Politecnico di Torino

FONDAZIONE LINKS
PASSION FOR INNOVATION

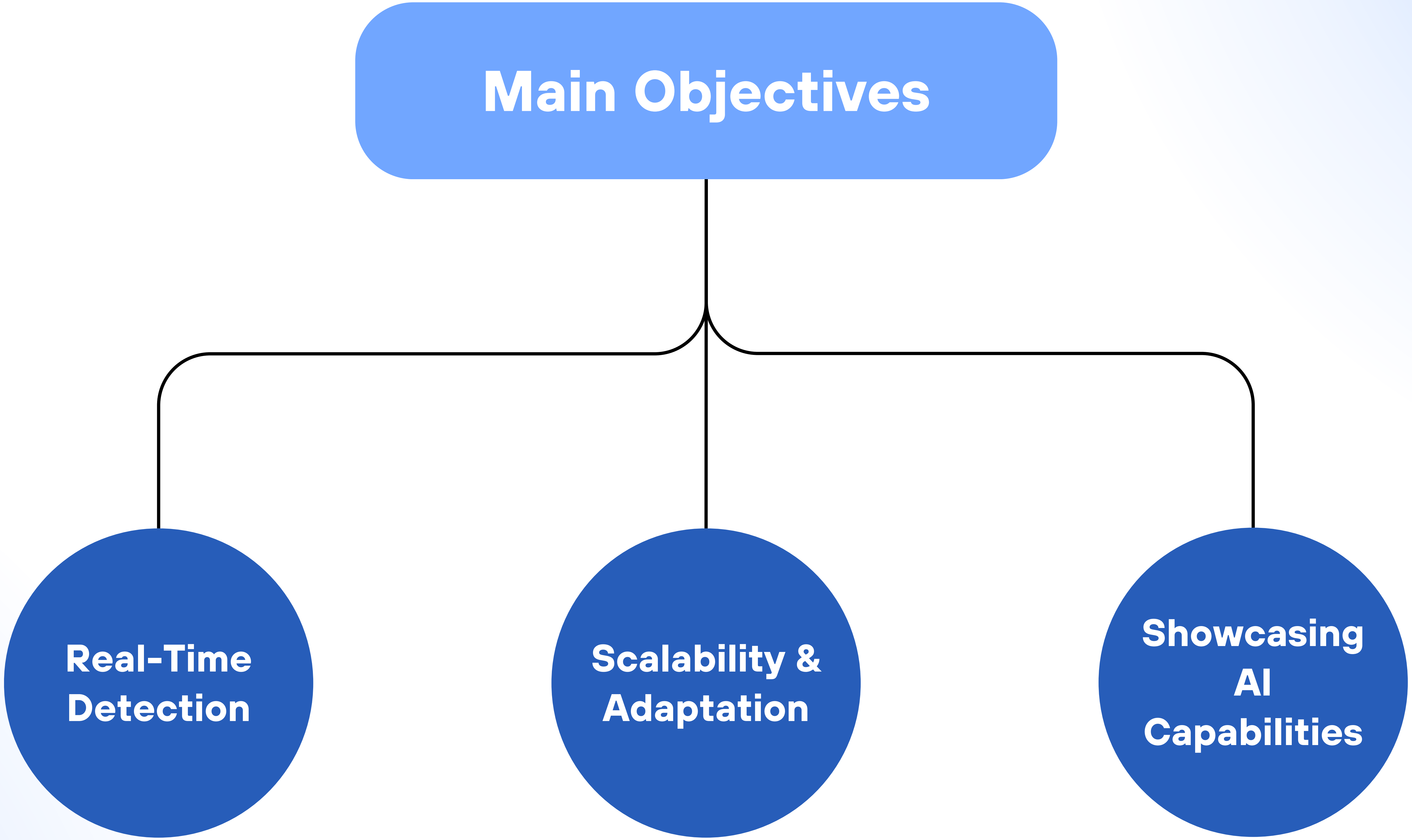
Foosball Table Real-Time Object Detection

Team 9

Niusha Parsa
Sina Hamdani

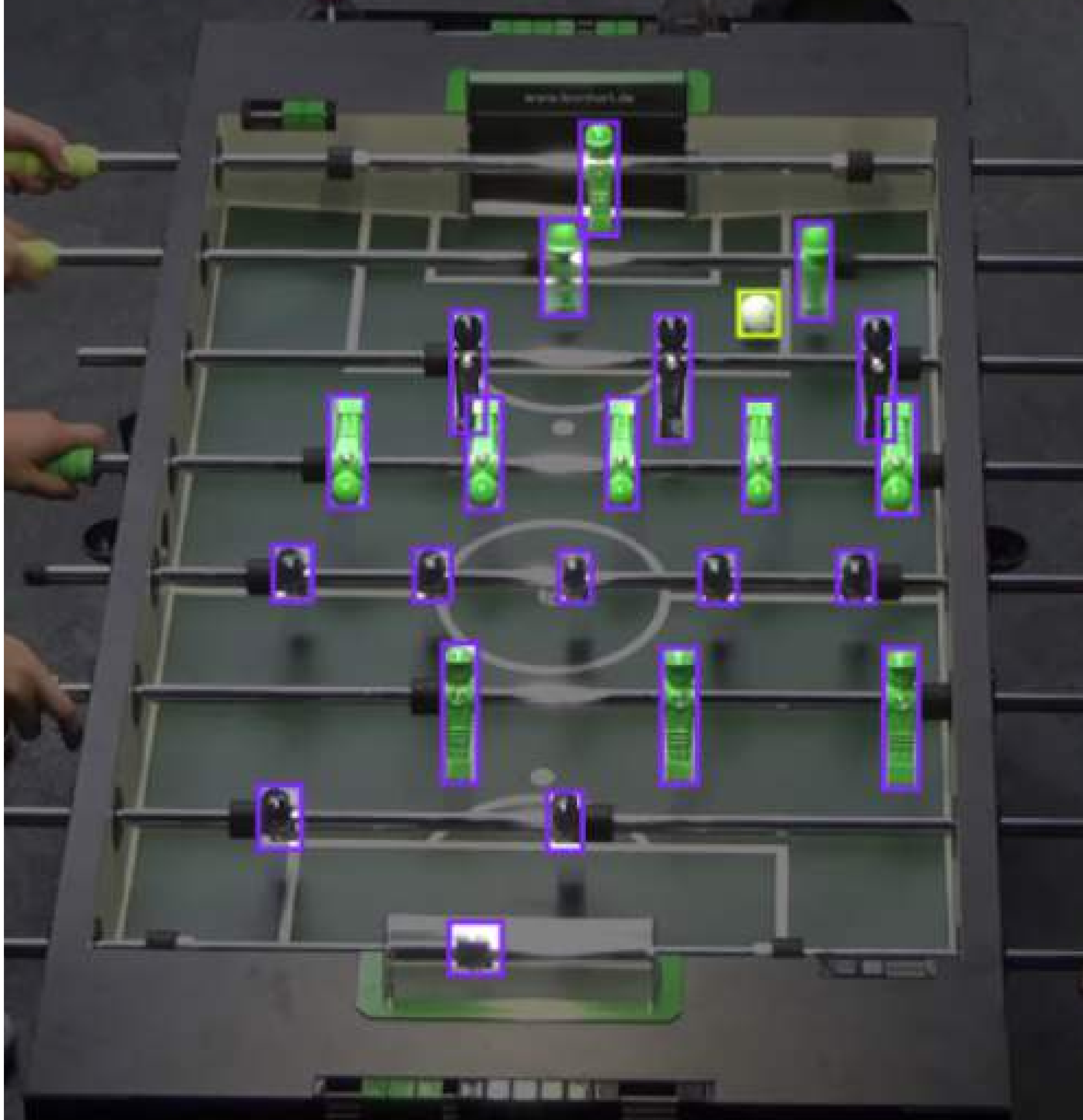
Using advanced computer vision, **our real-time foosball detection system** provides **immediate feedback, analytics, and insights** for LINKS Foundation teams and partners. It **showcases AI** on the LINKS ADS foosball table while delivering **exceptional accuracy, speed** beyond existing solutions.

Value Proposition


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

Object Detection Task with Two Classes:

1. Figure
2. Ball



Problem Statement

01

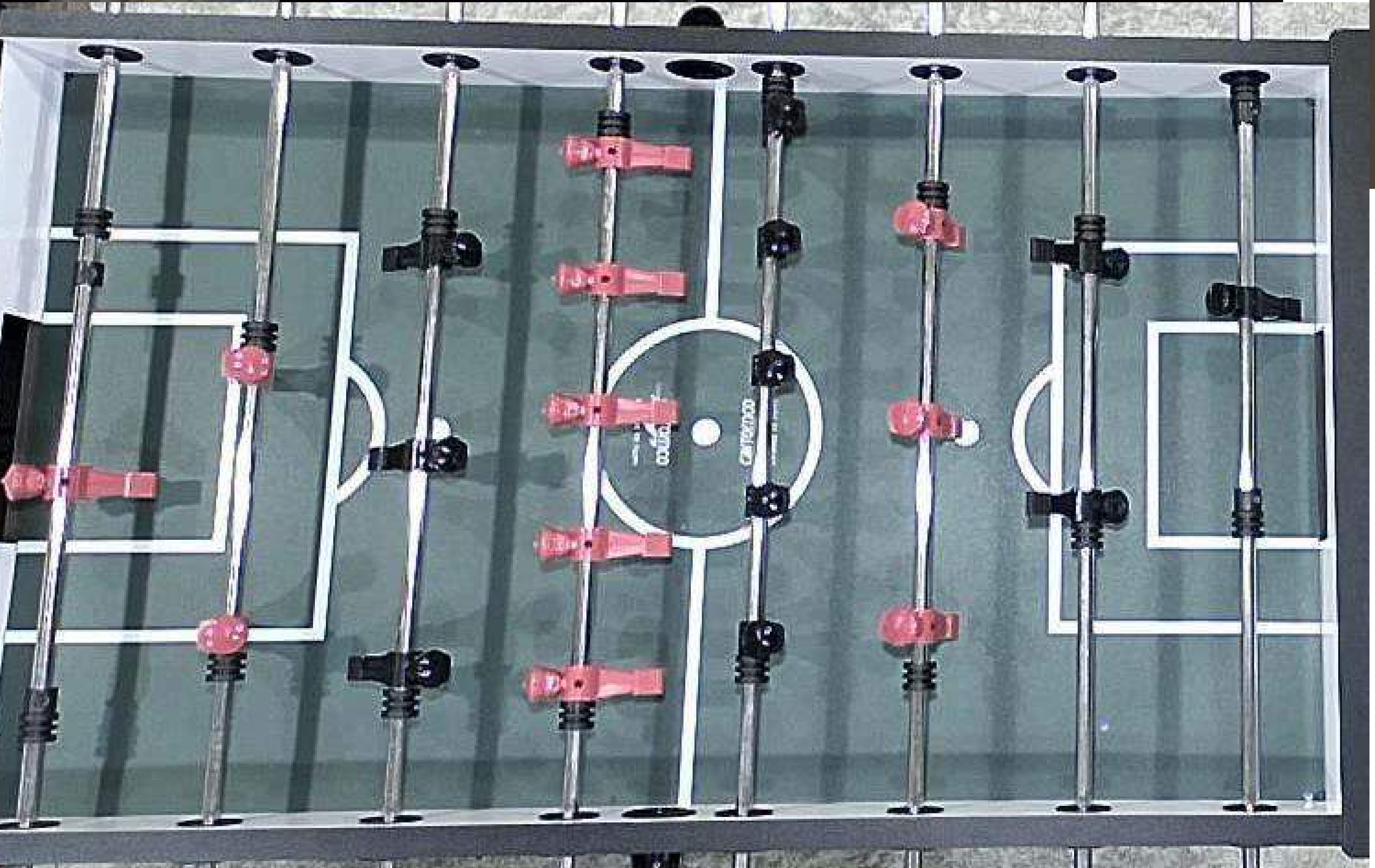
Detection Ambiguity

02

Color Similarity Issues

03

Perspective Variation and Domain Gap



Training Data Samples

Frames of LINKS Foosball Table

YOLO 11S

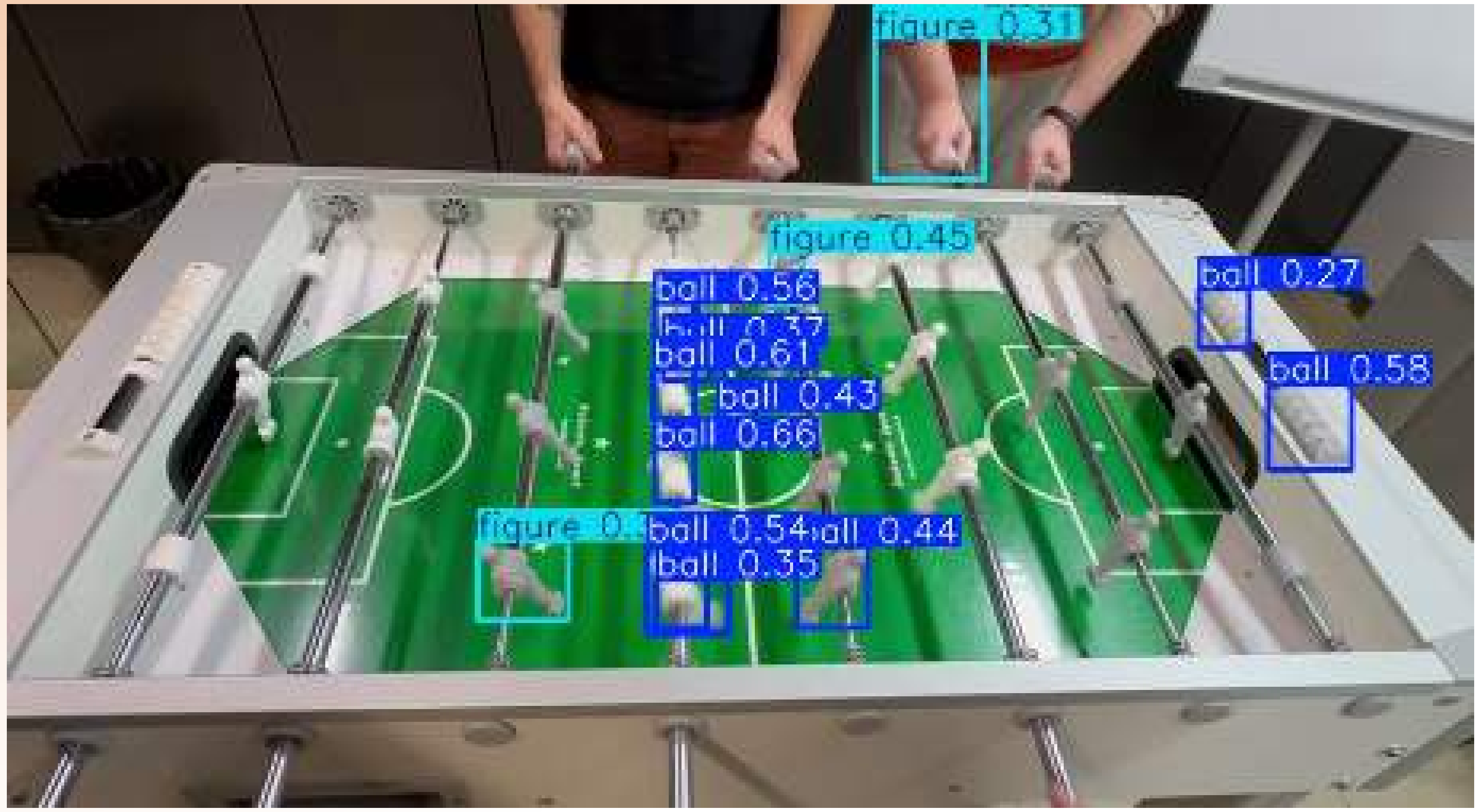
- Balanced Accuracy (mAP50-95)
- High Detection Accuracy (mAP50)
- High Real-Time Performance (FPS)
- Optimal Trade-Off Between Accuracy and Speed
- Scalability for Deployment

