

# Evaluating LLMs’ Multilingual Capabilities for Bengali: Benchmark Creation and Performance Analysis

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## Abstract

Bengali is an underrepresented language in NLP research. However, it remains a challenge due to its unique linguistic structure and computational constraints. In this work, we systematically investigate the challenges that hinder Bengali NLP performance by focusing on the absence of standardized evaluation benchmarks. We then evaluated 10 recent open source Large Language Models (LLMs) in 8 of the translated datasets and performed a comprehensive error analysis to pinpoint their primary failure modes. Our findings reveal consistent performance gaps for Bengali compared to English, particularly for smaller models and specific model families like Mistral. We also identified promising robustness in certain architectures, such as DeepSeek, that maintain more stable performance across languages. Our analysis reveals an inverse relationship between tokenization efficiency and LLM accuracy where models tend to perform worse when inputs are excessively tokenized, whereas more efficient & concise tokenization results in improved performance. These findings highlight critical areas where current models fall short and underscore the need for improved dataset quality and evaluation methodologies tailored to multilingual contexts. This work will catalyze further research on NLP for underrepresented languages, helping to democratize access to advanced language technologies worldwide. The code used in this research is publicly available at [GitHub](#). The translated Bengali datasets can be accessed on [Hugging Face](#).

of data and deep neural architectures to generate human-like text with fluency (Witteveen and Andrews, 2019). Controlled text generation approaches have also been explored to refine outputs and guide language models toward desirable properties (Yu et al., 2021). Although these research developments have been substantial, text generation in under-resourced languages like Bengali remains a challenge.

Recent efforts have sought to extend LLM capabilities to Bengali, a language spoken by over 230 million people. While general-purpose LLMs perform well in high-resource languages like English and Chinese, Bengali NLP faces limitations due to its linguistic complexity and scarcity of large-scale datasets (Kabir et al., 2023). To address this, dedicated Bengali LLMs such as BanglaBERT (Bhattacharjee et al., 2021), BanglaGPT (Salim et al., 2023) have been developed. More recent Bengali-focused models like TituLLM (Nahin et al., 2025) and TigerLLM (Raihan and Zampieri, 2025) have also emerged, demonstrating promising results in various Bengali NLP tasks. These models aim to enhance performance in Bengali NLP tasks such as text classification, sentiment analysis and machine translation.

However, the development of robust Bengali LLMs is still faced by different challenges. First, the lack of large-scale, high-quality Bengali text corpora limits pre-training and fine-tuning efforts (Shahriar and Barbosa, 2024). While resources like the Sangraha corpus (Khan et al., 2024) developed by AI4Bharat offer numerous data across 22 Indian languages including Bengali, the quality and quantity of Bengali tokens remain limited compared to high-resource languages like English. The Sangraha corpus consists of about 251 billion tokens across all languages, but Bengali’s allocation is significantly smaller at about 30 billion tokens. In contrast, English has access to around 2 trillion tokens in large-scale multilingual corpora such as the Common Corpus (Langlais et al., 2025). This huge difference in token availability poses a major challenge in achieving comparable model performance in Bengali NLP. Second, the Bengali language’s rich morphology and complex writing system introduce significant tokenization chal-

## 1 Introduction

Large Language Models (LLMs) have transformed text generation enabling applications in machine translation, text summarization and conversational agents. These models such as GPT-2 and GPT-3 leverage vast amounts

allenges. Unlike English, which uses the Latin script with largely independent characters, Bengali employs an alphasyllabary script where base characters are frequently modified by diacritics and conjunct forms that alter pronunciation and meaning (Alam et al., 2021). These modifications can occur on either side of a base character, forming intricate multi-character grapheme clusters that do not align well with standard tokenization schemes used in LLMs. As a result, traditional sub-word tokenization methods such as Byte Pair Encoding (BPE) or WordPiece struggle to segment Bengali text effectively, leading to highly fragmented or inconsistent tokens (Shahriar and Barbosa, 2024). This increased token complexity means that models require more training data to learn meaningful inter-token relationships in Bengali than in English. Failure to capture these linguistic nuances not only increases computational overhead but also degrades model performance on downstream tasks. Third, Bengali NLP research suffers from the absence of standardized evaluation datasets, making it difficult to benchmark model performance effectively (Kabir et al., 2023).

This lack of evaluation datasets motivates the need for well-defined benchmark datasets for Bengali LLMs. Without standardized datasets, it is hard to compare models or track improvements in NLP research. While some efforts have been made to curate evaluation datasets (Shafayat et al., 2024) progress is still slow due to the extensive annotation and validation required.

Efforts to develop LLMs for underrepresented languages have explored various methodologies. The Khayyam Challenge (Ghahroodi et al., 2024) curated a large-scale Persian dataset using original non-translated content ensuring language-specific nuances are preserved. Similarly, Cohere’s Aya model (Üstün et al., 2024) employed instruction tuning across multiple low-resource languages to enhance linguistic adaptability. AI4Bharat’s Sangraha dataset tackled data scarcity by aggregating and refining multilingual corpora. In contrast, Turkish LLM research (Acikgoz et al., 2024) experimented with two approaches: adapting English-trained models via transfer learning and pretraining from scratch. While these efforts have proven effective their applicability to Bengali remains uncertain due to unique linguistic characteristics and uniqueness in Bengali.

