

Segmentation is all you need?

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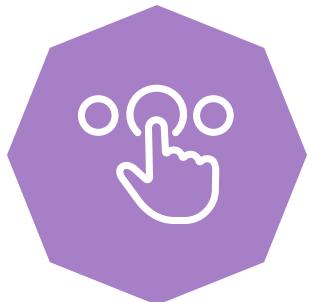
- 1 Introduction
- 2 Segmentation
- 3 Classification
- 4 Detection
- 5 Demo
- 6 Conclusion

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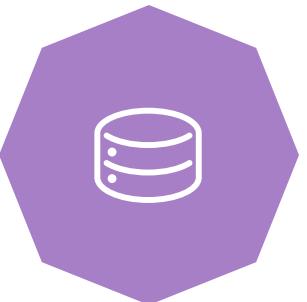
Introduction

Introduction

What does this work deal with?



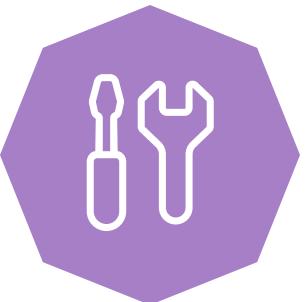
The problem



Dataset



The goal



Tools



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Segmentation

Segmentation

WHY IS IT USEFUL?

to simplify an image and reduce complexity

to extract meaningful information that can be exploited

to analyze an image more efficiently reducing time and costs

Segmentation

TECHNIQUES

1 Thresholding

2 Watershed

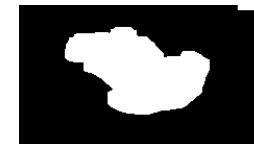
3 K-Means Clustering

4 K-Means Clustering adding pixel's coordinates

5 Mean Shift Clustering

Segmentation: Thresholding

- ★ The simplest type of image segmentation
- ★ Threshold has been found using Otsu's method
- ★ Estimated execution time for one image: ~0.492 seconds



Segmentation: Watershed



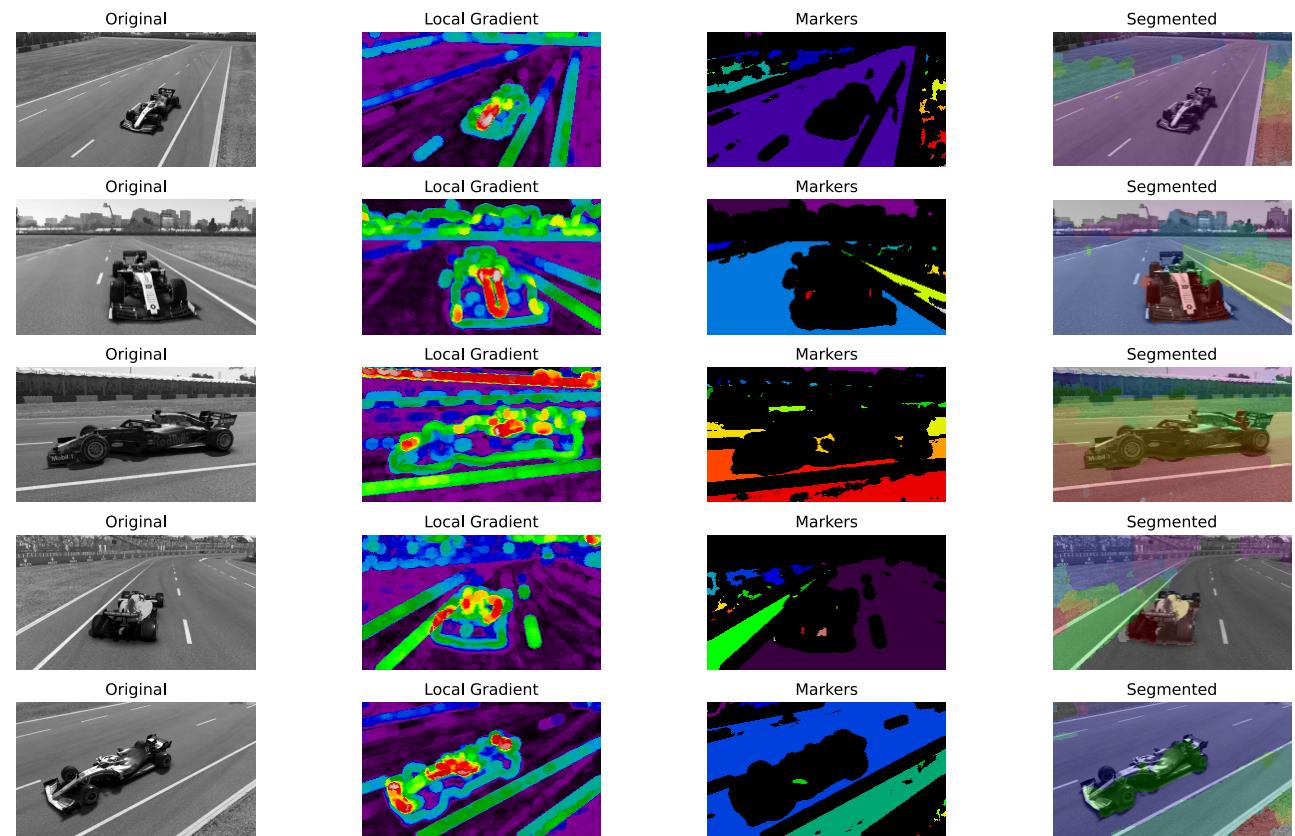
Watershed segmentation is a region-based technique that uses image's morphology



