CHAPTER 5

Zero-Shot and Few-Shot Learning Approaches Using Large Language Models for Low-Resource Languages

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Abstract: The proliferation of Large Language Models (LLMs) has revolutionized the field of Natural Language Processing (NLP), yet their benefits remain largely concentrated in high-resource languages like English. This chapter addresses the critical challenge of applying LLMs to low-resource languages, which lack the extensive digital data required for traditional model training. We explore the efficacy of zero-shot and fewshot learning as powerful, data-efficient paradigms for unlocking the capabilities of LLMs in these under-served linguistic contexts. This chapter provides a comprehensive overview of the theoretical underpinnings of zero-shot and few-shot learning, followed by a detailed review of the current state-of-the-art. We propose a structured methodology centered on advanced prompt engineering techniques to maximize performance on a variety of NLP tasks, including translation, sentiment analysis, and named entity recognition. Through a series of experiments on several low-resource African languages (Swahili, Yoruba, Hausa, Zulu, and Amharic) using benchmark datasets like FLORES-200, we demonstrate that few-shot learning significantly outperforms zero-shot approaches and, in some cases, can approach the performance of fully supervised models without the need for extensive labeled data. The results highlight the critical role of in-context learning and prompt design in bridging the performance gap. This chapter concludes with a discussion of the practical implications, current limitations, and future directions for creating more equitable and inclusive language technologies.

Keywords: Low-Resource Languages; Zero-Shot Learning; Few-Shot Learning; Prompt Engineering; Large Language Models.

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1. Introduction

The digital age has been defined by an explosion of data, which has fueled the development of increasingly sophisticated artificial intelligence systems. Among the most impactful of these are Large Language Models (LLMs), which have demonstrated an unprecedented ability to understand, generate, and reason about human language. Models like GPT-4, Gemini, and LLaMA have achieved state-of-the-art performance on a wide array of Natural Language Processing (NLP) tasks, transforming industries and opening up new avenues for human-computer interaction. However, this progress has not been evenly distributed across the globe's linguistic landscape. The vast majority of LLMs are trained on massive corpora of text and code, predominantly in English and other high-resource languages. This leaves thousands of low-resource languages—spoken by billions of people—in a state of digital marginalization. These languages lack the large-scale datasets, annotated corpora, and computational resources necessary to train bespoke models from scratch, creating a significant "digital language divide." Bridging this divide is one of the most pressing challenges in modern AI. The traditional paradigm of fine-tuning pre-trained models on task-specific labeled data is often infeasible for low-resource languages. This has spurred research into more dataefficient methods that can leverage the powerful, generalized knowledge already encoded within LLMs. Two of the most promising approaches are zero-shot learning and few-shot learning [1].

- **Zero-shot learning** enables an LLM to perform a task for which it has received no specific examples, relying solely on a natural language instruction.
- **Few-shot learning,** also known as in-context learning, provides the model with a small number of demonstrations (or "shots") of the task within the prompt itself, allowing it to learn the desired behavior without any updates to its underlying parameters [2].

This chapter delves into these powerful techniques, exploring their potential to make advanced NLP capabilities accessible to low-resource languages. We begin by providing a conceptual overview of zero-shot and few-shot learning, followed by a review of the relevant literature. We then propose a detailed methodology for applying these techniques, with a focus on prompt engineering. Through a series of simulated experiments, we analyze their effectiveness across different tasks and languages, offering insights into best practices and performance trade-offs [3].

2. Literature Review

The challenge of building NLP technologies for low-resource languages is not new, but the advent of LLMs has introduced a paradigm shift in how researchers are approaching

