MUTANT: A Recipe for Multilingual Tokenizer Design

Souvik Rana, Arul Menezes, Ashish Kulkarni, Chandra Khatri, Shubham Agarwal
Krutrim AI, Bangalore, India
{souvik.rana, ashish.kulkarni, shubham.agarwal1}@olakrutrim.com

Abstract

Tokenizers play a crucial role in determining the performance, training efficiency, and the inference cost of Large Language Models (LLMs). Designing effective tokenizers for multilingual LLMs is particularly challenging due to diverse scripts and rich morphological variation. While subword methods like Byte Pair Encoding (BPE) are widely adopted, their effectiveness in multilingual settings remains underexplored. We present MUTANT, a recipe for building multilingual tokenizers, with careful vocabulary and training data design, language-aware pre-tokenization, and subword and multiword aware training. We also introduce MUTANT-Indic, a tokenizer for India-specific multilingual LLMs, that produces linguistically coherent tokens and achieves state-of-the-art performance. Evaluated across English, 22 Indian languages and code data, our tokenizer improves the average fertility score by 39.5% over LLaMA4 and by 18% over Sutra (the current best). This translates to 44% improvement in inference throughput over LLaMA4 while maintaining comparable performance on English and Indic benchmarks. We present detailed ablations across tokenizer training data size, vocabulary size, merging techniques, and pre-tokenization strategies, demonstrating the robustness of our design choices.

1 Introduction

Large Language Models (LLMs) (Touvron et al., 2023; Grattafiori et al., 2024; Abdin et al., 2025; Guo et al., 2025; Yang et al., 2025; Gemma Team, 2025) rely on the crucial step of tokenization, the process of converting raw text into discrete units called *tokens*. Among the many proposed approaches, subword tokenization schemes such as BPE (Sennrich et al., 2016a), Unigram (Kudo, 2018), WordPiece (Song et al., 2021), and their byte-level extensions have become the de facto choice. However, tokenization remains an understudied topic within the LLM literature (Dagan et al., 2024; Mielke et al., 2021), especially in multilingual settings (Petrov et al., 2023), where, skewed fertility scores across languages, often lead to concerns around fairness, high inference latency, cost and context size. For instance, with the 22 languages listed in the Eighth Schedule of the Constitution of India[1], these issues are especially pronounced for Indic languages comprising multiple scripts and a rich morphology. A key metric for evaluating tokenizers is the "fertility score" (or token-to-word ratio) (Ali et al., 2024) where, a lower fertility score is desirable due to more efficient (and hence cheaper) LLM training and inference. Our analysis suggests that tokenizers of popular multilingual LLMs (Gemma Team, 2025; OpenAI, 2025; Meta, 2025), largely designed for English, could produce fertility scores as high as 10.5 (LLaMA-4 tokenizer for Oriya; Table 3) for Indic languages, far worse than the near-ideal scores achieved for English. This leads to longer token sequences, higher compute overheads, and poor alignment with linguistic units.

Designing an efficient tokenizer involves making careful choices around the the tokenization algorithm, size of the vocabulary (of tokens) as well as tokenizer training data. In this work, we address five core questions and investigate how to design effective multilingual tokenizers by i) examining trade-offs between low- and high-resource languages, ii) joint versus language-specific training, iii) multilingual data balancing, iv) the role of pre-tokenization, and v) the benefits of incorporating multi-word expressions via curriculum training.

Supported by controlled experiments and systematic ablations, we present MUltilingual Tokenizer optimization ANd Training (MUTANT) as a practical and reproducible recipe (see Figure 1) for building equitable, efficient, and linguistically grounded multilingual tokenizers for LLMs. We apply our recipe to train MUTANT-Indic, a state-of-the-art tokenizer for Indic LLMs, demonstrating

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[1] `https://en.wikipedia.org/wiki/Languages_with_official_recognition_in_India`

