Universidad del País Vasco
Euskal Herriko Unibertsitatea

VITORIA-GASTEIZKO INGENIARITZA ESKOLA
ESCUELA DE INGENIERÍA DE VITORIA-GASTEIZ

centro stirling

DEEP LEARNING IN COOKING ENVIRONMENTS

2nd Basque Conference on Cyber Physical Systems and Artificial Intelligence 2023

Presentado por: Iker Azurmendi Marquinez

Fecha: 18-07-2023

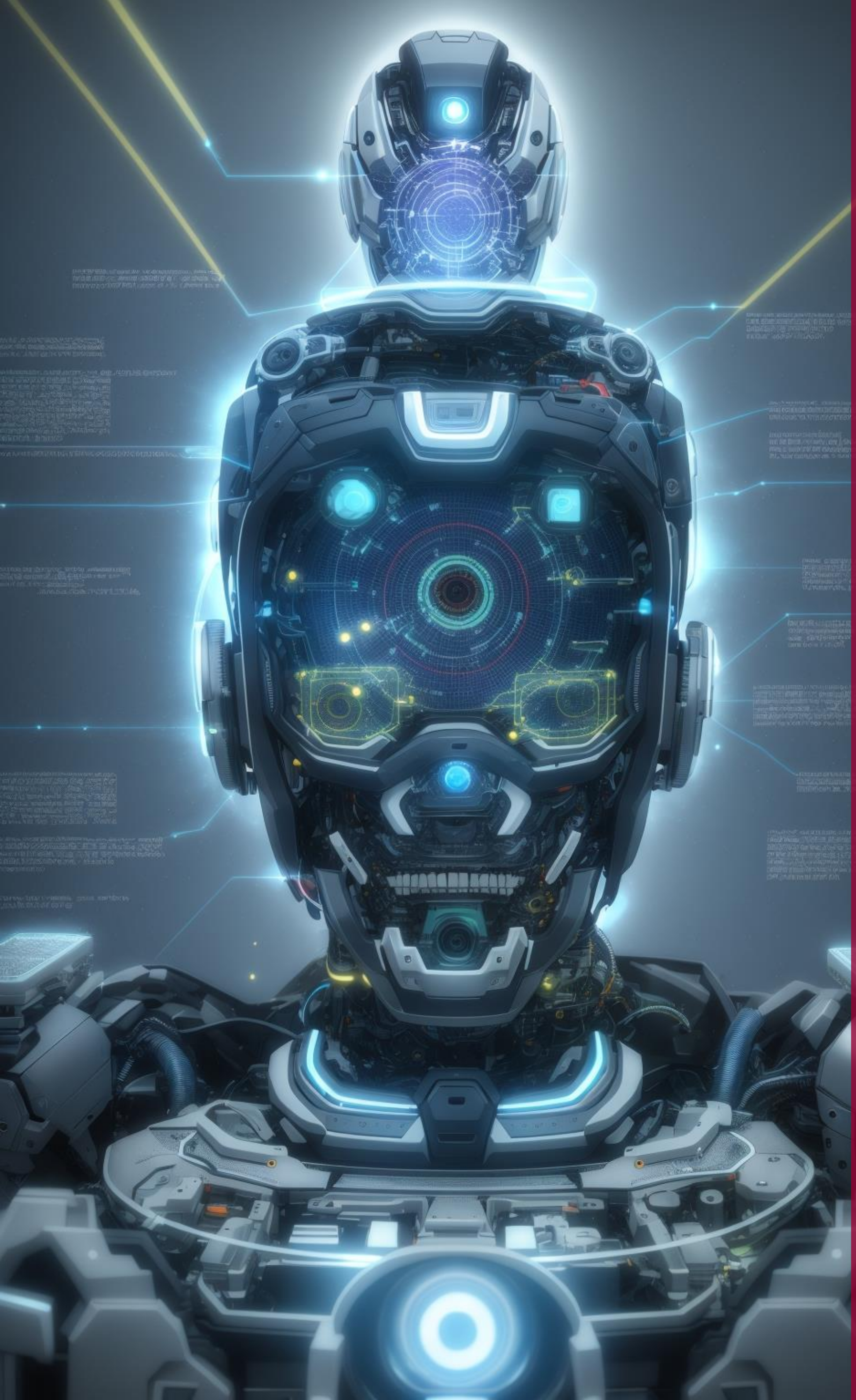


TABLE OF CONTENTS

Introduction

Deep Learning in Cooking Environments

Datasets & Methods

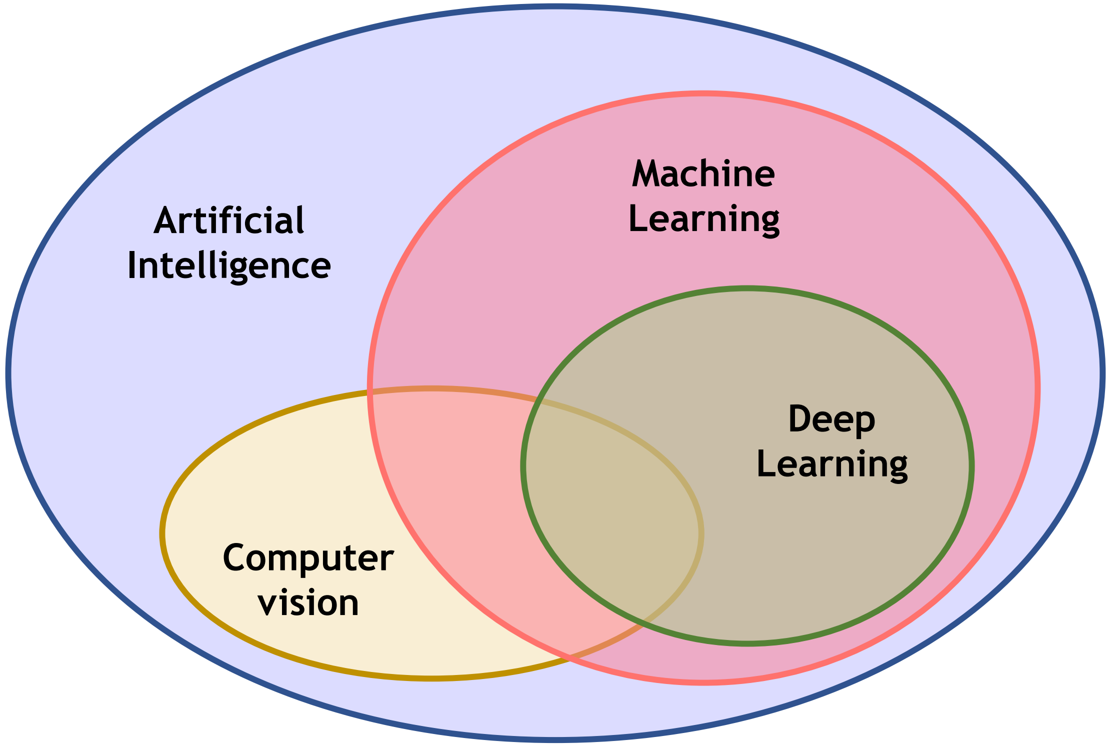
Results

Conclusions & Future work

AI & CV

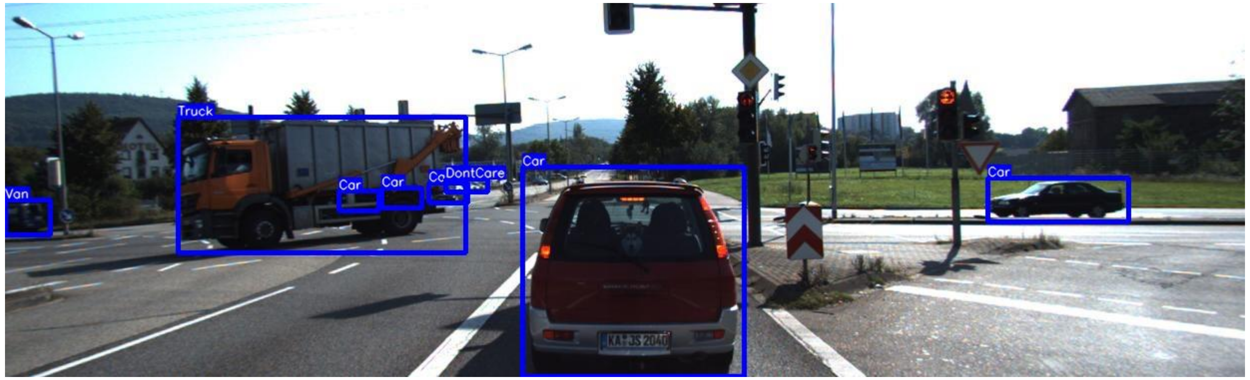
In recent years, AI is experiencing monumental growth. For this reason, researchers and enthusiasts are working on numerous aspects of this field. One of these area is **computer vision**.

The goal of this field is to enable machines to **see the world and use knowledge as humans do**.



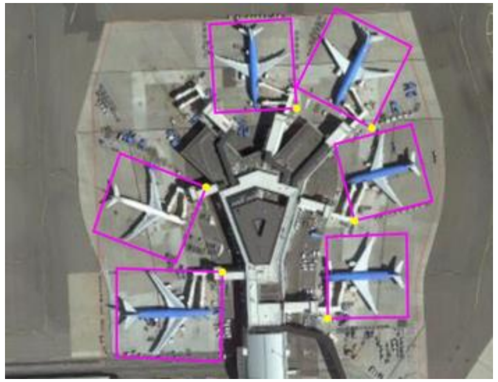
OBJECT DETECTION

