

Jordanian Coin Quest

The Visual Journey



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Challenges

manual currency detection and counting pose significant challenges to businesses, banks, and financial institutions. The reliance on manual processes not only consumes valuable time and resources but also introduces risks and inefficiencies into currency management

Challenges faced include:

- **Time-Consuming Processes.**
- **Human Error.**
- **Security Risks.**



Our Goal :

- 1-Efficiently recognizing Jordanian coins from digital images to streamline financial transactions and enhance operational accuracy.**

- 2- Automating the identification and classification of different denominations of Jordanian currency for improved currency handling.**

- 3- Developing the system to be able to count the coins in the images**



METHODOLOGY





Data Collection

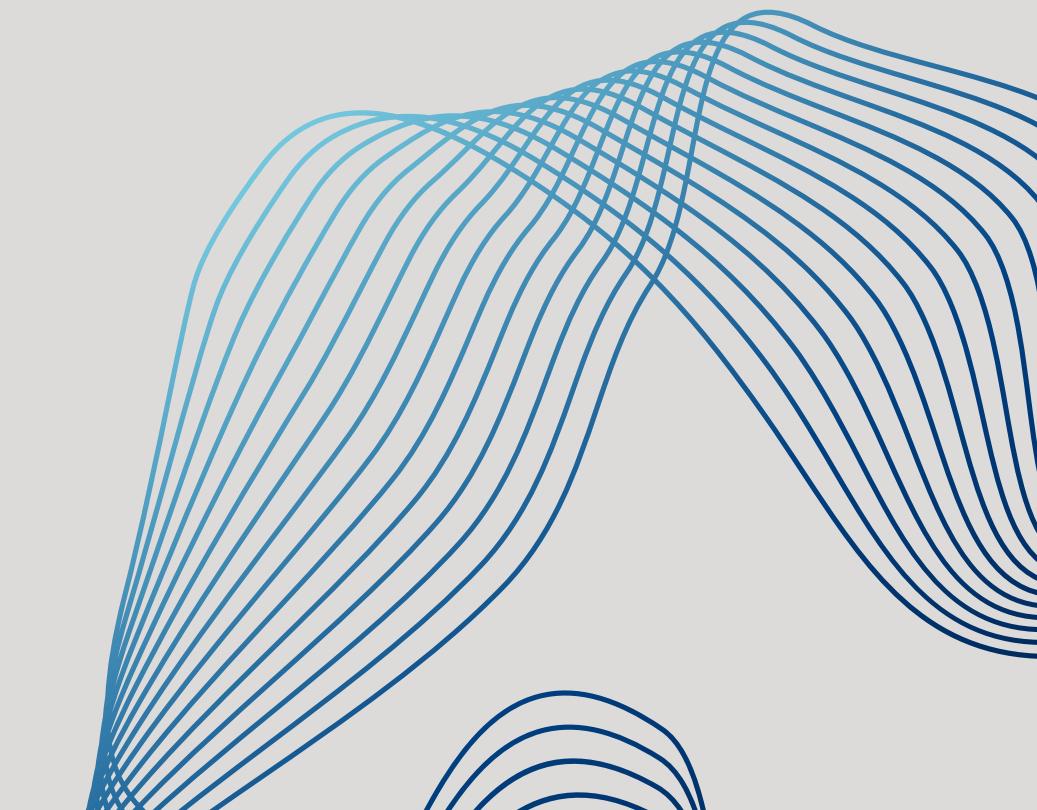
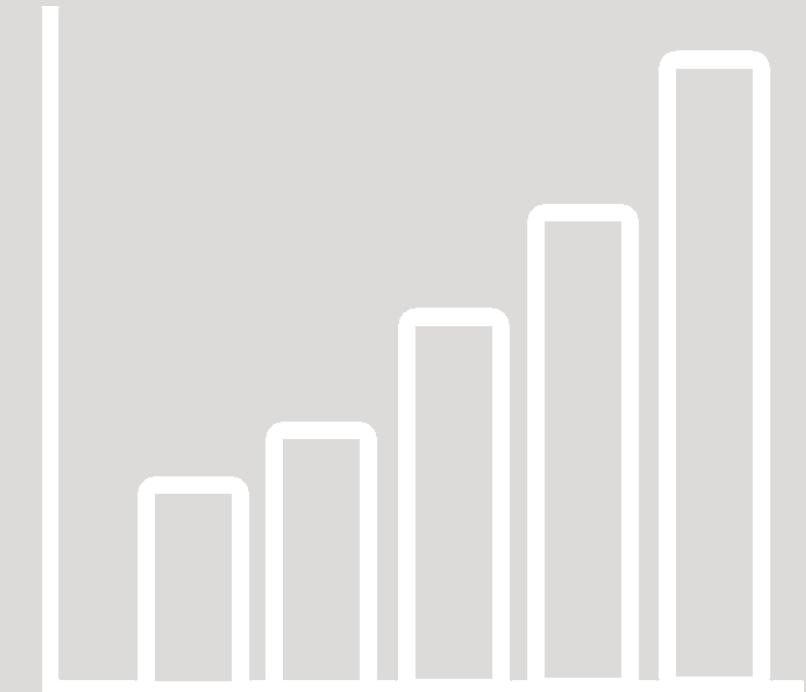
Data Collection



Our dataset for currency images was compiled from a diverse range of sources. Furthermore, a significant portion of our dataset was augmented through the manual capture of images using cameras to simulate varied conditions, ensuring comprehensive coverage and diversity in the dataset used for training and testing our currency detection and counting system.

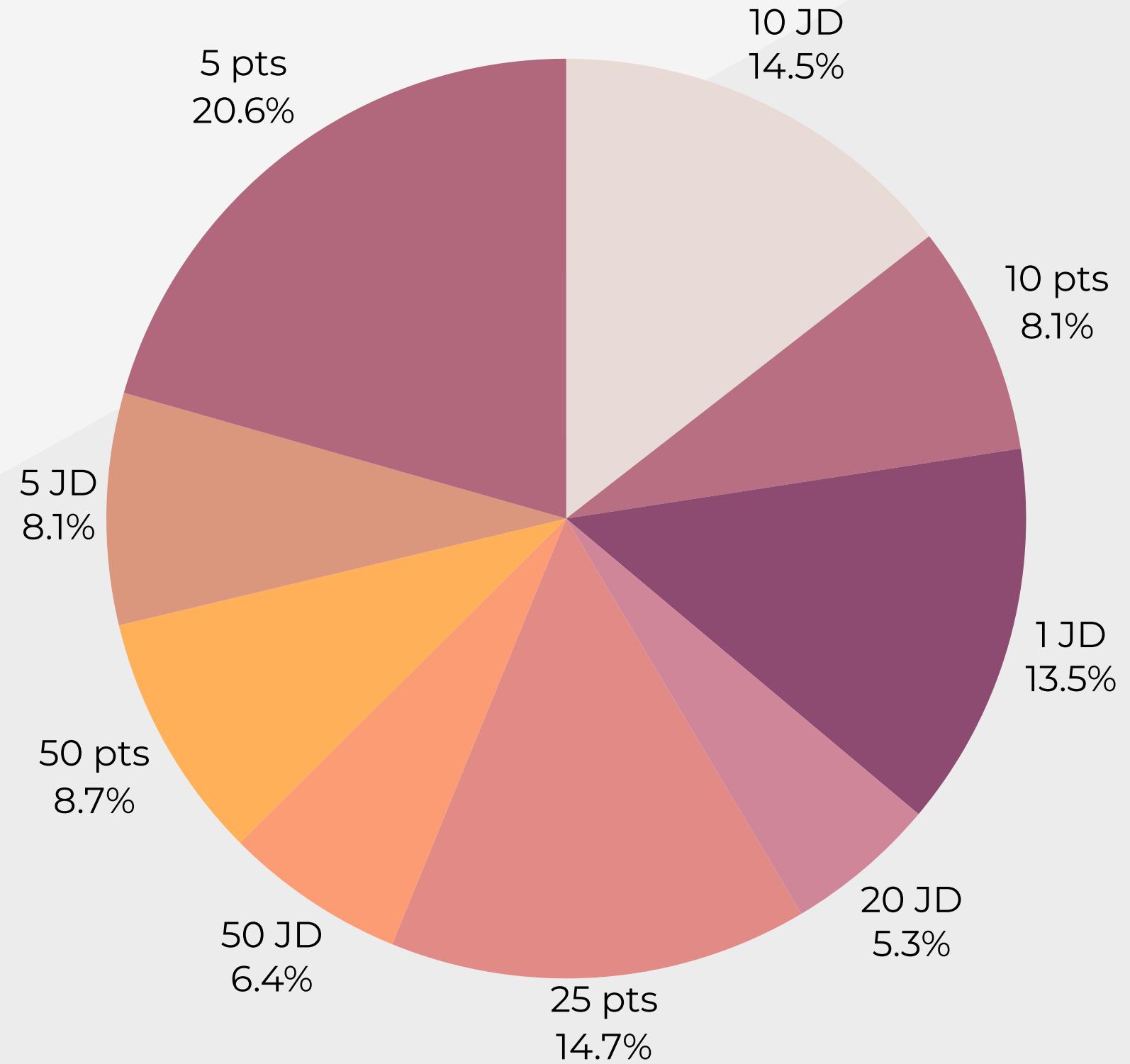
Data Consist of 9 classes :

- 5pts
- 10pts
- 25pts
- 50pts
- 1JD
- 5JD
- 10JD
- 20JD
- 50JD



IMAGES DISTRIBUTION

- The dataset's currency distribution reveals a predominance of 10 JD and 1 JD images, suggesting a focus on higher-value notes. However, fewer instances of 20 JD and 50 JD notes highlight potential class imbalances, requiring attention to ensure model robustness





