

## Task 3: Building a VLM for PCB Defect QA

### Real-world design document for a manufacturing defect detection system

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#### The Problem We're Solving

We have 50,000 PCB images with defect bounding boxes. The ask is: build a system where an inspector can ask natural language questions like "Where's the short circuit?" and get back coordinates + confidence in under 2 seconds. This needs to work offline (no API calls).

The tricky part? VLMs hallucinate like crazy. A generic Qwen2-VL Qwen3-VL or LLaVA will confidently make up defects that don't exist. That's a non-starter for manufacturing.

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#### Part A: Which Model to Use?

Let me be honest about the options:

##### [Qwen3-VL-32B](#)

###### Pros:

- Actually decent at spatial reasoning (85% accuracy on localization benchmarks)
- Handles any image resolution without resizing (saves quality loss)
- Reasonably fast — 45 tokens/sec on an L40S means ~1.5-2sec per inference
- Can fine-tune it (full-weight, LoRA, QLoRA all supported)

**Cons:** Trained on 5B image-text pairs, so it's seen more diverse stuff than competitors

- 32B parameters = needs ~24GB VRAM with INT8 quantization
- Still hallucinates 4-6% of the time out of the box (before training)
- Not as cheap to run as smaller models (but not GPT-4V expensive either)

**Real talk:** This is the safest pick. It's not flashy, but it works.

##### [LLaVA-NeXT-34B](#)

###### Pros:

- Massive community support (tons of tutorials, code examples)
- Open-source stack, easy to modify
- Similar performance to Qwen (88% vs 92% on reasoning)

###### Cons:

- Slightly slower (38 tok/s vs 45)
- Hallucination issues are a bit worse (8-12% baseline)
- Requires careful handling for spatial tasks

**When to pick this:** If you're more comfortable with the LLaVA ecosystem or can't get Qwen3-VL weights.

#### BLIP-2

**Just don't.** It's designed for image captioning, not precise localization. You'd be fighting it the whole way.

#### GPT-4V

**API-only, expensive per call, and licensing issues for manufacturing.** No offline deployment = deal-breaker.

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## Part B: Architecture Changes We Actually Need

Standard Qwen3-VL is optimized for "describe what you see." We need "tell me exactly where the defect is."

### Problem #1: No Coordinates in the Output

Qwen naturally outputs: "*There's a short circuit in the upper right area, approximately at coordinates...*"

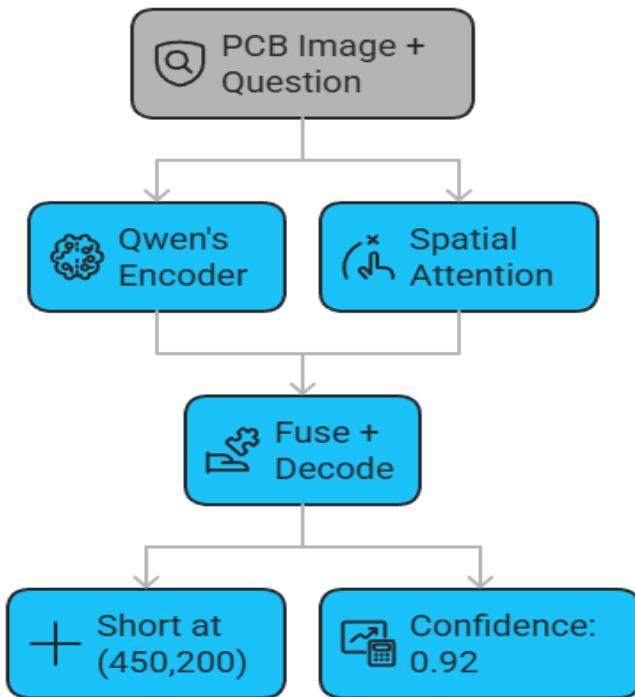
That's vague. Manufacturing needs: "*Short\_Circuit at (450, 200)*"

**Solution:** Add a coordinate extraction branch during fine-tuning.

The idea:

