Foosball Table Real-Time Object Detection

Team 9

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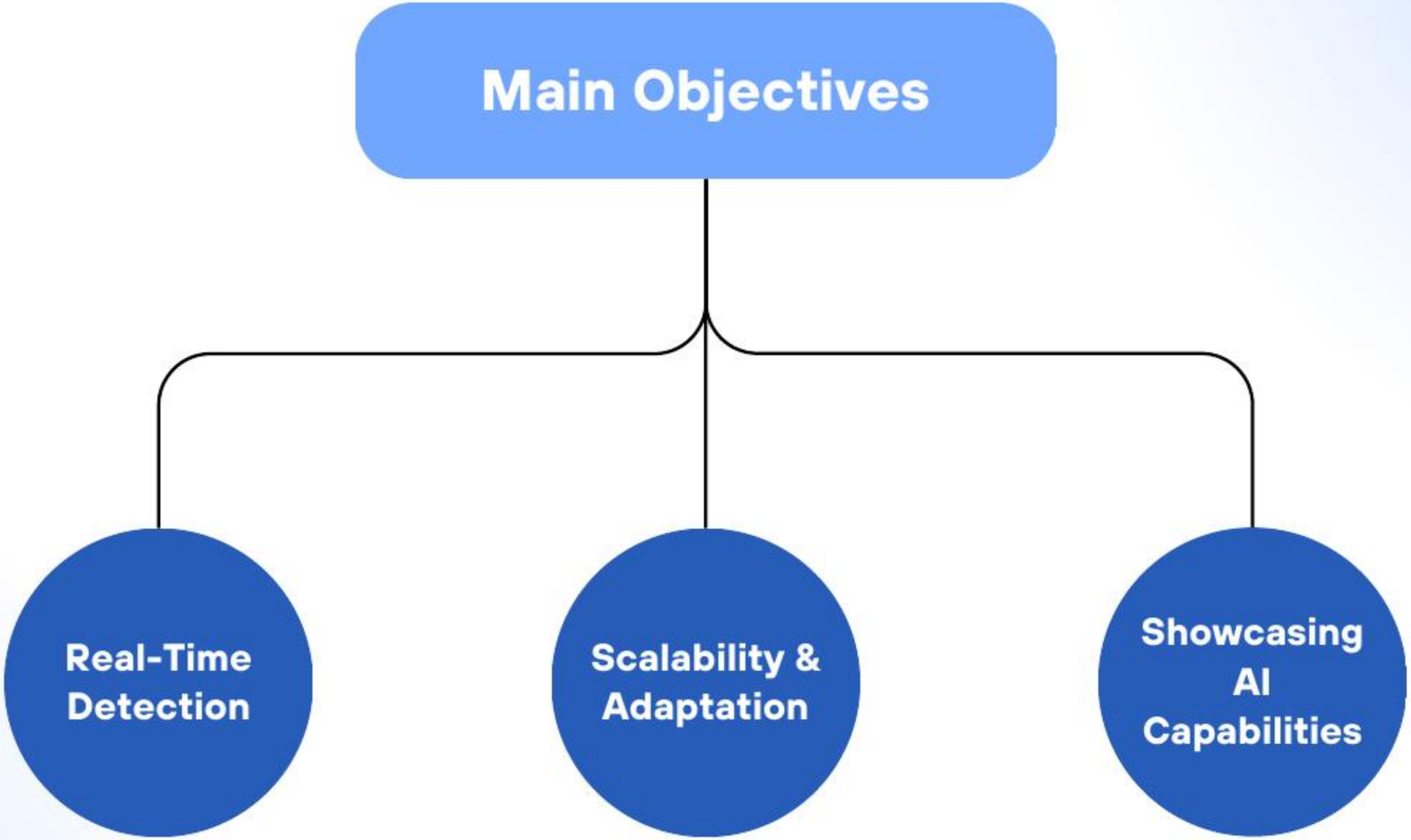
Using advanced computer vision, **our real-time foosball detection system** provides **immediate feedback, analytics, and insights** for LINKS Foundation teams and partners. It **showcases AI** on the LINKS ADS foosball table while delivering **exceptional accuracy, speed** beyond existing solutions.

Value Proposition


Main Objectives
Real-Time Detection
Scalability & Adaptation
Showcasing AI Capabilities

Research Questions

01

Detection and Accuracy

02

Model Selection

03

Real-Time Performance

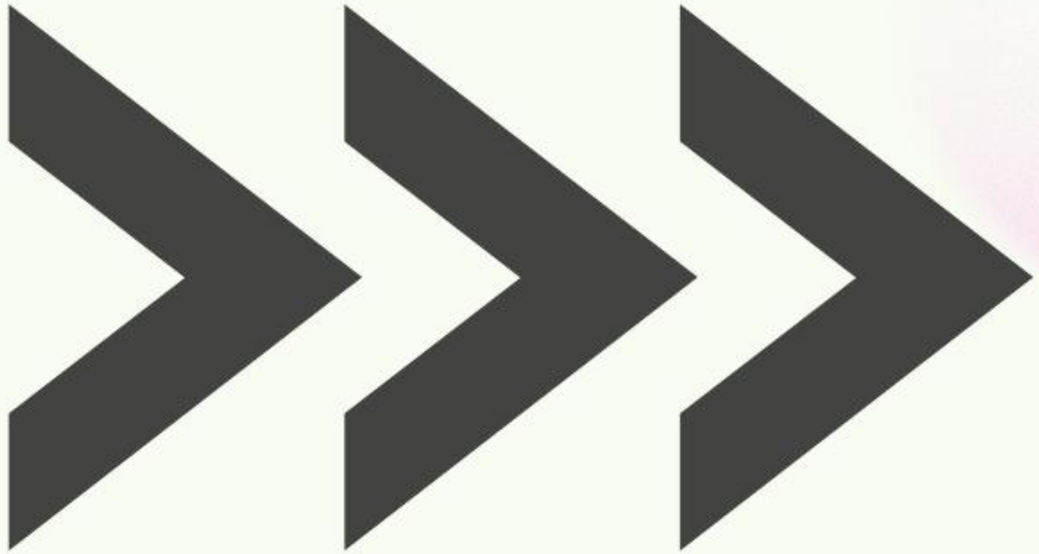
04

Adaptability

05

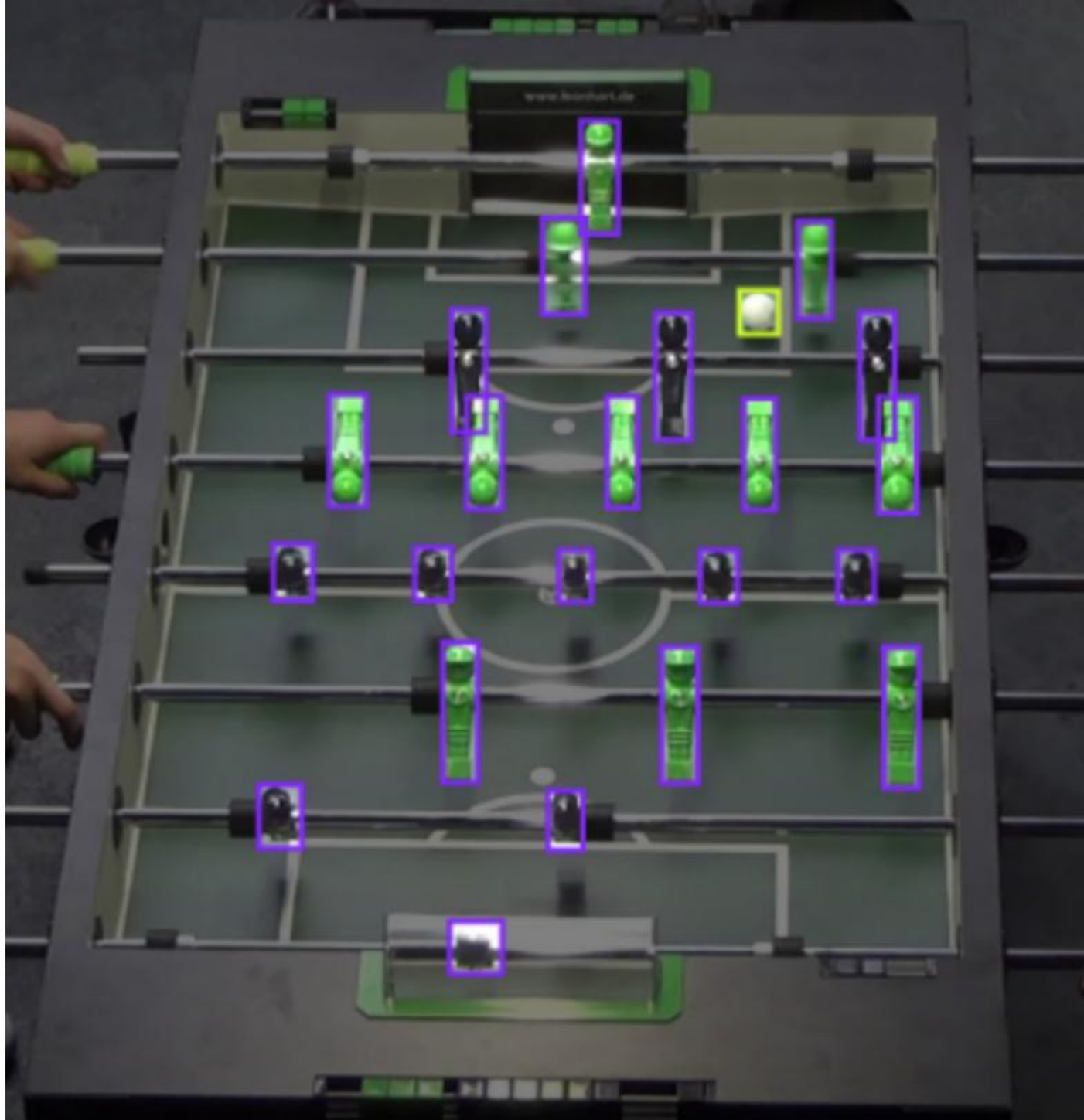
Scalability

Method



Object Detection Task with Two Classes:

1. Figure
2. Ball



YOLO 11S

- Balanced Accuracy (mAP50-95)
- High Detection Accuracy (mAP50)
- High Real-Time Performance (FPS)
- Optimal Trade-Off Between Accuracy and Speed
- Scalability for Deployment

roboflow

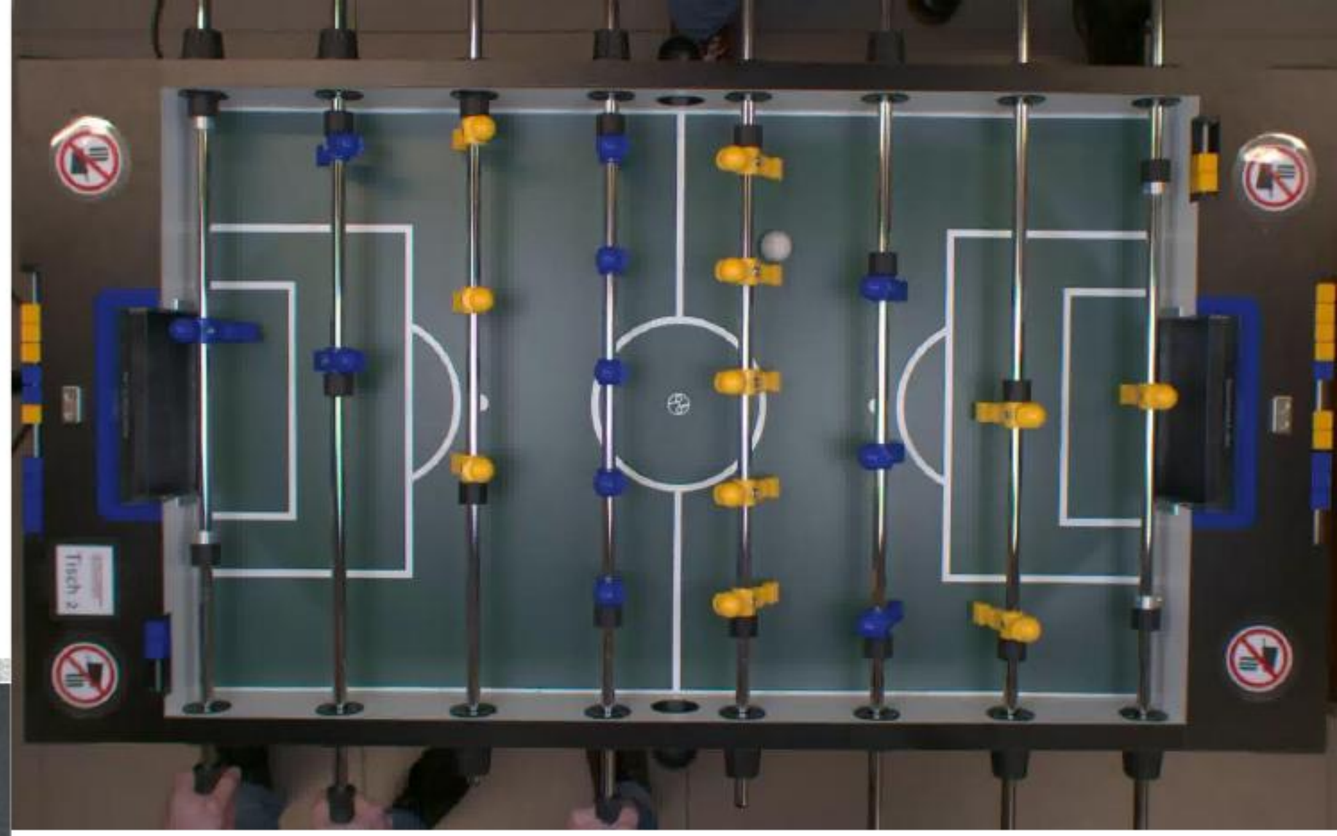
Big foosball detection dataset

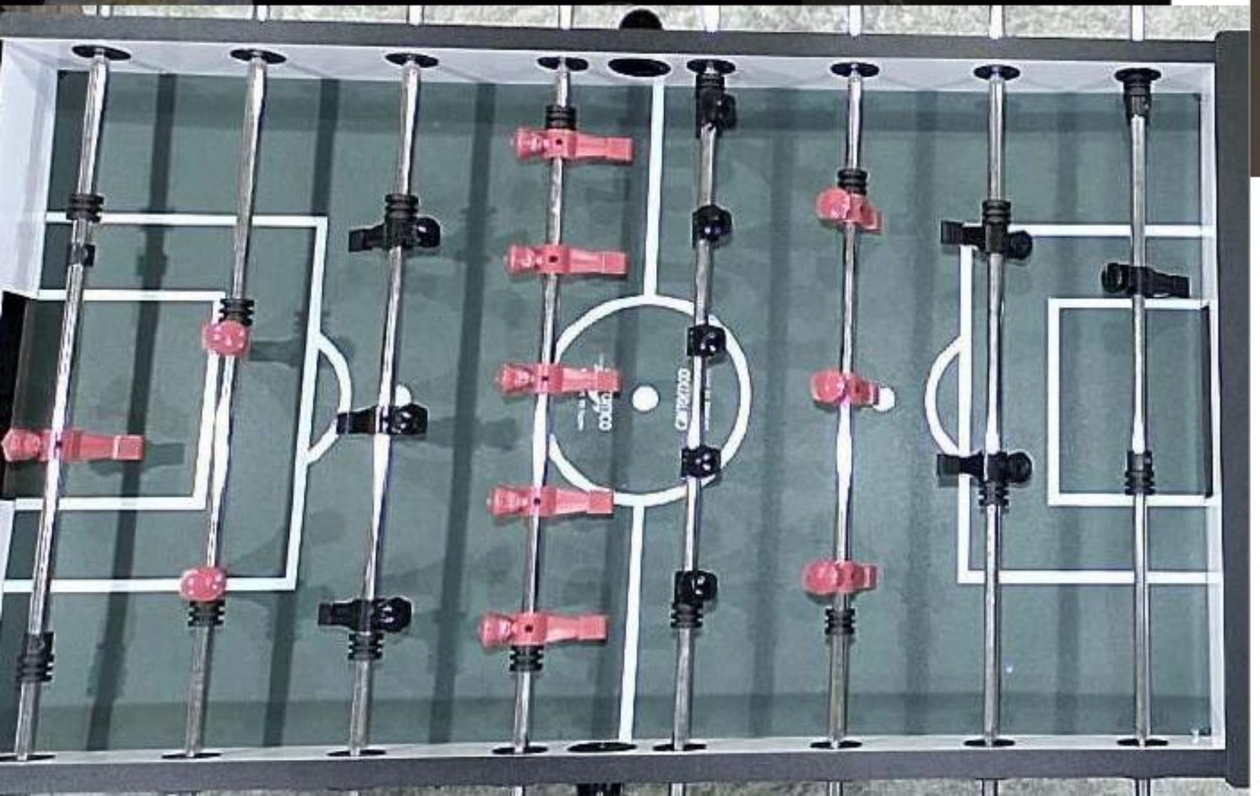
Computer Vision Project

- Includes 5111 Train Data
- Annotated & Labeled for Efficiency
- Comprehensive Dataset
- Real-World Applicability

The Domain Shift Between the Original Training Data and The Target, Links Foundation Foosball Table

- Color Differences
- Camera Perspectives/Angles
- Lighting Conditions





Training Data Samples

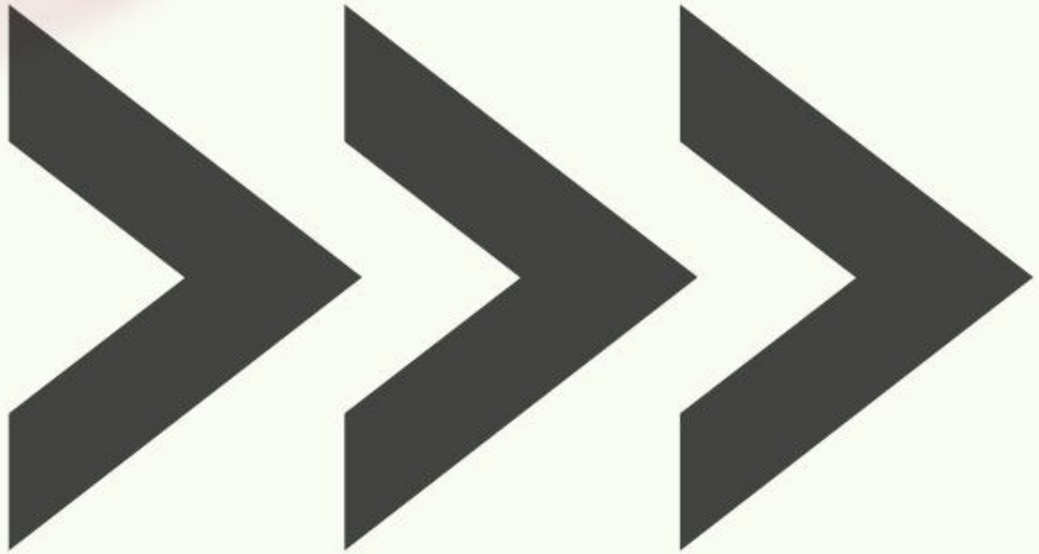
Frames of LINKS Foosball Table

Augmentation & Strategy Plan

Our Plan: Make the model learn shape-based features and become less reliant on color cues and reduce the models bias towards perspective.