The watershed transform decomposes an image into catchment basins



Estimated execution time for one image: ~1.266 seconds



Segmentation: K-Means Clustering



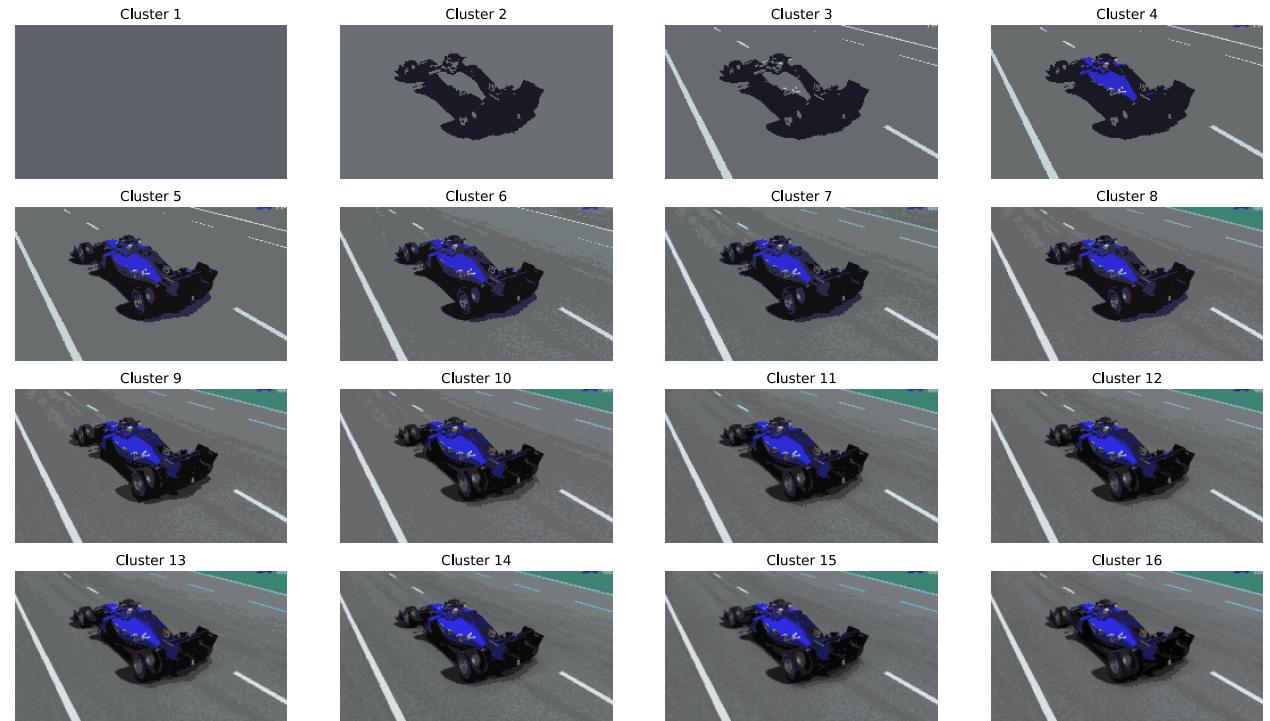
K-Means clustering is an unsupervised algorithm that can be used to reduce the complexity of the image



