# YOLO-LITE

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## Collaborators

Special thanks to all my collaborators on this project:

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## Outline

- I. Introduction
  - I. Object Detection
  - II. Convolutional Neural Networks
  - III. YOLO
- II. YOLO-LITE
  - I. Architecture
  - II. Results
- III. Web Implementation
- IV. Conclusion

Introduction

YOLO-LITE

Web Implementation

Conclusion

YOLO-LITE

Web Implementation

Conclusion

## INTRODUCTION

INTRODUCTION



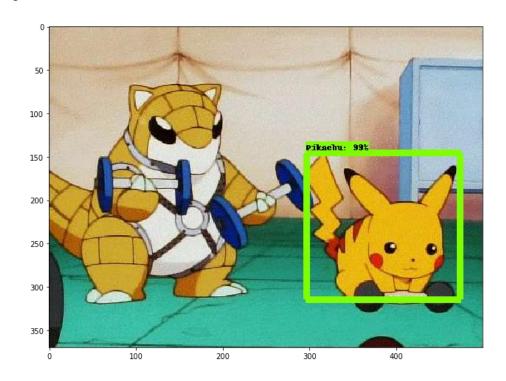
Conclusion

## What is Object Detection?

**Definition:** A field of computer vision to **detect** and **classify** objects.

#### **Applications:**

- Self-driving vehicles
- Traffic monitoring
- Video surveillance



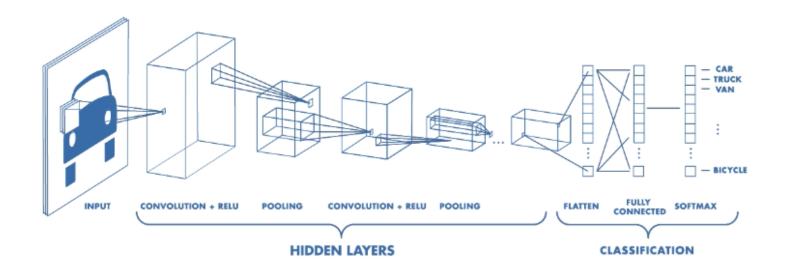
https://towards datascience.com/detecting-pikachu-on-android-using-tensorflow-object-detection-15464c7a60cd, which is a substantial content of the content

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Web Implemen

#### Conclusion

### Convolutional Neural Networks



- Convolution
- Activation Function
- Pooling
- Classification

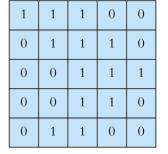
https://medium.freecodecamp.org/an-intuitive-guide-to-convolutional-neural-networks-260c2 de 0 a 0 50 a convolutional-neural-networks-260c2 de 0 a convolutional-neur

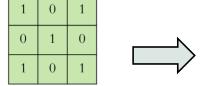
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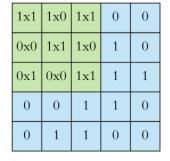
Web Implementation

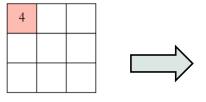
Conclusion

### Convolutional Neural Networks

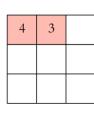








1	1x1	1x0	0x1	0
0	1x0	1x1	1x0	0
0	0x1	1x0	1x1	1
0	0	1	1	0
0	1	1	0	0



Input

Filter / Kernel

Input x Filter

Feature Map

Input x Filter

Feature Map

https://towards datascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584 bc 134 c1e2

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Web Implementat

Conclusion

## YOLO

You-Only-Look-Once: **Detects** and **classifies** at the same time.

#### **Steps:**

- I. Divide image into S x S grid.
- II. Creates bounding boxes in each grid cell.
- III. Each cell predicts class probability.



YOLO diagram [2]

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Web Implementation

Conclusion

## YOLO

Version	mAP	FPS (GPU)	Dataset
YOLOv1	63.4	45	VOC
Tiny-YOLOv1	52.7	155	VOC
YOLOv2	48.1	40	COCO
Tiny-YOLOv2	23.7	244	COCO
YOLOv3	57.9	20	COCO
Tiny-YOLOv3	33.1	220	COCO

Tiny-yolov2-VOC without a GPU runs at around 2.4 FPS.

YOLO-LITE

Web Implementation

Conclusion

# YOLO-LITE

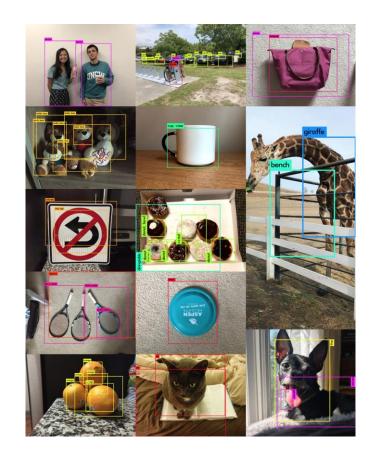
YOLO-LITE 10

### **YOLO-LITE**

Developed to run **real-time object detection** on portable devices such as a laptop or cellphone without a **Graphics Processing Unit** (GPU).