- **Offline modifications** (Brightness, Saturation, Contrast, Grayscale, Partial Binary).
- **On-the-fly YOLO parameters** (HSV (Color Jitter), Random Perspective, Shear, etc.).

Experiments



TRIALS / ITERATIONS

01 Offline Augmentation in Brightness/Saturation/Contrast

10 epochs

Result Observation:
Model Failed to be Trained due to the intensity of changes.

02 YOLO's Built-in HSV Augmentations (Color Jitter)

10 epochs

Result / Observation:
Model performed well in the training and validation but poorly on LINKS Foosball Table data.

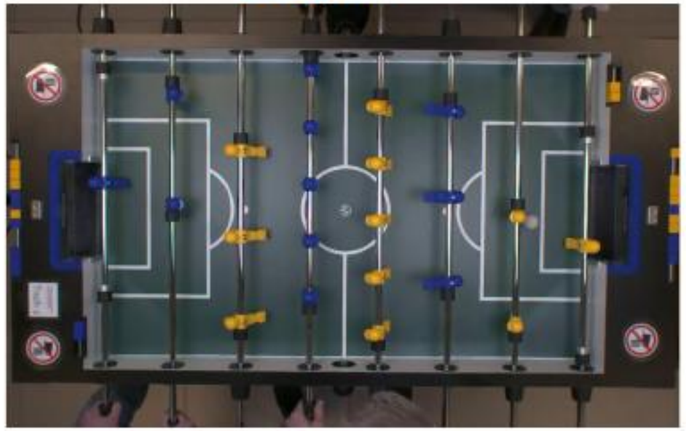
03 More Intense Shift in HSV Augmentation

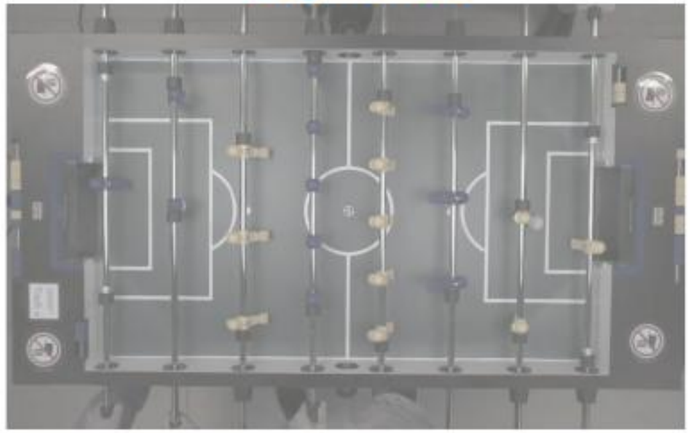
20 epochs

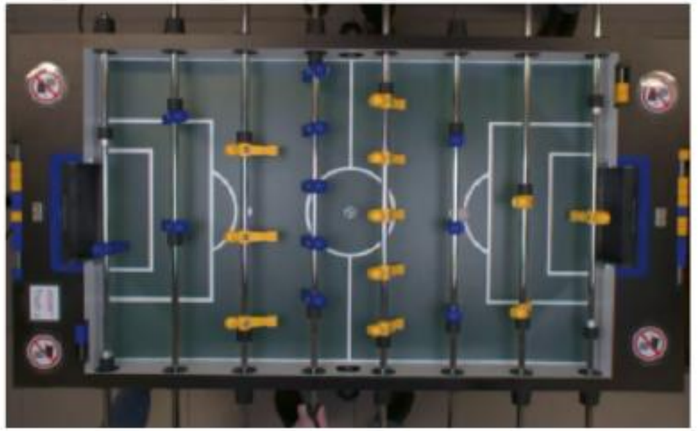
Result / Observation:
Model performed well in the training and validation but not noticeable improvement in LINKS Foosball Table data detection.

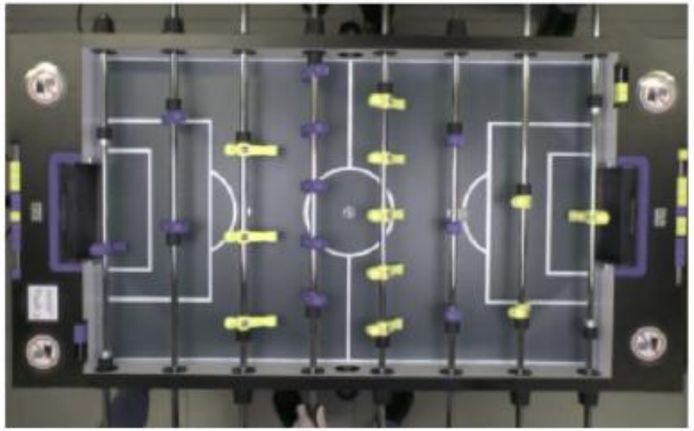
Original

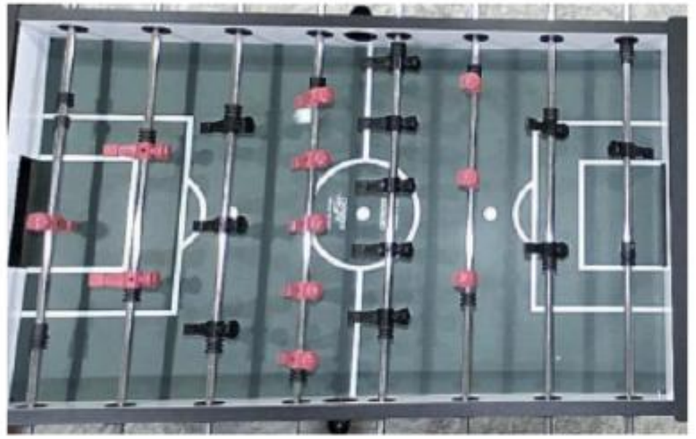
Augmented

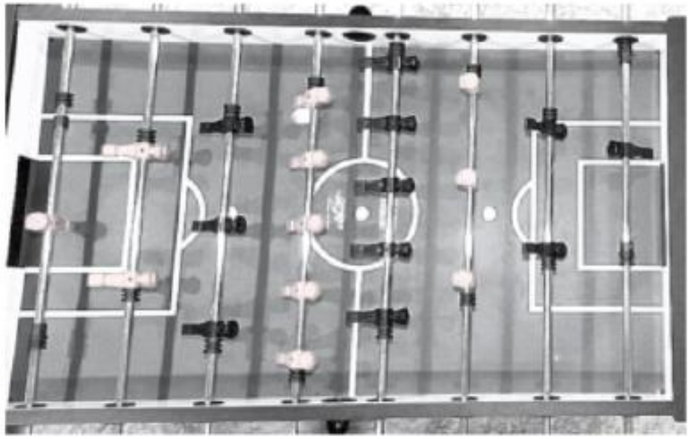












TRIALS / ITERATIONS

04 Offline 30% Grayscale Augmentation

25 epochs

Result / Observation:

Model performed well in the training and validation but no significant detection improvement was observed in LINKS Foosball Table data.

05 Offline 30% Partial Binary Augmentation

No training has been occurred

Result / Observation:

Binary images would be unrecognizable to the model and were practically useless.

