Bullseye Detection using YOLOv8 and ONNX

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Introduction & Aim

- Real-time bullseye detection
- Lack of specialized detectors for bullseye patterns
- Goal: build a robust, accurate, and fast detection system

Objectives

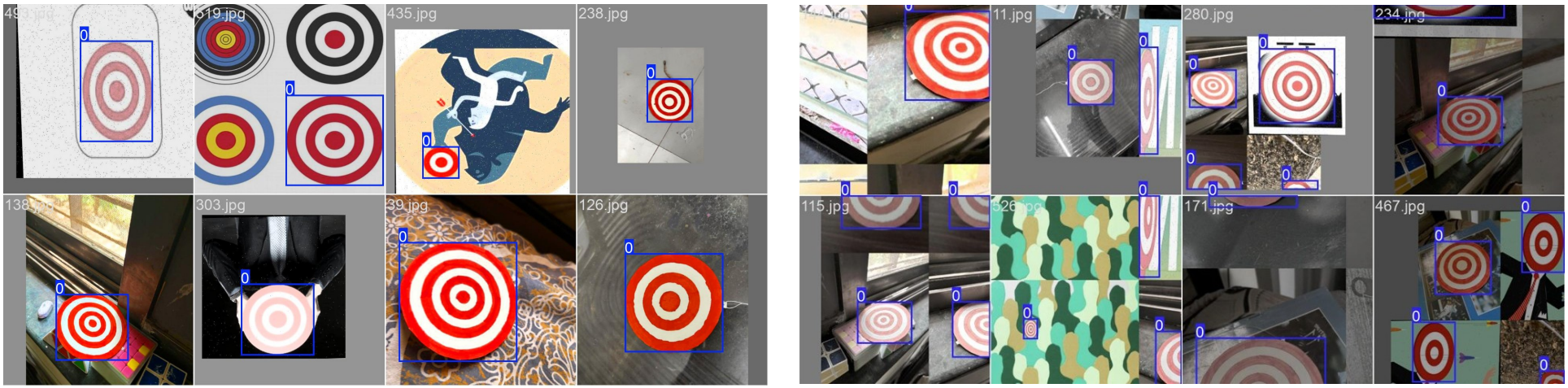
1. Create a diverse custom bullseye dataset
2. Fine-tune YOLOv8 and MobileNetSSD models
3. Evaluate performance: mAP, IoU, precision, recall
4. Optimize and export model to ONNX/TensorRT

Data Collection Overview

- **Hand-drawn captures**: varied lighting, backgrounds, angles
- **Online sources**: Google Images for red/white bullseyes
- **Roboflow Universe**: additional labeled samples