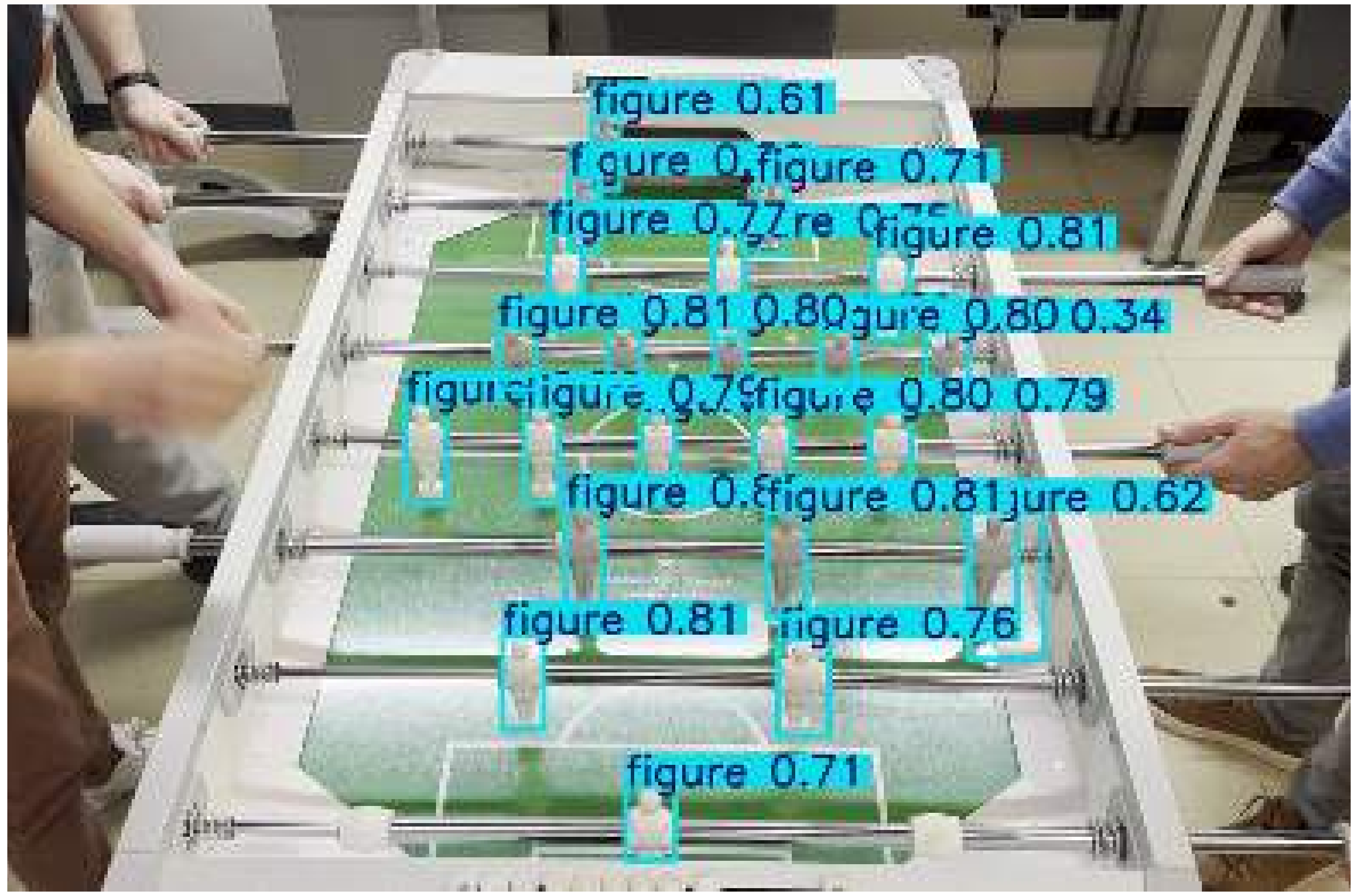
roboflow

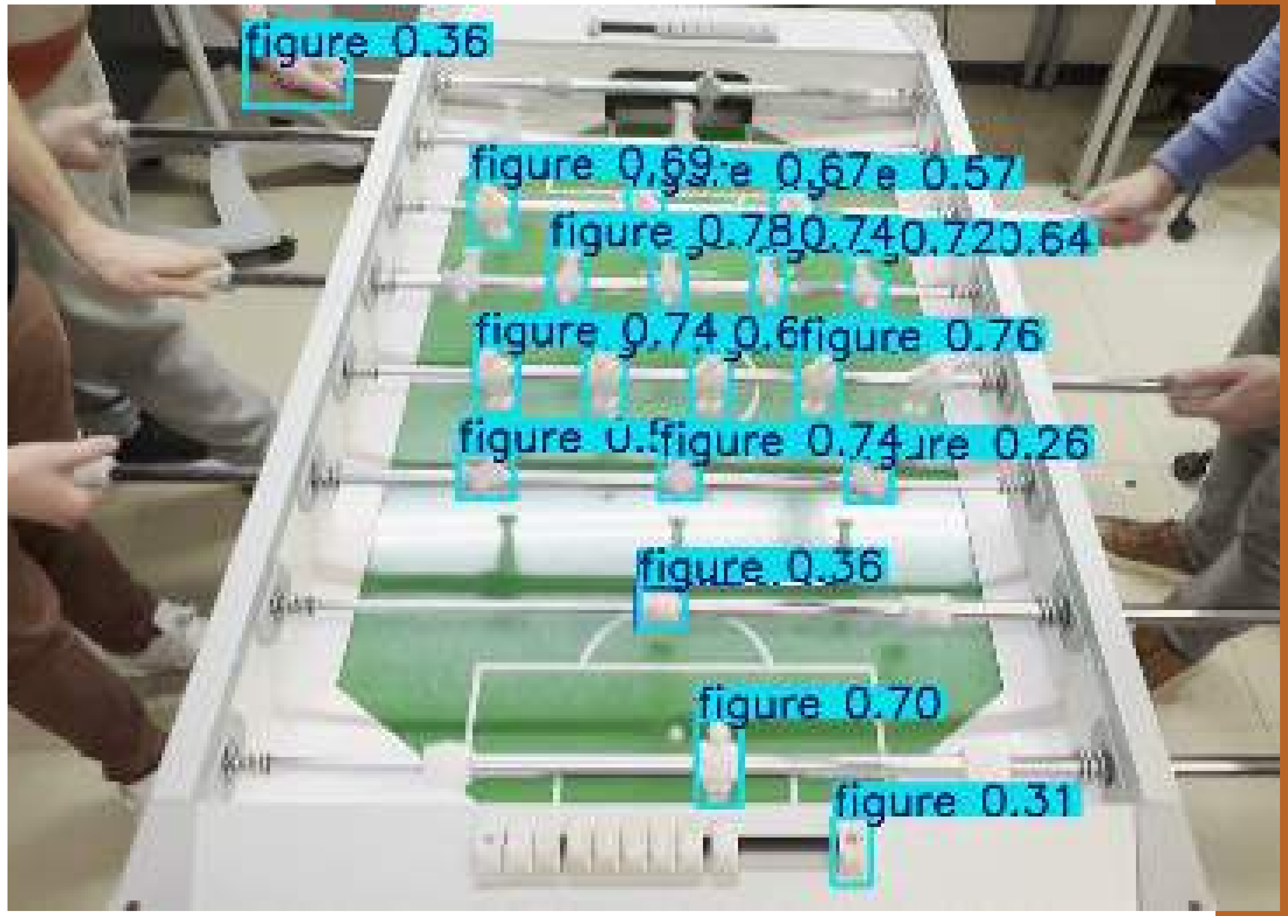
Big foosball detection dataset
Computer Vision Project

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

10 Epochs Trained Yolo11s on Original Dataset, Without Augmentation







Some Test Results

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.).
- **Dual-Model Inference:** Both the figures-only model and the ball-only model are used to predict on the same test images.

Experiments

TRIALS / ITERATIONS

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

40 epochs

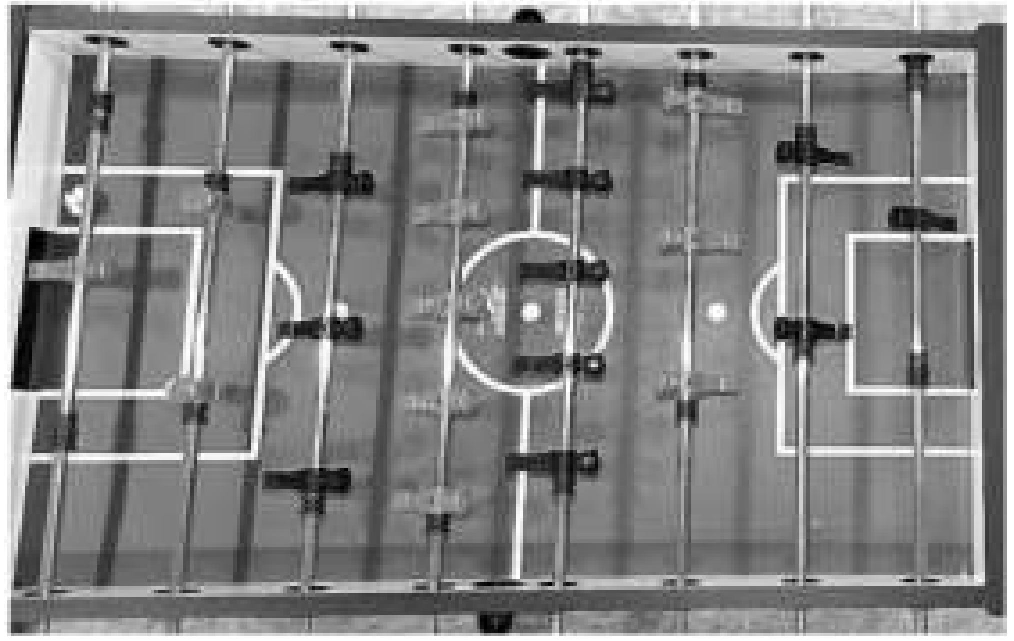
Result / Observation:
Model performed well in the training and validation. Tested on Adjusted LINKS Foosball Table frames. Best performance on LINKS Foosball Table data has been seen in this experiment.