Although substantial progress has been made in developing NLP resources for Bengali, there remain opportunities to accelerate advancement further. Typically, when creating initial benchmarks for lower-resourced languages, researchers bootstrap by translating existing English datasets into the target language, as demonstrated in prior works for Persian and Turkish. However, this initial step has not yet been widely adopted for Bengali, largely due to practical constraints, including the substantial manual validation effort required to correct machine translation errors, associated time investments, and overall costs. Because current machine translation systems often introduce inaccuracies and lose linguistic nuance, manual intervention becomes necessary to

refine and validate the translated data. In this study, we directly address these challenges by systematically translating major English benchmark datasets into Bengali and did a performance analysis on them.

Motivated by these challenges, this research aims to bridge the existing gaps in Bengali NLP by constructing high-quality evaluation datasets. To address these limitations, this work contributes in a few key areas.

- We publicly release a comprehensive suite of high-quality Bengali benchmark datasets, along with the accompanying translation pipeline and codebase to facilitate reproducible research and future advancements in Bengali NLP evaluation.
- We describe the methodology used to translate and curate high-quality datasets.
- We conduct inference experiments and analyze results to assess model effectiveness of open source multilingual models.
- We analyze tokenization behavior across Bengali and English benchmarks, revealing that Bengali inputs produce significantly larger token counts per instance and per word with dataset remaining consistent across both languages.
- We identify the impact of tokenization granularity on performance, showing that higher tokens per row often correlate with lower model scores (due to noise) while more compact per-word tokenization tends to improve accuracy.
- We examine language-specific encoding efficiencies, demonstrating that English tokens carry higher average bytes per token compared to Bengali with implications for model resource requirements.

In Section 2, we describe the datasets that were translated, outline the translation methodologies, and explain the rationale behind the choice of translation models. In Section 3, we detail the experimental procedures, including the datasets selected for inference, the evaluation metrics used, and the results obtained. Section 4 presents an analysis of the results, summarizes key findings, and outlines directions for future work. Finally, in Section 5, we discuss the challenges encountered during translation and highlight the limitations of our approach.

## 2 Methodology

The translation pipeline for converting English NLP benchmarks begins with dataset selection and blind review using multiple models. GPT-4o-mini was chosen for translation, supported by prompt engineering. The post-processing steps addressed translation errors and formatting issues. The final output includes 8 cleaned Bengali datasets completed at a cost of approximately \$200.

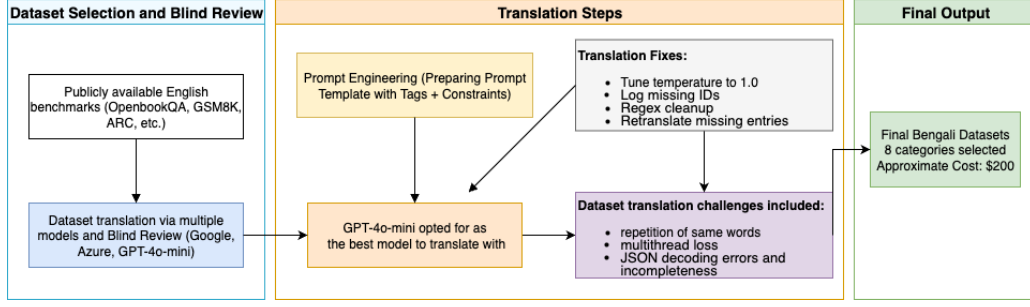


Figure 1: Methodology Overview

## 2.1 Dataset Selection

To select appropriate datasets, we refer to the methodology used in the white paper by LLaMA, identifying commonly used datasets that align with our research objectives. This approach allowed us to ensure the inclusion of high-quality, diverse and representative text corpora for Bengali language modeling. A summary of the dataset statistics is attached.

## 2.2 Translation

For the translation process, we utilized OpenAI’s gpt-4o-mini-2024-07-18 model to translate the selected datasets from English to Bengali while preserving linguistic accuracy and contextual integrity.

The model was instructed through comprehensive prompting to properly translate the dataset and not change the underlying meaning of the original text. Special attention was given to preserving the integrity of ground truth values to prevent any corruption. Temperature values ranging from 0.0 to 1.0 were used to control the translation quality and creativity. As the model sometimes responds with elaborate and redundant answers, special care for that was taken during the prompting process. An example of the prompting template is shown in Table 2.

## 2.3 Translation Decisions

In our study, we performed a blind review of translations generated by three different services: Google Translate, Azure’s Translation Endpoint and OpenAI’s gpt-4o-mini-2024-07-18. Each translation was assessed by human reviewers without revealing its source. Based on the reviewers’ feedback, we determined that gpt-4o-mini-2024-07-18 produced the most accurate and coherent translations among the three.

