MicroViT and LLM Models

Technical Documentation

MicroVIT Robotics System

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1. Overview

The MicroVIT robotics system uses a two-stage AI pipeline for intelligent perception and natural language generation:

Stage	Model	Purpose	Device
Vision Processing	MicroViT (MobileViT)	Fast image understanding and feature extraction	Jetson Orin
Text Generation	Qwen2.5:0.5B (via Ollama)	Natural language message generation	Jetson Orin

This hybrid approach combines the speed of lightweight vision models with the creativity of large language models, enabling real-time AI message generation on edge devices with limited computational resources.

2. MicroViT Model (Vision Transformer)

2.1 Introduction

MicroViT is a lightweight Vision Transformer architecture designed for edge devices. In this project, we use **MobileViT** (apple/mobilevit-small) as a proxy implementation since MicroViT is not available as a pre-trained model. MobileViT follows similar design principles: efficient attention mechanisms, hybrid CNN-ViT architecture, and optimization for mobile/edge deployment.

2.2 Architecture Details

Component	Specification
Base Model	MobileViTForImageClassification
Model Name	apple/mobilevit-small
Parameters	~5.6 million
Input Size	256×256 pixels
Feature Dimensions	320 (S1 variant)
Pre-training Dataset	ImageNet-1k (1000 classes)
Architecture Type	Hybrid CNN-ViT (MobileViT blocks)
Attention Mechanism	Efficient Single Head Attention (ESHA)
Model Size	~22 MB (FP32) / ~11 MB (FP16)

2.3 Variants

The implementation supports three MicroViT variants (S1, S2, S3) with different feature dimensions:

Variant	Feature Dimensions	Channels	Use Case
S1	320	[128, 256, 320]	Default - Balanced speed/accuracy
S2	448	[128, 320, 448]	Higher accuracy, slower
S3	512	[192, 384, 512]	Highest accuracy, slowest

2.4 Processing Pipeline

Step 1: Image Preprocessing
• Decode base64 JPEG string to PIL Image
• Convert to RGB format
• Resize to 256×256 pixels (model input size)
• Normalize pixel values to [-1, 1] range
• Convert to PyTorch tensor [1, 3, 256, 256]

■■ Time: ~5-10ms

Step 2: Feature Extraction
• Forward pass through MobileViT encoder
• Extract features from last encoder layer (before classification head)
• Global average pooling if needed
• Extract CLS token or pooled features
■■ Time: ~9ms (GPU) / ~50-200ms (CPU)

Step 3: Classification
• Forward pass through classification head
• Softmax to get class probabilities
• Extract top-5 predictions
• Map ImageNet class IDs to human-readable labels

Step 4: Feature-to-Text Conversion
• Convert class probabilities to natural language
• Format: 'Primary object detected: {class} ({confidence}%)'
• Add secondary detections if confidence > 5%
• Add contextual descriptions based on detected class
• Output: Structured text description for LLM

2.5 ImageNet Class Recognition

MicroViT recognizes 1000 ImageNet classes. The system focuses on common objects relevant to robotics:

Category	Examples
Traffic Infrastructure	stop_sign, traffic_light, fire_hydrant, parking_meter
Vehicles	bicycle, motorcycle, bus, train, truck, boat, airplane
People & Animals	person, bird, cat, dog, horse, cow, elephant
Furniture	chair, couch, bed, dining_table, toilet
Electronics	tv, laptop, mouse, keyboard, cell_phone, remote
Household Items	bottle, cup, bowl, book, clock, vase, scissors
Outdoor Objects	bench, backpack, umbrella, suitcase, frisbee

2.6 Example Output

Input: Image of a turnstile/gate captured by Nano camera

```
MicroViT Output:
'Primary object detected: turnstile (45.2% confidence). Other possibilities:
metal gate (12.3%), fence (8.1%), barrier (5.4%). Traffic infrastructure
detected, road environment context.'
```

3. LLM Model (Qwen2.5:0.5B)

3.1 Introduction

Qwen2.5:0.5B is a lightweight Large Language Model developed by Alibaba Cloud. It is specifically designed for edge devices with limited computational resources. The model has approximately 0.5 billion parameters, making it suitable for real-time text generation on devices like Jetson Orin.

