PlayCDC - Playing Card Detection

Learning to detect suits and ranks of playing cards

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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

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.

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Methods

The dataset creation pipeline

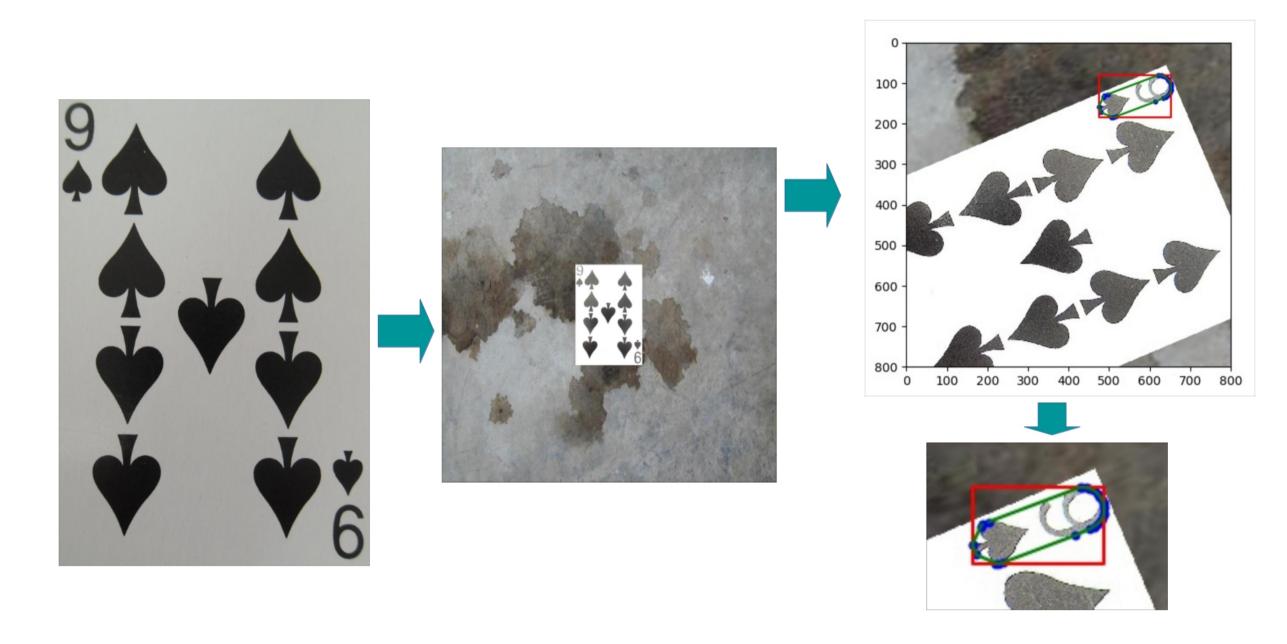


Figure 1: The dataset creation pipeline: paste photographs of images onto textures and apply random transformations to both images and corresponding convex hulls/bounding boxes

The YOLO approach to object detection

The general steps can be subsumed as follows:

Predict candidate bounding boxes

Class Prediction

Predictions Across Scales

Training using the Darknet-53 feature extractor

tiny-YOLO-v3

The particular architecture we used for training on our dataset is **tiny YOLOv3** which essentially is a smaller version of YOLO for constrained environments.

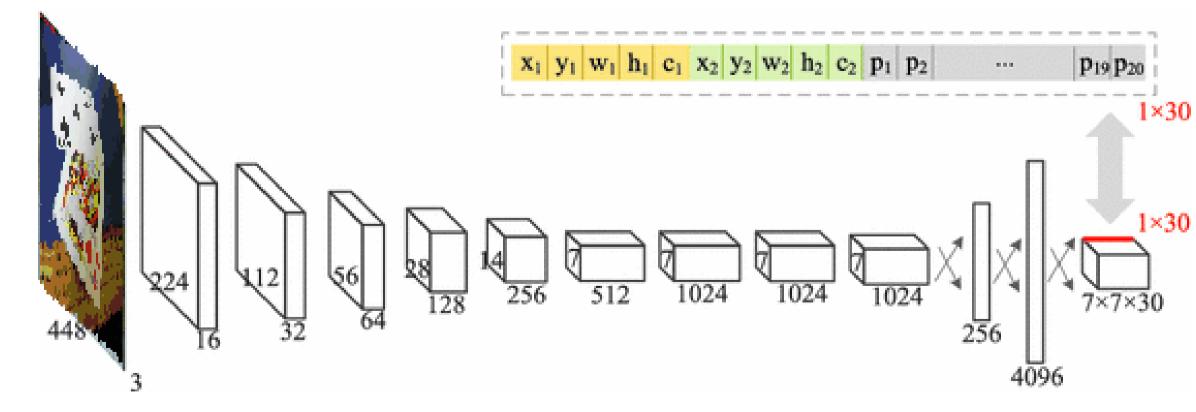


Figure 2: Figure caption

Evaluation strategy

$$E = mc^2 ($$

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

$$\cos \bar{\phi}_{k} Q_{j,k+1,t} + Q_{j,k+1,x} + \frac{\sin^{2} \bar{\phi}_{k}}{T \cos \bar{\phi}_{k}} Q_{j,k+1} = -\cos \phi_{k} Q_{j,k,t} + Q_{j,k,x} - \frac{\sin^{2} \phi_{k}}{T \cos \phi_{k}} Q_{j,k}$$
(2)

