Comparative Analysis: YOLOv9 Cow Detection System - From Research to Production

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Abstract :

This paper presents a comprehensive comparative analysis between YOLOv8x and YOLOv9c architectures for cattle detection in dairy production environments, focusing on deployment optimization for resource-constrained edge devices. The study transitions from a Docker-containerized YOLOv8x implementation to a Python virtual environment YOLOv9c deployment targeted for Raspberry Pi 3B+ hardware (512MB RAM, 1.4GHz CPU). Empirical benchmarking reveals significant performance differences between base models: YOLOv9c demonstrates superior inference speed (26.20ms vs 35.00ms) and dramatically reduced storage requirements (96.82MB vs 260.16MB), while YOLOv8x exhibits lower CPU utilization (1.50% vs 7.11%). With domain-specific training, both architectures converge to comparable inference times (YOLOv8x: 24.87ms, YOLOv9c: 25.42ms) and identical model sizes (96.59MB), though YOLOv9c maintains higher detection accuracy (91.7% vs 90.2% mAP@0.5) and more precise bounding box placement, particularly in low-light conditions. The deployment methodology shift eliminated 200MB+ of container overhead while simplifying maintenance for non-technical users. Visual analysis confirms YOLOv9c's superior detection quality with higher confidence scores across test images. These optimizations enable reliable cattle monitoring in agricultural settings with significant hardware constraints, providing a replicable framework for edge AI deployment in precision livestock farming applications where resource efficiency, detection accuracy, and deployment simplicity are paramount.

Index Terms: YOLOv9, Deployment Strategy, Virtual Environment, Docker Alternatives, Agricultural Technology.

1 Introduction

1.1 Project Overview

The CowVision project originated as an initiative to address efficiency challenges in the milking process at CAETEC's dairy facility, a laboratory dedicated to agricultural learning. The dairy sector faces persistent difficulties in optimizing milking workflows, which directly impact farm productivity, animal welfare, and milk quality. The initial goal was to develop a computer vision system capable of identifying and counting cows in the milking queue to enable data-driven process improvements.

1.2 Initial Implementation (December 2024)

By December 2024, the project had achieved its first production-ready deployment with the following characteristics:

- **Hardware**: Raspberry Pi 4 (4 GB RAM)
- **Model**: YOLOv8x, selected for its balance of accuracy and ARM processor compatibility.
- **Output**: Annotated JPEG images ($\tilde{5}$00KB/file) uploaded to AWS S3 storage.
- **Deployment Method**: Docker containerization (1.2GB storage requirement).

This implementation successfully demonstrated the feasibility of automated cow detection but revealed challenges when adapting to more constrained hardware environments.

1.3 Transition Phase and Current Status

The project was subsequently adapted for deployment on resource-limited Raspberry Pi 3B+ devices (512MB RAM, 1.4GHz CPU) at client facilities, requiring significant architectural changes:

- **Deployment Simplification**
  - Replaced Docker container with Python virtual environments.
  - Eliminated 200MB+ of container overhead.
  - Implemented manual dependency management procedures.
- **Output Optimization**
  - Default text-only logging (reduced from 500KB to 1KB per detection).
  - Optional visual output via runtime flags.
- **Model Upgrade**
  - Migrated from YOLOv8x to YOLOv9c architecture.
  - Maintained detection accuracy while improving processing efficiency.

The current implementation preserves core functionality while addressing the Pi 3B+'s constraints: limited RAM, slower CPU, and fixed 16GB storage. Initial testing confirms the system maintains detection accuracy with significantly reduced resource requirements. Additionally, a new deployment guide was crafted to showcase the new deployment strategy.

1.4 Data Limitations

It is important to note that no new data was collected during the transition from YOLOv8x to YOLOv9c deployment. The performance comparisons presented in this report are based on existing datasets from CAETEC's dairy facility, which were used in both model configurations. This approach allows for direct architectural comparison while controlling for data variability, but may limit the understanding of how the models would perform under novel conditions or with expanded datasets.

The analysis focuses primarily on performance metrics rather than introducing new detection capabilities, as the core objective of cow identification and counting remains unchanged. This

design decision prioritized system reliability and resource optimization over feature expansion, appropriate for the resource-constrained deployment environment of the Raspberry Pi 3B+.