Data Samples



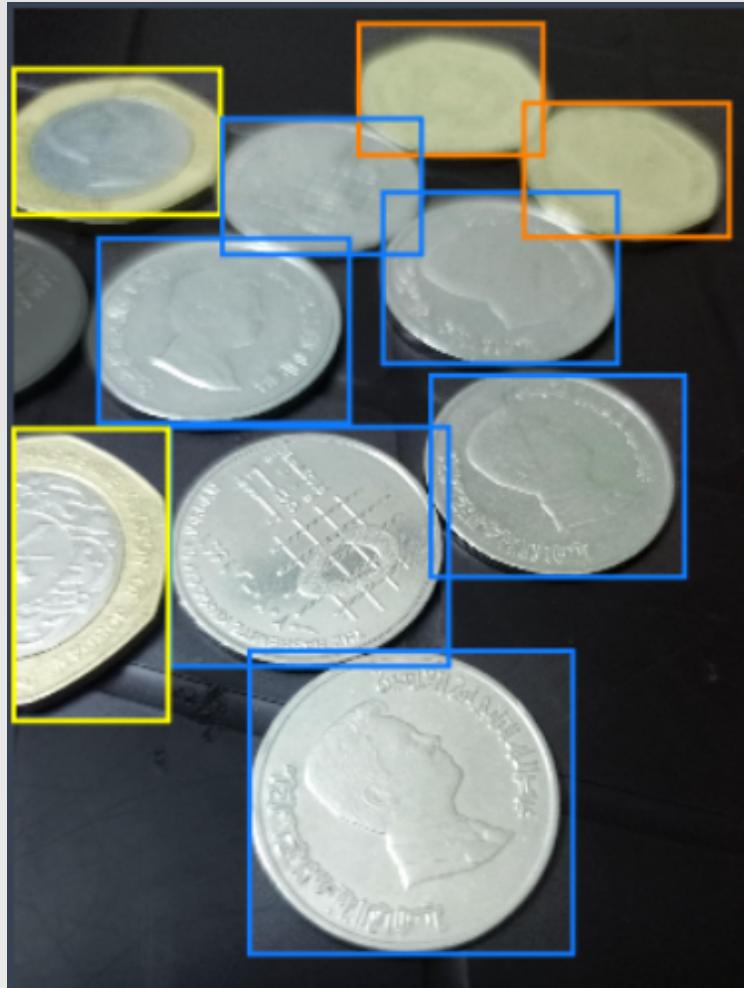
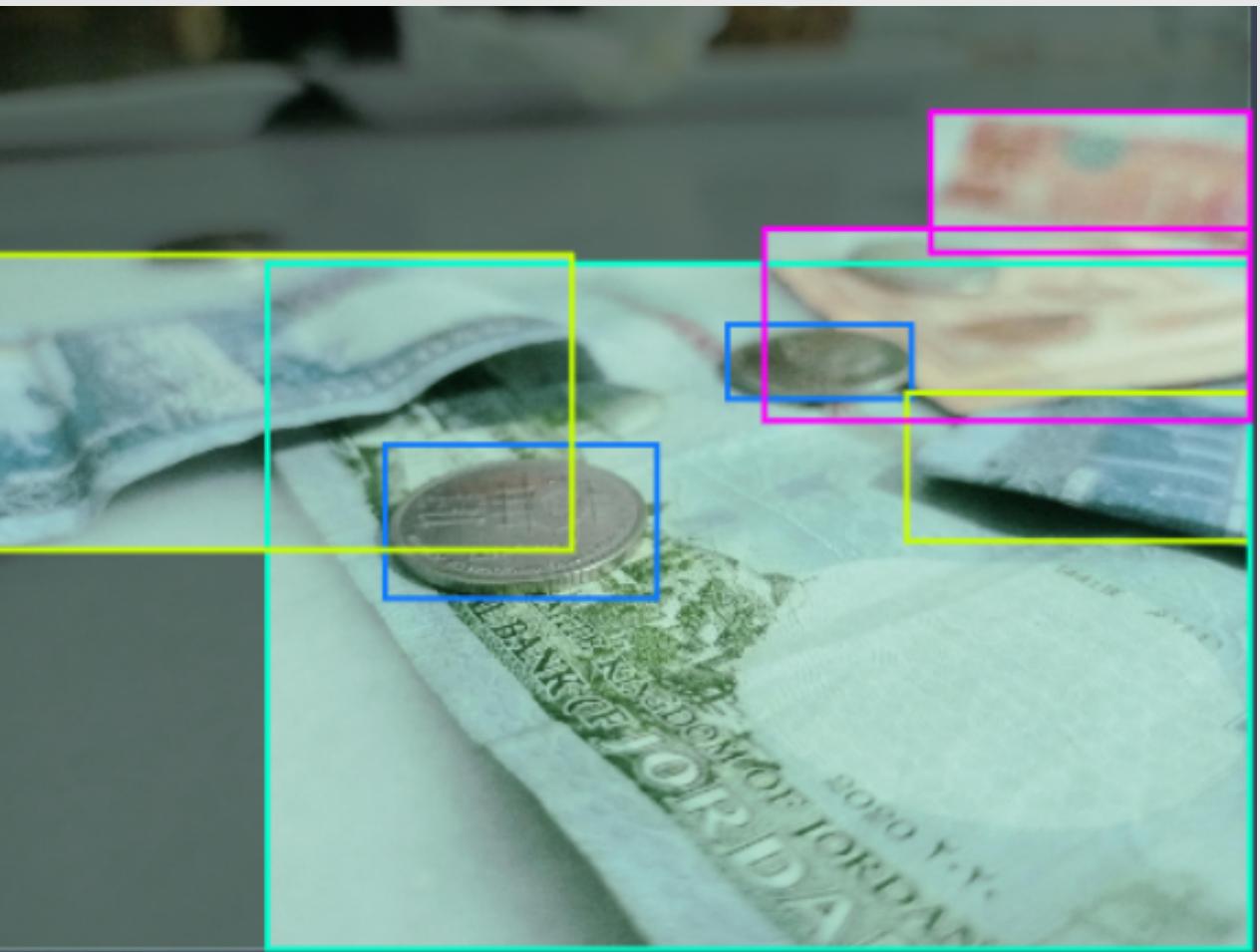


Data Annotation

Data Annotation

We used Roboflow to annotate our dataset

We used Bounded boxes tool



Data Information

Images

2,898

1 missing annotations
0 null examples

Annotations

7,916

2.7 per image (average)
across 9 classes

Average Image Size

1.92 mp

from 0.01 mp
to 15.93 mp

Median Image Ratio

1200×1200

square

Class Balance

Class Management

all train valid test

5pts

1JD

25pts

10JD

5JD

50JD

10pts

50pts

20JD

1,832

1,073

1,060

1,056

694

660

582

576

383

over represented

under represented

under represented

under represented



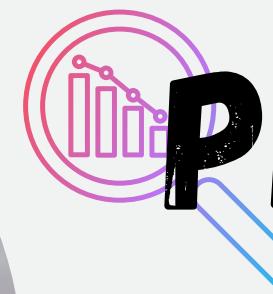
Data Preprocessing





PREPARING IMAGES

Robust preprocessing techniques are pivotal for accurate money image detection. Steps such as resizing, noise reduction, color space conversion, and data augmentation are crucial for optimizing data quality and improving model performance, ensuring reliable results in the detection of currency in images.



PREPROCESSING STEPS

We used three preprocessing steps:

- 1- Auto-Orient
- 2-Resize(640*640)
- 3-Grayscale

The first two steps are applied in all versions but the third one applied only in two versions

