

PlayCDC - Playing Card Detection

Learning to detect suits and ranks of playing cards

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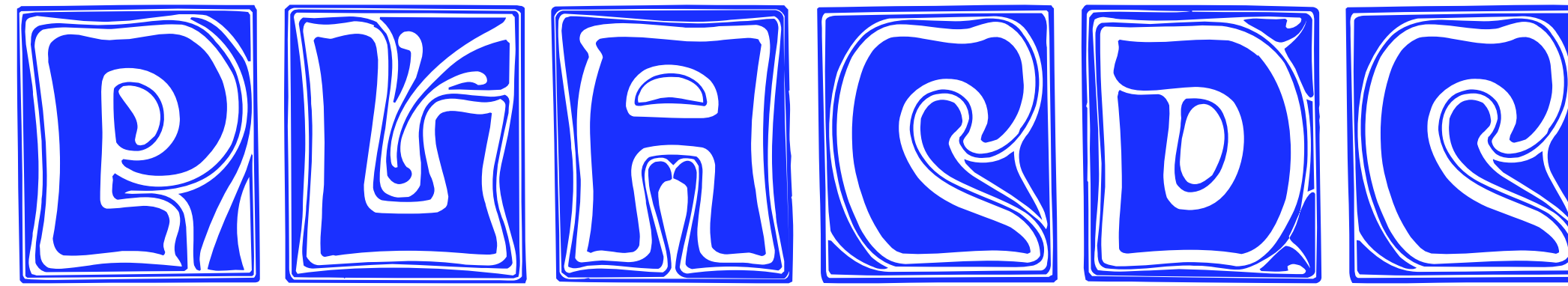
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Abstract

With the capabilities of upcoming small video capturing devices in, for example, smart contact lenses with built-in camerass, whole new ways of cheating in certain cardgames emerge. In order to help facilitate these cheating endeavours, we implement an algorithm that detects the suits and ranks of playing cards in the field of view of a camera using the latest iteration of the YOLO object recognition algorithm.

Introduction

Object detection deals with detecting instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos.

Main Objectives

The objectives of this project are summarized as follows:

Create a general dataset of a standard, 52-card deck of playing cards in different poses, brightness situations and blurring levels annotated with bounding boxes around the ranks and suits and corresponding class information.

Train an object detection algorithm on these synthesized data that performs bounding box localization and regression for classification. In particular, we train the latest iteration of the YOLO object detection algorithm [RF18] end-to-end.

Evaluate the algorithm on a hold-out validation dataset covering all classes. As a performance metric, mean Average Precision (mAP) is used.

Deploy the model on a smartphone camera as a proof of concept.

Methods

The dataset creation pipeline

The dataset was created in manly 2 big steps.

First, we took two photos for each card in a deck of 52 cards, crop the cards to a selection and rescale the result by 600x900 pixels. This was done manually using the selection/rotation/cropping/re-scale -tools provided by GIMP. Concluding this, we manage to detect the convex hulls of the cards suits and ranks using the SciPy library.

The next step was to generate a big amount of data for each card applying linear transformations, as well as blurring and sharpening on the image. First we paste the images in canvances using the Describable Textures Dataset [cite], in order to have different textures around the image. For the next, we use the imgaug library in order to perform the mentioned transformations, keeping track of the convex hulls.

For each of the 52 cards of the deck, we generate in total 450 images for trainig.