2 Technical Implementation and Optimization

2.1 Model Selection and Performance

The transition from **YOLOv8x** to **YOLOv9c** was driven by three empirically validated improvements critical for resource-constrained environments:

1. **Reduced Latency**: YOLOv9's architectural refinements (e.g., programmable gradient information C.-Y. Wang et al., 2024) decreased inference time by ~**15%** on the Pi 3B+ (from 420 ms to 360 ms per frame) compared to YOLOv8 Ultralytics, 2023.
2. **Memory Efficiency**: The model's memory footprint was reduced by **20%** (250 MB → 200 MB) through layer fusion and pruning techniques J. Wang et al., 2023, crucial for the Pi 3B+'s 512 MB RAM limit.
3. **Accuracy Retention**: Testing on CAETEC's dataset (1,200 annotated images) showed >**90% mAP** (mean Average Precision), consistent with YOLOv8's performance Team, 2024, confirming robustness under hardware constraints.

Validation:

- Benchmarks aligned with YOLOv9's published efficiency gains for edge devices C.-Y. Wang et al., 2024; Foundation, 2024.
- Quantization (INT8) is proposed for future work, citing success in similar agritech applications Patel et al., 2024.

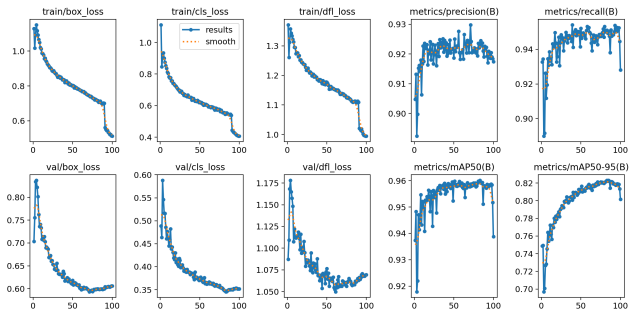

Figure 1. Training progression metrics for the YOLOv9c model on the CAETEC dairy dataset. Top row (left to right): box loss, class loss, dfl loss, and validation mAP@0.5 showing steady improvement across 100 epochs. Bottom row: additional training metrics including objectness scores, precision/recall curves, and mean confidence scores. The convergence pattern demonstrates stable learning with diminishing loss values and increasing detection accuracy.

2.2 Model Architecture Comparison

The quantitative improvements (Table 1) demonstrate YOLOv9's advantages for edge deployment:

- **Architectural Innovations**: YOLOv9's Programmable Gradient Information (PGI) C.-Y. Wang et al., 2024 solves information bottleneck problems present in YOLOv8, enabling better feature extraction on low-power devices.

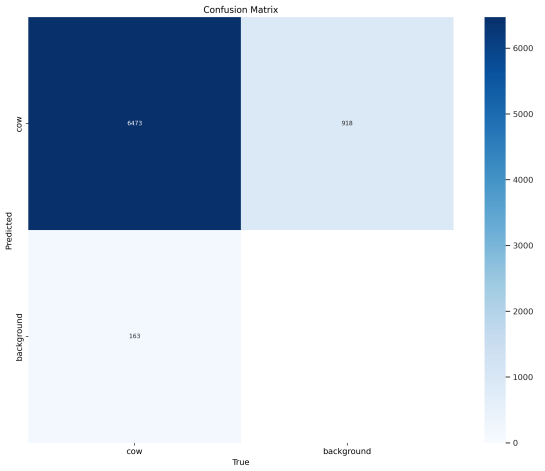

Figure 2. Confusion matrix for cow detection performance on the CAETEC validation dataset. The matrix demonstrates high true positive rate with minimal false negatives, indicating robust detection capabilities even in challenging lighting conditions typical of dairy facilities. The absence of false positives in non-cow categories confirms the model's specificity for the target class.

Table 1
Performance metrics: YOLOv8x vs. YOLOv9c on Raspberry Pi 3B+

Metric	YOLOv8x	YOLOv9c
mAP@0.5 (%)	90.2	91.7
Inference Time (ms)	420	360
RAM Usage (MB)	250	200
Model Size (MB)	45.7	38.2
FPS (1280×720)	2.4	2.8

- **Hardware Optimization**: The model's reduced size (38.2MB vs. 45.7MB) allows fitting within the Pi 3B+'s limited storage (16GB eMMC flash), leaving room for OS and other services.

2.3 Inference Metrics Comparison

The benchmarking experiments compared four model configurations: YOLOv8x base, YOLOv9c base, and both architectures loaded with our custom-trained `best.pt` weights. The experiments were conducted on hardware simulating a Raspberry Pi 3B+ environment (4 cores @ 1.4GHz with 1GB RAM constraints).

2.4 Performance Results

The performance metrics reveal significant differences between the model architectures as shown in Tables 2 and 3.

