UNIVERSITY OF PADUA

INFORMATION ENGINEERING DEPARTMENT (DEI)

MASTER'S DEGREE IN COMPUTER ENGINEERING

Computer Vision Report

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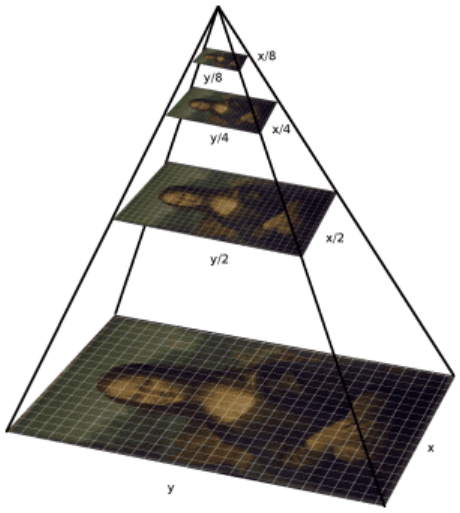
Contents

Chapter 1

Hand Detection

In this project, the key idea is to convert an image classifier into an object detector. In particular, we explore a pre-trained ResNet50V2 CNN trained on the ImageNet dataset. Moreover, we make use of image pyramid and sliding windows. Regarding image pyramid, it consists of different layers, each one representing an image at a different scale and usually a smoothing filter is applied. In our code, we implement *getGaussianPyramid(cv::Mat image)* that computes image pyramid by employing a gaussian filter.
Another essential tool in our work is sliding windows. A sliding window is composed by a rectangle of a given size that we translate from left-to-right and top-to-bottom into an image. For each window, we compute the subsequent steps:

1. Obtain the region of interest
2. Apply the image classifier to the ROI
3. Get the final predictions, together with the confidence score

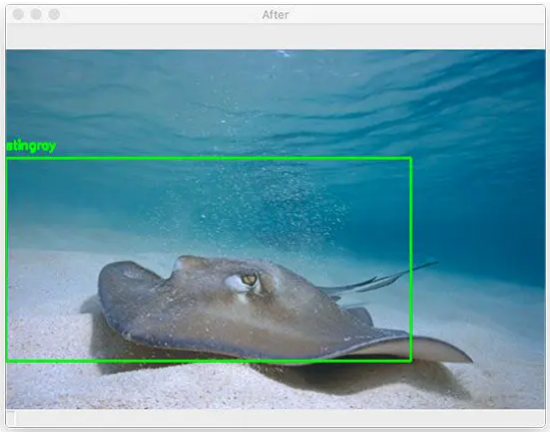


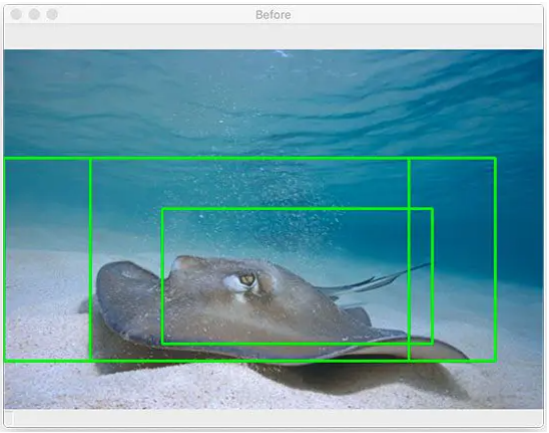
Thanks to image pyramid and sliding windows, we can consider a rectangle at various locations and various scales of the input image. The problem with this procedure are the different bounding boxes surrounding the same object. To deal with this issue, we apply non-maxima suppression. This method allows to maintain only the stronger bounding box, eliminating the extraneous ones. Consider the set P of all the predicted bounding boxes, comprehensive of the confidence score and the overlap threshold, the non-maxima suppression approach goes as follow:

1. Delete from P the bounding box S with the top confidence score, and add it to a list F, initially empty, representing the predictions that we maintain

2. Compute IoU between S and any other prediction T present in P. Delete T from P only if each resulting IoU is greater than the overlap threshold.

3. If P is empty return F and stop, otherwise compute step 1 and step 2





Finally, the last step applied is one that is used to remove occlusions. Such step consist of removing the bounding boxes obtained after Non Maxima Suppression that may not contain an hand. In particular such step consist of, for each bounding box after Non Maxima Suppresion (notice that, this step can be only applied if the orginal image was not a grayscale image) :

1. Get the ROI identified by selected bounding boxes

2. Convert the ROI to an image into the color space YCrCb

3. Threshold the ROI with a certain range of colors (range of the skin color)

4. Compute $percentage = \frac{\#pixels\ equal\ to\ 255\ in\ thresholded\ image}{image\ size}$

5. Reject the bounding box if $percentage \leq threshold$

The detection task is quite time-consuming, principally do to the sliding window method. As future work, we suggest to reduce the computational complexity by using an alternative approach of sliding window.

Chapter 2

Hand Segmentation

We based our segmentation approach on DeepLabV3+ using ResNet18 as a backbone and perform the traininig in matlab. We combine four existing datasets: hand gesture dataset, hand over face dataset, egohand dataset and GTEA dataset. The resulting dataset was cleaned by removing images containing arm parts and test set images. Our final dataset is composed by 1003 images. The loss function employed in this project is the dice loss.

2.1 Data Augmentation

We use a data augmentation technique with the aim of increasing the size of the starting dataset and therefore increasing the performance of the classification system. We use both shape-based and color-based transformation and in particular eleven artificial images are created for each image in the dataset. The operations performed are:

1. The image is displaced to the right or the left.
2. The image is displaced up or down.
3. The image is rotated by an angle randomly selected from the range [0° 180°].
4. Horizontal or vertical shear by using the function *randomAffine2d*.
5. Horizontal or vertical flip.
6. Change in the brightness levels by adding the same value to each RGB channel.
7. Change in the brightness levels by adding different values to each RGB channel.
8. Add speckle noise by using the function *imnoise*.
9. Application of the technique "Contrast and Motion Blur", described below.
10. Application of the technique "Shadows", described below.
11. Convertion of the truecolor image RGB to the grayscale image.

2.1.1 Contrast and Motion Blur

This transformation is the composition of two alterations: firstly, it is necessary to modify the contrast of the original image, increasing or decreasing it, then a filter that simulates the movement of the camera is

applied. Two functions to modify the contrast are implemented, but only one randomly chosen between the two is applied to the image. The first contrast function is based on the following equation:

$$\frac{(x-\frac{1}{2})\sqrt{1-\frac{k}{4}}}{\sqrt{1-k(x-\frac{1}{2})^2}}+0.5, k \leq 4$$

The parameter k controls the contrast, there is an increase in contrast if $k < 0$, a decrease in contrast if $0 < k \leq 4$, the image remains the same when $k = 0$. In the code, k is chosen randomly from a specific range, randomly chosen among the following four:

- U(2.8, 3.8) $\rightarrow$ Hard decrease in contrast.
- U(1.5, 2.5) $\rightarrow$ Soft decrease in contrast.
- U(-2, -1) $\rightarrow$ Soft increase in contrast.
- U(-5, -3) $\rightarrow$ Hard increase in contrast.

