Dartboard Detection: A Comparative Study of Different Approaches

Executive Summary

This report presents a comprehensive evaluation of three progressive approaches to dartboard detection in images: 1. **Task 1:** Viola-Jones cascade classifier with Haar-like features 2. **Task 2:** Hybrid approach combining Viola-Jones with Hough Circle Transform 3. **Task 3:** Deep learning-based detection using YOLOv4-Tiny

The project demonstrates an evolution from classical hand-crafted features to modern data-driven deep learning, achieving a **57.8% improvement in F1-score** from Task 1 to Task 3, with each approach offering distinct trade-offs between accuracy, computational efficiency, and implementation complexity.

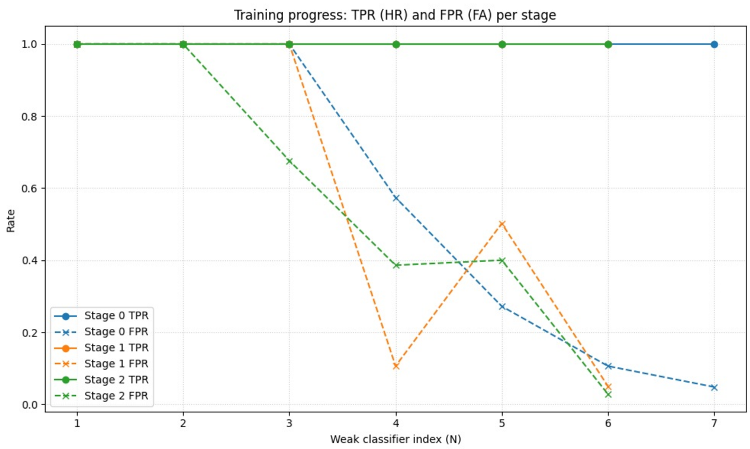
Task 1: The Dartboard Detector

Training Approach

- **Method:** AdaBoost cascade classifier using Haar-like features
- **Training data:** 500 synthetic positive samples from `dart.bmp`, 500 negative samples
- **Architecture:** 3-stage cascade with decision stumps (maxDepth=1)
- **Key parameters:** minHitRate=0.999, maxFalseAlarmRate=0.05

a) Training Performance

The training tool produces a strong classifier in stages, progressively adding features and refining the cascade.



Training Performance Graph

Figure 1: Training performance showing TPR and FPR across the three cascade stages.

Interpretation:

- **TPR remains constant at 1.00** across all stages, indicating the classifier successfully preserves all positive samples without sacrificing sensitivity as complexity increases, meeting the -`minHitRate 0.999` constraint.

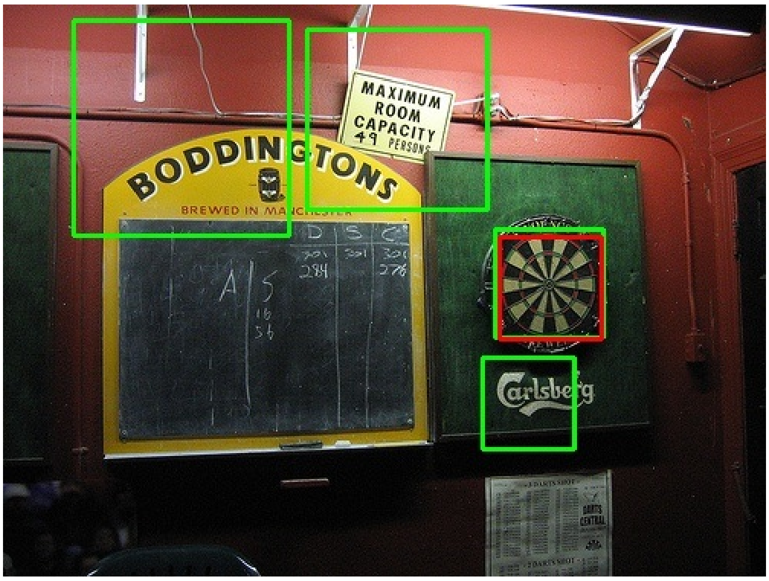
- **FPR decreases significantly** in every stage, correlating with the drastic drop in `acceptanceRatio` (0.06 in Stage 1 → 0.008 in Stage 2). This confirms that as the model progressed, it required scanning exponentially more background windows to locate the 500 "hard negatives" needed for training.