08 Yolo11s with No Augmentations (Original Dataset)

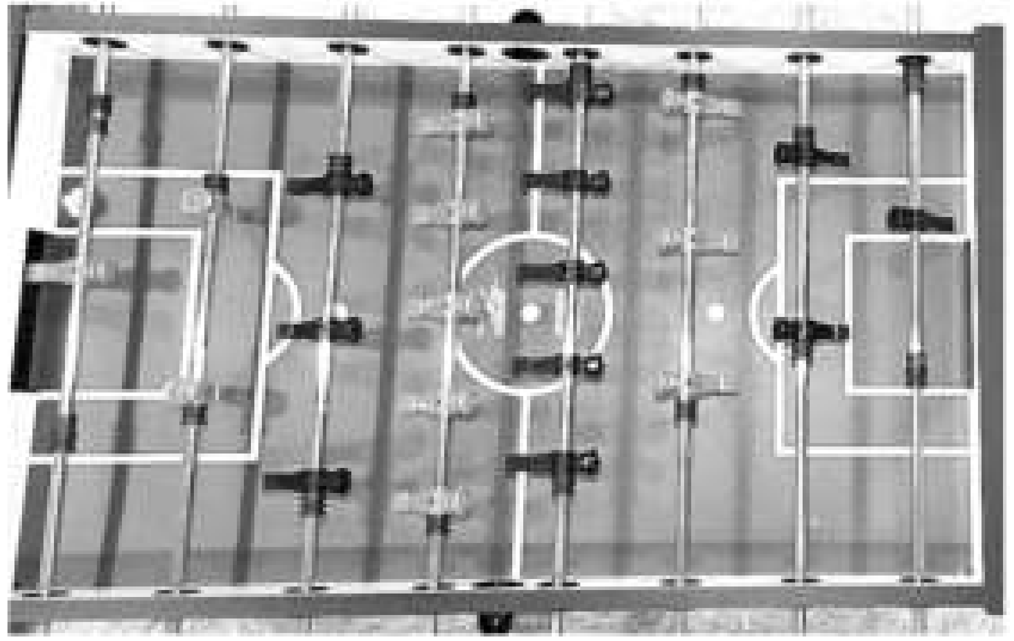
100 epochs

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



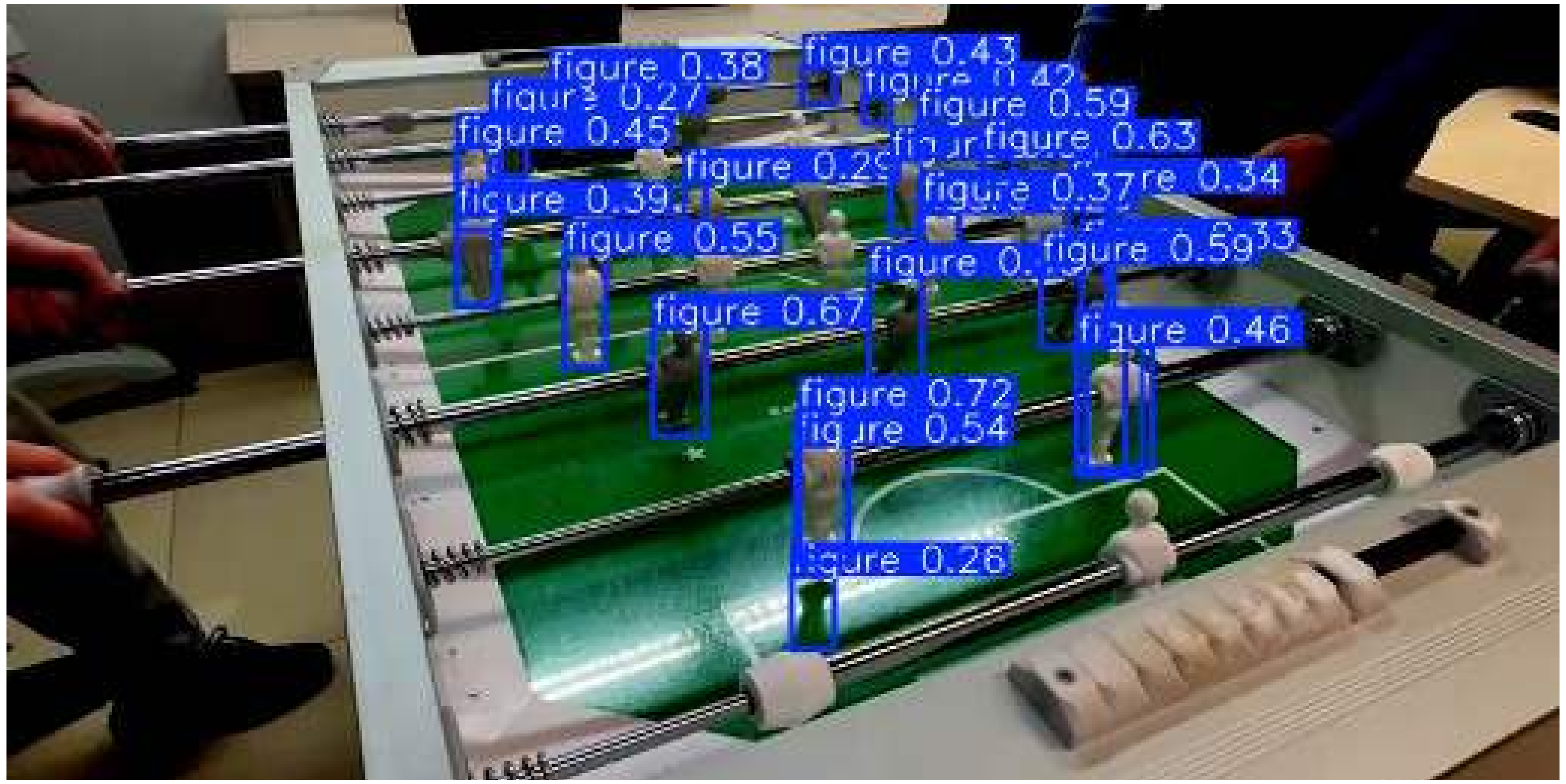
09 The Ultimate Experiment / Leveraging Transfer learning and Layer Freezing: Sequential YOLO11s Training for Foosball Detection: Separately Training on Figures and Ball Data with Layer Freezing.(1 Class for each model.)