Groups pixel's in n given **clusters** based on a distance functions

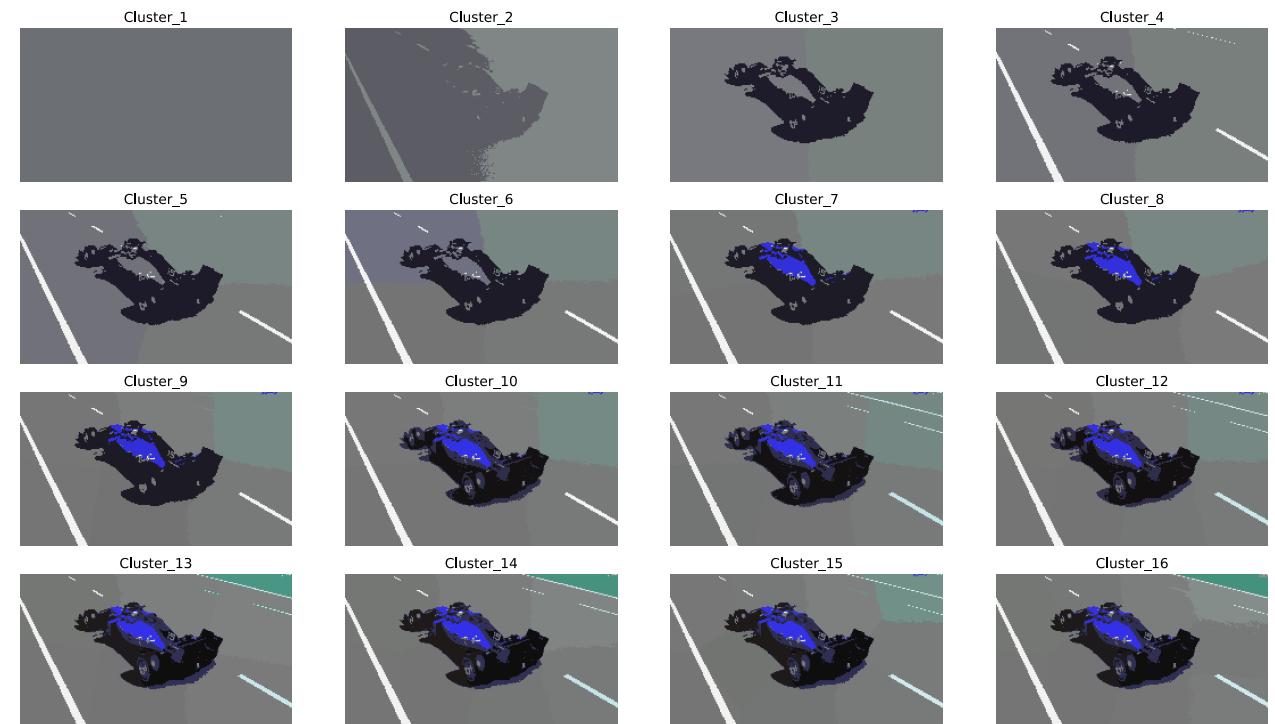


Estimated execution time for one image: ~0.402 seconds (depending on the number of clusters)



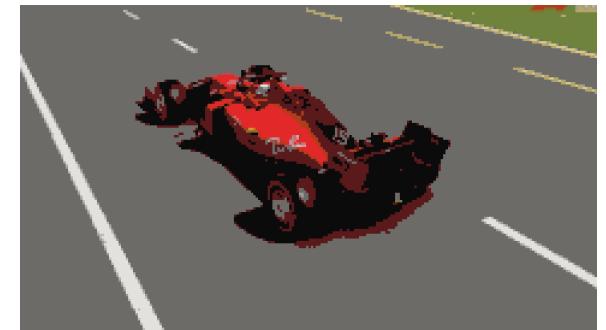
Segmentation: K-Means Clustering adding pixel's coordinates