The problem definition of object detection is to determine where objects are in each image (**object localization**) and which category belongs to each object (**object classification**)



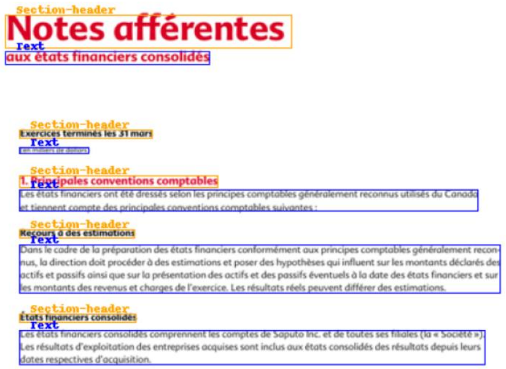
Kitti dataset

Source: https://www.cvlibs.net/datasets/kitti/



DOTA dataset

Source: https://captain-whu.github.io/DOTA/dataset.html



DocLayNet

Source: https://github.com/DS4SD/DocLayNet

1. Dataset generation
2. Model selection
3. Training & validation
4. Testing the model
5. Improving accuracy

DL IN COOKING ENVS

Nowadays, it is difficult to find any research that uses this technology to detect and recognize common household objects in realistic environments, even though it is one of the key factors for service robotics.

Computer vision in cooking environments shows that this technology is used for tasks such as cooking state recognition, collaborative cooking, and assistive cooking using augmented reality.

The main **objective** of this investigation is to develop a model that helps to **modify and improve the user experience** in the use of cooking appliances.