The second contrast function is based on the following equation:

$$y = \begin{cases} \frac{1}{2}(\frac{x}{0.5})\alpha, & 0 \leq x < \frac{1}{2} \\ 1-\frac{1}{2}(\frac{1-x}{0.5})\alpha, & \frac{1}{2} \leq x \leq 1 \end{cases}$$

The parameter α controls the contrast, there is an increase in contrast if $\alpha > 1$, a decrease in contrast if $0 < \alpha < 1$ and the image remains the same when $\alpha = 1$. This parameter is chosen randomly from four possible ranges:

- U(0.25, 0.5) $\rightarrow$ Hard decrease in contrast.
- U(0.6, 0.9) $\rightarrow$ Soft decrease in contrast.
- U(1.2, 1.7) $\rightarrow$ Soft increase in contrast.
- U(1.8, 2.3) $\rightarrow$ Hard increase in contrast.

2.1.2 Shadows

The final image is obtained by applying a shadow to the left or the right of the original image. In particular, the intensities of the columns are multiplied by the following equation:

$$y = \begin{cases} \min\left\{0.2+0.8\sqrt{\frac{x}{0.5}}, 1\right\} & direction = 1 \\ \min\left\{0.2+0.8\sqrt{\frac{1-x}{0.5}}, 1\right\} & direction = 0 \end{cases}$$

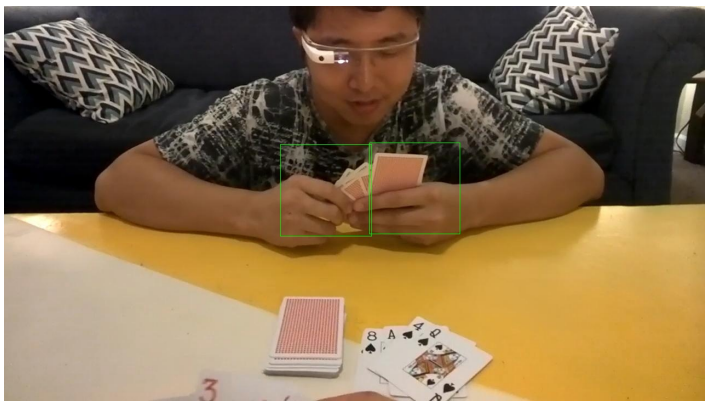
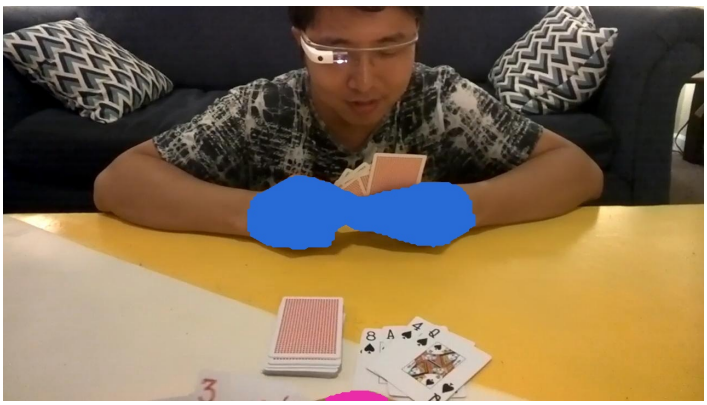
Chapter 3

Results

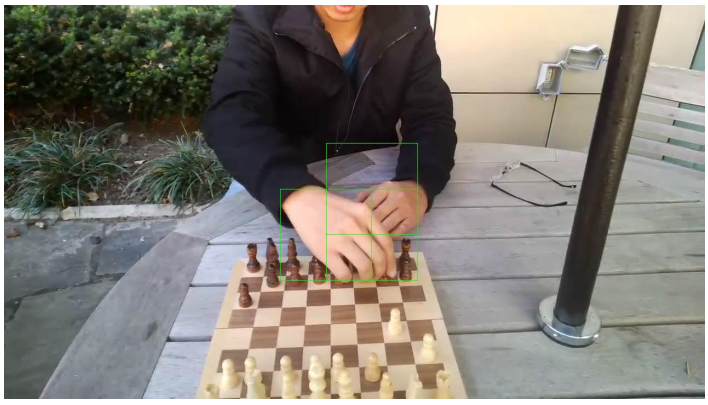
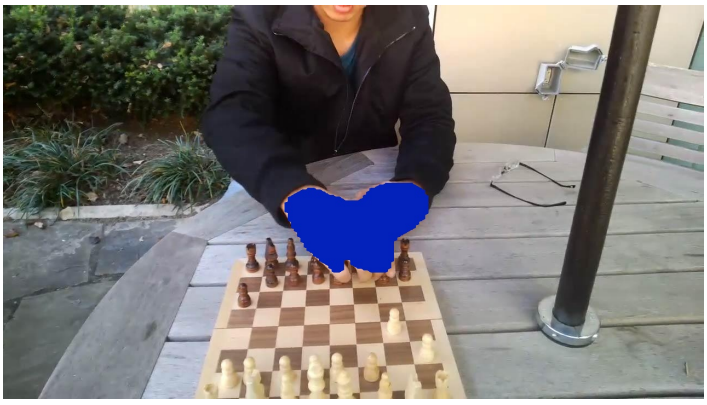
3.1 Ouput Images

The results will be listed below for each image of the test set :
(Notice that all the images will be displayed in the following way : Detection Image, Segmented Image)

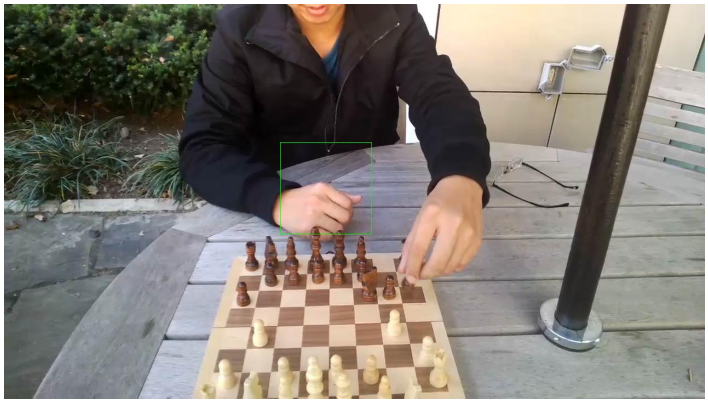
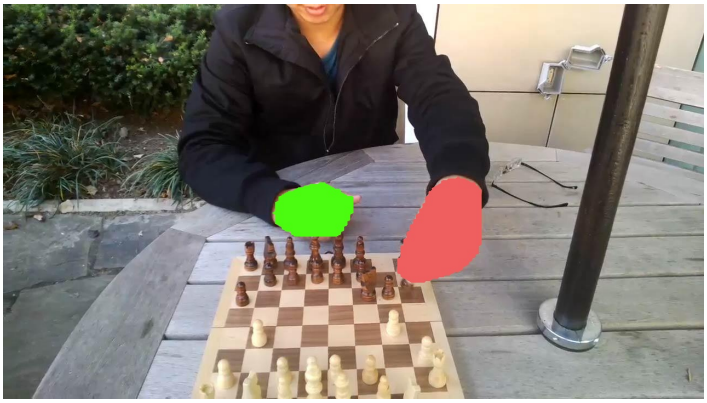
- 01.jpg:

- 02.jpg:

- 03.jpg:

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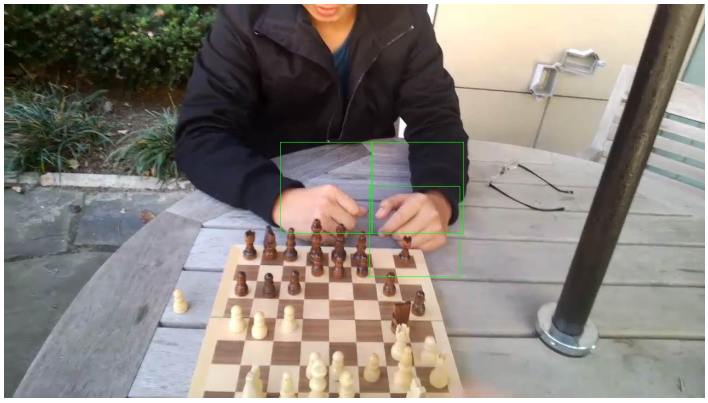
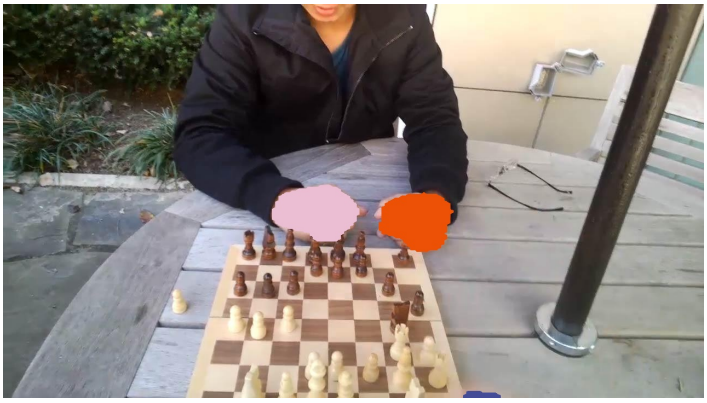

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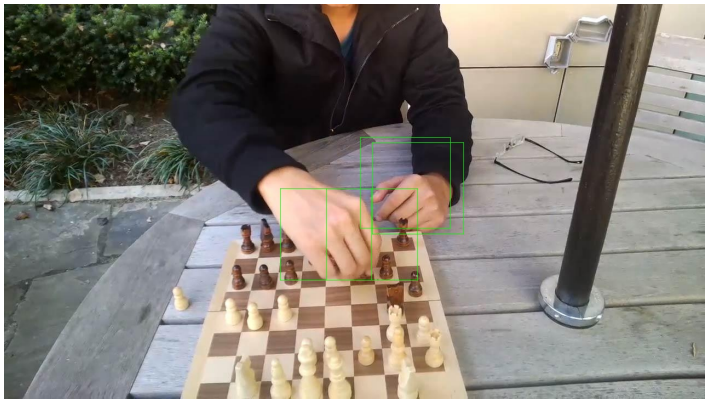
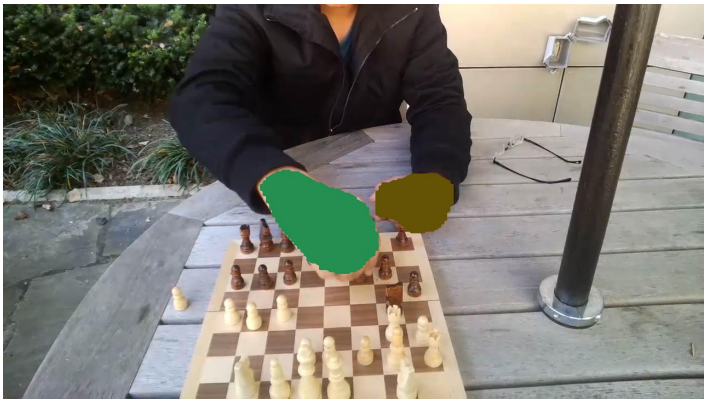

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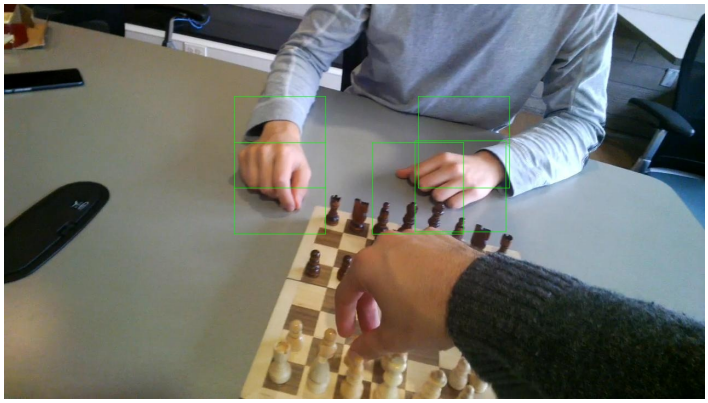
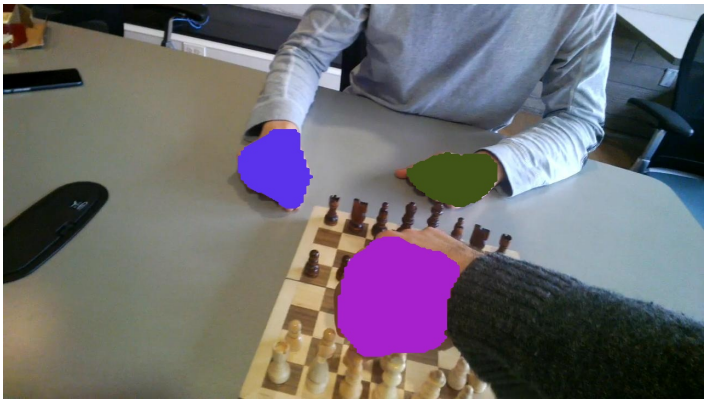