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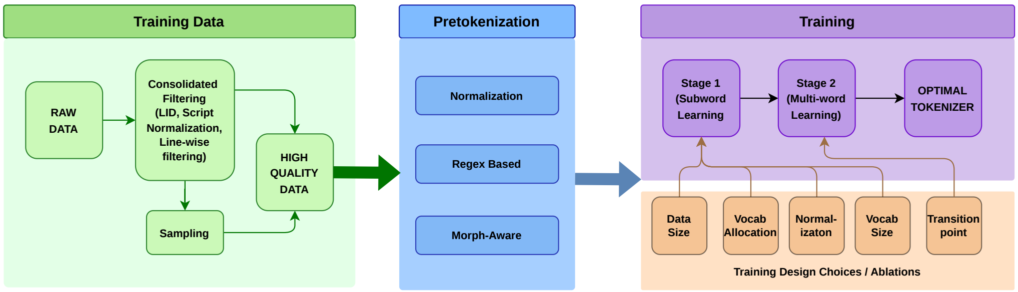

Figure 1: MUTANT: Multilingual tokenizer training recipe. Raw text is filtered and consolidated before a two-stage training process consisting of subword and multi-word learning with ablations to identify efficient design choices.

the benefits of our methodology in a real-world multilingual setting. MUTANT-Indic combines linguistically grounded pre-tokenization with a two-stage subword–multi-word learning process (Liu et al., 2025a), yielding a compact and semantically faithful vocabulary. Figure 3 illustrates some examples where our approach avoids fragmenting common words or idiomatic phrases into unnatural subunits across different languages. We make the following contributions:

- We propose MUTANT, a principled and general recipe for training optimal multilingual tokenizers. We systematically study the effect of vocabulary size, data distribution, language-specific pre-tokenization and multi-stage training on multilingual performance.
- We demonstrate the effectiveness by training MUTANT-Indic, that achieves state-of-the-art (SOTA) performance for Indic languages.
- To the best of our knowledge, we are the first to carry out a comprehensive benchmarking of tokenizers across multiple intrinsic and downstream LLM performance measures in both pretraining from scratch as well as continual pretraining settings. We publicly release the evaluation framework[2] and the evaluation dataset[3] to enable reproducibility and community benchmarking.

2 Related Work

Multilingual Tokenizers. Multilingual tokenization faces challenges from script diversity, morphology, and structural variation. Comparative studies show that vocabulary size and construction strategies strongly affect performance for morphologically rich languages (Karthika et al., 2025a), while inefficiencies in underrepresented ones, such as Ukrainian, translate to higher fertility and computational costs (Maksymenko and Turuta, 2025). Tokenization also influences how multilingual models encode morphology, as demonstrated in mT5 vs. ByT5 (Dang et al., 2024). For Indic languages, tailored resources (Kakwani et al., 2020) and IndicBERT (AI4Bharat, 2022) highlight the value of domain-specific tokenization. Recent benchmarks further reveal economic implications, with BLOOM's tokenizer achieving the best cost efficiency among popular multilingual LLMs (ADA Sci, 2024). Together, these studies show that current multilingual tokenizers fragment low-resource and morphologically rich languages, motivating approaches that combine normalization, language-tailored pre-tokenization, and multi-word learning to achieve better efficiency and fairness.

Tokenization Algorithms. Tokenization strategies differ in both theory and practice. While alternate sub-word tokenization algorithms have been explored in the past such as WordPiece (Song et al., 2021), Unigram LM (Kudo and Richardson, 2018), Byte Pair Encoding (BPE) remains the most widely adopted. Originally developed for compression (Gage, 1994) and later adapted for neural MT (Sennrich et al., 2016b), BPE merges frequent character pairs to balance coverage with efficiency. Its variants aim to address inefficiencies: PickyBPE (Chizhov et al., 2024) discards uninformative merges to improve vocabulary utility, while Scaffold-BPE (Lian et al., 2024) iteratively prunes low-frequency scaffold tokens to reduce imbalance and enhance downstream performance. Recent extensions like SuperBPE (Liu et al., 2025b) expand beyond word boundaries, jointly learning subwords and multi-words yielding improved compression and inference efficiency in a 2-stage curriculum. BoundlessBPE (Schmidt et al., 2024), another con-

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[2] `https://github.com/ola-krutrim/MUTANT`