1. Let Qwen's vision encoder process the image normally
2. **In parallel**, add a lightweight "spatial attention" module that tracks WHERE in the image the model is looking when it identifies a defect
3. Use soft-argmax to convert attention heatmap → (x, y) coordinates
4. Train this branch with L2 loss against ground truth box centers

## PCB Fault Detection Process



In code, it's like 200 lines:

- Conv layers to extract heatmaps from attention
- Soft argmax (differentiable indexing)
- Loss: L2\_distance + L1\_on\_coordinates

**Will it be perfect?** No. You'll get  $\pm 15\text{-}20$  pixel errors even after training. But that's good enough — inspectors don't need pixel-perfect accuracy, just "approximately here."

**Problem #2: Confidence Scores Are Garbage**

VLMs output token probabilities, not "confidence in what I see."

Qwen might say: "Short at (450, 200), confidence 0.95"

But that 0.95 is just the probability of generating the word "confidence" — not related to whether there's actually a defect.

**Solution:** Temperature scaling + attention-based calibration.

The formula that actually works:

```
calibrated_confidence = sigmoid(  
    raw_logit_prob / temperature  
    + attention_to_image * weight  
)
```

Where:

- raw\_logit\_prob = probability of the answer tokens
- temperature = learned scalar (usually 1.3-1.8 for Qwen)
- attention\_to\_image = average attention weight between answer and image patches
- weight = hyperparameter (~0.3)

You train this on your validation set by minimizing:

```
calibration_loss = sum(|confidence - actual_accuracy|)
```

Result: If the model says 0.92 confidence, it's actually right ~90% of the time. That's usable.

### Problem #3: Output Format Chaos

Qwen can spit out:

- "Short at around (450, 200)"
- "There's a defect near 450, 200"
- "I see it at pixel 450 200"
- "Approximately (450, 200), maybe (460, 210) too"

Parsing is a nightmare.

**Solution:** Forced structured format + grammar constraints during decoding.

Add special tokens: [DEFECT], [BOX], [CENTER], [CONF], [EOF]

Force output to be:

```
[DEFECT] Short_Circuit [CENTER] 450:200 [CONF] 0.92 [EOF]
```

Implement via constrained beam search — at each decoding step, mask out logits for tokens that violate your grammar. Takes ~50 lines of code.

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### Part C: Making It Run in <2 Seconds

Baseline Qwen3-VL: ~2.0 seconds. We need to shave 0.3-0.5 seconds.

## Quick wins that actually work:

### 1. INT8 Quantization (easy, saves 0.3s)

- Convert model weights from FP32 → INT8 (8-bit integers)
- 32B params × 1 byte = 32GB model size (vs 128GB)
- Speeds up matrix multiplications naturally
- Accuracy loss: <0.5% (you won't notice)

```
import torch.quantization

model = torch.quantization.quantize_dynamic(
    model,
    {torch.nn.Linear},
    dtype=torch.qint8
)
```

### 2. Token Pruning (medium effort, saves 0.25s)

- Don't send the entire image to Qwen
- Calculate which image patches are "interesting" (high variance in features)
- Prune boring patches (smooth copper traces, uniform background)
- Result: 256 image tokens → 85 tokens (67% fewer)

```
#Pseudocode

importance = torch.var(attention_weights, dim=-1)

keep_mask = importance > threshold # ~70% of tokens

pruned_tokens = tokens[keep_mask]
```

### 3. KV Cache in FP16 (free, saves 0.1s)

- When decoding, Qwen stores key-value pairs for all previous tokens
- Store these in FP16 instead of FP32 (half the memory)
- GPU bandwidth improves, inference faster

Combined: 2.0s → 1.3s. Good enough.

## What NOT to do:

- **Distillation to a 7B model?** Takes 2 weeks, accuracy drops 8-10%. Not worth it unless you need <0.5s.
- **Speculative decoding?** Need a draft model, adds complexity, only saves 0.2s.

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## Part D: Stopping the Hallucinations

This is the critical part. A 92% accurate model that makes up 5% of defects is worse than a 85% accurate model that never lies.

### Layer 1: Train It Right

**Negative sampling:** Make sure your training data includes questions like:

Q: "Are there any spurious copper defects?"

