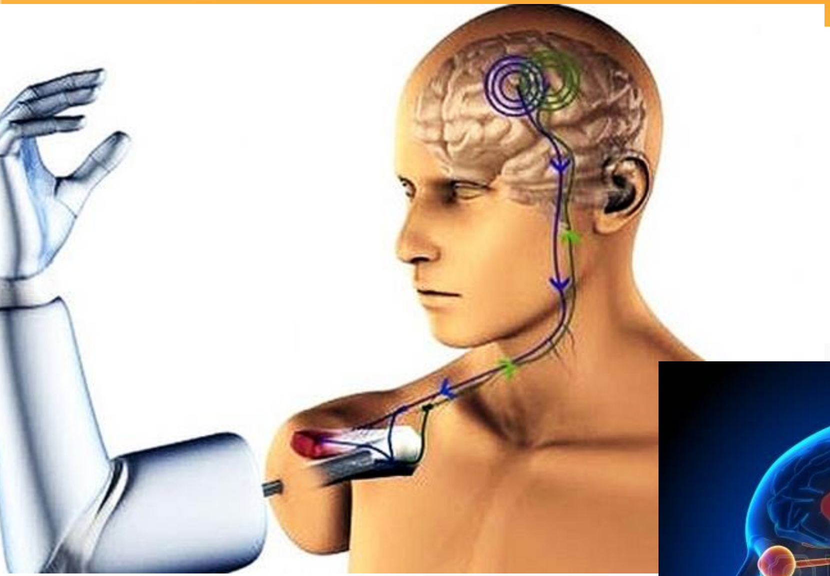
Deep Learning Frameworks

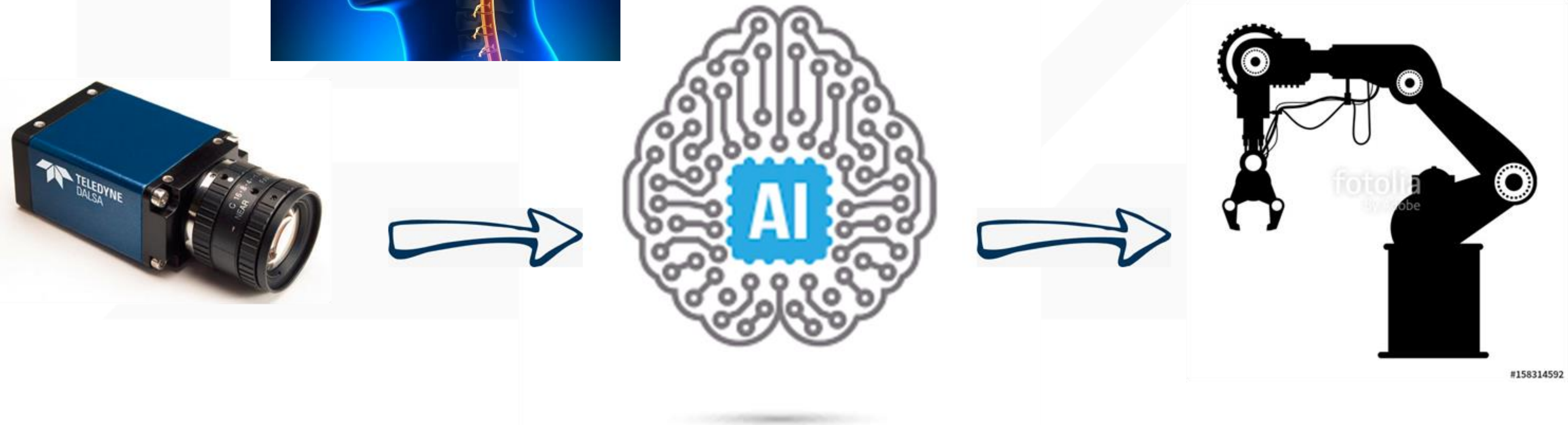
Caffe | Microsoft CNTK | DEEPLEARNING4J

dmlc mxnet | TensorFlow | theano

torch

Azure | AWS | Google Cloud





Sensors

Brain

Actuators

Center of Industrial Robots and Automation (CiRA)

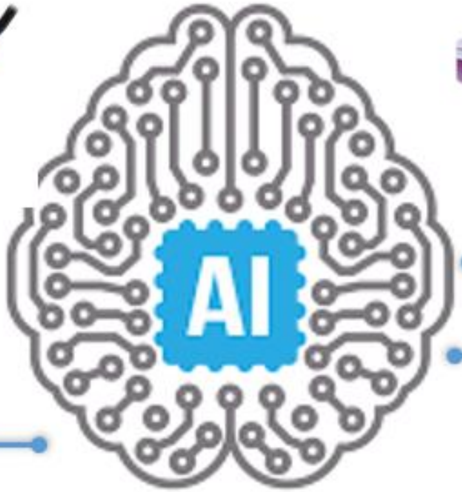
สวทช NSTDA

SEAGATE

CPF

CiRA ROBOTICS

Vision and Sensors in Manufacturing process



Modbus

MQTT.ORG

REST API

EtherCAT.

Industrial protocols

Cloud Computing

CiRACORE

Customized / Commercial ROBOTs and Automation

สกว TRF

TSC THAI STEEL CABLE PCL

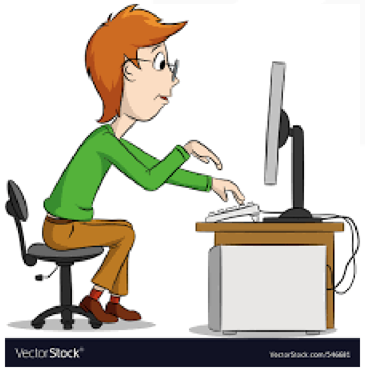
STM

SCG

Industrial AI Enabler

CiRA CORE = BRAIN POWER + CONNECTIVITY

YAHOO!



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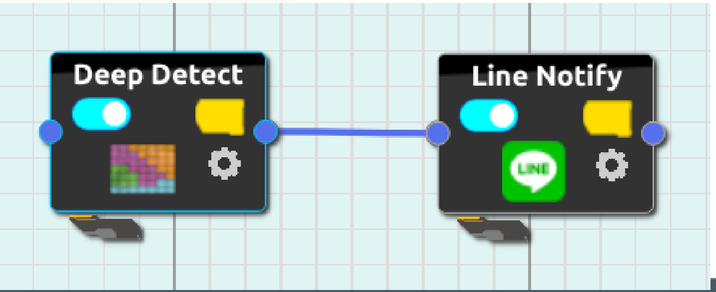

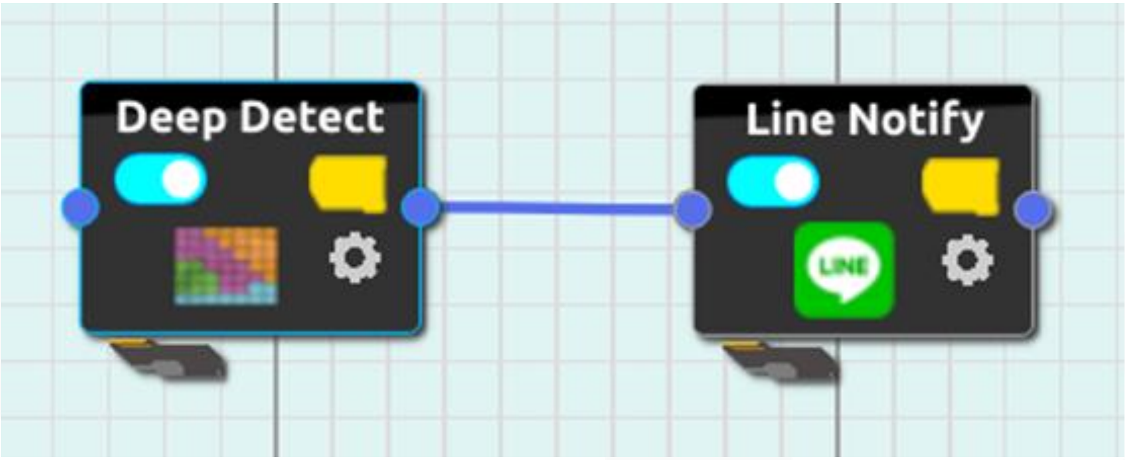

1. CPP objects to complete specified tasks

2. Reusable code and run-time ready module

3. Ease of information transfer between app via JSON format

4. SDK ready for specific module development

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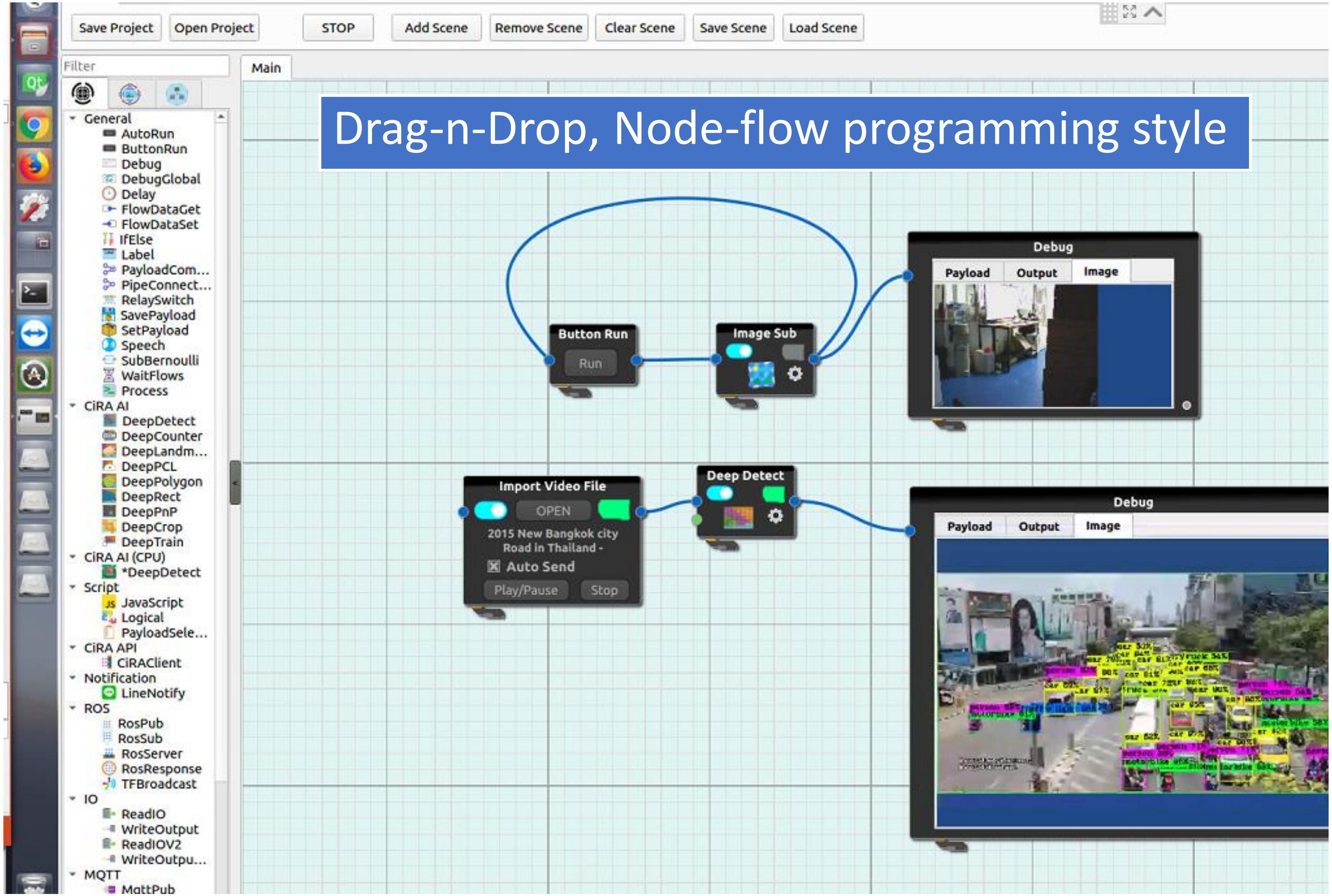
Industrial AI Enabler

No license fee

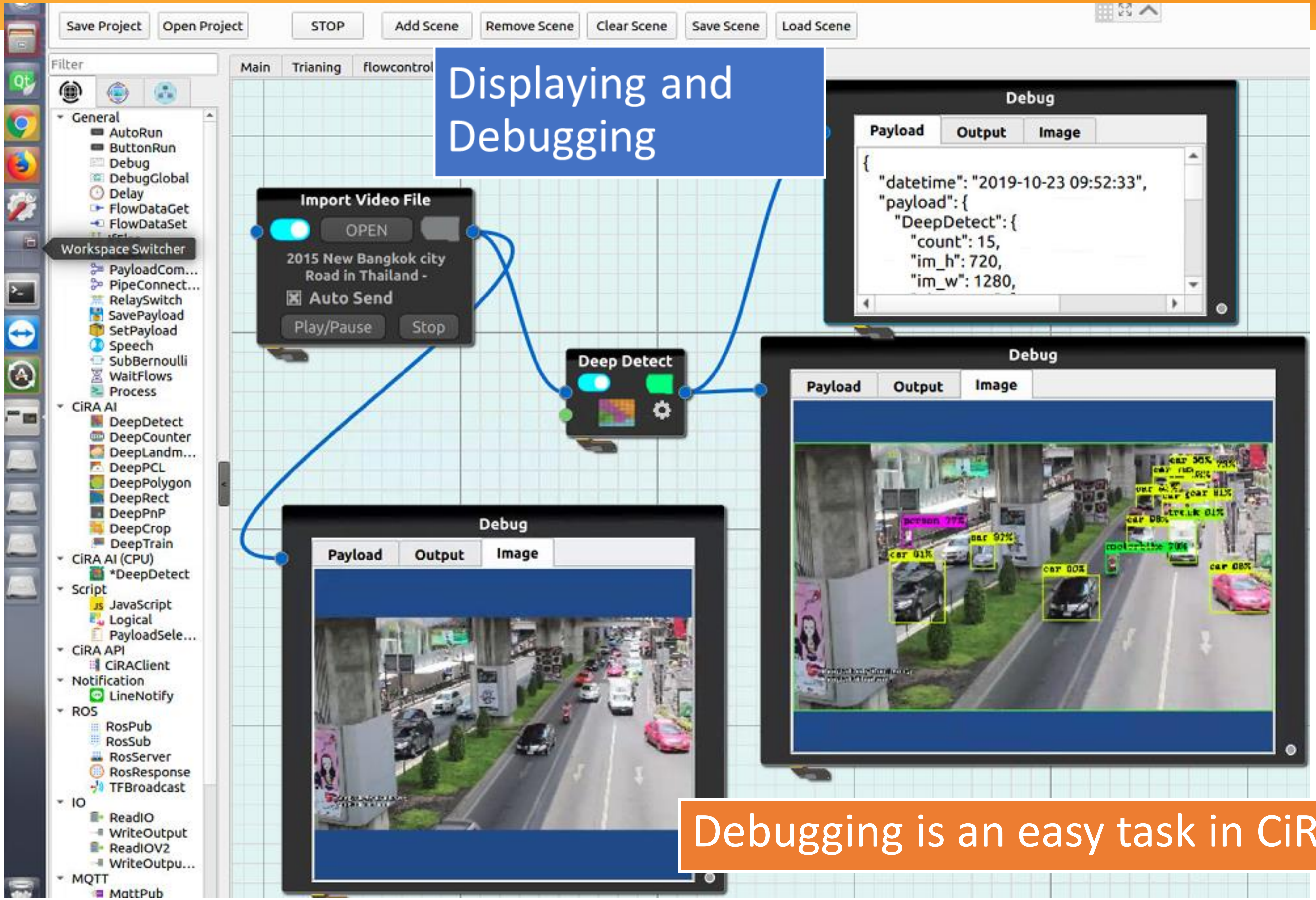
for

Thai Government Organization

Drag-n-Drop, Node-flow programming style

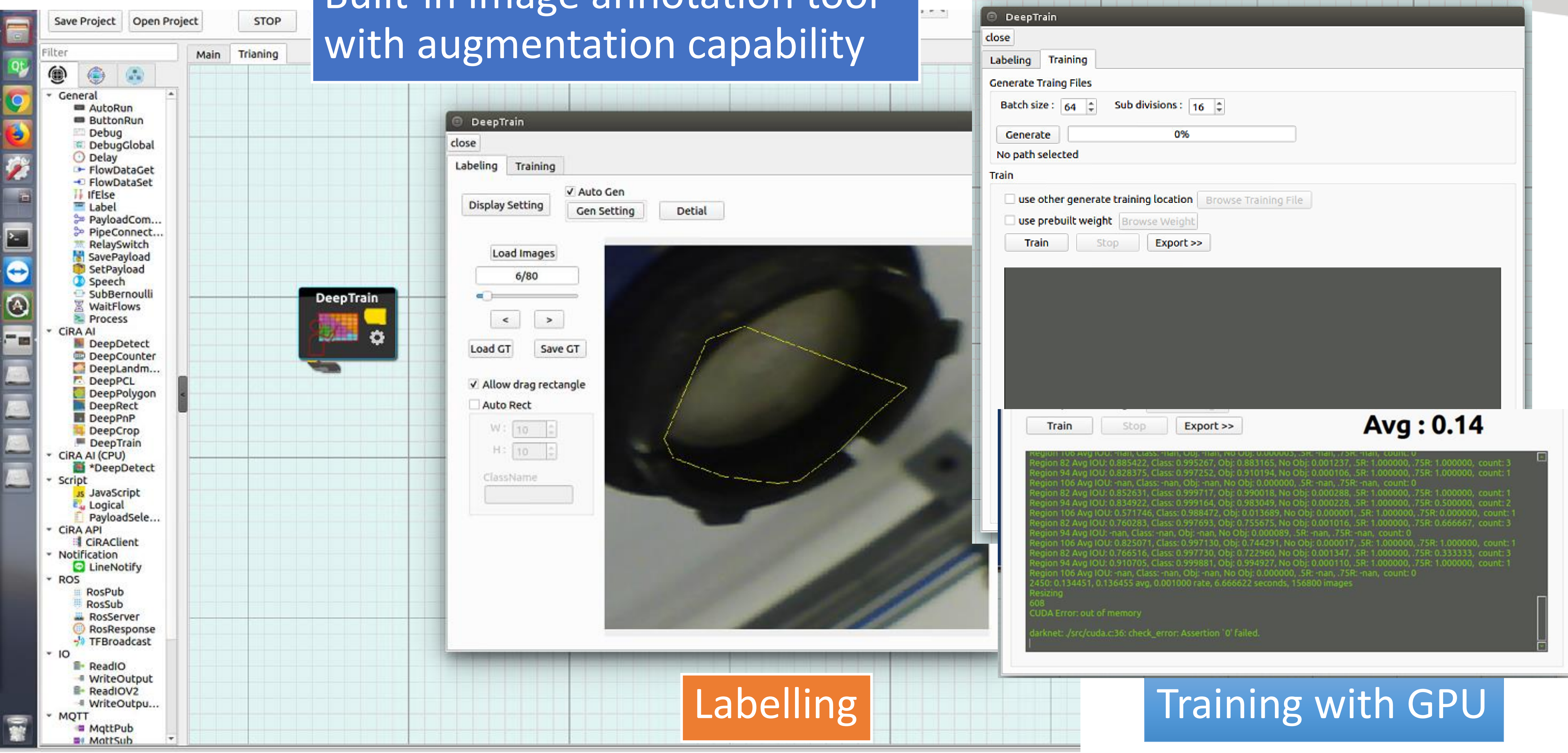


Displaying and Debugging



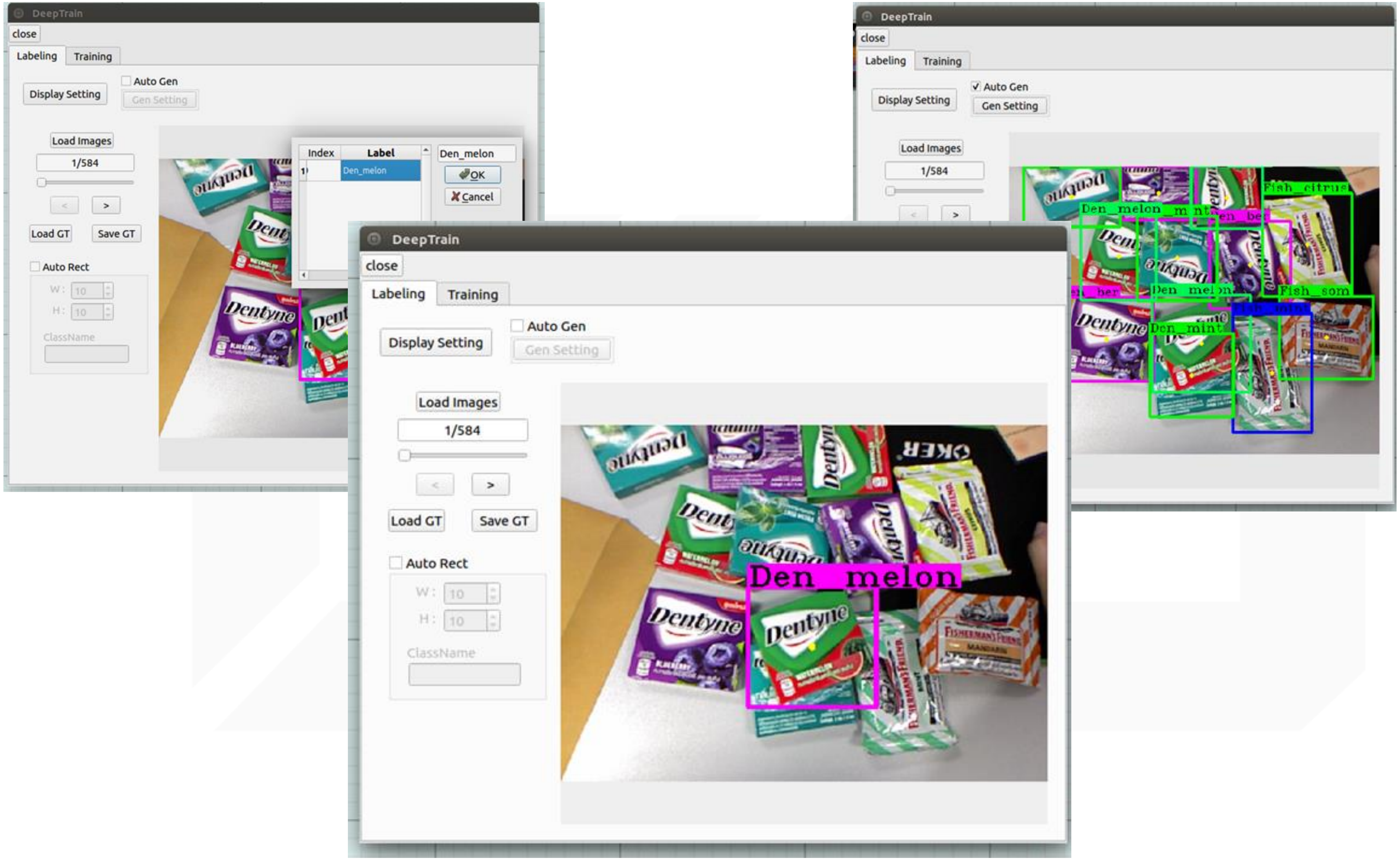
Debugging is an easy task in CiRACORE

Built-in image annotation tool with augmentation capability



Labelling

Training with GPU



DeepTrain
close
Labeling
Training
Display Setting
Auto Gen
Gen Setting
Load Images
1/584
<
>
Load GT
Save GT
Auto Rect
W :
H :
10
ClassName
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Label
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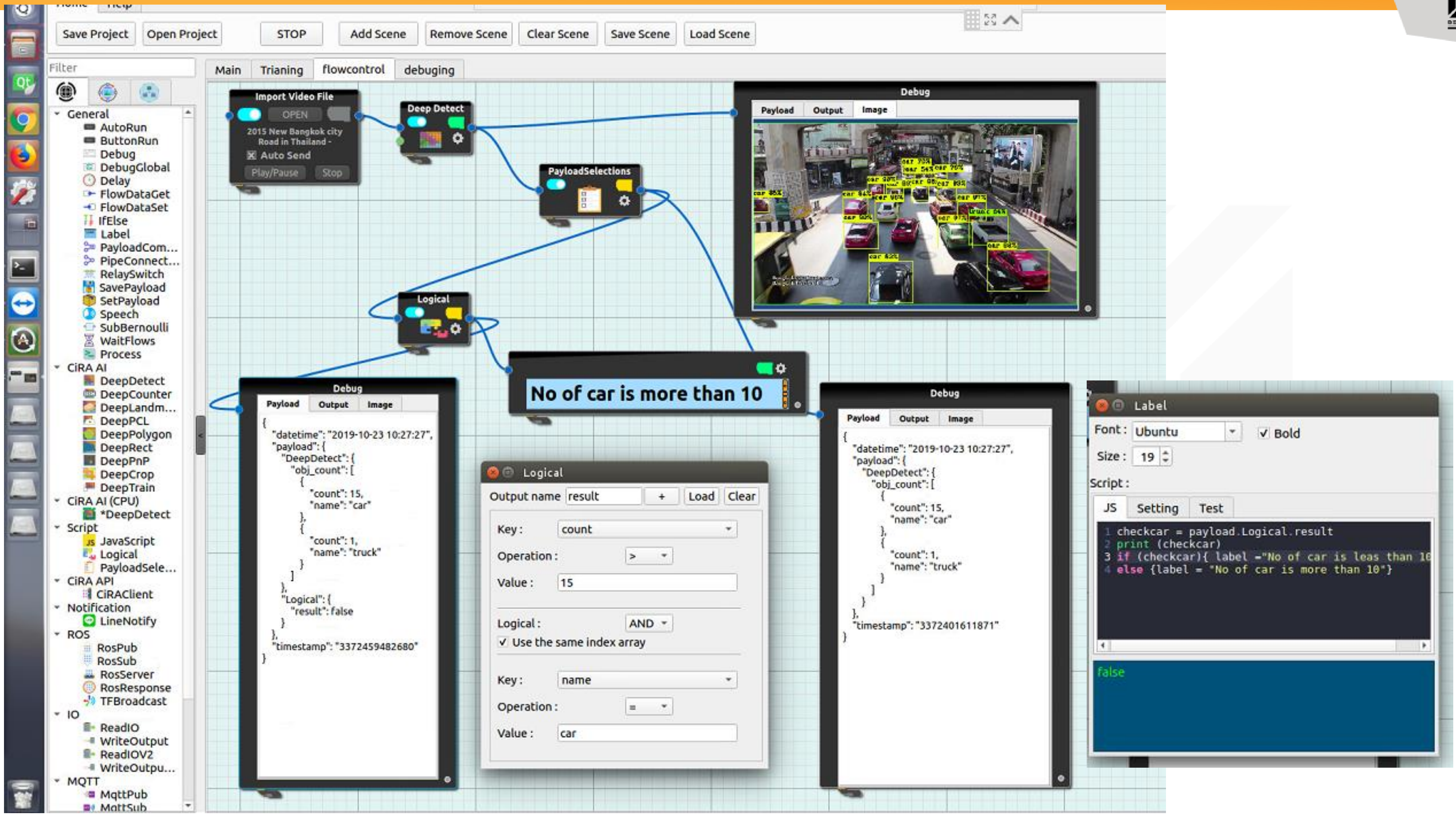
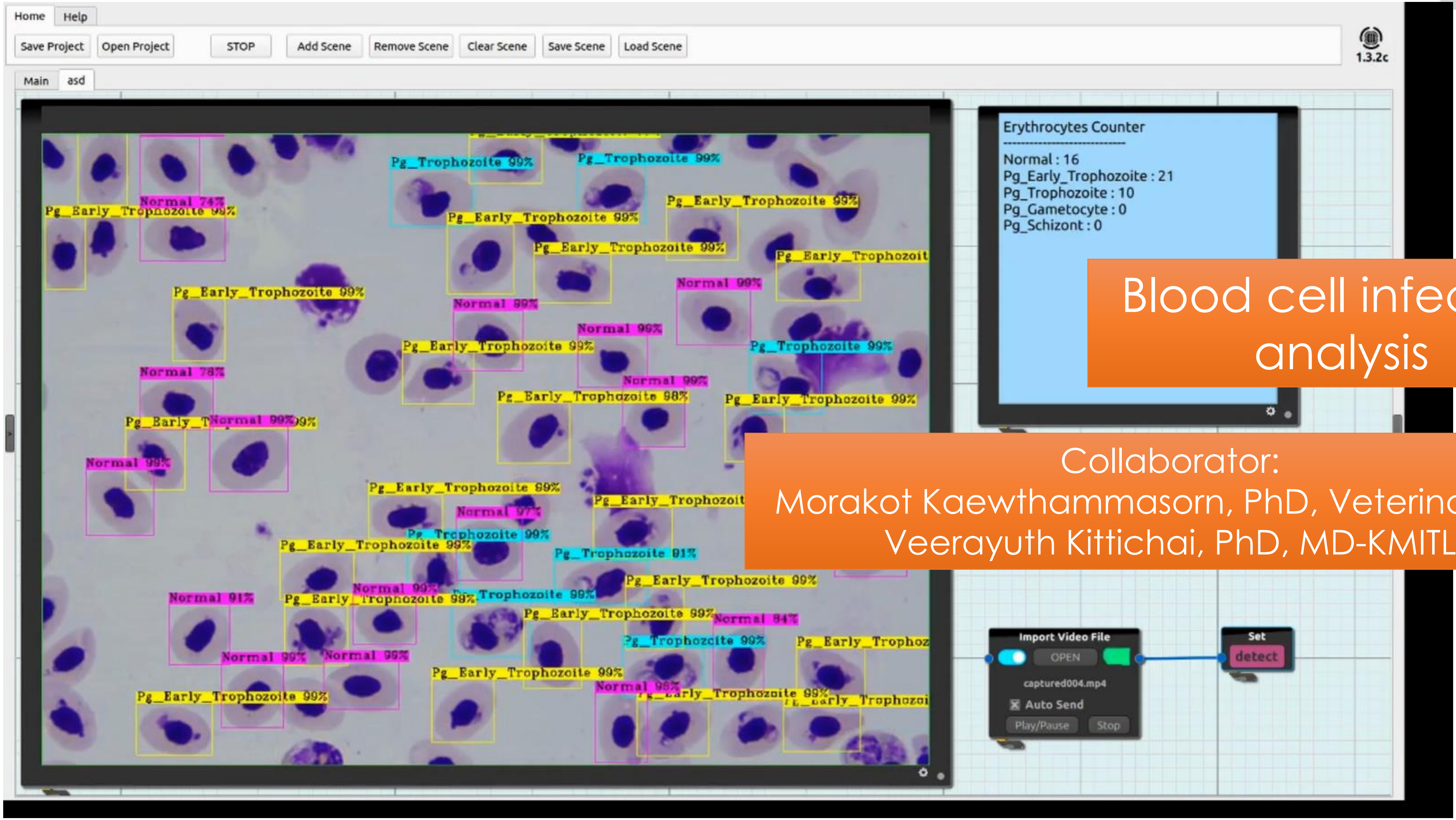
Cancel
Den_melon
Fish_citrus
Den_mint
Fish_som