[3] `https://huggingface.co/datasets/krutrim-ai-labs/MUTANT`

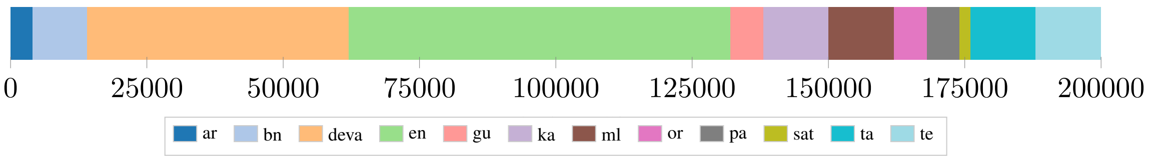


Figure 2: Vocabulary size distribution across language scripts. See Appendix A for script details.

temporary work, relaxes the Pre-tokenization word boundary constraint in an single stage learning step. Our work compares these two recent approaches and shows that two-stage curriculum preserves subword coverage while capturing larger semantic units in morphologically rich Indian languages.

Pre-tokenization. Pre-tokenization plays a pivotal role in shaping token boundaries, directly influencing both compression efficiency and reasoning performance (Xue et al., 2024). SentencePiece (Kudo and Richardson, 2018) introduced a language-agnostic approach by treating input as raw streams, effective for languages without whitespace boundaries. More recent approaches like BoundlessBPE (Schmidt et al., 2024) relax pre-token constraints to improve frequency distributions, while regex-based designs continue to prove crucial for capturing script-specific structures.

3 MUTANT: Tokenizer Training Recipe

Language modeling involves estimating the probability distribution over text sequences, $P(S)$, where S may represent a sentence, paragraph, or document. To achieve this, the text is first converted into a sequence of discrete tokens through a tokenization function $g(S) = X = (X_1, X_2, \ldots, X_n) \in V^n$, where V denotes the vocabulary and n the sequence length. Tokenizers can be open-vocabulary, ensuring any string can be represented (e.g., byte-level), or closed-vocabulary, where unseen text maps to an out-of-vocabulary symbol (e.g., word lists) (Rae et al., 2021). In our work, we adopt an open-vocabulary approach that combines byte-pair encoding (BPE) with a UTF-8 byte fallback, following Radford et al. (2018). In this section, we present a systematic recipe for designing multilingual tokenizers that jointly addresses data curation, pre-tokenization, and subword–multiword learning. Figure 1 provides an end-to-end overview of the pipeline, illustrating how raw multilingual text is filtered and sampled, transformed through a fixed pre-tokenization stage, and used to train a two-stage tokenizer with explicit design choices on vocabulary size and allocation, detailed below.

3.1 Training Data and Vocabulary

The composition of the training data and the vocabulary size are design choices that directly impact the quality of tokens and the tokenizer efficiency.

Training data volume: Effective tokenizer training relies on a sufficiently large carefully curated multilingual corpus; beyond moderate scale, further data scaling yields diminishing returns (Reddy et al., 2025) in quality (Section 5).

Data quality and diversity: We combine diverse, high-quality sources that is representative of natural language use (Hayase et al., 2024), such as, the Web, curated multilingual datasets, Wikipedia, math, code and others. The raw data is further subjected to filtering for language/script mixing, normalization, short documents (or lines) and controlled source-wise sampling (see Appendix B.1 for MUTANT-Indic).

Vocabulary size and multilingual allocation: In multilingual settings, vocabulary allocation must be explicitly language (or script)-aware to preserve subword and multi-word granularity across both high- and low-resource languages. We determine script-wise vocabulary budgets through ablations that vary allocation across scripts, identifying distributions that balance fragmentation and coverage (Figure 2). To realize these target allocations in practice, we evaluate two strategies: *i) explicit merging*, where we train script-specific tokenizers and concatenates their vocabularies via rule stacking; and *ii) corpus-driven alignment*, where we train a single tokenizer on a multilingual corpus whose data proportions are aligned with the desired script-wise vocabulary budgets.

