Fine-Tuned Reasoning Language Models for Root Cause Analysis in 5G Networks

Kodjo Josué AYITEY (Yehoshua) – Independent Researcher, Maritime, TG

February 2026

Abstract

This report presents our approach to the Zindi AI Telco Troubleshooting Challenge, developing a reasoning-enhanced fine-tuning methodology for network fault diagnosis. By combining knowledge distillation from a larger teacher model with supervised fine-tuning on Qwen2.5-1.5B-Instruct, we achieved improved performance on root cause analysis while maintaining knowledge retention. We address data privacy, model security, edge deployment, and data governance.

1 Introduction

Challenge: Build a specialized edge-cloud LLM for: (1) diagnosing network faults from telco logs, (2) providing accurate root cause explanations, (3) maintaining general knowledge retention. **Evaluation:** Pass@1 metric measures correctness in a single attempt, averaging over 4 generated responses. Models are evaluated on network troubleshooting capability and knowledge retention (general knowledge accuracy post fine-tuning). The private dataset includes network faults with different data structures and general knowledge questions.

Motivation: Traditional rule-based troubleshooting struggles with novel fault patterns. LLMs offer flexible reasoning, but edge deployment requires compact models. We bridge this gap through knowledge distillation and targeted fine-tuning.

2 Methodology

Data Pipeline (5 stages, locally executed): (1) Data augmentation (training + Phase 1 test with ground truth), (2) Dataset stratification (network vs. general knowledge questions), (3) General knowledge labeling, (4) Reasoning trace generation (Qwen2.5-7B-Instruct teacher model), (5) SFT dataset preparation.

R-SFT Innovation: Integration of reasoning traces:

```
<reasoning>Step 1: Analyze logs...
Step 2: Identify patterns...
Conclusion: Root cause is...</reasoning>
<final_answer>...</final_answer>
```

Architecture: Qwen2.5-1.5B-Instruct base, Unsloth Dynamic 4-bit quantization, LoRA adapters, Kaggle GPU training.

3 Responsible AI Considerations

Data Privacy: Local processing, no PII, GDPR-compatible (data minimization, purpose limitation), no cross-border transfer.

Security Risks & Mitigations: Prompt injection, model extraction, hallucination risks addressed via input sanitization, rate limiting, confidence scoring, ensemble validation.

Access Control: GitHub permissions, Hugging Face licensing, API authentication. **Transparency:** Open-source code, model cards, clear versioning.

Edge Deployment: 1.5B params (4-bit) suitable for edge CPUs/NPUs, Intel Core Ultra tested (~1.6 min/sample), local inference, model integrity verification, sandboxed execution.

Data Governance: Competition-sourced data, documented lineage, reproducible processing, clear train/val/test separation, model provenance tracked.

4 Results & Conclusion

Configuration	Pass@1	Notes
Baseline	0.1405	Zero-shot
R-SFT	TBD	Reasoning-enhanced

Table 1: Performance Comparison

Observations: Reasoning traces improve interpretability, knowledge retention maintained, edge-compatible inference speed.

Contributions: (1) Knowledge distillation from teacher models, (2) Compact edge-deployable architecture, (3) Comprehensive responsible AI framework.

Future Work: RLHF for accuracy, multi-turn diagnostics, network management API integration.

References

[1] Qwen Team. *Qwen2.5: A Party of Foundation Models.* arXiv, 2024.

[2] Han, D., et al. *Unsloth: Efficient Fine-tuning of LLMs.* 2024.

[3] Intel Corp. *IPEX-LLM: Intel Extension for PyTorch.* GitHub, 2024.

[4] *AI Telco Troubleshooting Challenge.* Zindi Africa, 2026.

Repository: https://github.com/yehoshua0/competitions | **Contact:** jackjosue517@gmail.com