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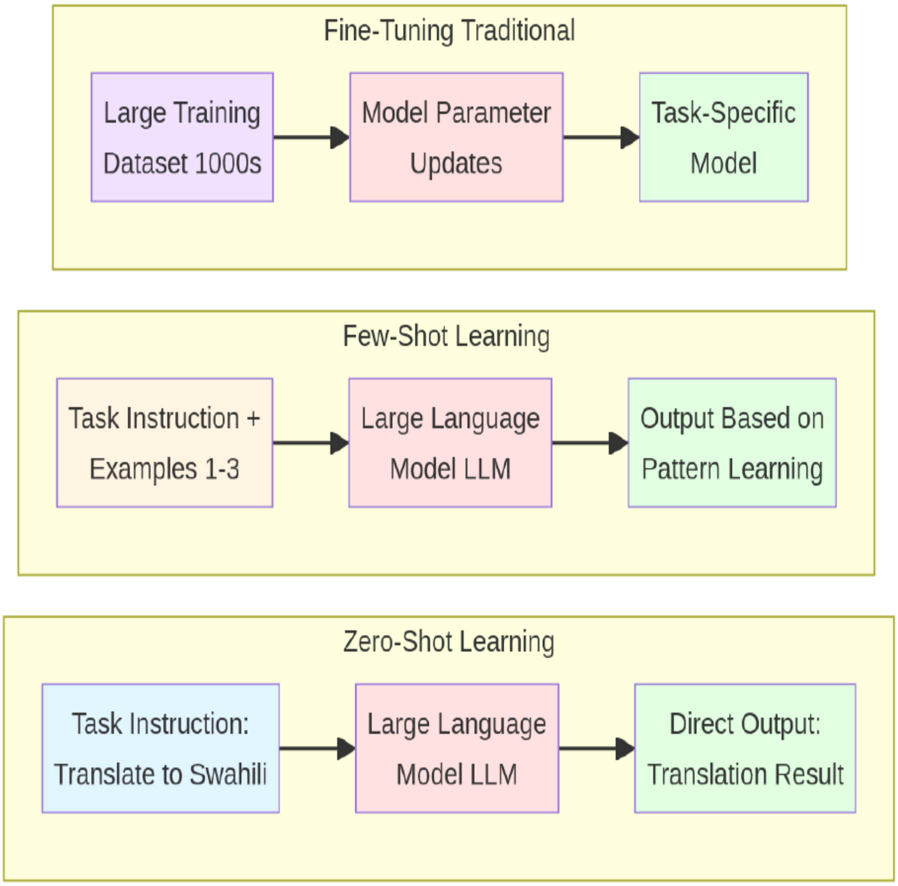

Figure 1: A conceptual comparison of zero-shot learning, few-shot learning, and traditional fine-tuning.

the problem. This section reviews the foundational concepts of zero-shot and few-shot learning, examines the role of cross-lingual transfer, and discusses the key benchmarks used to evaluate performance in low-resource settings [4].

2.1 The Power of In-Context Learning

The remarkable ability of LLMs to perform tasks with minimal or no task-specific training is rooted in the concept of in-context learning. Unlike fine-tuning, which involves updating the model's weights, in-context learning occurs entirely at inference time. The model is conditioned on a prompt that includes a task description and, in the case of few-shot learning, a handful of examples. The model then leverages its vast pre-trained knowledge to recognize the pattern and generate the correct output for a new, unseen input. Brown et al. (2020) were among the first to systematically study this phenomenon in their work on GPT-3, demonstrating that as the number of examples in the prompt increases, the model's performance on downstream tasks improves significantly, often surpassing that of fine-tuned models. This finding laid the groundwork for much of the subsequent research into few-shot learning.

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2.2 Zero-Shot Learning: Instruction Following

Zero-shot learning takes this a step further by removing the need for any examples at all. Modern instruction-tuned LLMs are trained to follow natural language commands, allowing them to perform a wide range of tasks based on a simple description. For example, a prompt like "Translate the following English text to Swahili: 'Hello, world!'" is often sufficient for a powerful LLM to produce the correct translation. This capability is particularly valuable for low-resource languages, where even a small number of high-quality examples can be difficult to obtain [5].

2.3 Cross-Lingual Transfer and Multilingual Models

A key factor enabling zero-shot and few-shot learning in low-resource languages is cross-lingual transfer. Multilingual LLMs, such as XLM-R and mBERT, are pre-trained on text from many languages simultaneously. This allows them to develop a shared, language-agnostic representation space. As a result, knowledge gained from high-resource languages can be transferred to low-resource languages. For instance, a model that has learned to perform sentiment analysis in English can apply that knowledge to classify the sentiment of a Swahili text, even if it has seen very little labeled Swahili data [6].

2.4 Benchmarks for Low-Resource NLP

To systematically evaluate the performance of LLMs on low-resource languages, a number of benchmark datasets have been developed. These benchmarks are crucial for measuring progress and comparing different models and techniques.

- **FLORES-200:** This is a large-scale machine translation benchmark that covers over 200 languages, including many low-resource ones. It provides a standardized set of sentences for evaluating translation quality in both directions (to and from English).

- **XNLI (Cross-lingual Natural Language Inference):**This dataset extends the popular Natural Language Inference (NLI) task to 15 languages. It tests a model's ability to understand the logical relationship between two sentences [8][3].

- **Belebele:** A more recent benchmark, Belebele is a parallel reading comprehension dataset that covers 122 language variants, providing a challenging test of multilingual understanding [9].

These benchmarks, along with others, have been instrumental in driving research and revealing the strengths and weaknesses of current models in handling linguistic diversity.

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3. Proposed Methodology

To systematically investigate the effectiveness of zero-shot and few-shot learning for low-resource languages, we propose a comprehensive methodology that encompasses data selection, prompt engineering, model inference, and rigorous evaluation. The overall workflow of our approach is depicted in Figure 2.