Explicit merging introduces distributional interference and inconsistent segmentation across scripts (Table 10). In contrast, corpus-driven alignment allows the learned vocabulary to naturally converge toward the target script-wise proportions, better mirroring corpus composition (Table 9) and achieving consistently lower fertility across scripts (Table 3), outperforming both explicit merging and

	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
Size (MB)	56	562	13	4	1	148	67	83	422	30	252	60	311	34	152	82	46	144	110	0.47	38	502	486	38
# Lines (K)	65	681	19	118	2	449	135	91	545	21	273	129	337	64	257	126	59	198	139	1	69	658	773	27
Avg W/Line	51	47	41	3	43	56	37	59	59	145	41	39	35	43	33	40	45	57	36	26	70	32	32	185

Table 1: Evaluation corpus statistics across 22 Indic languages, English, and code in Section 3.4 including size (in MB), number of lines (in K) and average words per line. We report standard ISO codes here (Appendix Section A).

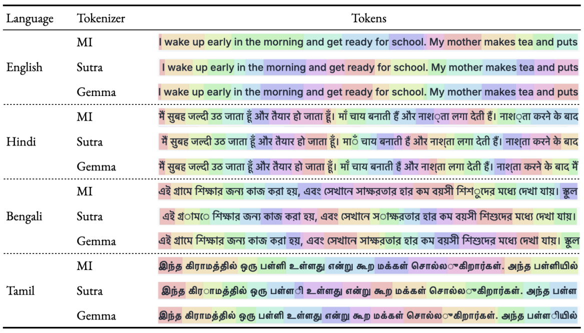
public baselines.

3.2 Tokenizer Training

We adopt a two-stage curriculum following the framework of Liu et al. (2025b). This procedure forms the training strategy used in MUTANT and its Indic instantiation, MUTANT-Indic.

Stage 1 (Subword Learning): Training begins with standard byte-pair encoding (BPE) applied after whitespace pre-tokenization. This ensures that merges occur only within word boundaries, allowing the tokenizer to learn fine-grained *subword units* such as roots, affixes, and common morphemes. Stage 1 continues until the vocabulary reaches a pre-defined *transition point* t ($< |V|$).

Stage 2 (Multi-word Learning): After reaching t, training resumes without whitespace constraints, allowing BPE to merge across word boundaries. This enables the formation of *multi-words*, frequent multiword expressions or collocations (e.g., “in the morning” in Figure 3) improving compression and reducing token counts for common phrases.



Language	Tokenizer	Tokens
English	MI	I wake up early in the morning and get ready for school. My mother makes tea and puts
	Sutra	I wake up early in the morning and get ready for school. My mother makes tea and puts
	Gemma	I wake up early in the morning and get ready for school. My mother makes tea and puts
Hindi	MI	मैं सुबह जल्दी उठ जाता हूँ और तैयार हो जाता हूँ। माँ चाय बनाती हैं और नाश◌्ता लगा देती हैं। नाश◌्ता करने के बाद
	Sutra	मैं सुबह जल्दी उठ जाता हूँ और तैयार हो जाता हूँ। मा◌ँ चाय बनाती हैं और नाश्ता लगा देती हैं। नाश्ता करने के बाद
	Gemma	मैं सुबह जल्दी उठ जाता हूँ और तैयार हो जाता हूँ। माँ चाय बनाती हैं और नाश्ता लगा देती हैं। नाश्ता करने के बाद मैं
Bengali	MI	এই গ্রামে শিক্ষার জন্য কাজ করা হয়, এবং সেখানে সাক্ষরতার হার কম বয়সী শিশ◌ুদের মধ্যে দেখা যায়। স্কুল
	Sutra	এই গ্র◌াম◌ে শিক্ষার জন্য কাজ করা হয়, এবং সেখানে স◌াক্ষরতার হার কম বয়সী শিশুদের মধ্যে দেখা যায়।
	Gemma	এই গ্রামে শিক্ষার জন্য কাজ করা হয়, এবং সেখানে সাক্ষরতার হার কম বয়সী শিশুদের মধ্যে দেখা যায়। স্কুল
Tamil	MI	இந்த கிராமத்தில் ஒரு பள்ளி உள்ளது என்று கூற மக்கள் சொல்ல◌ுகிறார்கள். அந்த பள்ளியில்
	Sutra	இந்த கிர◌ாமத்தில் ஒரு பள்ள◌ி உள்ளது என்று கூற மக்கள் சொல்ல◌ுகிறார்கள். அந்த பள்ள
	Gemma	இந்த கிராமத்தில் ஒரு பள்ளி உள்ளது என்று கூற மக்கள் சொல்ல◌ுகிறார்கள். அந்த பள்ள◌ியில்

Figure 3: MUTANT-Indic (MI) captures multi-words (e.g. “wake up", “in the morning") and avoids fragmenting Indic words (see for e.g. Bengali, Tamil).