Save Project
Open Project
STOP
Add Scene
Remove Scene
Clear Scene
Save Scene
Load Scene
Main
Trianing
flowcontrol
debuging
Import Video File
Deep Detect
PayloadSelections
Debug
Logical
No of car is more than 10
Logical
Output name result
Key : count
Operation : >
Value : 15
Logical : AND
Use the same index array
Key : name
Operation : =
Value : car
Label
Font : Ubuntu
Bold
Size : 19
Script :
JS
Setting
Test
checkcar = payload.Logical.result
print (checkcar)
if (checkcar){ label ="No of car is leas than 10
else {label = "No of car is more than 10"}
false



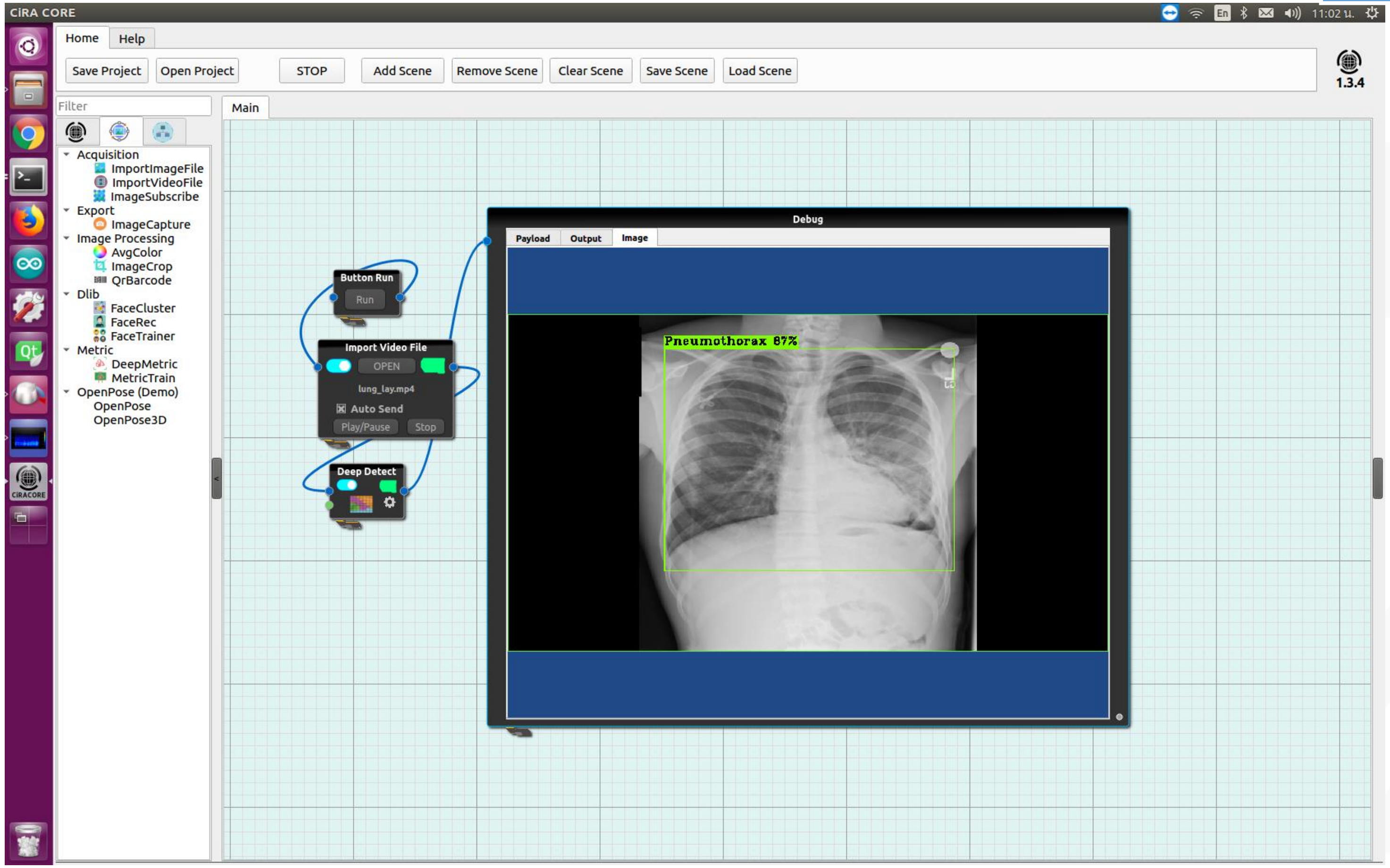
Blood cell infection analysis

Collaborator:

Morakot Kaewthammasorn, PhD, Veterinary, CU

Veerayuth Kittichai, PhD, MD-KMITL

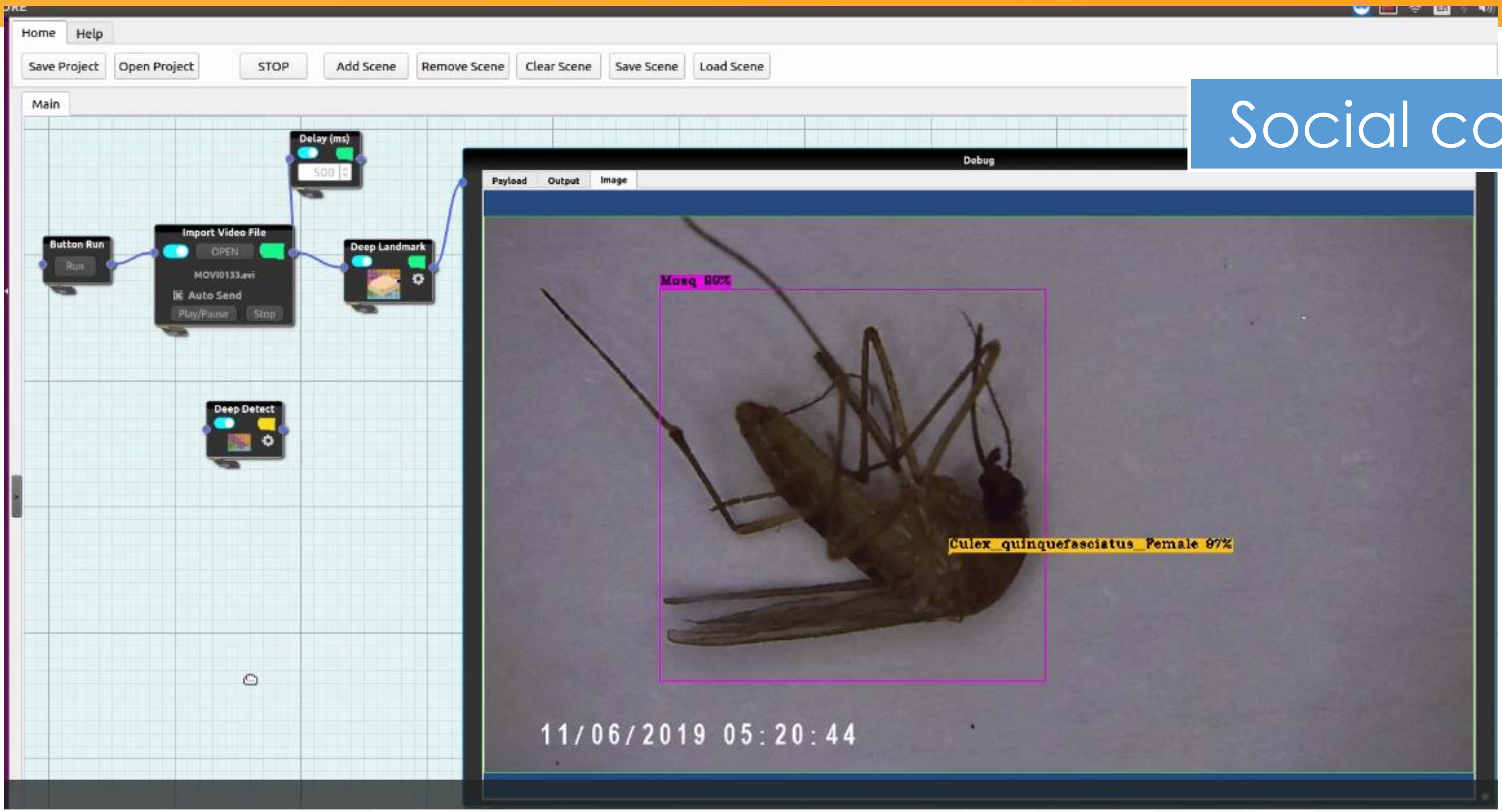
Social contributions



Chest X-RAY screening
Using deep learning

Collaborator:
Pisal Puengpipattrakul, medical Radiologist, MD-KMITL

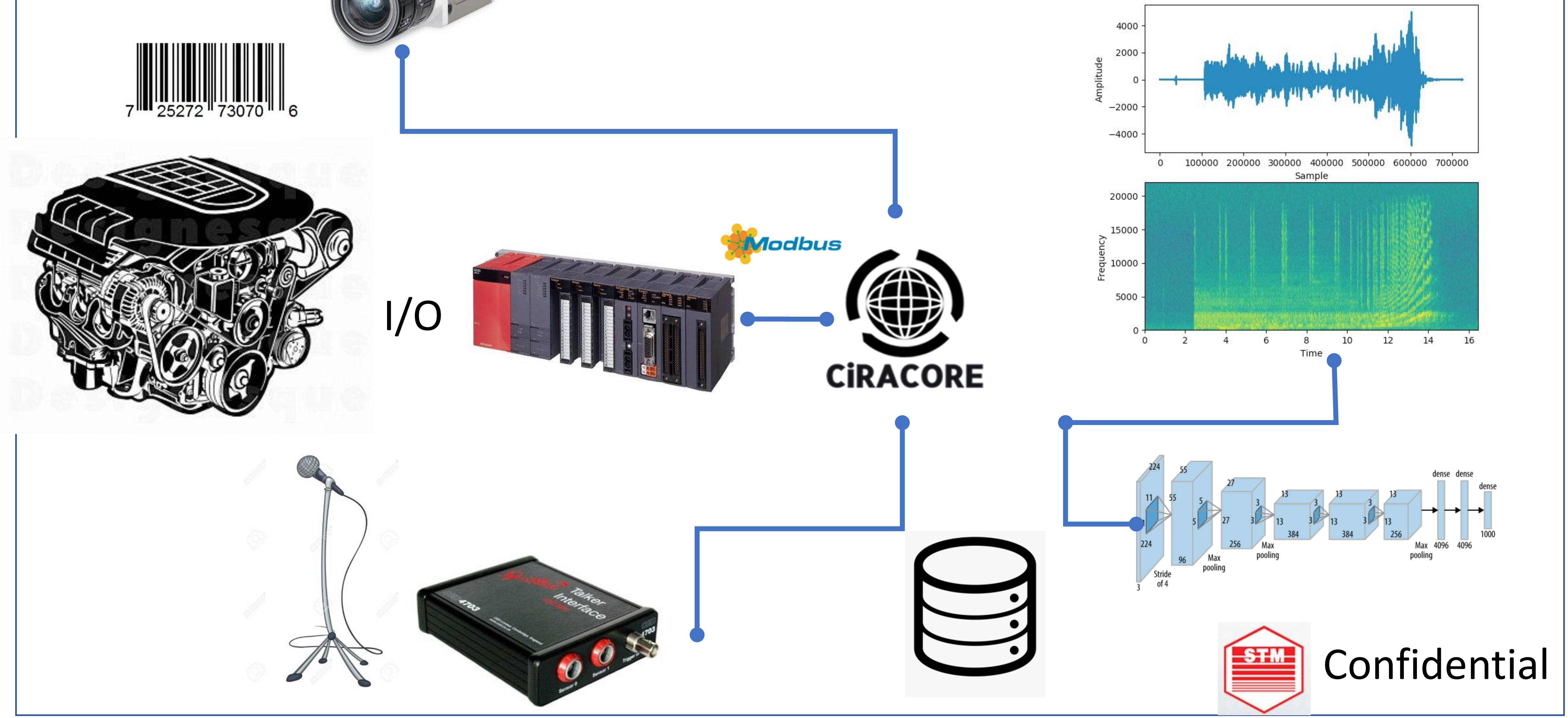
Social contributions

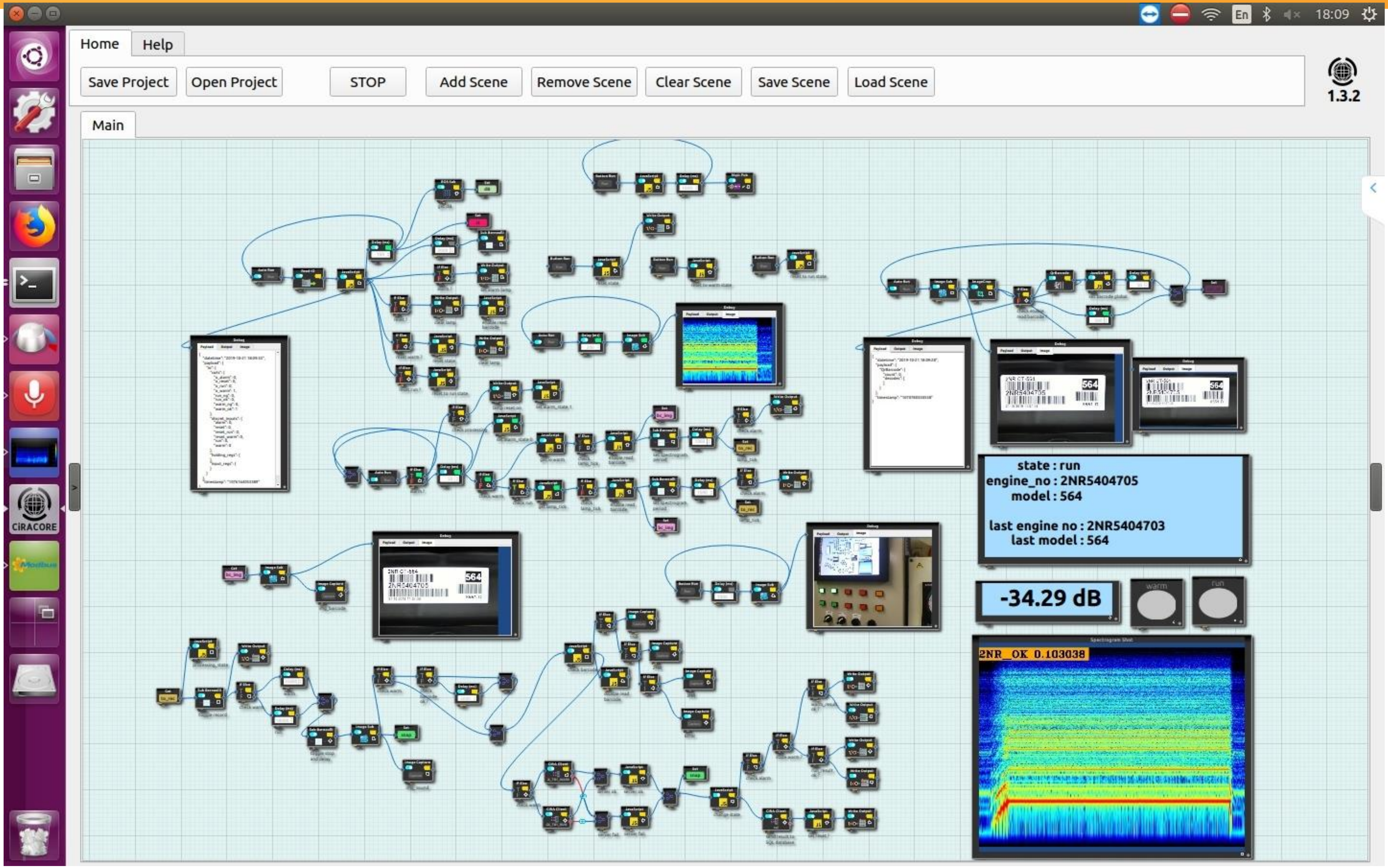


Mosquito gender, species and genus identification
Using deep learning

Collaborator:
Patchara Sriwichai, PhD
Yutthana Samung, Dept. Medical Entomology, MU

Industrial used cases




Home
Help
Save Project
Open Project
STOP
Add Scene
Remove Scene
Clear Scene
Save Scene
Load Scene
1.3.2
Main
state : run
engine_no : 2NR5404705
model : 564
last engine no : 2NR5404703
last model : 564
-34.29 dB
warm
run
2NR_OK 0.103038
CiRACORE
18:09

Mosquito Detection with Neural Networks: The Buzz of Deep Learning

Ivan Kiskin[1,2], Bernardo Pérez Orozco[1,2], Theo Windebank[1,3], Davide Zilli[1,2], Marianne Sinka[4,5], Kathy Willis[4,5,6], and Stephen Roberts[1,2]

[1] University of Oxford, Department of Engineering, Oxford OX1 3PJ, UK,
[2] {ikiskin, ber, dzilli, sjrob}@robots.ox.ac.uk,
[3] theo.windebank@stcatz.ox.ac.uk,
[4] University of Oxford, Department of Zoology, Oxford OX2 6GG, UK,
[5] {marianne.sinka, kathy.willis}@zoo.ox.ac.uk
[6] Royal Botanic Gardens, Kew, Richmond, Surrey, TW9 3AE, UK.

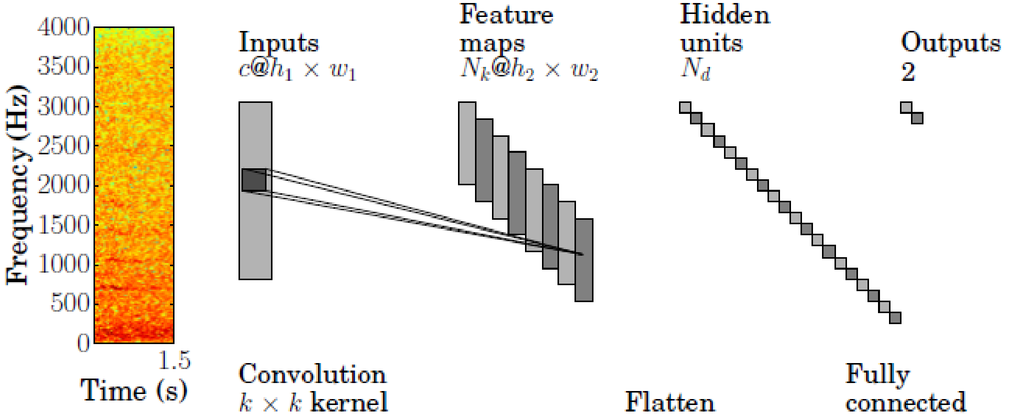


Fig. 1: The CNN pipeline. 1.5 s wavelet spectrogram of mosquito recording is partitioned into images with $c = 1$ channels, of dimensions $h_1 \times w_1$. This serves as input to a convolutional network with N_k filters with kernel $\mathbf{W}_p \in \mathbb{R}^{k\times k}$. Feature maps are formed with dimensions reduced to $h_2 \times w_2$ following convolution. These maps are fully connected to N_d units in the dense layer, fully connected to 2 units in the output layer.

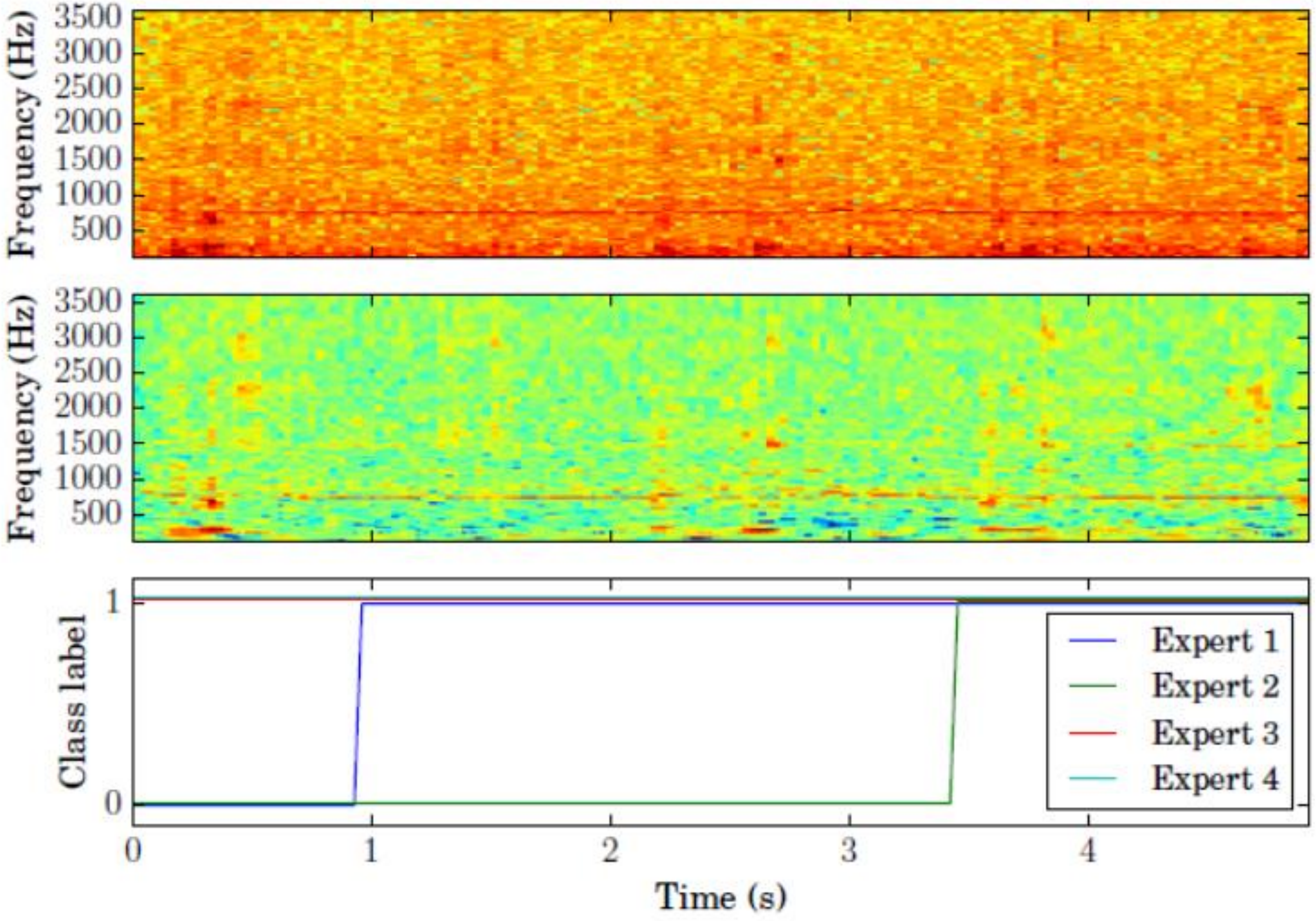
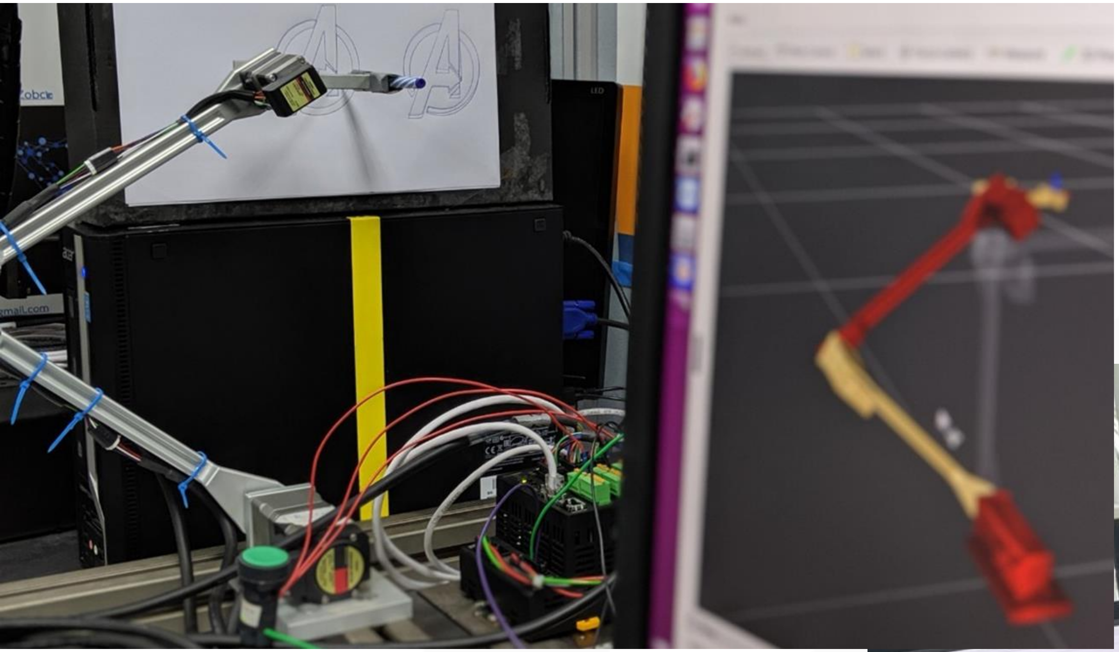


Fig. 3: STFT (top) and wavelet (middle) representations of signal with $h_1 =$ 256 frequency bins and wavelet scales respectively. Corresponding varying class labels (bottom) as supplied by human experts. The wavelet representation shows greater contrast in horizontal constant frequency bands that correspond to the mosquito tone.