This study will show that by combining artificial vision with deep learning, further improvements in cooking automation, safety and energy efficiency can be achieved.

IDEA

It is desired to identify situations such as:

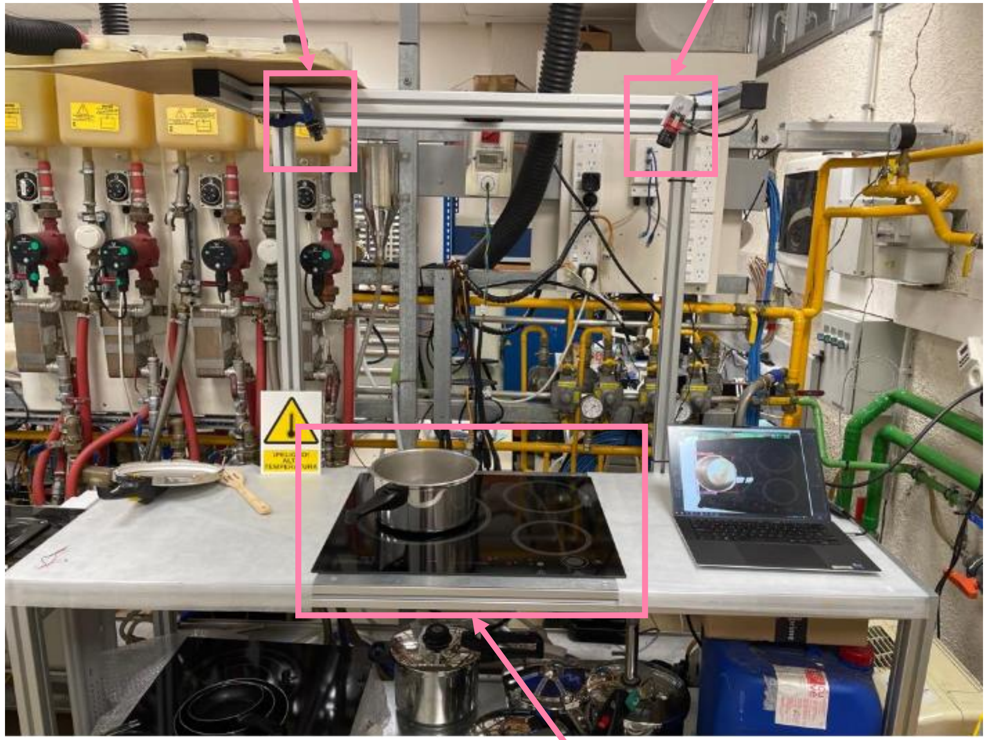
1. Presence or non-presence of utensils on lit hobs
2. Fire
3. Boiling and smoke
4. Presence of user manipulating the cookware
5. Good adjustmentg of the pot/pan size