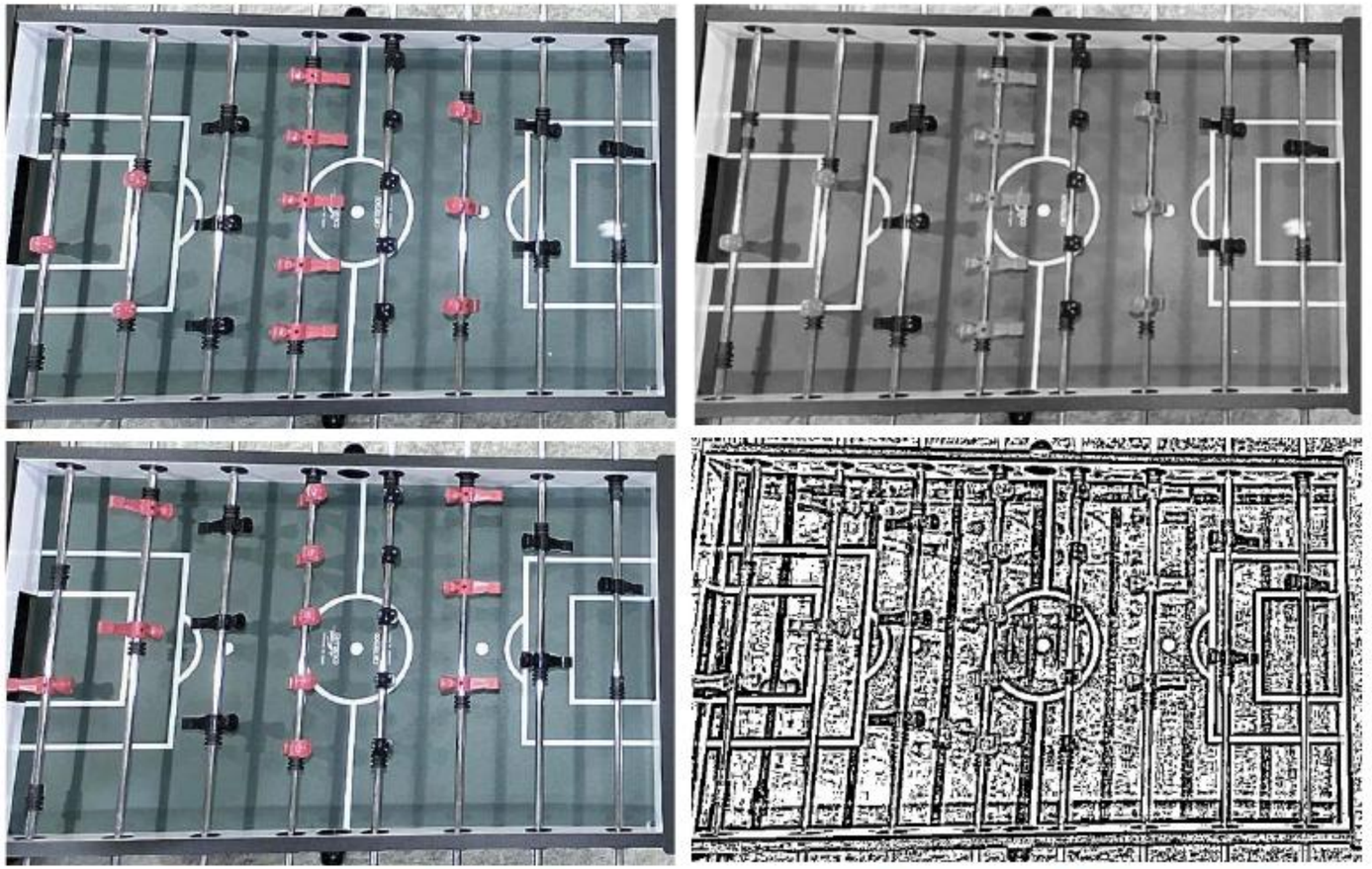
06 Adjust Target Test Images (Brightness/Contrast)

In Test Phase

Result / Observation:

It slightly improved overall detection in the experiments but not significantly.

Original **Augmented**



TRIALS / ITERATIONS

07 Strong Shift in HSV + Random Perspective + Offline 30% Grayscale Augmentation

40 epochs

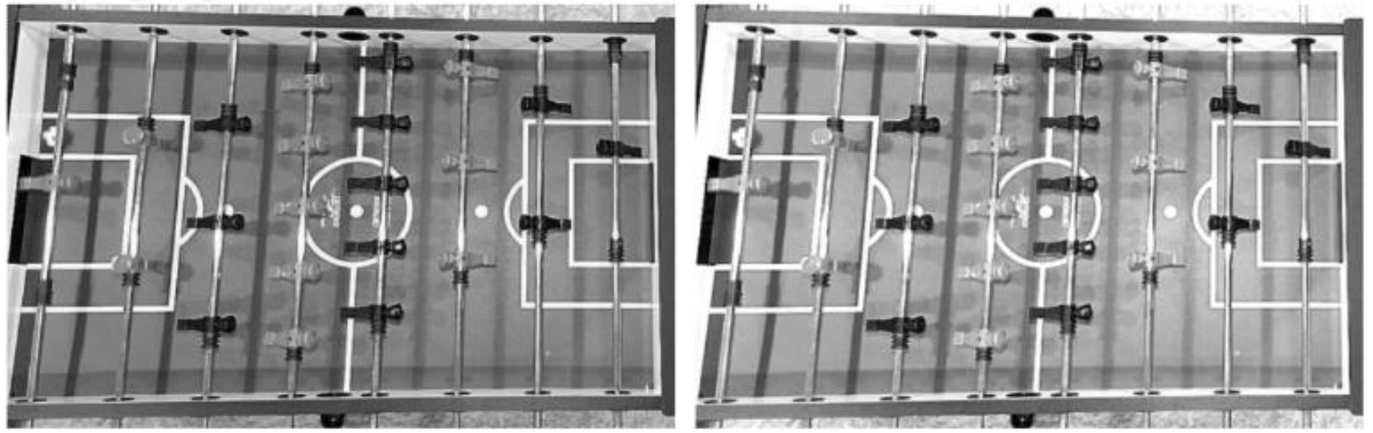
Result / Observation:
Model performed well in the training and validation. Tested on Adjusted LINKS Foosball Table frames. Best performance on LINKS Foosball Table data has been seen in this experiment.

08 Yolo11s with No Augmentations (Original Dataset)

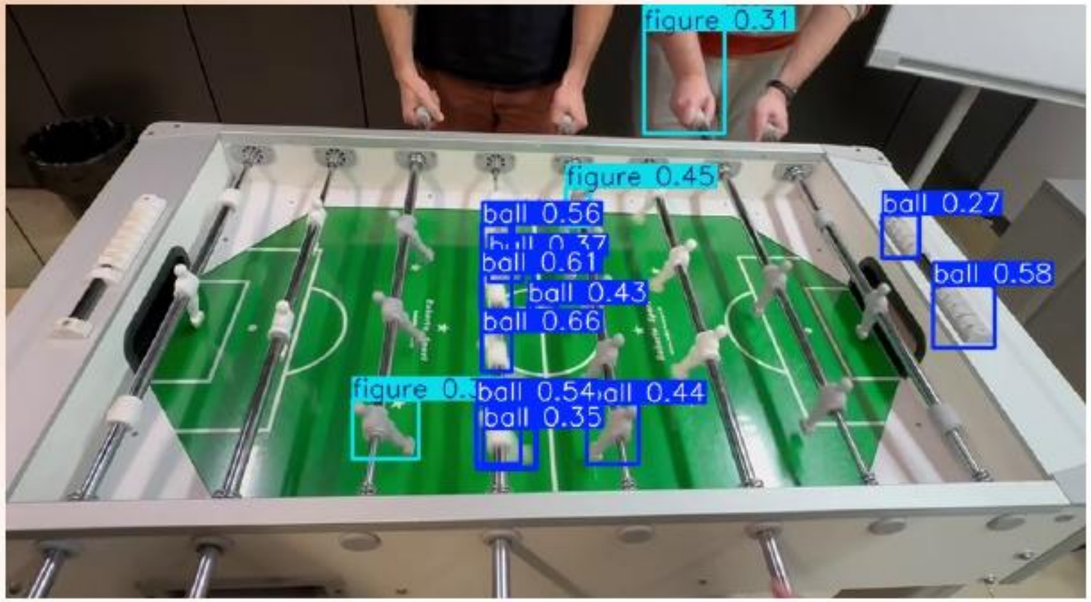
100 epochs

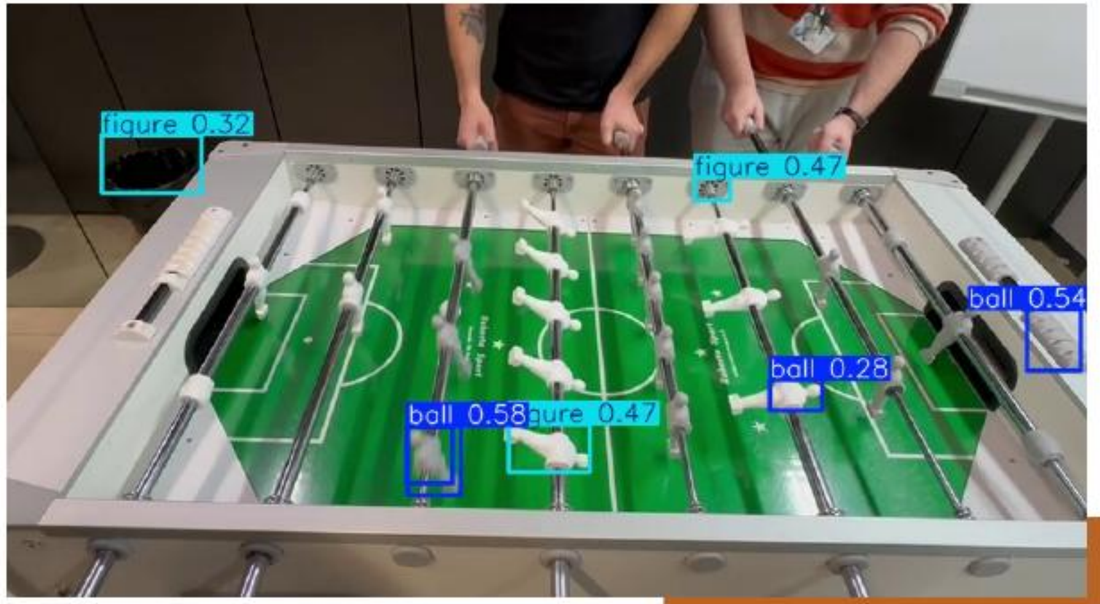
Result / Observation:
Model performed well in the training and validation, but poorly on LINKS Foosball Table data. The performance even fell compared to non augmented Yolo11s trained with 10 epochs.