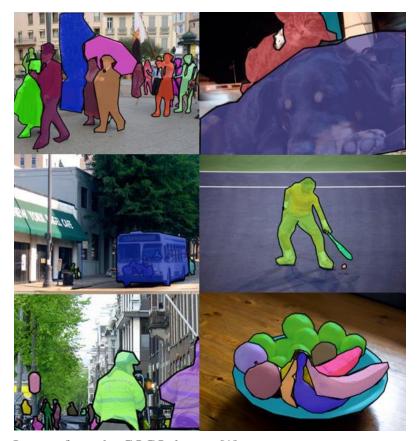
#### **Goals:**

- Achieve **real-time** object detection: 10 FPS.
- mAP: 30%.
- Implement resulting models onto a website.



## **Datasets**

Dataset	Training Images	Number of Classes
PASCAL VOC 2007 + 2012	5,011	20
COCO 2014	40,775	80



Images from the COCO dataset [1]

YOLO-LITE 12

YOLO-LITE

Web Implementati

Conclusion

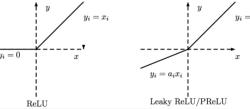
### **Architectural Elements**

#### **Batch Normalization:**

- Creates zero mean/unit variance for every input layer in a neural network.
- Increases mAP

#### **Activation Function:**

• Creates nonlinearity in order to determine output of neural networks.



#### **Input Image Size:**

- Tiny-YOLOv2-VOC input image size: 416 x 416
- YOLO-LITE input image size: 224 x 224

#### **Number of Layers and Filters:**

- Tiny-YOLOv2-VOC layers: 9
- YOLO-LITE layers: 7

https://towardsdatascience.com/activation-functions-and-its-types-which-is-better-a9a5310cc8id-

## Results

Dataset	mAP	FPS
PASCAL VOC	33.57	21
COCO	12.26	21

Tiny-	YOLOv2-	VOC
Laver	Filters	Size

Layer	Filters	Size	Stride
Conv1 (C1)	16	3	1
Max Pool (MP)		2	2
C2	32	3	1
MP		2	2
C3	64	3	1
MP		2	2
C4	128	3	1
MP		2	2
C5	256	3	1
MP		2	2
C6	512	3	1
MP		2	2
C7	1024	3	1
C8	1024	3	1
C9	125	1	1

#### YOLO-LITE

Layer	Filters	Size	Stride
C1	16	3	1
MP		2	2
C2	32	3	1
MP		2	2
C3	64	3	1
MP		2	2
C4	128	3	1
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Web Implementation

Conclusion

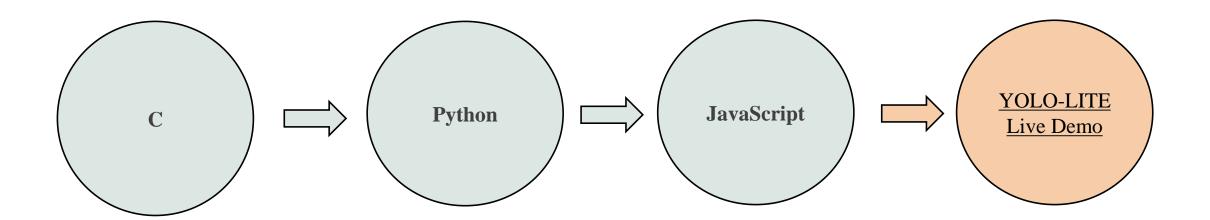
# Web Implementation

YOLO-LITE

Web Implementation

Conclusion

## Web Implementation



YOLO-LITE

Web Implementation

Conclusion

## Conclusion

CONCLUSION 17

### Conclusion

YOLO-LITE: **Lighter** model

Achieves **real-time object** detection without GPU.



Widely accessible

#### **Future Work:**

- Increase mAP:
  - **Pretraining** on ImageNet or CIFAR-10
  - Combining **R-CNN** and YOLO
  - Pruning weights

18 **CONCLUSION** 

#### References

- [1] COCO. Coco common objects in context. http://cocodataset.org/, Last accessed on 2018-07-18.
- [2] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi. You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 779–788, 2016.
- [3] J. Redmon and A. Farhadi. Yolo9000: Better, faster, stronger. arXiv preprint, 2017.
- [4] PASCAL. The pascal visual object classes home-page. http://host.robots.ox.ac.uk/pascal/VOC/index.html, Last accessed on 2018-07-18.

# Questions?