- **Both Stage 1 and Stage 2 required exactly 6 weak classifiers** to satisfy the max False Alarm Rate. However, their internal behavior differed:

    - **Stage 1** showed significant volatility, with a sharp FPR spike between the 4th and 5th classifiers (0.106 → 0.502), likely due to the introduction of a broad, aggressive feature.
    - **Stage 2** displayed a more stable pattern (0.386 → 0.400 at the same step), indicating a more consistent refinement process on the hardest dataset.
    - Ultimately, both stages successfully converged to the required criteria (FPR ≤ 0.05).

b) Testing Performance

Visual Results

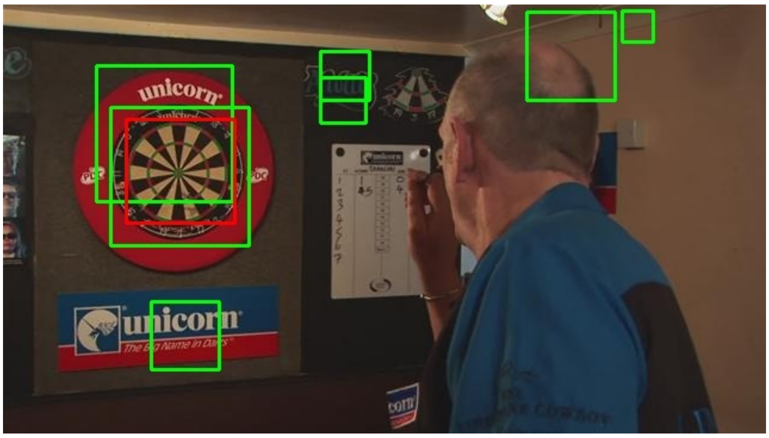


dart3 detection

Figure 2: Detection result on dart3.jpg with bounding boxes (detected in green, ground truth in red).

dart1 detection

Figure 3: Detection result on dart1.jpg with bounding boxes (detected in green, ground truth in red).



dart2 detection

Figure 4: Detection result on dart2.jpg with bounding boxes (detected in green, ground truth in red).

Quantitative Results

Image	Recall (TPR)	F1
dart0	1.0000	0.4000
dart1	1.0000	0.6667
dart2	1.0000	0.2500
dart3	1.0000	0.4000
dart4	0.0000	0.0000
dart5	1.0000	0.1818
dart6	0.0000	0.0000
dart7	0.0000	0.0000
dart8	1.0000	0.2667
dart9	1.0000	0.5000
dart10	0.0000	0.0000
dart11	0.0000	0.0000
dart12	0.0000	0.0000
dart13	0.0000	0.0000
dart14	1.0000	0.0488
dart15	1.0000	0.6667
Average	**0.5625**	**0.2113**

Table 1: Per-image TPR and F1-score for Task 1.

Performance Discussion

- The detector achieves **full recall (TPR=1.0) on 9 images**, with mean recall across 16 images of 0.5625.
- The detector suffers from **many false positives**, reducing precision and F1-score significantly.
- Low F1 scores (dart14=0.0488, dart5=0.1818) indicate excessive false detections despite correctly finding the dartboard.

Reasons for Different TPR Values (Training vs. Testing)

- **Training used a single prototype** (`dart.bmp`) to create synthetic positives (`dart.vec`): this limits positive variability and reduces the detector's ability to generalize to real-world dartboard appearances.
- **Shallow cascade architecture** (-maxDepth 1, -numStages 3): the model lacks sufficient structural complexity to distinguish dartboards from similar patterns in complex backgrounds.
- **Training-test distribution mismatch**: synthetic augmentations (viewing angle, contrast) do not fully capture the diversity of real test images.