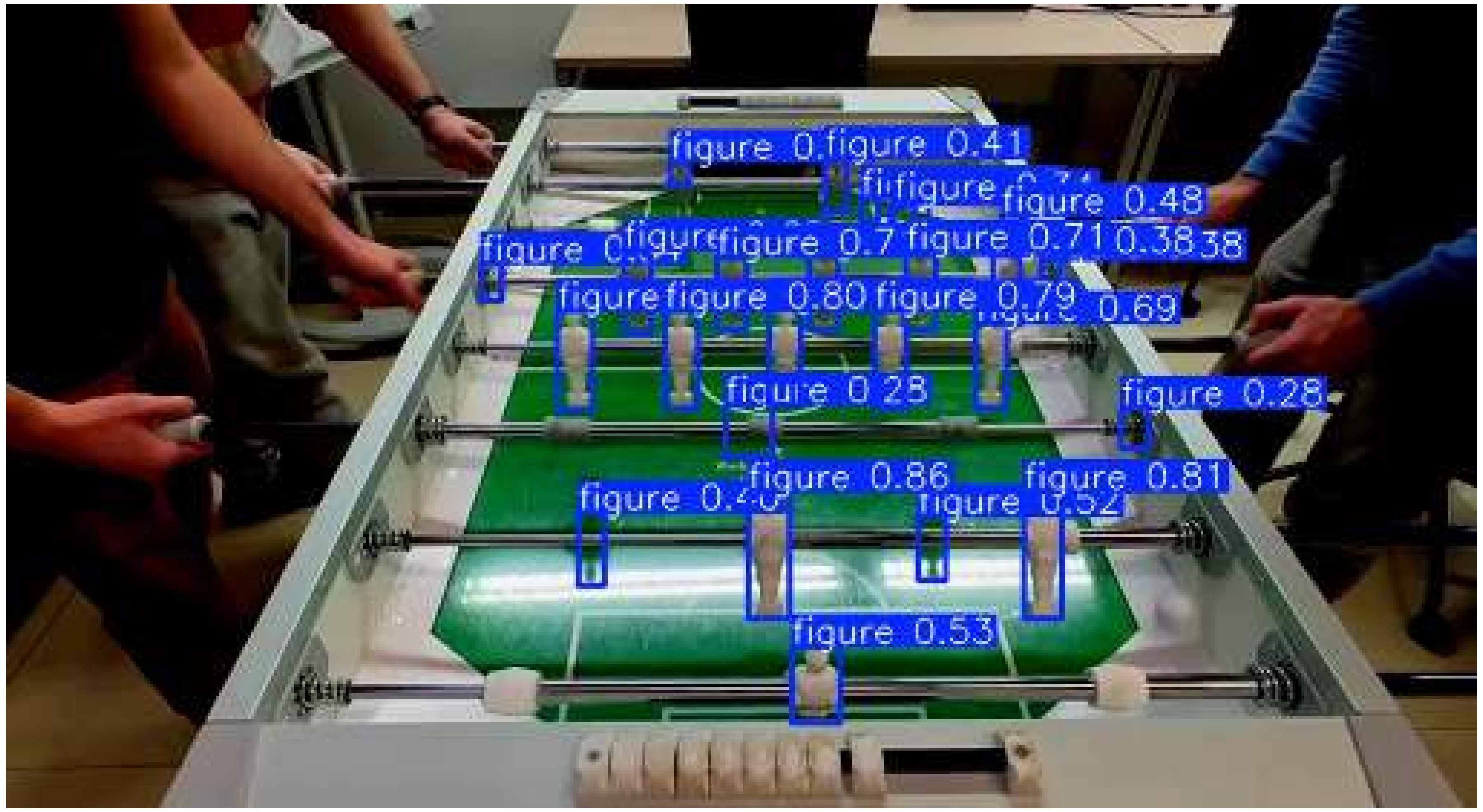
20 epochs on each model

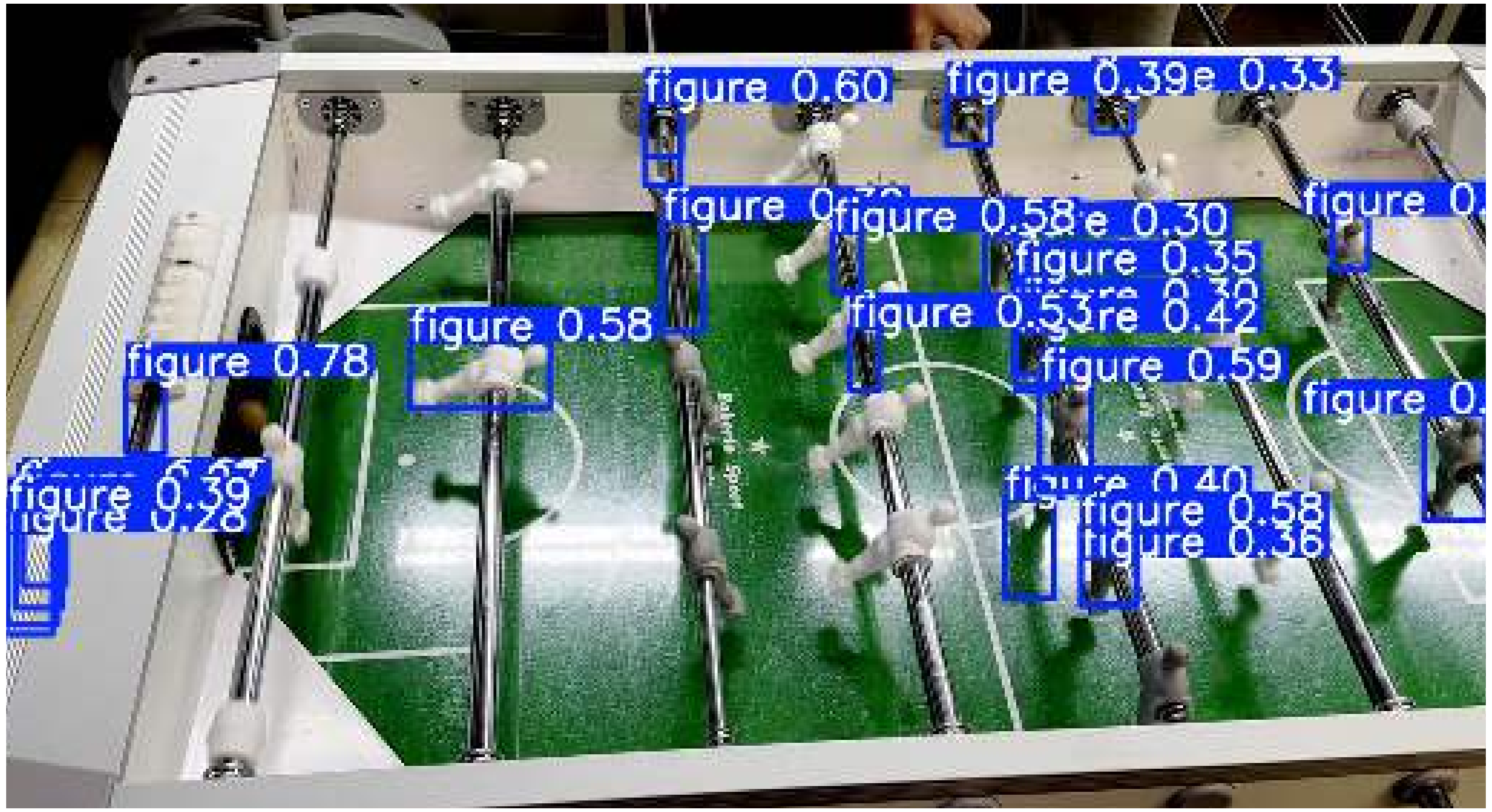
Result / Observation:

Despite strong training and validation performance, the final fine-tuned model performed poorly on the target dataset—failing to detect both figures and the ball accurately, and no significant improvement has detected in comparison to the performance of Yolo11s with 2 classes. Which highlights the need of leveraging various augmentations as well.

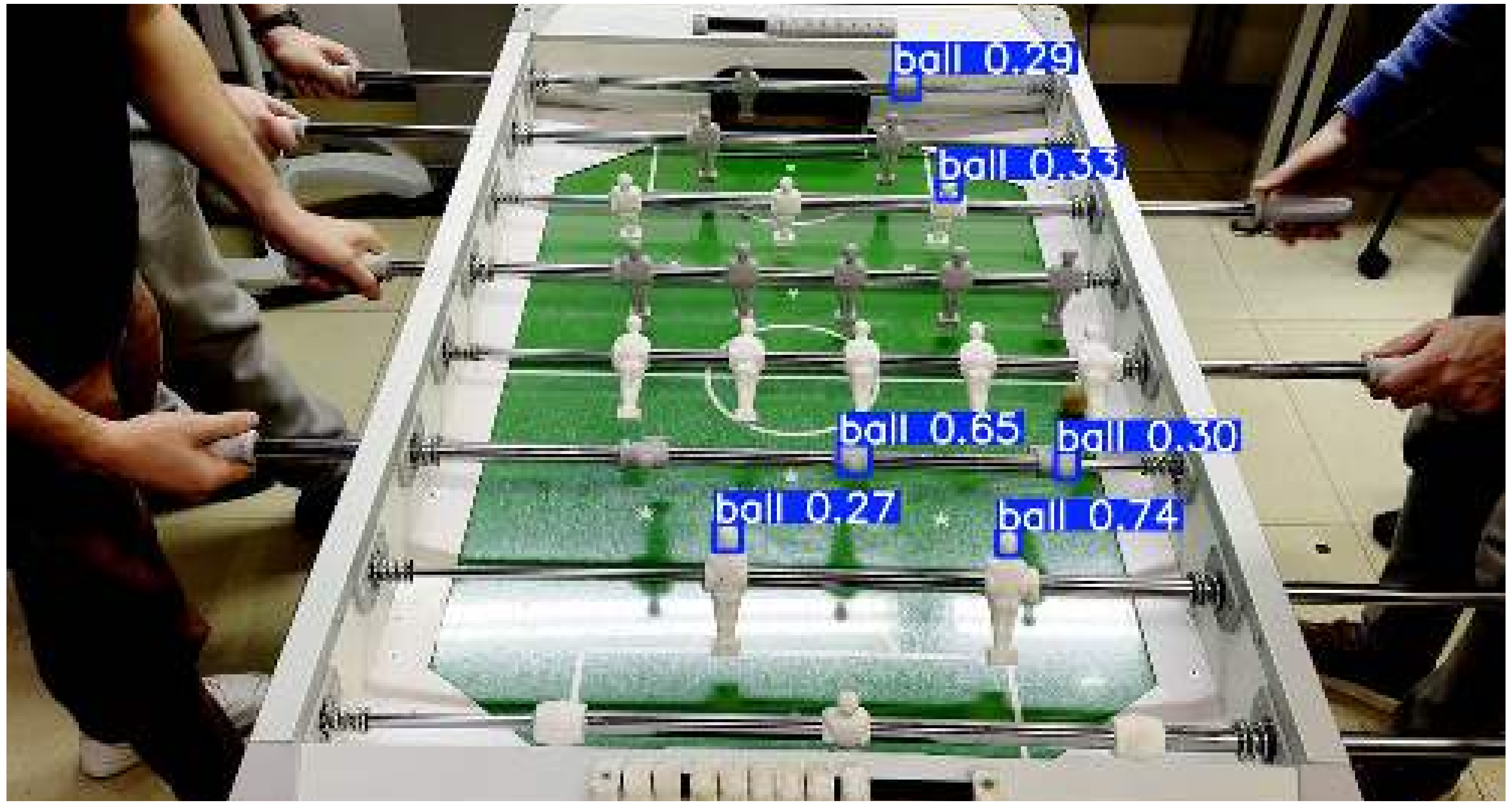
Sample of performance of the model trained with the figure dataset