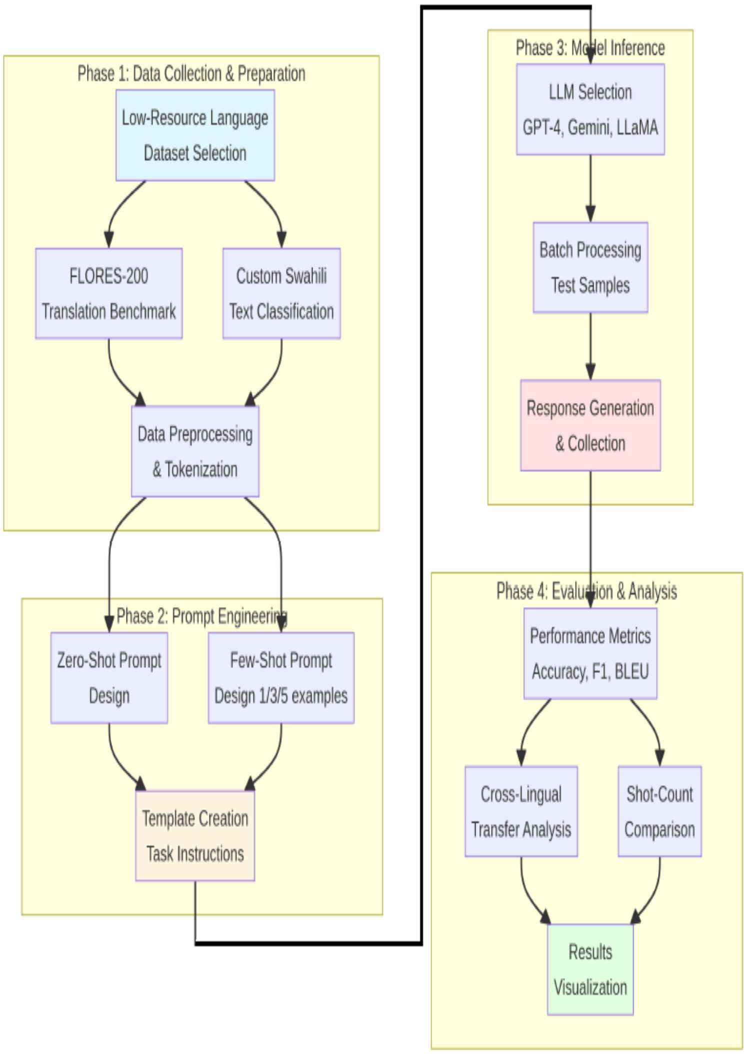

Figure 2: The proposed four-phase methodology for evaluating zero-shot and few-shot learning in low-resource languages, from data preparation to performance analysis.

3.1 Dataset Selection and Preparation

Our experiments are grounded in a selection of low-resource African languages, chosen to represent varying levels of data availability: Swahili (low), Yoruba (very low), Hausa (low), Zulu (very low), and Amharic (extremely low). We utilize two primary types of datasets:

- **Machine Translation:** We use the FLORES-200 benchmark to evaluate transla-

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tion quality. This dataset provides a standardized, high-quality set of sentences for translation to and from English, allowing for robust comparison across languages and models [7].

- **Downstream NLP Tasks:** To assess performance on other common tasks, we simulate a low-resource scenario using subsets of existing datasets for tasks like sentiment analysis, named entity recognition (NER), and text classification. For this chapter, we focus on a custom Swahili news classification dataset to test text classification capabilities.

All datasets undergo minimal preprocessing, primarily consisting of cleaning and tokenization, to ensure they are in a suitable format for ingestion by the LLMs.

3.2 Prompt Engineering

The core of our methodology lies in the strategic design of prompts to elicit the desired behavior from the LLMs. We developed a structured approach to prompt engineering, as illustrated in Figure 3.