- ★ An experiment to improve K-Means
- ★ Each pixels also contains the (x,y) coordinates of the matrix
- ★ Pixel that are close in the image have higher probability to be grouped together
- ★ Estimated execution time for one image: ~0.379 seconds (depending on the number of clusters)



Segmentation: Mean Shift Clustering

- ★ Unsupervised Learning algorithm that aims to group pixel in n cluster
- ★ The number of clusters is not given in advance
- ★ It discovers blobs in a density of samples
- ★ Computationally Expensive: $O(T*n^2)$ where T is the number of points and n is the number of samples
- ★ Estimated execution time for one image: ~ 2.782 seconds (depending on the given bandwidth)



Segmentation

TECHNIQUES

1 Thresholding

2 Watershed

3 K-Means Clustering

4 K-Means Clustering adding pixel's coordinates

5 Mean Shift Clustering

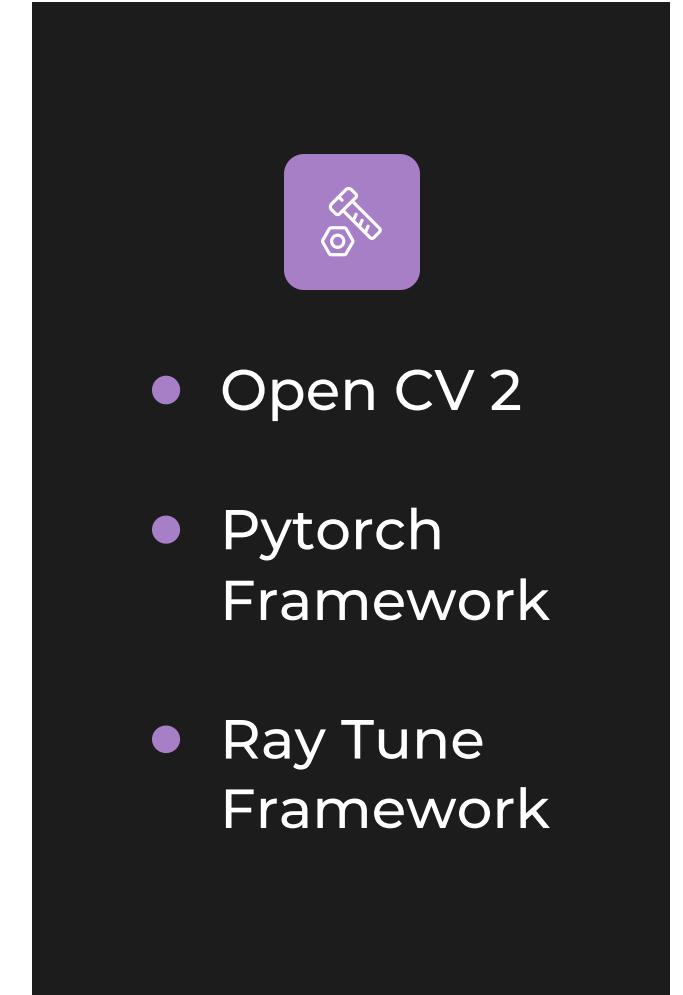
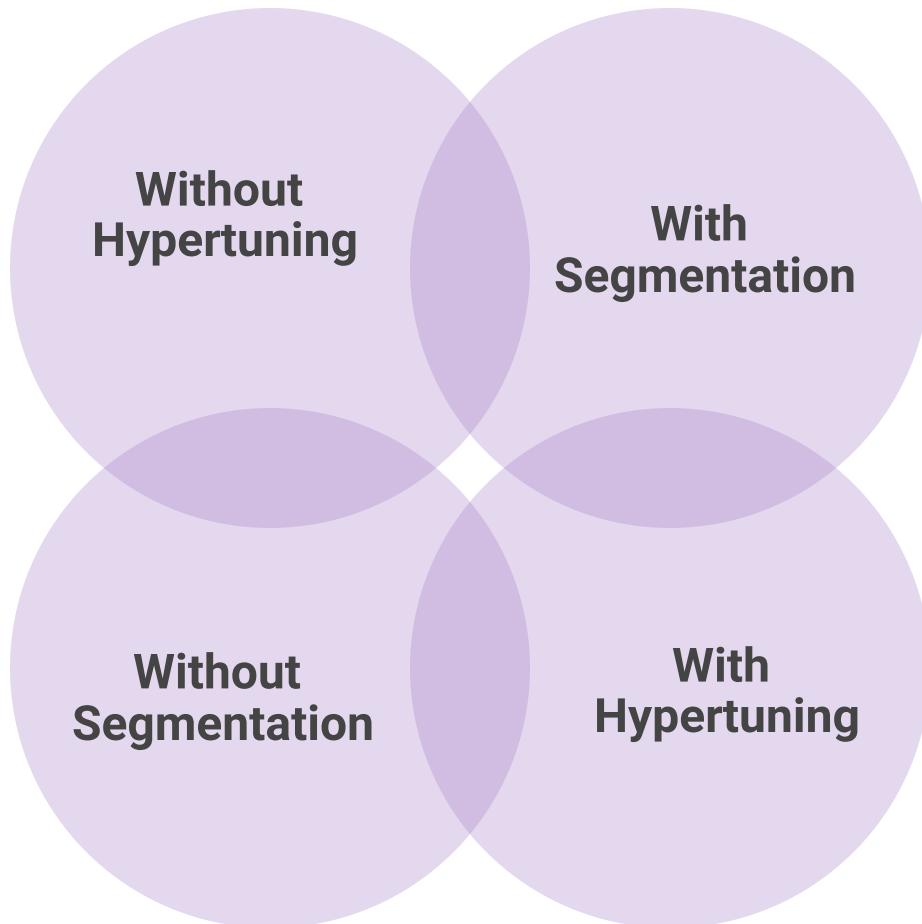