## 2.4 Translation Challenges

During the translation process, we encountered several issues:

- **Repetitive Translations:** Some words were being repeated excessively, leading to unnatural sentence structures. To mitigate this, we increased the temperature parameter to 1 while keeping other parameters constant, which helped introduce variability and improve translation quality.

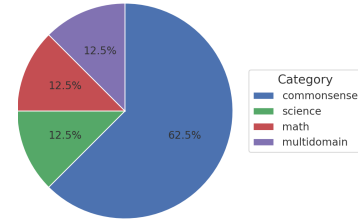


Figure 2: Dataset Distribution

- **Missing Entries Due to Multithreading:** Some dataset entries were skipped due to parallel processing errors. We resolved this issue by analyzing logs and re-processing the missing translations to ensure dataset completeness.
- **Decoding Errors:** Some dataset entries had decoding errors due to the JSON not being parsed properly. These errors include missing comma(,)delimiters, unclosed quotation marks(“”), mismatched key-value pairs, missing “bangla translation” tags, unescaped json quotes etc. This was resolved by updating the corresponding regex and escaping response strings as necessary.
- **Incomplete Translations:** Some translated dataset entries contained incomplete sentences, missing answer-key values and missing options. Such sentences had to be retranslated to fix the issue.

## 2.5 Translation Results

Twenty major LLM benchmark datasets were translated into Bengali. From these, eight datasets were selected, spanning the Commonsense, Science, Math, and Multidomain categories. The total cost of translation amounted to approximately \$200.

## 3 Experimental Details

We selected eight benchmark datasets spanning four high-level categories for our evaluations. In the **Commonsense** category, we included HELLASWAG, WINOGRANDE, COMMONSENSEQA, BOOLQ and OPENBOOKQA. For **Science**, we used ARC. In the **Math** category, we chose GSM8K-MAIN and for **Multidomain**, we selected MMLU. Each dataset was translated into

| Dataset Name  | Train | Dev.  | Test  | Task Type   | Dataset Type                      |
|---------------|-------|-------|-------|-------------|-----------------------------------|
| OpenbookQA    | 4957  | 500   | 500   | MCQ         | Multi-step reasoning, commonsense |
| ARC           | 3370  | 869   | 3548  | MCQ         | Grade-school science              |
| BigBenchHard  | -     | -     | Var.  | MCQ         | Logical reasoning                 |
| Alpaca Eval   | -     | -     | 10465 | Instruction | Benchmark                         |
| Anthropic     | 86372 | -     | 35006 | -           | Safety, helpfulness               |
| Apps          | 5000  | -     | 5000  | -           | Coding                            |
| BFCL          | -     | -     | 250   | -           | Function calling                  |
| BoolQ         | 9427  | 3270  | -     | -           | Reading comprehension             |
| CommonSenseQA | 9741  | 1221  | 1140  | MCQ         | Commonsense reasoning             |
| Dolly         | -     | -     | 7295  | Instruction | Varied NLP tasks                  |
| GSM8k         | 7473  | -     | 1319  | Numbers     | Grade-school math                 |
| Hellaswag     | 39905 | 10042 | 10003 | -           | Commonsense reasoning             |
| HumanEval     | -     | -     | 164   | -           | Code generation                   |
| MATH          | 8599  | -     | 4999  | Exact Match | Math reasoning                    |
| MMLU          | 98487 | 1528  | 13869 | MCQ         | College-level reasoning           |
| MMLU-Pro      | -     | 70    | 12032 | -           | College-level reasoning           |
| MR-GSM8k      | -     | -     | 12024 | Exact Match | Math reasoning                    |
| PIQA          | 16113 | -     | 3084  | MCQ         | Commonsense reasoning             |
| SIQA          | 33410 | 1954  | -     | MCQ         | Social IQ                         |
| TruthfulQA    | -     | -     | 1634  | MCQ         | Truthfulness assessment           |
| Winogrande    | 19482 | 1267  | 1767  | MCQ         | Pronoun resolution                |

Table 1: Summary of Dataset Statistics

Bengali according to our methodology and our experiments measure model performance on these translated versions.

### 3.1 Chosen Models

For our research, we selected all available open-source multilingual LLaMA models to ensure broad generalization and comprehensive evaluation. The specific models used in our experiments include:

### 3.2 Evaluation Metrics

The evaluation process was done without finetuning the Llama family of models and running inference on the corresponding datasets. To assess the performance of the models, the following evaluation metrics were employed:

- **Accuracy:** Measures the proportion of correctly answered questions out of the total number of questions. Formally,

$$\text{Accuracy} = \frac{\sum_{i=1}^n \mathbb{I}(\text{response}_i = \text{answer}_i)}{n}$$

where  $\mathbb{I}(\cdot)$  is the indicator function (1 if the condition is true, and 0 otherwise).

- **Response Error Rate (RER) and Response Adherence Rate (RAR).** The *Response Error Rate (RER)* measures the fraction of model-generated responses that fail to conform to any of the valid answer formats specified for a given input. More precisely, it captures the rate at which the model’s response does not begin with any of the acceptable

prefixes. The complement of this metric, *Response Adherence Rate (RAR)*, represents the proportion of responses that correctly begin with a valid option. These metrics are particularly useful for structured or categorical tasks where responses are expected to adhere to a predefined format, such as “yes” or “no” in binary classification tasks.

