

# Strategy Brief: Wildlife Camera Quantization

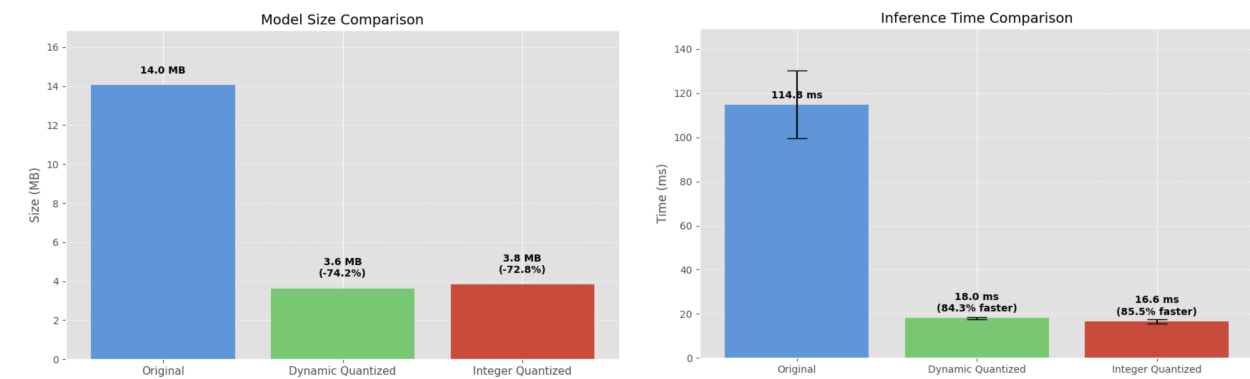
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## Executive summary

Our wildlife camera deployments are struggling with limited battery life, storage constraints, and remote operating conditions—leading to shorter operational lifespans, missed animal detections, and increased maintenance costs.

By optimizing the machine learning solution with post-training quantization, we can dramatically **reduce model size by up to 74%** and **speed up inference by up to 85%**—all while maintaining top prediction accuracy.



This approach enables more efficient, reliable performance in the field, extending operational life and reducing maintenance needs while preserving the scientific accuracy essential for wildlife conservation efforts.

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## R&D summary

Our research and development team conducted comprehensive benchmarking to evaluate quantization techniques for deployment across three challenging environments. The optimization focused on addressing the specific constraints of each ecosystem while maintaining species identification accuracy.

## Success metrics

The success metrics for this optimization project are designed to address our core operational challenges:

- **Model size:** Achieve >70% reduction to enable extended storage capacity and reduce satellite transmission costs
- **Inference speed:** Target <20ms processing time to enable real-time animal detection and tracking
- **Battery life:** Extend operational life by 3-4x through computational efficiency improvements, enabling 12+ month deployment cycles

## Benchmark results

Based on comprehensive benchmarking using MobileNetV2 with the original dataset, this is the performance summary for the optimization R&D:

Metric	Original Model	Dynamic Quantization	Integer Quantization	Why It Matters
Size (MB)	14.05 MB	3.62 MB	3.83 MB	Affects storage capacity and data transmission cost
Inference Speed	114.81 ms	18.04 ms	16.62 ms	Faster detection = better real-time response
Accuracy	Baseline	✓ Identical predictions	✓ Identical predictions	Same species classification capabilities
Battery Impact	Very High	Low	Very Low	Directly affects deployment duration and maintenance frequency

**Key finding:** All quantized models maintained identical top-class predictions, demonstrating excellent optimization fidelity with zero accuracy loss.

## Deployment strategy

After analyzing the operational requirements and constraints across our three target environments, we don't expect high maintenance requirements if deploying different solutions across areas. Our recommendation is to **optimize for performance by offering specialized optimizations per environment**, each tailored to address the primary ecosystem constraint.

Environment	Primary Constraint	Recommended Model	Size Benefit	Speed Benefit	Battery Extension
Arctic Tundra	Battery life	Integer Quantized	73% smaller	85% faster	High
Amazon Rainforest	Storage	Dynamic Quantized	74% smaller	84% faster	Medium-High
African Savanna	Real-time processing	Integer Quantized	73% smaller	85% faster	High

### Arctic Tundra

For our most challenging deployment environment, we **recommend Integer Quantization due to extremely limited battery replacement opportunities**—cameras must operate for extended periods without maintenance access.