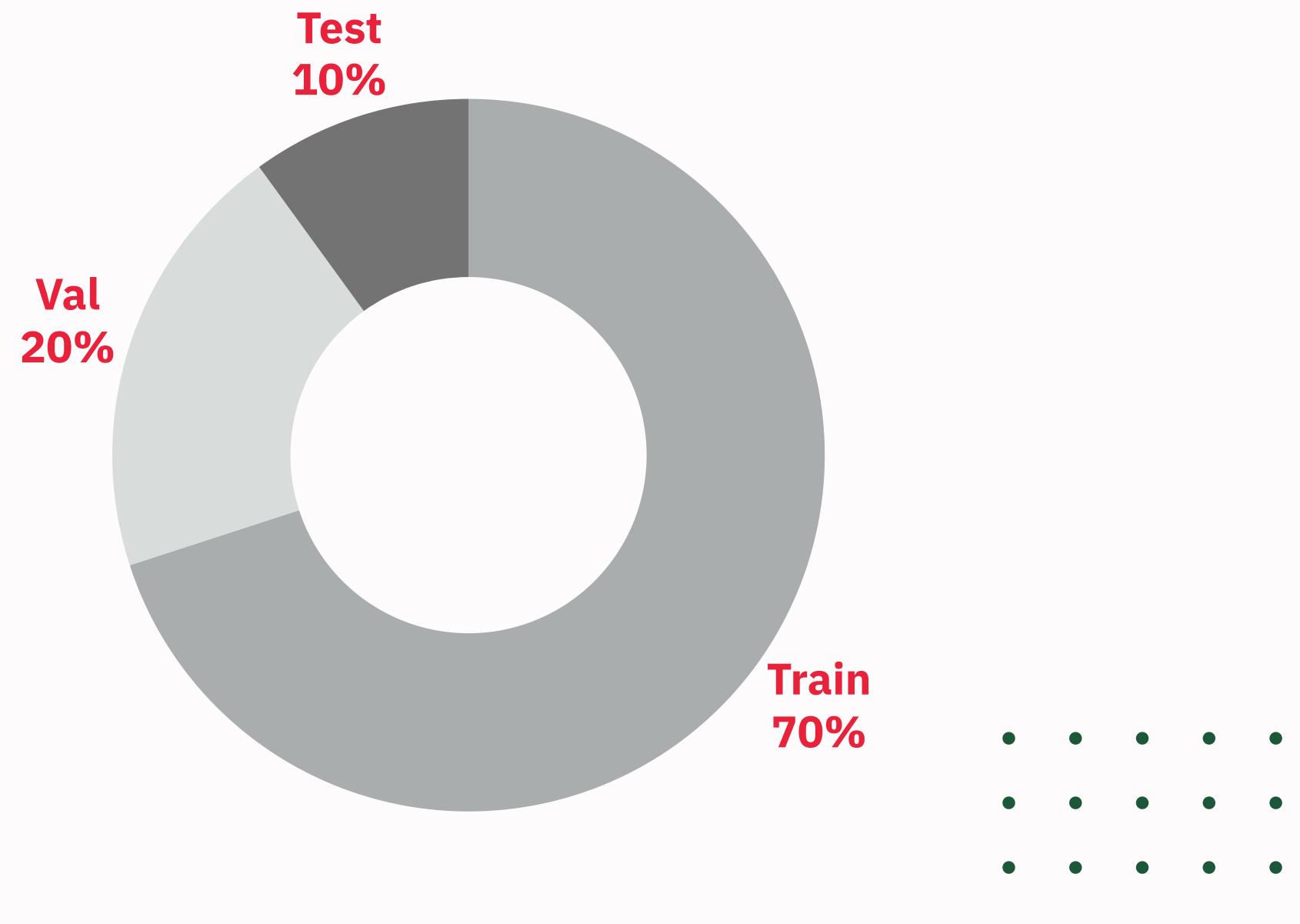


Data Split

Data Splitting



By implementing a systematic data splitting strategy, we aim to achieve a balance between model training, validation, and testing, facilitating robust performance assessment and generalization





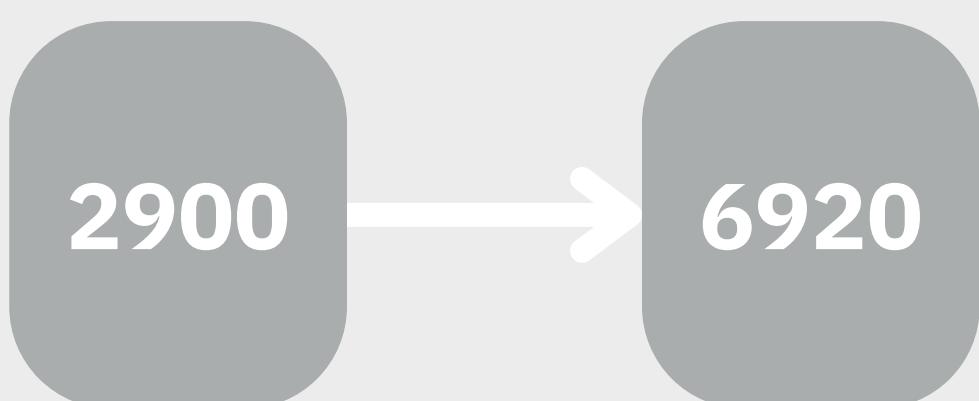
Data Augmentation



IMAGES AUGMENTATION

- We used Roboflow augmentation capabilities to increase our training dataset samples

This step varies from one version
to another



**Image Augmentation
Ratio**

58%



VERSIONS



Preprocessing	Auto-Orient: Applied Resize: Stretch to 640x640
Augmentations	No augmentations were applied.



Preprocessing	Auto-Orient: Applied Resize: Stretch to 416x416
Augmentations	Outputs per training example: 3 Rotation: Between -15° and +15° Shear: ±10° Horizontal, ±10° Vertical Grayscale: Apply to 15% of images Hue: Between -15° and +15°



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VERSIONS



Preprocessing

Auto-Orient: Applied

Resize: Stretch to 640x640

Augmentations

Outputs per training example: 3

Shear: $\pm 13^\circ$ Horizontal, $\pm 13^\circ$ Vertical

Hue: Between -115° and $+115^\circ$

Brightness: Between -36% and +36%

Blur: Up to 2.5px

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Preprocessing

Auto-Orient: Applied

Resize: Stretch to 640x640

Augmentations

Outputs per training example: 3

90° Rotate: Clockwise, Counter-Clockwise, Upside Down

Rotation: Between -15° and $+15^\circ$

Brightness: Between -25% and +0%

Noise: Up to 1.96% of pixels





VERSIONS



Preprocessing	Auto-Orient: Applied Resize: Stretch to 640x640 Grayscale: Applied
Augmentations	Outputs per training example: 3 Flip: Horizontal, Vertical 90° Rotate: Clockwise, Counter-Clockwise, Upside Down Shear: $\pm 10^\circ$ Horizontal, $\pm 10^\circ$ Vertical Blur: Up to 3.1px



Preprocessing	Auto-Orient: Applied Resize: Stretch to 640x640 Grayscale: Applied
Augmentations	Outputs per training example: 3 Flip: Horizontal, Vertical 90° Rotate: Clockwise, Counter-Clockwise, Upside Down Shear: $\pm 10^\circ$ Horizontal, $\pm 10^\circ$ Vertical Grayscale: Apply to 15% of images Blur: Up to 3.1px





Modeling Section



Roboflow Model

The **MS COCO** (Microsoft Common Objects in Context) model by Microsoft is a pre-trained deep learning model utilized for object detection, segmentation, and captioning tasks. Leveraging the MS COCO dataset with annotated images. Renowned for its versatility, it finds applications across various domains, serving as a benchmark in computer vision.

○ ○ ○ ○ ROBOFLOW MODEL

We used the Roboflow capabilities to train Model
in two ways :

1- Train from public check point



Model Type: Roboflow 3.0 Object Detection (Fast)

RECOMMENDED

☒ Train from Previous Checkpoint

Start from one of your previous training runs to speed up training and improve accuracy. This option is best if you already successfully trained a model on this project.

★ Train from Public Checkpoint

Use a pre-trained benchmark model or a starred Universe project to imbue your model with prior knowledge, reduce training time, and improve performance.

NOTE: Only models with the same model type as above are available as checkpoints.

Select Model

MS COCO

Select Model Version

v7 - Best (Common Objects, 37.3% mAP)

🏃 Train from Random Initialization

Not recommended; almost always produces worse results.

○ ○ ○ ○ ROBOFLOW MODEL

2- Train from the previous checkpointt

Model Type: Roboflow 3.0 Object Detection (Fast)

RECOMMENDED

☒ Train from Previous Checkpoint

Start from one of your previous training runs to speed up training and improve accuracy. This option is best if you already successfully trained a model on this project.

NOTE: Only models with the same model type as above are available as checkpoints.

Select Model

object detection count

Select Model Version

v3 - 2024-02-19 6:56am (0, 84.6% mAP)

★ Train from Public Checkpoint

Use a pre-trained benchmark model or a starred Universe project to imbue your model with prior knowledge, reduce training time, and improve performance.

-worker Train from Random Initialization

Not recommended; almost always produces worse results.

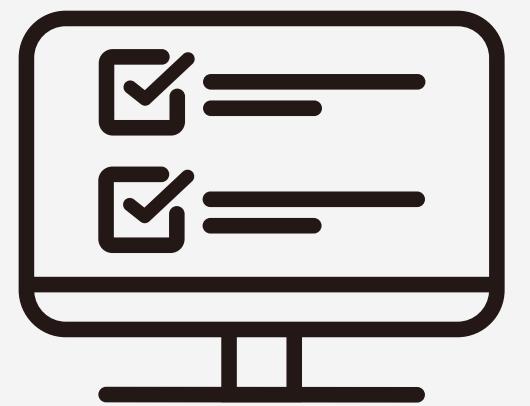
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YOLOV8 MODEL

We trained the YOLO model for 20 epochs on Google Colab, the performance of the trained YOLO model did not meet our expectations. The achieved accuracy did not exceed 64% on the validation set, indicating suboptimal performance. Due to the model's performance falling below our desired threshold, we made the decision not to upload the results to Robo Flow.



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Results



VERSIONS RESULTS:

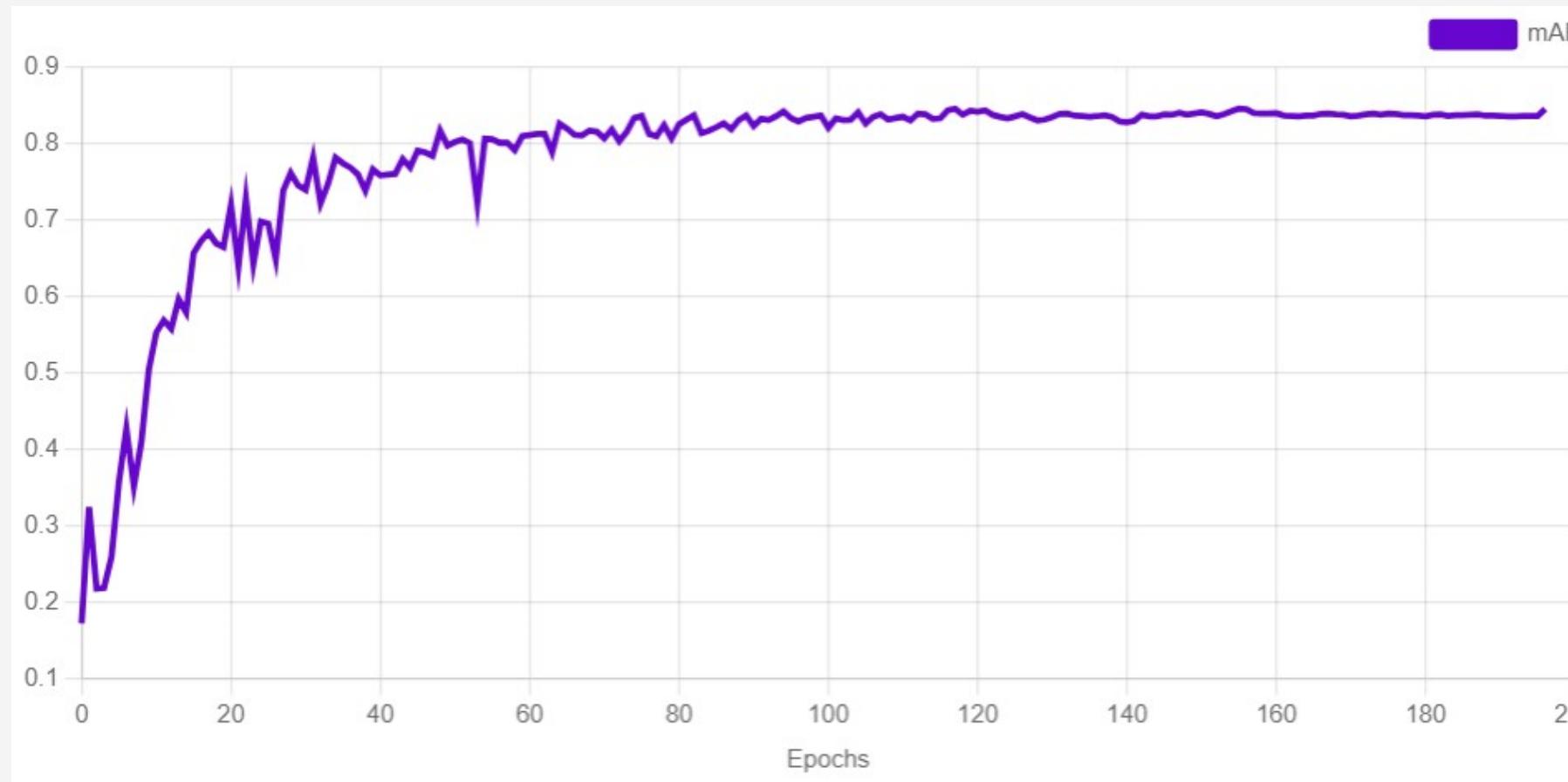
	mAP	Precision	Recall
Version1	63.4%	75.4%	60.8%
Version2	59.3%	71.6%	53%
Version3	65.5%	78.2%	58.6%

VERSIONS RESULTS:

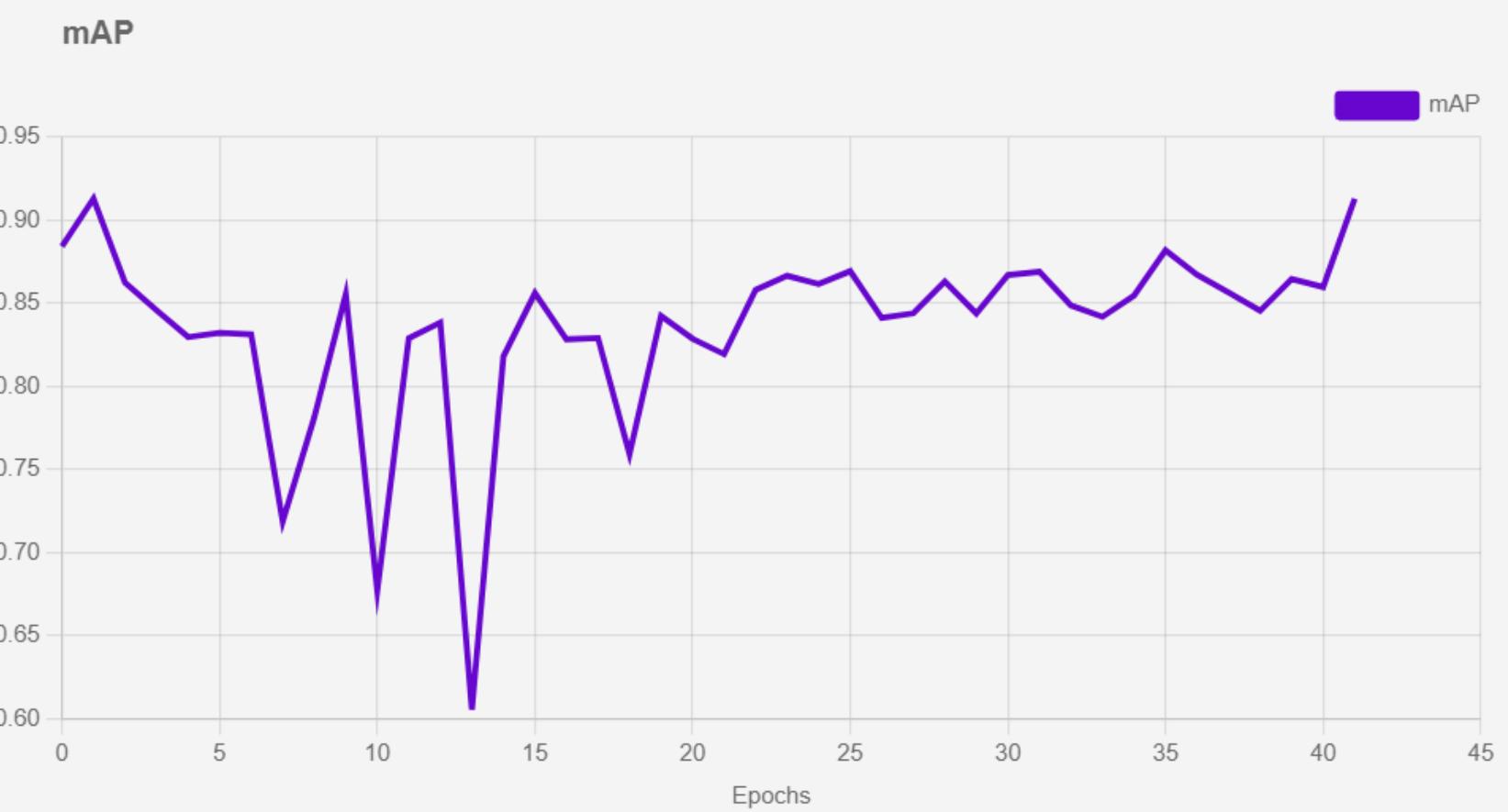
Version	mAP	Precision	Recall
Version5	84.6%	80.4%	80.8%
Version6	91.3%	90%	85.1
Version4	71.4%	76%	68.8%

TRAINING CURVE :

The fluctuations in the (mAP) curve are specifically related to the last training checkpoint, it suggests that the model's performance may vary at different stages of training.