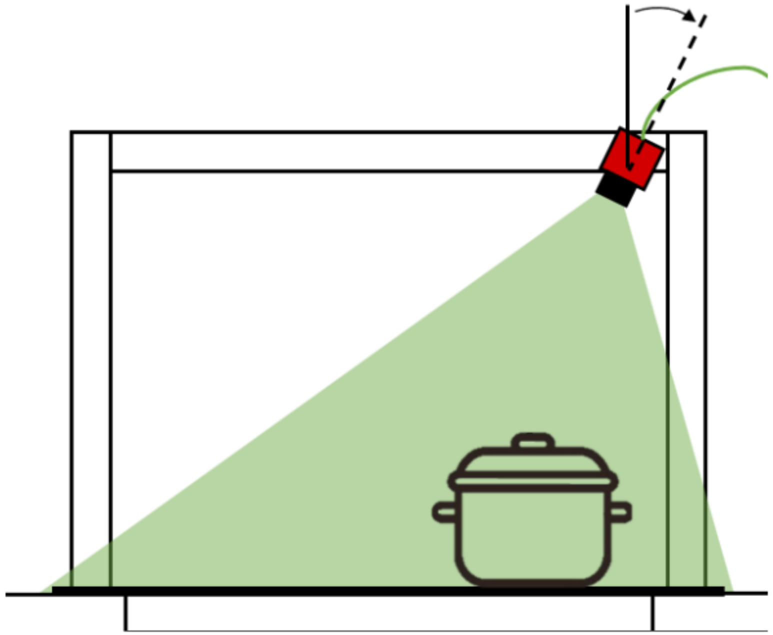
SET-UP

kitchenware

camera 1

camera 2





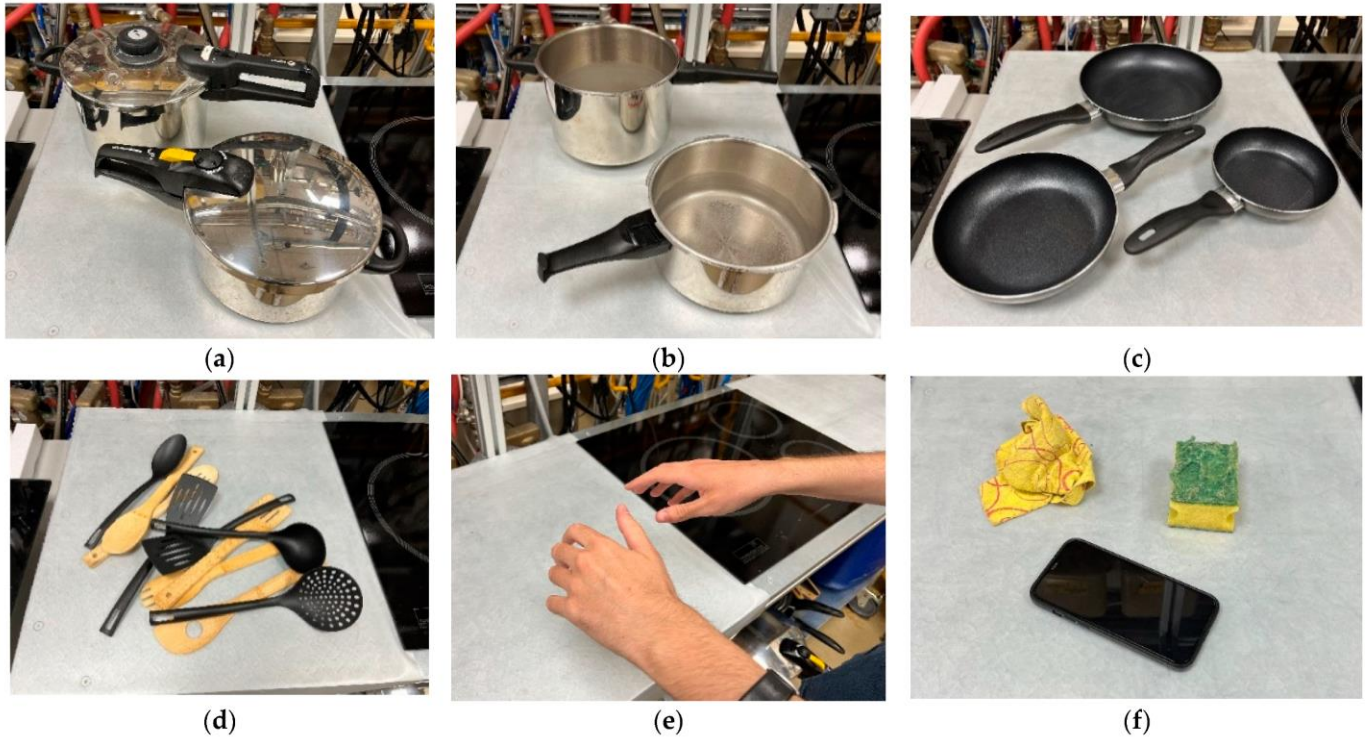
Functional mock-up where the experiments have been carried out

Schematic diagram of lateral camera positioning

cooktop with Bluetooth connectivity

DATASET

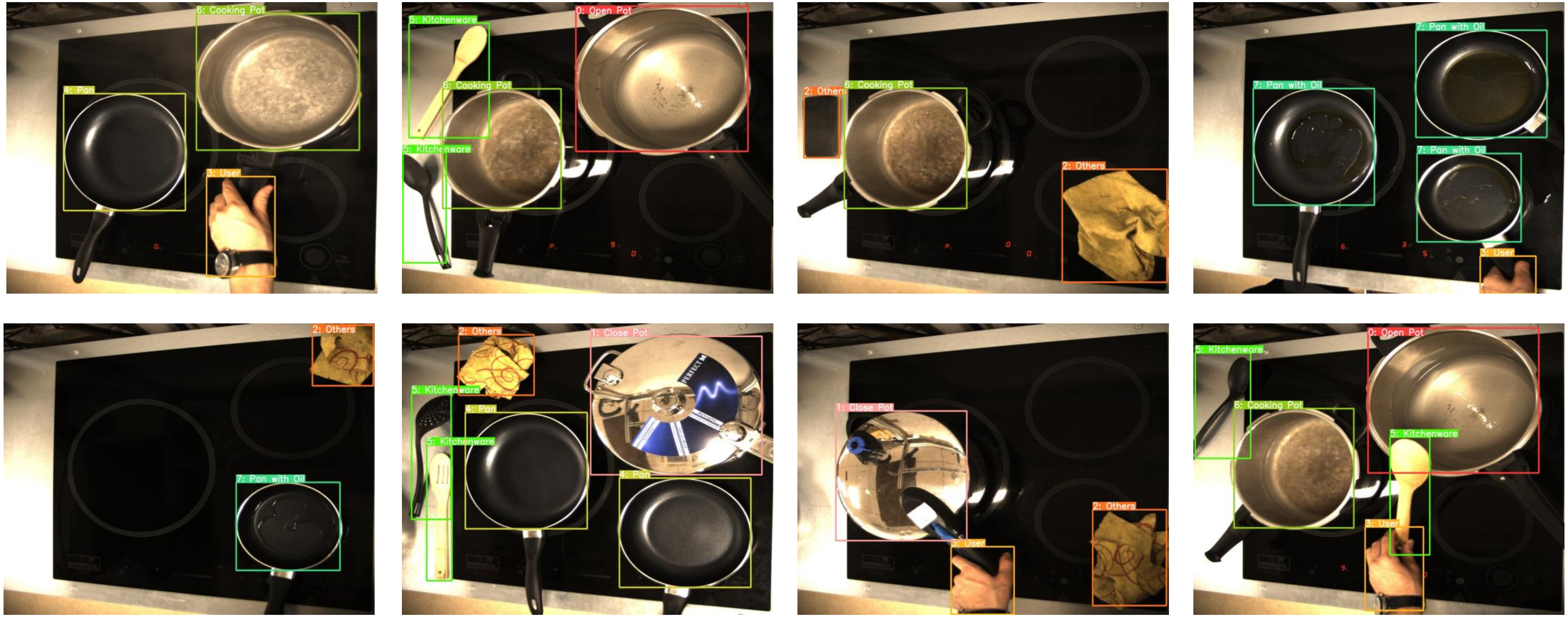
“ The generated dataset must be representative of deployed environment. For real-world use cases we recommend images from different times of day, different seasons, different weather, different lighting, different angles, different sources (scraped online, collected locally, different cameras) etc. ” (source: https://docs.ultralytics.com/yolov5)



Object detection dataset classes: (a) Closed pots; (b) Open pots; (c) Pans; (d) Kitchenware; (e) User; and (f) Others.