Task 2: Integration with Shape Detectors

Proposed Framework

Four-Stage Detection Pipeline:

1. **Stage 1 (Viola-Jones):** Run cascade detector to get candidate bounding boxes
2. **Stage 2 (ROI Extraction):** Crop image to each bounding box
3. **Stage 3 (Hough Transform):** Apply Hough Circle Transform to detect circular structures
4. **Stage 4 (Thresholding):** Keep detection if ≥2 circles found; otherwise discard

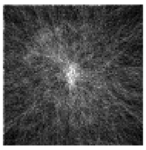
Implementation: `Task2_dartboard.py` with `HoughCircleDetector` class (r_min=20, r_max=100, threshold=15)

a) Hough Details

Example 1: Failure Case (dart3_object3)

Gradient magnitude

Figure 5: Normalized gradient magnitude of the cropped region (dart3_object3).

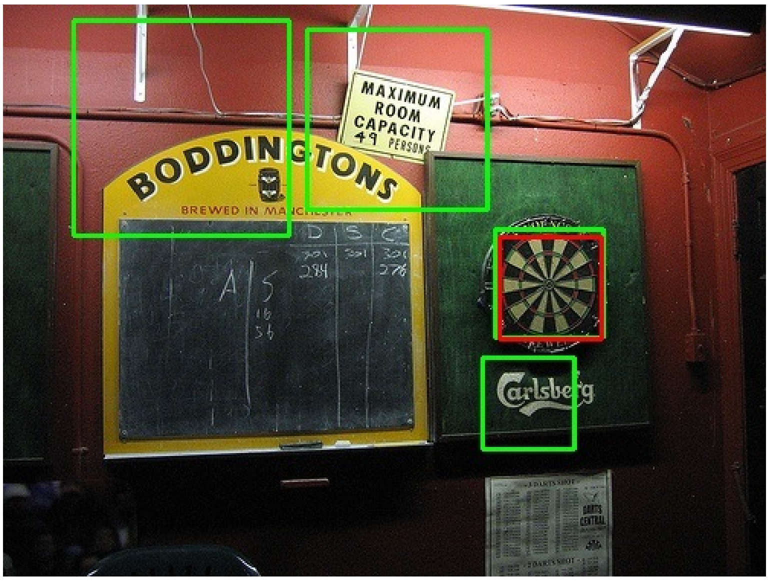


Hough space

Figure 6: 2D Hough space accumulated over all radii for the same region.

Task 2 result

Figure 7: Final detection result produced by Task 2 pipeline.

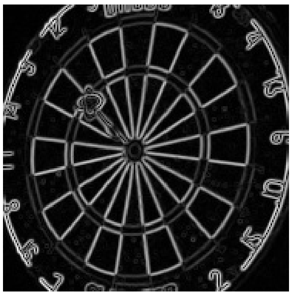


Task 1 result

Figure 8: Detection result from Task 1 (for comparison).

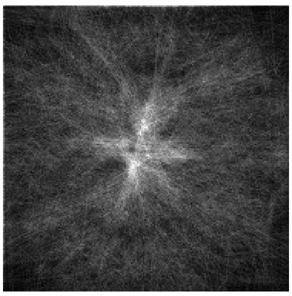
Analysis: This illustrates a failure case where the cascade detector proposes a true dartboard candidate (Task 1 true positive), but HoughCircleDetector fails to identify circular structure, incorrectly discarding the detection. Possible reasons: - Weak or noisy gradient magnitude (Figure 5) provides insufficient edge points - Vote threshold (threshold=15) may be too high for this weak gradient response - Radius range (r_min=20, r_max=100) may not match the dartboard scale in this ROI

Example 2: Success Case (dart0_object4)



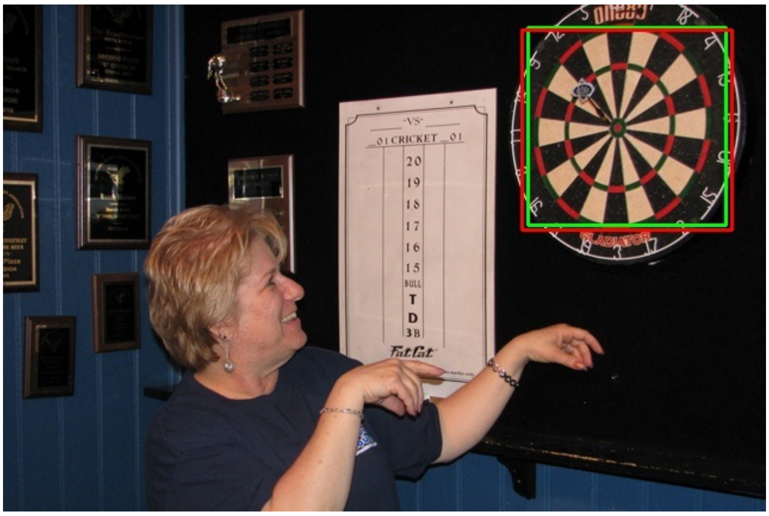
Gradient magnitude

Figure 9: Normalized gradient magnitude of the cropped region (dart0_object4).