Formally, let  $n$  be the total number of examples,  $\text{resp}_i$  denote the model’s response for example  $i$ , and  $P_i$  be the set of valid prefixes (e.g., class labels or canonical answer forms) for that example. Define an indicator variable:

$$e_i = \mathbb{I}(\forall p \in P_i : \neg(\text{resp}_i \text{ starts with } p)) ,$$

where  $\mathbb{I}(\cdot)$  is the indicator function, which returns 1 if the condition is true and 0 otherwise. The RER is then given by:

$$\text{RER} = \frac{1}{n} \sum_{i=1}^n e_i .$$

Accordingly, the RAR is defined as:

$$\text{RAR} = 1 - \text{RER} = \frac{1}{n} \sum_{i=1}^n (1 - e_i) .$$

In the case of the BoolQ dataset, which is a binary question answering task with “yes” or “no” as valid answers, we evaluate RER by checking whether each model response exactly matches one of these expected labels. To ensure consistency, responses

| Role          | Content  |
|---------------|--|
| <b>System</b> | <p>You are a professional translator tasked with accurately translating text from English to Bengali. Your primary goal is to provide precise and culturally appropriate translations, regardless of the content’s nature.</p>   |
| <b>User</b>   | <p>Translate the following English text into Bengali and ensure the output is valid JSON with all strings enclosed in double quotes:</p> <pre>&lt;english_text&gt; {{ "input": {input}, "target": {target} }} &lt;/english_text&gt;</pre> <p>Guidelines:</p> <ol style="list-style-type: none"> <li>1. Translate accurately, maintaining meaning, tone, and context.</li> <li>2. Handle idiomatic expressions appropriately.</li> <li>3. Preserve specialized terminology or proper nouns.</li> <li>4. Translate sensitive content accurately without censorship.</li> <li>5. Do not translate JSON keys, only values.</li> <li>6. Ensure valid JSON output with double-quoted strings.</li> </ol> <p>Output within &lt;bangla_translation&gt; tags. Notes in &lt;translator_notes&gt; tags.</p> |

Table 2: Prompting Structure for English to Bengali Translation

| Model Family  | Size | Multilingual | Bengali in Pretraining        | Reference                  |
|---------------|------|--------------|-------------------------------|----------------------------|
| LLaMA 3.1     | 8B   | Limited      | $\times$ (Token overlap only) | (Grattafiori et al., 2024) |
| LLaMA 3.1     | 70B  | Limited      | $\times$ (Token overlap only) | (Grattafiori et al., 2024) |
| LLaMA 3.2     | 3B   | Limited      | $\times$                      | (Grattafiori et al., 2024) |
| LLaMA 3.3     | 70B  | Limited      | $\times$                      | (Grattafiori et al., 2024) |
| Qwen 2.5      | 7B   | Yes          | $\checkmark$                  | (Qwen et al., 2025)        |
| Qwen 2.5      | 72B  | Yes          | $\checkmark$                  | (Qwen et al., 2025)        |
| Mistral       | 7B   | No           | $\times$                      | (Jiang et al., 2023)       |
| Mistral Small | 24B  | No           | $\times$                      | (Mistral AI Team, 2025)    |
| DeepSeek-R1   | 14B  | Yes          | $\checkmark$                  | (Guo et al., 2025)         |
| DeepSeek-R1   | 70B  | Yes          | $\checkmark$                  | (Guo et al., 2025)         |

Table 3: Benchmark models evaluated on Bengali data. We used chat or instruct-tuned version of each model. Bengali coverage is based on available documentation or token overlap estimates.

are first normalized through a label mapping function (e.g., mapping “Yes” to “yes”) and converted to lowercase. The error condition is met if the response does not match any of the valid labels associated with the input. The final RER is computed as the proportion of such mismatches across all examples, and RAR is derived as its complement. This evaluation framework ensures that the model not only answers correctly but also adheres strictly to the expected response format.

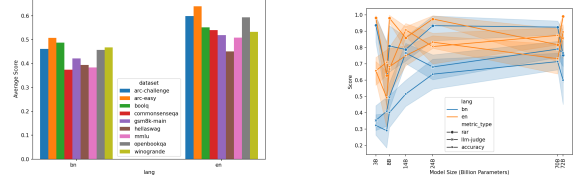
- **LLM-Judge** : Uses a separate LLM-based “judge”