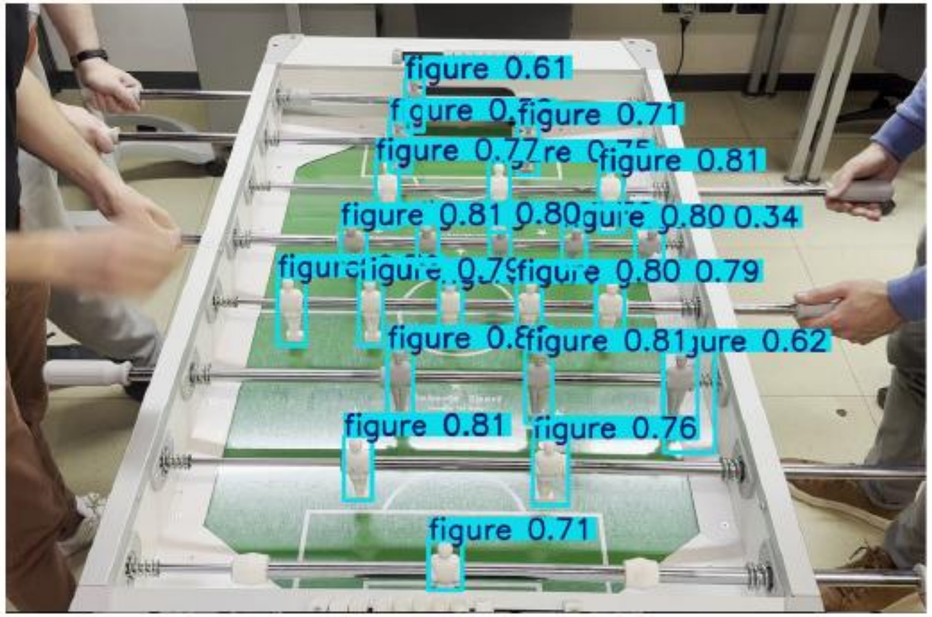
Original **Augmented**

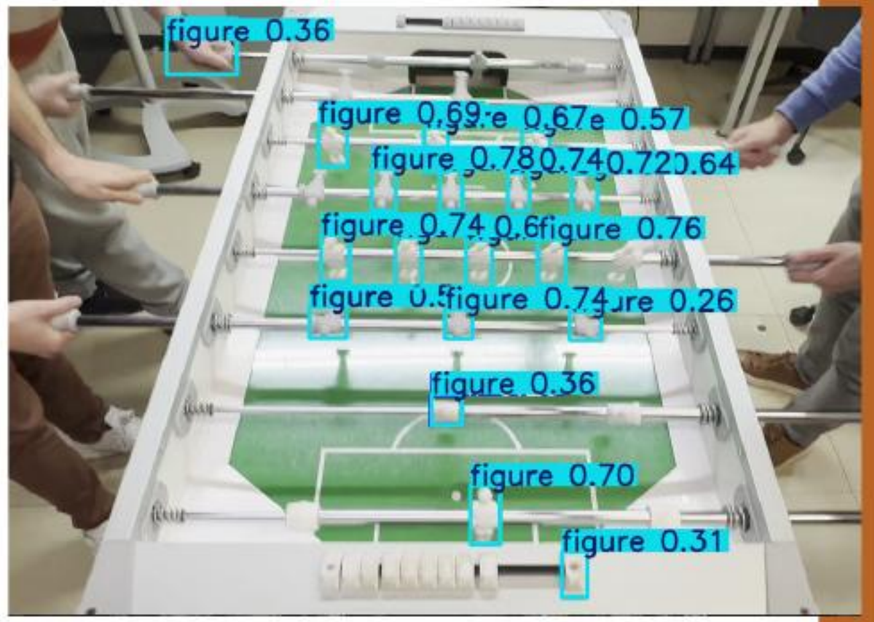


10 Epochs Trained Yolo11s on Original Dataset, Without Augmentation



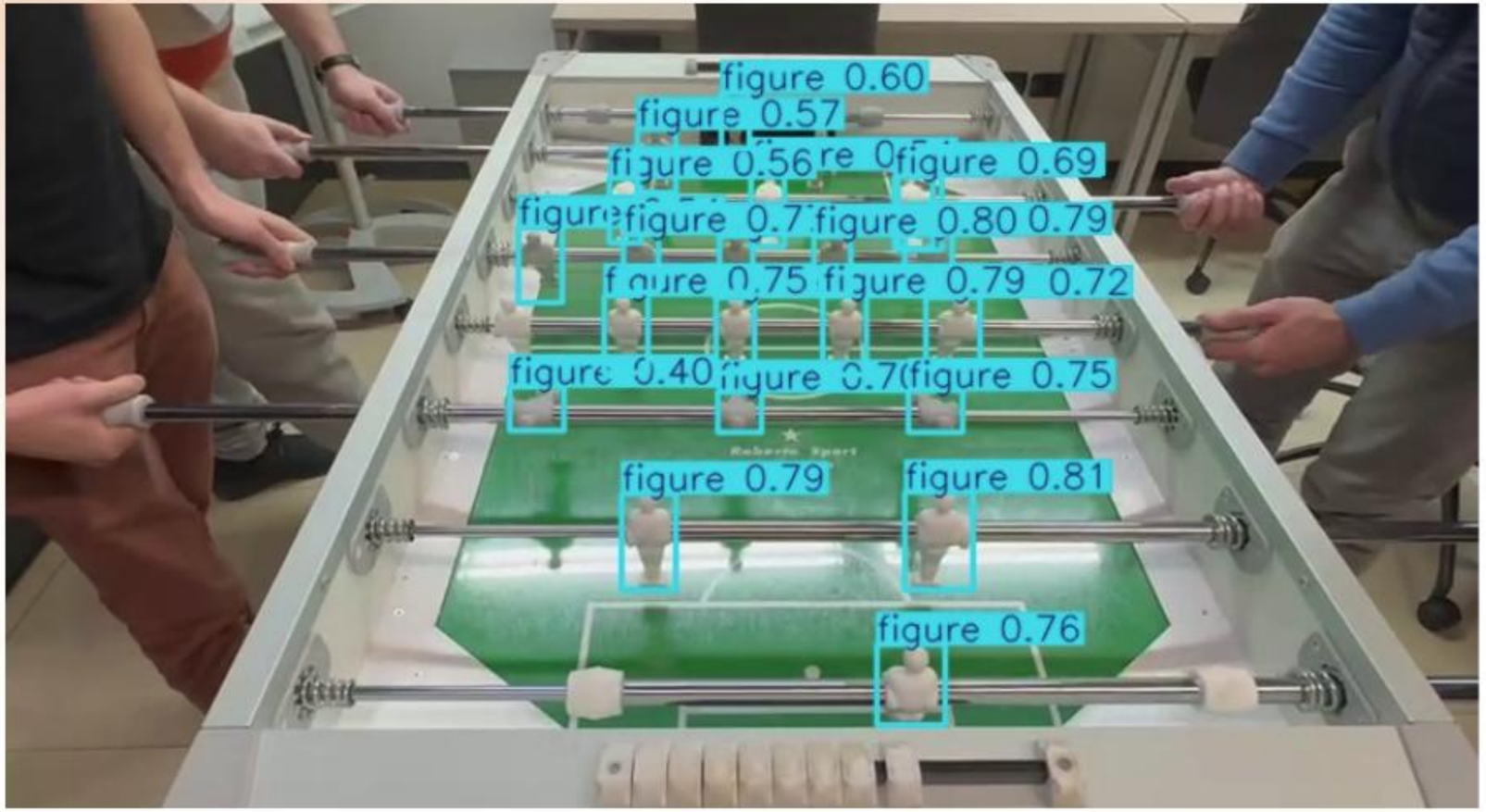






Some Test Results

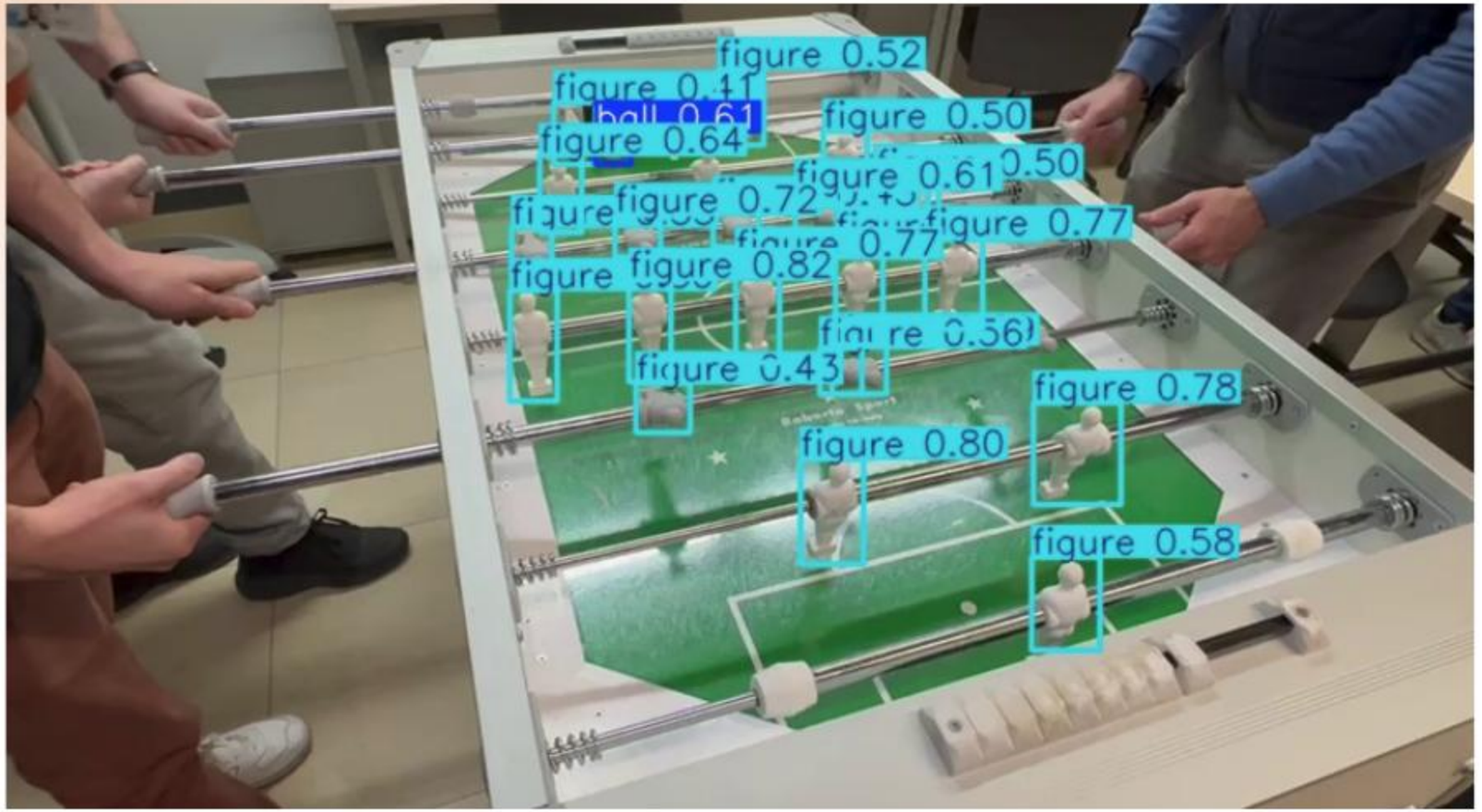
Best Performance in Results



Resulted from Strong Shift in HSV + Random Perspective + Offline 30% Grayscale Augmentation