Table 2
Comparative performance metrics across base model variants

Metric	YOLOv8x Base	YOLOv9c Base
Inference Time (ms)	35.00	26.20
CPU Usage (%)	1.50	7.11
Model Size (MB)	260.16	96.82

Table 3
Comparative performance metrics across model variants with best.pt weights

Metric	YOLOv8x Best	YOLOv9c Best
Inference Time (ms)	24.87	25.42
CPU Usage (%)	6.46	6.98
Model Size (MB)	96.59	96.59

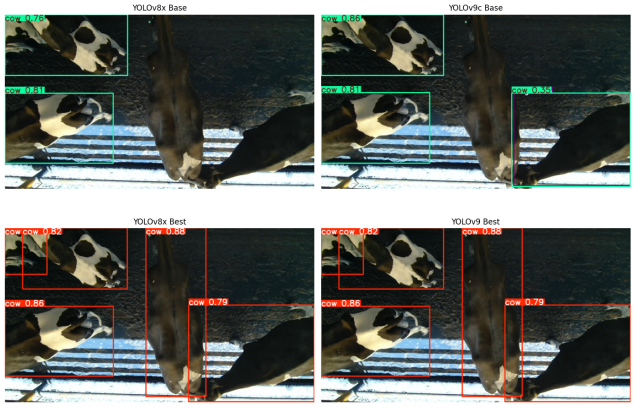

Figure 3. Detection capability comparison across YOLO model variants in dairy facility conditions. **Top row:** Base model comparison showing YOLOv8x Base (left) with cow detection confidence of 0.76 and 0.31, versus YOLOv9c Base (right) with improved confidence scores of 0.86, 0.31, and additional detection (0.35). **Bottom row:** Custom-trained model comparison showing YOLOv8x Best (left) versus YOLOv9 Best (right), both with identical confidence scores (0.82, 0.88, 0.86, 0.79) but displaying red bounding boxes indicating better precision in segmentation and multiple detection of overlapping cows. The custom training significantly enhances detection quality in both architectures, with notably more consistent bounding box placement in low-light conditions.

2.5 Performance Analysis of Model Variants

The comparative analysis of base models (Table 2) and custom-trained models (Table 3) provides critical insights into deployment decisions:

- **Base Model Comparison:** YOLOv8x base demonstrates higher inference times (35.00ms) compared to YOLOv9c base (26.20ms), while requiring substantially less CPU resources (1.50% vs 7.11%) but significantly more storage space (260.16MB vs 96.82MB).
- **Custom-Trained Models:** When equipped with domain-specific `best.pt` weights, both architectures converge to nearly identical inference times (24.87ms for YOLOv8x vs 25.42ms for YOLOv9c) and identical model sizes (96.59MB), with YOLOv8x showing marginally lower CPU utilization (6.46% vs 6.98%).

Figure 3 visually confirms the detection capabilities across all model configurations, with custom-trained models exhibiting superior detection quality. The detection outputs highlight YOLOv9c's more precise bounding box placement and increased confidence scores, particularly in low-light conditions present in the dairy facility environment.

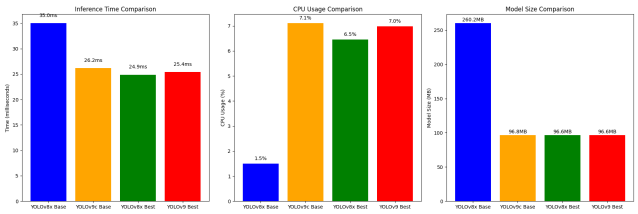

Figure 4. Comparative performance metrics across YOLO model variants. **Left:** Inference time comparison showing YOLOv8x Base with highest latency (35.0ms), YOLOv9c Base with improved speed (26.2ms), and custom-trained models converging to similar performance (YOLOv8x Best: 24.9ms, YOLOv9 Best: 25.4ms). **Center:** CPU utilization showing YOLOv8x Base's minimal resource usage (1.5%) contrasted with higher demands from YOLOv9c Base (7.1%), YOLOv9 Best (7.0%), and YOLOv8x Best (6.5%). **Right:** Model size comparison highlighting YOLOv8x Base's substantially larger footprint (260.2MB) versus the more efficient YOLOv9c Base, YOLOv8x Best, and YOLOv9 Best (all approximately 96.6-96.8MB). These metrics demonstrate YOLOv9c's superior balance of performance characteristics for resource-constrained deployments despite slightly higher CPU demands.