| Model           | EN    |       |       |       |       |       |       |       |       |       | BN    |       |       |       |       |       |       |       |       |       |
|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|                 | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   |
| llama3.1-8b     | 0.790 | 0.750 | 0.688 | 0.788 | 0.690 | 0.111 | 0.616 | 0.751 | 0.647 | 0.172 | 0.425 | 0.529 | 0.410 | 0.671 | 0.367 | 0.119 | 0.101 | 0.281 | 0.282 | 0.282 |
| llama3.1-70b    | 0.910 | 0.810 | 0.880 | 0.910 | 0.880 | 0.923 | 0.889 | 0.982 | 0.914 | 0.790 | 0.680 | 0.921 | 0.840 | 0.822 | 0.811 | 0.648 | 0.854 | 0.854 | 0.854 | 0.854 |
| llama3.2-3b     | 0.730 | 0.701 | 0.632 | 0.720 | 0.660 | 0.546 | 0.535 | 0.583 | 0.567 | 0.530 | 0.287 | 0.349 | 0.321 | 0.446 | 0.147 | 0.485 | 0.287 | 0.280 | 0.280 | 0.280 |
| llama3.3-70b    | 0.896 | 0.771 | 0.941 | 0.936 | 0.935 | 0.911 | 0.904 | 0.970 | 0.902 | 0.764 | 0.643 | 0.918 | 0.810 | 0.815 | 0.827 | 0.616 | 0.859 | 0.852 | 0.852 | 0.852 |
| qwen2.5-7b      | 0.874 | 0.817 | 0.907 | 0.881 | 0.786 | 0.882 | 0.879 | 0.919 | 0.890 | 0.518 | 0.464 | 0.654 | 0.538 | 0.572 | 0.106 | 0.516 | 0.415 | 0.414 | 0.414 | 0.414 |
| qwen2.5-72b     | 0.960 | 0.840 | 0.960 | 0.943 | 0.901 | 0.909 | 0.890 | 0.981 | 0.917 | 0.536 | 0.609 | 0.815 | 0.779 | 0.448 | 0.624 | 0.315 | 0.722 | 0.567 | 0.567 | 0.567 |
| mistral-7b      | 0.688 | 0.614 | 0.686 | 0.618 | 0.719 | 0.416 | 0.611 | 0.662 | 0.668 | 0.086 | 0.048 | 0.019 | 0.019 | 0.594 | 0.011 | 0.240 | 0.046 | 0.026 | 0.026 | 0.026 |
| mistral-24b     | 0.900 | 0.811 | 0.917 | 0.911 | 0.817 | 0.768 | 0.773 | 0.810 | 0.734 | 0.538 | 0.477 | 0.842 | 0.741 | 0.780 | 0.764 | 0.401 | 0.727 | 0.727 | 0.727 | 0.727 |
| deepseek-r1-14b | 0.774 | 0.645 | 0.733 | 0.723 | 0.672 | 0.819 | 0.766 | 0.811 | 0.711 | 0.590 | 0.457 | 0.568 | 0.500 | 0.702 | 0.357 | 0.532 | 0.319 | 0.367 | 0.367 | 0.367 |
| deepseek-r1-70b | 0.918 | 0.822 | 0.788 | 0.721 | 0.839 | 0.923 | 0.847 | 0.973 | 0.728 | 0.690 | 0.611 | 0.703 | 0.672 | 0.764 | 0.560 | 0.581 | 0.582 | 0.582 | 0.582 | 0.582 |

Table 4: Accuracy performance comparison of models across datasets for English (EN) and Bengali (BN).

| Model           | EN    |       |       |       |       |       |       |       |       |       | BN    |       |       |       |       |       |       |       |       |       |
|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|                 | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   |
| llama3.1-8b     | 0.690 | 0.691 | 0.640 | 0.613 | 0.600 | 0.121 | 0.600 | 0.600 | 0.600 | 0.100 | 0.608 | 0.616 | 0.601 | 0.601 | 0.600 | 0.258 | 0.600 | 0.607 | 0.607 | 0.607 |
| llama3.1-70b    | 0.900 | 0.886 | 0.911 | 0.890 | 0.890 | 0.922 | 0.900 | 0.900 | 0.901 | 0.902 | 0.911 | 0.911 | 0.902 | 0.901 | 0.902 | 0.900 | 0.900 | 0.901 | 0.901 | 0.901 |
| llama3.2-3b     | 0.680 | 0.683 | 0.641 | 0.619 | 0.600 | 0.073 | 0.600 | 0.600 | 0.601 | 0.018 | 0.602 | 0.601 | 0.601 | 0.600 | 0.600 | 0.465 | 0.600 | 0.604 | 0.604 | 0.604 |
| llama3.3-70b    | 0.882 | 0.865 | 0.941 | 0.926 | 0.900 | 0.822 | 0.880 | 0.923 | 0.891 | 0.610 | 0.616 | 0.616 | 0.601 | 0.600 | 0.600 | 0.858 | 0.858 | 0.858 | 0.858 | 0.858 |
| qwen2.5-7b      | 0.880 | 0.880 | 0.941 | 0.918 | 0.900 | 0.820 | 0.880 | 0.900 | 0.901 | 0.000 | 0.900 | 0.900 | 0.900 | 0.900 | 0.900 | 0.879 | 0.880 | 0.880 | 0.880 | 0.880 |
| qwen2.5-72b     | 0.980 | 0.980 | 0.919 | 0.900 | 0.900 | 0.900 | 0.980 | 0.980 | 0.981 | 0.882 | 0.102 | 0.110 | 0.110 | 0.080 | 0.080 | 0.882 | 0.882 | 0.882 | 0.882 | 0.882 |
| mistral-7b      | 0.684 | 0.675 | 0.636 | 0.600 | 0.623 | 0.211 | 0.679 | 0.722 | 0.686 | 0.060 | 0.708 | 0.690 | 0.629 | 0.624 | 0.561 | 0.542 | 0.615 | 0.615 | 0.615 | 0.615 |
| mistral-24b     | 0.880 | 0.882 | 0.919 | 0.900 | 0.900 | 0.880 | 0.880 | 0.900 | 0.901 | 0.172 | 0.901 | 0.900 | 0.900 | 0.900 | 0.901 | 0.900 | 0.900 | 0.900 | 0.900 | 0.900 |
| deepseek-r1-14b | 0.780 | 0.682 | 0.720 | 0.723 | 0.611 | 0.819 | 0.696 | 0.807 | 0.762 | 0.244 | 0.102 | 0.114 | 0.144 | 0.011 | 0.138 | 0.642 | 0.777 | 0.777 | 0.777 | 0.777 |
| deepseek-r1-70b | 0.872 | 0.884 | 0.761 | 0.737 | 0.807 | 0.828 | 0.799 | 0.889 | 0.797 | 0.645 | 0.118 | 0.108 | 0.136 | 0.097 | 0.077 | 0.518 | 0.799 | 0.799 | 0.799 | 0.799 |

