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Mitigating Hallucinations in Large Language Models for Burmese Domain-Specific Question Answering

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Abstract

Large Language Models (LLMs) have achieved remarkable success in multilingual commonsense reasoning. However, their reliability drastically degrades when deployed in low-resource, domain-specific settings, often resulting in factual fabrications known as hallucinations. This vulnerability is especially acute for the Burmese language, due to its structural complexities, tokenization artifacts, and the dearth of high-quality localized datasets.

In this paper, we present a systematic framework to quantify and mitigate hallucinations in Burmese domain-specific question answering. We introduce MM-AgriQA, a novel, manually annotated gold-standard dataset specifically curated for agricultural query answering under strict context boundaries. We evaluate multiple alignment and mitigation strategies, comparing fine-tuned low-resource models against vanilla commercial systems. Our empirical results demonstrate that incorporating advanced Retrieval-Augmented Generation (RAG) combined with strict syntactic prompt constraints reduces hallucination rates by up to 42.5% while preserving semantic alignment.

1 Introduction

The democratization of generative Artificial Intelligence (AI) has shifted the paradigm of information retrieval toward natural language question-answering systems. Despite these milestones, commercial and open-source Large Language Models (LLMs) continue to suffer from objective infidelities—commonly conceptualized as hallucinations—where the generated text is syntactically coherent but factually ungrounded. For high-stakes domains such as medicine, law, or agriculture in developing countries, these fabrications present significant real-world risks.

This task is very challenging especially in the case of low resource languages such as Burmese. Burmese features complex morphological boundaries, non-standardized orthography,

and historical font-encoding disparities. Furthermore, pre-training corpora for state-of-the-art LLMs contain less than 0.01% of Burmese text, forcing models to rely heavily on cross-lingual transfer learning. Consequently, when prompted with specialized localized queries, the model often experiences conceptual blending, mapping non-existent semantic relations to Burmese syntax and generating convincing hallucinations.

Prior attempts to suppress hallucinations have predominantly focused on high-resource languages through reinforcement learning from human feedback (RLHF) or external knowledge graphs. However, these approaches are limited by computational costs and the lack of scalable local data infrastructure in Myanmar.

To bridge this gap, we propose a tailored high-fidelity pipeline for domain-specific question answering in Burmese. Our primary contributions are threefold:

1. We construct and release MM-AgriQA, the first human-annotated, domain-specific evaluation dataset in Burmese designed to benchmark factual veracity and model resilience against unanswerable questions.

2. We introduce a tailored Retrieval-Augmented Generation (RAG) framework for the Burmese language utilizing character-level chunking and cross-lingual dense retrievers for optimal contextual alignment.

3. We conduct an extensive empirical evaluation of open-source models (e.g., Llama-3, SeaLLaMA) and commercial baselines, analyzing their structural failure modes when dealing with low-resource domain queries.

2 Related Work

2.1 Hallucination Detection and Mitigation

Hallucination in autoregressive language models is generally attributed to distorted parametric memory, flawed decoding strategies, or exposure to low-quality pre-training corpora. Mitigations broadly fall into two categories: parametric updates (such as supervised fine-tuning and direct preference optimization) and non-parametric context injection (Retrieval-Augmented Generation). While RAG has emerged as an industry standard for expanding external memory boundaries, its effectiveness depends heavily on the accuracy of the underlying embedding spaces and retrieval mechanics.

2.2 Low-Resource Burmese NLP

Natural Language Processing for the Burmese language has long faced structural constraints. The early research focused mainly on basic tasks like syllable segmentation, word boundary detection, optical character recognition.

The emergence of multilingual pre-trained representations such as mBERT and XLM-R has enabled successful cross-lingual transfer but they still lag behind in downstream generative tasks due to the vocabulary bottleneck. Recent initiatives, such as the introduction of the myMNIST benchmark and regional LLM adaptations like SeaLLaMA, have catalyzed generative capabilities in Southeast Asian scripts. Despite these developments, domain-specific evaluation frameworks and systematic investigations into generative errors remain virtually non-existent for Burmese.

3 The MM-AgriQA Dataset

To establish a rigorous foundation for evaluating factual adherence, we curated MM-AgriQA, an agricultural knowledge base and QA benchmark. Agriculture was selected as it is so integral to Myanmar's socio-economic landscape that misinformation can cause crop failure and financial hardship.

3.1 Data collection and text processing

Authoritative textual data were collected from official agriculture handbooks, academic extensions and validated regional crop management guidelines in Myanmar. The raw corpus was consolidated and processed to eliminate legacy font encoding artifacts (converting Zawgyi variants into standard Unicode). The cleaned text was then partitioned into discrete semantic chunks based on syntactic paragraph boundaries, resulting in a core reference corpus comprising 2,500 highly specific text passages.

3.2 Annotation Protocols

We designed a rigorous annotation framework involving three native Burmese annotators with computational linguistics expertise. Annotators were asked to generate text pairs in the following three categories for each text passage:

1. True QA: a direct question whose exact answer is explicitly present in the corresponding text passage.

2. Unanswerable QA: A question that shares the same semantic keywords as the passage but cannot be answered using only the passage. This is meant to check that the model does not guess.

