Optimal LLM Size for Medical Document Classification Using Context Engineering

Data Sovereignty Procedures for Doctors (DSP4D)

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Abstract

This paper investigates the minimum viable Large Language Model (LLM) size required for reliable medical document classification and clinical action generation. We evaluate multiple context engineering strategies—including few-shot learning, retrieval-augmented generation (RAG), and long-context approaches—to determine optimal trade-offs between model size, inference cost, and clinical accuracy. Our experiments focus on edge deployment scenarios where data sovereignty requirements mandate local processing.

Keywords: Large Language Models, Few-Shot Learning, Medical Document Classification, Edge Deployment, Data Sovereignty

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1 Introduction

Doctors face an increasing volume of medical documents requiring timely review and action. After office hours, the challenge of efficiently processing X-ray results, lab reports, and specialist referrals becomes critical for patient care.

This research addresses a fundamental question: *What is the smallest LLM that can reliably classify medical documents and generate appropriate clinical actions?*

1.1 Motivation

1.2 Research Questions

1. What is the minimum model size for reliable document classification (>95% accuracy)?
2. How do different context engineering strategies affect the size-accuracy trade-off?
3. Can sub-3B parameter models achieve clinical safety standards with appropriate context?

1.3 Contributions

- A systematic evaluation framework for medical document classification with LLMs
- Comparative analysis of context engineering strategies (few-shot, RAG, long-context)
- Practical deployment recommendations for edge devices

2 Background

2.1 Large Language Models and Scaling Laws

2.2 Context Engineering Strategies

2.2.1 Few-Shot Learning

In-context learning enables models to perform tasks by conditioning on examples provided in the prompt (Brown et al. 2020).

2.2.2 Retrieval-Augmented Generation

2.2.3 Long-Context Approaches

2.3 Medical Document Processing

3 Methodology

3.1 Document Types

We evaluate five medical document categories:

1. **X-Ray Results** — Radiology reports with findings
2. **Lab Reports** — Blood work, urinalysis, cultures
3. **Medical Imaging** — CT, MRI, ultrasound reports
4. **Prescriptions** — Medication orders
5. **Referrals** — Specialist consultation requests

3.2 Experimental Setup

3.2.1 Models Evaluated

Model	Parameters	Deployment
Llama 3.2	1B	Edge/WebLLM
Llama 3.2	3B	Edge
Phi-3 Mini	3.8B	Edge/WebLLM
Llama 3.1	7B	Hosted

3.2.2 Context Strategies

1. **Zero-Shot** — Instructions only (baseline)

2. **One-Shot** — Single example
3. **Few-Shot** — 3-5 curated examples
4. **RAG** — Retrieved guidelines/similar cases

3.3 Evaluation Metrics

- **Classification Accuracy** — Correct document type identification
- **Action Appropriateness** — Clinical validity of suggested actions
- **Latency** — Inference time on target hardware

4 Experiments

4.1 Classification Task

4.2 Action Generation Task

4.3 Breakpoint Analysis

5 Results

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Brown, Tom B., Benjamin Mann, Nick Ryder, et al. 2020. "Language Models Are Few-Shot Learners." *Advances in Neural Information Processing Systems* 33: 1877–901.