EXAMPLES

The generated dataset contains more than **7500** labelled **images**

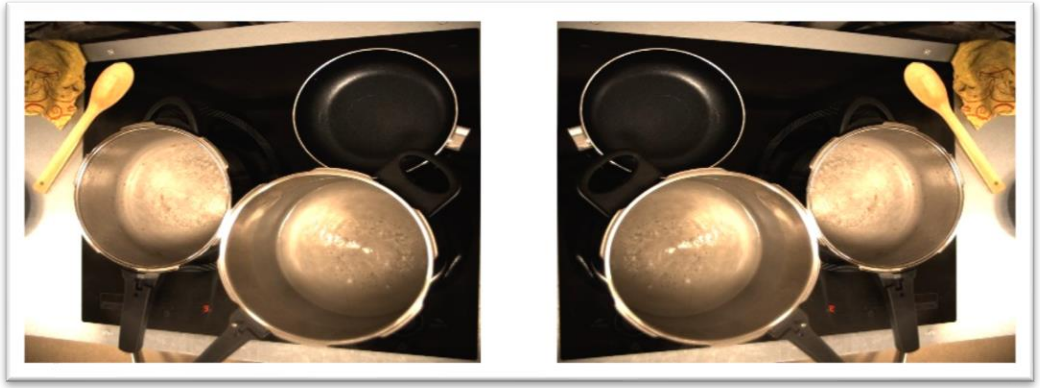


Examples of labelled images

DATA AUGMENTATION

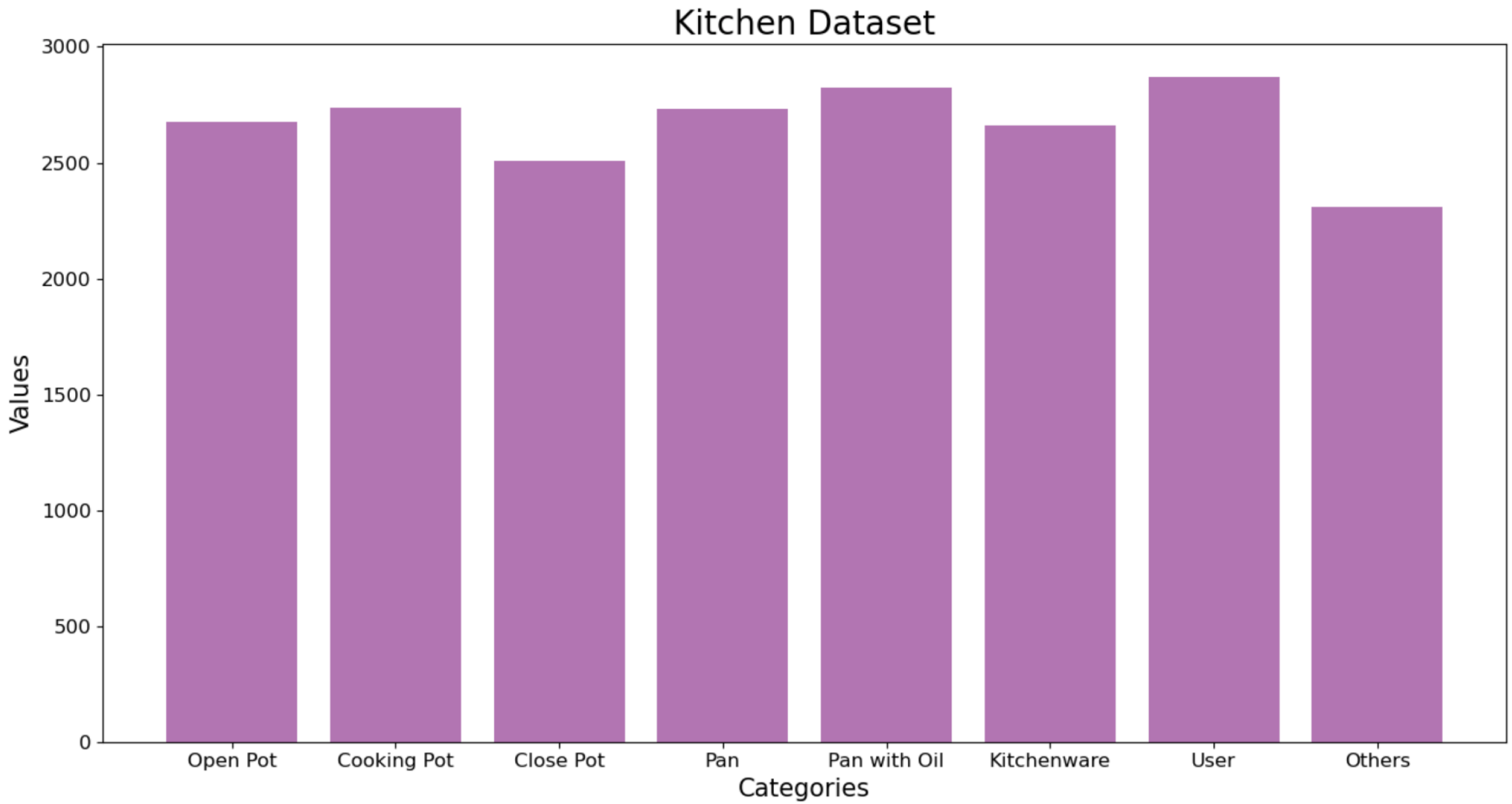
Data augmentation is a technique of artificially increasing the training set by creating modified copies of a dataset using existing data.