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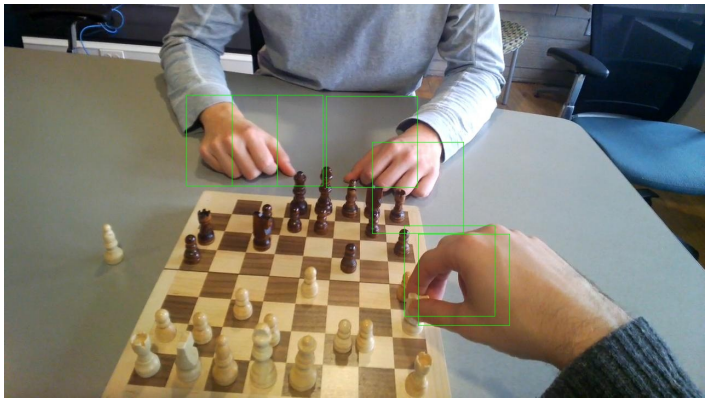
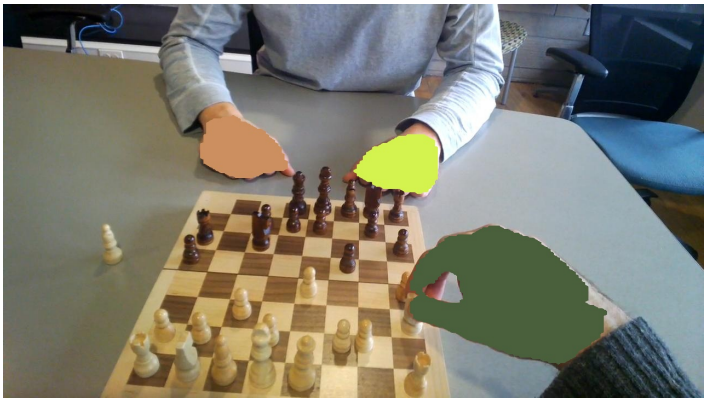

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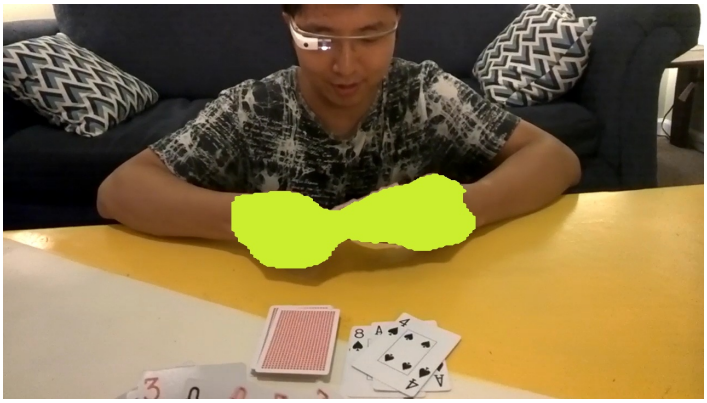

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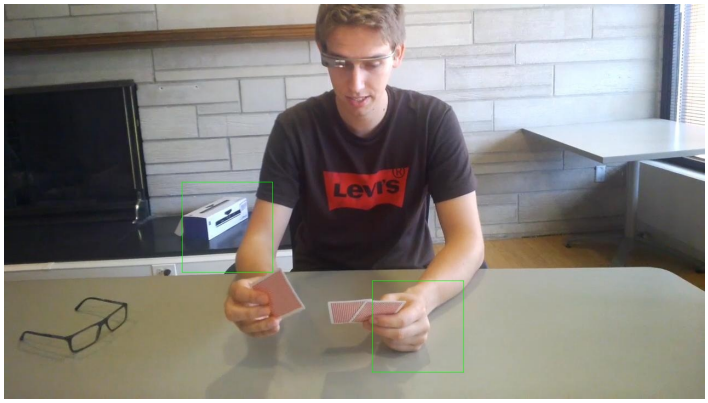
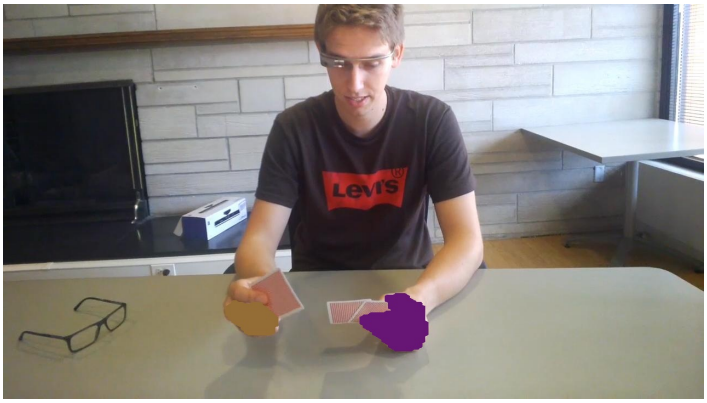

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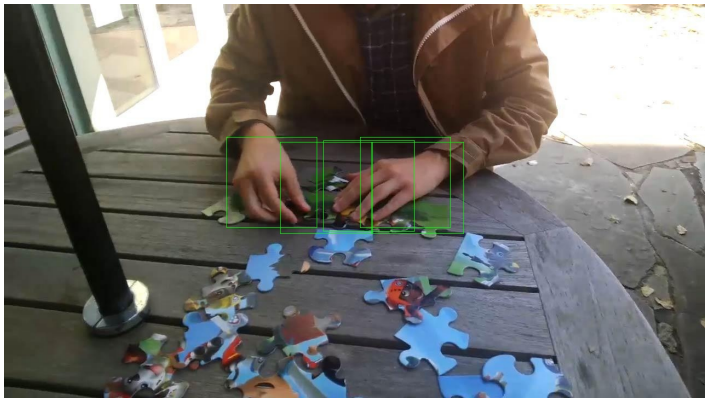


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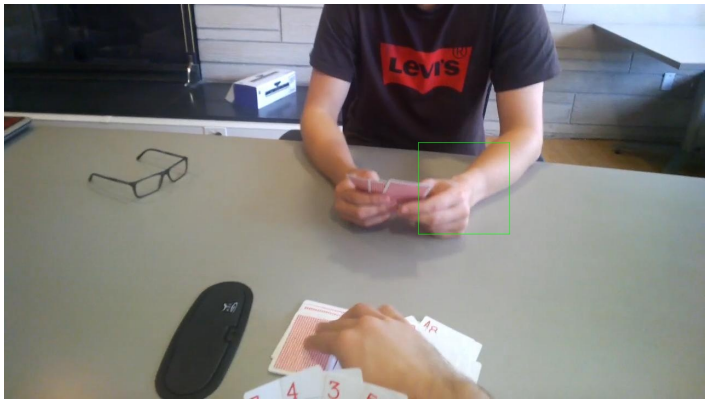
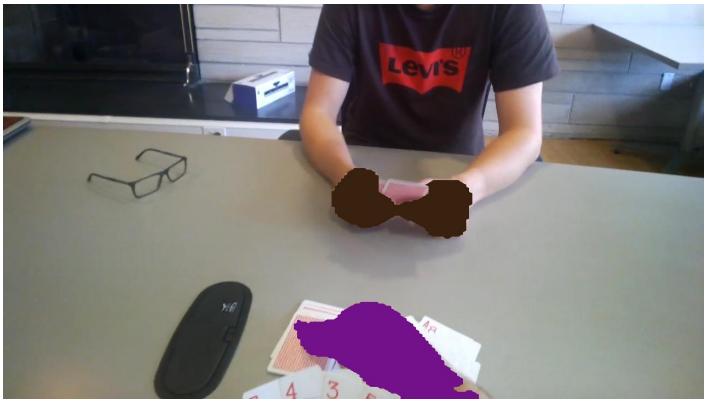