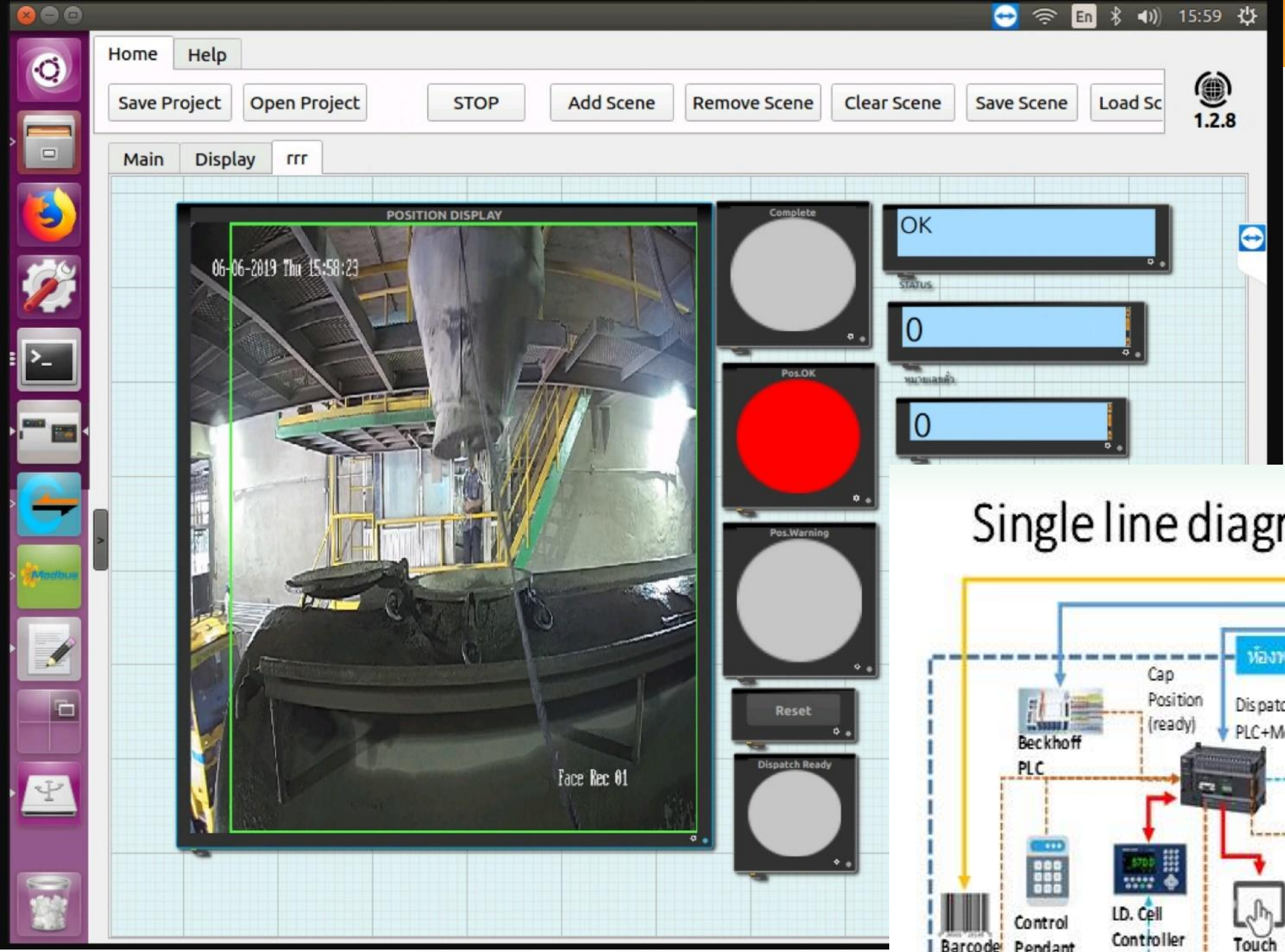
Table 2: Summary classification metrics. The metrics are evaluated from a single run on test data, following 10-fold cross-validation of features and hyperparameters on training dataset.

Classifier	Features	F_1 score	TPR	TNR	ROC area	PR area
MLP	STFT	0.751	0.65	0.96	0.858	0.830
MLP	Wavelet	0.745	0.63	0.97	0.921	0.875
CNN	STFT	0.779	0.69	0.96	0.871	0.853
CNN	Wavelet	**0.817**	0.73	**0.97**	**0.952**	**0.909**
Naive Bayes	STFT	0.521	0.65	0.74	0.743	0.600
Naive Bayes	RFE_{88}	0.484	0.51	0.83	0.732	0.414
Random Forest	STFT	0.674	0.69	0.89	0.896	0.733
Random Forest	RFE_{88}	0.710	0.68	0.93	0.920	0.800
SVM	STFT	0.685	**0.83**	0.81	0.902	0.775
SVM	RFE_{88}	0.745	0.73	0.93	0.928	0.831
CNN, median filter	Wavelet	0.854	0.78	0.98	0.970	0.939
Expert 1	N/A	0.819	0.89	0.85	0.873	0.843
Expert 2	N/A	0.856	0.92	0.88	0.901	0.873
Expert 3	N/A	0.852	0.77	0.98	0.874	0.901

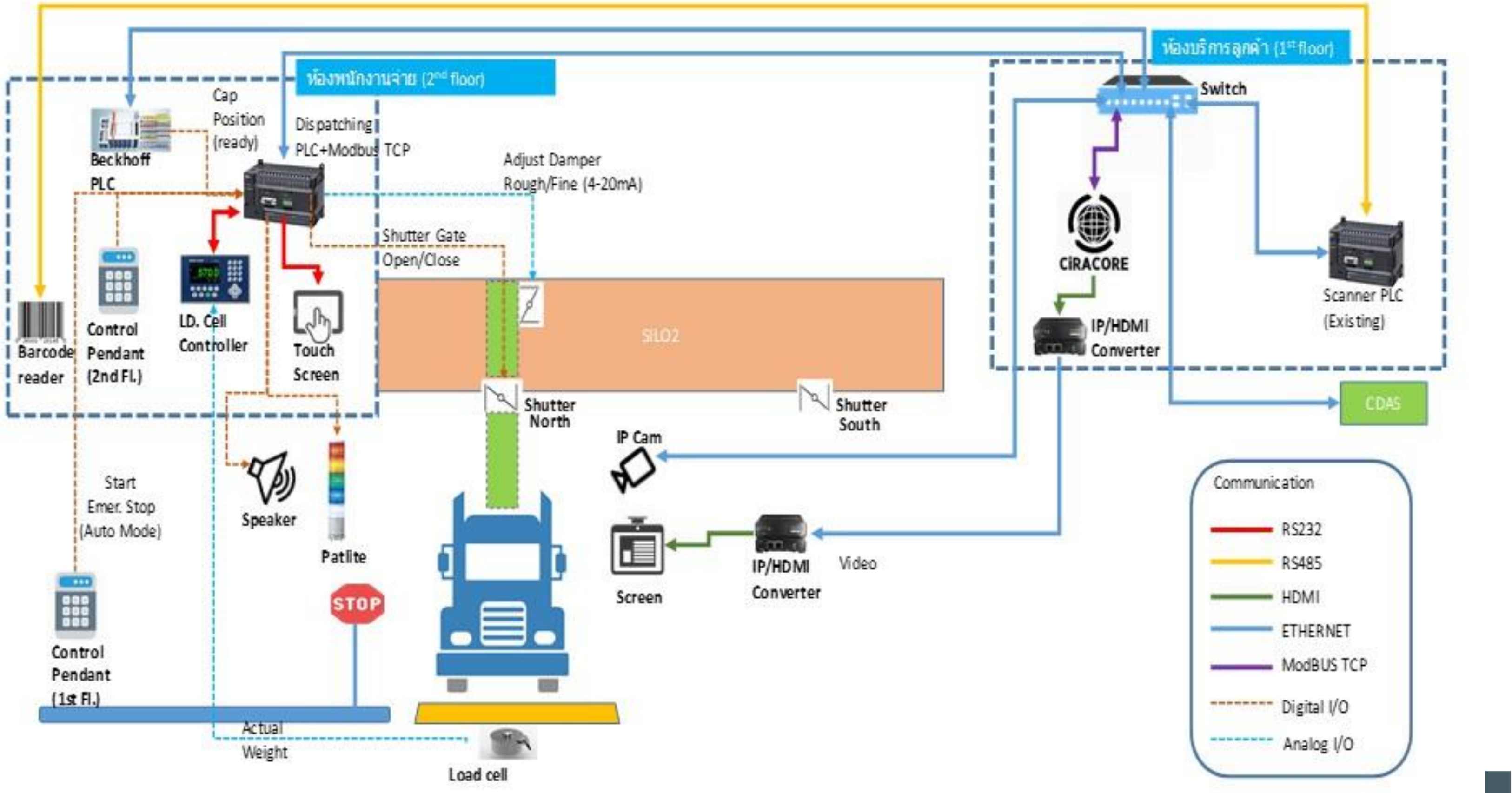
Industrial used cases



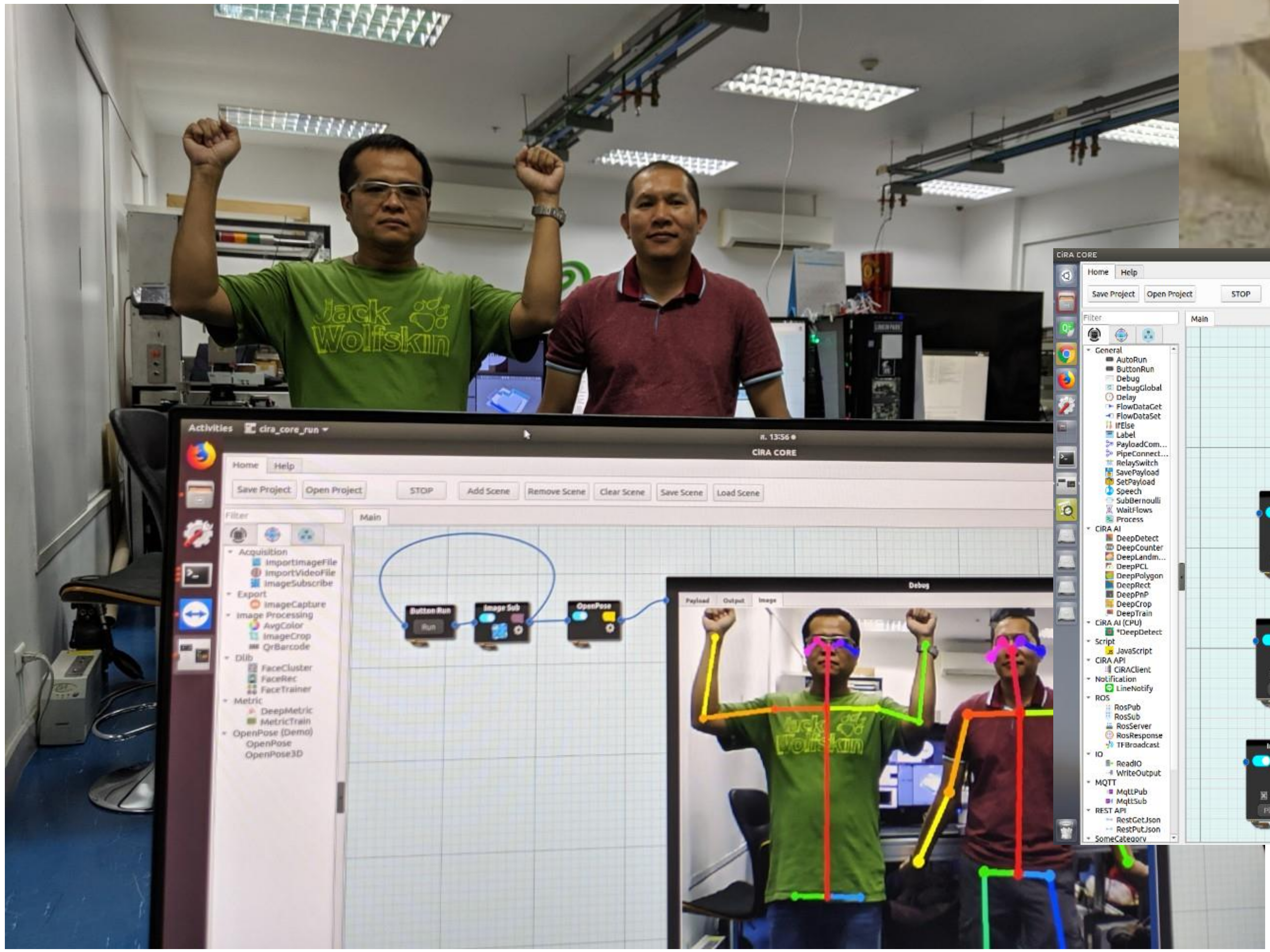
Industrial used cases

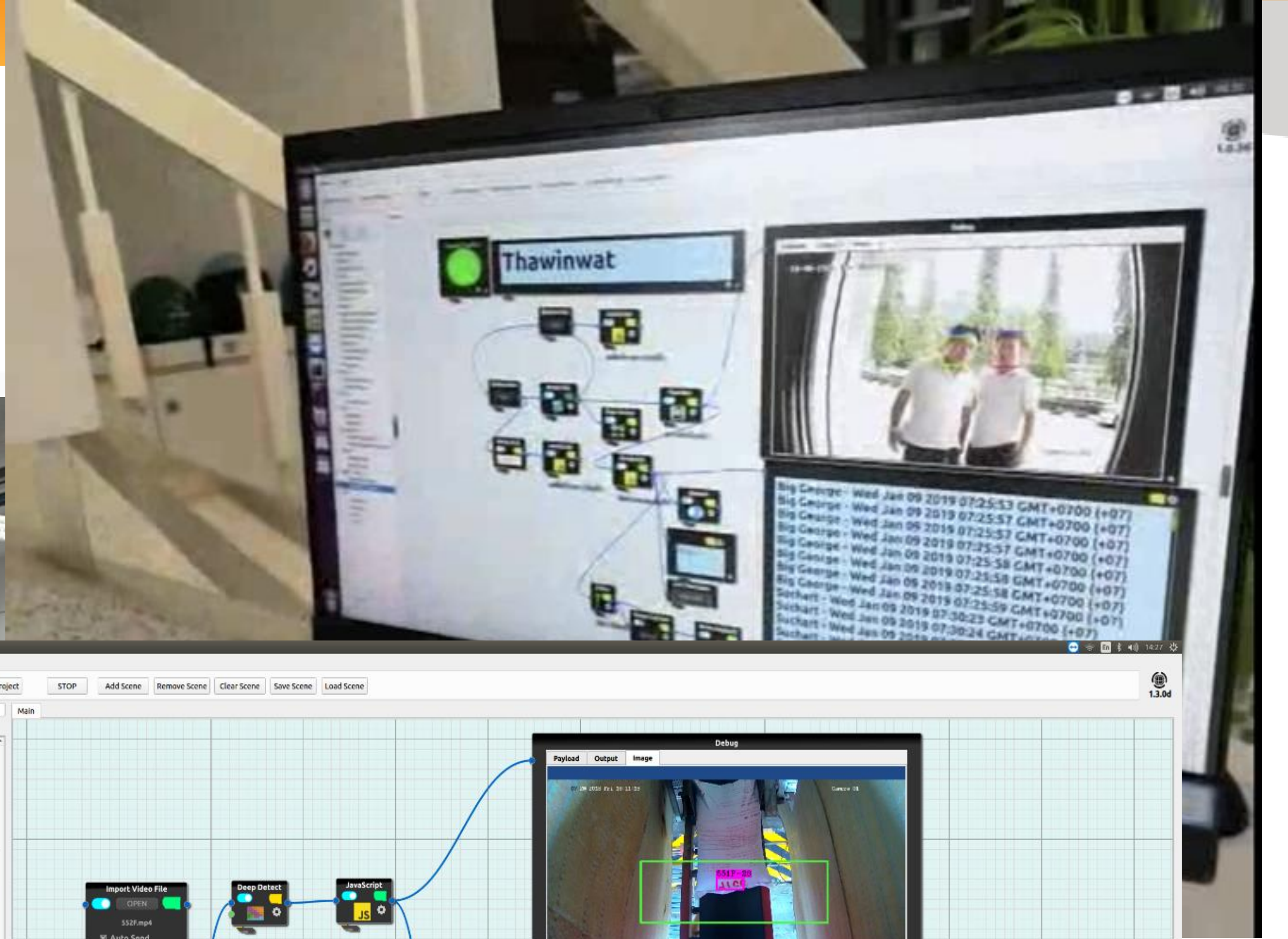


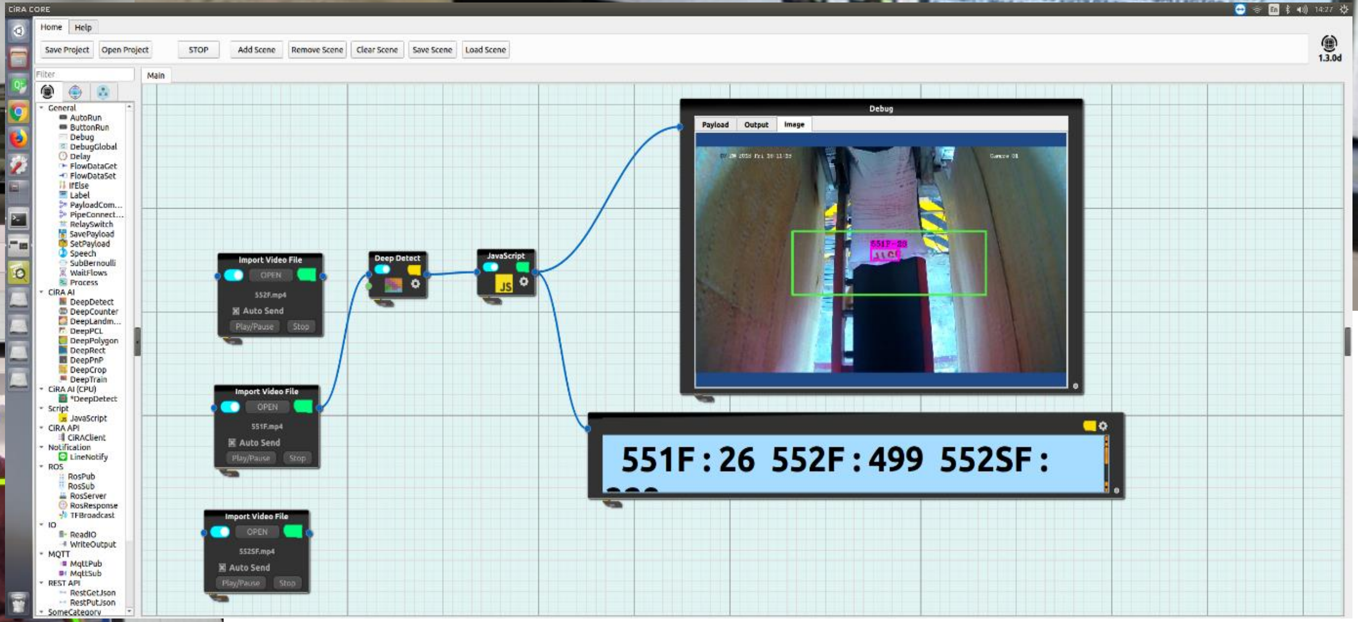
Single line diagram



CiRA CORE :
Deep learning real-time applications







Social contributions

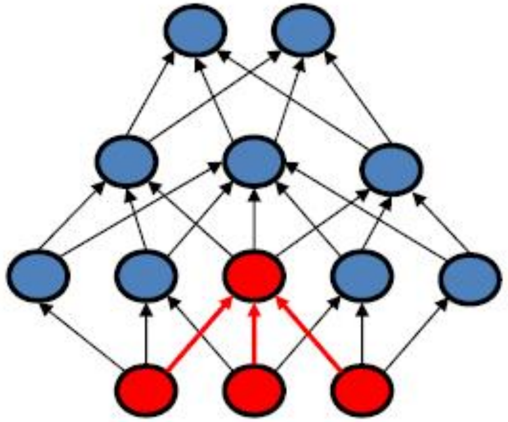
CiRA CORE for kids

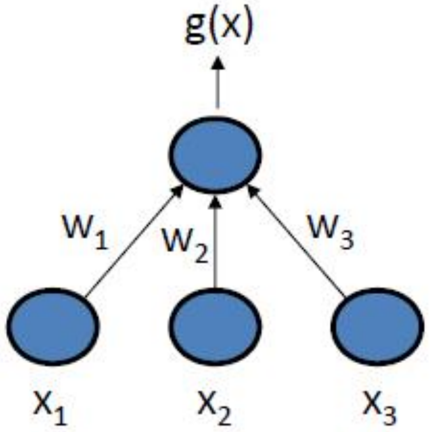
Deep Learning

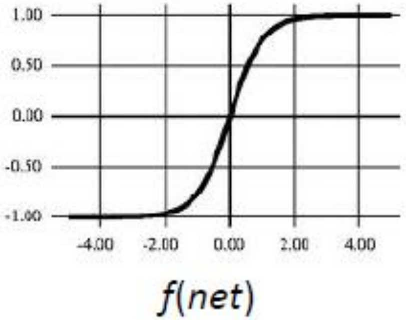
Neural network
Back propagation

Nature

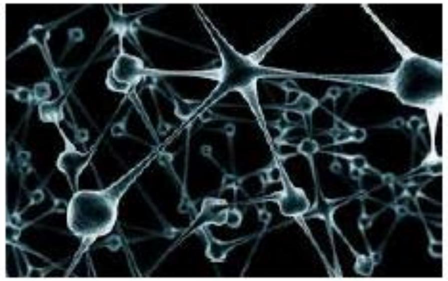
1986





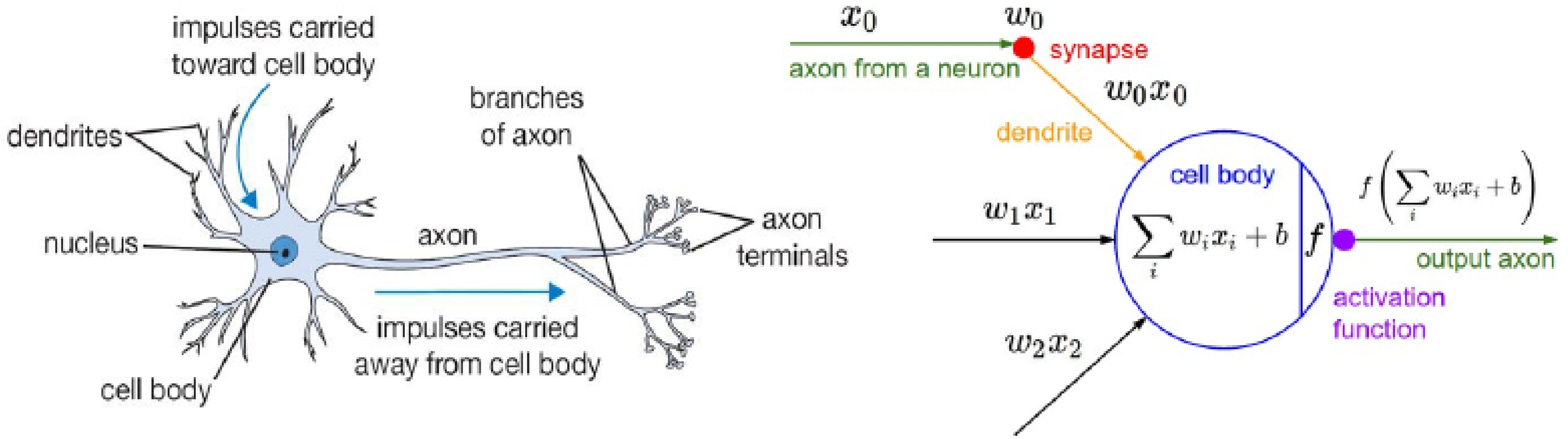


$$g(\mathbf{x}) = f\left(\sum_{i=1}^{d} x_i w_i + w_0\right) = f(\mathbf{w}^t \mathbf{x})$$



Deep Learning - Basics

The Neuron

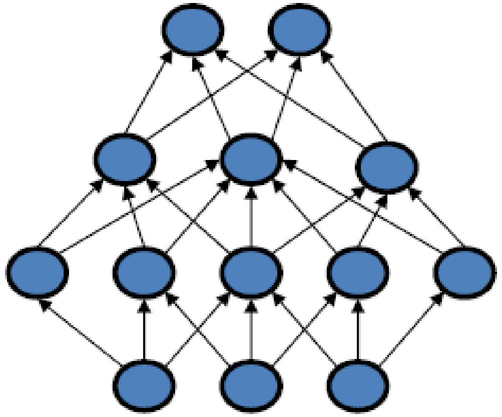


An artificial neuron contains a nonlinear activation function and has several incoming and outgoing weighted connections.