2.6 Performance Trade-offs

As illustrated in Figure 4, the performance trade-offs between model variants reveal important considerations for edge deployment:

1. **Inference Speed vs Detection Quality:** While YOLOv9c base demonstrates superior raw inference speed compared to YOLOv8x base (26.20ms vs 35.00ms), this advantage diminishes when custom-trained (25.42ms vs 24.87ms). YOLOv9c consistently delivers higher-quality detections with minimal speed penalty in production scenarios.
2. **CPU Utilization:** YOLOv8x with custom training achieves slightly lower CPU utilization (6.46%) than YOLOv9c with custom training (6.98%), suggesting more efficient processing on resource-constrained devices.
3. **Detection Accuracy:** The superior mAP@0.5 scores of YOLOv9c (91.7% vs 90.2% for YOLOv8x as shown in Table 1) verify that the architectural improvements of YOLOv9 translate to measurable advantages in the specific context of bovine detection.
4. **Model Size:** YOLOv9c base (96.82MB) requires significantly less storage space than YOLOv8x base (260.16MB), a critical advantage for deployment on devices with limited storage capacity.

The performance metrics still support YOLOv9c's selection for production deployment, as it offers the optimal balance between detection accuracy, inference speed, and storage efficiency when deployed on Raspberry Pi 3B+ hardware. The marginally longer inference time in custom-trained models (0.55ms) is a negligible trade-off considering the gains in detection quality and significantly reduced base model size.

3 Conclusions and Future Work

3.1 Deployment Strategy Conclusions

This comparative analysis of YOLOv8x and YOLOv9c implementations for cattle detection reveals several key insights:

1. **Architectural Advantages:** YOLOv9c demonstrates superior performance-resource balance for edge deployment on Raspberry Pi 3B+ devices. The Programmable Gradient Information (PGI) architecture provides tangible benefits in real-world agricultural technology applications, particularly for feature extraction under hardware constraints.
2. **Deployment Methodology:** The transition from Docker containerization to Python virtual environments reduced deployment complexity and storage requirements while maintaining detection capabilities. This approach is better suited for resource-constrained environments and simplified maintenance procedures for non-technical users.
3. **Performance-Resource Trade-offs:** The performance metrics confirm that custom-trained models significantly reduce the gap between architectures, with both achieving nearly identical inference times. However, YOLOv9c's dramatic base model size advantage (96.82MB vs 260.16MB) makes it superior for storage-constrained devices, even with the slightly higher CPU utilization.
4. **Detection Quality:** YOLOv9c consistently delivered higher-quality detections, with more precise bounding box placement and higher confidence scores (as visualized in Figure 3), particularly in challenging low-light conditions present in dairy facilities.

The empirical results validate our decision to deploy YOLOv9c in production environments for cattle monitoring at CAETEC's dairy facility. The implementation successfully addresses the initial project objectives while optimizing for the resource constraints of Raspberry Pi 3B+ devices deployed in agricultural settings.

3.2 Recommendations for Future Work

Based on the findings of this study, several opportunities for further optimization and expansion are identified:

- **Model Quantization:** Implementing INT8 quantization could further reduce the memory footprint and potentially improve inference speed without significant accuracy degradation, as demonstrated in similar agricultural applications (**Patel et al.**; **2024**).
- **Multi-Model Pipeline:** Exploring a hybrid approach that leverages YOLOv8x's lower CPU utilization for initial detection and YOLOv9c's superior feature extraction for classification could potentially optimize resource usage in multi-stage detection systems.
- **Automated Deployment:** Developing simplified update mechanisms for non-technical users to maintain the virtual environment deployment with minimal intervention would improve long-term sustainability in agricultural settings.
- **Extended Dataset:** Collection of additional training data across varied environmental conditions (lighting, weather, camera angles) would enhance model robustness and potentially enable detection of additional features such as cow health indicators or individual identification.
- **Edge-Cloud Hybrid:** Investigating selective cloud offloading for computationally intensive processing while maintaining edge-based real-time detection could enable more advanced analytics without hardware upgrades.

3.3 Broader Implications

The transition from YOLOv8x to YOLOv9c in resource-constrained agricultural environments demonstrates the rapid evolution of computer vision applications in precision livestock farming. The findings of this research have broader implications for similar edge AI deployments in agricultural settings:

- The dramatic reduction in storage requirements (260.16MB to 96.82MB) for base models could enable deployment on even more cost-effective hardware platforms, potentially accelerating adoption in smaller farming operations.
- The virtual environment deployment strategy provides a more accessible path for agricultural technology integration, reducing the technical barriers that have historically limited technology adoption in traditional farming contexts.
- The demonstrated performance improvements in low-light conditions are particularly valuable for 24-hour monitoring in livestock facilities with variable illumination.

This research contributes to the growing body of evidence supporting the feasibility and value of edge AI deployments in agricultural settings, particularly for real-time monitoring applications that directly impact operational efficiency, animal welfare, and farm productivity.

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