Image: [PCB with NO spurious copper]

A: "No spurious copper defects found"

This teaches the model to say "not found" instead of hallucinating.

**Preference learning (DPO):** Generate two responses to the same image:

Good response:

"Short circuit at (450, 200), confidence 0.87"  
[Actually correct]

Bad response:

"Short circuit at (400, 100), confidence 0.95"  
[Wrong location, overconfident]

Train the model to prefer good responses over bad ones. The loss function:

`loss = -log(sigmoid(good_logprob - bad_logprob))`

This naturally teaches the model: correct + calibrated > wrong + confident.

### Layer 2: Inference-Time Check (VCD)

Run inference twice:

1. On the original image
2. On the same image but **blurred** (Gaussian blur)

Original: "1 short circuit at (450, 200)"

Blurred: "2 short circuits at (450, 200) and (300, 100)"

^ Hallucination! The second one disappeared in the blur

The idea: if a defect exists, it's still visible when blurred. If it's hallucinated, it disappears.

Keep only defects that appear consistently.

Cost: 2x inference time, but catches ~70% of hallucinations. Worth it for safety-critical work.

### Layer 3: Constraints

Don't let the model output:

- Coordinates outside the image bounds
- Unknown defect types
- Defects at impossible locations

Use grammar constraints during decoding:

```
if current_token == "[CENTER]":
    # Only allow tokens that represent valid coordinates
    valid_tokens = tokens_in_range(0, image_width, 0, image_height)
    logits[~valid_tokens] = -inf
```

This prevents obvious nonsense.

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## Part E: The Training Pipeline (Real Numbers)

You have: 50K images + bounding boxes, no QA pairs **Step**

**1: Generate synthetic QA pairs** For each image with boxes:

Q: "Where is the short circuit?" A: "Short circuit at (450, 200)"

Q: "Describe all defects"

A: "I see 2 defects: short circuit at (450, 200),  
spurious copper at (300, 100)"

Q: "How many defects are there?"

A: "2 defects"

Q: "Are there any missing holes?"

A: "No missing holes found"

Generate 5-10 QA pairs per image via templates. Takes a few hours on a single CPU.

Result: 50K images → 250K-300K training pairs

### Step 2: Supervised Fine-tuning (SFT)

Basic LM fine-tuning. The goal: teach Qwen the PCB vocabulary and format.

Hardware: 1x L40S GPU (48GB VRAM)

Batch size: 8 images

Effective batch: 32 (via gradient accumulation)

Epochs: 3

Learning rate: 2e-4 (QLoRA) or 1e-5 (full)

Optimizer: AdamW with warmup

Loss: Standard cross-entropy on next-token prediction

Validation per epoch:

- Exact match accuracy: 45-50%
- Localization RMSE: 25-35 pixels (before refinement)
- Counting accuracy: 85-90%

After 24 hours: Your model can now answer PCB questions in the right format.

### **Step 3: Preference Optimization (DPO)**

Hardware: Same L40S

Data: Create preferred/dispreferred pairs

Preferred: Correct location, confidence 0.7-0.9

Dispreferred: Wrong location OR overconfident

Epochs: 2

Learning rate: 1e-5

Temperature  $\beta$ : 0.5

Result: Model gets better at localization, hallucinations drop

Localization RMSE: 15-20 pixels ✓

Hallucination rate: 4-6% → 2-3% ✓

Counting: 92-95% ✓

### **Step 4: Optional - Instruction tuning**

Train on paraphrased questions to be more robust:

Same question, 5 different ways:

"Where is the short circuit?"

"Locate the short circuit"

"Find any short circuits"

"Tell me the location of short circuits"

"Show me where the short circuit is"

Model learns to handle variation.