Neural network
Back propagation

Nature

1986



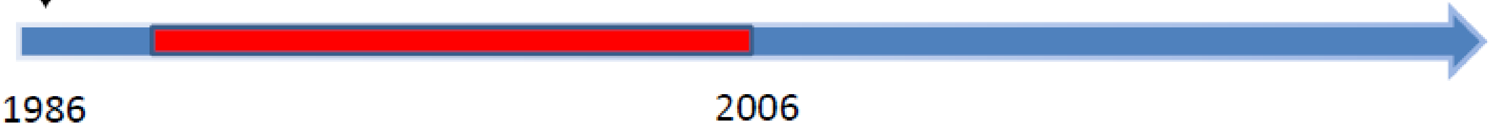
- Solve general learning problems
- Tied with biological system

But it is given up…

- Hard to train
- Insufficient computational resources
- Small training sets
- Does not work well

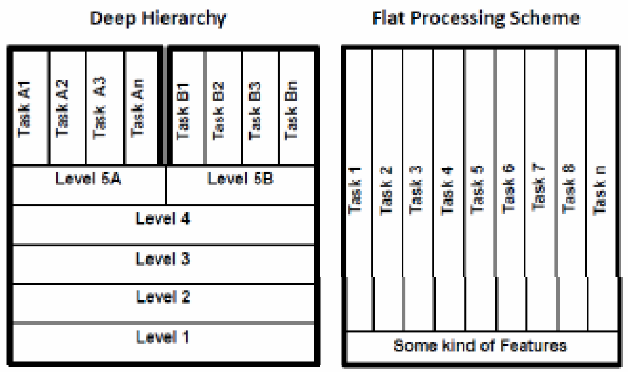
Neural network
Back propagation

Nature

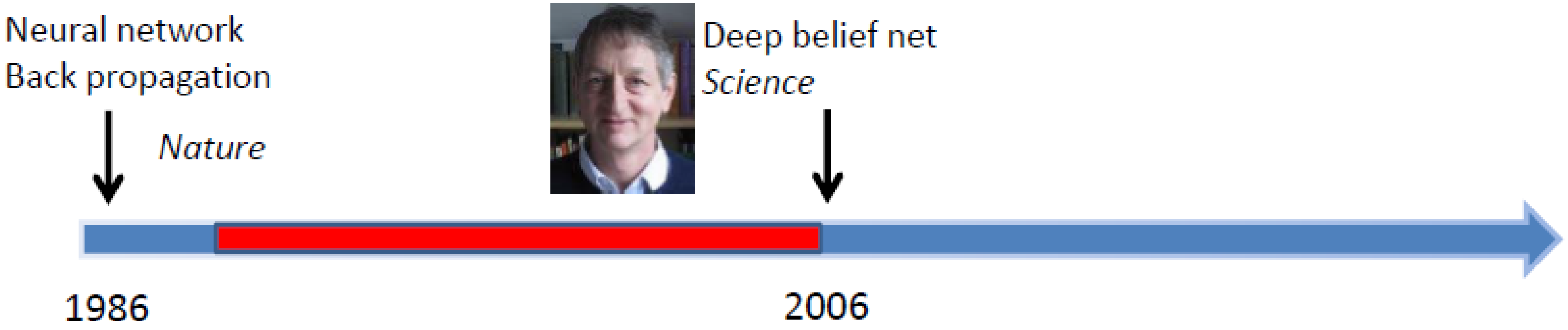


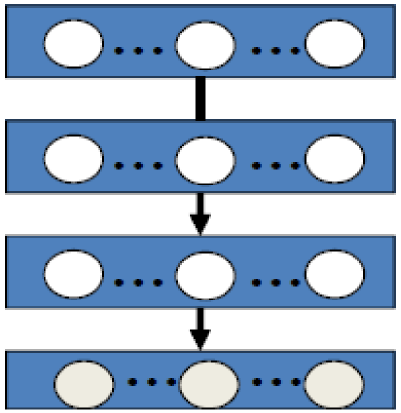
- SVM
- Boosting
- Decision tree
- KNN
- …

- Flat structures
- Loose tie with biological systems
- Specific methods for specific tasks
  - Hand crafted features (GMM-HMM, SIFT, LBP, HOG)



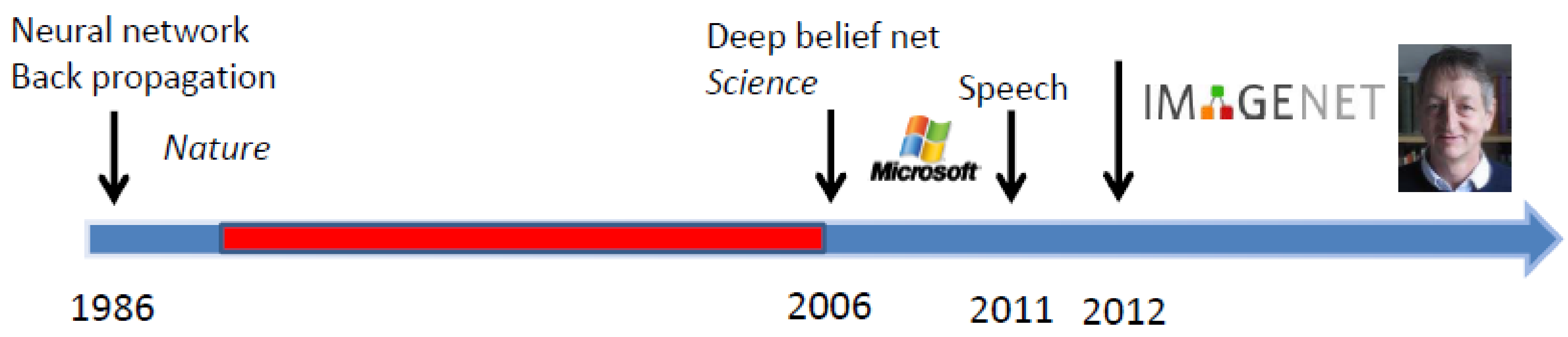
Kruger et al. TPAMI'13





- Unsupervised & Layer-wised pre-training
- Better designs for modeling and training (normalization, nonlinearity, dropout)
- New development of computer architectures
  - GPU
  - Multi-core computer systems
- Large scale databases

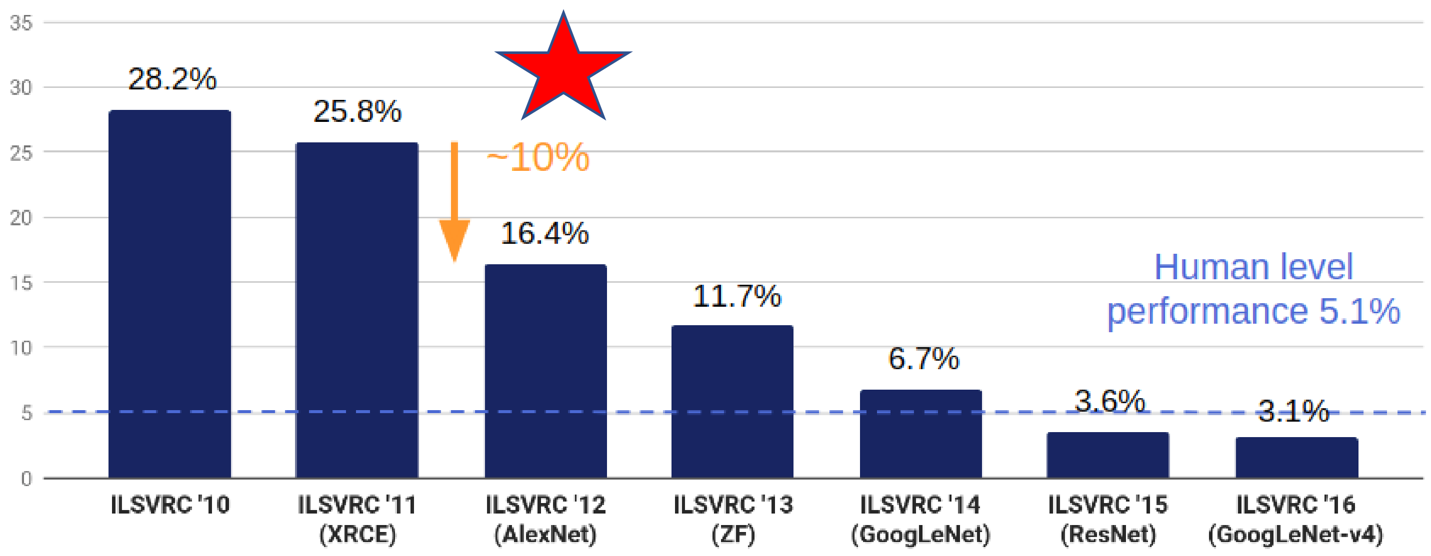
Big Data !



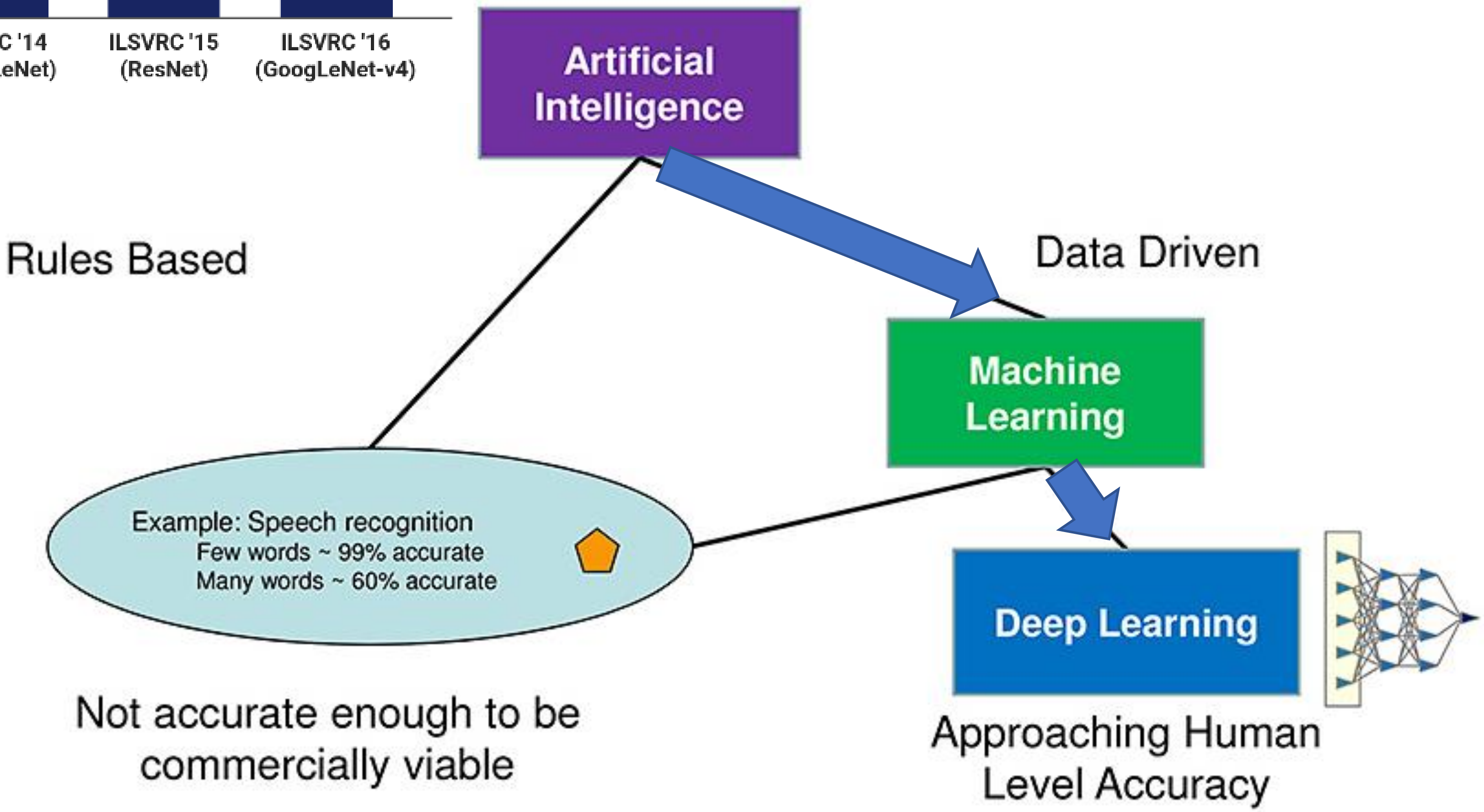
Rank	Name	Error rate	Description
1	**U. Toronto**	0.15315	Deep learning
2	U. Tokyo	0.26172	Hand-crafted features and learning models. Bottleneck.
3	U. Oxford	0.26979	
4	Xerox/INRIA	0.27058	

Object recognition over 1,000,000 images and 1,000 categories (2 GPU)

A. Krizhevsky, L. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” NIPS, 2012.

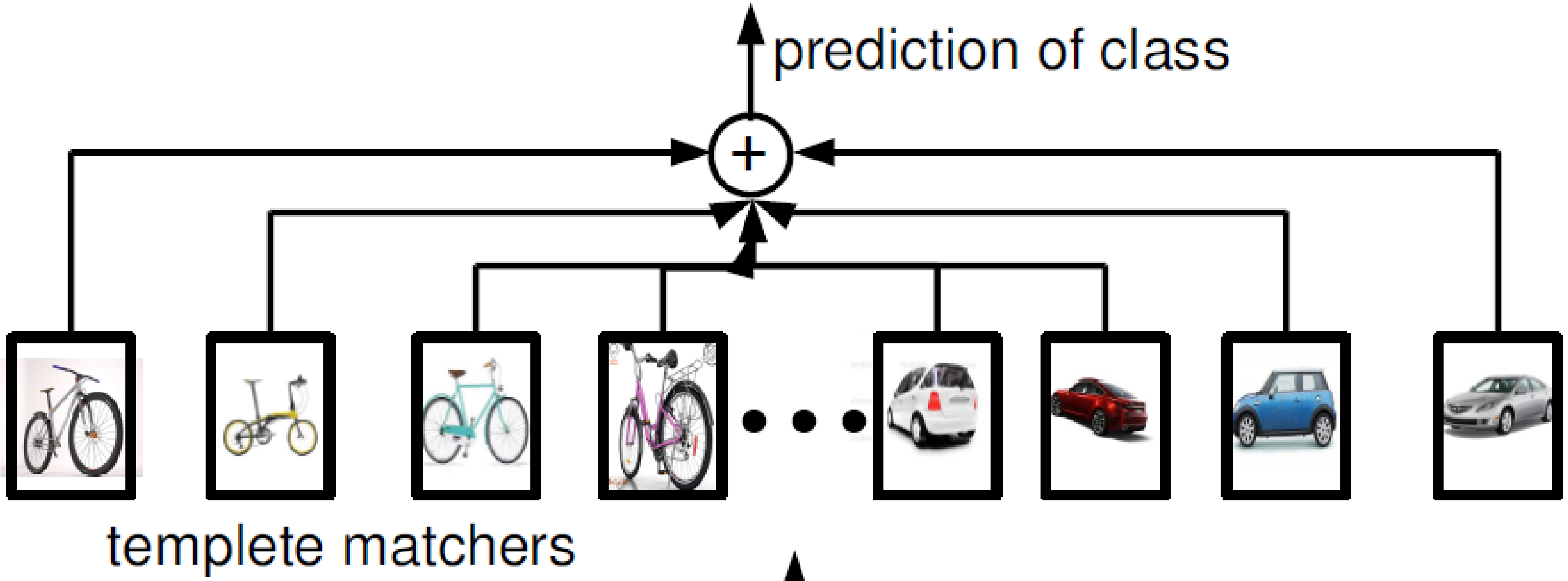


Alex Krizhevsky and Ilya Sutskever from the University of Toronto.



Outperformed all previous traditional machine learning models on ImageNet dataset by a big margin. The architecture is called AlexNet

Linear Combination



Input image

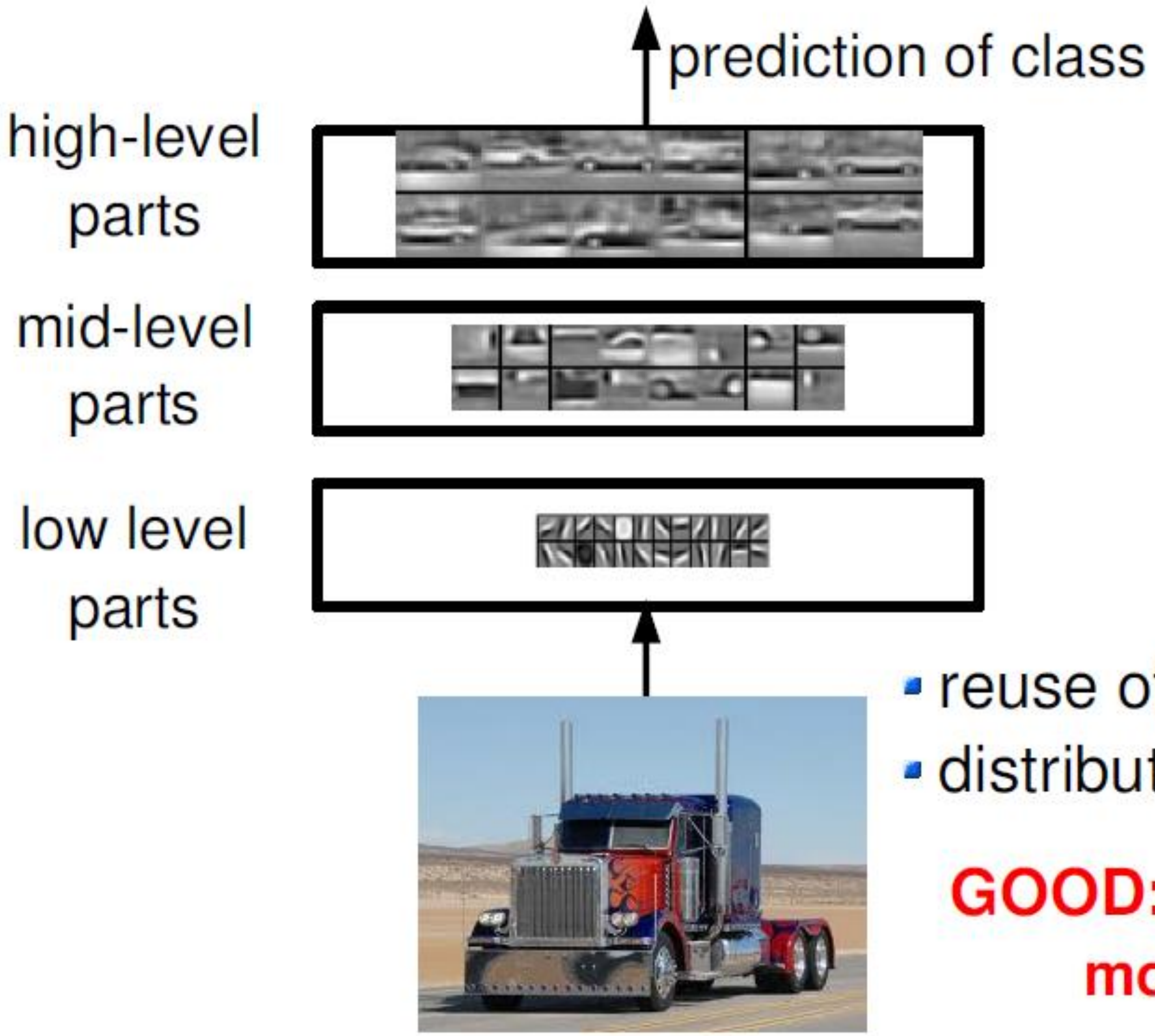
BAD: it may require an exponential nr. of templates!!!

Shallow learning (1-2 layers)
Bayesian inference
Support Vector Machines
Decision trees
K-means clustering
K-nearest neighbor

Less number of parameters <100

Handcrafted feature engineering

Composition



Input image

- reuse of intermediate parts
- distributed representations

GOOD: (exponentially) more efficient

Deep learning
(5-20 layers)

Neural Nets (NN)

Other methods

Convolutional nets (images)

Recurrent nets (text, speech)

Huge number of parameters > 10 Millions

Learned features from **DATASET**

WHY IS DEEP LEARNING HOT *NOW*?

THREE DRIVING FACTORS…

1 - Big Data Availability

facebook 350 millions images uploaded per day

Walmart 2.5 Petabytes of customer data hourly

YouTube 100 hours of video uploaded every minute

2 - New ML Techniques

Deep Neural Networks

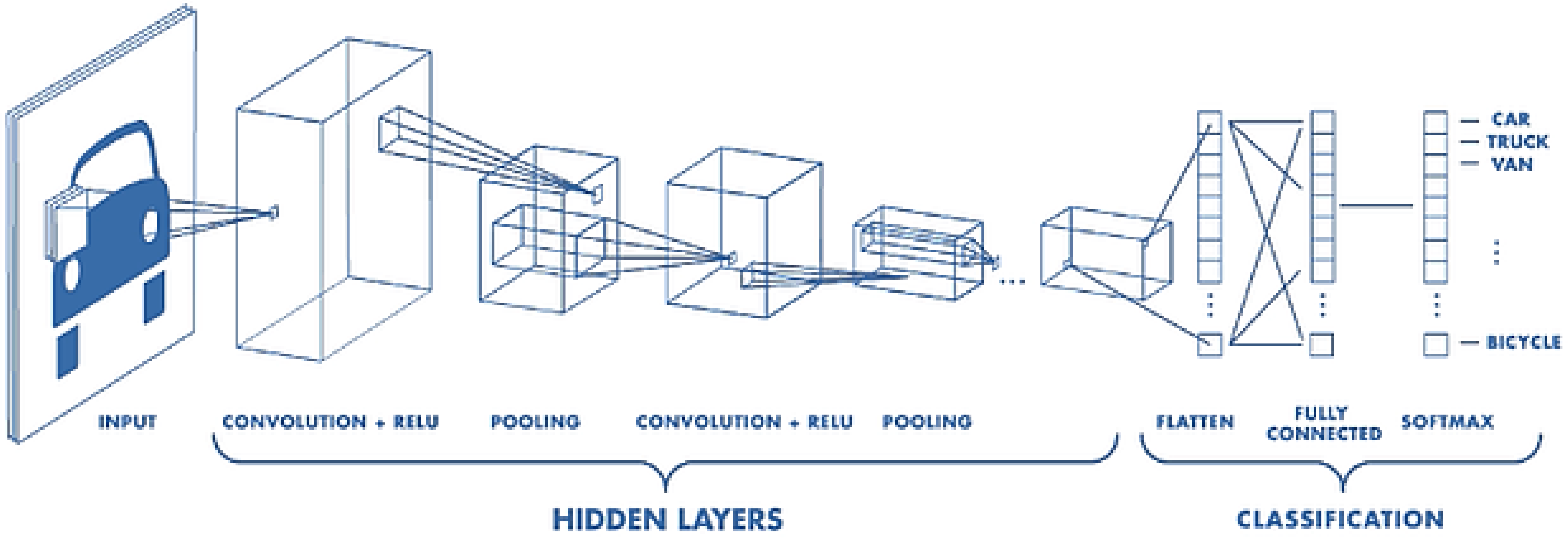
3 - Compute Density

GPUs

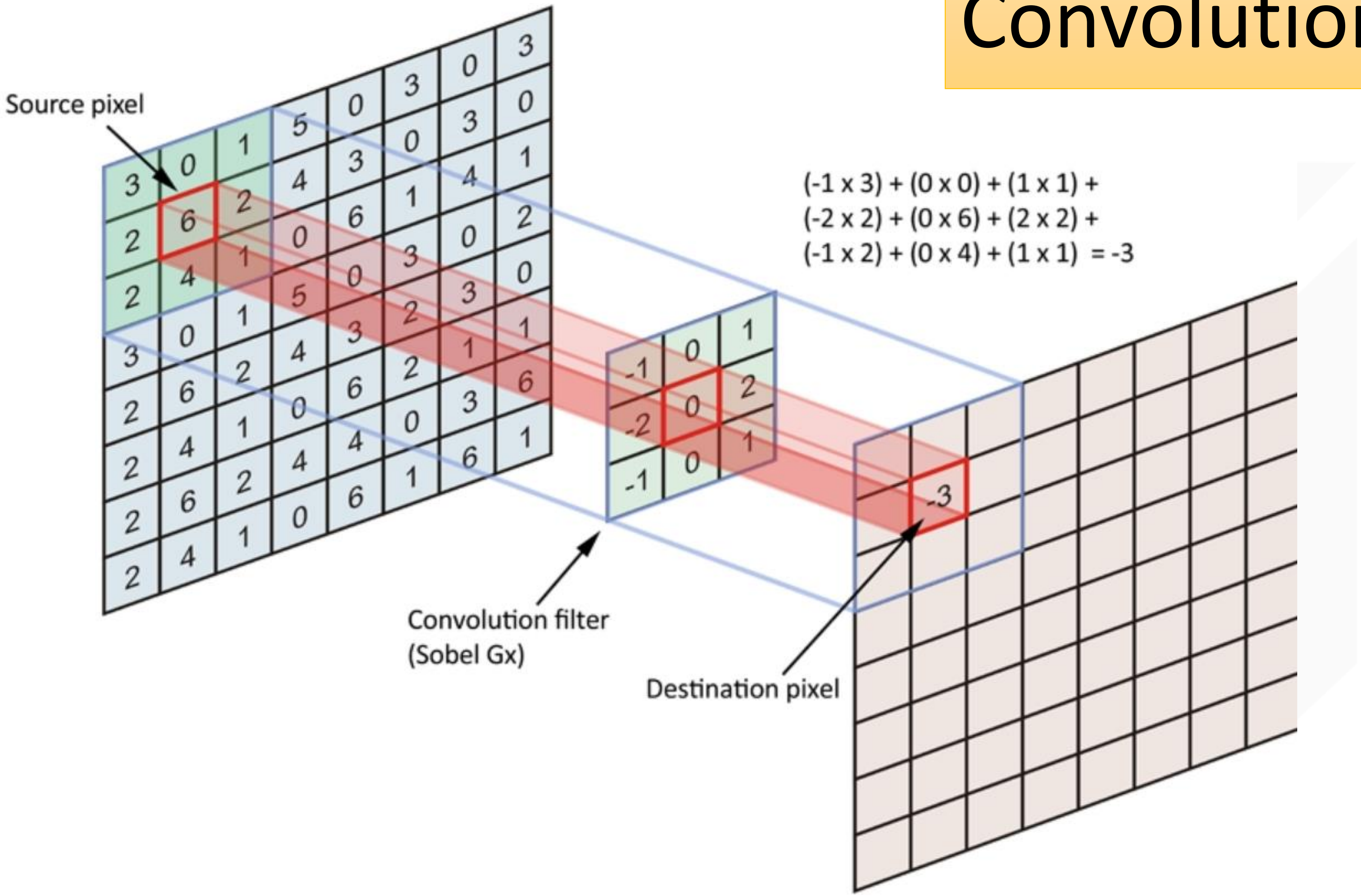
Deep Learning for

- Object classification
- Object Detection
- Object Segmentation

Image recognition and classification

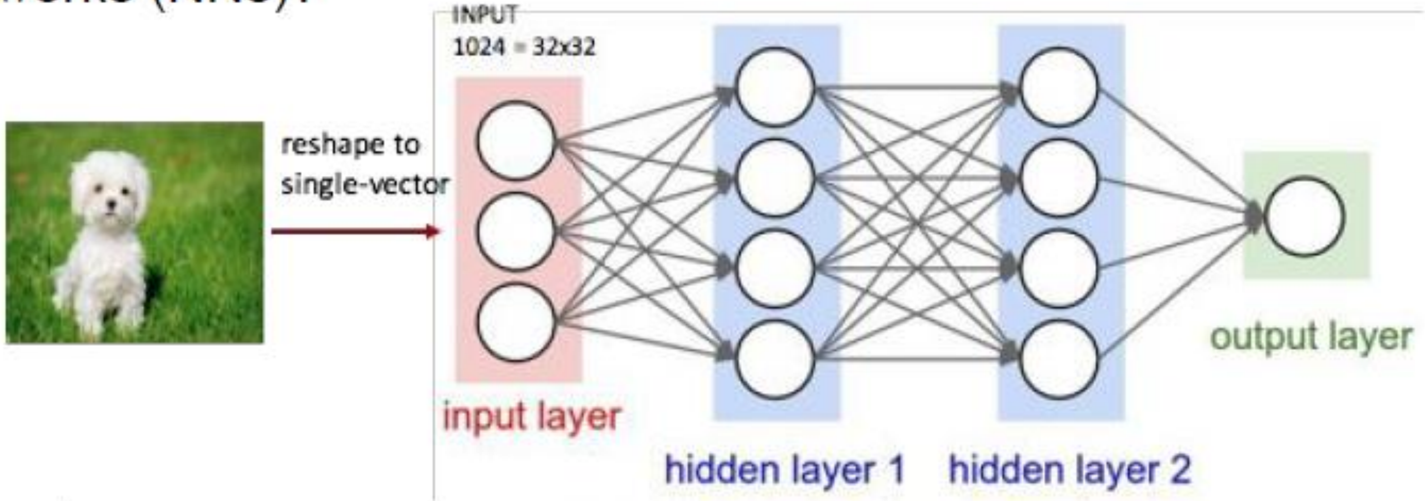


Convolution?



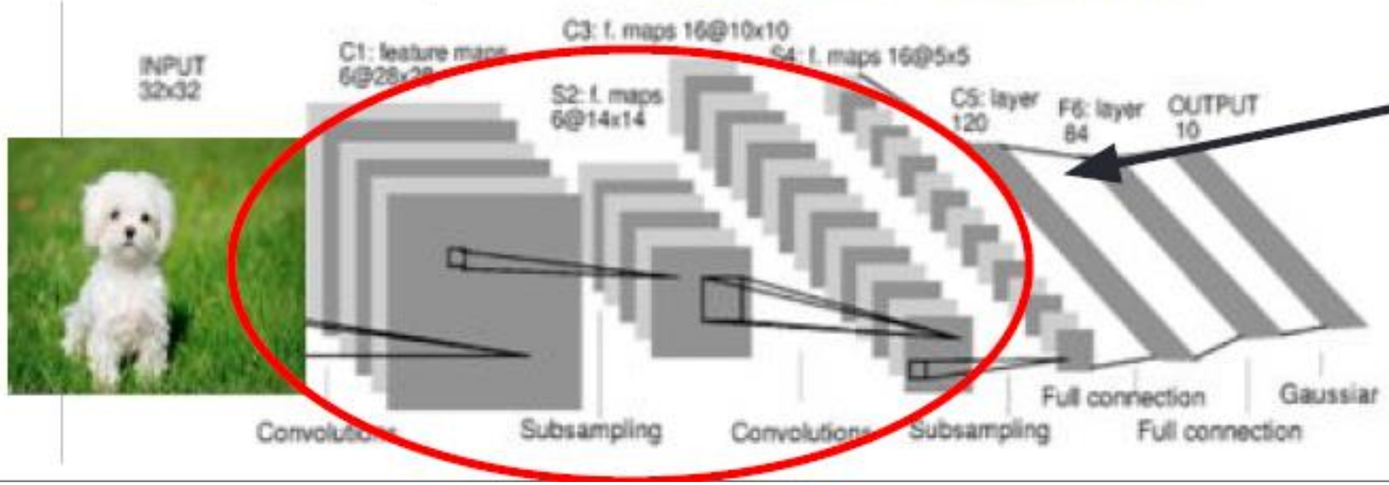
Question : what is the difference between Convolutional Neural Networks (CNNs) and Artificial Neural Networks (NNs)?