Some Test Results

Best Performance in Results



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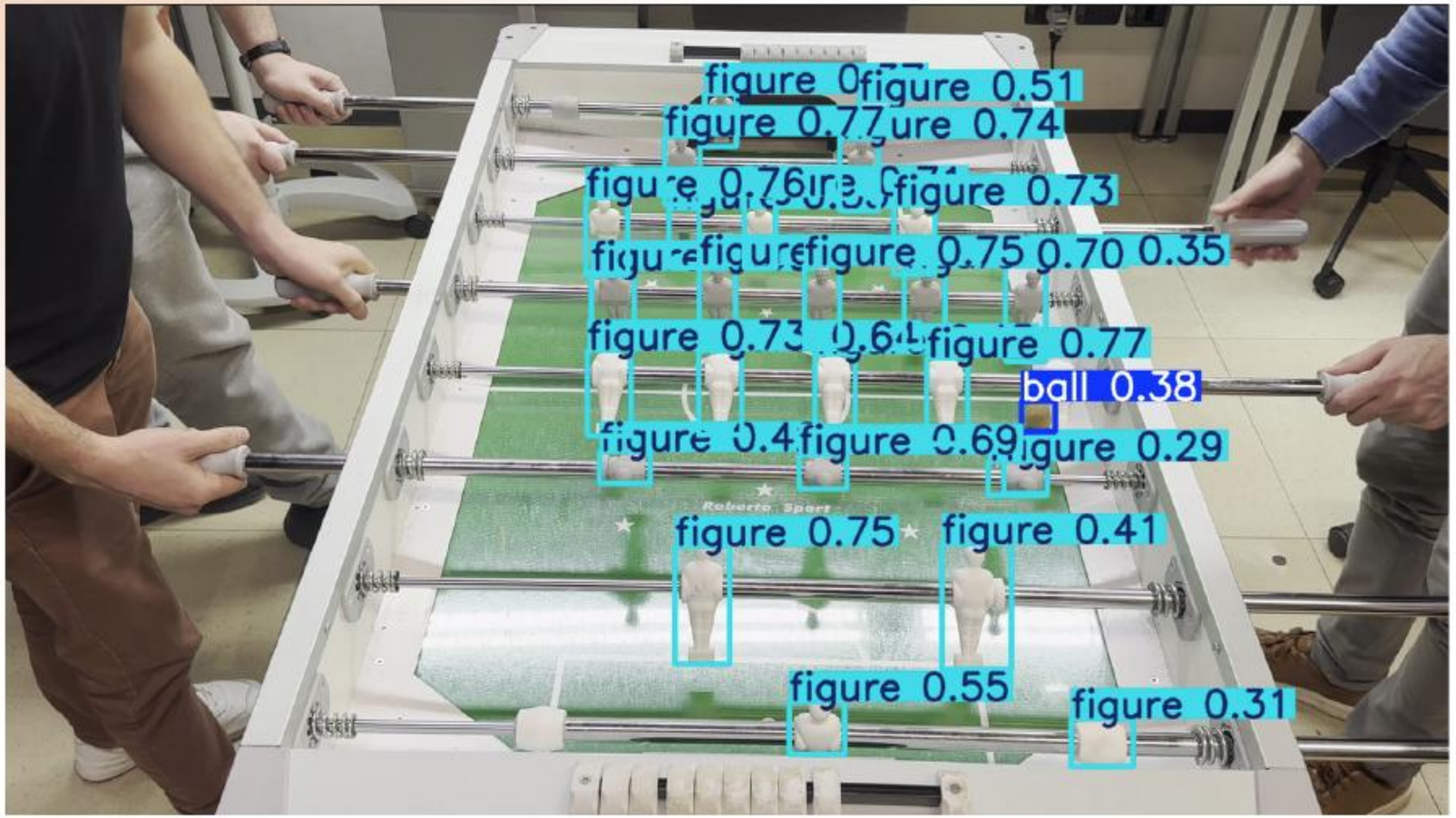
Some Test Results

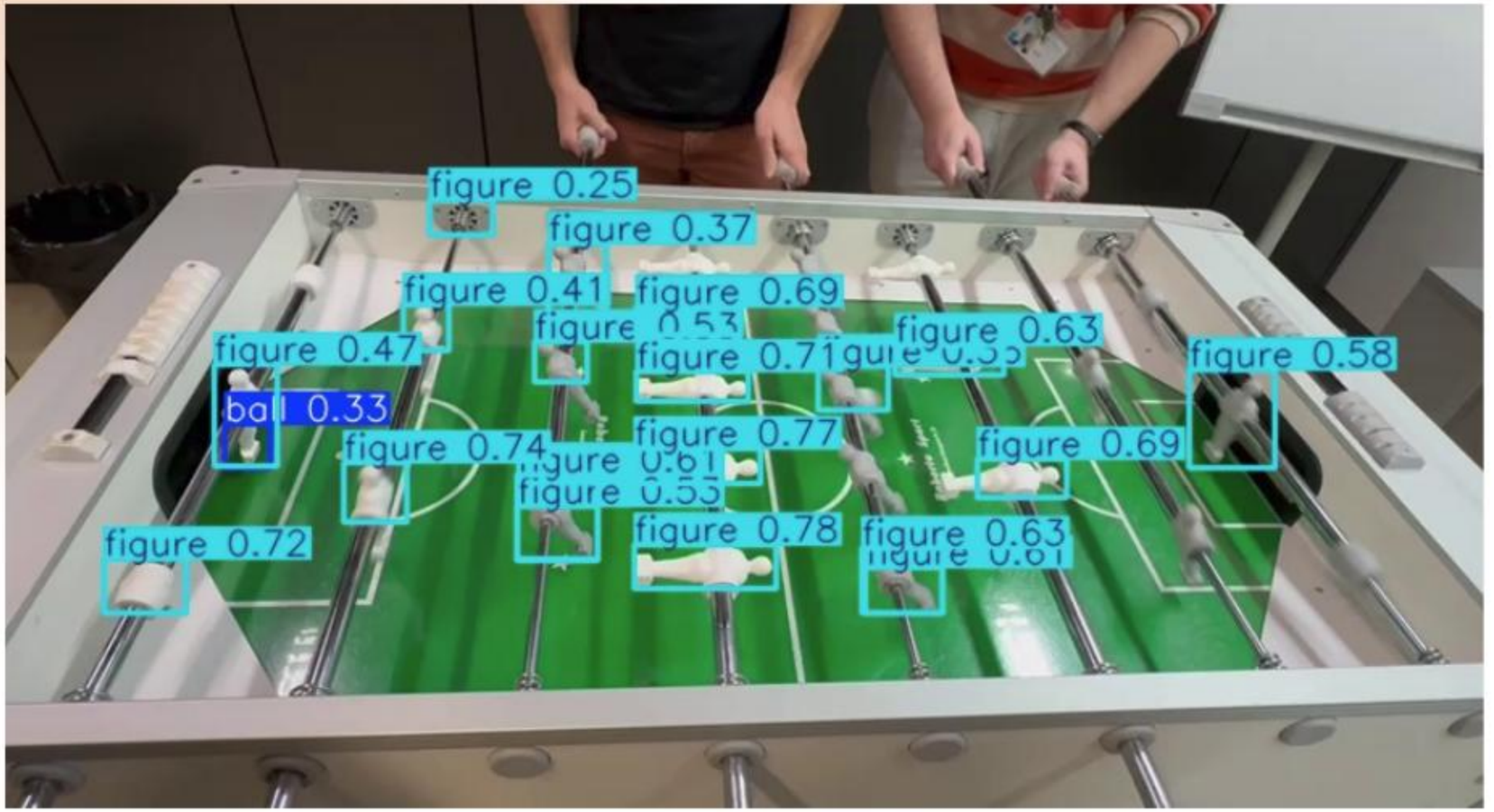
Best Performance in Results



Resulted from Strong Shift in HSV + Random Perspective + Offline 30% Grayscale Augmentation