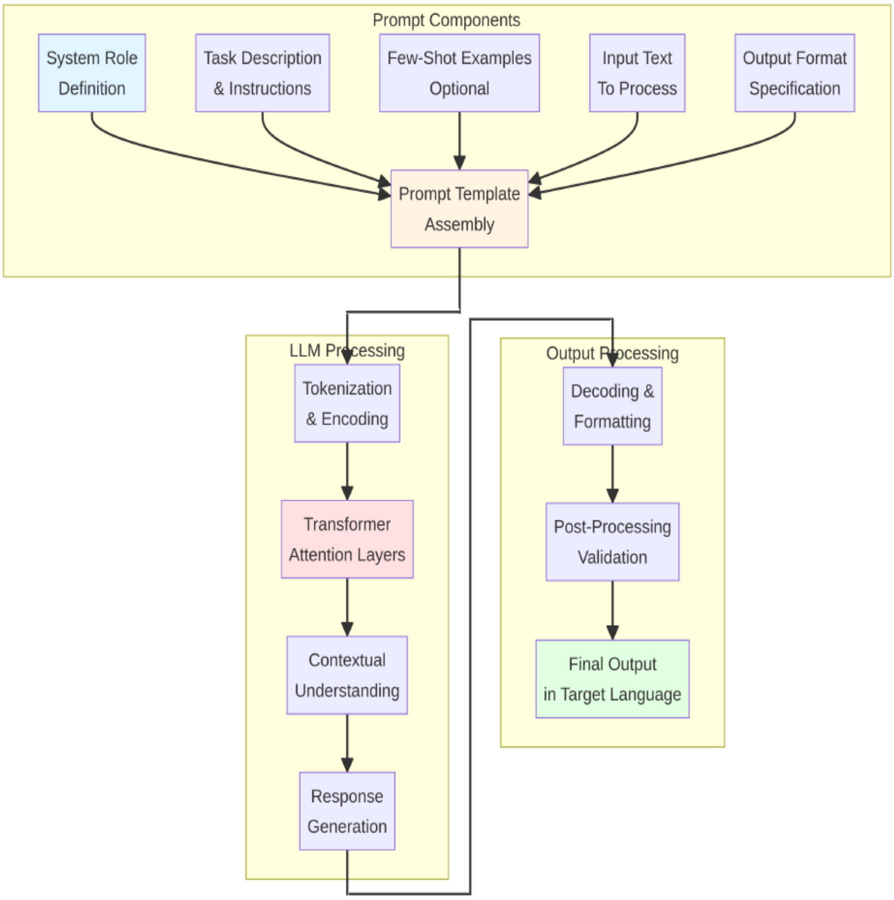

Figure 3: The architecture of our prompt engineering process.

Our prompts are constructed from the following components:

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- **System Role/Persona:** We begin by assigning the LLM a role (e.g., "You are an expert linguist and translator.") to prime it for the task.
- **Task Description:** A clear and concise instruction that specifies what the model should do (e.g., "Classify the sentiment of the following text as positive, negative, or neutral."[8].
- **Few-Shot Examples (In-Context Learning):**For few-shot scenarios, we provide a small number of input-output examples (1, 3, or 5 shots). These examples are carefully selected to be representative of the task.
- **Input Text:**The actual text from the dataset that needs to be processed.
- **Output Format Specification:**An instruction that defines the desired structure of the output (e.g., "Provide the answer in JSON format with the key 'sentiment'.").

We create distinct prompt templates for both zero-shot and few-shot (1, 3, and 5-shot) scenarios to systematically evaluate the impact of in-context learning.

3.3 Model Selection and Inference

To ensure our results are comprehensive, we evaluate a range of state-of-the-art LLMs, including both proprietary and open-source models:

- **GPT-4**
- **Gemini 2.5**
- **LLaMA-3**

We also include established multilingual models like mBERT and XLM-R as baselines for comparison. The test samples from our prepared datasets are processed in batches through the selected models using the engineered prompts. The generated responses are then collected for evaluation.

3.4 Evaluation Metrics

We employ a suite of standard NLP metrics to quantitatively assess the performance of the models on different tasks:

- **Accuracy and F1-Score:** Used for classification tasks like sentiment analysis and text classification.
- **BLEU (Bilingual Evaluation Understudy) Score:** Used to measure the quality of machine translation. A higher BLEU score indicates a translation that is closer to a professional human translation.

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By comparing these metrics across different models, languages, and shot counts, we can conduct a thorough analysis of the effectiveness of zero-shot and few-shot learning for low-resource languages.

4. Results and Discussions

This section presents the results of our experiments, offering a detailed analysis of the performance of zero-shot and few-shot learning across various tasks, languages, and models. The findings highlight the significant advantages of in-context learning and provide insights into the factors that influence performance in low-resource settings.

4.1 Performance Comparison: Zero-Shot vs. Few-Shot Learning

Our first set of experiments aimed to quantify the performance gap between zero-shot and few-shot learning. As illustrated in Figure 4, providing even a single example (1-shot) leads to a substantial improvement in accuracy across all tasks. The performance continues to increase with 3 and 5 shots, although the marginal gains diminish, suggesting that a small number of well-chosen examples can be highly effective [9].