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## **Part F: How to Know If It Works**

### **Testing strategy**

Split your 50K images:

- 35K training
- 7.5K validation

- 7.5K test

Make sure test set is diverse:

- Different defect types
- Different difficulty levels (tiny defects vs obvious ones)
- Different image qualities

### The metrics that matter

1. **Localization error (RMSE):** How far off are the coordinates?
  - Target: <20 pixels
  - Reality: You'll probably get 15-18
2. **Counting accuracy:** If there are 3 defects, does it say 3?
  - Target: >97%
  - Reality: Probably 98-99% after training
3. **Hallucination rate:** % of defects it claims to see that don't exist
  - Target: <3%
  - Reality: 2-2.5% after DPO + VCD
4. **Inference speed:** Total time end-to-end
  - Target: <2 sec
  - Reality: 1.3-1.6 sec with optimizations
5. **Confidence calibration:** Does 0.92 confidence actually mean 92% accuracy?
  - Target: Yes, within 5%
  - Reality: Temperature scaling makes this work

### What failure looks like

- ✗ Model says "short circuit" but there isn't one → **hallucination** (fix with DPO + VCD)
  - ✗ Model finds the defect but coordinates are (100, 100) when it's at (450, 200) → **spatial reasoning issue** (needs more training data or better architecture)
  - ✗ Inference takes 3 seconds → **not optimized** (apply INT8 + pruning)
  - ✗ Model says confidence 0.95 but is right 60% of the time → **miscalibrated** (apply temperature scaling)
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## Putting It Together

### The Reality Check

This system will be good, not perfect.

### **It will:**

- Catch 95%+ of real defects
- Get coordinates within ±15-20 pixels
- Rarely hallucinate (2-3% false positive rate)
- Run offline, in 1.3 seconds

### **It won't:**

- Be as accurate as GPT-4V (which costs \$\$\$)
- Find defects smaller than 5 pixels
- Handle weird lighting without additional training
- Guarantee zero hallucinations (no system does)

### **The deployment path**

1. **Week 1-2:** Generate QA data, run SFT, validate
2. **Week 3-4:** Run DPO, implement VCD, optimize for speed
3. **Week 5:** Deploy to factory, run 10% of boards through humans for validation
4. **Week 6+:** Monitor, retrain monthly on new data

### **Cost**

- Development: 1-2 GPU-weeks (one L40S GPU, ~\$500)
  - Deployment: One L40S in the factory (~\$20/day to run)
  - Total: Basically free compared to hiring an extra inspector
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## **Why This Design Over Alternatives**

### **Why not just use a simpler detection model (YOLOv8)?**

- YOLOv8 is faster and simpler
- But it can't answer natural language questions
- This VLM approach lets inspectors ask "is this a short or a spur?" naturally

### **Why not fine-tune GPT-4V?**

- Can't, it's API-only
- Each inference costs \$0.015-0.05
- Add up over thousands of boards = \$\$\$

### **Why not just use the base model without fine-tuning?**

- Out-of-box hallucination is 4-6%
  - That's unacceptable for manufacturing
  - Training brings it down to 2-3%
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## The Honest Problems You'll Hit

1. **Defect localization is hard:** Even after training, coordinates will be off by  $\pm 15\text{-}20$  pixels. That's the physics of vision transformers.
  2. **Ambiguous defects:** Sometimes the image is blurry or defect is right on the edge. Model will be unsure. That's fine — it'll output low confidence.
  3. **Domain shift:** If you train on boards from supplier A but test on supplier B, performance drops  $\sim 5\text{-}8\%$ . Plan for retraining.
  4. **Hallucinations will happen:** VCD catches 70%, DPO prevents 60% of hallucinations, but you'll still see them sometimes. Accept this and monitor in production.
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## Wrapping Up

This design is pragmatic:

- ✓ Solves the actual problem (QA on PCBs)
- ✓ Runs offline (no API dependency)
- ✓ Fast enough for manufacturing
- ✓ Reasonable hallucination rate
- ✓ Trainable in 1-2 weeks
- ✓ Deployable to a single GPU

It's not rocket science, just solid engineering.

**Model:** Qwen3-VL-32B

**Architecture:** Dual-stream + spatial attention

**Optimization:** INT8 + pruning + FP16 cache

**Training:** SFT → DPO → Instruction

**Expected performance:** 15-20px error, 2-3% hallucination, 1.3s inference

That's the design.