Some Test Results

Poor Performance in Results



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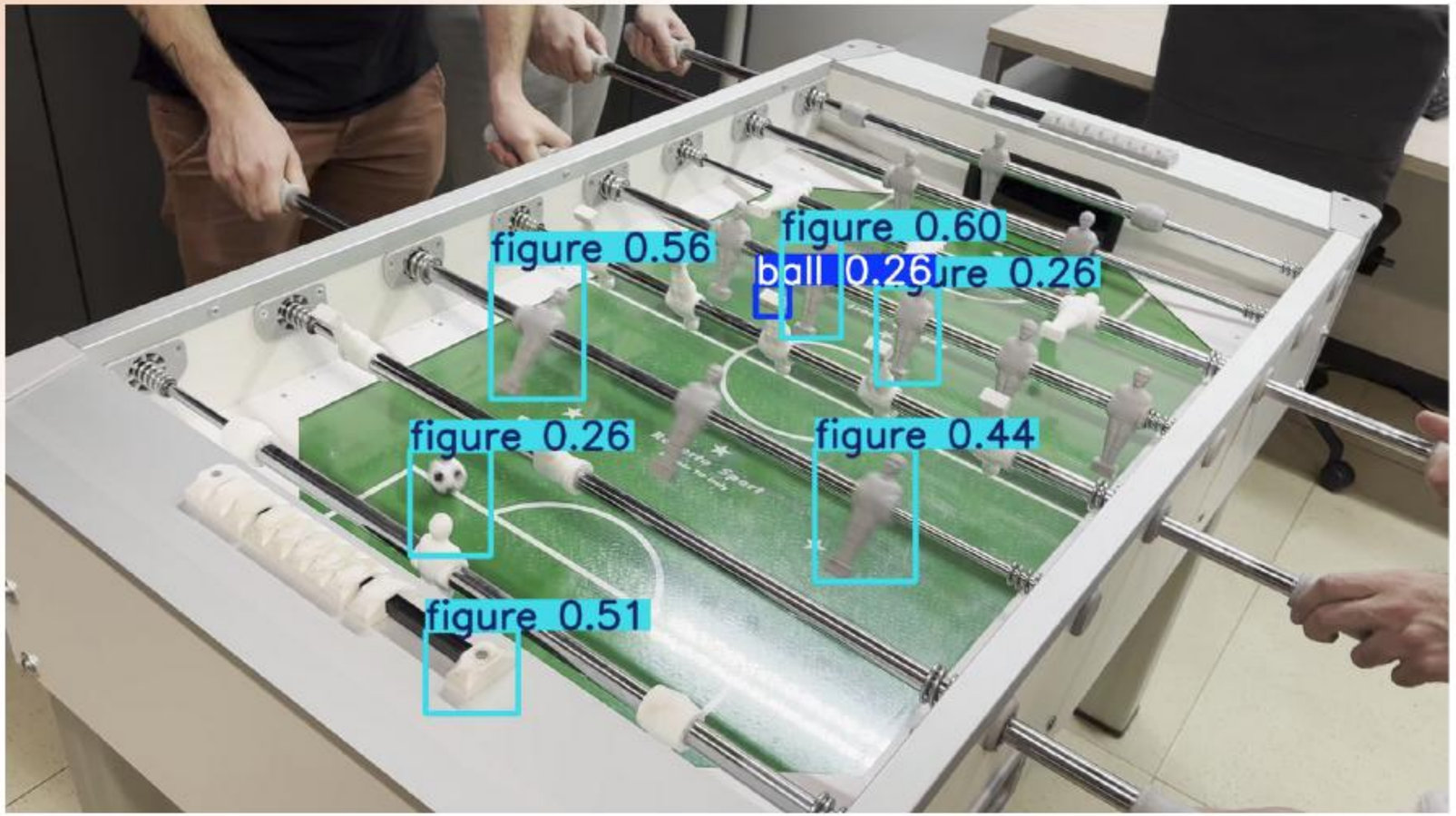
Some Test Results

Poor Performance in Results



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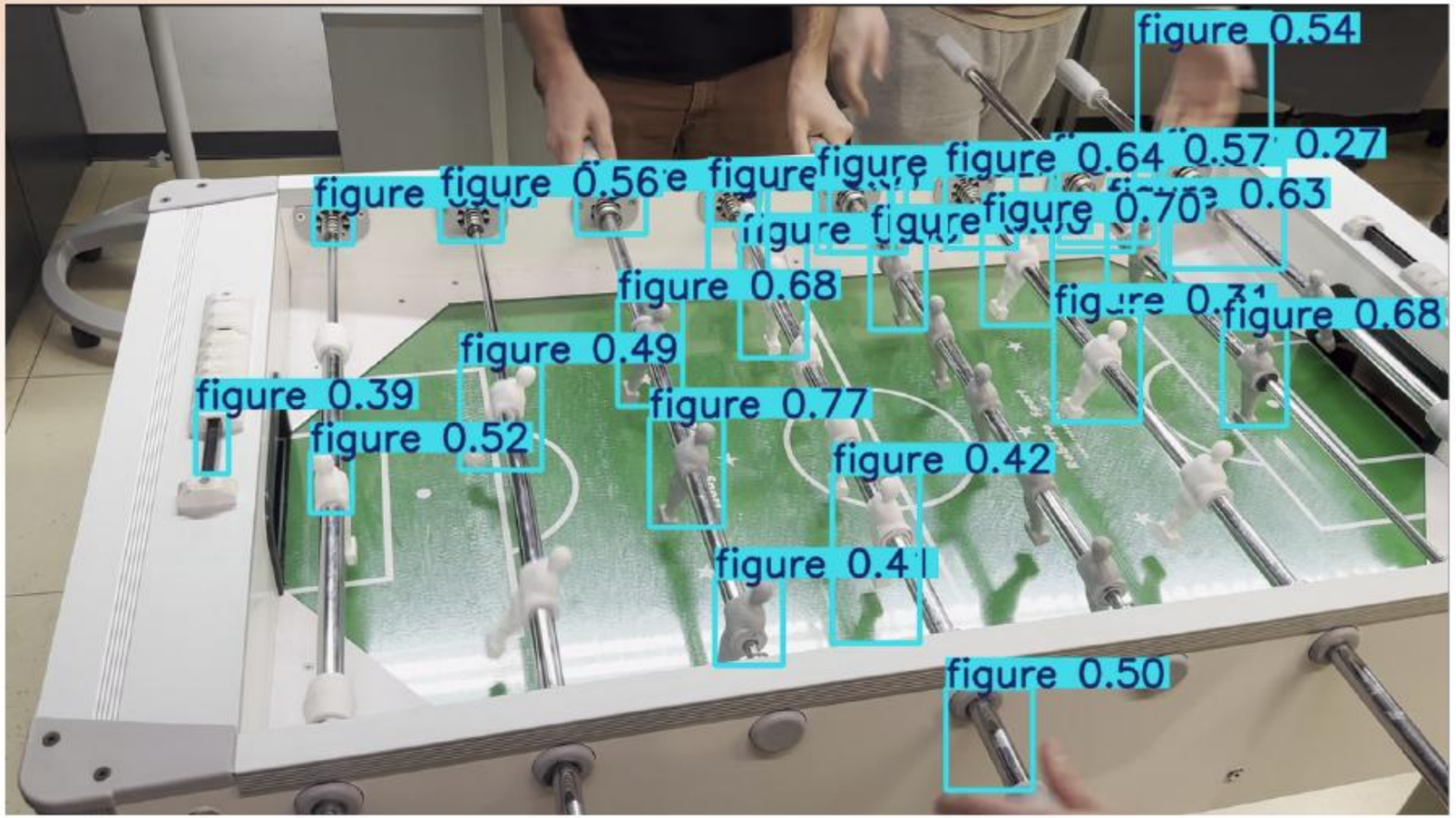
Some Test Results