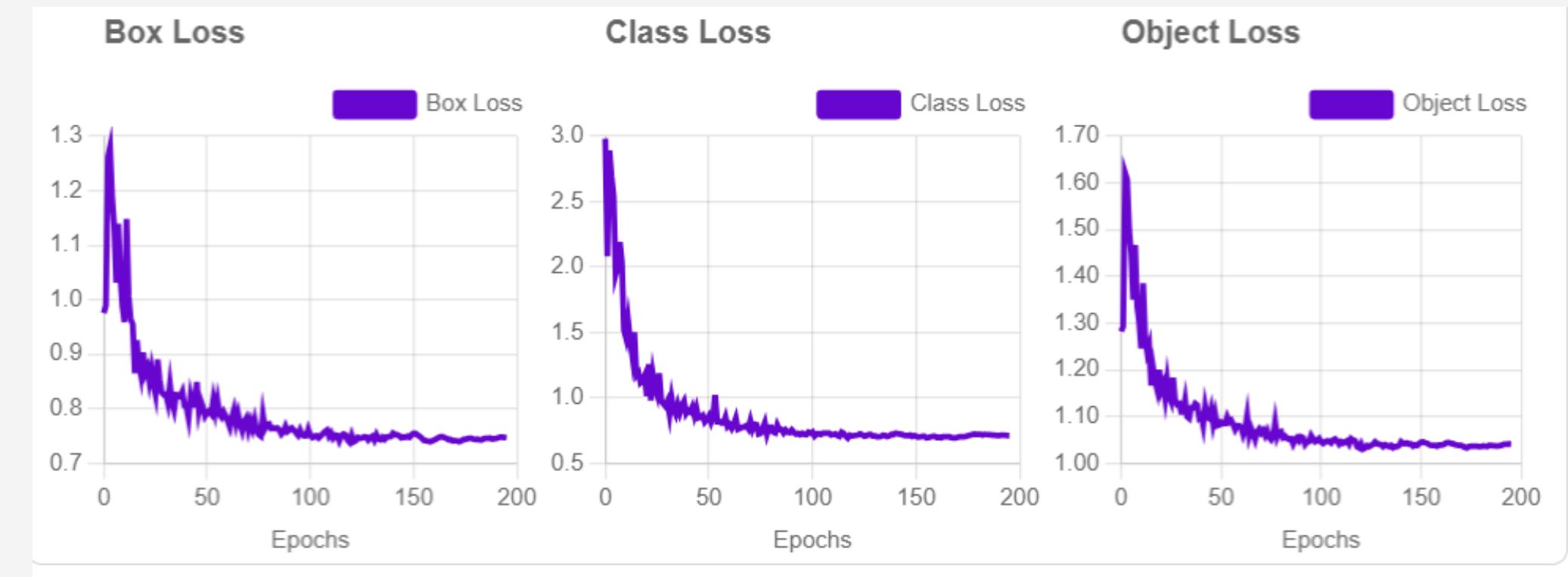
Version 5



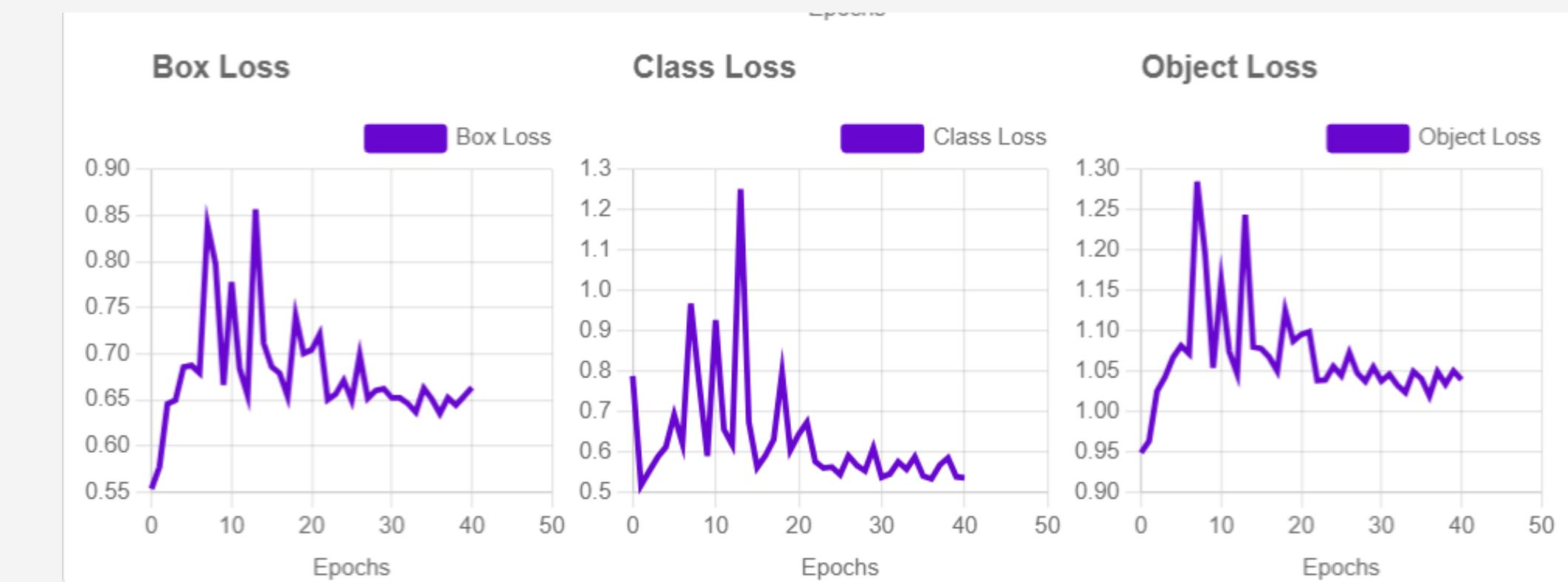
Version6

LOSSES CURVES :

Version5

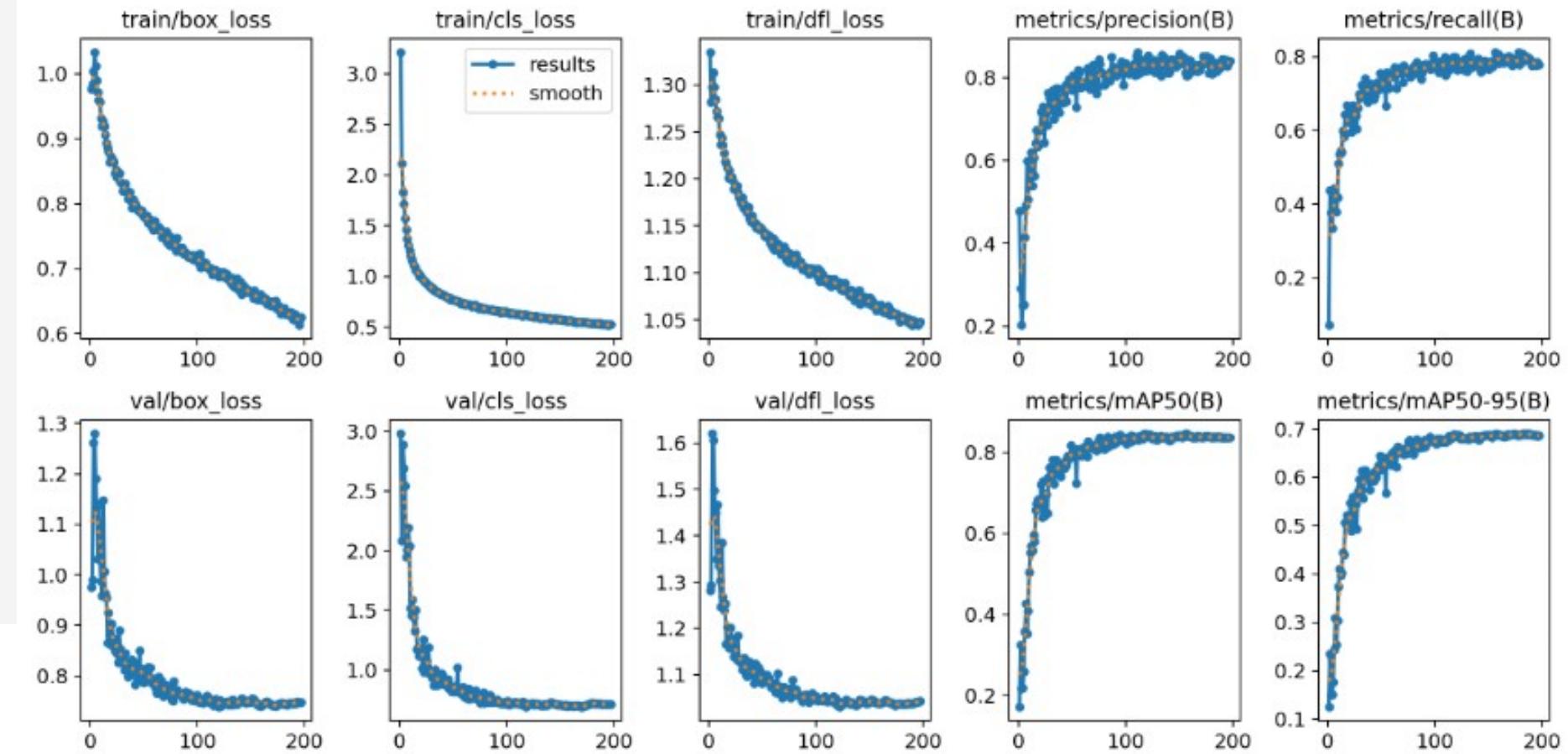
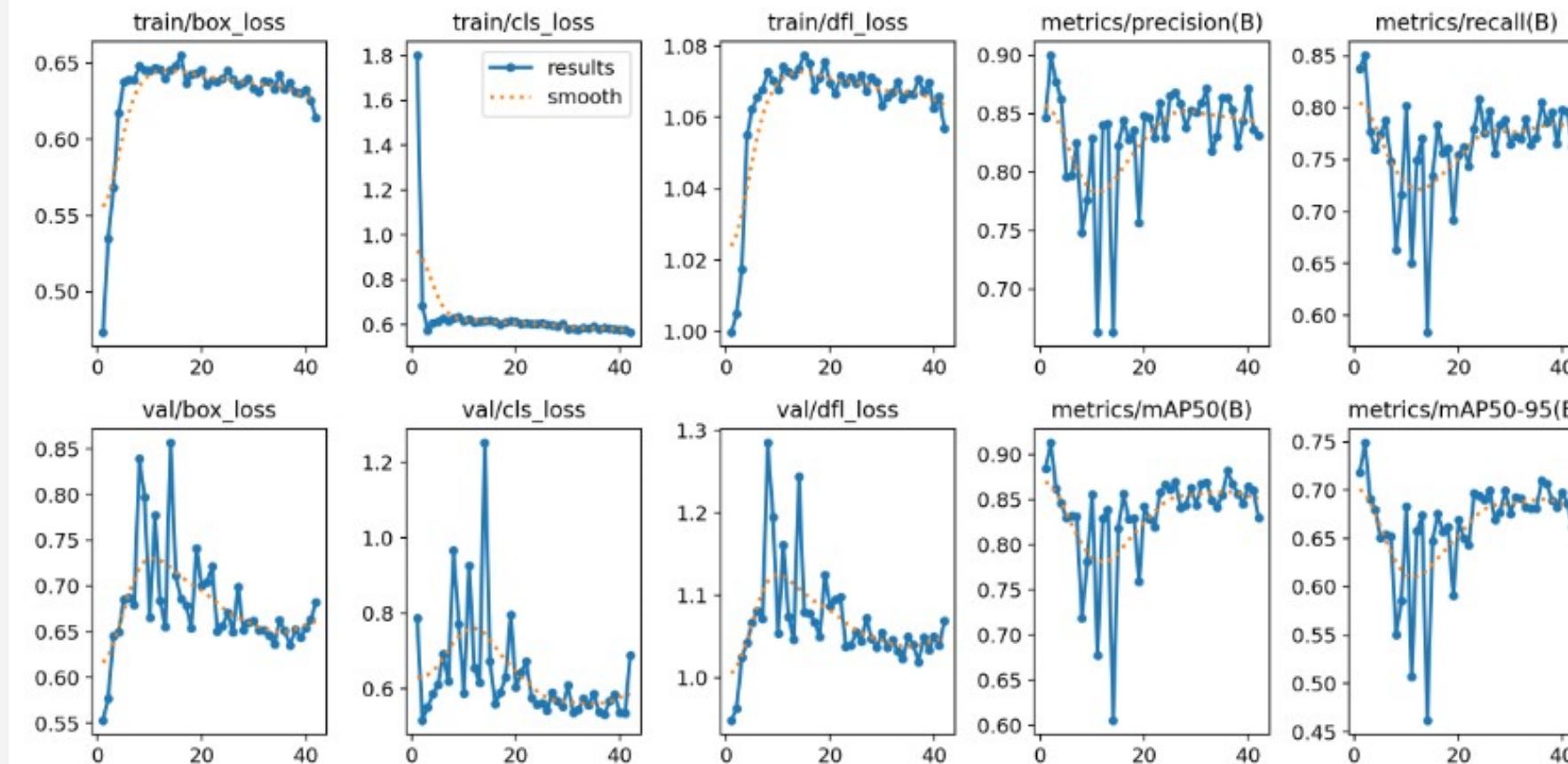