ANN

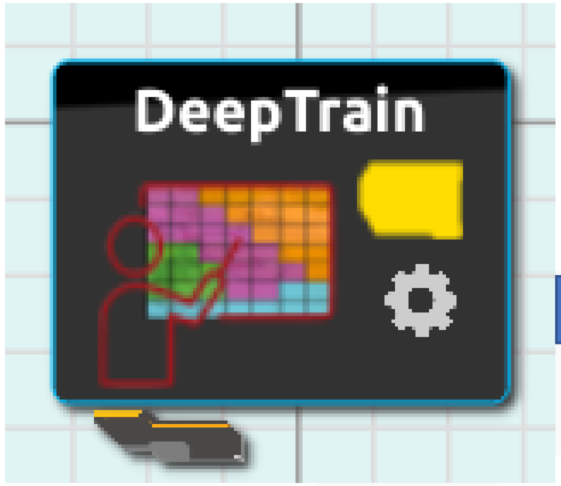


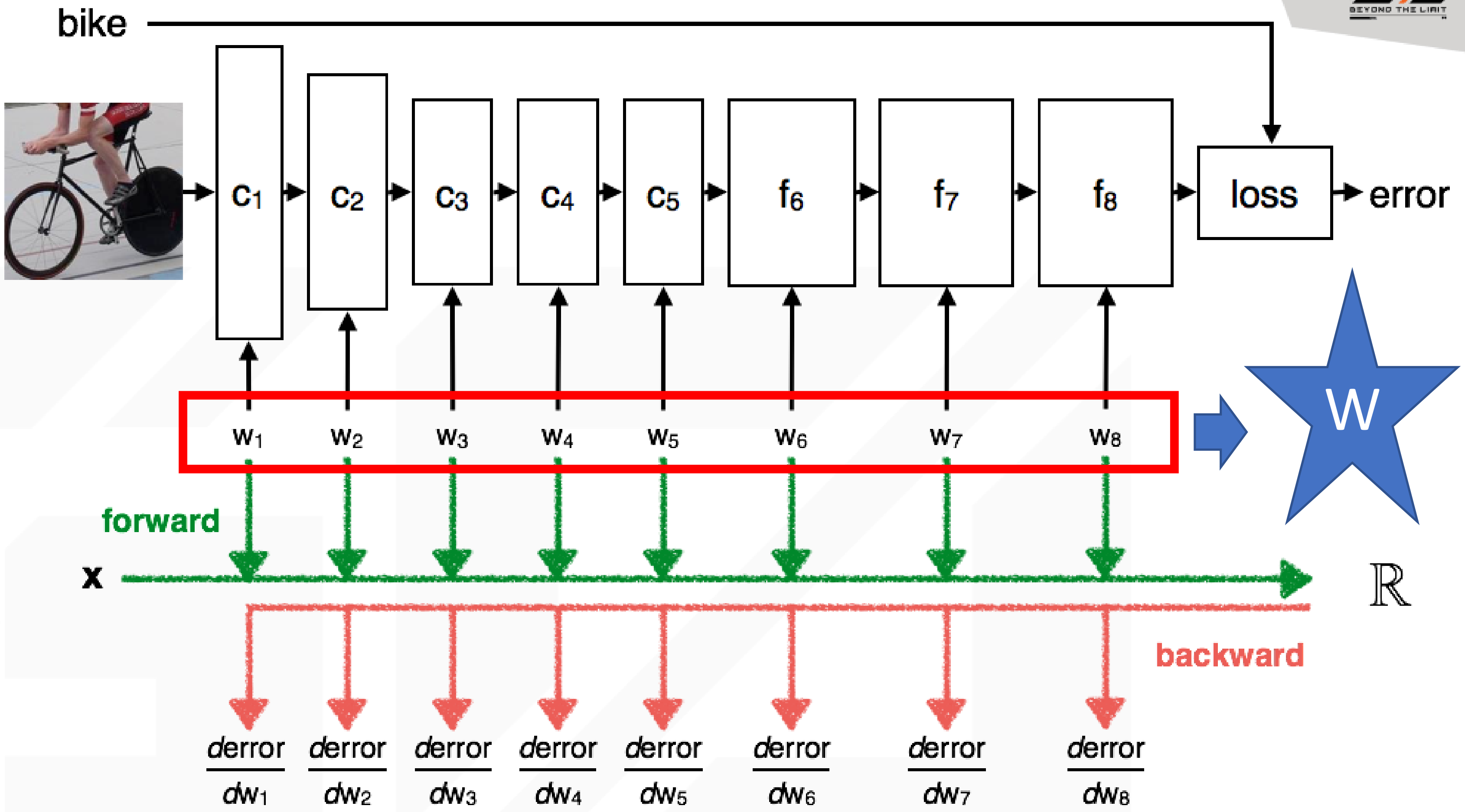
Spatial information is lost!

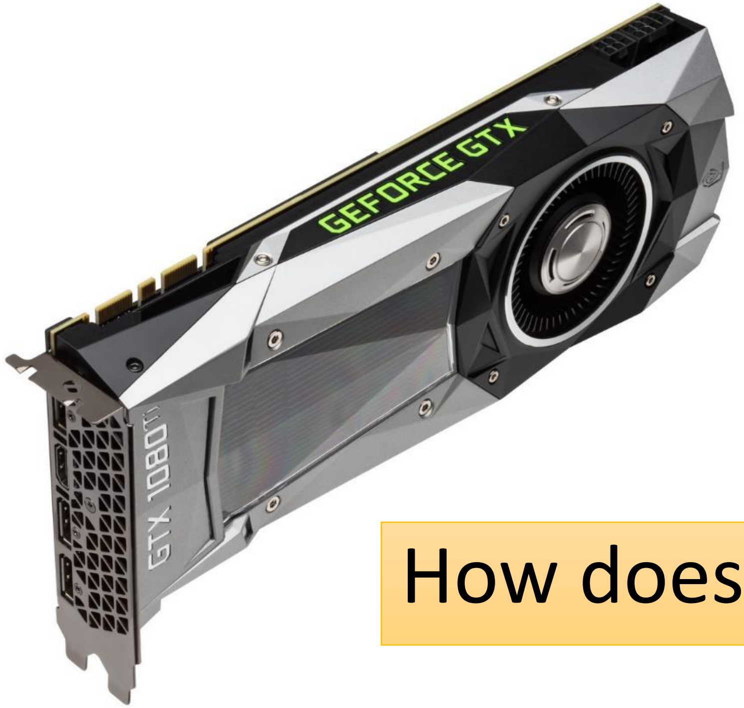
CNN



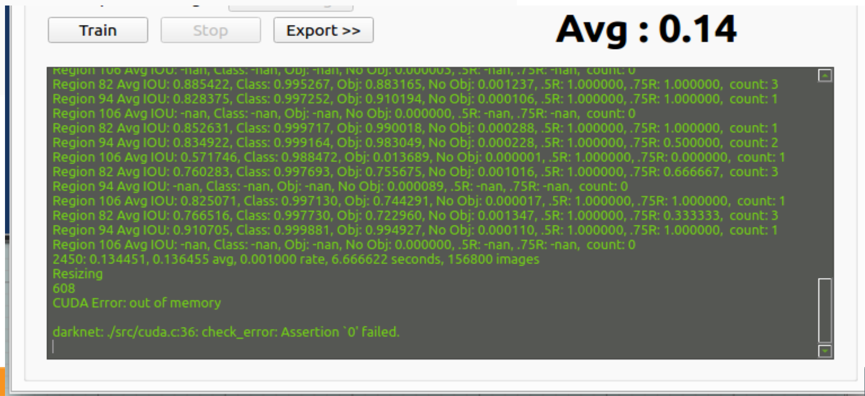
Can learn spatial correlations!



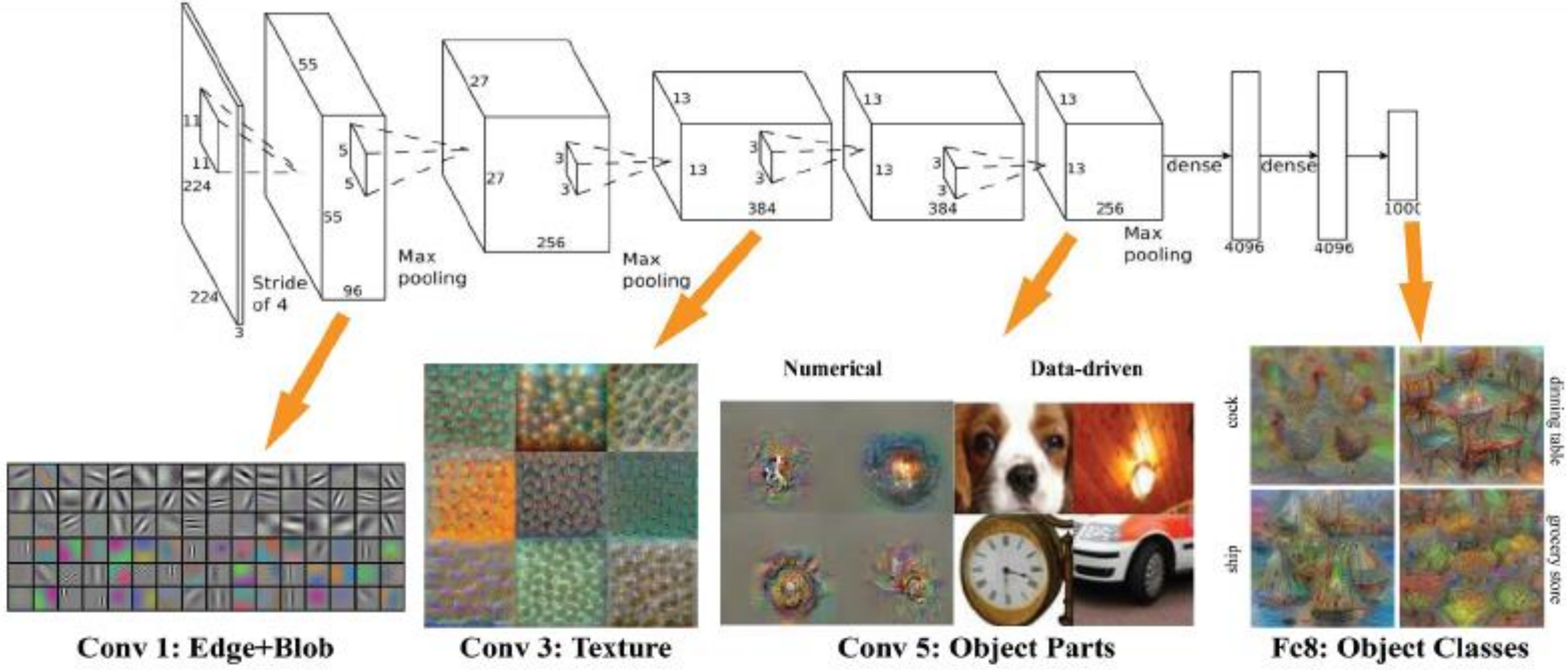


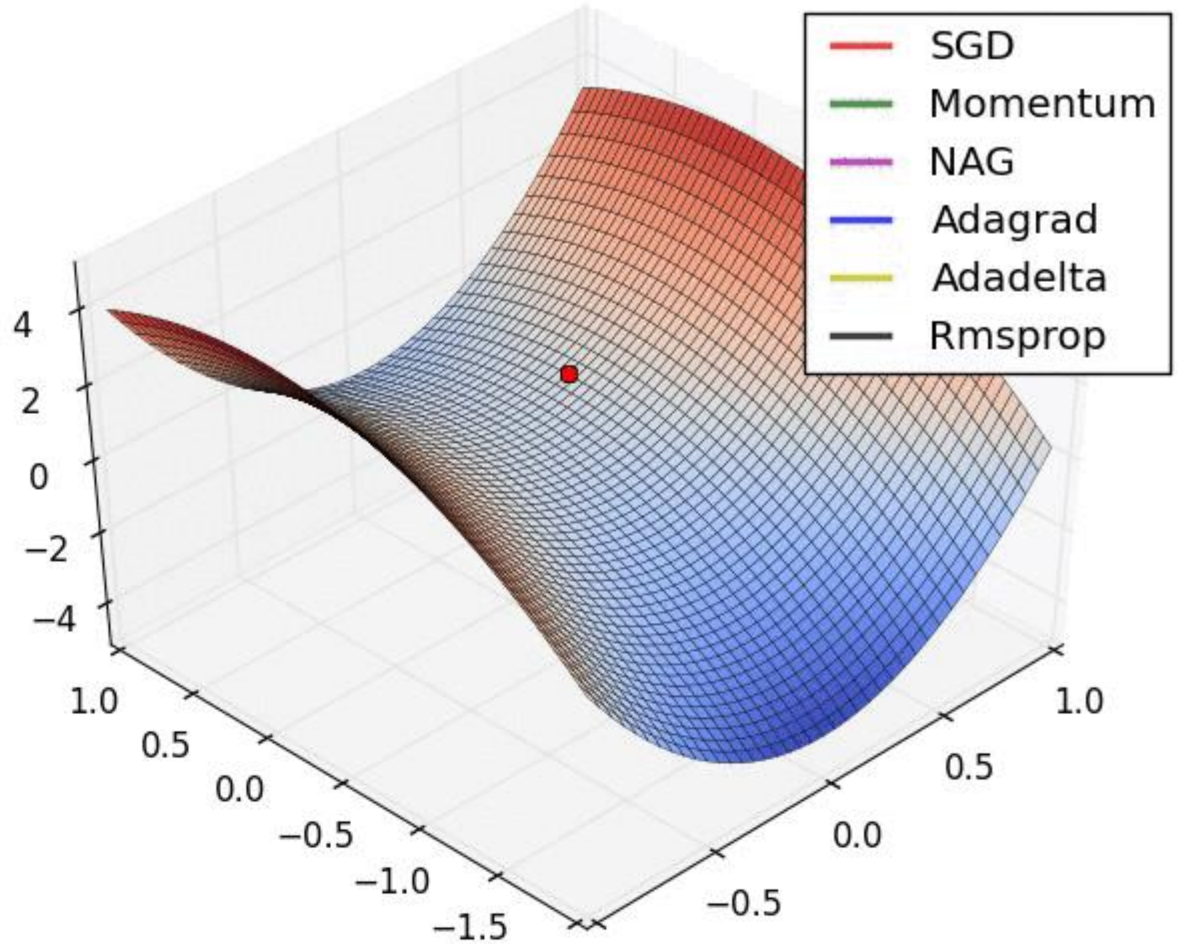


How does the model learn?

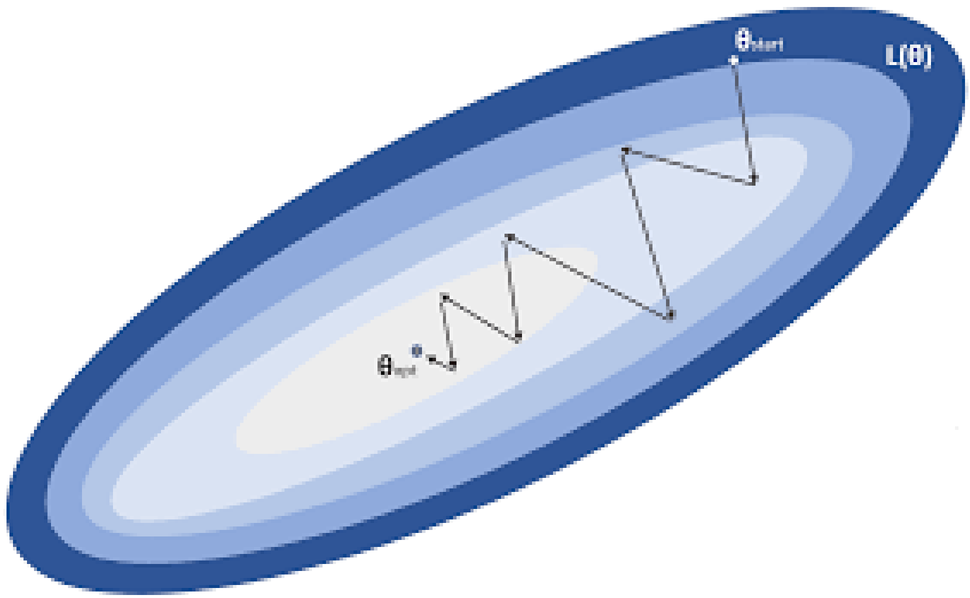


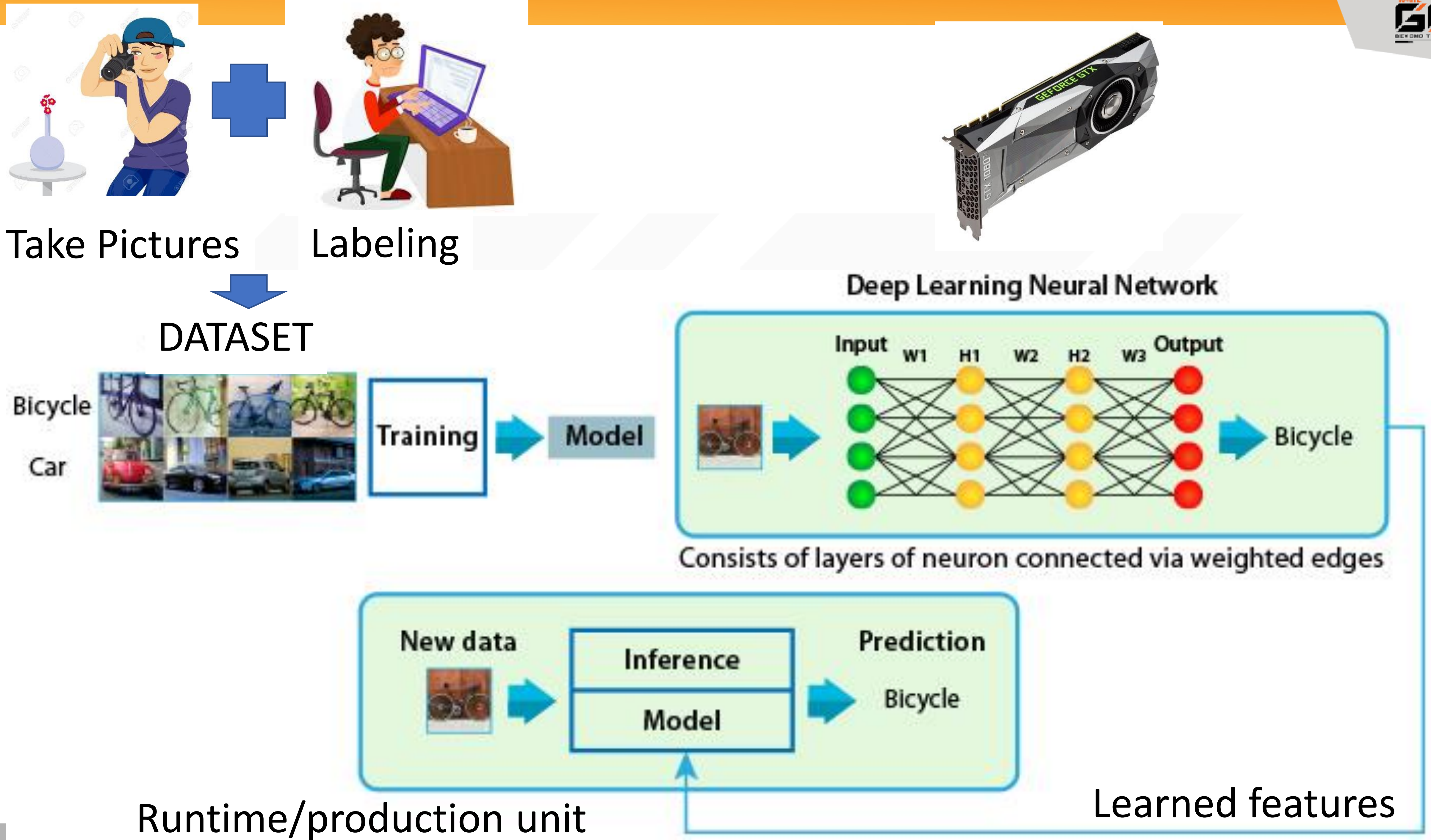
What is learned feature? →Feature Map



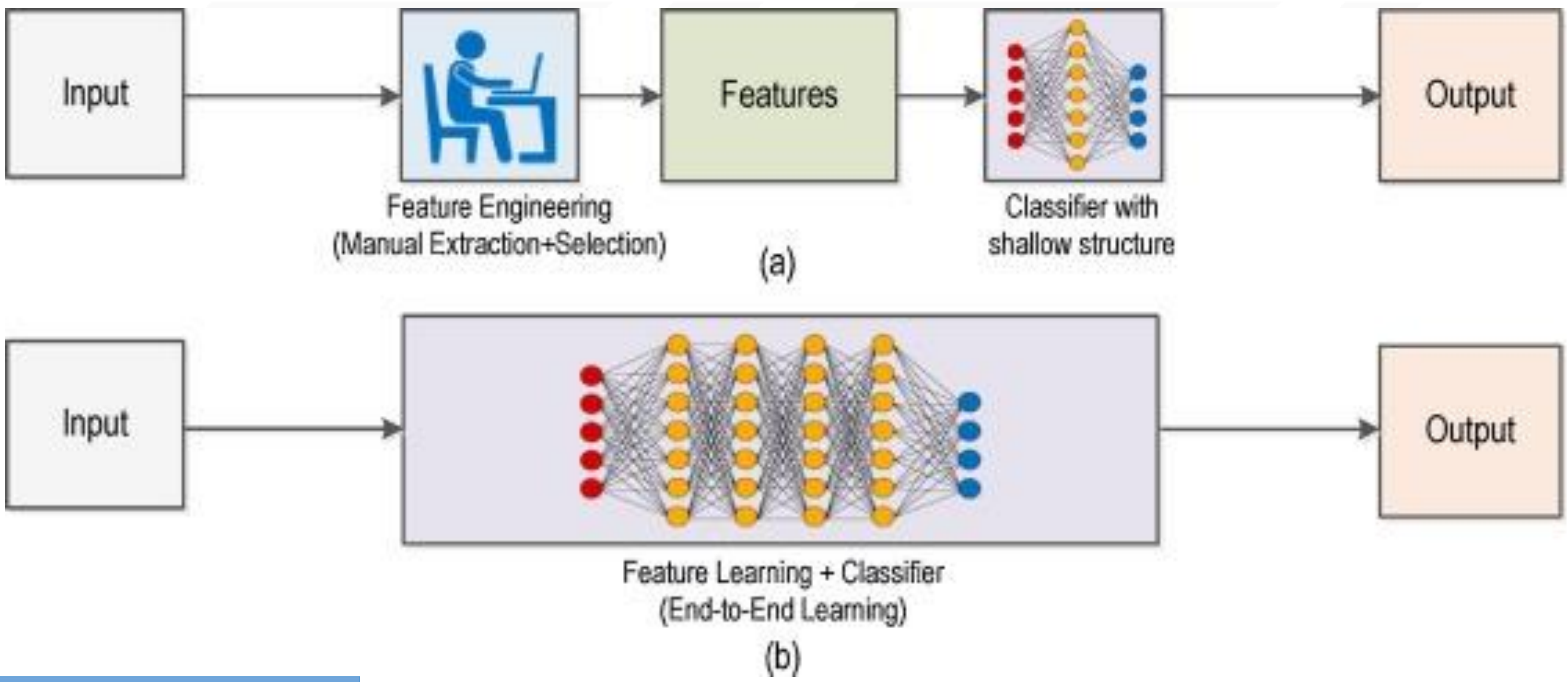

SGD
Momentum
NAG
Adagrad
Adadelta
Rmsprop
4
2
0
−2
−4
1.0
0.5
0.0
−0.5
−1.0
−1.5
1.0
0.5
0.0
−0.5


Train
Stop
Export >>
Avg : 0.14
Region 82 Avg IOU: 0.885422, Class: 0.995267, Obj: 0.883165, No Obj: 0.001237, .5R: 1.000000, .75R: 1.000000, count: 3
Region 94 Avg IOU: 0.828375, Class: 0.997252, Obj: 0.910194, No Obj: 0.000106, .5R: 1.000000, .75R: 1.000000, count: 1
Region 106 Avg IOU: -nan, Class: -nan, Obj: -nan, No Obj: 0.000000, .5R: -nan, .75R: -nan, count: 0
Region 82 Avg IOU: 0.852631, Class: 0.999717, Obj: 0.990018, No Obj: 0.000288, .5R: 1.000000, .75R: 1.000000, count: 1
Region 94 Avg IOU: 0.834922, Class: 0.999164, Obj: 0.983049, No Obj: 0.000228, .5R: 1.000000, .75R: 0.500000, count: 2
Region 106 Avg IOU: 0.571746, Class: 0.988472, Obj: 0.013689, No Obj: 0.000001, .5R: 1.000000, .75R: 0.000000, count: 1
Region 82 Avg IOU: 0.760283, Class: 0.997693, Obj: 0.755675, No Obj: 0.001016, .5R: 1.000000, .75R: 0.666667, count: 3
Region 94 Avg IOU: -nan, Class: -nan, Obj: -nan, No Obj: 0.000089, .5R: -nan, .75R: -nan, count: 0
Region 106 Avg IOU: 0.825071, Class: 0.997130, Obj: 0.744291, No Obj: 0.000017, .5R: 1.000000, .75R: 1.000000, count: 1
Region 82 Avg IOU: 0.766516, Class: 0.997730, Obj: 0.722960, No Obj: 0.001347, .5R: 1.000000, .75R: 0.333333, count: 3
Region 94 Avg IOU: 0.910705, Class: 0.999881, Obj: 0.994927, No Obj: 0.000110, .5R: 1.000000, .75R: 1.000000, count: 1
Region 106 Avg IOU: -nan, Class: -nan, Obj: -nan, No Obj: 0.000000, .5R: -nan, .75R: -nan, count: 0
2450: 0.134451, 0.136455 avg, 0.001000 rate, 6.666622 seconds, 156800 images
Resizing
608
CUDA Error: out of memory
darknet: ./src/cuda.c:36: check_error: Assertion `0' failed.