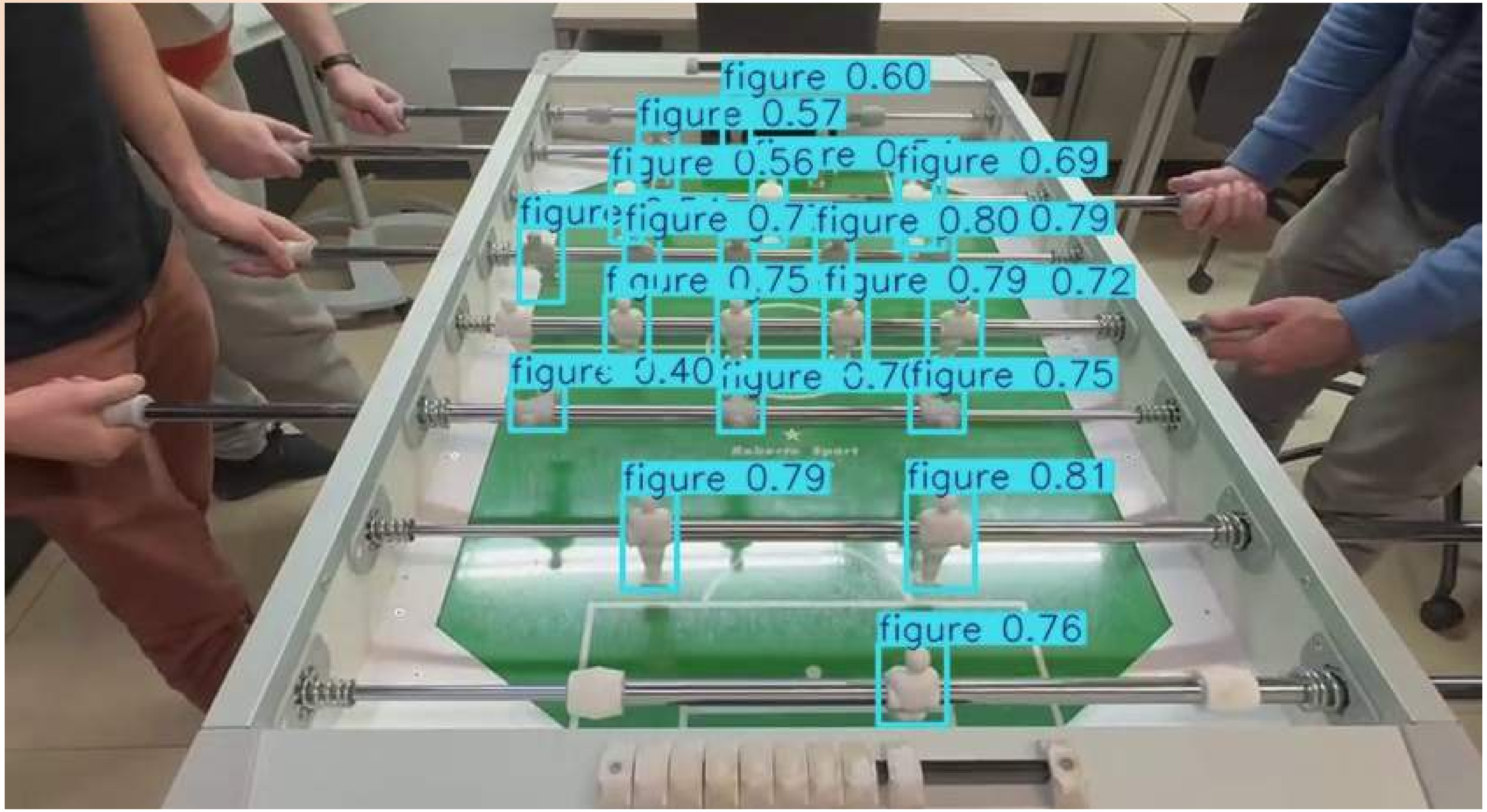




Sample of performance of the model fine-tuned with the ball dataset



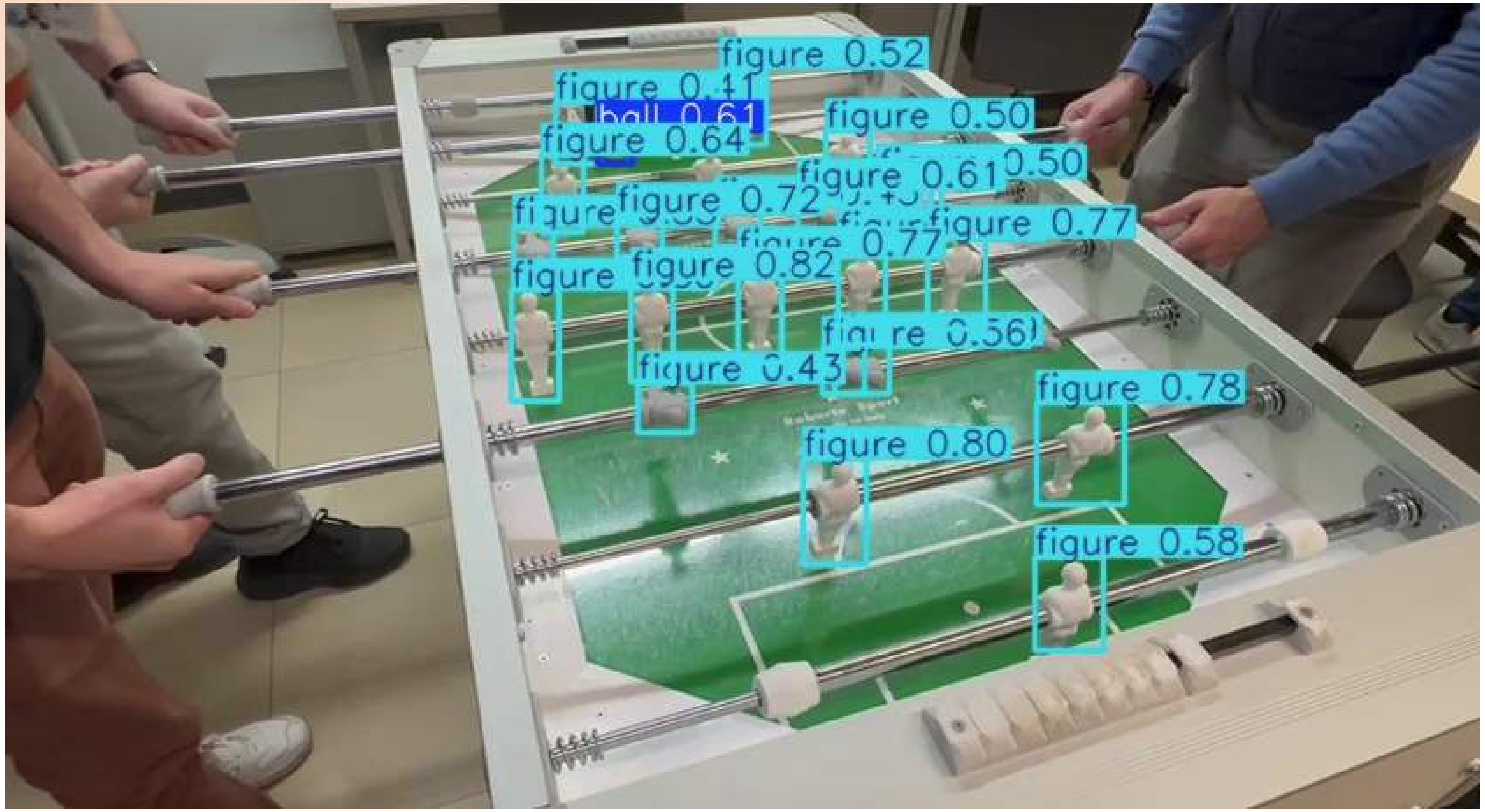
Best Performance in Results



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

Some Test Results

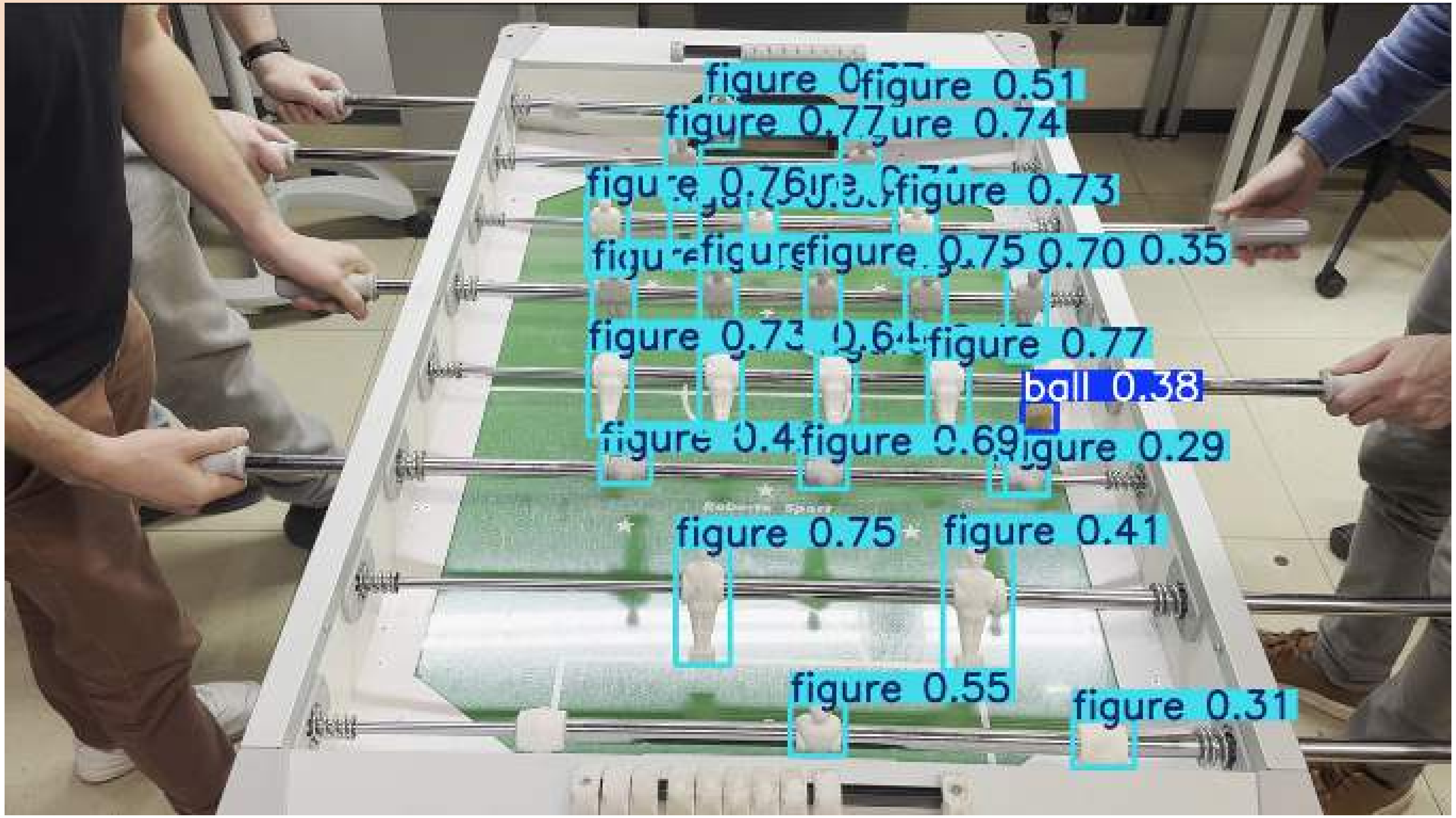
Best Performance in Results



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

Some Test Results

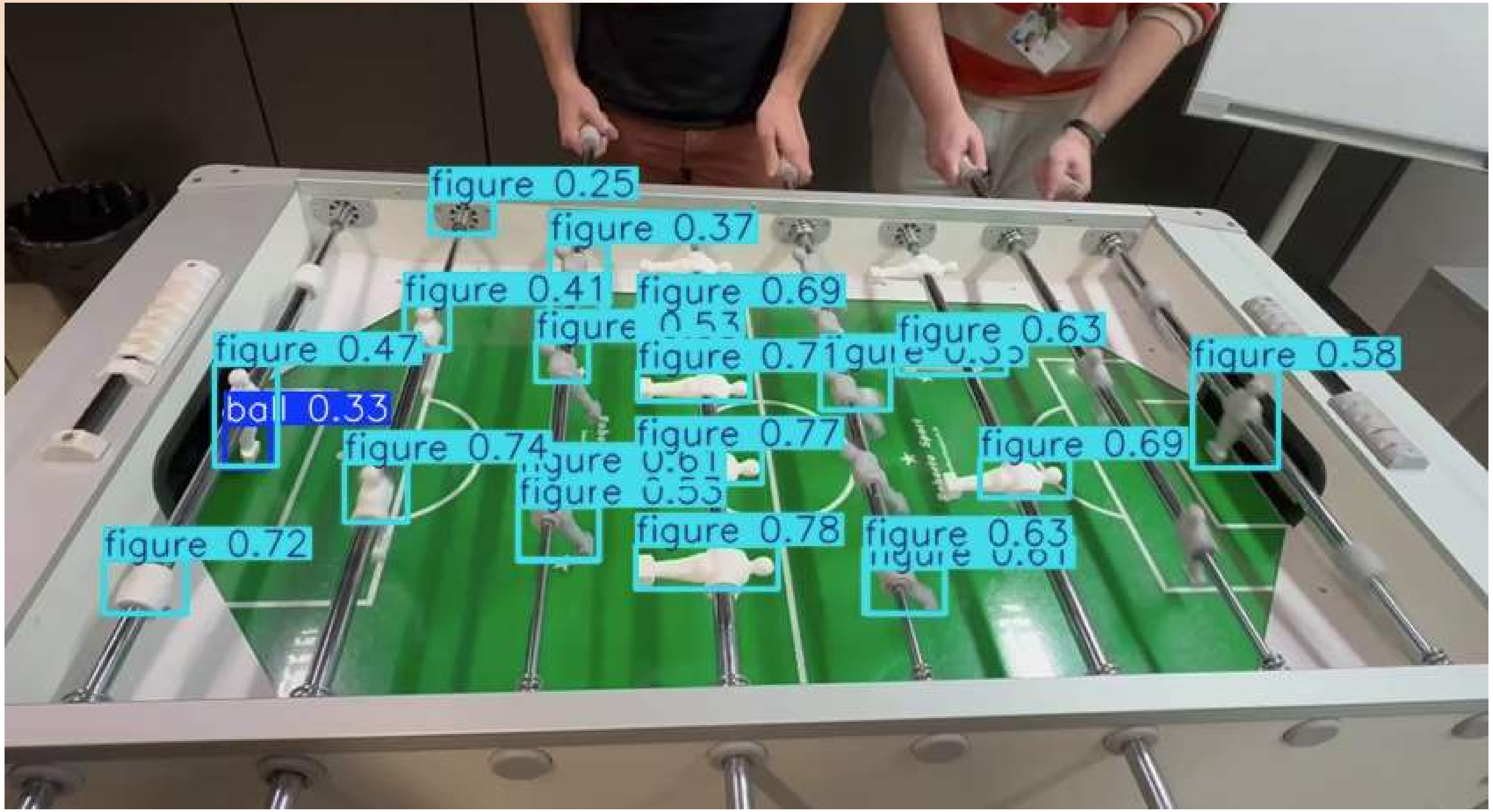
Best Performance in Results