This two-stage tokenizer training is particularly effective for scripts with complex variations where, meaningful subwords are first anchored and then composed into frequent multiword units.

3.3 Pre-tokenization

As illustrated in Figure 1, pre-tokenization is a fixed, upstream component of our tokenizer design. It segments raw text before subword learning to improve token consistency and efficiency. For MUTANT-Indic, we explore regex-based, Unicode normalization, and morphology-aware strategies. Unicode-aware regex separates punctuation, handles numeric groups, and aligns tokens with semantic units, while NFKC normalization standardizes visually identical characters to reduce orthographic sparsity (Table 25). To improve robustness across Indic scripts, we explore GPT-2 pre-tokenization rules against LLaMA-4 regex in Stage 1, where the latter yields substantially lower token fragmentation and improving token-to-word ratios by 38–40% on Indic languages (Table 2).

Script-agnostic segmentation (as in LLaMA-4 regex rules) across Indic as well as non-Indic scripts helps reduce token fragmentation, while relaxing whitespace constraints in Stage 2 enables the learning of frequent multi-word expressions (see Appendix C.7). However, unconstrained merging can destabilize generation by creating sentence-crossing tokens. Enforcing additional sentence-level boundary constraints in Stage 2 regex prevents this while preserving multi-word modeling benefits.

Additionally, morphology-aware segmentation decomposes words into roots and affixes to capture recurring morphemes. Although we explore morphology-aware segmentation, integrating it into the tokenization pipeline without incurring latency overhead is challenging (Appendix C.2).

3.4 Evaluation Framework

We develop a modular evaluation framework supporting HuggingFace[4], SentencePiece[5], and TikToken[6] tokenizers along with a comprehensive set of intrinsic metrics (Appendix D), including Fertility score, Normalized Sequence Length (NSL), Rényi entropy and efficiency, and Bytes Per Token (BPT). All metrics are computed at the line level and aggregated to the language level. To assess tokenizer behavior in Indic use cases, we construct an evaluation set spanning 22 Indic languages, English,

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[4] `https://github.com/huggingface/tokenizers`

[5] `https://github.com/google/sentencepiece`

[6] `https://github.com/openai/tiktoken`

Regex	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
GPT-2	4.36	4.72	4.67	1.57	2.88	1.32	3.95	4.12	3.47	2.47	5.95	3.17	7.08	3.30	4.86	4.37	4.44	3.28	5.97	2.71	1.30	6.53	5.61	1.29
LLaMA-4	1.83	1.74	1.99	1.54	1.56	1.33	2.17	1.83	1.36	1.36	2.15	1.56	2.24	2.27	1.61	1.59	1.65	1.47	2.51	3.60	1.45	2.07	1.83	1.47

Table 2: Fertility scores (↓) showing LLaMA-4 regex outperforms GPT-2 in Stage-1 tokenizer training.