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Classification

Classification

STRATEGIES



Classification

WITHOUT HYPERTUNING

1 Convolutional Neural Network

2 Dropout Layer to avoid over-fitting

3 Simple Data Augmentation

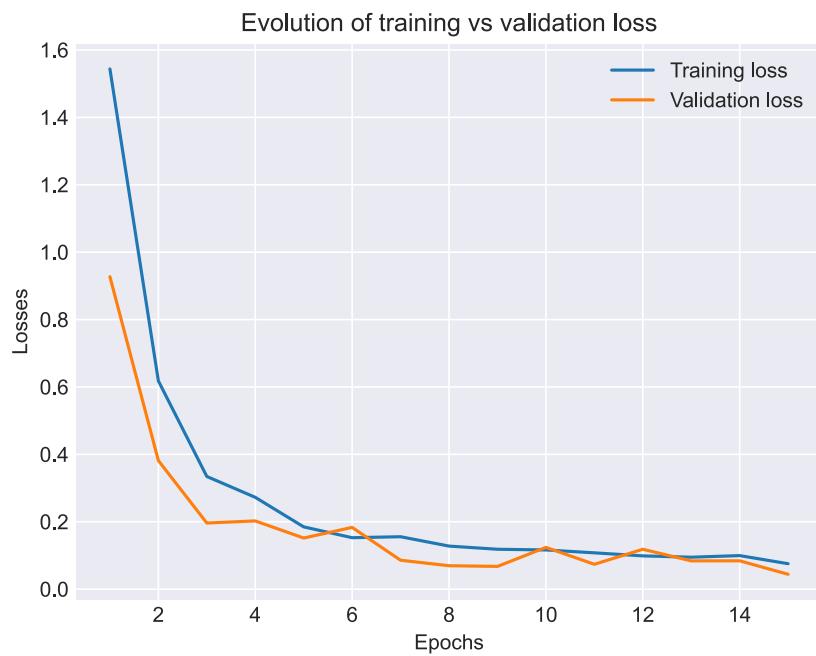
4 Early stopping

5 Weighed Cross Entropy

```
ConvNet(  
    (layer1): Sequential(  
        (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
        (1): ReLU()  
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    )  
    (layer2): Sequential(  
        (0): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
        (1): ReLU()  
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    )  
    (layer3): Sequential(  
        (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
        (1): ReLU()  
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
        (3): Dropout(p=0.5, inplace=False)  
    )  
    (flatten): Flatten(start_dim=1, end_dim=-1)  
    (fc): Sequential(  
        (0): Linear(in_features=30720, out_features=512, bias=True)  
        (1): ReLU()  
        (2): Linear(in_features=512, out_features=10, bias=True)  
    )  
)
```