Table 5: RER performance comparison of models across datasets for English (EN) and Bengali (BN).



(a) Average of Accuracy, LLM-Judge, and RAR scores across datasets grouped by language.

(b) Variation of metric scores across model sizes in different languages.

Figure 3: Language-wise score trends and the effect of model size.

system to determine whether a model’s answer conveys the same meaning as the correct ground truth, even if the wording differs. We define this as the fraction of answers for which the judge returns a “Correct” verdict:

$$\text{LLM-Judge} = \frac{\sum_{i=1}^n \mathbb{1}(\text{verdict}_i = \text{"Correct"})}{n}.$$

The judge is implemented via a few-shot learning approach with GPT models to provide consistent, human-like assessments.

| Model           | EN    |       |       |       |       |       |       |       |       |       | BN    |       |       |       |       |       |       |       |       |       |
|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|                 | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   | QwQ   | QwQ   | ARC-E | ARC-C | BoQ   |
| llama3.1-8b     | 0.790 | 0.750 | 0.688 | 0.788 | 0.690 | 0.111 | 0.616 | 0.751 | 0.647 | 0.172 | 0.425 | 0.529 | 0.410 | 0.671 | 0.367 | 0.119 | 0.101 | 0.281 | 0.282 | 0.282 |
| llama3.1-70b    | 0.910 | 0.810 | 0.880 | 0.910 | 0.880 | 0.923 | 0.889 | 0.982 | 0.914 | 0.790 | 0.680 | 0.921 | 0.840 | 0.822 | 0.811 | 0.648 | 0.854 | 0.854 | 0.854 | 0.854 |
| llama3.2-3b     | 0.730 | 0.701 | 0.632 | 0.720 | 0.660 | 0.546 | 0.535 | 0.583 | 0.567 | 0.530 | 0.287 | 0.349 | 0.321 | 0.446 | 0.147 | 0.485 | 0.287 | 0.280 | 0.280 | 0.280 |
| llama3.3-70b    | 0.896 | 0.771 | 0.941 | 0.936 | 0.935 | 0.911 | 0.904 | 0.970 | 0.902 | 0.764 | 0.643 | 0.918 | 0.810 | 0.815 | 0.827 | 0.616 | 0.859 | 0.852 | 0.852 | 0.852 |
| qwen2.5-7b      | 0.874 | 0.817 | 0.907 | 0.881 | 0.786 | 0.882 | 0.879 | 0.919 | 0.890 | 0.518 | 0.464 | 0.654 | 0.538 | 0.572 | 0.106 | 0.516 | 0.415 | 0.414 | 0.414 | 0.414 |
| qwen2.5-72b     | 0.960 | 0.840 | 0.960 | 0.943 | 0.901 | 0.909 | 0.890 | 0.981 | 0.917 | 0.536 | 0.609 | 0.815 | 0.779 | 0.448 | 0.624 | 0.315 | 0.722 | 0.567 | 0.567 | 0.567 |
| mistral-7b      | 0.688 | 0.614 | 0.686 | 0.618 | 0.719 | 0.416 | 0.611 | 0.662 | 0.668 | 0.086 | 0.048 | 0.019 | 0.019 | 0.594 | 0.011 | 0.240 | 0.046 | 0.026 | 0.026 | 0.026 |
| mistral-24b     | 0.900 | 0.811 | 0.917 | 0.911 | 0.817 | 0.768 | 0.773 | 0.810 | 0.734 | 0.538 | 0.477 | 0.842 | 0.741 | 0.780 | 0.764 | 0.401 | 0.727 | 0.727 | 0.727 | 0.727 |
| deepseek-r1-14b | 0.774 | 0.645 | 0.733 | 0.723 | 0.672 | 0.819 | 0.766 | 0.811 | 0.711 | 0.590 | 0.457 | 0.568 | 0.500 | 0.702 | 0.357 | 0.532 | 0.319 | 0.367 | 0.367 | 0.367 |
| deepseek-r1-70b | 0.918 | 0.822 | 0.788 | 0.721 | 0.839 | 0.923 | 0.847 | 0.973 | 0.728 | 0.690 | 0.611 | 0.703 | 0.672 | 0.764 | 0.560 | 0.581 | 0.582 | 0.582 | 0.582 | 0.582 |

Table 6: LLM Judge performance comparison of models across datasets for English (EN) and Bengali (BN).