L(θ)


Take Pictures
Labeling
DATASET
Bicycle
Car
Training
Model
GEFORCE GTX
GTX 1080
Deep Learning Neural Network
Input
W1
H1
W2
H2
W3
Output
Bicycle
Consists of layers of neuron connected via weighted edges
New data
Inference
Model
Prediction
Bicycle
Learned features
Runtime/production unit

Deep learning and Conventional processing

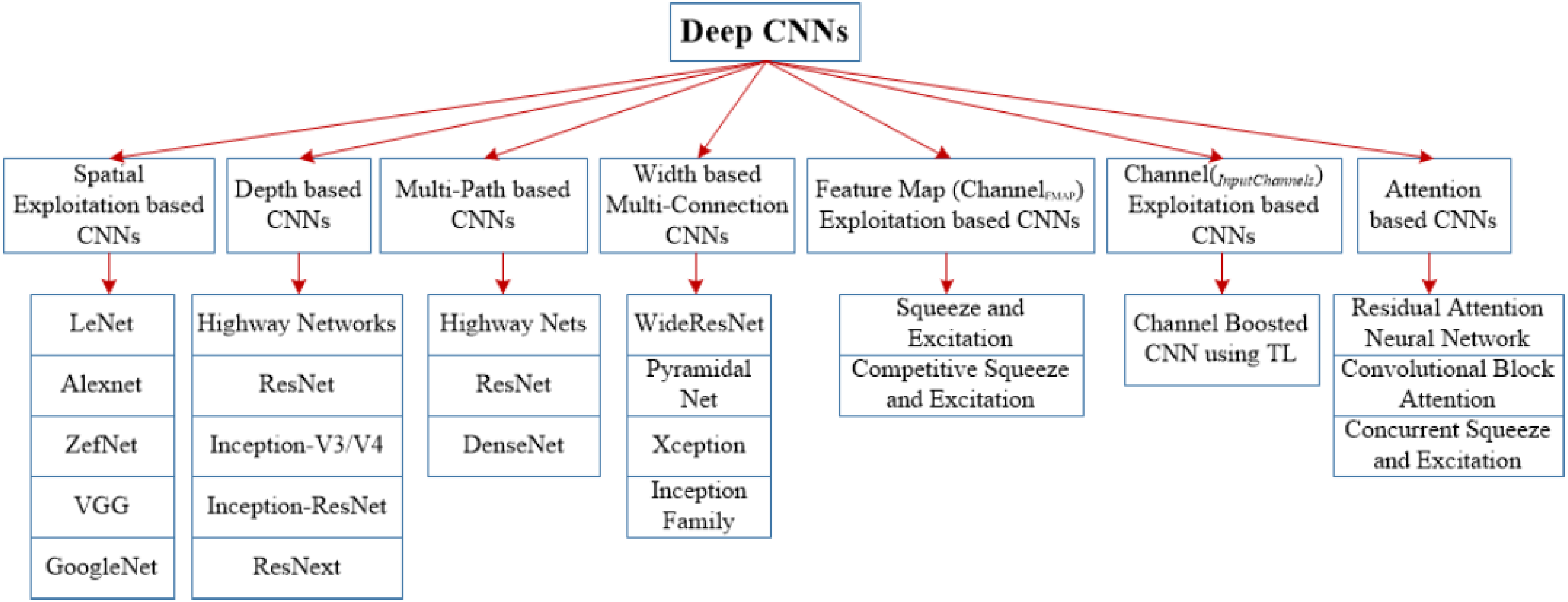


Dataset preparation

J. Wang et al. / Journal of Manufacturing Systems

Image classification

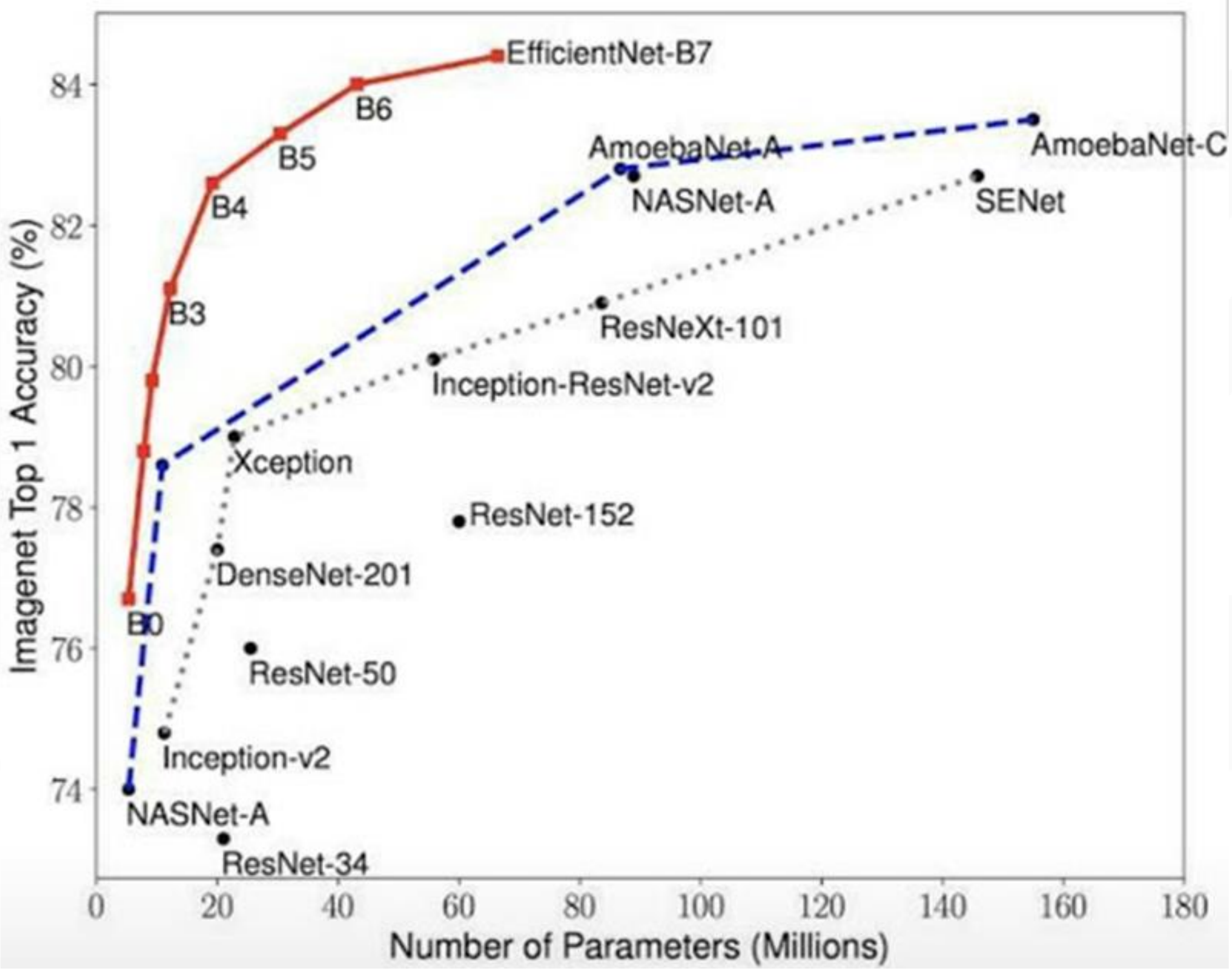
1 .



Architecture Name	Year	Main contribution	Parameters	Error Rate	Depth	Category	Reference
LeNet	1998	- First Popular CNN architecture	0.060 M	[dist]MNIST: 0.8 MNIST: 0.95	7	Spatial Exploitation	[65]
AlexNet	2012	- Deeper and wider than the LeNet - Uses Relu ,Dropout and overlap Pooling - GPUs NVIDIA GTX 580	60 M	ImageNet: 16.4	8	Spatial Exploitation	[21]
ZefNet	2014	- Intermediate layers feature visualization	60 M	ImageNet: 11.7	8	Spatial Exploitation	[28]
VGG	2014	- Homogenous topology - Small kernel size	138 M	ImageNet: 7.3	19	Spatial Exploitation	[29]
GoogLeNet	2015	- Split Transform Merge - Introduces block concept	4 M	ImageNet: 6.7	22	Spatial Exploitation	[99]
Inception-V3	2015	- Handles the problem of a representational bottleneck - Replace large size filters with small filters - Replaces the bigger filter with smaller filters	23.6 M	ImageNet: 3.5 Multi-Crop: 3.58 Single-Crop: 5.6	-	Depth	[100]
Highway Networks	2015	- Multi-Path Idea	2.3 M	CIFAR-10: 7.76	19	Depth + Multi-Path	[101]
Inception-V4	2016	- Split, Transform, Merge Uses asymmetric filter	-	ImageNet: 4.01	-	Depth	[100]
Inception-ResNet	2016	- Split, Transform, Merge and Residual Links	-	ImageNet: 3.52		Depth + Multi-Path	[100]
ResNet	2016	- Residual Learning and Identity mapping based skip connection	6.8 M 1.7 M	ImageNet: 3.6 CIFAR-10: 6.43	152 110	Spatial Exploitation + Depth + Multi-Path	[31]
DelugeNet	2016	- Allow cross layer information inflow in Deep Networks	20.2 M	CIFAR-10: 3.76 CIFAR-100: 19.02	146	Multi-path	[108]
				CIFAR-10: 7.27 CIFAR-10+: 4.60			

Architecture Name	Year	Main contribution	Parameters	Error Rate	Depth	Category	Reference
FractalNet	2016	- Different path lengths are interacting with each other without any residual connection	38.6 M	CIFAR-10++: 4.59 CIFAR-100: 28.20 CIFAR-100+: 22.49 CIFAR100++: 21.49	40	Multi-Path	[113]
WideResNet	2016	- Width is increased and depth is decreased	36.5 M	CIFAR-10: 3.89 CIFAR-100: 18.85	28 -	Width	[34]
Xception	2017	- Depth wise Convolution followed by point wise convolution	22.8 M	ImageNet: 0.055	36	Width	[114]
Residual Attention Neural Network	2017	- Introduces Attention Mechanism	8.6 M	CIFAR-10: 3.90 CIFAR-100: 20.4 ImageNet: 4.8	452	Attention	[38]
ResNexT	2017	- Cardinality - Homogeneous topology - Grouped convolution	68.1 M	CIFAR-10: 3.58 CIFAR-100: 17.31 ImageNet: 4.4	29 101	Spatial Exploitation	[115]
Squeeze & Excitation Networks	2017	- Models Interdependencies between feature maps	27.5 M	ImageNet: 2.3	152	Feature Map Exploitation	[116]
DenseNet	2017	- Cross-layer information flow	25.6 M 25.6 M 15.3 M 15.3 M	CIFAR-10+: 3.46 CIFAR100+: 17.18 CIFAR-10: 5.19 CIFAR-100: 19.64	190 190 250 250	Multi-Path	[107]
PolyNet	2017	- Experimented structural diversity - Introduces Poly Inception Module - Generalizes residual unit using Polynomial	92 M	ImageNet: Single:4.25 Multi:3.45	- -	Width	[117]

Image/Video Classification



RESEARCH ARTICLE

Application of convolutional neural networks for classification of adult mosquitoes in the field

Daniel Motta[1☯], Alex Álisson Bandeira Santos[1‡], Ingrid Winkler[1‡], Bruna Aparecida Souza Machado[1,2☯*], Daniel André Dias Imperial Pereira[1☯], Alexandre Morais Cavalcanti[1☯], Eduardo Oyama Lins Fonseca[2‡], Frank Kirchner[3‡], Roberto Badaró[1,2☯]

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Citation: Motta D, Santos AÁB, Winkler I, Machado BAS, Pereira DADI, Cavalcanti AM, et al. (2019) Application of convolutional neural networks for classification of adult mosquitoes in the field. PLoS ONE 14(1): e0210829. https://doi.org/10.1371/journal.pone.0210829

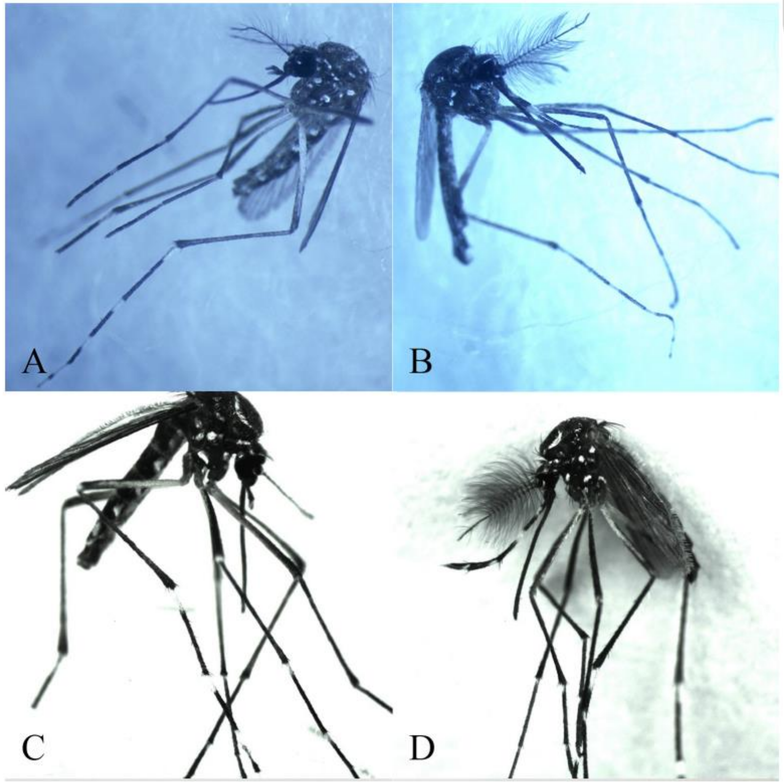

Table 3. Confusion matrix showing the results of the testing phase for the LeNet neural network.

Class	*Ae. aegypti* female	*Ae. aegypti* male	*Ae. albopictus* female	*Ae. albopictus* male	*C. quinquefasciatus* female	*C. quinquefasciatus* male	Accuracy (%)
Ae. aegypti female	7	1	2	4	0	0	50.00
Ae. aegypti male	5	6	3	0	0	0	42.86
Ae. albopictus female	1	2	10	0	1	0	71.43
Ae. albopictus male	2	0	0	7	3	2	50.00
C. quinquefasciatus female	1	0	1	1	9	2	64.29
C. quinquefasciatus male	2	3	2	0	2	5	35.71

https://doi.org/10.1371/journal.pone.0210829.t003

Table 4. Confusion matrix showing the results of the testing phase for the AlexNet neural network.

Class	*Ae. aegypti* female	*Ae. aegypti* male	*Ae. albopictus* female	*Ae. albopictus* male	*C. quinquefasciatus* female	*C. quinquefasciatus* male	Accuracy (%)
Ae. aegypti female	5	1	6	0	1	1	35.71
Ae. aegypti male	2	7	2	1	0	2	50.00
Ae. albopictus female	1	1	11	1	0	0	78.57
Ae. albopictus male	0	2	3	9	0	0	64.29
C. quinquefasciatus female	2	4	0	0	2	6	14.29
C. quinquefasciatus male	2	1	0	0	2	9	64.29

https://doi.org/10.1371/journal.pone.0210829.t004

Table 5. Confusion matrix showing the results of the testing phase for the GoogLeNet neural network.

Class	*Ae. aegypti* female	*Ae. aegypti* male	*Ae. albopictus* female	*Ae. albopictus* male	*C. quinquefasciatus* female	*C. quinquefasciatus* male	Accuracy (%)
Ae. aegypti female	9	3	2	0	0	0	64.29
Ae. aegypti male	1	12	1	0	0	0	85.71
Ae. albopictus female	0	1	12	1	0	0	85.71
Ae. albopictus male	0	1	0	13	0	0	92.86
C. quinquefasciatus female	1	1	0	0	8	4	57.14
C. quinquefasciatus male	0	0	0	1	3	10	71.43

https://doi.org/10.1371/journal.pone.0210829.t005

Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images

Sivaramakrishnan Rajaraman[1], Sameer K. Antani[1], Mahdieh Poostchi[1], Kamolrat Silamut[2], Md. A. Hossain[3], Richard J. Maude[2,4,5], Stefan Jaeger[1] and George R. Thoma[1]

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[2] Mahidol-Oxford Tropical Medicine Research Unit, Mahidol University, Bangkok, Thailand
[3] Department of Medicine, Chittagong Medical Hospital, Chittagong, Bangladesh
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[5] Harvard TH Chan School of Public Health, Harvard University, Boston, MA, United States of America

Submitted 8 January 2018
Accepted 13 March 2018
Published 16 April 2018

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Academic editor
Henkjan Huisman

Additional Information and Declarations can be found on page 13

DOI 10.7717/peerj.4568

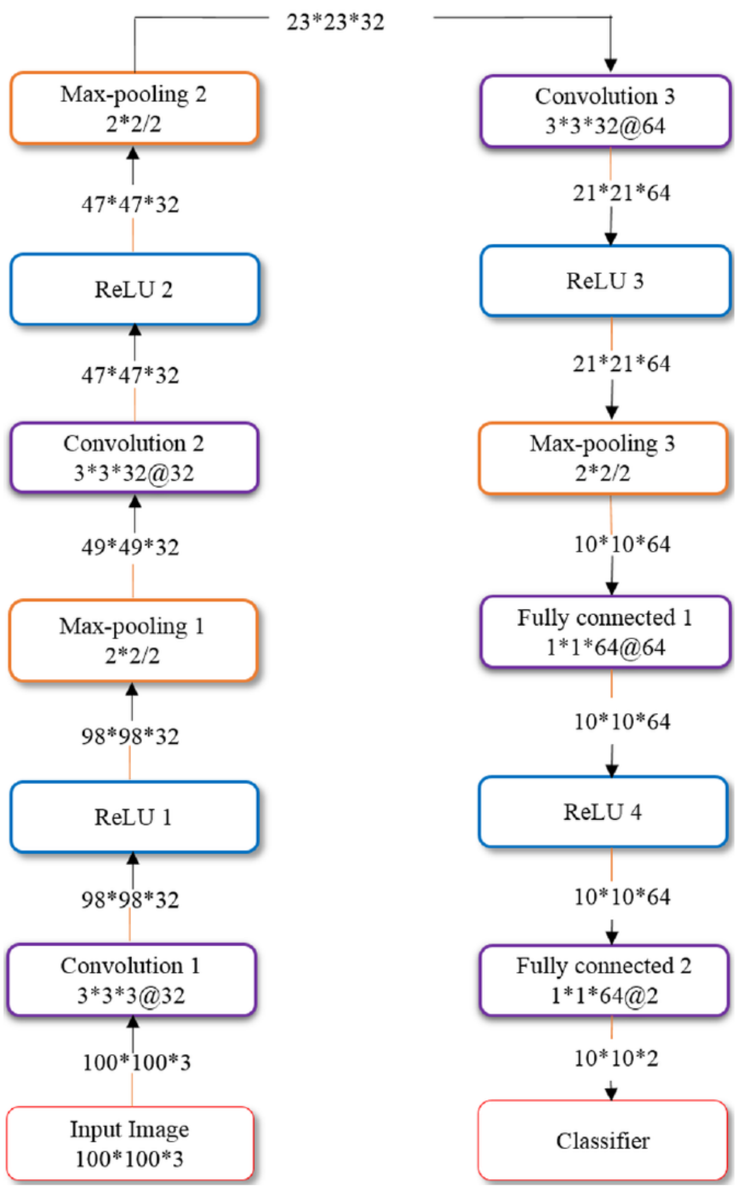


Figure 1 Architecture of the customized model.

Full-size DOI: 10.7717/peerj.4568/fig-1

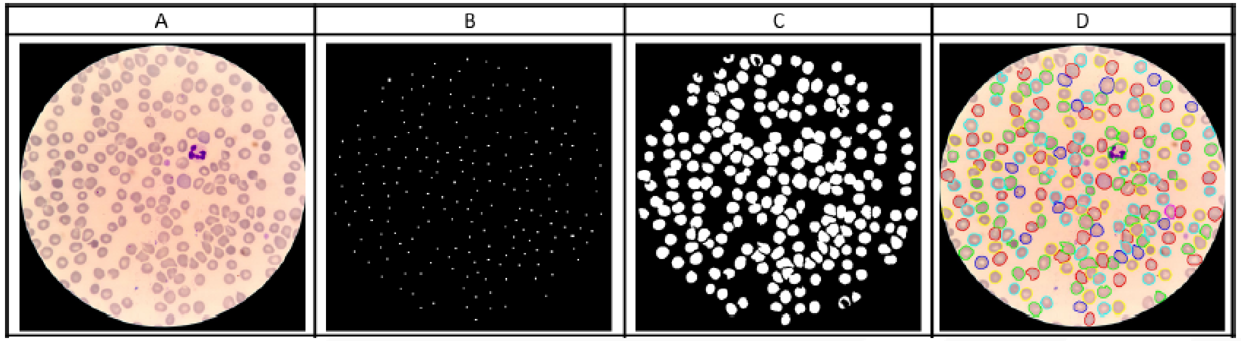


Table 4 Performance metrics achieved with feature extraction from optimal layers.

Models	Accuracy	AUC	Sensitivity	Specificity	F1-score	MCC
AlexNet	0.944 ± 0.010	0.983 ± 0.006	0.947 ± 0.016	0.941 ± 0.025	0.944 ± 0.010	0.886 ± 0.020
VGG-16	**0.959 ± 0.009**	**0.991 ± 0.004**	0.949 ± 0.020	0.969 ± 0.016	**0.959 ± 0.009**	0.916 ± 0.017
ResNet-50	**0.959 ± 0.008**	**0.991 ± 0.005**	0.947 ± 0.015	**0.972 ± 0.010**	**0.959 ± 0.009**	**0.917 ± 0.017**
Xception	0.915 ± 0.005	0.965 ± 0.019	0.925 ± 0.039	0.907 ± 0.120	0.918 ± 0.042	0.836 ± 0.088
DenseNet-121	0.952 ± 0.022	**0.991 ± 0.004**	**0.960 ± 0.009**	0.944 ± 0.048	0.953 ± 0.020	0.902 ± 0.041
Customized	0.927 ± 0.026	0.978 ± 0.012	0.905 ± 0.074	0.951 ± 0.031	0.928 ± 0.041	0.884 ± 0.002

Notes.

Deep Learning for Smartphone-based Malaria Parasite Detection in Thick Blood Smears

Feng Yang*, Mahdieh Poostchi, Hang Yu, Zhou Zhou, Kamolrat Silamut, Jian Yu, Richard J Maude, Stefan Jaeger*, Sameer Antani

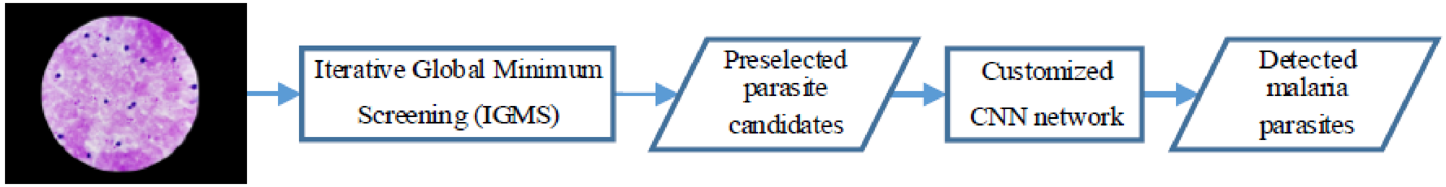


Fig. 2. Pipeline of the proposed system for automated parasite detection.

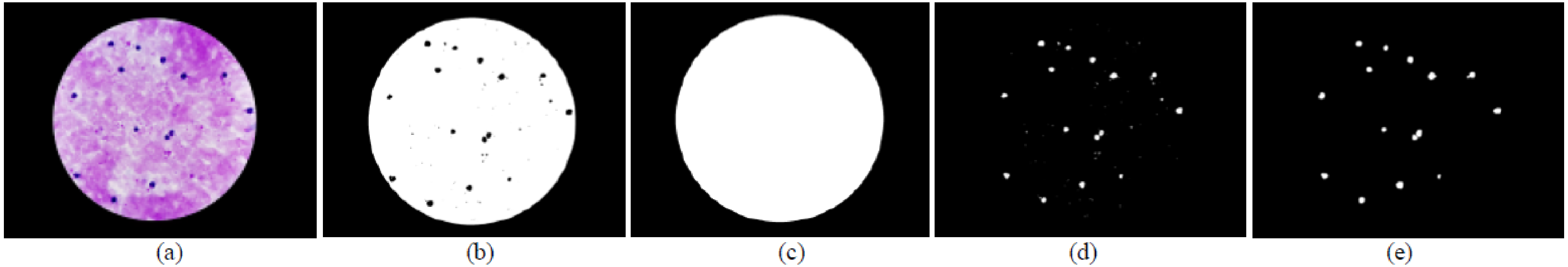


Fig. 3. Example of WBC detection. (a) A sample slide image of a thick blood smear acquired with a smartphone. (b) Detected objects after using Otsu thresholding. (c) Detected field of view ROI mask. (d) Detected WBCs including small areas of noise. (e) Detected WBCs after filtering noise in (e).

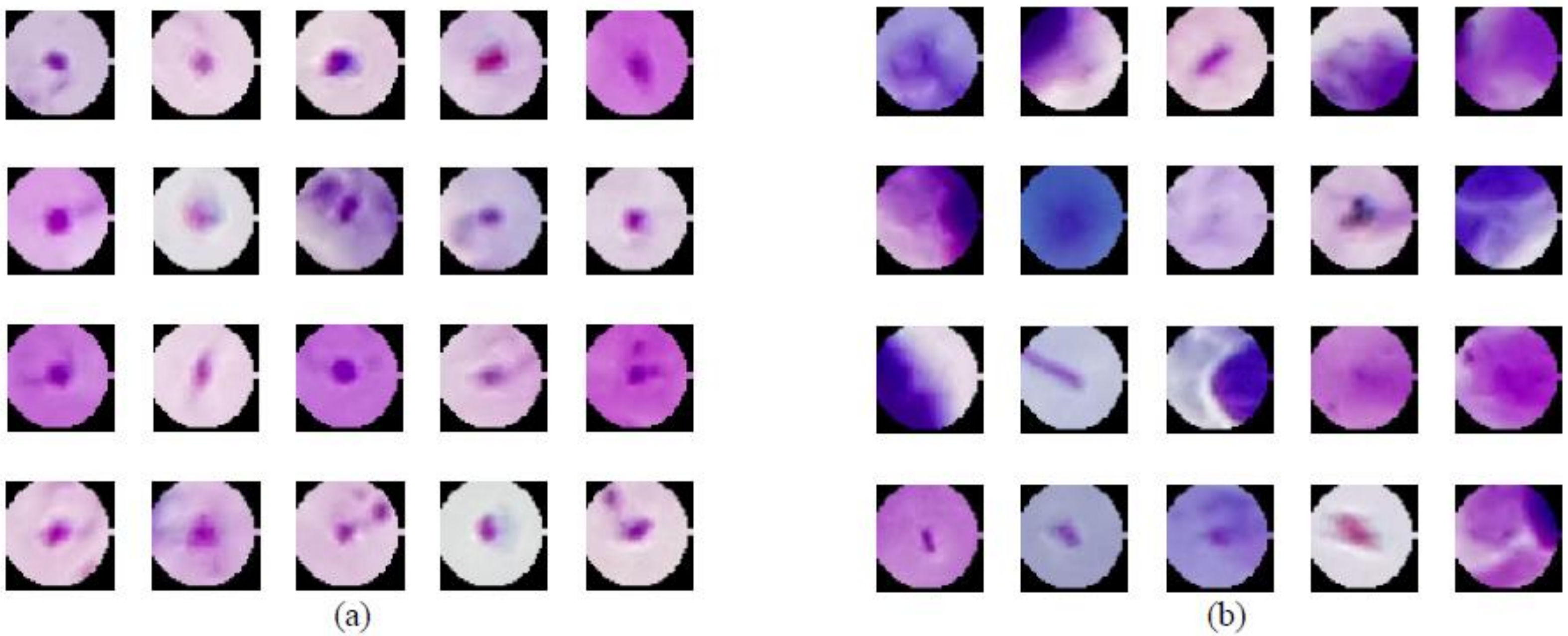


Fig. 5. Parasite candidates generated by the IGMS method. (a) 20 positive patches. (b) 20 negative patches.