3.2 Model Specifications

Property	Value
Model Name	Qwen2.5:0.5B
Parameters	~0.5 billion (494.03M)
Model Format	GGUF (quantized)
Quantization	Q4_K_M (4-bit, medium quality)
Model Size	~380 MB (compressed)
Context Length	512 tokens (configurable)
Max Tokens	500 tokens (configurable)
Architecture	Decoder-only Transformer
Framework	Ollama (local inference)
Execution Mode	CPU-only (OLLAMA_NO_GPU=1)

3.3 Why Qwen2.5:0.5B?

Advantages for Edge Deployment:
- **Small Size:** ~380MB fits in limited RAM
- **Fast Inference:** ~200-500ms per generation on CPU
- **Good Quality:** Despite small size, generates coherent text
- **Multilingual:** Supports multiple languages
- **Quantized:** Q4_K_M quantization balances quality and speed
- **Ollama Integration:** Easy deployment via Ollama framework

3.4 Text Generation Process

Step 1: Prompt Construction
The system creates a structured prompt combining:
- MicroViT visual description
- LiDAR sensor data (distance, direction, confidence)
- Robot position and status
- Task instructions (generate status message)

Step 2: Ollama API Call
• POST request to http://localhost:11434/api/generate
• Model: qwen2.5:0.5b
• Temperature: 0.8 (creative but focused)
• Max tokens: 500 (configurable)
• Stream: false (wait for complete response)

Step 3: Response Generation
• Ollama processes prompt token by token
• Generates natural language response
• Returns complete message
■■ Time: ~3-5 seconds (CPU mode)

3.5 Example Prompt

```
You are Robot robot1_orin at location (0.00, 0.00). Based on my visual
analysis (preprocessed with MicroViT), I can see: Primary object detected:
turnstile (45.2% confidence). Other possibilities: metal gate (12.3%), fence
(8.1%). Traffic infrastructure detected, road environment context. My LiDAR
sensors report: - Distance to nearest obstacle: 0.5 meters - Obstacle
direction: 0.0 degrees - Obstacle size: 0.5 meters - Sensor type: LiDAR
(REAL) - Confidence level: 0.95 Generate a creative, informative status
message (under 150 words) that: 1. Describes what I can see visually based on
the preprocessed image features 2. Reports what my LiDAR sensors detect 3.
Provides a combined assessment of the situation 4. Suggests what action I
should take Make it sound like a robot reporting to other robots. Be engaging
and specific about my location.
```

3.6 Example Generated Message

```
Hello everyone! Thank you for asking. Based on my visual analysis with
MicroViT, I can see that one possible object in your environment is the
turnstile. This is not an accident but rather an expected feature due to the
distance from where I am to the nearest obstacle and the size of the
obstacle. My LiDAR sensors detected an object within a 0.5-meter range with
no obstacles around it. The sensor report indicates confidence at 95%, which
is appropriate for detecting small objects like this. Based on my
observations, I suggest that you take a closer look to see if there are any
other interesting or unexpected features in the area where the turnstile
might be located. If you encounter anything out of place or need additional
assistance, please don't hesitate to let me know! Thank you for your
understanding. Have a great day!
```

4. Integration Architecture

4.1 Two-Stage Pipeline

The system uses a two-stage approach to separate visual understanding from language generation:

Stage	Component	Input	Output	Time
1	Image Capture	Camera feed	Base64 JPEG	~10-20ms
2	MicroViT Processing	Base64 image	Text description	~50-200ms
3	Prompt Construction	MicroViT + LiDAR	Structured prompt	<1ms
4	Ollama Generation	Prompt	Natural language	~3-5s
5	MQTT Publishing	AI message	MQTT topic	~10-50ms

4.2 Data Flow

Nano → Orin (XML-RPC):
Camera image (base64 JPEG) → XML-RPC server → Orin AI service

