

# 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 Data Source: GraSCCo

Instead of generic document types, this research utilizes the **Graz Synthetic Clinical text Corpus (GraSCCo)** (Lohr et al. 2025; Modersohn et al. 2022). GraSCCo is the first publicly shareable, multiply-alienated German clinical text corpus, designed specifically for clinical NLP tasks without compromising patient privacy.

The corpus provides a diverse set of clinical scenarios, which we use to evaluate the models’ ability to classify document intent and generate appropriate clinical actions based on German-language clinical narratives.

### 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

### 5.1 Size vs. Accuracy Trade-offs

### 5.2 Impact of Context Engineering

### 5.3 Deployment Viability

## 6 Discussion

### 6.1 Implications for Clinical Practice

### 6.2 Limitations

### 6.3 Future Work

## 7 Conclusion

## 8 Data Availability

The datasets generated and/or analyzed during the current study are available in the Zenodo repository: **Graz Synthetic Clinical text Corpus (GraSCCo) v2** (Lohr et al. 2025).

## 9 References

- 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.
- Lohr, Christina, Franz Matthies, Jakob Faller, et al. 2025. *GraSCCo\_PII\_V2 - Graz Synthetic Clinical text Corpus with PII Annotations*. Version v2. <https://doi.org/10.5281/zenodo.15747389>.
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