Total images: 550

Sample Dataset Images



figureExamples of bullseye images used for training

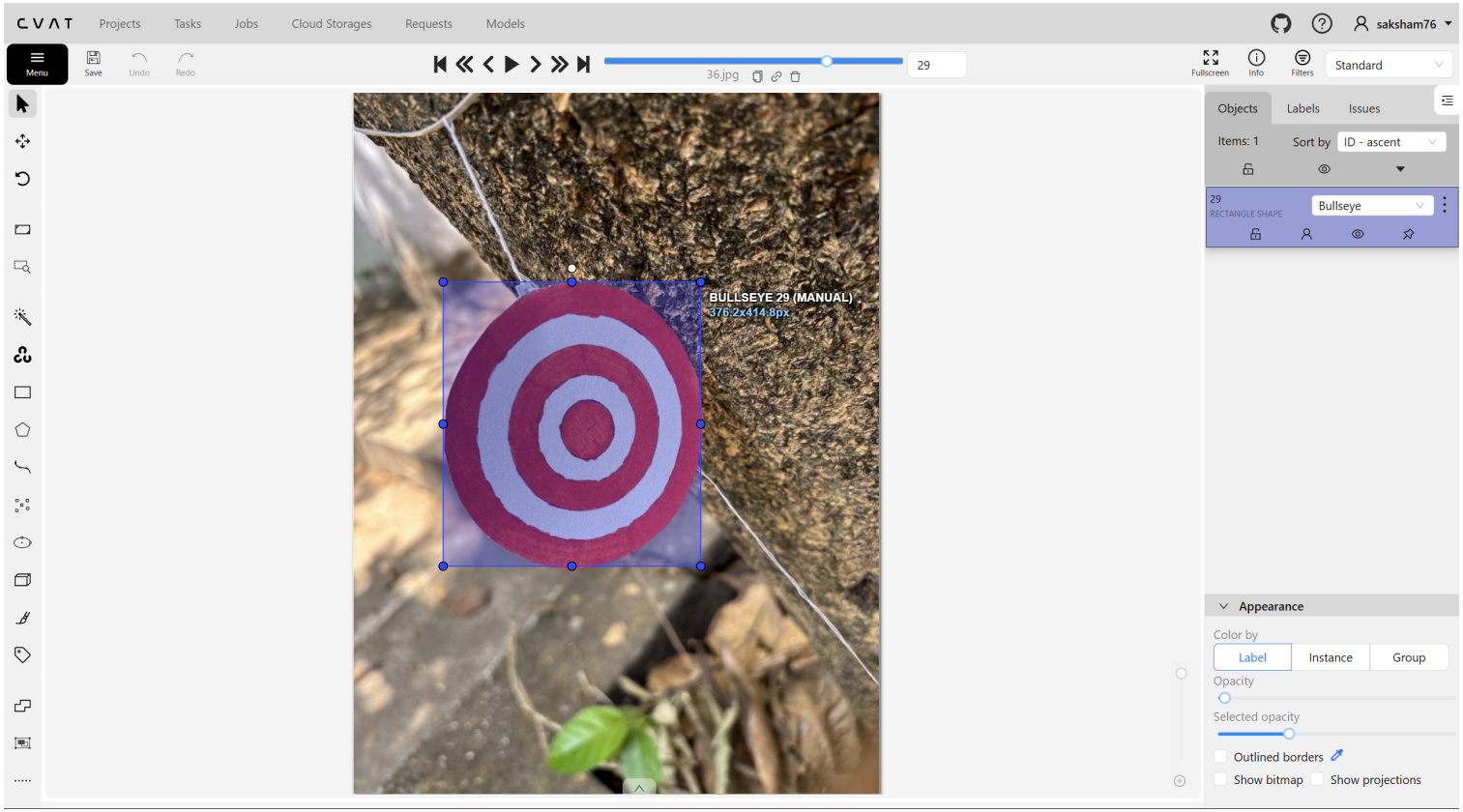
Preprocessing Pipeline

1. HEIC conversion via `pillow-heif` + PIL
2. Resize to 768x1024 with padding using OpenCV
3. Sequential renaming for YOLO compatibility
4. Train/Validation split

Key script: aspect ratio preservation ensures no distortion

Annotation with CVAT

- Tool: CVAT for precise bounding boxes
- Export: YOLO TXT format (class, x_center, y_center, width, height) normalized
- Folder structure: `images/train`, `labels/train`, etc.



CVAT annotation interface example

Model Selection

- **YOLOv8m**: 25.9M params, balanced speed/accuracy
- **Other variants**: nano (3.2M), small (11.2M), large (43.7M)
- Chosen for real-time capability on RTX 4070

Hyperparameters

Parameter	**Value**
Model	YOLOv8m
Batch Size	32
Epochs	100
Image Size	640x640
Workers	4
Learning Rate	0.01 (default)
Momentum	0.937 (default)
Weight Decay	0.0005 (default)
Device	NVIDIA RTX 4070

Table: Training Configuration Summary

Training Command

```
import torch

from ultralytics import YOLO

model = YOLO("yolov8m.yaml")

results = model.train(
    data="config.yaml",
    epochs=100,
    batch=32,
    workers=4,
    device=0
)
```

Data Augmentation

Default YOLOv8 augmentations:

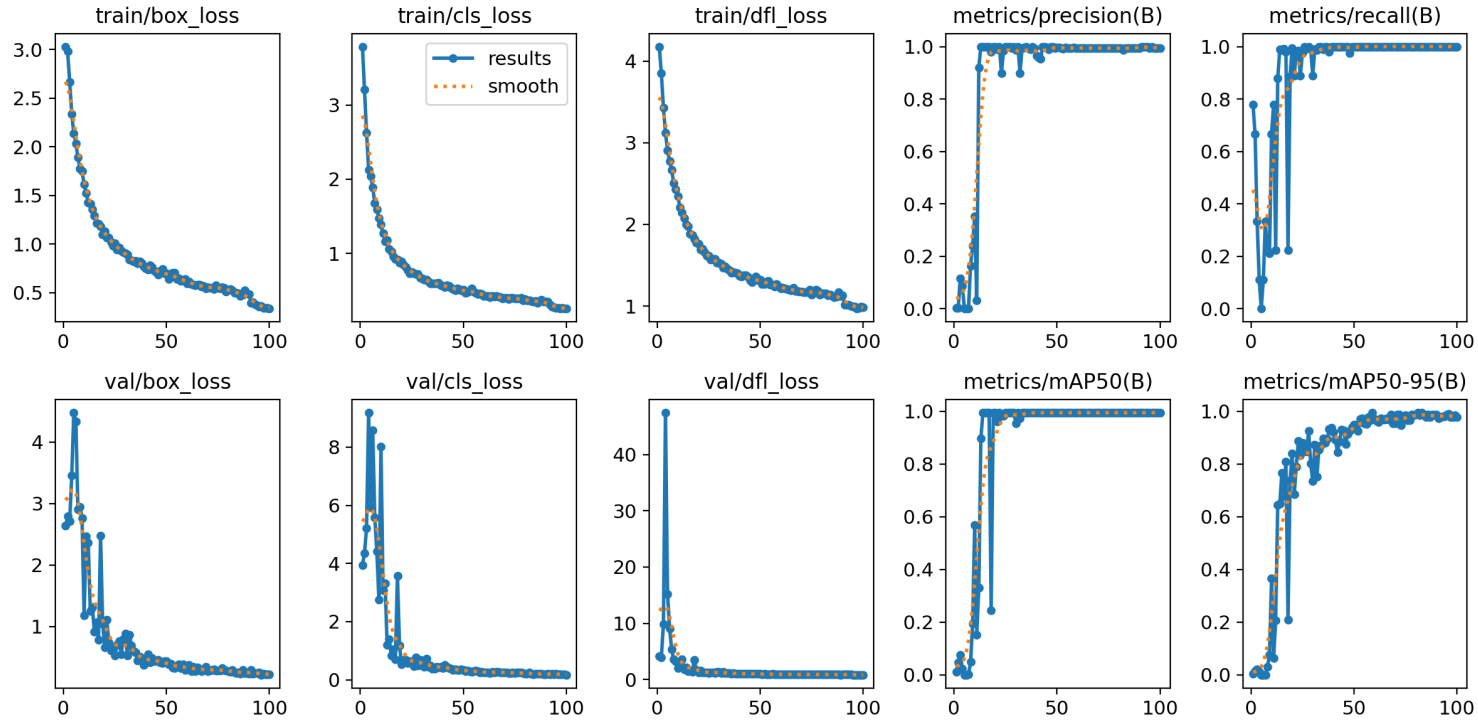
- Mosaic (enabled)
- HSV color jitter (h=0.015, s=0.7, v=0.4)
- Horizontal flip (0.5)
- Scaling, translation, rotation
- Perspective/stretch

Improves model robustness without manual tuning.

Quantitative Results

- Precision: 0.995
- Recall: 1.000
- mAP@0.5: 0.995
- mAP@0.5:0.95: 0.9785

Loss Curves



Training & Validation Loss vs. Epochs

Per-Class Performance

- Class "bullseye": AP@0.5 = 0.995

Exporting to ONNX

Conversion Command

```
yolo export model=runs/detect/train/weights/best.pt
format=onnx
```

- ONNX size: 98 MB

Side-by-Side Video

Play Original

Play Output

Key Challenges

- HEIC conversion aspect ratio preservation
- Annotation
- Ensuring GPU utilization in training

Solutions Applied

- Used `pillow-heif` + padding script
- Validated YOLO format via CVAT checks
- Configured torch CUDA and conda environment

Timeline of Work

[5 April] Assignment reviewed and setup
[6 April] Dataset collection and script development
[7-8 April] Annotation and preprocessing
[9 April] Model training and evaluation
[10 April] Model export and report writing

Conclusion

- High accuracy detection achieved
- Real-time inference demonstrated
- ONNX export enables flexible deployment

Future Work

- Deploy on edge devices with TensorRT
- Expand dataset with varied bullseye designs
- Implement tracking and multi-object scenarios

Questions?

Thank you!