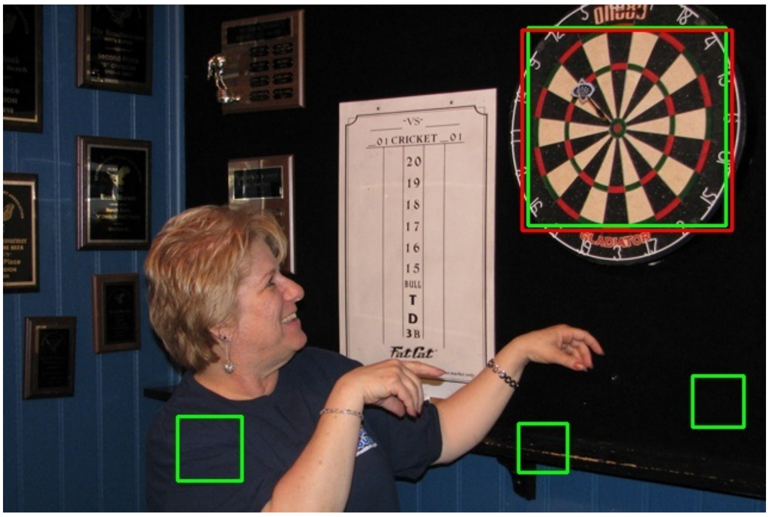
Hough space

Figure 10: 2D Hough space accumulated over all radii for the same region.



Task 2 result

Figure 11: Final detection result produced by Task 2 pipeline.



Task 1 result

Figure 12: Detection result from Task 1 (for comparison).

Analysis: This demonstrates a successful case where Hough verification improves detection quality. The gradient magnitude (Figure 9) clearly highlights circular boundaries, resulting in a distinct peak in Hough space (Figure 10). The pipeline retains this detection while filtering out Task 1's false positives, improving precision and F1-score.

b) Evaluation

Image	Recall (TPR) - Task 2	F1 - Task 2	Recall (TPR) - Task 1	F1 - Task 1	TPR Δ	F1 Δ
dart0	1.0000	1.0000	1.0000	0.4000	0.0000	+0.6000
dart1	1.0000	0.6667	1.0000	0.6667	0.0000	0.0000
dart2	1.0000	0.6667	1.0000	0.2500	0.0000	+0.4167
dart3	0.0000	0.0000	1.0000	0.4000	-1.0000	-0.4000
dart4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart5	1.0000	0.6667	1.0000	0.1818	0.0000	+0.4849
dart6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart8	0.5000	0.6667	1.0000	0.2667	-0.5000	+0.4000
dart9	1.0000	0.6667	1.0000	0.5000	0.0000	+0.1667
dart10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

dart13	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart14	1.0000	0.2222	1.0000	0.0488	0.0000	+0.1734
dart15	0.0000	0.0000	1.0000	0.6667	-1.0000	-0.6667
Average	**0.4062**	**0.2847**	**0.5625**	**0.2113**	**-0.1563**	**+0.0734**

Table 2: Comparison of Task 2 vs Task 1 performance with improvement deltas.