Tokenizer (↓)	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
Gemma-3	2.65	**1.69**	2.84	1.79	1.69	1.39	2.60	2.50	1.47	1.48	3.34	1.91	3.45	2.07	2.03	2.03	4.42	2.83	3.37	5.16	2.03	2.50	2.94	1.44
GPT-OSS	2.66	2.41	3.17	1.51	1.89	1.33	2.73	2.37	1.72	1.58	3.34	2.01	3.51	2.41	2.61	2.10	6.26	2.71	3.89	13.01	1.76	3.18	3.13	1.51
LLaMA-4	4.40	2.93	3.34	1.46	2.00	1.34	2.84	3.37	1.83	1.72	4.23	2.28	4.95	2.73	2.79	2.46	10.51	3.23	4.12	9.04	2.13	5.87	4.53	1.76
Sarvam	4.24	1.91	2.92	2.14	1.85	1.66	3.01	2.11	1.53	1.91	2.53	2.11	3.19	4.60	1.94	2.35	2.43	1.67	3.78	13.07	7.62	2.49	2.63	7.93
Sutra	2.12	2.07	3.06	2.12	1.78	1.17	2.68	2.15	1.62	1.48	2.71	2.08	3.10	2.40	2.18	2.01	2.24	1.50	3.76	**2.03**	2.23	2.58	2.77	1.55
MUTANT-Indic	**1.85**	1.74	**2.04**	1.47	**1.45**	**1.12**	**2.17**	**1.77**	**1.23**	**1.21**	**2.19**	**1.58**	**2.30**	2.28	**1.63**	**1.62**	**1.65**	**1.39**	**2.59**	3.72	**1.45**	**2.12**	**1.88**	**1.44**

Table 3: Fertility score (↓) comparison for Indic focused and good Indic support tokenizers across languages. MUTANT-Indic performs best in 20 of 24 languages. An extended version in Table 23 (Appendix).

and code. Table 1 reports dataset statistics: text volume, number of lines, and average words per line per language.

4 Experiments and Results

In our work, we compare MUTANT-Indic, trained using our recipe, against 9 tokenizers, comprising: *i) Indic-focused tokenizers:* tokenizers designed primarily for Indian languages: Sutra (Tamang and Bora, 2024) and Sarvam-2B (Sarvam, 2024) (referred as Sarvam). *ii) Good Indic support tokenizers:* multilingual tokenizers with demonstrated capabilities for Indic languages: Gemma-3-27B-it (Gemma Team, 2025) (referred as Gemma-3), GPT-OSS (OpenAI, 2025) and LLaMA-4 (Meta, 2025). *iii) General tokenizers:* tokenizers of widely-used general-purpose LLMs: Qwen3-32B (Qwen, 2024) (referred as Qwen-3), LLaMA-3.2-1B (Dubey et al., 2024), Mistral-Nemo (Mistral, 2024) and DeepSeek-R1 (DeepSeek, 2025).

4.1 Intrinsic Evaluation of Tokenizers

We evaluate tokenization quality using four complementary intrinsic metrics that capture efficiency, granularity, and information utilization: (i) **Fertility score** (Rust et al., 2021; Scao et al., 2022), measuring subword fragmentation; (ii) **Normalized Sequence Length (NSL)** (Dagan et al., 2024), quantifying relative compression against a base tokenizer; (iii) **Rényi entropy and efficiency** (Zouhar et al., 2023), assessing information density and vocabulary utilization; and (iv) **Bytes per token** (Kocetkov et al., 2022), reflecting memory and storage efficiency. All metrics are reported as micro-averages per line at the language level. Formal definitions are provided in Appendix D.

As shown in Table 3, MUTANT-Indic achieves state-of-the-art fertility scores across most languages, consistently yielding the lowest token-to-word ratios among nine tokenizers with strong Indic support (see Appendix Table 23 for extended comparisons). This indicates substantially reduced fragmentation, particularly for morphologically rich scripts. We also evaluate our Stage-1 tokenizer (trained with BPE on the same data and LLaMA-4 pretokenization). As shown in Table 24 in Appendix, our Stage-1 tokenizer, already achieves state-of-the-art (SOTA) performance across most Indic languages. Bytes-per-token results (Table 4) show that MUTANT-Indic achieves higher values across languages, reflecting more information-dense tokens and improved sequence compactness. Normalized Sequence Length scores (Table 5) further confirms that MUTANT-Indic produces shorter tokenized sequences relative to baseline tokenizers, indicating superior compression efficiency. Finally, Rényi entropy and efficiency results (Table 7) demonstrate that MUTANT-Indic achieves consistently higher efficiency across languages, reflecting effective and balanced utilization of the vocabulary. Collectively, these intrinsic results establish MUTANT-Indic as a robust and efficient tokenizer across diverse scripts and languages.