image flipping



random brightness and contrast

CLASS DISTRIBUTION

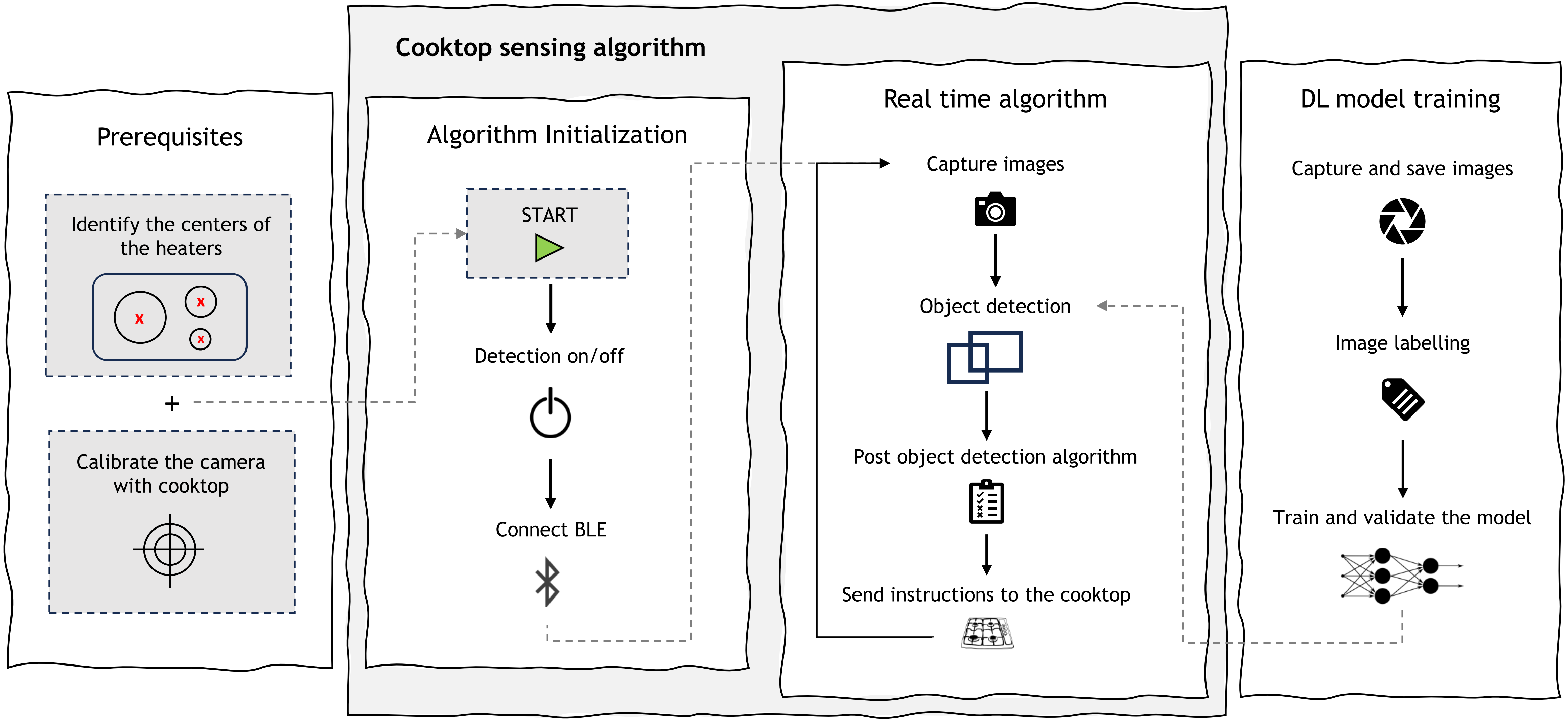


RESULTS

The results do not vary considerably between the different architectures: the maximum difference between all the models is less than 1%

Model	Params (M)	Batch size	Precision	Recall	mAP 0.5	FPS	Inference time (ms)	Training time (h)
YOLOv5n	1.9	32	0.988	0.992	0.994	84	9.3	5.48
YOLOv6n	4.3	32	0.984	0.990	0.994	43	17.2	6.07
YOLOv5s	7.2	32	0.991	0.993	0.994	80	10.3	5.88
YOLOv6s	17.2	16	0.994	0.990	0.997	42	20.6	9.38
YOLOv5m	21.2	16	0.992	0.995	0.994	73	11.9	10.45
YOLOv6m	34.3	8	0.995	0.990	0.997	39	23.5	20.71
YOLOv7	36.9	16	0.992	0.992	0.997	61	15	15.15
YOLOv5l	46.5	8	0.993	0.996	0.994	61	14.7	17.48

WORKFLOW



Cooktop sensing algorithm
Prerequisites
Identify the centers of the heaters
+
Calibrate the camera with cooktop
Algorithm Initialization
START
Detection on/off
Connect BLE
Real time algorithm
Capture images
Object detection
Post object detection algorithm
Send instructions to the cooktop
DL model training
Capture and save images
Image labelling
Train and validate the model

RESULTS

Automatic detection of kitchen switch-on and Bluetooth connection

(a) (b) (c)

Kitchen BLE connection sequence. (**a**) Kitchen and BLE off; (**b**) Kitchen ON and connecting BLE; and (**c**) Kitchen and BLE ON.