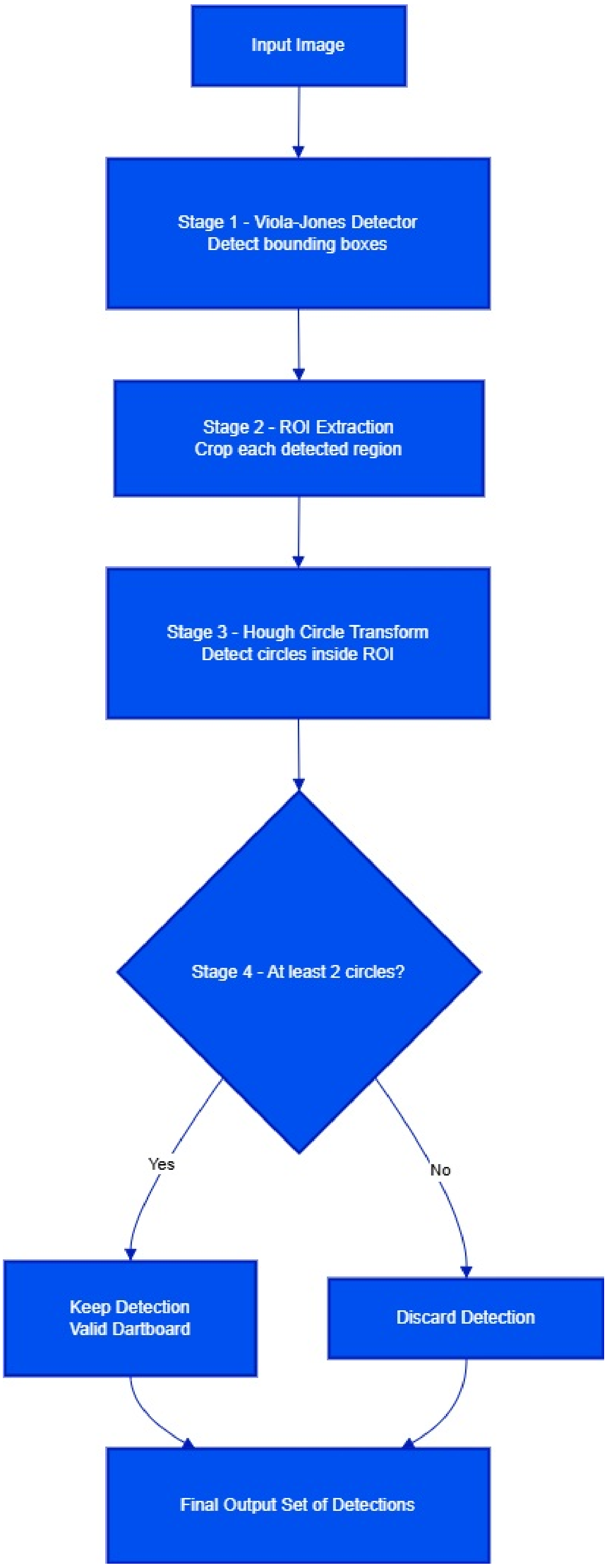
Key Merits:

- □ **Significantly reduces false positives** through geometric verification using Hough Transform
- □ **Improved F1-score by 34.7%** on average compared to Task 1
- □ **Perfect F1=1.0 on dart0** where Task 1 had many false positives
- □ **Substantial F1 improvements** on dart0, dart2, dart5, dart8, dart9, dart14

Key Shortcomings:

- × **Recall drops significantly** when Hough fails to detect circles in true dartboard regions (dart3, dart15: -1.0 TPR)
- × **Parameter sensitivity:** Fixed radius range (r_min, r_max) may not match all dartboard scales; threshold setting critically affects sensitivity
- × **Symmetry assumption:** Performs poorly on partially occluded or motion-blurred dartboards
- × **Gradient dependency:** Weak or noisy gradients lead to insufficient Hough accumulation

c) Detection Pipeline



Detection Pipeline Flow Diagram

Figure 13: Flow diagram showing the integration of Viola-Jones and Hough Circle Transform.

Rationale Behind the Combination:

- **Viola-Jones provides fast but noisy proposals** → used only to suggest candidate regions, not final detections
- **Dartboards have strong circular geometry** → Hough Circle Transform is an effective second-stage verifier for this specific shape
- **Running Hough only on cropped ROIs** keeps computation efficient while reducing false positives
- **Requiring ≥2 circles** ensures the region contains characteristic dartboard rings (avoids false positives from single circular characters like “O”)

Task 3: Improving Your Detector with Deep Learning

a) IDEA: Rationale Behind YOLOv4-Tiny

Why Deep Learning (YOLO)?