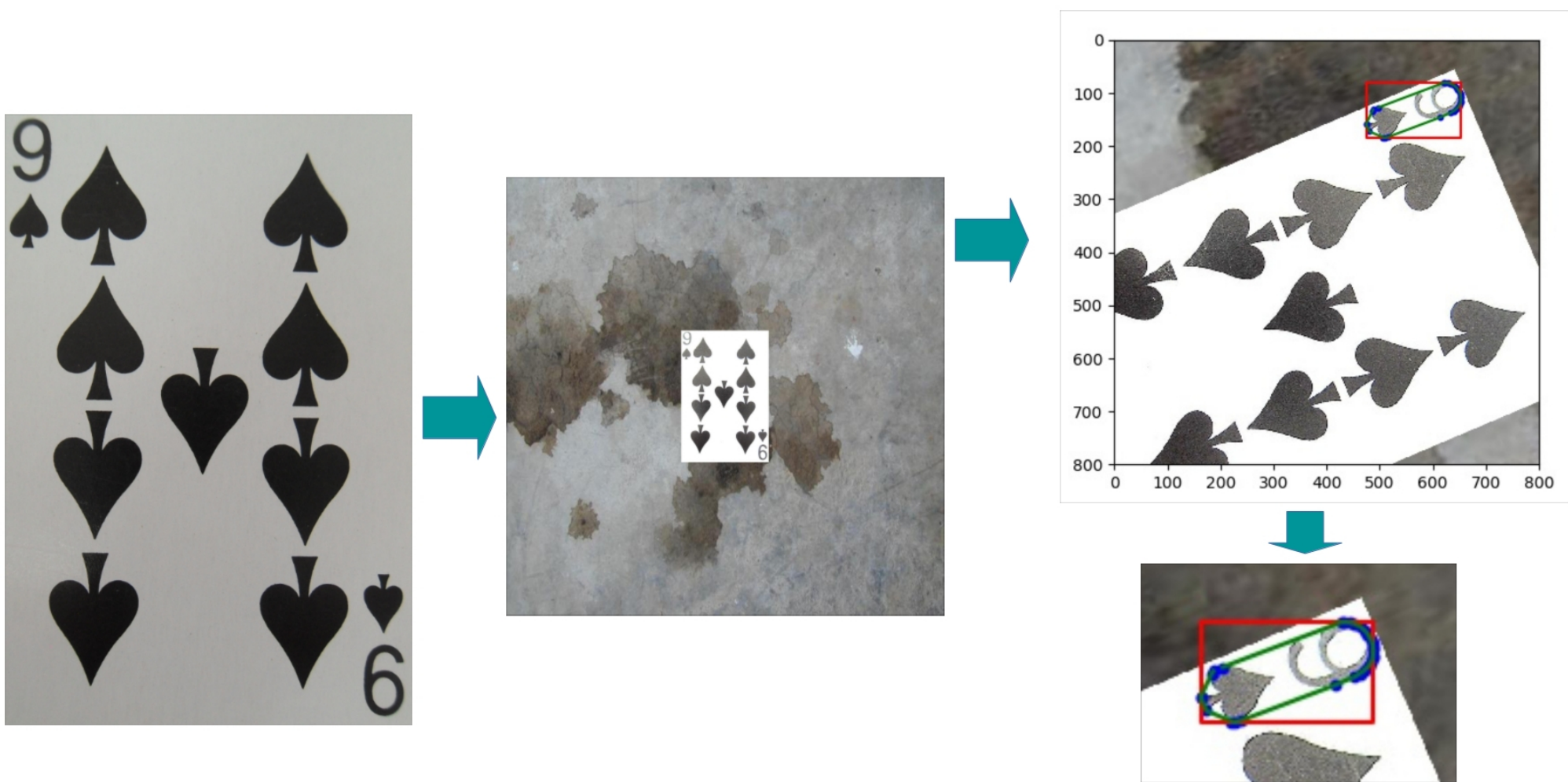


Figure 1: Figure caption

The tiny-YOLO-v3 object detection algorithm

Nulla vel nisl sed mauris auctor mollis non sed.

Evaluation strategy

$$E = mc^2 \quad (1)$$

Curabitur mi sem, pulvinar quis aliquam rutrum. (1) edf (2) , $\Omega = [-1, 1]^3$, maecenas leo est, ornare at. $z = -1$ edf $z = 1$ sed interdum felis dapibus sem. x set y ytruem. Turpis j amet accumsan enim y -lacina; ref k -viverra nec porttitor x -lacina.

Vestibulum ac diam a odio tempus congue. Vivamus id enim nisi:

$$\begin{aligned} \cos \bar{\phi}_k Q_{j,k+1,t} + Q_{j,k+1,x} + \frac{\sin^2 \bar{\phi}_k}{T \cos \bar{\phi}_k} Q_{j,k+1} = \\ - \cos \phi_k Q_{j,k,t} + Q_{j,k,x} - \frac{\sin^2 \phi_k}{T \cos \phi_k} Q_{j,k} \end{aligned} \quad (2)$$

and

$$\begin{aligned} \cos \bar{\phi}_j Q_{j+1,k,t} + Q_{j+1,k,y} + \frac{\sin^2 \bar{\phi}_j}{T \cos \bar{\phi}_j} Q_{j+1,k} = \\ - \cos \phi_j Q_{j,k,t} + Q_{j,k,y} - \frac{\sin^2 \phi_j}{T \cos \phi_j} Q_{j,k}. \end{aligned} \quad (3)$$

Results

Donec faucibus purus at tortor egestas eu fermentum dolor facilisis. Maecenas tempor dui eu neque fringilla rutrum. Mauris *lobortis* nisl accumsan. Aenean vitae risus ante. Pellentesque condimentum dui. Etiam sagittis purus non tellus tempor volutpat. Donec et dui non massa tristique adipiscing.

Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table 1: Table caption

Nulla ut porttitor enim. Suspendisse venenatis dui eget eros gravida tempor. Mauris feugiat elit et augue placerat ultrices. Morbi accumsan enim nec tortor consectetur non commodo. Pellentesque condimentum dui. Etiam sagittis purus non tellus tempor volutpat. Donec et dui non massa tristique adipiscing. Quisque vestibulum eros eu. Phasellus imperdiet, tortor vitae congue bibendum, felis enim sagittis lorem, et volutpat ante orci sagittis mi. Morbi rutrum laoreet semper. Morbi accumsan enim nec tortor consectetur non commodo nisi sollicitudin.

Placeholder
Image

Figure 2: Figure caption

In hac habitasse platea dictumst. Etiam placerat, risus ac. Adipiscing lectus in magna blandit:

Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
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Table 2: Table caption

Vivamus sed nibh ac metus tristique tristique a vitae ante. Sed lobortis mi ut arcu fringilla et adipiscing ligula rutrum. Aenean turpis velit, placerat eget tincidunt nec, ornare in nisl. In placerat.

Placeholder
Image

Figure 3: Figure caption

Conclusions

- Using an artificially created dataset, we achieve a mAP score of 95.10% on a holdout dataset.
- The task of object detection on ranks/suits of playing cards appears to be rather easy - it can be thought of being 2D rather than 3D.

- Deploying the model on a webcam results in 180 FPS on a 480x480 resolution, which is state-of-the-art fast.

Forthcoming Research

Vivamus molestie, risus tempor vehicula mattis, libero arcu volutpat purus, sed blandit sem nibh eget turpis. Maecenas rutrum dui blandit lorem vulputate gravida. Praesent venenatis mi vel

lorem tempor at varius diam sagittis. Nam eu leo id turpis interdum luctus a sed augue. Nam tellus.

References

[RF18] Joseph Redmon and Ali Farhadi. Yolov3: An incremental improvement. *CoRR*, abs/1804.02767, 2018.

Acknowledgements

Etiam fermentum, arcu ut gravida fringilla, dolor arcu laoreet justo, ut imperdiet urna arcu a arcu. Donec nec ante a dui tempus consectetur. Cras nisi turpis, dapibus sit amet mattis sed, laoreet.