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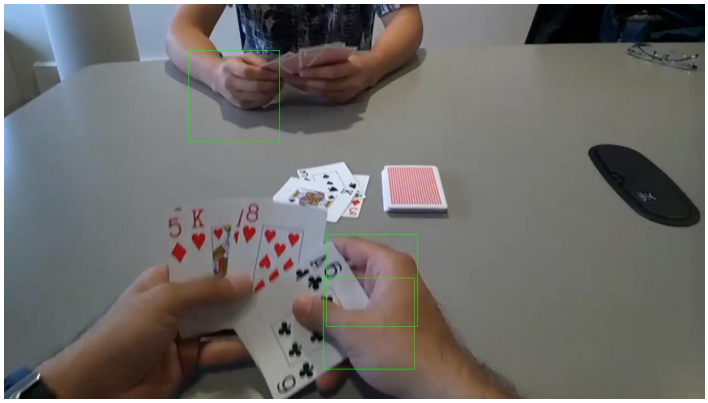


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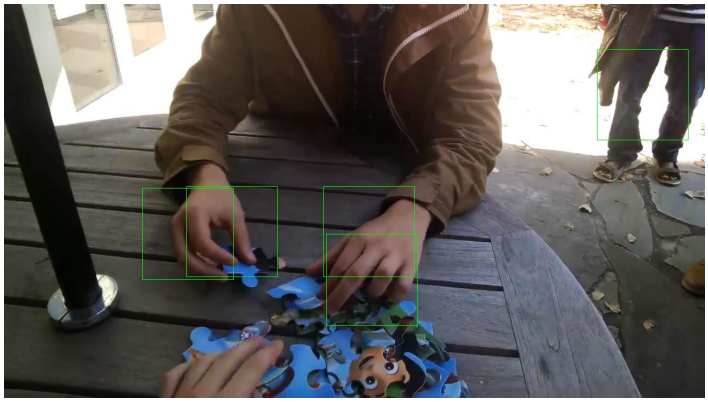


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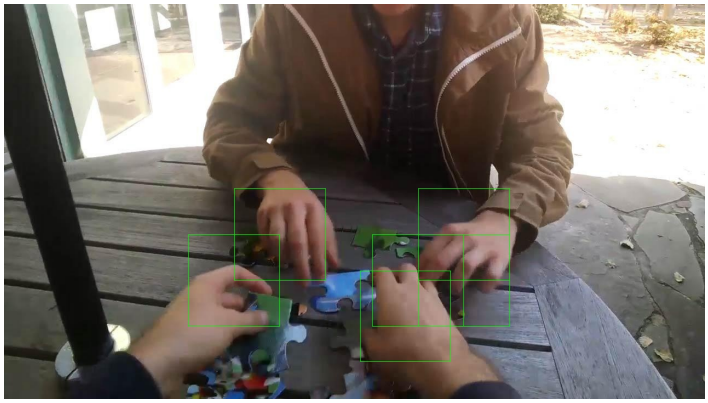


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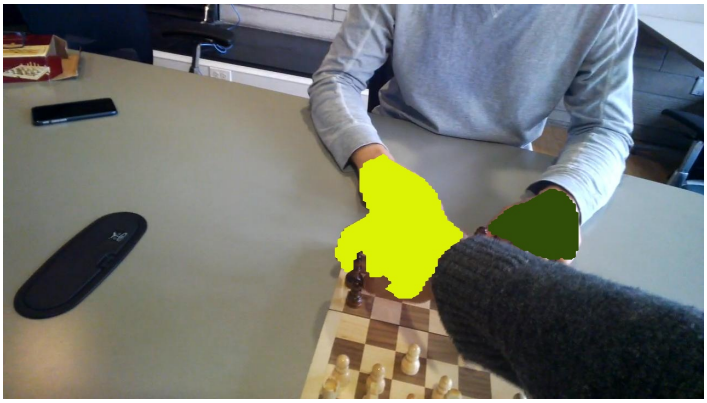

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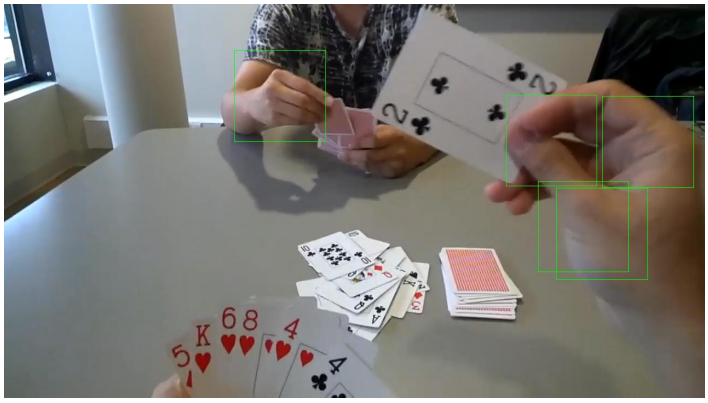


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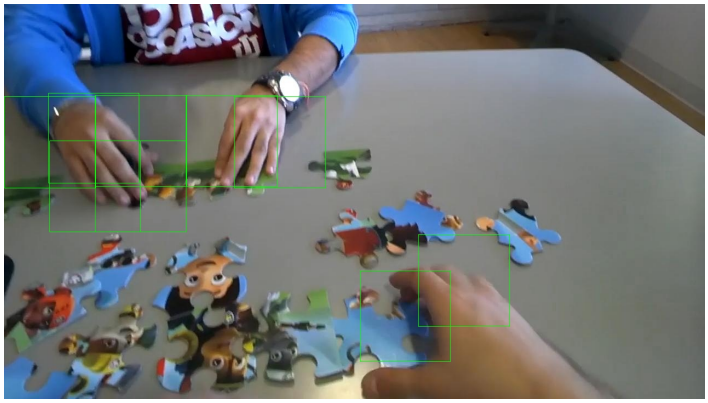
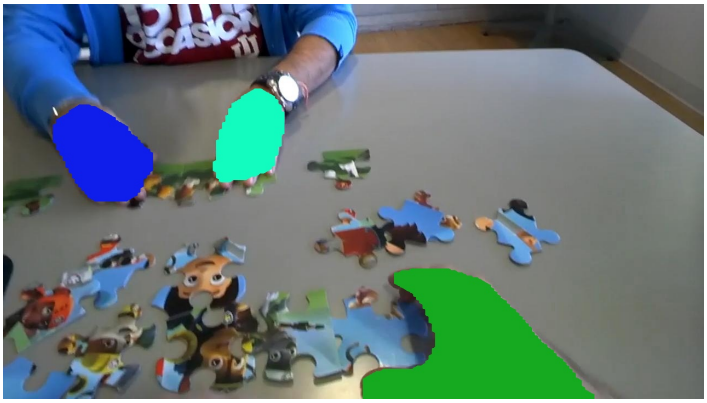