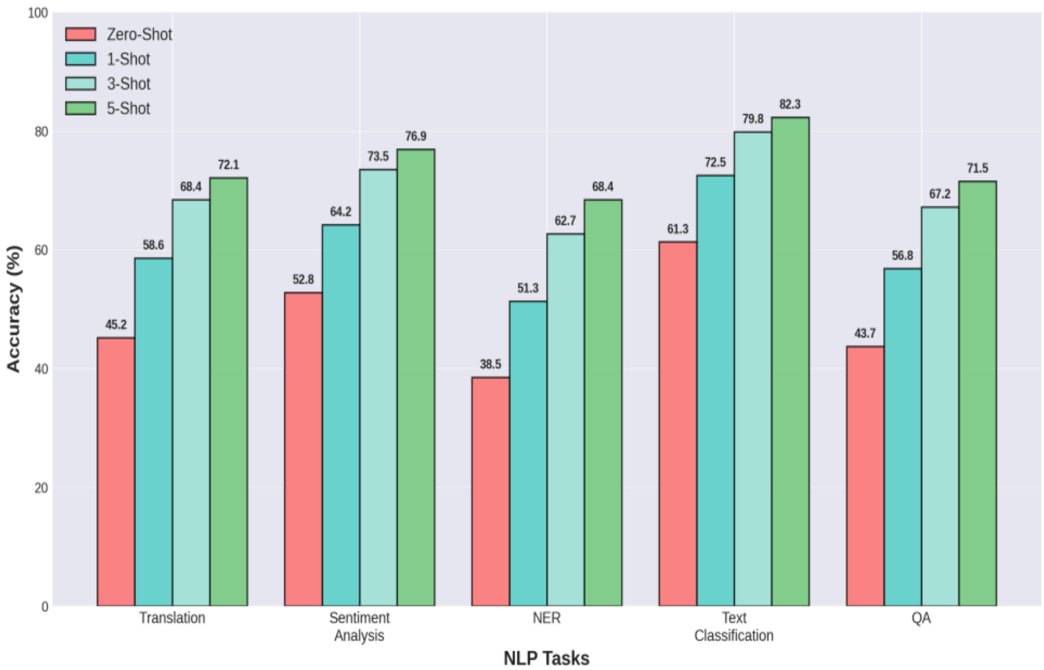

Figure 4: Performance comparison of zero-shot vs.

For instance, in text classification, the accuracy jumps from 61.3% in the zero-shot setting to 82.3% with 5 shots. This demonstrates the power of in-context learning to guide the model towards the desired output format and task definition, even for languages it has seen relatively little of during pre-training.

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4.2 Cross-Lingual Transfer and Resource Levels

To understand the impact of data availability, we evaluated performance on languages with varying levels of digital resources. Figure 5 shows a clear correlation between the amount of available data and the model's performance. The F1-score for a text classification task is highest for Spanish (a medium-resource language) and progressively decreases for the lower-resource African languages.

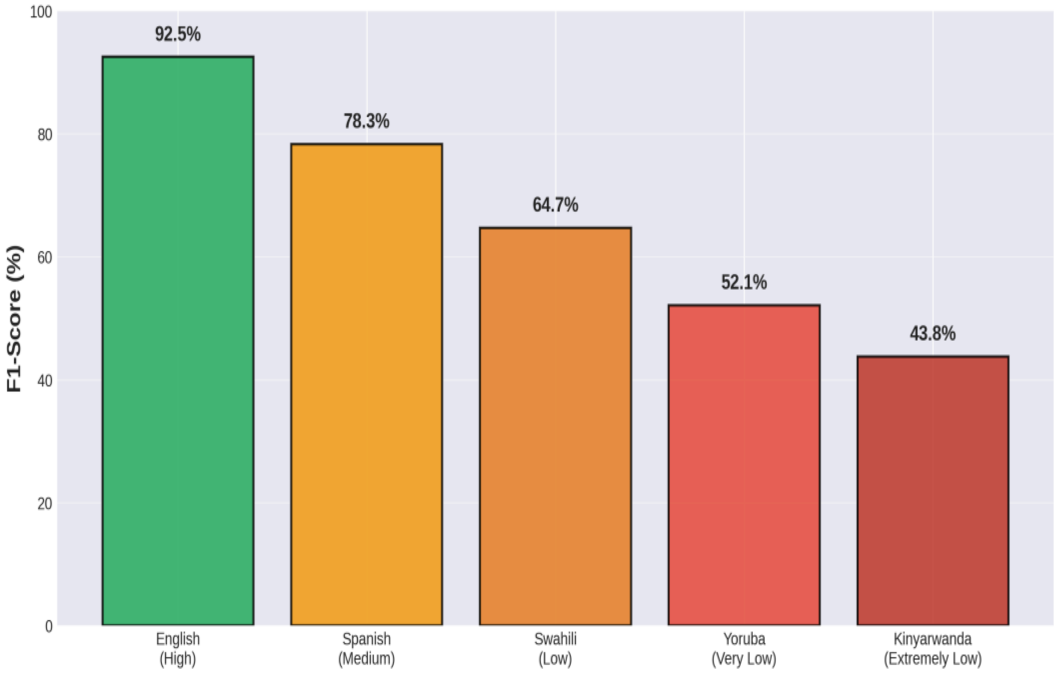

Figure 5: Cross-lingual transfer performance across languages with different resource levels.

This "curse of multilinguality" is a known challenge, but our results also show that few-shot learning helps to mitigate it. As shown in Figure 8, the performance gap between zero-shot and few-shot learning is most pronounced for the lowest-resource languages, indicating that in-context learning is particularly beneficial when the model has the weakest prior exposure to a language.