RESULTS

Cooking states recognition + automatic cooktop regulation

(a) (b) (c)

Boiling situation identification. (**a**) Open pot with maximum power but without boiling; (**b**) Open pot with boiling; and (**c**) Open pot without boiling and power has been reduced.

(a) (b) (c)

Pan with oil identification. (**a**) Normal pan without oil; (**b**) Identification of pan with oil; and (**c**) Pan with oil and power has been increased.

RESULTS

Recommendation of the best kitchen heater

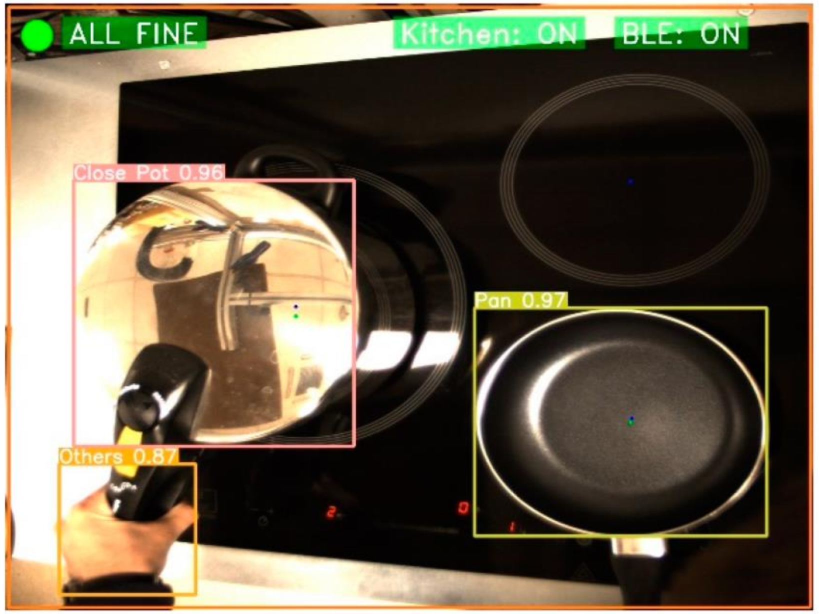
(a) (b) (c)

Example of a recommendation of the best kitchen heater. (**a**) Both pans can be repositioned; (**b**) The pan is in the right heater, but its position can be improved; and (**c**) The pans are perfectly placed.

RESULTS

User identification

(a)



(b)

User identification. (**a**) No user; and (**b**) User manipulating

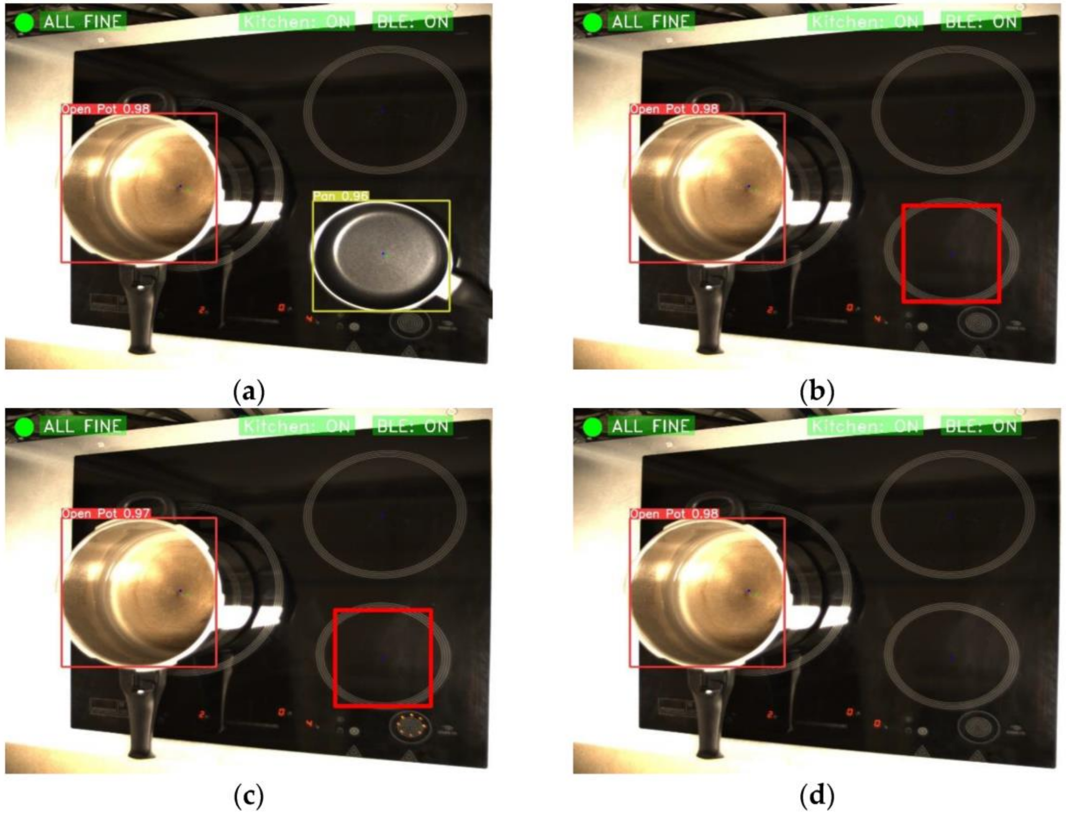
RESULTS

Recognition of high amount of kitchenware

Example of high amount of kitchenware. (**a**) Good situation; and (**b**) Identification of high amount of kitchenware.