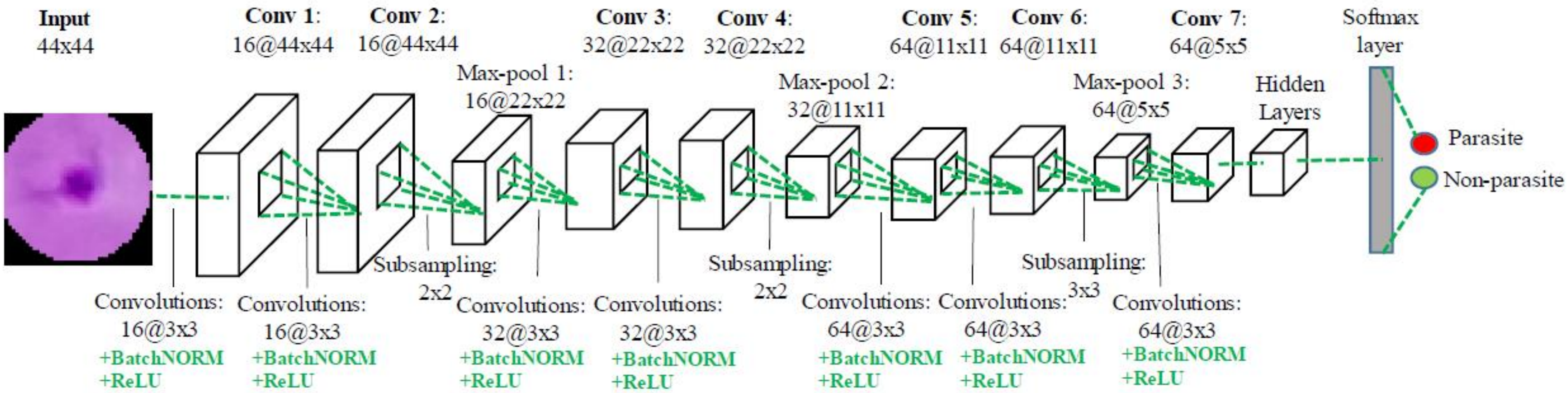


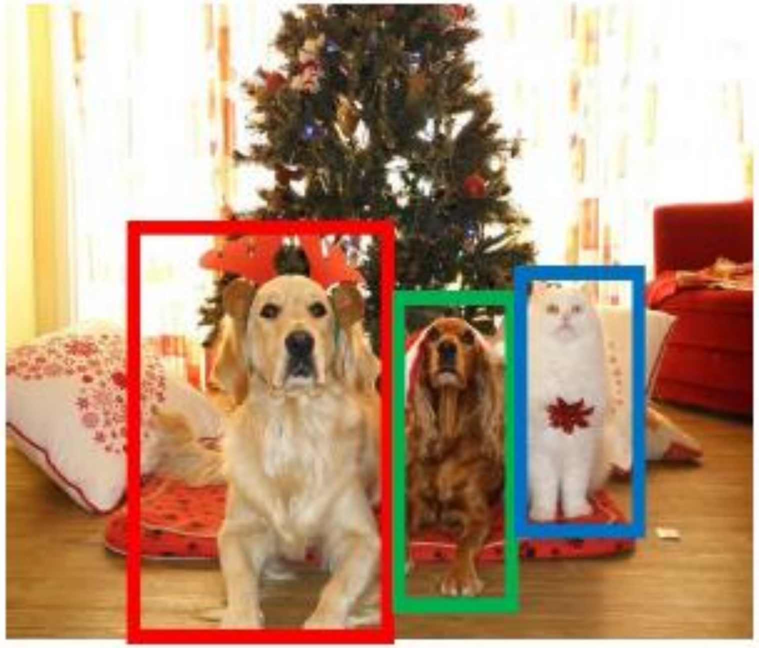
Fig. 7. Smartphone-based malaria data acquisition and parasite detection.

TABLE V. PERFORMANCE COMPARISON BETWEEN THE CUSTOMIZED CNN MODEL AND DL MODELS IN THE LITERATURE ON SET A.

Network	CPU or GPU	Learning rate	Training time	Accuracy
ResNet50	CPU	0.001	47382	92.55%
VGG19	GPU	0.001	13698	91.72%
AlexNet	GPU	0.001	1613	92.21%
Our CNN	GPU	0.001	1487	93.46%

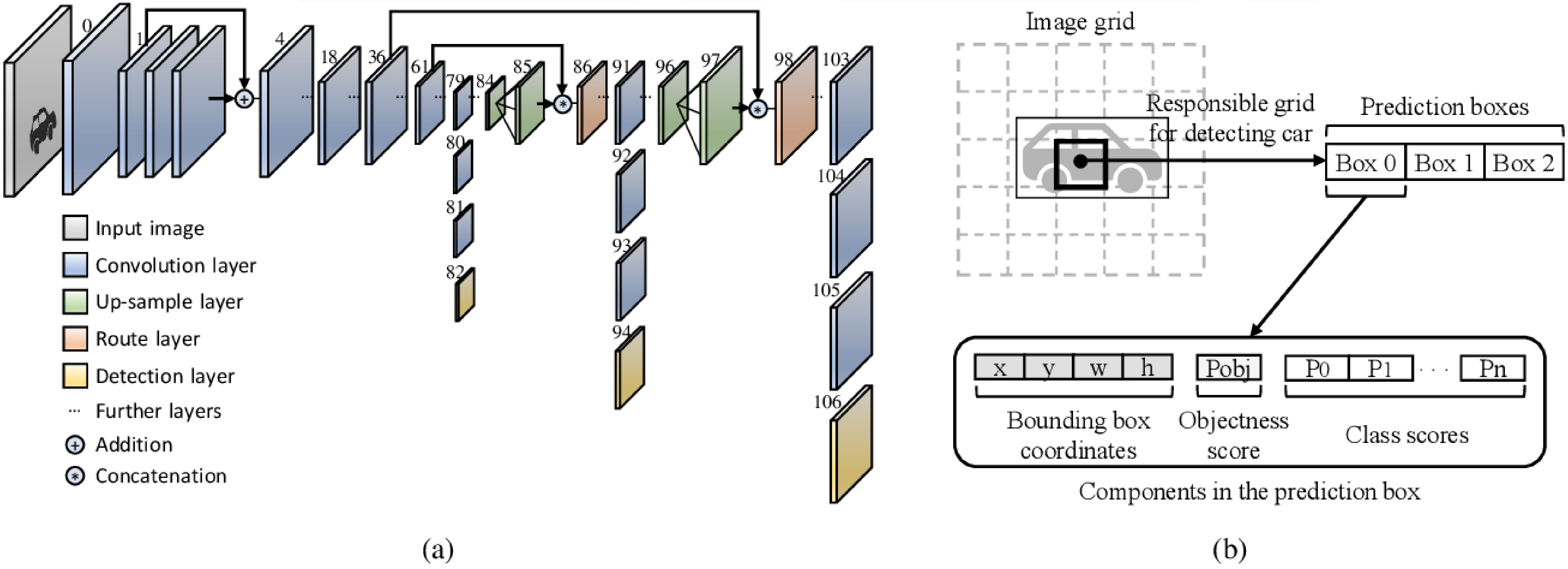
Classification + Localization → Object Detection

CAT

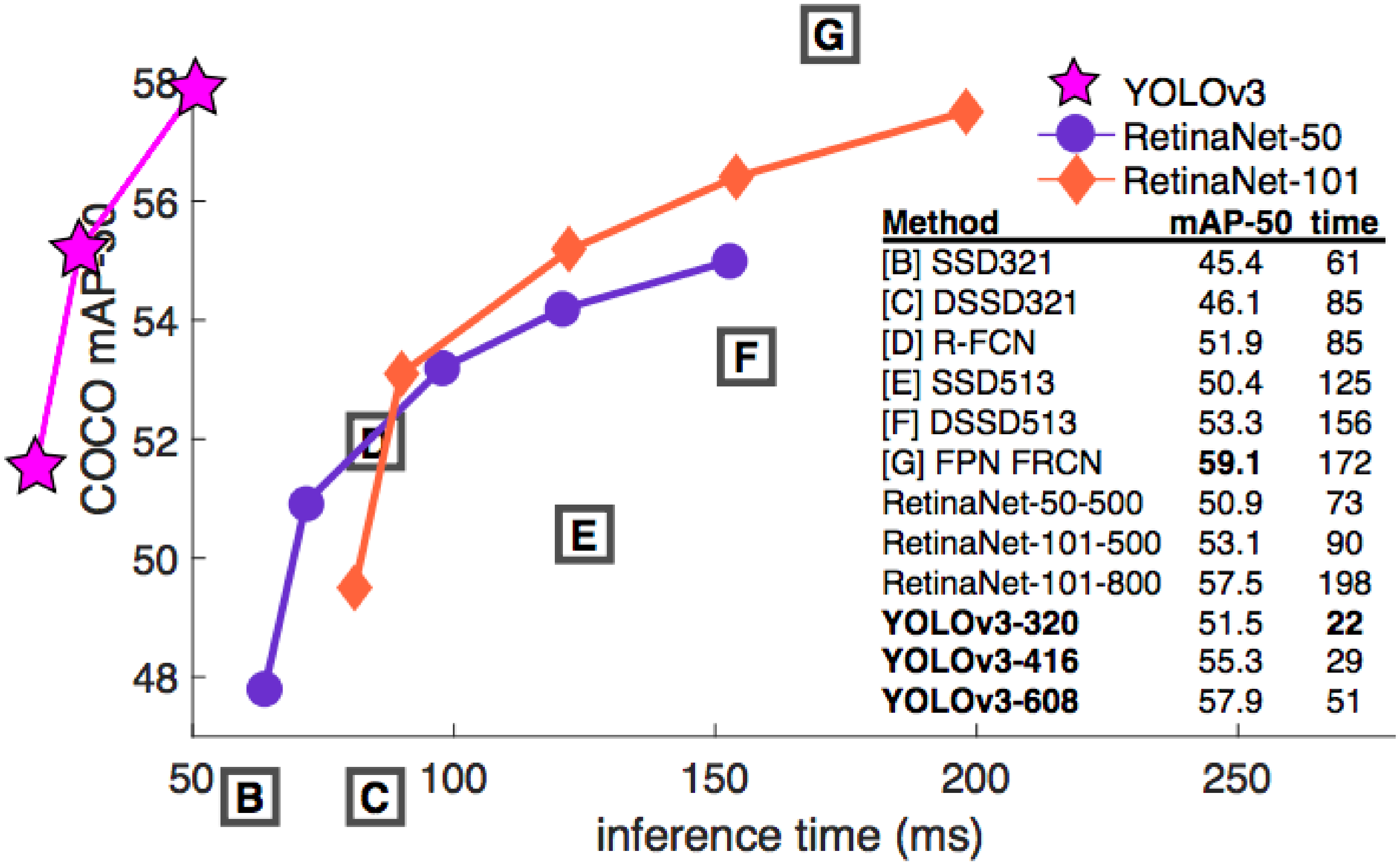


DOG, DOG, CAT

YOLO V3



(8 Apr 2018)



Method	mAP-50	time
[B] SSD321	45.4	61
[C] DSSD321	46.1	85
[D] R-FCN	51.9	85
[E] SSD513	50.4	125
[F] DSSD513	53.3	156
[G] FPN FRCN	**59.1**	172
RetinaNet-50-500	50.9	73
RetinaNet-101-500	53.1	90
RetinaNet-101-800	57.5	198
YOLOv3-320	51.5	**22**
YOLOv3-416	55.3	29
YOLOv3-608	57.9	51

mAP = mean Average Precision

YOLOv3: An Incremental Improvement

Joseph Redmon, Ali Farhadi
University of Washington

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Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Aedes mosquito detection in its larval stage using deep neural networks☆

Antonio Arista-Jalife [a], Mariko Nakano [a,*], Zaira Garcia-Nonoal [a],
Daniel Robles-Camarillo [b], Hector Perez-Meana [a], Heriberto Antonio Arista-Viveros [c]

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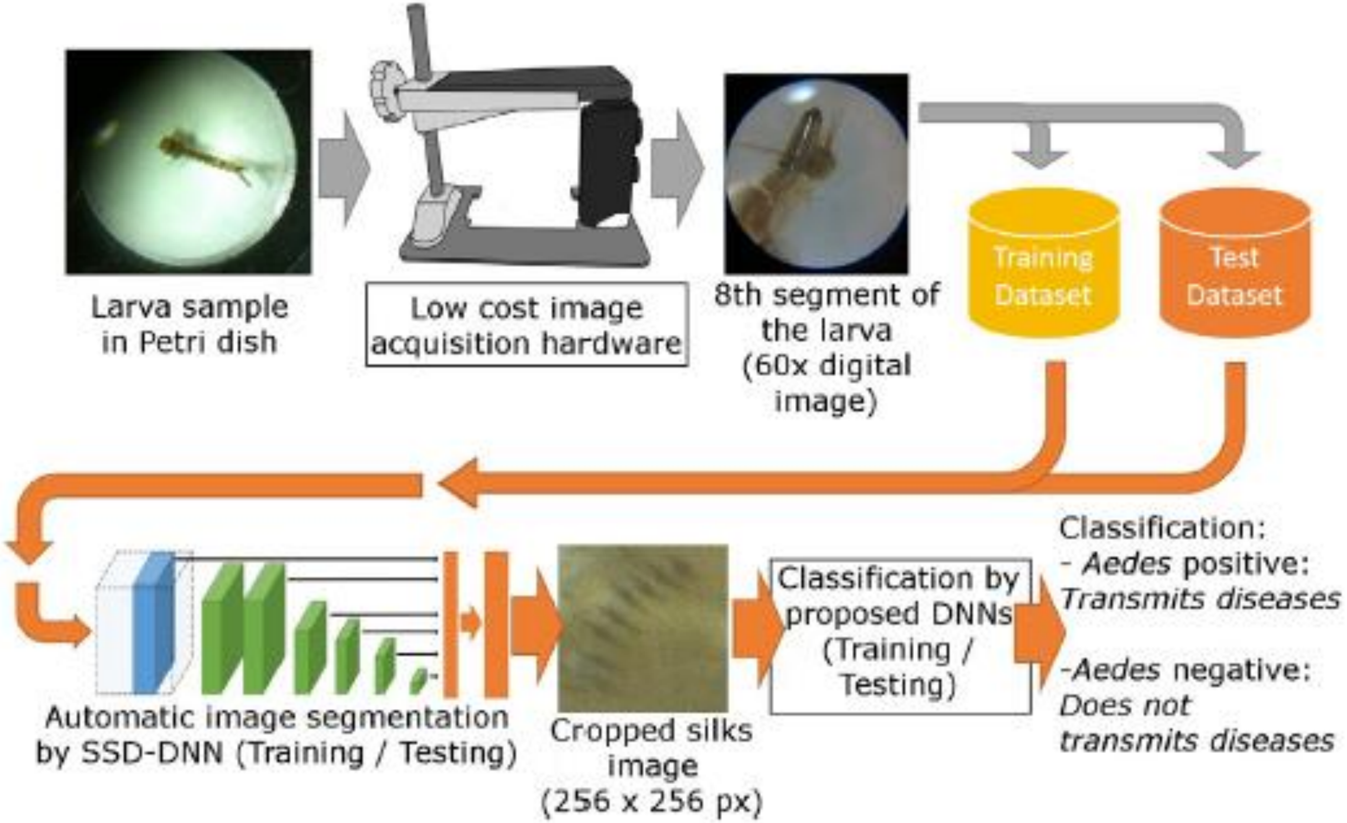
Article history:
Received 4 February 2019
Received in revised form 17 May 2019
Accepted 10 July 2019
Available online xxxx

Keywords:
Mosquito larval surveillance
Deep neural networks
Automatic segmentation
Vector control
Dengue fever
Zika fever



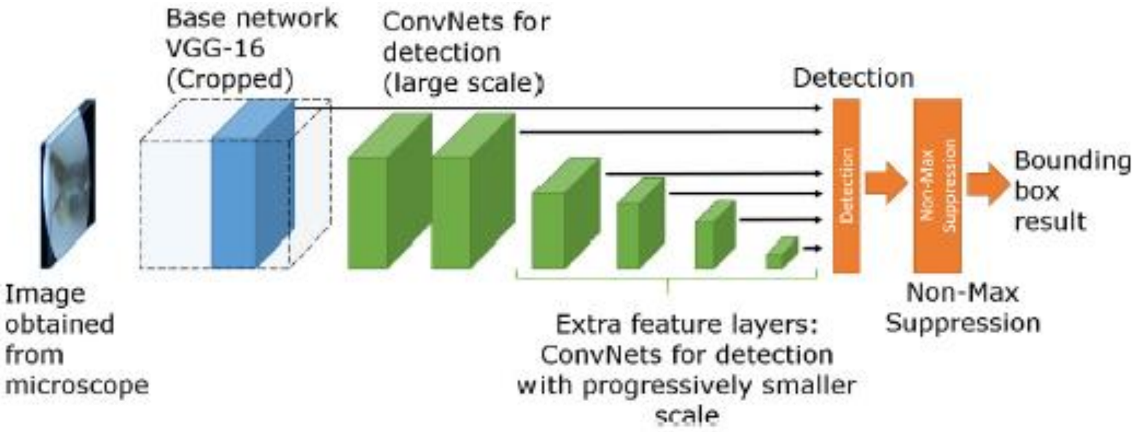


Fig. 9. Simplified SSD Architecture. In an SSD-DNN, several convolutional layers in a progressively reduced scale are employed to detect smaller objects in the image. Further details can be found in [42].

Table 6
Comparison of related works.

Segmentation +Recognition strategy	Accuracy (%)	TPR (%)	TNR (%)
No segmentation +AlexNet DNN [13]	80.92	100.00	70.00
Manual segmentation +Concurrence matrix SVM [12]	67.00	64.51	58.06
Manual segmentation +Local Binary Pattern SVM [12]	72.00	67.74	77.41
Manual segmentation +2D Gabor filter SVM [12]	79.00	77.41	80.64
Manual segmentation +Dual-Source DNN [14]	91.28	94.18	88.37
Automatic segmentation +Dual-Source DNN [14]	75.96	86.04	65.89
Automatic segmentation +Shallow Network (Proposed)	**88.50**	**87.59**	**87.58**
Automatic segmentation +Deep Slim Network (Proposed)	**87.98**	**81.39**	**94.57**
Automatic segmentation +Deep Robust Network (Proposed)	**94.19**	**94.57**	**93.79**

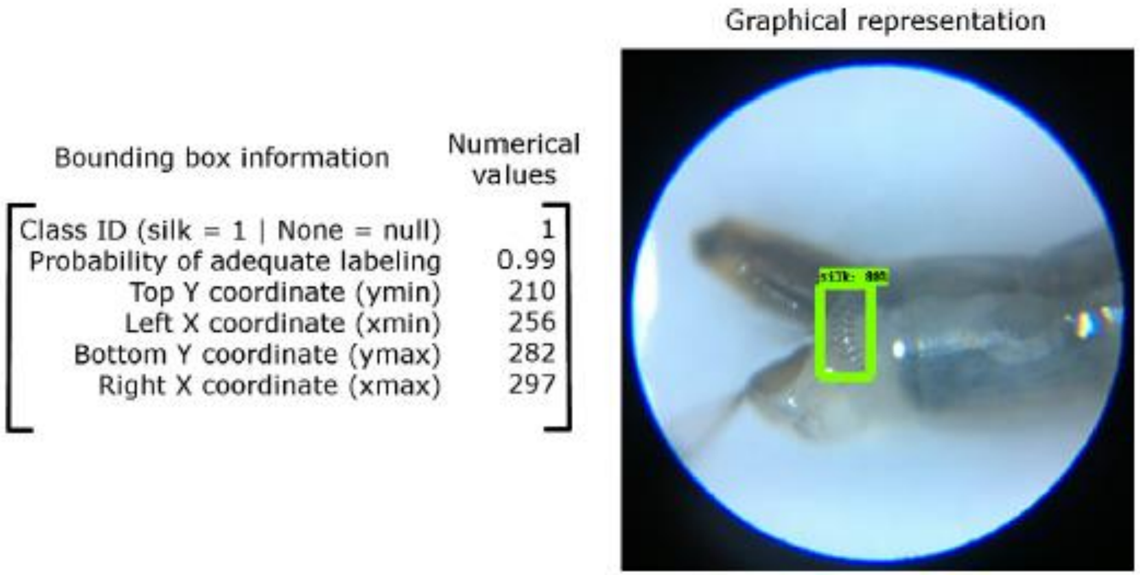


Fig. 10. Bounding box representation. The bounding box information and the numerical values are outputted from a trained SSD-DNN.

RESEARCH ARTICLE

Deep learning approach to peripheral leukocyte recognition

Qiwei Wang[1], **Shusheng Bi**[1] *, **Minglei Sun**[1], **Yuliang Wang**[1], **Di Wang**[2], **Shaobao Yang**[2]

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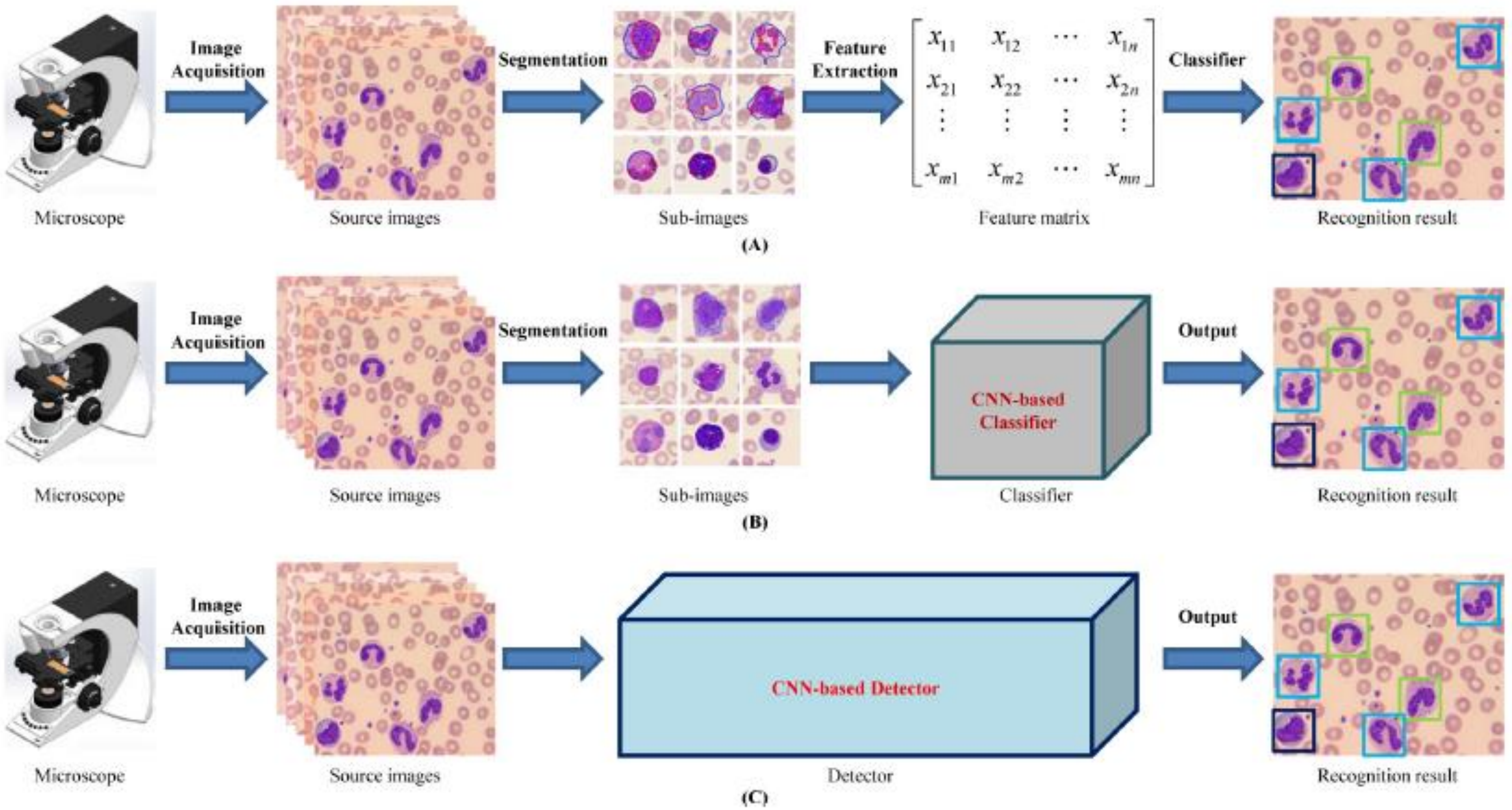
Citation: Wang Q, Bi S, Sun M, Wang Y, Wang D, Yang S (2019) Deep learning approach to peripheral leukocyte recognition. PLoS ONE 14(6): e0218808. https://doi.org/10.1371/journal.pone.0218808

Editor: Jie Zhang, Newcastle University, UNITED KINGDOM

Received: April 10, 2019

Accepted: June 10, 2019

Published: June 25, 2019



Single Shot Multibox Detector (SSD)

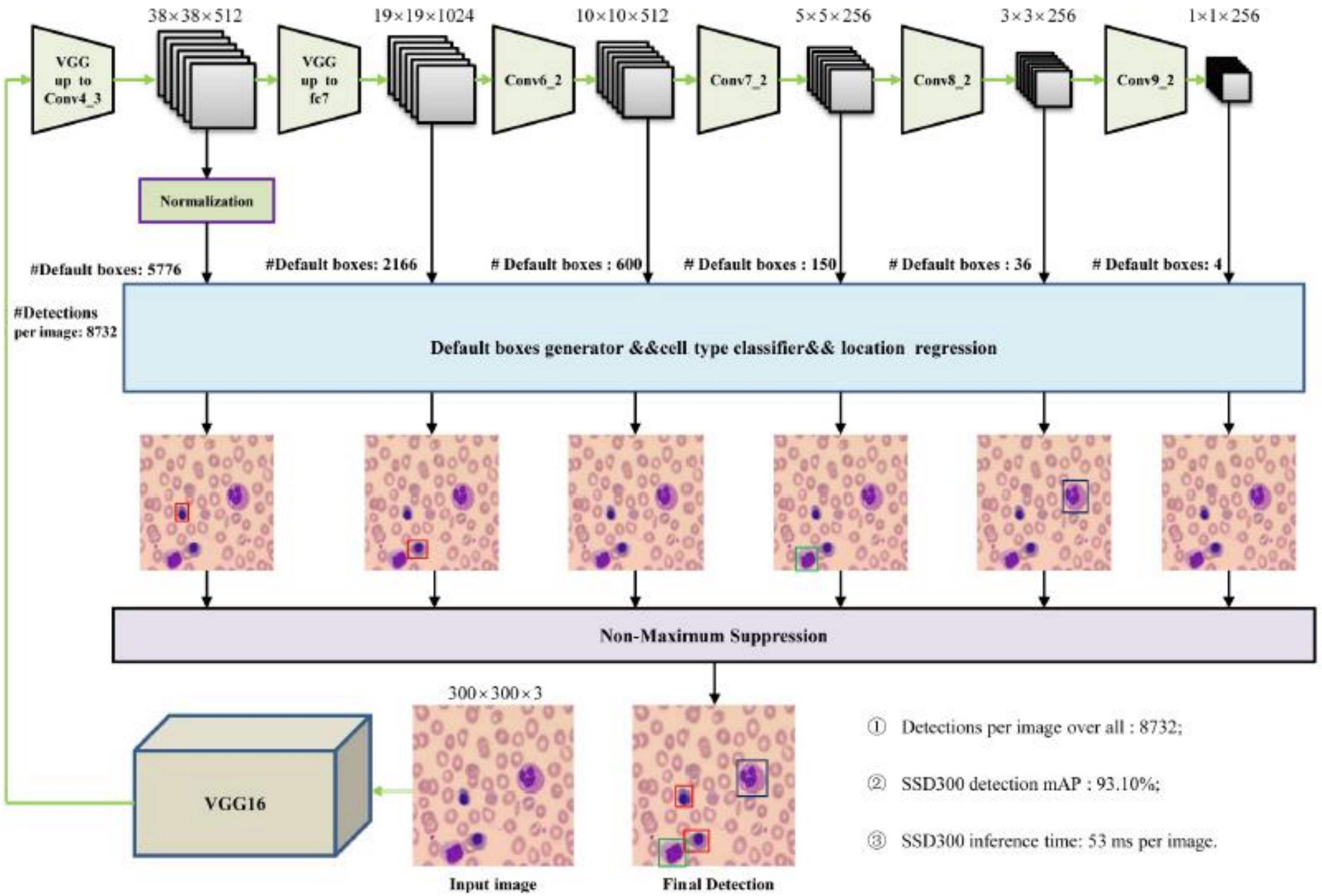
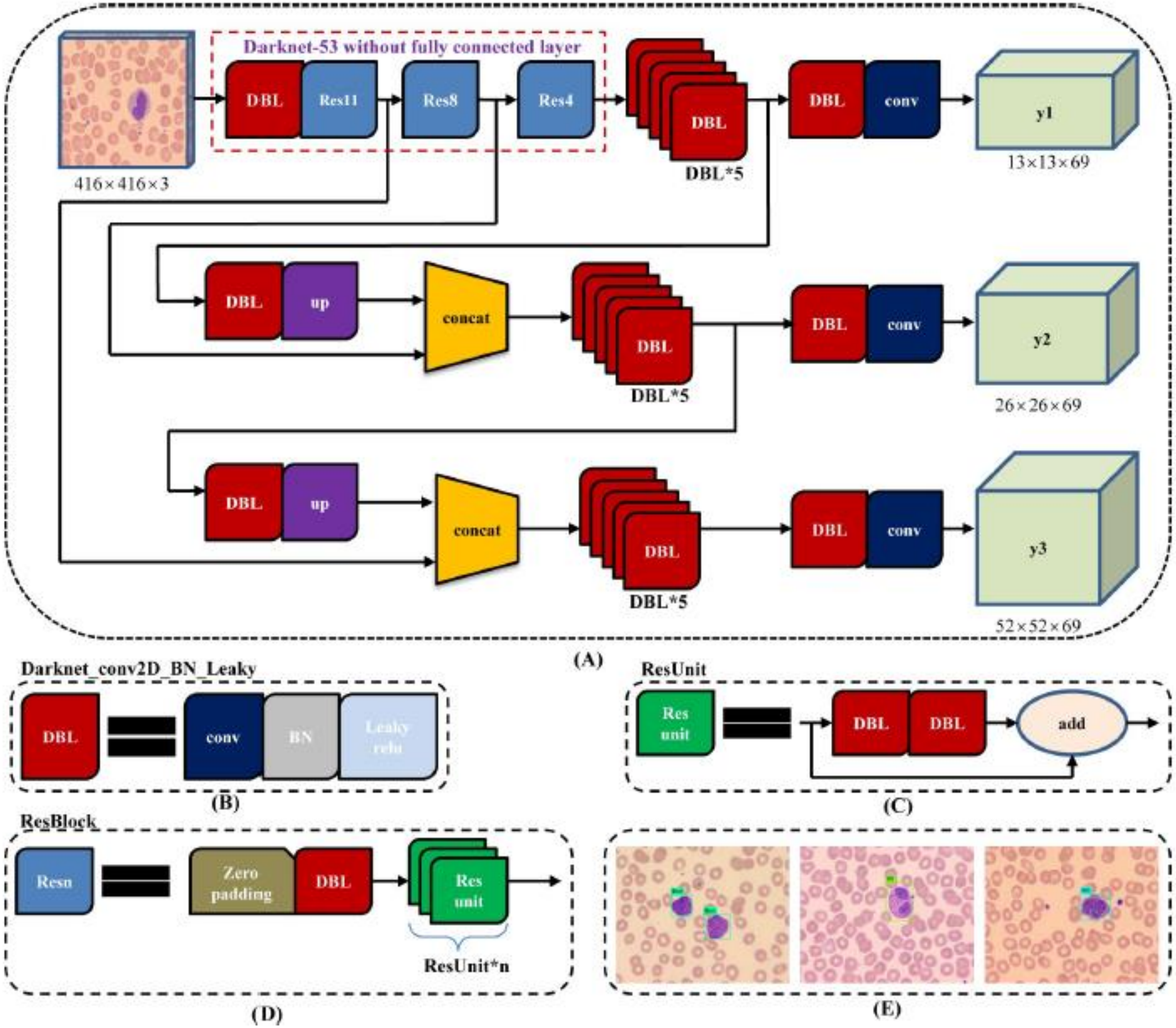


Fig 4. SSD architecture. To multi-scale feature maps for detection, several feature layers (Conv6_2, Conv7_2, Conv8_2 and Conv9_2) were added to the end of base network (VGG16), where the larger size feature maps, such as Conv4_3, were used to detect small size leukocytes while the smaller size feature map to detect the large size.