Version6



TRAINING GRAPHS :

Version5



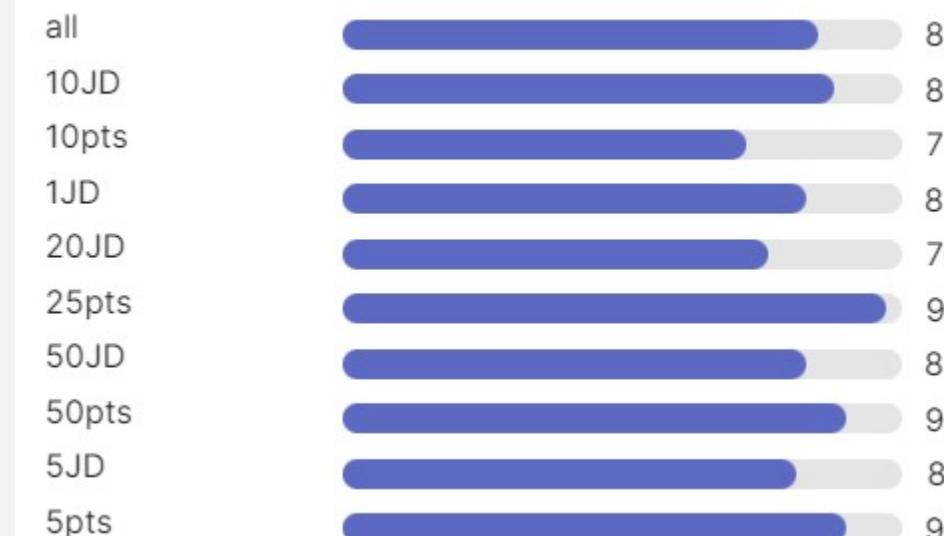
Version6

AVERAGE PRECISION BY CLASS :

Version5

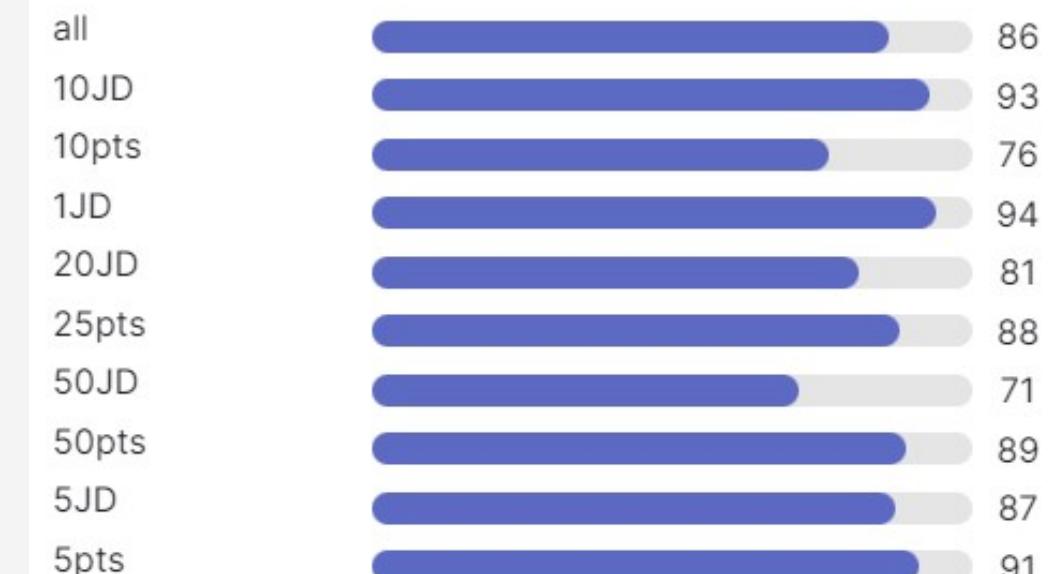
Validation

Average Precision by Class



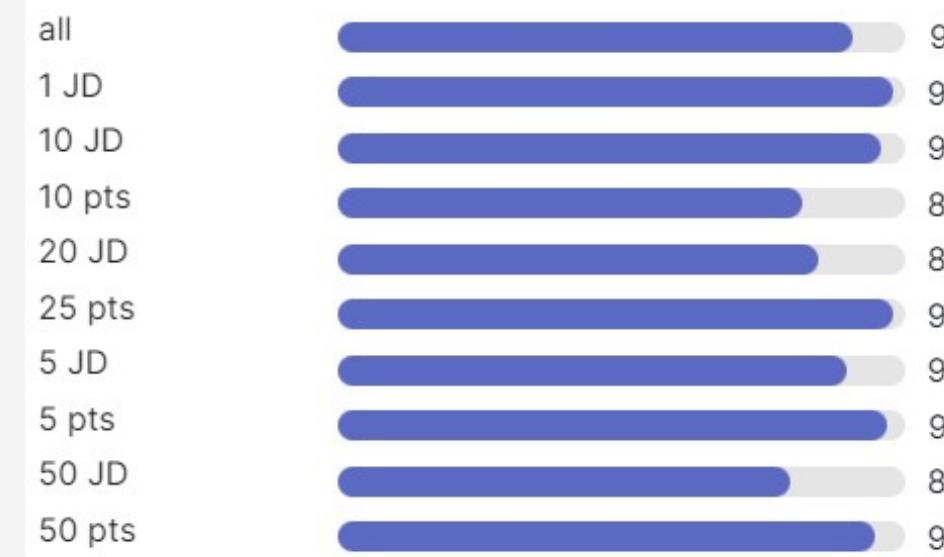
Test

Average Precision by Class



Version6

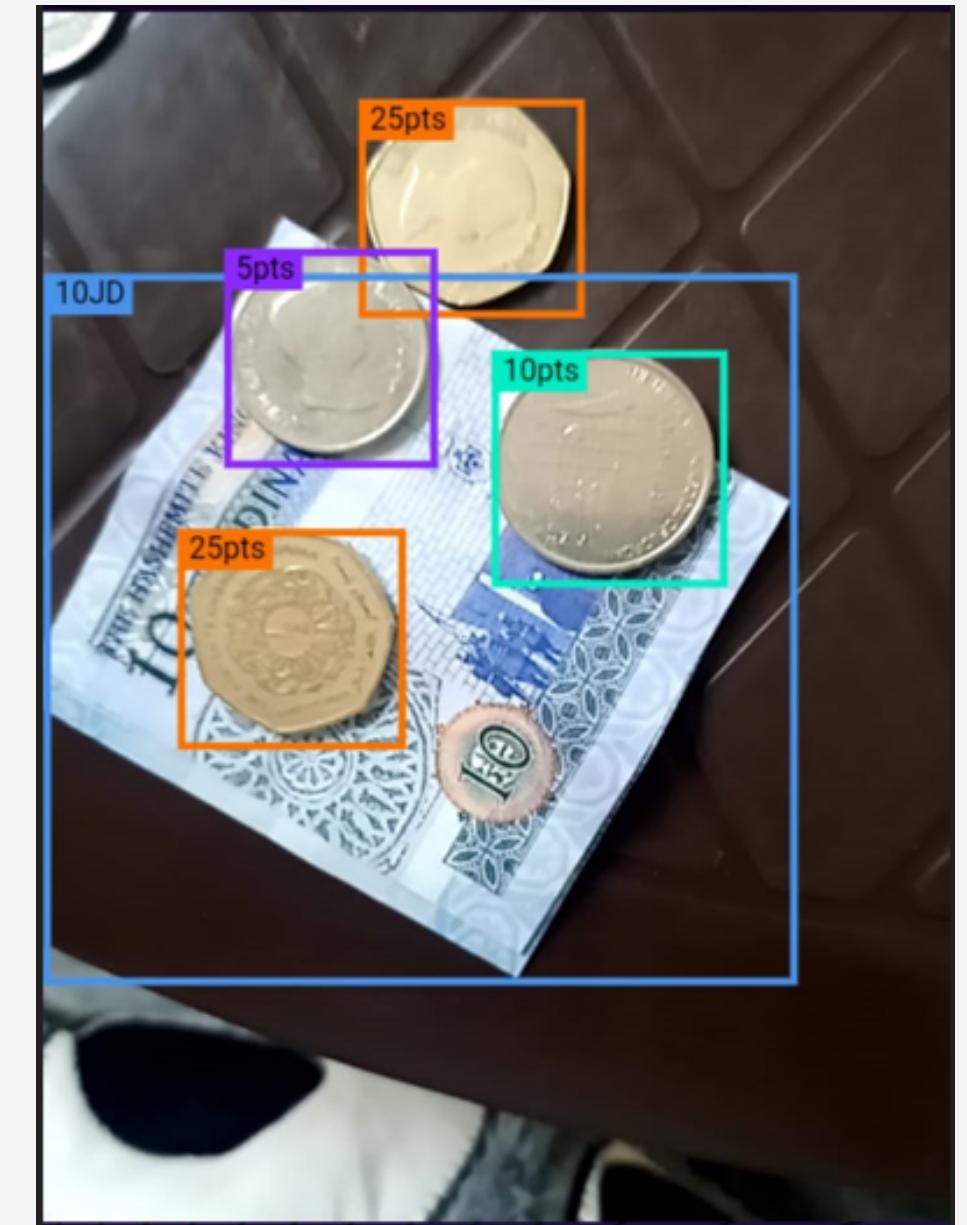
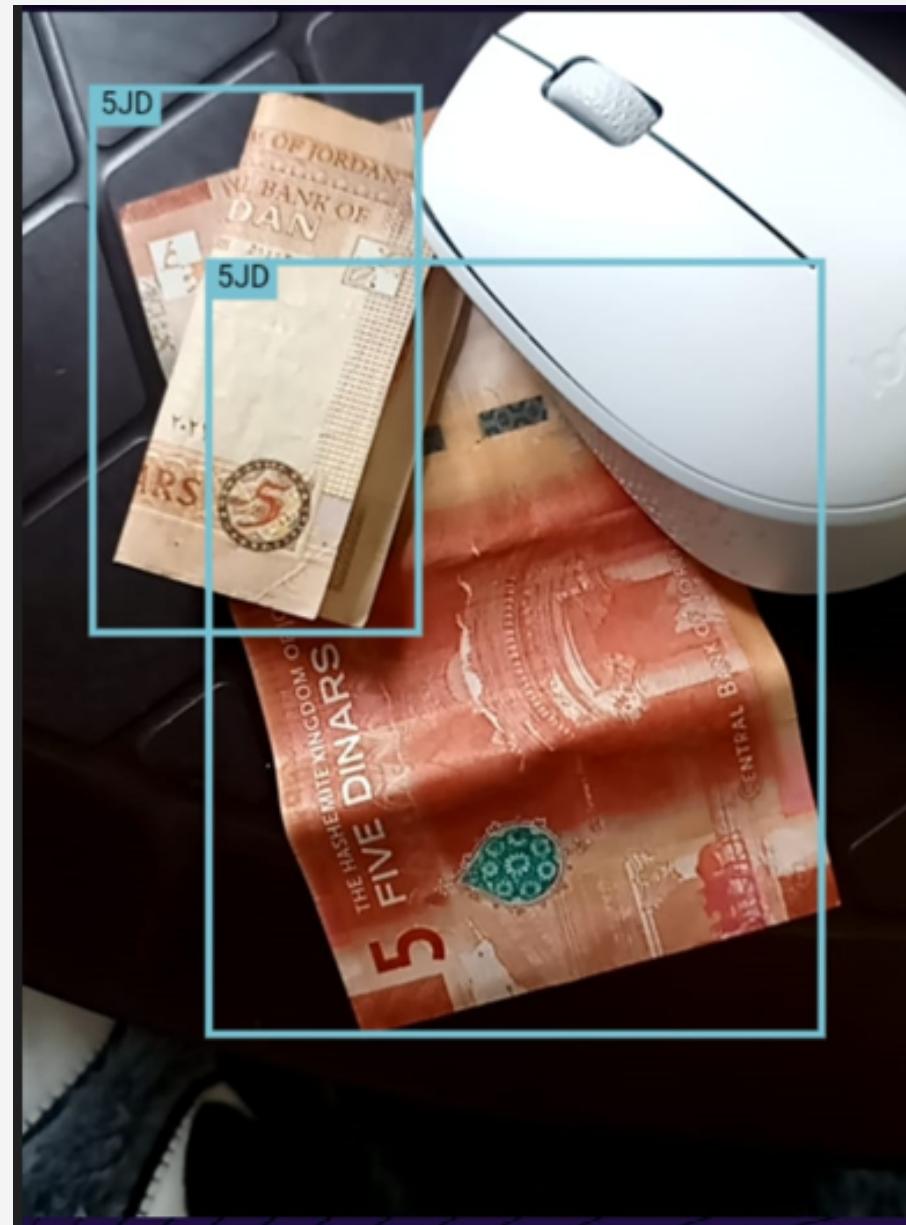
Average Precision by Class