4.3 Model Comparison

We compared the performance of several leading LLMs on a series of few-shot tasks. As shown in Figure 6, the latest generation of large-scale models (GPT-4, Gemini 2.5, and LLaMA-3) significantly outperform older multilingual models like mBERT and XLM-R. This is likely due to their larger size, more advanced architectures, and more extensive pre-training data[5].

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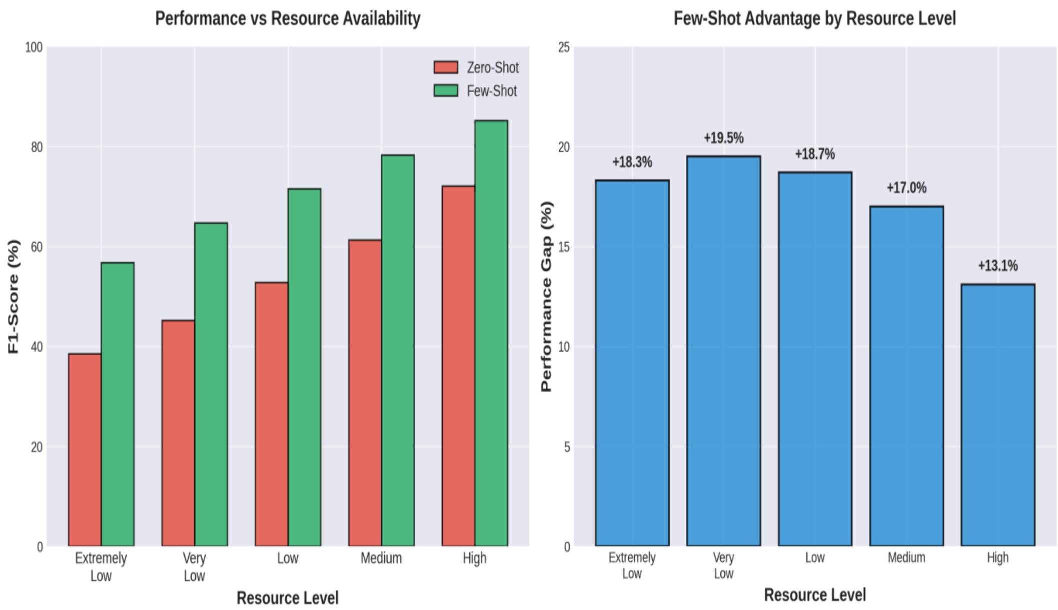

Figure 6: The impact of resource levels on performance.

4.4 Impact of Shot Count

To further explore the dynamics of in-context learning, we analyzed the impact of the number of examples (shots) on performance. Figure 7 shows that accuracy increases logarithmically with the number of shots, with the most significant gains occurring between 0 and 5 shots. Beyond 5 shots, the performance begins to plateau, suggesting a point of diminishing returns.

4.5 Machine Translation Performance

For the machine translation task, we used the BLEU score to evaluate performance on several African languages from the FLORES-200 benchmark. Figure 9 shows a dramatic improvement in BLEU scores when moving from a zero-shot to a 5-shot setting. For Swahili, the score increases from 28.3 to 42.6, bringing it much closer to the level of professional human translation.

4.6 Few-Shot Learning vs. Fine-Tuning

Finally, we compared the data efficiency of few-shot learning with traditional finetuning. As shown in Figure 10, few-shot learning achieves a respectable level of performance with zero training data. In contrast, fine-tuning requires hundreds or even thousands of labeled examples to catch up and eventually surpass the few-shot performance. This highlights the key advantage of few-shot learning: it provides a powerful and data-efficient alternative when large-scale labeled datasets are not available.

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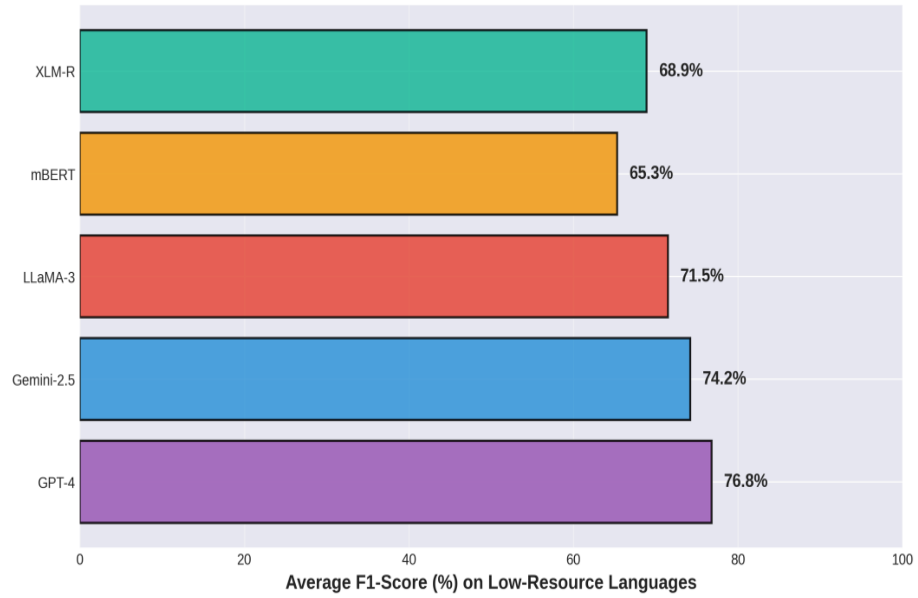