Classification

WITHOUT HYPERTUNING



Without Segmentation

- Accuracy: 99%
- Training time: ~52 minutes



With Segmentation

- Accuracy: 95%
- Training time: ~70 minutes

Classification

SEGMENTATION WITH HYPERTUNING

1 Convolutional Neural Network

2 Tuned params:

- *num of layers*
- *output of convolutional layers*
- *output of linear layer*
- *learning rate*
- *weight decay*
- *dropout probability*

```
ConvNet(  
    (layer1): Sequential(  
        (0): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
        (1): ReLU()  
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
    )  
    (layer2): Sequential(  
        (0): Conv2d(16, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
        (1): ReLU()  
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)  
        (3): Dropout(p=0.5, inplace=False)  
    )  
    (flatten): Flatten(start_dim=1, end_dim=-1)  
    (fc): Sequential(  
        (0): Linear(in_features=253440, out_features=256, bias=True)  
        (1): ReLU()  
        (2): Linear(in_features=256, out_features=10, bias=True)  
    )  
)
```

Classification

SEGMENTATION WITH HYPERTUNING



Results

- Accuracy: 95%
- Training time: 25 min



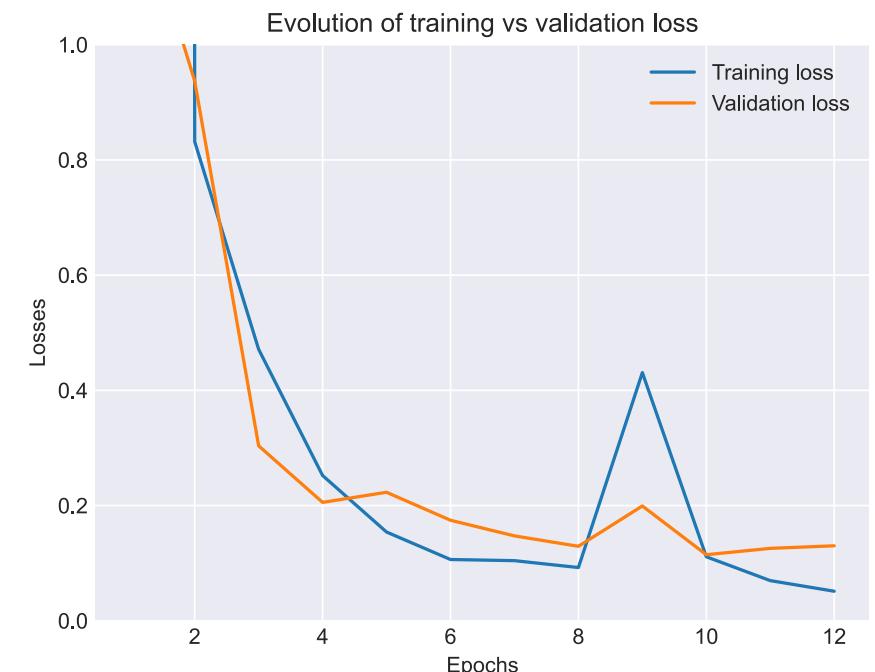
Training time reduced from both of the two previous model



Same accuracy of the non-hypertuned model but lower than the model without segmentation