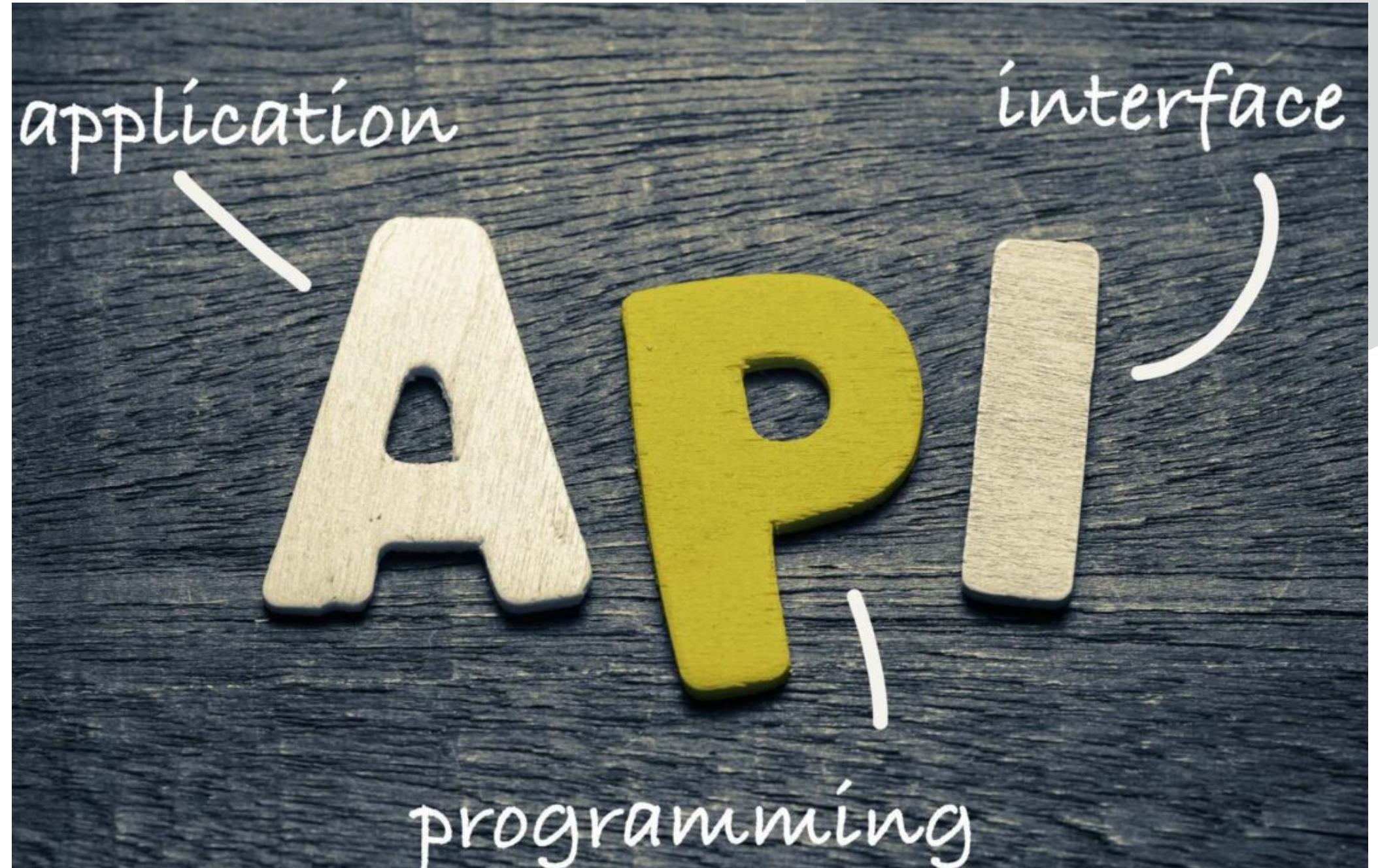
Average Precision by Class



SAMPLES FROM OUTPUT:



Through execution of the model trained on Roboflow using its API, particularly Roboflow's, serve as the backbone of this integration, providing a standardized interface for seamless interaction between our model and Roboflow's platform. Additionally, this cohesive connection allows for the implementation of sophisticated counting techniques, empowering our model with advanced capabilities, such as efficient currency counting.



DEMO



This workspace reached its quota for training credits. [Upgrade your plan.](#)

Switch Model:

v249 coins-udg7d/249

Trained On: coins-udg7d 6,20 Images View Version →
Model Type: Roboflow 3.0 Object Detection (Fast)
Checkpoint: coins-udg7d/249

mAP ② 91.3% | Precision ② 90.0% | Recall ② 85.1%
[View Model Graphs →](#)

Samples from Test Set

View Test Set →

Upload Image or a Video File

Drop files here or [Select File](#)

Paste YouTube or Image URL

Paste a link...

Confidence Threshold: 50%
0% 100%

Overlap Threshold: 50%
0% 100%

Label Display Mode:
[Draw Confidence](#)