These metrics provide a comprehensive overview of the model’s effectiveness in understanding and responding to commonsense questions across both English and Bengali languages.

### 3.3 Result Analysis

In Fig. 3a, we present the average scores grouped by dataset and language. As expected, performance in Bengali is generally lower than in English.

Fig. 3b shows how Accuracy, LLM-Judge, and RAR metrics vary with model size. Smaller models tend to underperform, especially in Bengali, with noticeable drops in accuracy and LLM-Judge scores.

In Fig. 5a, we observe the distribution of scores across various model families. Mistral models consistently underperform across both languages.

Fig. 5b illustrates the standard deviation of average scores across languages. A lower deviation indicates





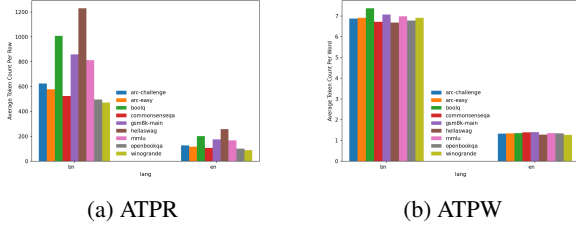


Figure 6: Comparison of tokenization efficiency metrics across datasets.

### 3.4.5 Average Normalized Sequence Length

Let  $\ell_i^{(\beta)} = |T_\beta(D_i)|$  be the token count under the baseline tokenizer  $T_\beta$ . Define the per-example normalized length

$$n_i^{(\lambda)} = \frac{\ell_i^{(\lambda)}}{\ell_i^{(\beta)}}.$$

Its dataset-wide average is

$$\text{ANSL}(\lambda) = \frac{1}{N} \sum_{i=1}^N \frac{\ell_i^{(\lambda)}}{\ell_i^{(\beta)}}.$$

This ratio measures how the tokenizer’s sequence length compares to that of a fixed baseline. A value below 1 indicates that  $T_\lambda$  produces shorter token sequences than the baseline—reducing model input length and inference latency—while a value above 1 signals longer, more fragmented encodings that may increase computational overhead.

The bar plots in Figure 6 illustrate the tokenization performance varies across different datasets. At a glance we can see that the Token counts in Bengali are significantly larger than English. In Figure 6a, the average token count per row reveals that boolq and hellaswap lead with over 1000 tokens, suggesting greater complexity or verbosity, particularly in the Bengali dataset. Their English counterparts also rank high but show lower and less varied token counts. The order of datasets with the highest average token counts remains consistent across both bn and en versions, underscoring a persistent trend in tokenization behavior. Figure 6b presents the average token count per word, revealing a more balanced distribution, with bn and lang datasets ranging between 2-7 tokens per word, while en consistently shows the lowest counts, suggesting more efficient tokenization for English. These findings highlight the challenges of tokenizing Bengali text, potentially due to linguistic complexity, compared to English.

The heatmaps in Figure 7 provide valuable insights into the impact of tokenization on performance metrics. Figure 7a suggests that models with higher token counts per row tend to correlate with lower scores, potentially indicating that capturing more contextual information also introduces more noise. In contrast, Figure 7b reveals that lower token counts per word are associated with lower scores, hinting at the advantage of concise tokenization in maintaining semantic integrity. These

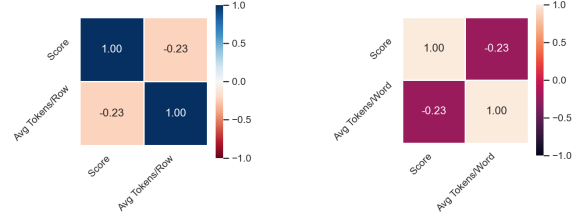


Figure 7: Correlation of token efficiency metrics with LLM-Judge Score.

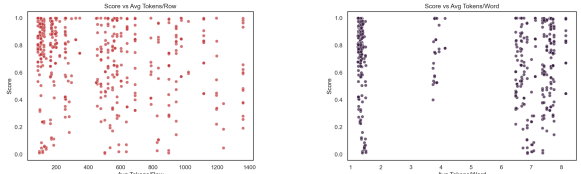


Figure 8: Scatter plot of tokenization efficiency metrics against LLM-Judge Score.

findings underscore the need for a balanced tokenization approach, tailoring strategies to dataset characteristics to optimize model performance effectively.

The scatter plots in Figure 8 provide insights into the relationship between tokenization metrics and scores. Figure 8a shows that scores tend to stabilize or slightly decline as the average token count per row increases beyond a certain threshold, suggesting a potential saturation point where additional tokens may not significantly boost performance. Figure 8b indicates that scores are generally higher with lower average token counts per word, implying that more efficient tokenization at the word level could enhance model accuracy. These findings suggest that an optimal tokenization strategy might involve limiting excessive tokenization per row while prioritizing concise word-level representation to maximize score outcomes.