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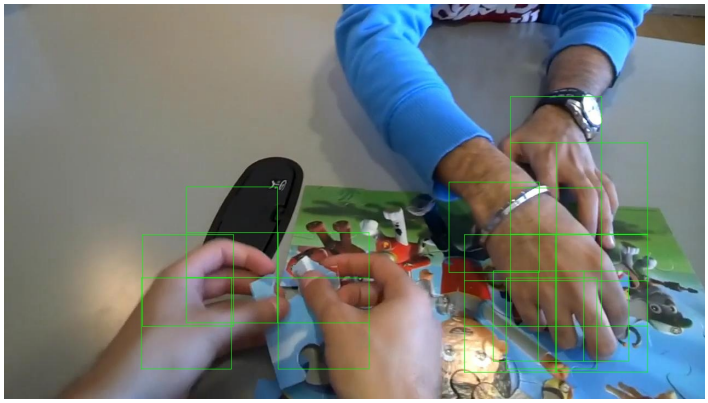


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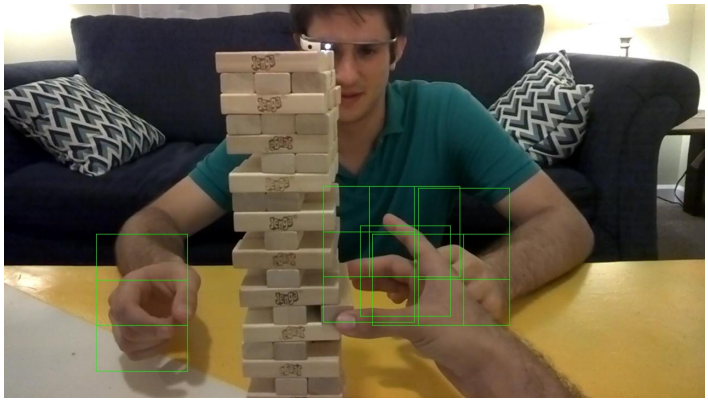
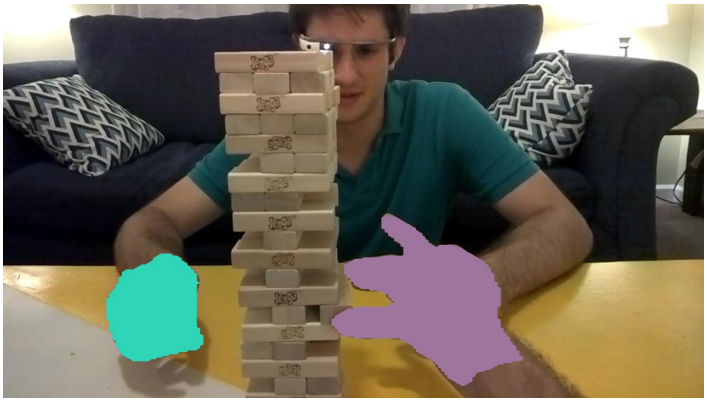
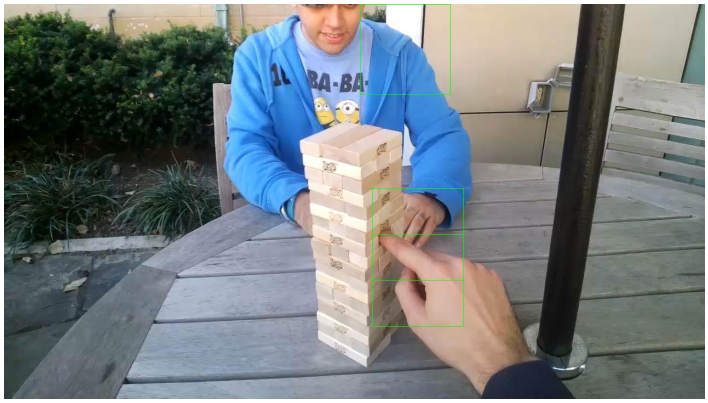
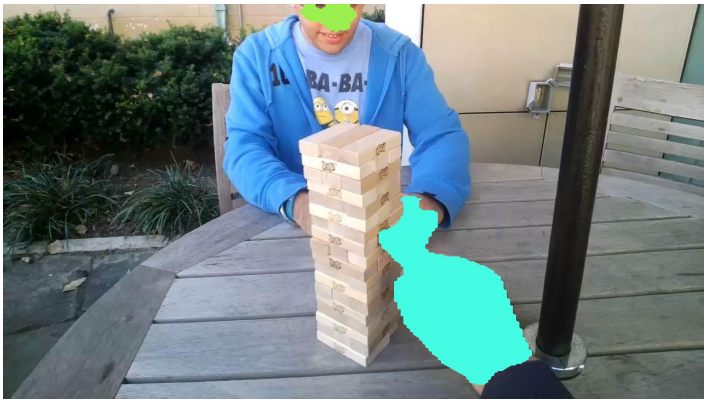



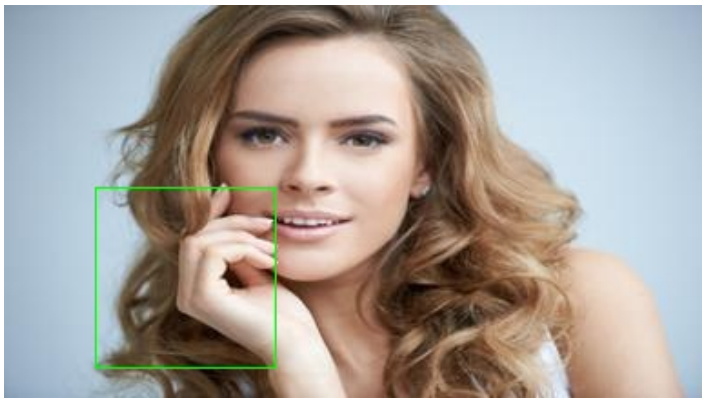
- 20.jpg:

- 21.jpg:


- 22.jpg:


- 23.jpg:



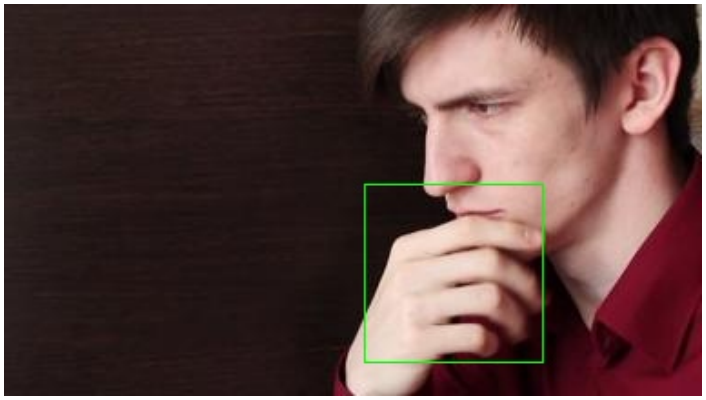

- 24.jpg:


- 25.jpg:


- 26.jpg:


- 27.jpg:


- 28.jpg:

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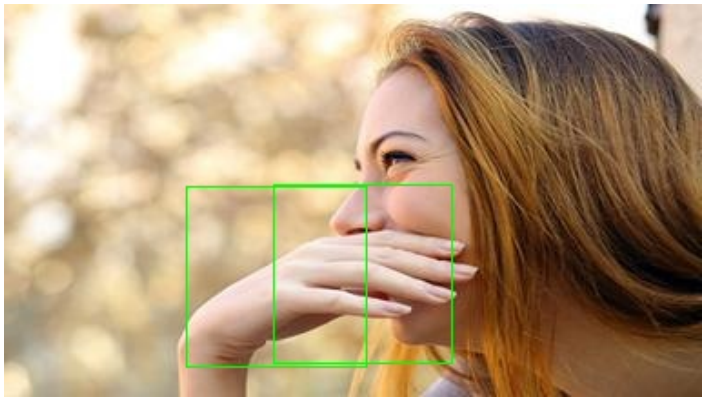


- 30.jpg:

3.2 Intersection Over Unions

Here will be shown the values of IOUs computed for each image :

Name Image	Intersection Over Union		
01.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 667 Y: 249 W: 166 H: 166	X: 631 Y: 318 W: 217 H: 217	0.428918
	X: 504 Y: 252 W: 168 H: 168	X: 453 Y: 308 W: 175 H: 175	0.367544
02.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 588 Y: 252 W: 168 H: 168	X: 641 Y: 322 W: 133 H: 133	0.355330
	X: 504 Y: 336 W: 168 H: 168	X: 518 Y: 339 W: 201 H: 201	0.702322
03.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 504 Y: 252 W: 168 H: 168	X: 727 Y: 322 W: 153 H: 153	0.000000
	X: 504 Y: 252 W: 168 H: 168	X: 493 Y: 328 W: 162 H: 162	0.452597
04.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 667 Y: 333 W: 166 H: 166	X: 682 Y: 347 W: 138 H: 138	0.530846
	X: 504 Y: 252 W: 168 H: 168	X: 489 Y: 331 W: 172 H: 172	0.430163
05.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 672 Y: 252 W: 168 H: 168	X: 669 Y: 316 W: 151 H: 151	0.529127
	X: 504 Y: 336 W: 168 H: 168	X: 483 Y: 312 W: 201 H: 201	0.712781
06.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 672 Y: 252 W: 168 H: 168	X: 620 Y: 414 W: 235 H: 235	0.012332
	X: 750 Y: 249 W: 167 H: 167	X: 730 Y: 273 W: 181 H: 181	0.508381
	X: 420 Y: 252 W: 168 H: 168	X: 437 Y: 224 W: 125 H: 125	0.492529
07.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 756 Y: 420 W: 168 H: 168	X: 740 Y: 413 W: 400 H: 400	0.283374
	X: 588 Y: 168 W: 168 H: 168	X: 627 Y: 221 W: 164 H: 164	0.439881
	X: 333 Y: 166 W: 167 H: 167	X: 365 Y: 190 W: 154 H: 154	0.606553
08.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 420 Y: 336 W: 168 H: 168	X: 627 Y: 314 W: 247 H: 247	0.000000
	X: 420 Y: 336 W: 168 H: 168	X: 430 Y: 339 W: 187 H: 187	0.663680
09.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 672 Y: 504 W: 168 H: 168	X: 668 Y: 533 W: 109 H: 109	0.341481
	X: 325 Y: 324 W: 166 H: 166	X: 406 Y: 490 W: 98 H: 98	0.000000
10.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 650 Y: 243 W: 166 H: 166	X: 608 Y: 276 W: 211 H: 211	0.595996
	X: 406 Y: 243 W: 166 H: 166	X: 421 Y: 234 W: 143 H: 143	0.813092
11.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 756 Y: 252 W: 168 H: 168	X: 557 Y: 545 W: 276 H: 276	0.000000
	X: 756 Y: 252 W: 168 H: 168	X: 734 Y: 325 W: 121 H: 121	0.297203
	X: 756 Y: 252 W: 168 H: 168	X: 598 Y: 302 W: 121 H: 121	0.000000
12.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 583 Y: 499 W: 167 H: 167	X: 68 Y: 469 W: 375 H: 375	0.000000
	X: 583 Y: 499 W: 167 H: 167	X: 536 Y: 430 W: 316 H: 316	0.311860
	X: 583 Y: 499 W: 167 H: 167	X: 525 Y: 93 W: 162 H: 162	0.000000
	X: 336 Y: 84 W: 168 H: 168	X: 385 Y: 96 W: 113 H: 113	0.408376