Try this model on images, video, or use your webcam

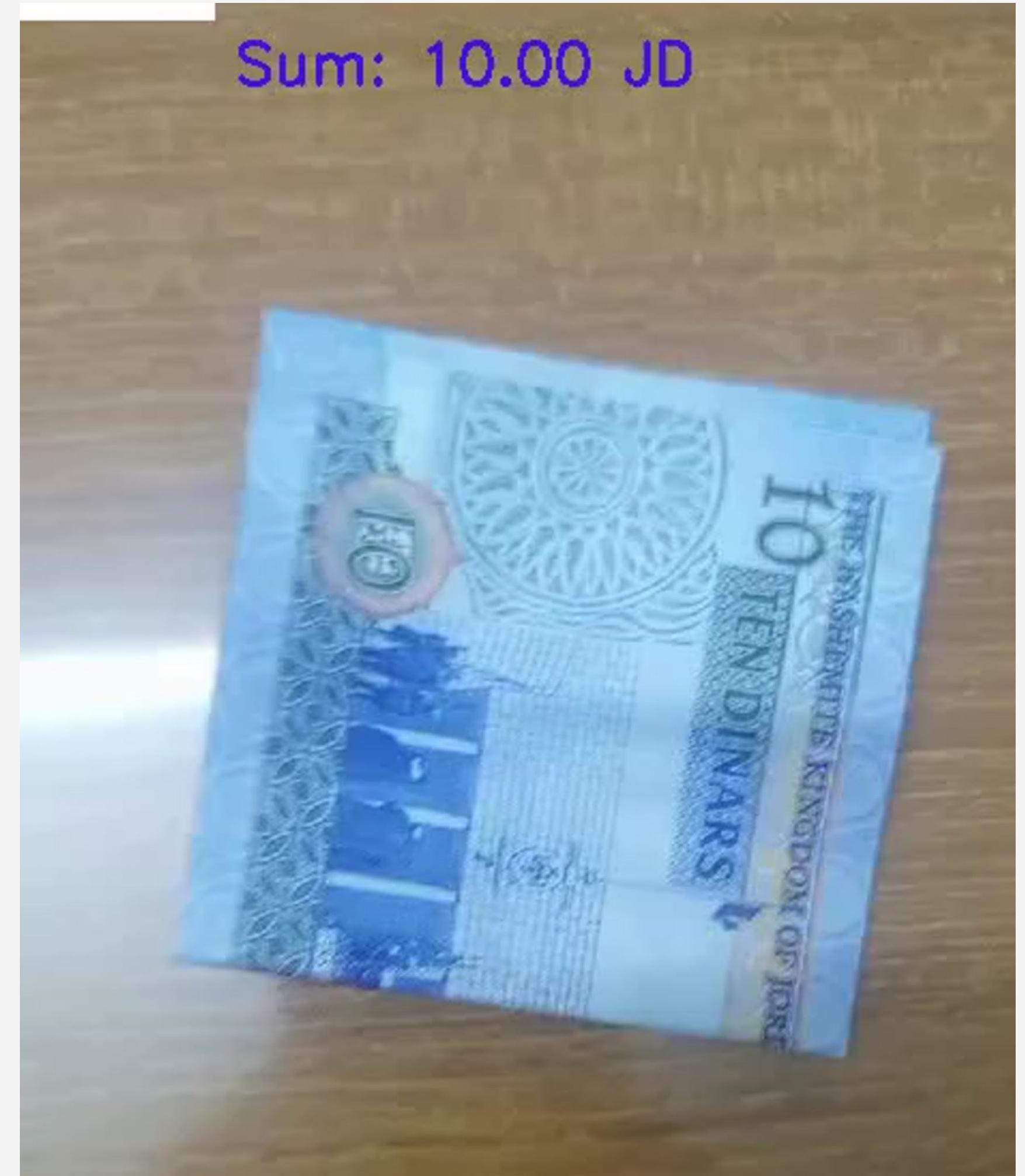
COUNTING



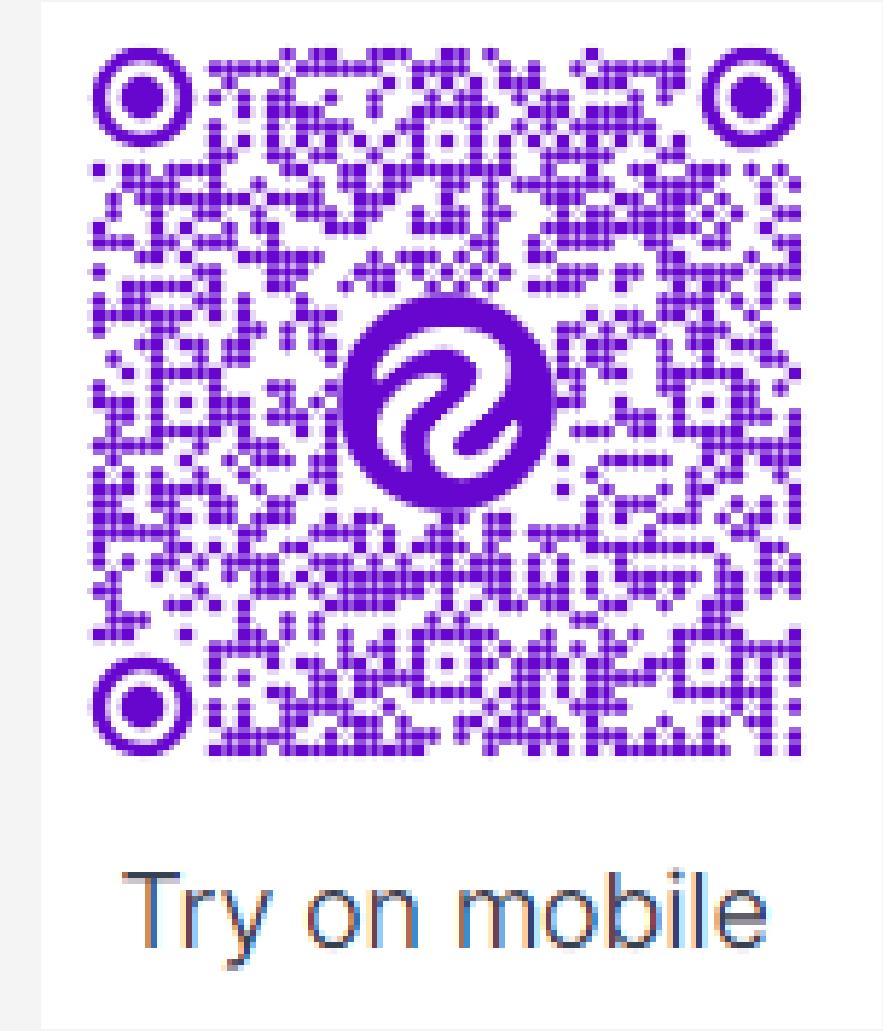
COUNTING IN IMAGE:



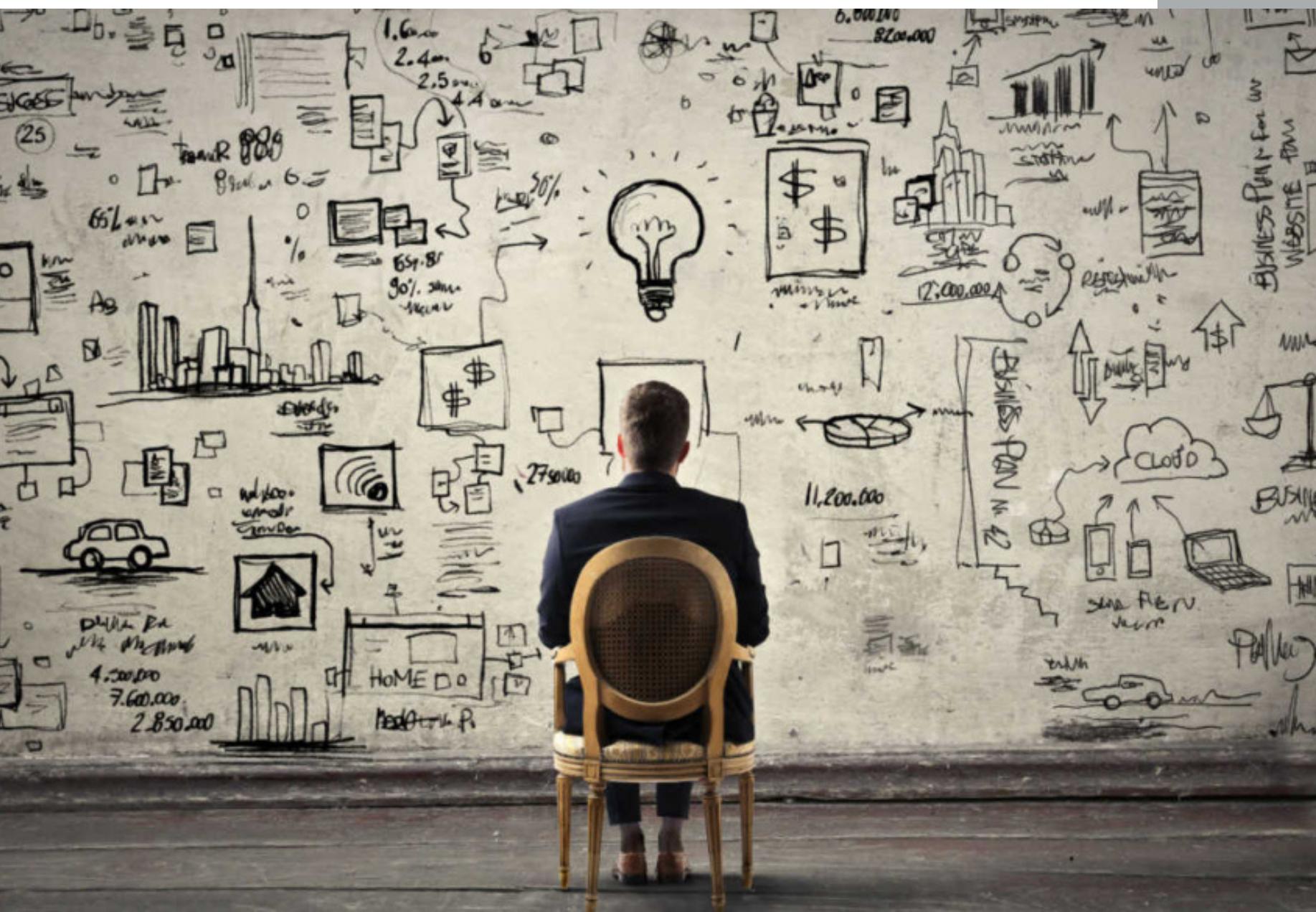
COUNTING IN VIDEO:



COUNTING IN VIDEO:



Future Work



1.

Localization and OCR

Integrate optical character recognition (OCR) capabilities to extract and recognize text such as serial numbers

2.

Security and Fraud Detection

Explore techniques for detecting counterfeit currency notes or fraudulent activities.

3.

Multi-Currency Support

Extend the training dataset and model architecture to support multiple currencies beyond Jordanian currency.

THANK YOU

FOR LISTENING