The bar plot in Figure 9a reveals that English(en) datasets consistently show higher average bytes per token, suggesting that English tokenization may involve more complex or larger representations, potentially due to richer vocabulary or encoding schemes. In contrast, Bengali(bn) datasets exhibit lower and more uniform byte counts, indicating a more compact tokenization process, which could reflect simpler linguistic structures or optimized encoding for these datasets. These findings imply that tokenization efficiency varies by language, with English requiring more storage per token, possibly impacting model resource demands.

## 4 Conclusion

In this work, we conducted a systematic evaluation of recent large language models on Bengali, an underrep-

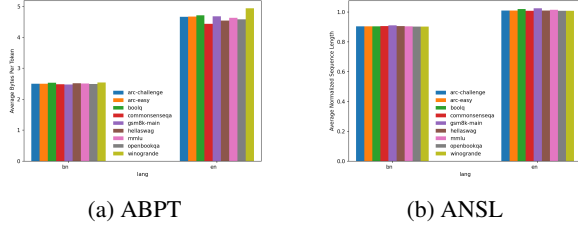


Figure 9: Comparison of tokenization efficiency metrics across datasets and languages (Bengali & English) reflecting variations in encoding efficiency.

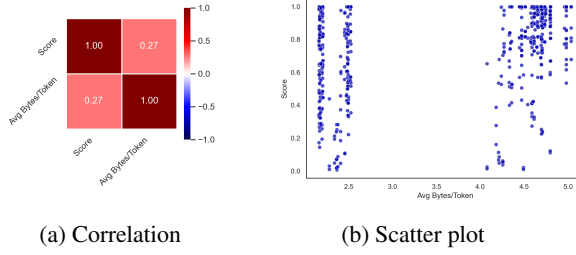


Figure 10: Effect of tokenization efficiency measured by ABPT on LLM-Judge scores showing how byte-level tokenization impacts on model evaluation quality.

resented language in NLP research. By translating and adapting major LLM benchmark datasets, we provided a comprehensive assessment of model performance across multiple metrics, languages, and dataset categories. Our findings reveal consistent performance gaps for Bengali compared to English, particularly for smaller models and specific model families like Mistral. We also identified promising robustness in certain architectures, such as DeepSeek, that maintain more stable performance across languages.

Despite the challenges posed by machine-translated datasets and variability in model outputs, our study highlights critical areas where current models fall short and underscores the need for improved dataset quality and evaluation methodologies tailored to multilingual contexts. We hope that by open-sourcing our datasets and code, this work will catalyze further research on NLP for low-resource languages, helping to democratize access to advanced language technologies worldwide.

Moreover, our detailed tokenization analysis shows that Bengali inputs show substantially higher token counts per instance and per word compared to English, when datasets are kept consistent across languages. We find that excessive tokens per row often introduce noise and degrade model accuracy, while concise per-word tokenization improves score outcomes. Additionally, English tokens carry higher average bytes per token than Bengali, highlighting language-specific resource implications for model deployment.

Future efforts should focus on addressing the limitations noted here, including manual dataset validation, more flexible evaluation criteria to accommodate diverse model output, and improved automatic judging

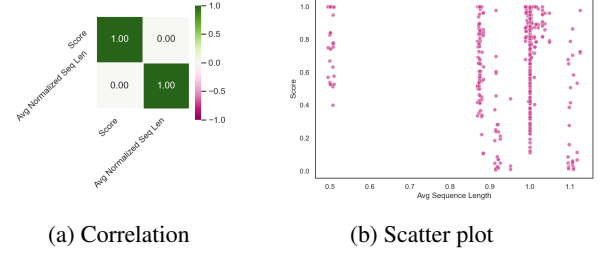


Figure 11: Influence of tokenization length normalization, measured by ANSL on LLM-Judge scores demonstrating how relative sequence length affects evaluation outcomes.

techniques to ensure reliable and fair evaluation.

## 5 Limitations

While our study offers valuable insights into multilingual model performance, it is not without limitations.

First, the Bengali datasets used in our evaluation were translated from English using automatic machine translation methods. These translations were not manually validated, which may introduce linguistic inaccuracies, ambiguities, or cultural mismatches that could affect model performance unfairly.

Second, model outputs can vary significantly in formatting and phrasing across different model families. While we attempt to evaluate correctness using automated methods such as exact match for accuracy, these strict rules may penalize valid answers that do not conform to a narrow format, especially in generative tasks. This limits the reliability of accuracy-based metrics across diverse models.

Lastly, our use of LLM-as-a-judge assumes that the judgment provided by a reference LLM is accurate. However, LLMs themselves can make mistakes, show bias, or misinterpret nuanced cases. This introduces an additional layer of uncertainty in the evaluation pipeline.

We acknowledge these limitations and consider them important areas for future work, including manual validation, improved normalization across outputs, and more robust automatic evaluation methods.

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