13.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 333 Y: 333 W: 167 H: 167	X: 285 Y: 611 W: 229 H: 229	0.000000
	X: 588 Y: 420 W: 168 H: 168	X: 554 Y: 365 W: 226 H: 226	0.502155
	X: 333 Y: 333 W: 167 H: 167	X: 299 Y: 305 W: 161 H: 161	0.533938
14.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 336 Y: 420 W: 168 H: 168	X: 256 Y: 477 W: 235 H: 235	0.273295
	X: 650 Y: 486 W: 166 H: 166	X: 659 Y: 473 W: 202 H: 202	0.564895
	X: 756 Y: 336 W: 168 H: 168	X: 757 Y: 391 W: 186 H: 186	0.536001
	X: 420 Y: 336 W: 168 H: 168	X: 459 Y: 312 W: 153 H: 153	0.583333
15.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 672 Y: 252 W: 168 H: 168	X: 617 Y: 366 W: 214 H: 214	0.153860
	X: 924 Y: 336 W: 168 H: 168	X: 893 Y: 337 W: 158 H: 158	0.522181
	X: 672 Y: 252 W: 168 H: 168	X: 654 Y: 271 W: 152 H: 152	0.512800
16.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 917 Y: 166 W: 166 H: 166	X: 264 Y: 670 W: 61 H: 61	0.000000
	X: 1008 Y: 336 W: 168 H: 168	X: 873 Y: 142 W: 405 H: 405	0.159837
	X: 917 Y: 166 W: 166 H: 166	X: 633 Y: 219 W: 162 H: 162	0.000000
	X: 420 Y: 84 W: 168 H: 168	X: 440 Y: 127 W: 160 H: 160	0.507814
17.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 650 Y: 486 W: 166 H: 166	X: 654 Y: 482 W: 432 H: 432	0.262064
	X: 333 Y: 166 W: 167 H: 167	X: 389 Y: 156 W: 122 H: 122	0.599011
	X: 81 Y: 162 W: 166 H: 166	X: 97 Y: 181 W: 181 H: 181	0.567167
18.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 250 Y: 499 W: 166 H: 166	X: 150 Y: 430 W: 360 H: 360	0.269250
	X: 500 Y: 499 W: 167 H: 167	X: 542 Y: 456 W: 255 H: 255	0.280827
	X: 924 Y: 252 W: 168 H: 168	X: 917 Y: 192 W: 207 H: 207	0.543218
	X: 924 Y: 420 W: 168 H: 168	X: 880 Y: 346 W: 261 H: 261	0.356891
19.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 672 Y: 420 W: 168 H: 168	X: 619 Y: 390 W: 295 H: 295	0.324321
	X: 756 Y: 420 W: 168 H: 168	X: 785 Y: 447 W: 130 H: 130	0.580357
	X: 168 Y: 504 W: 168 H: 168	X: 187 Y: 479 W: 174 H: 174	0.600541
20.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 672 Y: 420 W: 168 H: 168	X: 686 Y: 413 W: 266 H: 266	0.367250
	X: 672 Y: 336 W: 168 H: 168	X: 729 Y: 342 W: 77 H: 77	0.270089
	X: 672 Y: 336 W: 168 H: 168	X: 544 Y: 348 W: 22 H: 22	0.000000
21.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 231 Y: 112 W: 76 H: 76	No Detections	0.000000
22.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 0 Y: 100 W: 100 H: 100	X: 145 Y: 41 W: 38 H: 38	0.000000
	X: 0 Y: 100 W: 100 H: 100	X: 15 Y: 168 W: 62 H: 62	0.194777
23.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 50 Y: 100 W: 100 H: 100	X: 94 Y: 96 W: 81 H: 81	0.418931
24.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 100 Y: 50 W: 100 H: 100	X: 110 Y: 81 W: 76 H: 76	0.421815
25.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 100 Y: 100 W: 100 H: 100	X: 89 Y: 115 W: 141 H: 141	0.581674
	X: 150 Y: 100 W: 100 H: 100	X: 132 Y: 106 W: 133 H: 133	0.622640

26.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 100 Y: 50 W: 100 H: 100	X: 73 Y: 71 W: 125 H: 125	0.382170
27.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 100 Y: 50 W: 100 H: 100	X: 135 Y: 64 W: 55 H: 55	0.441437
	X: 100 Y: 50 W: 100 H: 100	X: 230 Y: 100 W: 82 H: 82	0.000000
28.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 198 Y: 99 W: 99 H: 99	X: 188 Y: 115 W: 114 H: 114	0.638462
29.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 100 Y: 100 W: 100 H: 100	X: 95 Y: 124 W: 167 H : 167	0.492675
30.jpg	Bounding Box Detected	Bounding Box Ground Truth	IOUs
	X: 89 Y: 90 W: 68 H: 68	No Detections	0.000000

3.3 Pixel Accuracy

Here will be shown the values of Pixel Accuracies computed for each image :

Name Image	Pixel Accuracy
01.jpg	0.992141
02.jpg	0.995846
03.jpg	0.995306
04.jpg	0.994716
05.jpg	0.993231
06.jpg	0.98774
07.jpg	0.986778
08.jpg	0.987347
09.jpg	0.993686
10.jpg	0.993523
11.jpg	0.988424
12.jpg	0.974098
13.jpg	0.988409
14.jpg	0.975737
15.jpg	0.988674
16.jpg	0.955056
17.jpg	0.983872
18.jpg	0.962644
19.jpg	0.980672
20.jpg	0.987248
21.jpg	0.996202
22.jpg	0.972186
23.jpg	0.988329
24.jpg	0.980469
25.jpg	0.971161
26.jpg	0.984074
27.jpg	0.967496
28.jpg	0.989969
29.jpg	0.977913
30.jpg	0.994816

Chapter 4

Contribution

4.1 Hours of work

- Francesco Caldivezzi : In this project I have worked the following amount of hours :
  - Roughly 60 hours to develop the C++ code
  - Roughly 50 hours to develop the python and matlab code and write the README file
  - Roughly 30 hours to find a suitable solution for the project after the first several trials
  - Roughly 15 hours to write the report
- Daniela Cuza :
  - Roughly 30 hours to find and try various ideas (most of them didn't work)
  - Roughly 15 hours to search the datasets, combine and clean them (also from "black masks"), resize and convert the images into the correct format
  - Roughly 15 hours to develop the data augmentation technique
  - Roughly 20 hours to compute various tests by changing the backbone, data augmentation method and loss function, in order to find the approach with the best performance
  - Roughly 15 hours to write the report
- Simone D'antimo :
  - Roughly 15 hours to search for a suitable solution for project, dataset etc..
  - Roughly 2 hours for cleaning data
  - Roughly 30 hours to try to implement a CNN based solution for Segmentation problem (that wasn't supported by c++ OPENCV library)
  - Roughly 50 hours to develop C++ code
  - 2 hours to write and correct typo of the report

Chapter 5

Conclusions

5.1 Results Discussions

For what concerns the detection part, we can immediately observe that, some images have bounding boxes well detected, others instead not or they do not have any detections at all. The main reason why there are those problems are :

- Some of the images contains hands with different point of view and, by using a window with static size for all the images (different size for images from 01 to 20 and from 21 to 30) there are multiple detections for the same hand because it is too big compared to the window size. (This can be seen in images like 17,18.19,20 etc.)
- Moreover, other images have no detection at all, and this may be cause by the fact that some of the hands have very strong illumination like images 21 and 30.

Therefore, even if the result is not 100% accurate, still it's quite good, because there are only 14 values of the IOU out of 68 that have value equal to 0. So, we can say that the main issue of this solution is the time taken for processing a single image which is very high.

For what concerns instead the segmentation part, we can observe that, most of the hands are segmented quite well, in fact, all the values of pixel accuracy are above 0.95. However, some different hands have been interpreted (colored) as a single one. (For example in image 01, 02, 14, 15, 18 etc.). This is due to the fact that, when two hands are overlapping one to another the mask produced by the model is connected instead of being separated.

5.2 Future Works

To solve the problems of the detection solution proposed, we can adopt more sophisticated techniques like ad-hoc Neural Networks that are able to recognize objects, by fine-tuning them, in order to recognize only hands (i.e. Yolo, Fast-RCNN, Faster-RCNN, SSD).

To solve the problem of the segmentation solution proposed, we can proceed by applying an erosion operation on the mask, however if we do so, we need to apply a very strong erosion, with the problem of reducing drastically the size of the mask and therefore the pixel accuracy value will become noticeably small compared to the ones used now. Another way to solve this problem is to use again, ad-hoc / state of the art segmentation methods that, instead of producing the masks as output they will produce the polygons which identify different objects, which, in this case are hands.