You Only Look Once.

Table 1. Comparison of detection results using SSD and YOLOv3 series models.

Model	Smin	Smax	mAP	Blast	PRO	MYE	MET	bNEU	sNEU	LYM	MON	EO	BA	rLYM
SSD300×300	0.2	0.9	**0.931**	**0.970**	**0.870**	0.862	**0.881**	**0.982**	0.970	0.884	**0.914**	**1.0**	**0.993**	0.913
	0.1	0.9	0.831	0.882	0.654	0.745	0.663	0.853	0.928	0.849	0.806	0.985	0.973	0.800
SSD512×512	0.2	0.9	0.687	0.651	0.453	0.682	0.499	0.777	0.741	0.409	0.756	0.907	0.891	0.790
YOLOv3_320×320 -			0.925	0.961	0.826	0.860	0.841	0.955	0.968	0.937	0.912	0.999	**0.993**	**0.920**
YOLOv3_416×416		-	0.921	0.958	0.824	0.862	0.826	0.947	0.968	**0.947**	0.894	0.999	0.987	0.915
YOLOv3_608×608		-	0.919	0.962	0.814	**0.864**	0.829	0.961	**0.974**	0.930	0.904	0.999	0.987	0.881
YOLOv3-tiny_416×416 -			0.772	0.941	0.469	0.701	0.372	0.758	0.915	0.871	0.674	0.993	0.982	0.815

SSD300×300 has an input size of 300×300, SSD512×512 increases it to 512×512, and YOLOv3 is the 3rd version of YOLO architecture, with the different backbone net (YOLOv3-tiny) and different input size: 320×320, 416×416, and 608×608.

https://doi.org/10.1371/journal.pone.0218808.t001

Special thank for financial supported both in-cash and in-kind to

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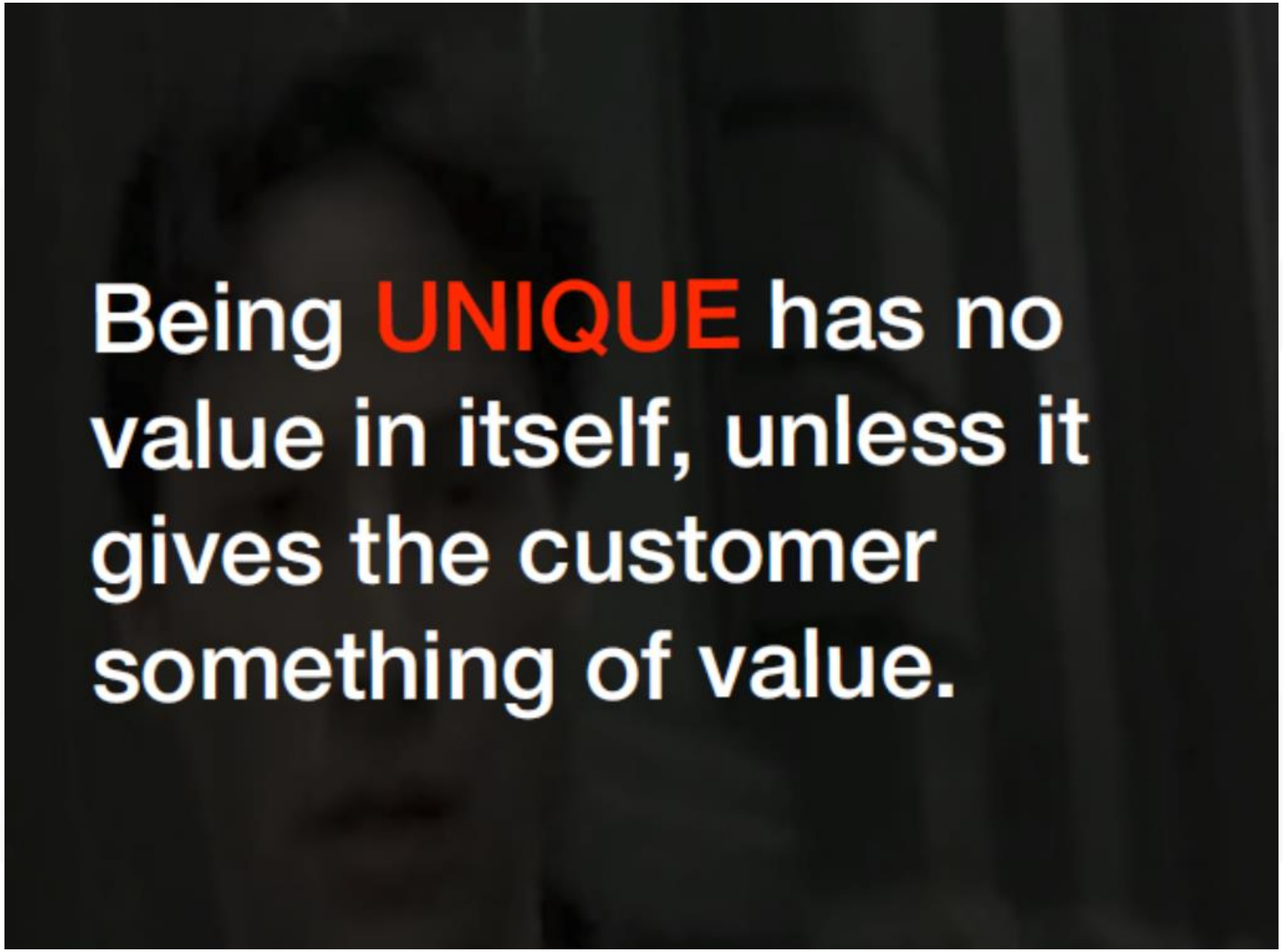
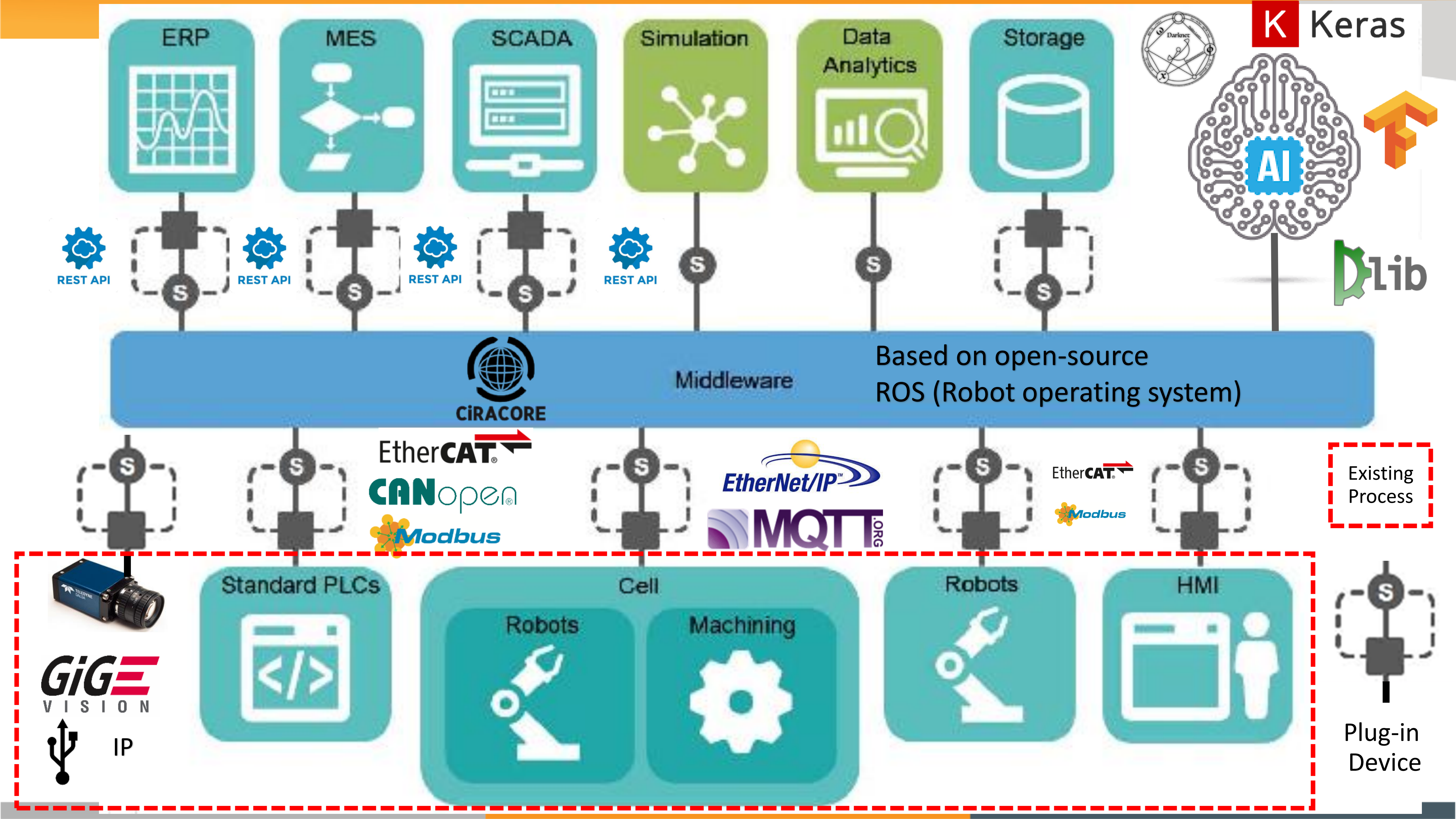

Being UNIQUE has no
value in itself, unless it
gives the customer
something of value.


“เศรษฐกิจพอเพียง...จะทำความเจริญให้แก่ประเทศได้
แต่ต้องมีความเพียร แล้วต้องอดทน ต้องไม่ใจร้อน
ต้องไม่พูดมาก ต้องไม่ทะเลาะกัน
ถ้าทำโดยเข้าใจกัน
เชื่อว่าทุกคนจะมีความพอใจได้...”
พระราชดำรัสของพระบาทสมเด็จพระเจ้าอยู่หัว พระราชทาน ณ วันที่ ๔ ธันวาคม ๒๕๔๑

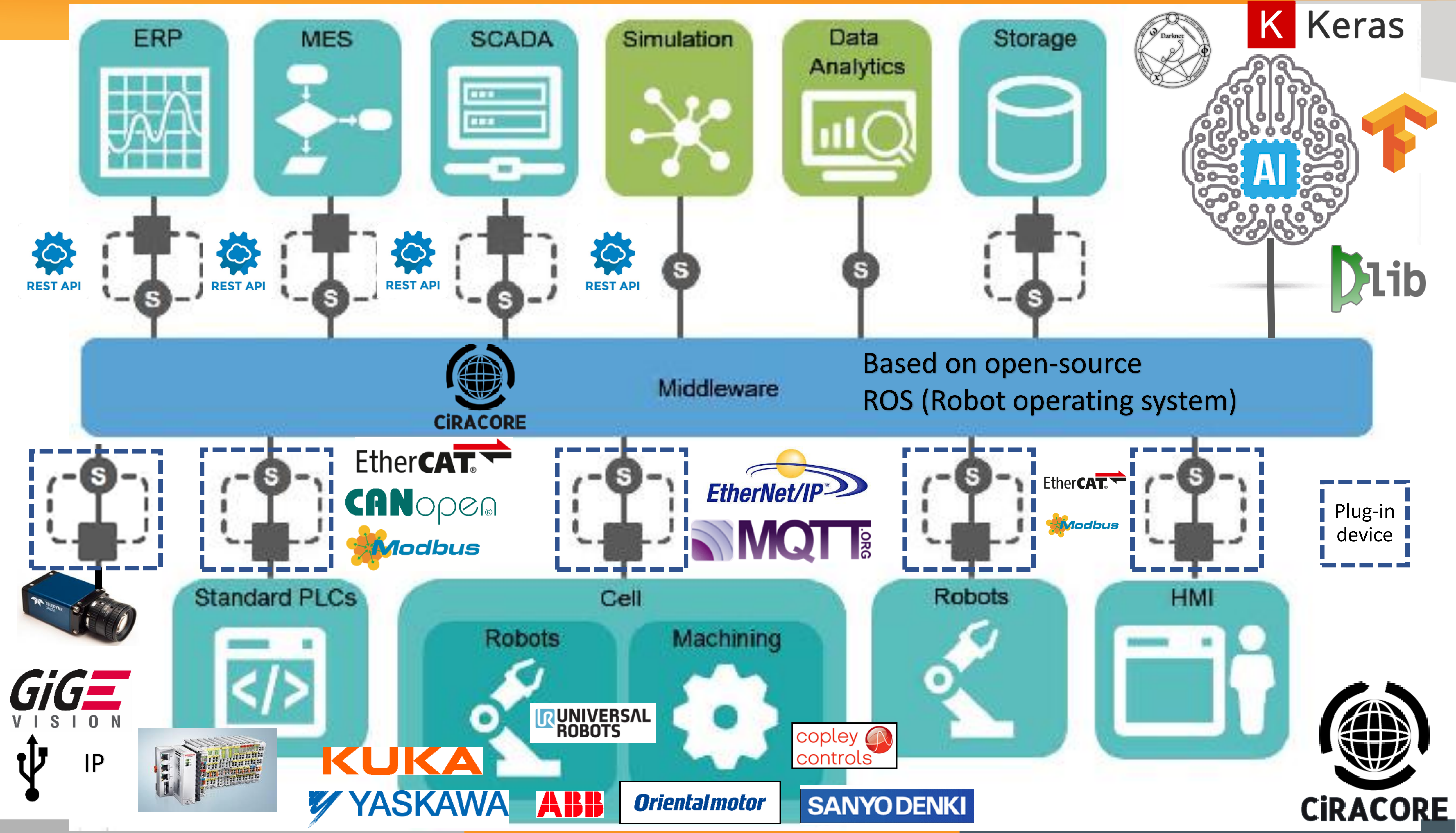
Agro and food products = Random shape + positions

Robots + A.I.→ Industrial application


GIT
ABB
DELL

ERP
MES
SCADA
Simulation
Data Analytics
Storage
Keras
Darknet
AI
lib
REST API
REST API
REST API
REST API
CiRACORE
Middleware
Based on open-source
ROS (Robot operating system)
EtherCAT
CANopen
Modbus
EtherNet/IP
MQTT.ORG
EtherCAT
Modbus
Existing Process
Standard PLCs
Cell
Robots
Machining
Robots
HMI
GiGE VISION
IP
Plug-in Device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Cell
Robots
Machining
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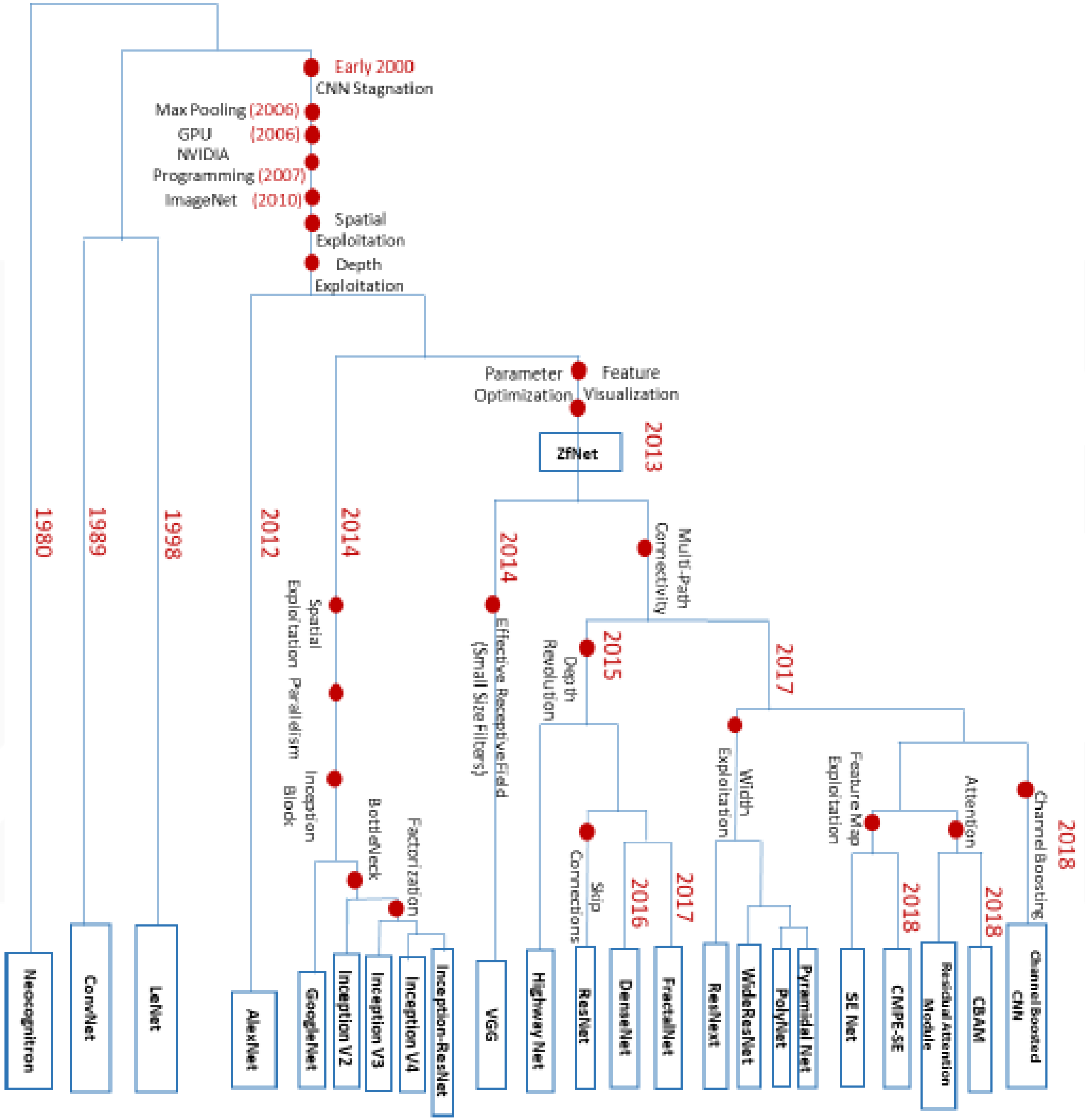
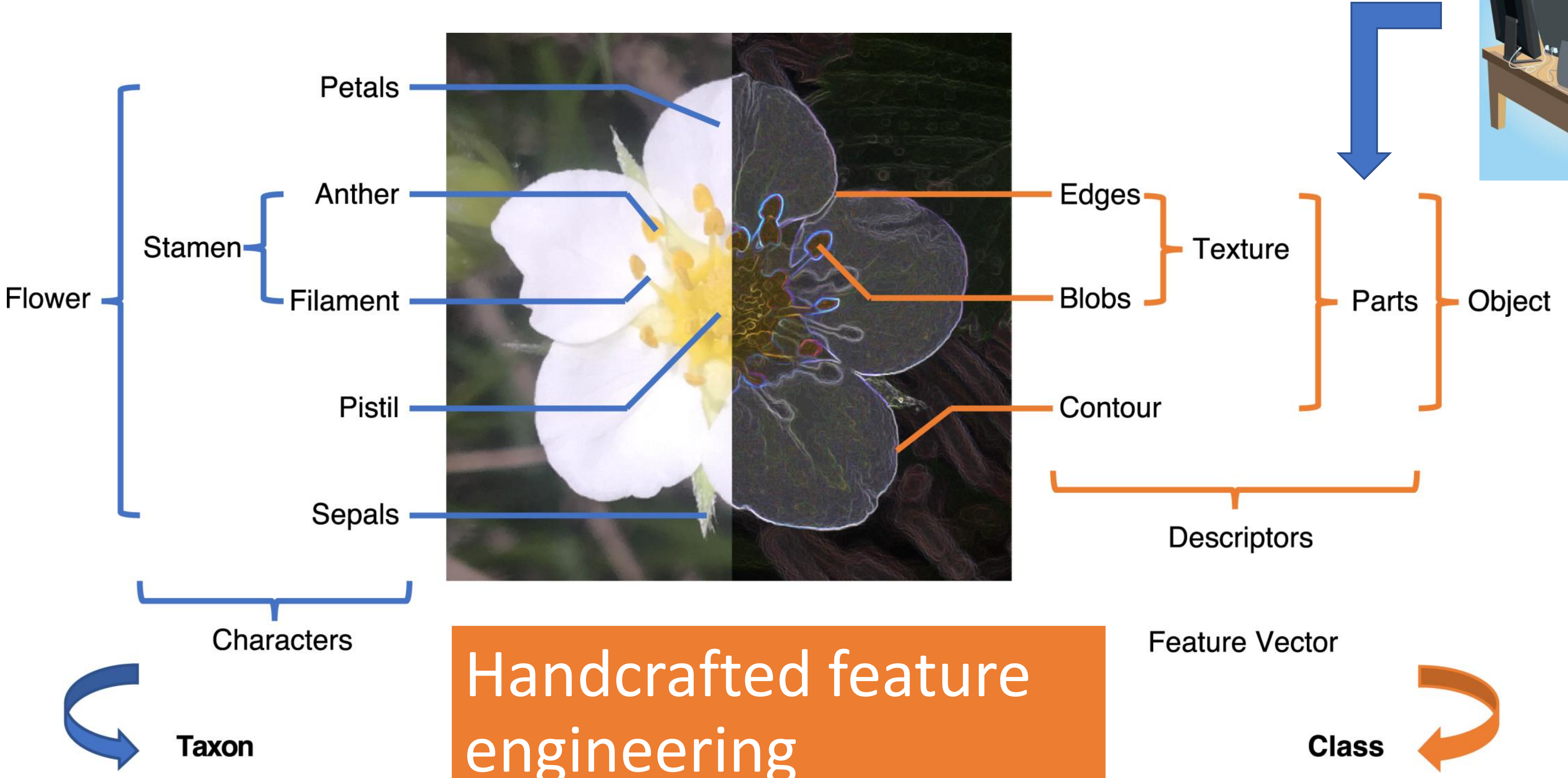
SANYO DENKI
CiRACORE


Early 2000
CNN Stagnation
Max Pooling (2006)
GPU (2006)
NVIDIA
Programming (2007)
ImageNet (2010)
Spatial Exploitation
Depth Exploitation
Parameter Optimization
Feature Visualization
ZfNet
2013
1980
1989
1998
2012
2014
Spatial Exploitation
Parallelism
Inception Block
BottleNeck
Factorization
2014
Effective Receptive Field (Small Size Filters)
Multi-Path Connectivity
2015
Depth Revolution
Skip Connections
2016
2017
2017
Width Exploitation
Feature Map Exploitation
Attention
Channel Boosting
2018
2018
2018
Neocognitron
ConvNet
LeNet
AlexNet
GoogleNet
Inception V2
Inception V3
Inception V4
Inception-ResNet
VGG
Highway Net
ResNet
DenseNet
FractalNet
ResNext
WideResNet
PolyNet
Pyramidal Net
SE Net
CMPE-SE
Residual Attention Module
CBAM
Channel Boosted CNN

Architecture Name	Year	Main contribution	Parameters	Error Rate	Depth	Category	Reference
FractalNet	2016	- Different path lengths are interacting with each other without any residual connection	38.6 M	CIFAR-10++: 4.59 CIFAR-100: 28.20 CIFAR-100+: 22.49 CIFAR100++: 21.49	20 40	Multi-Path	[113]
WideResNet	2016	- Width is increased and depth is decreased	36.5 M	CIFAR-10: 3.89 CIFAR-100: 18.85	28 -	Width	[34]
Xception	2017	- Depth wise Convolution followed by point wise convolution	22.8 M	ImageNet: 0.055	36	Width	[114]
Residual Attention Neural Network	2017	- Introduces Attention Mechanism	8.6 M	CIFAR-10: 3.90 CIFAR-100: 20.4 ImageNet: 4.8	452	Attention	[38]
ResNexT	2017	- Cardinality - Homogeneous topology - Grouped convolution	68.1 M	CIFAR-10: 3.58 CIFAR-100: 17.31 ImageNet: 4.4	29 101	Spatial Exploitation	[115]
Squeeze & Excitation Networks	2017	- Models Interdependencies between feature maps	27.5 M	ImageNet: 2.3	152	Feature Map Exploitation	[116]
DenseNet	2017	- Cross-layer information flow	25.6 M 25.6 M 15.3 M 15.3 M	CIFAR-10+: 3.46 CIFAR100+: 17.18 CIFAR-10: 5.19 CIFAR-100: 19.64	190 190 250 250	Multi-Path	[107]
PolyNet	2017	- Experimented structural diversity - Introduces Poly Inception Module - Generalizes residual unit using Polynomial compositions	92 M	ImageNet: Single:4.25 Multi:3.45	- -	Width	[117]



Handcrafted feature engineering

Industrial used cases