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

Some Test Results

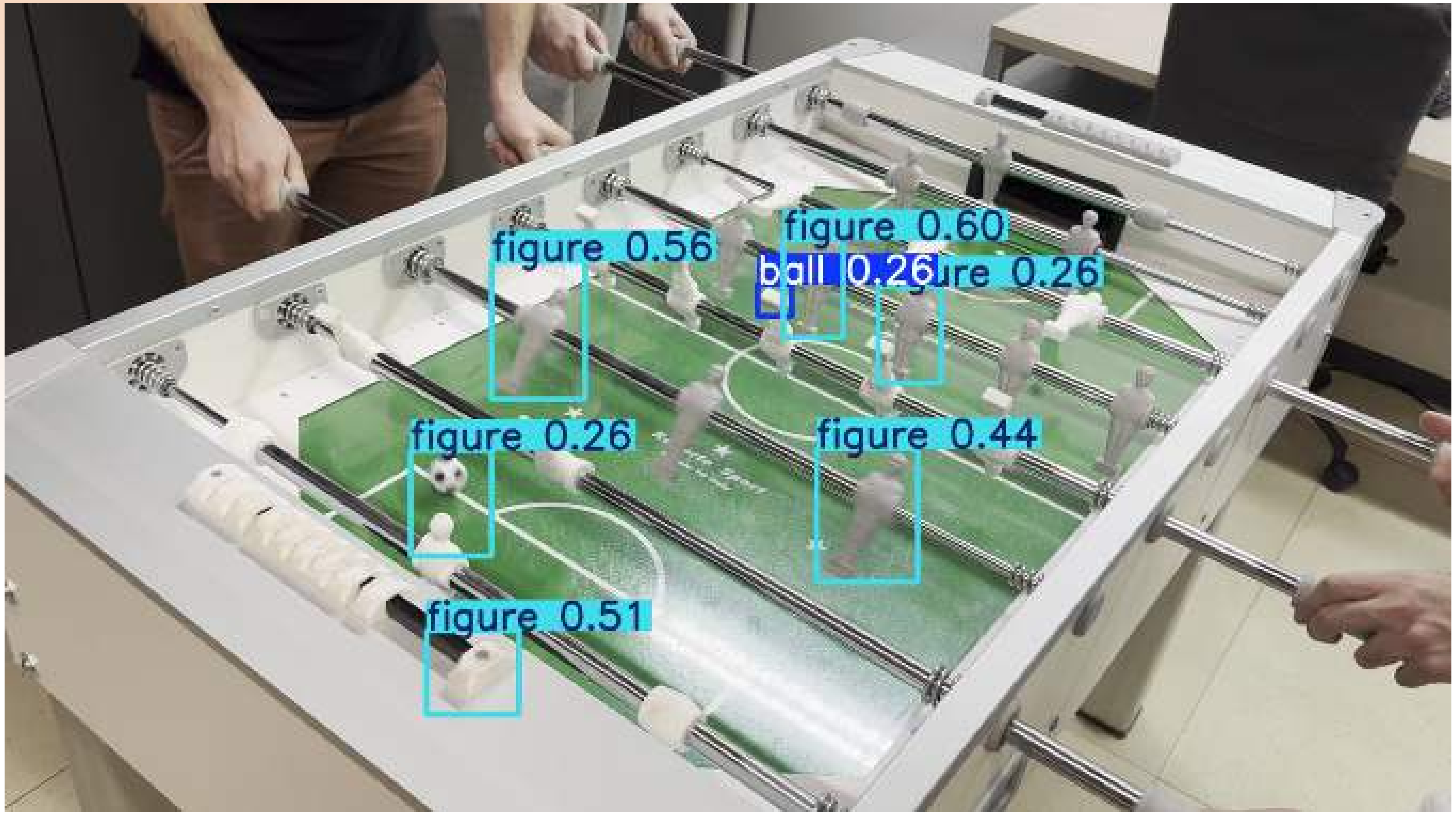
Poor Performance in Results



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

Some Test Results

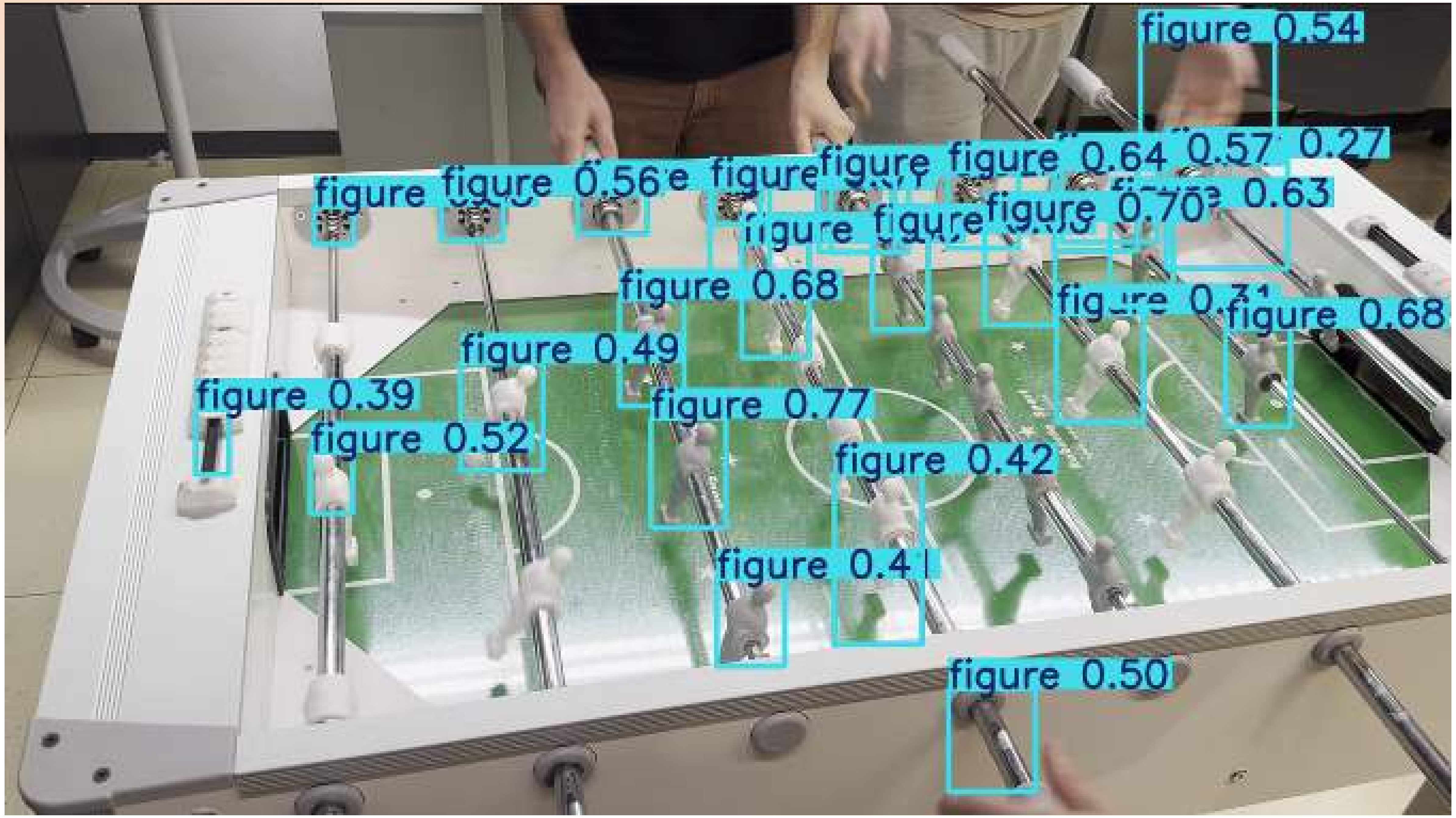
Poor Performance in Results



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

Some Test Results

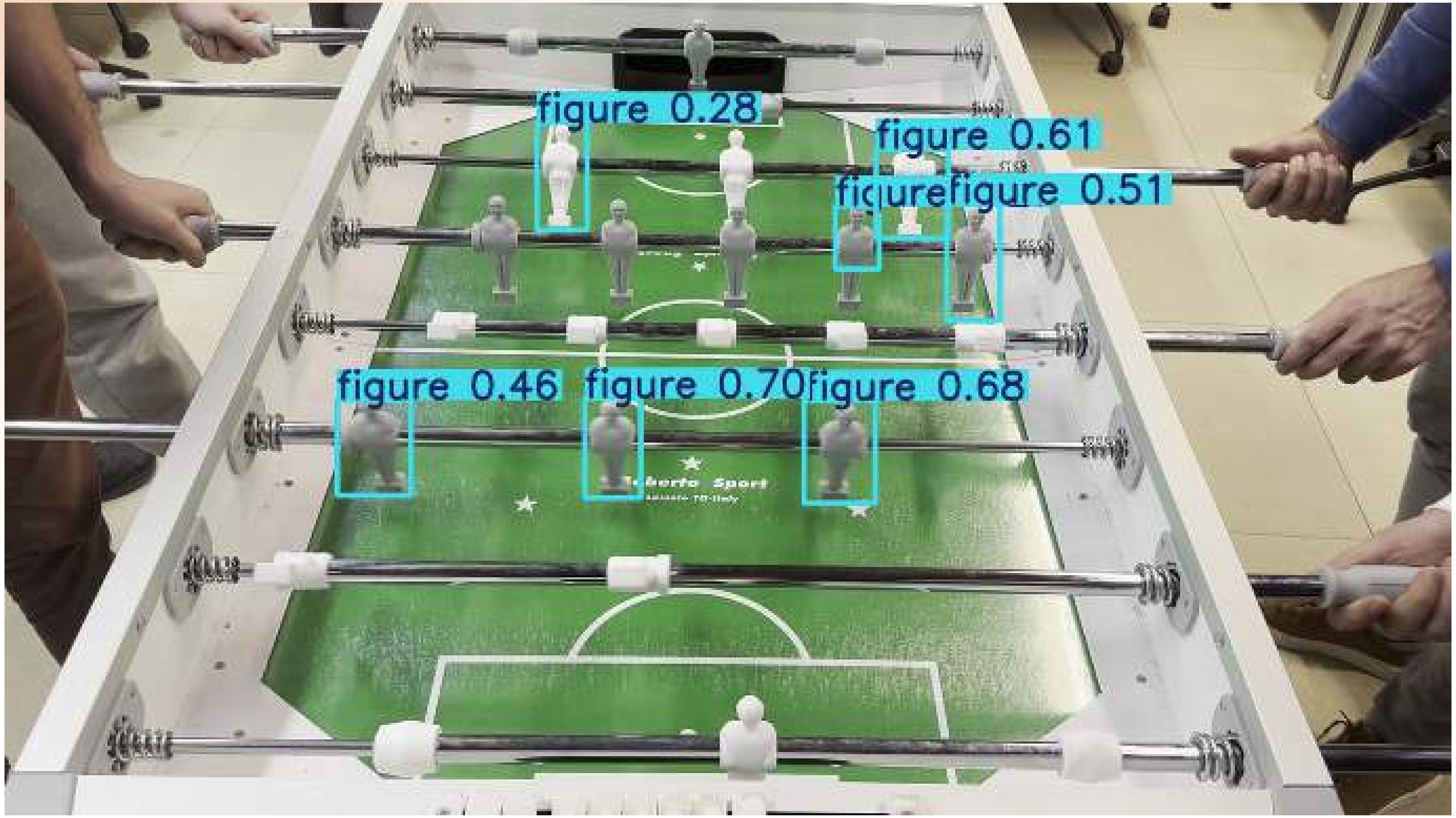
Poor Performance in Results



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

Some Test Results