3. Contradictory QA: Queries containing false premises or flipped polarities relative to the reference text.

3.3 Quality Assurance

To guarantee benchmark objectivity, we evaluated the consistency of annotations using Cohen's Kappa (κ) coefficient between independent reviewers. The inter-annotator agreement yielded an average score of $\kappa = 0.82$, reflecting high reliability and alignment across the evaluation pairs. The final dataset consists of 1,200 curated evaluation triplets.

4 Methodology

We evaluate three distinct architectural approaches to quantify and mitigate hallucinations within our low-resource setting.

4.1 Baseline Parametric Evaluation

The baseline configuration presents queries directly to the target LLM without supplementary context, relying entirely on the model's internal parametric memory acquired during its pre-training phase:

$$P(A \mid Q) = \prod_{i=1}^{n} P(a_i \mid a_{<i}, Q) \tag{1}$$

where Q represents the Burmese query and A is the generated response.

4.2 Advanced Burmese RAG Pipeline

To anchor model responses to verified facts, we implement a specialized Retrieval-Augmented Generation (RAG) pipeline. Given that standard sub-word tokenizers often fragment Burmese script into incoherent byte sequences, we deploy a character-aware dense retriever.

The reference corpus documents D are mapped into a dense vector space using a fine-tuned cross-lingual encoder (E). At inference time, the user query Q is embedded using the identical encoder, and top-k relevant passages are fetched via cosine similarity optimization:

$$\text{Score}(Q, D_j) = \frac{E(Q) \cdot E(D_j)}{\|E(Q)\| \|E(D_j)\|} \tag{2}$$

The selected passages are then appended to the contextual window alongside a strict structural prompt constraint: "If the provided context does not contain the answer, you must state '' (I do not know). Do not extrapolate."

4.3 Supervised Fine-Tuning (SFT)

As an alternative approach, we apply Parameter-Efficient Fine-Tuning (PEFT) using LoRA (Low-Rank Adaptation) on open-source multilingual base models. The optimization objective

focuses on minimizing negative log-likelihood on our specific Burmese instruction-tuning pairs, penalizing open-ended speculative generation.

5 Experimental Setup

5.1 Evaluated Models

Our experiments benchmark a spectrum of LLM configurations:

- Commercial Baselines: GPT-4o and Claude 3.5 Sonnet.
- Open-Source Multilingual Models: Llama-3-8B-Instruct and Mistral-7B-Instruct-v0.3.
- Regional Adapted LLMs: SeaLLaMA-7B-v2.

Model / Framework	**Faithful.**	**Rel.**	**Abstain %**
GPT-4o (Zero-Shot)	0.48	0.72	12.4%
SeaLLaMA-7B (Zero-Shot)	0.39	0.55	8.1%
Llama-3-8B (Zero-Shot)	0.31	0.49	4.3%
Llama-3-8B + SFT	0.62	0.68	39.5%
SeaLLaMA-7B + RAG	0.79	0.74	68.2%
GPT-4o + Advanced RAG	0.89	0.84	84.7%

Table 1: Hallucination mitigation performance across evaluated configurations on the MM-AgriQA benchmark.

5.2 Evaluation Metrics

We utilize the Ragas framework adapted for low-resource linguistics, alongside an LLM-as-a-judge paradigm validated by human cross-checks. Three core dimensions are measured:

- Faithfulness: The proportion of statements in the generated answer that can be directly inferred from the reference context (inversely proportional to hallucination).
- Answer Relevance: The semantic overlap and structural appropriateness of the answer relative to the initial prompt.
- Abstention Accuracy: The model's success rate in correctly outputting the refusal token (’’) when presented with unanswerable queries.

6 Results and Analysis

As illustrated in Table 1, standard zero-shot models display an acute susceptibility to hallucination when queried in Burmese. Llama-3-8B performs poorly on Faithfulness (0.31) often substituting missing localized facts with incorrect transliterations or off-topic ideas from its English-centric training data.

In all configurations, our RAG pipeline achieves substantial gains. GPT-4o achieves a Faithfulness score of 0.89 with external knowledge grounding. Notably, its Abstention Accuracy on unanswerable queries jumps from 12.4% to 84.7%. This highlights that explicit context injection is still a potent method for constraining model outputs, assuming the retriever can navigate the linguistic boundaries of Burmese text.

Our results also emphasize the importance of targeted fine-tuning: localizing smaller open-source architectures with SFT improves their baseline reliability to be competitive or even better than much larger generic models.

7 Conclusion and Future Work

In this work, we propose a systematic method to detect and reduce factual hallucinations in Burmese domain-specific question answering. By introducing the human-curated MM-AgriQA benchmark, we provide a structured framework to evaluate low-resource linguistic fidelity. Our empirical results show that although parametric gaps prone to hallucinations still exist in stand-alone models, combining character-aware dense retrieval mechanisms with strict prompt constraints significantly improves response veracity.

Future work will involve extending the retrieval space with hybrid lexical-dense architectures and evaluating tokenization-free language models to completely eliminate script segmentation bottlenecks.

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