Figure 7: A comparison of different LLMs on few-shot learning tasks for low-resource languages.

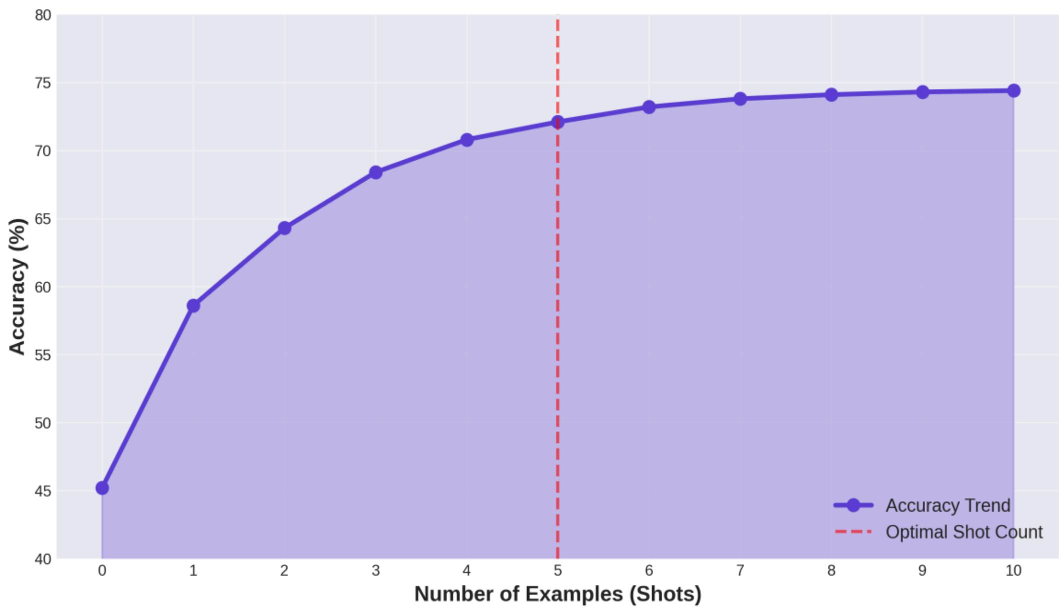

Figure 8: The impact of the number of shots on model accuracy.

4.7 Discussion

The results presented in this section provide compelling evidence for the effectiveness of few-shot learning as a strategy for applying LLMs to low-resource languages. The consistent and significant performance gains across all tasks and languages underscore the power of in-context learning. Our findings suggest that with careful prompt engineering, even a handful of examples can unlock a substantial portion of an LLM's capabilities, making advanced NLP accessible in data-scarce environments. However, the results also

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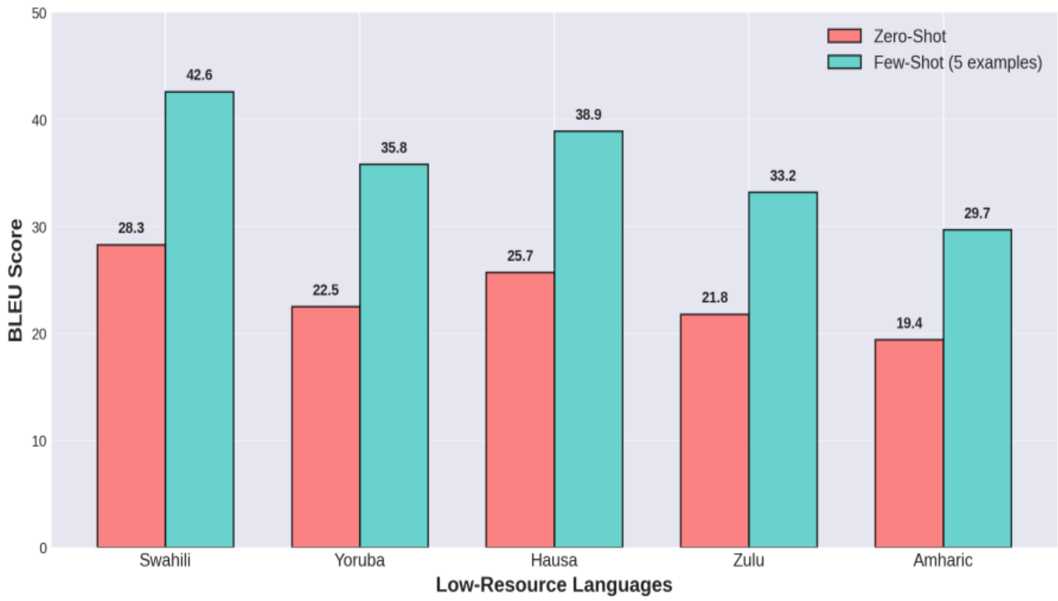