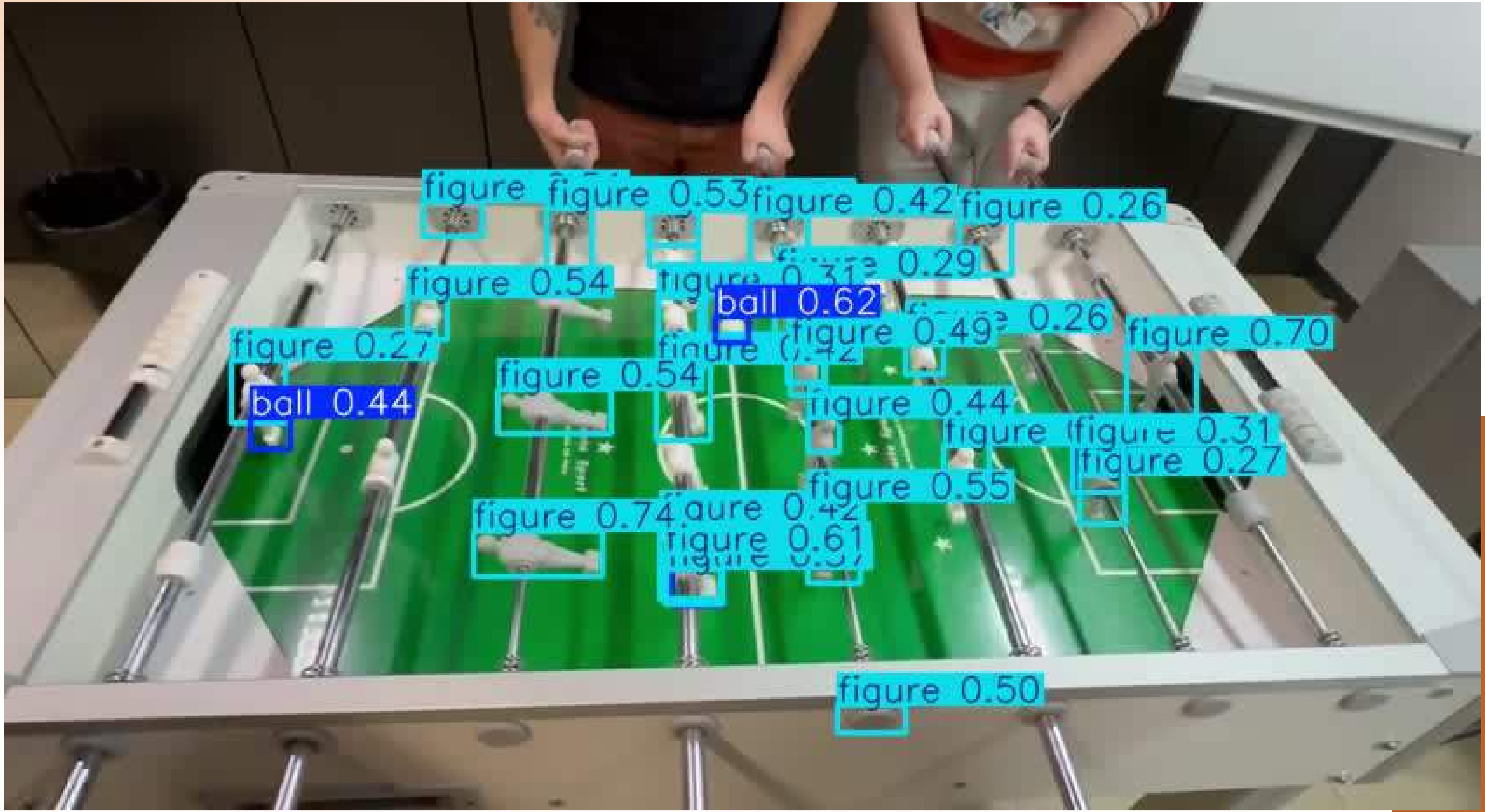
Poor Performance in Results



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.
- The sequential training approach alone is insufficient to force the model to rely solely on shapes and edges and more integrated or robust domain adaptation strategies may be required.

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.
- Leveraging the sequential training approach along with other effective augmentation techniques or domain adaptation strategies.

Thank you!