Poor Performance in Results



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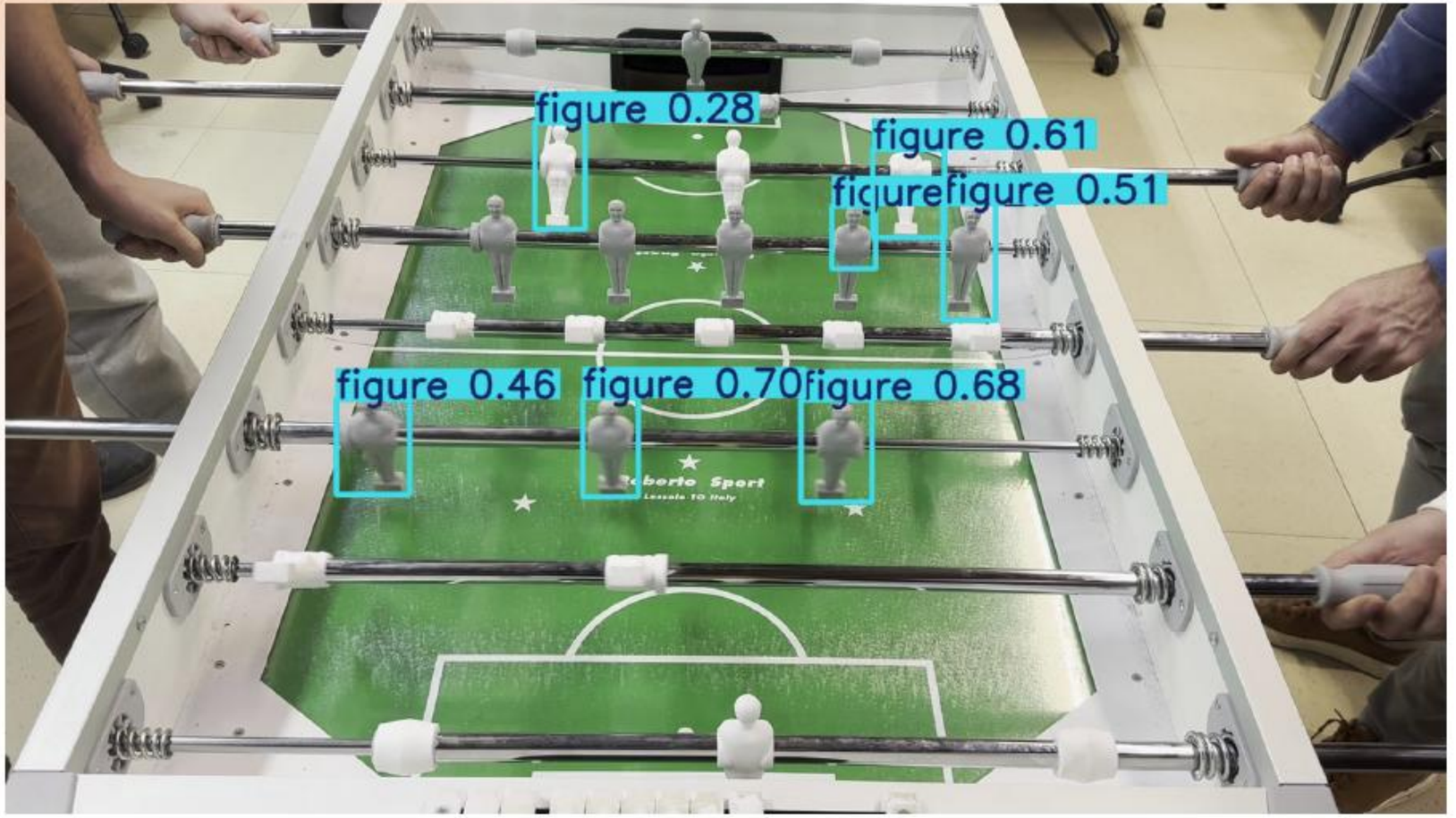
Some Test Results

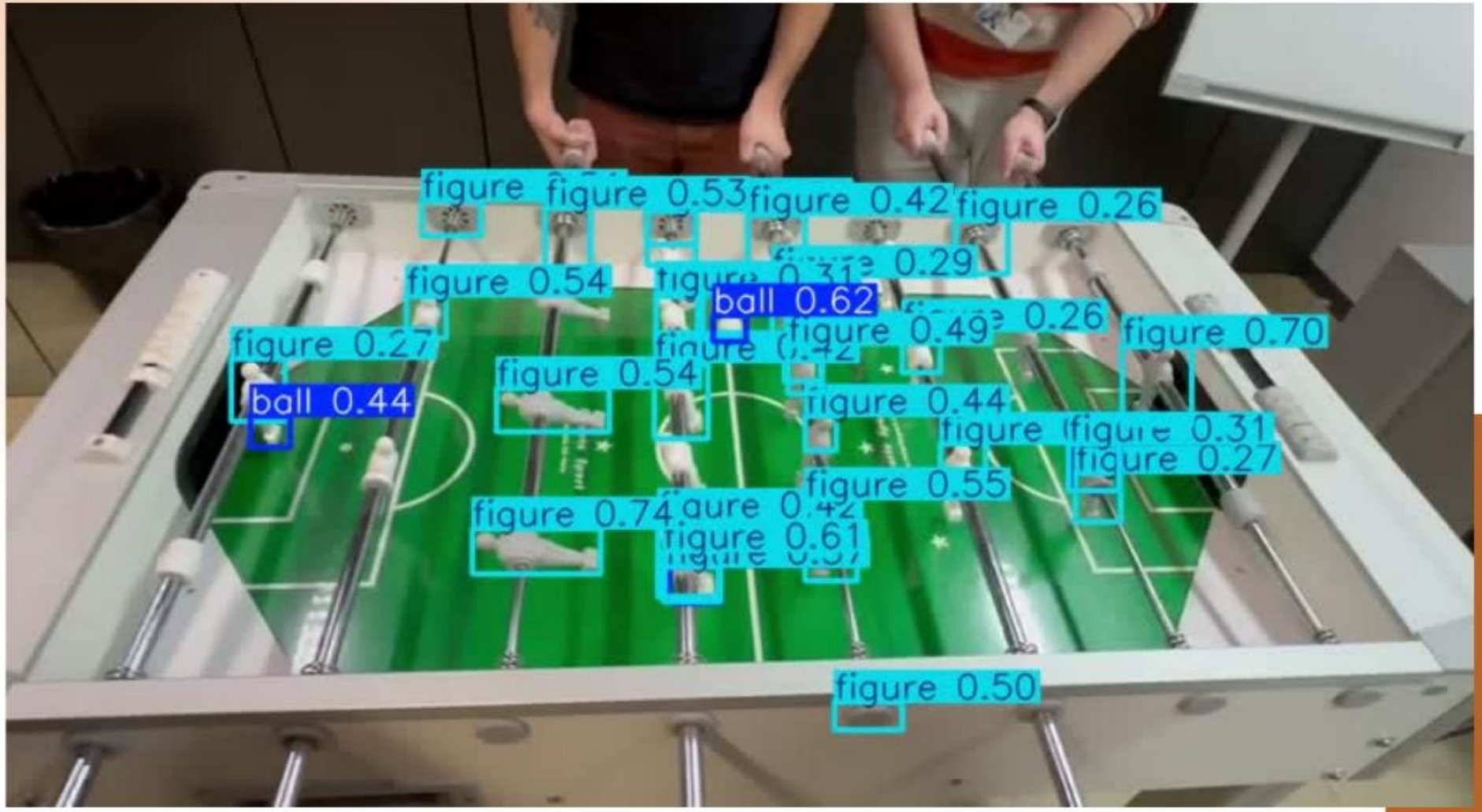
Poor Performance in Results



Resulted from Strong Shift in HSV + Random Perspective + Offline 30% Grayscale Augmentation

Some Test Results

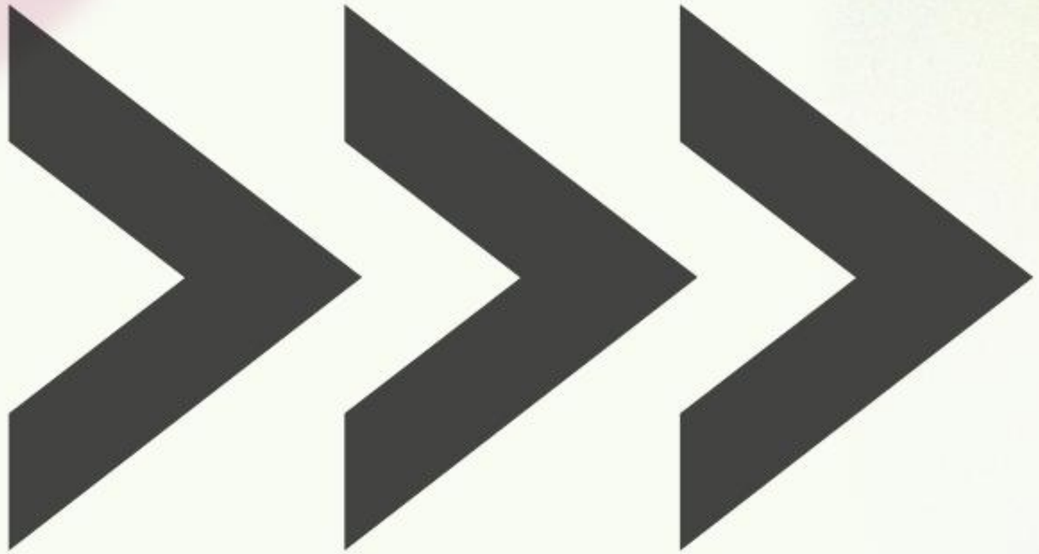
Real Time Detection Result



Resulted from Strong Shift in HSV + Random Perspective + Offline 30% Grayscale Augmentation

Some Test Results

Conclusion



Summary of Findings

- Longer training along with stronger augmentations improved results, but not uniformly.
- Shape-based approaches (Geometric Transforms) did help the model ignore color confusion.
- Color-based augmentations (Grayscale, Color Jitter) encouraged the model to rely on outlines and edges rather than color cues.
- However, detection can still fail if the angle, perspective or color is very different from the training data.

Future Work & Other Approaches

- Add more annotated and labeled data from the target domain (Links Foosball Table).
- Further refine the augmentation.
- Change model to a bigger YOLO variant or a different architecture (e.g., YOLOv8, Transformer-Based Detectors, etc.).
- Possibly look into more advanced techniques (Domain Adaptation or Style Transfer, Mosaic / MixUp Augmentation, Temporal or Post-Processing) for more advanced approach.
- Bounding box constraints if we are sure figures can’t overlap in some perspectives.

Thank you!