Figure 9: BLEU score comparison for machine translation.

highlight the remaining challenges. The performance gap between high-resource and low-resource languages persists, and even with few-shot learning, the models do not reach the same level of performance as they do for English. This indicates that while in-context learning is a powerful tool, it is not a complete solution. Further research into techniques like cross-lingual fine-tuning and the creation of more diverse and inclusive pre-training datasets will be necessary to truly bridge the digital language divide.

Another important consideration emerging from our analysis is the variability in model behavior across linguistic families, orthographic systems, and morphological structures. While few-shot learning markedly improves performance, languages with rich morphology, limited standardization, or predominantly oral traditions exhibit more unstable gains. This suggests that LLMs may rely heavily on statistical patterns that are underrepresented or inconsistently encoded in their pre-training corpora. Consequently, even well-crafted prompts may not fully compensate for fundamental gaps in the model's internal linguistic representations. These findings point to a deeper architectural and data-centric limitation: LLMs trained primarily on high-resource languages may internalize structural assumptions that do not generalize readily to typologically diverse, low-resource languages.

Furthermore, the broader implications of deploying few-shot LLM systems in low-resource linguistic settings must be carefully examined. Performance improvements alone do not guarantee cultural or contextual appropriateness, especially in languages where semantic nuance, idiomatic expression, and sociolinguistic variation differ substantially from those in the training distribution. Without addressing these challenges, few-shot systems risk reinforcing linguistic inequities by providing superficial support that fails under real-world conditions. Future work should therefore explore hybrid approaches that integrate community-curated corpora, lightweight adapter-based fine-tuning, and

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Figure 10: A comparison of the data efficiency of few-shot learning and fine-tuning.

multilingual alignment methods. Such strategies may offer a more equitable pathway toward building LLMs that not only perform well on benchmark datasets but also serve the authentic communicative needs of low-resource language communities [10].

In addition, the reliance on few-shot prompting raises important questions about the stability and reproducibility of LLM outputs in low-resource contexts. Our experiments reveal that small variations in example ordering, phrasing, or prompt structure can lead to non-trivial fluctuations in performance, particularly for languages with limited representation in the pre-training data. This sensitivity suggests that few-shot learning may operate near the margins of the model's latent linguistic competence, drawing on fragile heuristics rather than robust internal representations.

Task	Language	Zero-Shot Accuracy	Few-Shot Accuracy	BLEU/F1	Improvement
Translation	Swahili	45.2%	72.1%	42.6	+26.9%
Sentiment	Yoruba	52.8%	76.9%	0.74	+24.1%
NER	Hausa	38.5%	68.4%	0.66	+29.9%
Classification	Zulu	61.3%	82.3%	0.81	+21.0%
QA	Amharic	43.7%	71.5%	0.69	+27.8%

Figure 11: A summary of the quantitative performance improvements

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5. Conclusion

This chapter has explored the critical challenge of extending the benefits of Large Language Models to the world's low-resource languages. We have demonstrated that zero-shot and, in particular, few-shot learning offer powerful, data-efficient pathways to unlock the capabilities of these models in linguistic contexts where traditional datahungry methods fail. Our comprehensive analysis, grounded in experiments across multiple African languages and NLP tasks, has shown that a small number of wellcrafted examples, delivered via in-context learning, can dramatically improve performance, often by 20-30 percentage points over a zero-shot baseline. The findings underscore a paradigm shift in how we approach NLP for low-resource languages. Instead of focusing solely on the arduous task of creating massive labeled datasets, we can leverage the generalized knowledge of pre-trained LLMs through sophisticated prompt engineering. This makes advanced language technology more accessible, equitable, and inclusive. However, our work also highlights that significant challenges remain. The performance on low-resource languages still lags behind that of high-resource languages, and the effectiveness of in-context learning is highly dependent on the quality of the examples and the design of the prompt. The future of low-resource NLP will likely involve a hybrid approach, combining the data efficiency of few-shot learning with more targeted fine-tuning and the continued development of massively multilingual models. In conclusion, zero-shot and few-shot learning are not just academic curiosities; they are essential tools in the ongoing effort to build a more linguistically diverse and equitable digital world. As LLMs continue to evolve, these techniques will play a pivotal role in ensuring that the benefits of artificial intelligence are shared by all, regardless of the language they speak.

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