Lower accuracy per class with respect to both previous model



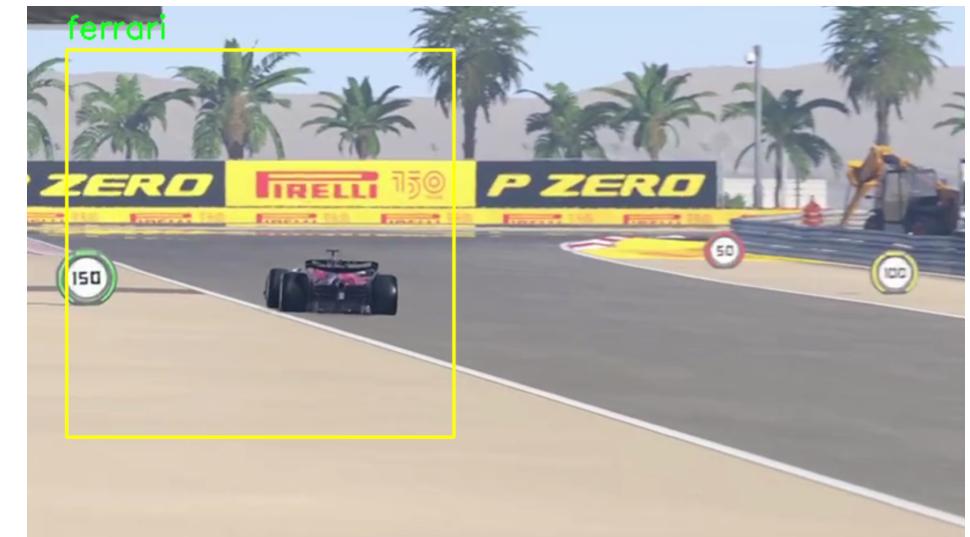
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Detection

Detection & Annotation

Detect Car using Haar
Cascade Classifiers

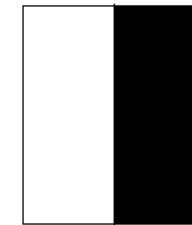
Predict team using
model previously trained



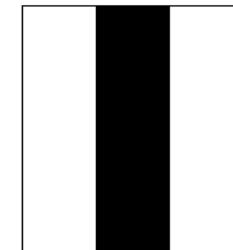
Detection & Annotation

CASCADE CLASSIFIER

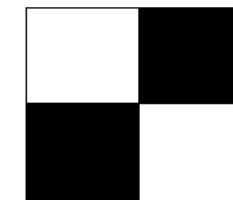
- Simple Machine Learning based approach
- Trained on positive and negative examples
- It works as a sliding windows through the image, for every window extracts Haar Features
- Haar Features are computed by subtracting the sum of the intensity of the pixels in the white region and the sum of the intensity of the pixels in the black region



a) Edge feature



b) Line feature



c) four-rectangle features

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Demo

Project Database

Commit SciView

Pull Requests Mintlify Doc Writer

Notifications

f1-cars-segmentation-and-classification ~/Documents/f1-cars-segmentation-and-classification

Run 'detection' ^R

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```
cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255, 255), 2)
crop_img = frame[y:y + h, x:x + w]

# prepare input for the model
input_frame = prepare_input(crop_img)
output = get_prediction(input_frame, model)

cv2.putText(frame, classes[str(output.item())], (x - 10, y - 10), cv2.FONT_HERSHEY_SIMPLEX, 0.9, (36, 255, 12), 2)
cv2.imshow('F1 Car Detection', frame)

# time.sleep(0.1)

if cv2.waitKey(1) == 13:
    break

video_cap.release()
cv2.destroyAllWindows()

if __name__ == '__main__':
    time.sleep(2)
    main()
```

Run: hypertuning x detection x

/Users/deborah/miniforge3/envs/torch-mac-hypertuning/bin/python /Users/deborah/Documents/f1-cars-segmentation-and-classification/src/detection/main.py

Process finished with exit code 0

Bookmarks

Structure

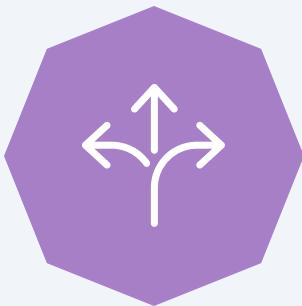
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Conclusions

Conclusions



Segmentation is not always step
that must be performed



Convolutional Neural Network is
always chosen for image
classification but other models can
be as accurate



Haar Cascade Classifiers are fast but
not many models already trained
are designed for cars

Thanks for the attention