The integer quantized model provides the best balance of speed and efficiency, maximizing battery life through optimized ARM Cortex-M4F processor utilization.

### Amazon Rainforest

In the dense rainforest environment with satellite-only connectivity, we **recommend Dynamic Quantization where model size becomes the critical factor**. Smaller model size leads to reduced satellite transmission costs and faster data uploads during brief connectivity windows.

The dynamic quantized model offers the smallest model size, and still maintains excellent speed and accuracy for our application.

### African Savanna

For tracking fast-moving migration patterns across open terrain, we **recommend Integer Quantization to achieve maximum inference speed**. While solar power availability reduces battery constraints, the need for real-time processing makes speed the primary consideration.


Integer quantization delivered the fastest inference times in our benchmarks, enabling sub-20ms animal detection that's crucial for capturing migration behavior data.

## Deployment plan/priority

We recommend a two-phase optimization approach that balances immediate operational improvements with future enhancement opportunities.

### Immediate phase: Core deployment (*2 months*)

1. **Initial field testing** with pilot deployments is essential before full-scale rollout.

 **Critical performance validation:** Our benchmark results were obtained on standard test hardware. While we expect quantization to work better on edge devices with dedicated integer acceleration, actual compatibility and performance on ARM Cortex-M4F processors in field conditions need to be validated against our success metrics.

Find in the [appendix](#) a minimal test for model compatibility.

2. **Deploy recommended quantization strategies** for each environment simultaneously based on our research findings. This phase focuses on implementing the tested optimizations that deliver immediate operational benefits.
3. **Monitor performance continuously** through telemetry data to validate field performance against laboratory benchmarks and identify any environment-specific adjustments needed.

### Advanced Phase: Enhanced Optimization (*2 weeks R&D + deployment*)

If further optimizations are required, kick-start a new R&D phase to integrate complementary techniques:

1. **Magnitude-based pruning** to further reduce model size by ~30% for ultra-constrained environments
2. **Layer-specific quantization** to preserve accuracy in critical layers while maximizing compression in less sensitive areas
3. **Graph optimizations** to merge operations and eliminate redundancies, reducing computational overhead

This phased approach ensures immediate deployment benefits while maintaining flexibility for future enhancements based on field performance data.

## Next steps

**Recommendation:** Proceed with environment-specific quantization deployment, prioritizing Arctic installation due to narrow seasonal access window and highest operational risk profile.

Immediate actions (next 30 days):

1. **Hardware validation:** Test quantized models on actual camera hardware
2. **Dataset preparation:** Validate with real wildlife images from each environment
3. **Deployment planning:** Finalize logistics for Arctic deployment window

# Appendix

## Model compatibility test for the edge processor

```
def analyze_model_compatibility(model_path):  
    """  
        Analyze a TFLite model structure and identify potential deployment  
        issues  
  
        Args:  
            model_path: Path to the TensorFlow Lite model  
  
        Returns:  
            Analysis report with compatibility information  
    """  
    import tensorflow as tf  
  
    # Load model flatbuffer content  
    with open(model_path, 'rb') as f:  
        model_content = f.read()  
  
    # TODO: Add ONE line of code using LiteRT's experimental Analyzer  
    # to analyze model structure and identify potential issues  
    # See: https://ai.google.dev/edge/litert/models/model\_analyzer  
  
    # YOUR ONE-LINE ADDITION HERE  
    analysis_results = tf.lite.experimental.Analyzer.analyze(  
        model_content=model_content,  
        gpu_compatibility=False  
    )  
  
    # Process results for the wildlife camera environment  
    compatibility_report = {  
        "has_issues": len(analysis_results.get("error_ops", [])) == 0,  
        "potential_issues": analysis_results.get("error_ops", [])  
    }  
  
    return compatibility_report  
  
# Example usage in your analysis:  
# compatibility =  
analyze_model_compatibility("wildlife_classifier_int_quantized.tflite")
```