Orin Internal Processing:
Base64 image → MicroViT → Feature extraction → Text description → Prompt construction → Ollama → Natural language message

Orin → Controller (MQTT):
AI message → MQTT broker → Controller analysis

5. Performance Characteristics

5.1 Speed Comparison

Model	GPU Inference	CPU Inference	Memory Usage	Accuracy
MicroViT (MobileViT)	~9ms	~50-200ms	~150MB	Good (ImageNet)
BLIP (captioning)	~500ms	~2-5s	~1GB	Excellent
ViT-Base	~20ms	~300-500ms	~500MB	Very Good
Qwen2.5:0.5B	N/A (CPU only)	~200-500ms	~400MB	Good

5.2 Total Pipeline Time

End-to-End Latency (CPU mode on Jetson Orin):
• Image capture: ~10-20ms
• MicroViT processing: ~50-200ms
• Ollama generation: ~3-5 seconds
• MQTT publishing: ~10-50ms
Total: ~3.1-5.3 seconds per message

With 30-second detection interval, this provides ample time for processing while maintaining real-time operation.

5.3 Memory Usage

Total System Memory (Jetson Orin):
• MicroViT model: ~150MB
• Qwen2.5:0.5B model: ~400MB
• System overhead: ~200MB
• Runtime buffers: ~100MB
Total: ~850MB (well within 8GB RAM limit)

6. Configuration and Usage

6.1 Environment Variables

Variable	Default	Description
USE_MICROVIT	true	Enable/disable MicroViT
MICROVIT_MODEL_NAME	apple/mobilevit-small	Hugging Face model name
MICROVIT_VARIANT	S1	Variant: S1, S2, or S3
MICROVIT_USE_CPU	true	Force CPU mode
OLLAMA_MODEL	qwen2.5:0.5b	Ollama model name
OLLAMA_TEXT_MODEL	qwen2.5:0.5b	Text generation model
OLLAMA_NO_GPU	1	CPU-only mode (avoid GPU OOM)
OLLAMA_MAX_TOKENS	500	Maximum tokens to generate
OLLAMA_CONTEXT_LENGTH	512	Context window size

6.2 Code Usage

```
# Initialize MicroViT from microvit_integration import MicroViTModel model =
MicroViTModel( model_name='apple/mobilevit-small', use_cpu=True, variant='S1'
) model.load_model() # Analyze image image_description =
model.analyze_image(base64_image_string) # Returns: "Primary object detected:
turnstile (45.2% confidence)..." # Use with Ollama prompt = f"Based on my
visual analysis: {image_description}" ai_message = ollama.generate(prompt)
```

7. Technical Specifications

7.1 MicroViT Technical Details

Specification	Value
Model Architecture	MobileViT (Hybrid CNN-ViT)
Attention Type	Efficient Single Head Attention (ESHA)
Patch Size	16×16 pixels
Embedding Dimension	320 (S1)
Number of Layers	Variable (MobileViT blocks)
Activation Function	GELU
Normalization	Layer Normalization
Optimizer (Training)	AdamW
Learning Rate (Training)	1e-4
Batch Size (Training)	256
Precision	FP32 (CPU) / FP16 (GPU)

7.2 Qwen2.5:0.5B Technical Details

Specification	Value
Architecture	Decoder-only Transformer
Context Window	512 tokens (configurable up to 32K)
Vocabulary Size	151,936 tokens
Number of Layers	24
Hidden Size	1,152
Attention Heads	12
FFN Dimension	2,816
Activation	SwiGLU
Position Encoding	RoPE (Rotary Position Embedding)
Quantization	Q4_K_M (4-bit, medium)
Framework	Ollama (GGUF format)

Conclusion

The MicroVIT robotics system successfully combines lightweight vision processing (MicroViT/MobileViT) with efficient language generation (Qwen2.5:0.5B) to enable real-time AI message generation on edge devices. This two-stage approach provides the optimal balance between speed, accuracy, and resource constraints, making it ideal for autonomous robotics applications with limited computational resources.