Results

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.example, smart contact lenses with built-in

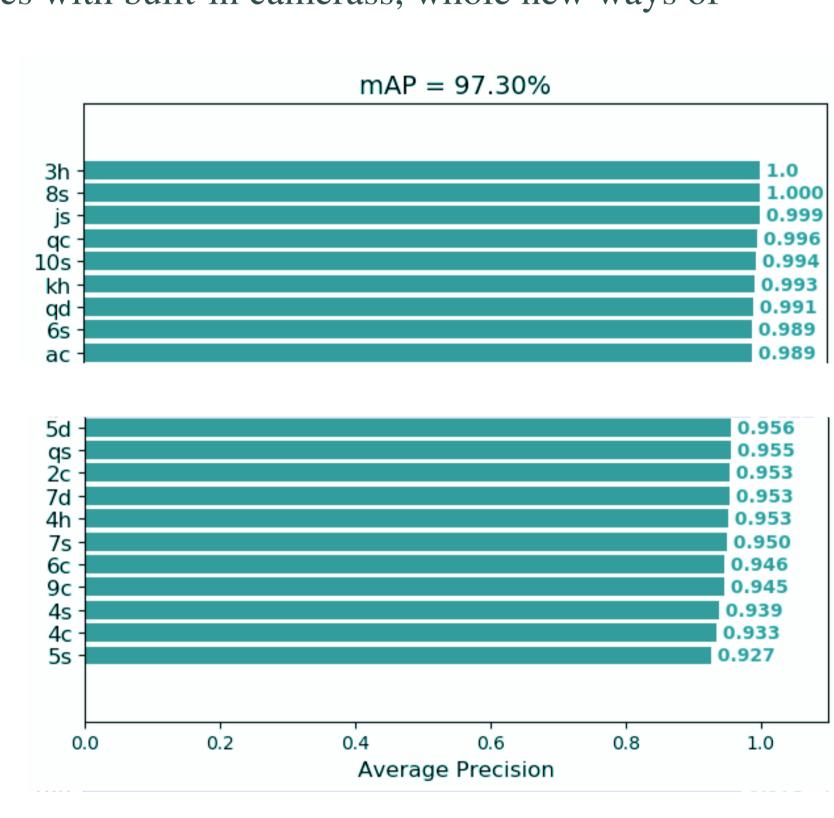


Figure 3: A gull

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.

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

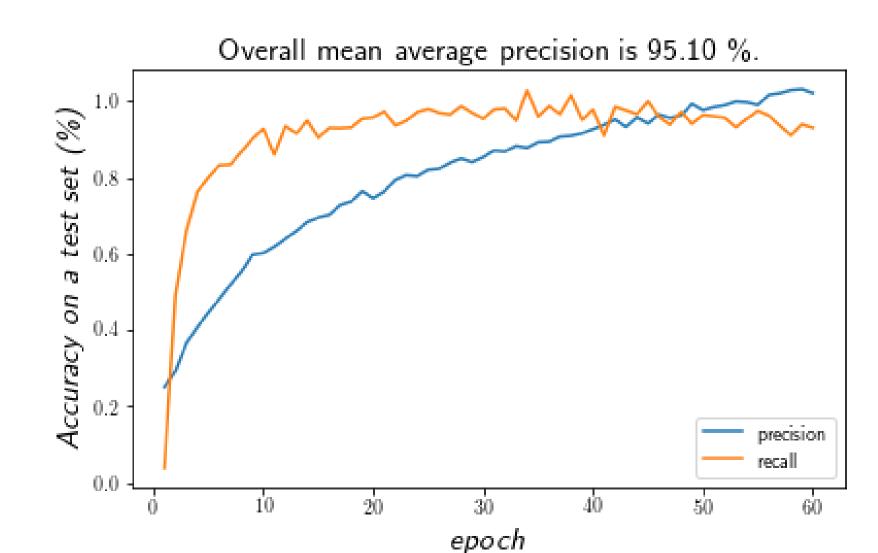


Figure 4: A gull

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.

References

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Acknowledgements

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