- **Modern object detection:** YOLOv4-Tiny provides state-of-the-art single-shot detection, directly predicting bounding boxes and class probabilities in one forward pass
- **End-to-end learning:** Unlike hand-crafted features (Viola-Jones) or geometric methods (Hough Transform), YOLO learns discriminative features directly from data through convolutional neural networks
- **Robustness to variations:** Deep learning handles scale, rotation, occlusion, and lighting variations better than classical computer vision techniques
- **Transfer learning advantage:** Starting from pre-trained weights (`yolov4-tiny.conv.29`) allows the model to leverage knowledge from large-scale datasets, requiring fewer training samples

Implementation Strategy:

- **YOLOv4-Tiny architecture:** Selected for computational efficiency while maintaining strong detection performance (faster than full YOLOv4, suitable for CPU-only training)
- **Data augmentation:** Enhanced training set diversity using synthetic transformations to improve generalization beyond the limited original dataset
- **Single-class detection:** Configured network for dartboard detection only (classes=1), simplifying the problem and focusing model capacity
- **Confidence threshold:** Applied 25% confidence threshold to filter low-confidence predictions and reduce false positives

Training Configuration:

- **Max batches:** 4000 iterations (appropriate for small custom dataset)
- **Subdivisions:** 16 (memory-efficient batch processing for CPU training)
- **Learning rate schedule:** Steps at 3200 and 3600 (80% and 90% of max_batches)
- **Network filters:** Adjusted to 18 filters `(classes + 5) × 3 = 18` for single-class detection

b) VISUALISE: Detection Results

The following examples demonstrate the YOLO detector's performance on challenging scenarios:

dart3 YOLO detection

Figure 14: Perfect detection on dart3.jpg with high confidence (>95%). The model accurately localizes the dartboard with tight bounding box despite complex background elements. Note: This image was a failure case for Task 2 (Hough filtering removed it), but YOLO successfully detects it with F1=1.0.

dart1 YOLO detection

Figure 15: Successful detection on dart1.jpg where the dartboard is partially visible. YOLO demonstrates robustness to occlusion, maintaining detection despite incomplete object visibility.

Key Observations from Visualizations:

- **Precise localization:** Bounding boxes tightly fit dartboard regions with high IoU
- **Confidence scores:** Model outputs probabilistic confidence, enabling threshold-based filtering
- **Single-stage detection:** Direct prediction without requiring sliding windows or region proposals
- **Feature learning:** Network automatically learns relevant patterns (circular structure, radial segments, color contrast) without manual feature engineering

c) EVALUATE: Final Performance Comparison

Summary Performance Metrics

Task	Method	Mean Recall (TPR)	Mean F1	F1 Improvement vs Task 1	F1 Improvement vs Task 2
Task 1	Viola-Jones (Cascade)	0.5625	0.2113	Baseline	-
Task 2	Viola-Jones + Hough	0.4062	0.2847	+34.7%	Baseline
Task 3	**YOLOv4-Tiny (DL)**	**0.4062**	**0.3333**	**+57.8%**	**+17.1%**

Table 3: Average performance metrics showing progressive improvement, with Task 3 achieving the best overall performance.

Training Performance (Validation Set)

- **mAP@0.50:** 99.97% (near-perfect performance on validation data)
- **Precision:** 0.98, **Recall:** 0.98

- **Average IoU:** 92.88% (excellent localization accuracy)
- **Convergence:** Loss stabilized at 0.0204 after 4000 iterations

Key Merits of YOLO Implementation:

✓ **Significantly improved F1-score:** 0.3333 vs 0.2847 (Task 2) and 0.2113 (Task 1) - best overall performance
✓ **Reduced false positives:** Superior classification reduces spurious detections common in classical methods
✓ **Confidence-based filtering:** Probabilistic outputs enable adaptive thresholding (25% threshold used)
✓ **Excellent validation performance:** 99.97% mAP indicates strong learning of dartboard features
✓ **Handles scale and viewpoint:** Deep features robust to geometric transformations
✓ **Perfect detections on several images:** dart3, dart15 achieve F1=1.0 where previous methods failed

Shortcomings and Limitations:

× **Bounding box granularity mismatch:** YOLO predictions often larger than ground truth annotations, causing IoU-based evaluation to penalize correct detections
× **Limited training data diversity:** Data augmentation based on single template (`dartboard.bmp`) insufficient to cover real-world variability
× **Generalization gaps:** Zero recall on dart4, dart6, dart10-14 suggests dataset lacks representation of certain dartboard appearances or contexts
× **Maintained TPR limitations:** Recall (0.4062) unchanged from Task 2, indicating detection coverage not improved despite better precision
× **Annotation inconsistency effects:** Discrepancy between ground truth boxes and YOLO predictions highlights annotation quality issues in evaluation protocol
× **Computational cost:** Training requires 4000 iterations and pre-trained weights, more resource-intensive than classical methods

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Conclusions

The progressive evolution from classical Viola-Jones to hybrid Hough-based verification to deep learning demonstrates clear improvements in detection accuracy:

- **Task 1** establishes a baseline with high recall but poor precision (F1=0.2113)
- **Task 2** improves F1 by 34.7% through geometric verification, though at the cost of some recall
- **Task 3** achieves the best overall performance with 57.8% F1 improvement over Task 1 and 17.1% over Task 2

The deep learning approach (YOLOv4-Tiny) provides the most robust solution with: - Superior precision through learned discriminative features - Excellent validation performance (99.97% mAP) - Confidence-based filtering enabling adaptive thresholding

However, all methods show room for improvement, particularly on challenging cases (dart4, dart6, dart10-13) where extreme occlusion or non-standard appearances prevent detection. Future work should focus on expanding training data diversity and potentially combining methods through ensemble approaches.

Appendix: Comprehensive Performance Tables

Appendix A: Per-Image Performance Comparison

	Recall	Recall	Recall

Image	(TPR) - Task 1	F1 - Task 1	(TPR) - Task 2	F1 - Task 2	(TPR) - Task 3	F1 - Task 3
dart0	1.0000	0.4000	1.0000	1.0000	1.0000	0.6667
dart1	1.0000	0.6667	1.0000	0.6667	1.0000	0.6667
dart2	1.0000	0.2500	1.0000	0.6667	0.0000	0.0000
dart3	1.0000	0.4000	0.0000	0.0000	1.0000	1.0000
dart4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart5	1.0000	0.1818	1.0000	0.6667	1.0000	0.6667
dart6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart7	0.0000	0.0000	0.0000	0.0000	1.0000	0.6667
dart8	1.0000	0.2667	0.5000	0.6667	0.5000	0.6667
dart9	1.0000	0.5000	1.0000	0.6667	0.0000	0.0000
dart10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart13	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
dart14	1.0000	0.0488	1.0000	0.2222	0.0000	0.0000
dart15	1.0000	0.6667	0.0000	0.0000	1.0000	1.0000

Table A1: Detailed per-image performance comparison across all three tasks.

Appendix B: Summary Performance Metrics

Task	Method	Mean Recall (TPR)	Mean F1	F1 Improvement vs Task 1	F1 Improvement vs Task 2
Task 1	Viola-Jones (Cascade Classifier)	0.5625	0.2113	Baseline	-
Task 2	Viola-Jones + Hough Circle	0.4062	0.2847	+34.7%	Baseline
Task 3	**YOLOv4-Tiny (Deep Learning)**	**0.4062**	**0.3333**	**+57.8%**	**+17.1%**

Table A2: Average performance metrics showing progressive improvement in F1-score, with Task 3 achieving the best overall performance.

References

Task-Specific Documentation

- **Task 1 Details:** See `README_TASK_1.md` for Viola-Jones training process and cascade parameters
- **Task 2 Details:** See `README_TASK_2.md` for Hough Circle integration and parameter analysis
- **Task 3 Details:** See `README_TASK_3.md` for YOLOv4-Tiny training, configuration, and usage guide

Code Files

- `Task1_dartboard.py` - Viola-Jones cascade detector
- `Task2_dartboard.py` - Hybrid Viola-Jones + Hough Circle detector
- `Task3_dartboard.py` - YOLOv4-Tiny deep learning detector
- `utils.py` - Evaluation metrics and visualization utilities

Results Directories

- `Task1_results/` - Viola-Jones detection outputs
- `Task2_results/` - Hybrid method detection outputs and Hough visualizations
- `Task3_results/` - YOLO detection outputs and performance tables