RESULTS

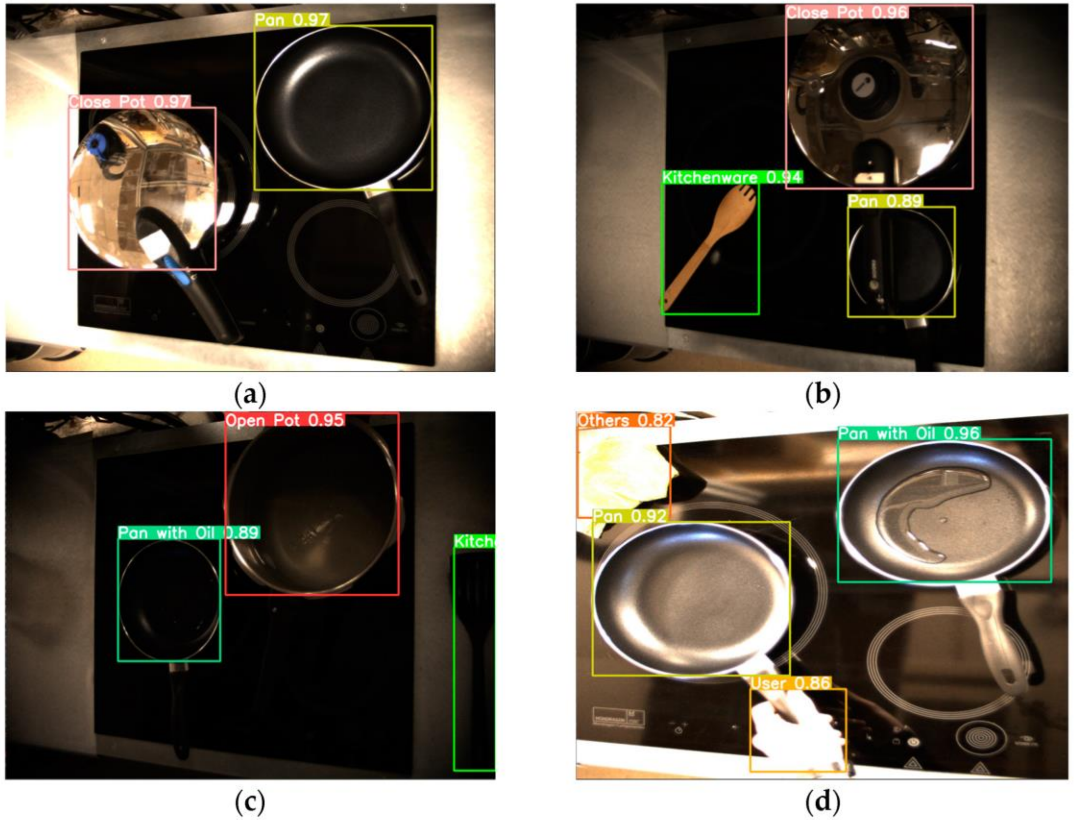
Example of detection of a heater with no cookware



Example of high amount of kitchenware. (**a**) Start situation of the example; (**b**) The algorithm has detected that a heater is ON without cookware; (**c**) The command to switch OFF the heater is sent; and (**d**) The burner is OFF.

RESULTS

Testing the algorithm under different light conditions & different image cropping



Developed algorithm under different light conditions. (**a**) Wider and lighter framing; (**b**) Wider framing and less light; (**c**) Wider framing and low light; and (**d**) Lighter and tighter framing.

CONCLUSIONS

1 First time DL to automatically control the cooktop

Good performance under different scenarios

YOLOv5 is good and fast for the application

Future work involves deploying the algorithm in a low-cost device (Coral, MCU...)

BIBLIOGRAPHY

[1] Sagues-Tanco, R.; Benages-Pardo, L.; Lopez-Nicolas, G.; Llorente, S. Fast Synthetic Dataset for Kitchen Object Segmentation in Deep Learning. IEEE Access 2020, 8, 220496–220506.

[2] Le, H.; Nguyen, M.; Yan, W.Q.; Nguyen, H. Augmented Reality and Machine Learning Incorporation Using YOLOv3 and ARKit. Appl. Sci. **2021**, 11, 6006.

[3] Karoly, A.I.; Galambos, P.; Kuti, J.; Rudas, I.J. Deep Learning in Robotics: Survey on Model Structures and Training Strategies. IEEE Trans. Syst. Man. Cybern. Syst. 2021, 51, 266–279.

[4] Mitchell, T.M. Machine Learning; McGraw Hill Series in Computer Science; McGraw-Hill: New York, NY, USA, 1997.

[5] He, X.; Zhao, K.; Chu, X. AutoML: A Survey of the State-of-the-Art. Knowl.-Based Syst. 2021, 212, 106622.

[6] Zhang, Y.; Gorriz, J.M.; Dong, Z. Deep Learning in Medical Image Analysis. J. Imaging 2021, 7, 74.

[7] Goodfellow, I.; Bengio, Y.; Courville, A. Deep Learning; MIT Press: Cambridge, CA, USA, 2016.

[8] LeCun, Y.; Bengio, Y.; Hinton, G. Deep Learning. Nature 2015, 521, 436–444.

[9] Glenn Jocher YOLOv5. Available online: https://github.com/ultralytics/yolov5.

** Some of the images have been generated with Leonardo AI **

Universidad del País Vasco
Euskal Herriko Unibertsitatea
VITORIA-GASTEIZKO INGENIARITZA ESKOLA
ESCUELA DE INGENIERÍA DE VITORIA-GASTEIZ

centro stirling

THANK YOU

iazurmendi@centrostirling.com iker.azurmendi@ehu.eus