4.2 Extrinsic Evaluation

We also evaluate the downstream model performance (see Table 6) by pretraining LLaMA-3.2 1B models using two tokenizers: i) MUTANT-Indic, our proposed tokenizer optimized for morphologically meaningful segmentation in Indic and multilingual settings, and (ii) LLaMA-4 tokenizer, chosen for comparable vocabulary size and widespread use. Both models were trained on the same dataset in iso-compute setting to ensure a fair comparison. More details in the Appendix B. We find that our tokenizer shows competitive performance across the English and Indic benchmarks. We additionally re-

Tokenizer (↑)	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
Gemma-3	6.37	**10.45**	5.87	2.33	6.75	4.36	5.29	6.31	9.16	7.01	6.73	6.42	7.57	6.23	8.90	8.31	3.76	4.62	6.66	2.59	3.87	9.60	6.82	5.55
GPT-oss	6.36	7.35	5.27	2.77	6.04	4.55	5.02	6.68	7.83	6.54	6.74	6.11	7.43	5.34	6.94	8.04	2.65	4.83	5.79	1.03	4.46	7.56	6.41	5.28
LLaMA-4	3.84	6.05	4.99	**2.85**	5.70	4.53	4.84	4.69	7.37	6.03	5.33	5.39	5.26	4.71	6.49	6.84	1.58	4.05	5.45	1.48	3.69	4.10	4.43	4.54
Sarvam-2B	3.92	9.42	5.70	1.95	6.16	3.65	4.55	7.62	8.92	5.29	9.07	5.83	8.63	2.81	9.46	7.20	7.17	7.95	6.03	1.02	1.02	9.74	8.46	1.00
Sutra	8.04	8.50	5.44	1.97	6.39	5.15	4.98	7.36	8.33	7.00	8.38	5.88	8.75	5.36	8.35	8.45	7.73	8.76	6.04	**6.59**	3.49	9.38	8.04	5.15
MUTANT-Indic	**9.12**	10.15	**8.18**	2.84	**7.86**	**5.44**	**6.29**	**8.95**	**11.01**	**8.59**	**10.30**	**7.80**	**11.33**	**5.67**	**11.11**	**10.39**	**10.07**	**9.40**	**8.70**	3.60	**5.40**	**11.32**	**10.70**	**5.55**

Table 4: Bytes-per-token score (↑) comparison for Indic focused and good support tokenizers across languages here. MUTANT-Indic performs best in 22 of 24 languages.

Tokenizer (↓)	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
Gemma-3	0.63	**0.59**	0.87	1.31	0.91	1.06	0.94	0.76	0.83	0.93	0.81	0.89	0.73	0.81	0.76	0.83	0.44	0.89	0.84	0.59	0.99	0.45	0.67	**0.85**
GPT-oss	0.63	0.83	0.95	1.03	0.96	1.00	0.96	0.71	0.94	0.95	0.79	0.90	0.72	0.89	0.94	0.85	0.60	0.85	0.94	1.43	0.83	0.56	0.71	0.88
Sutra	0.55	0.74	0.93	2.09	0.92	0.89	0.96	0.68	0.92	0.91	0.67	0.94	0.65	0.92	0.84	0.82	0.24	0.51	0.91	**0.26**	1.10	0.47	0.59	0.90
Sarvam	0.99	0.66	0.91	1.50	1.00	1.27	1.13	0.64	0.85	1.19	0.62	0.99	0.65	2.19	0.72	0.96	0.24	0.54	0.93	1.45	3.63	0.45	0.56	4.25
MUTANT-Indic	**0.45**	0.60	**0.65**	**0.94**	**0.78**	**0.85**	**0.82**	**0.54**	**0.68**	**0.80**	**0.53**	**0.76**	**0.50**	**0.91**	**0.61**	**0.67**	**0.18**	**0.45**	**0.66**	0.45	**0.72**	**0.38**	**0.44**	0.86

Table 5: NSL score (↓) comparison for Indic focused and Good Indic support tokenizers across languages here. MUTANT-Indic performs best in 23 of 24 languages. An extended version in Table 22 (Appendix).

Dataset	LLaMA-4	MUTANT-Indic
English Benchmarks		
HellaSwag	0.353	**0.357**
CommonsenseQA	**0.206**	0.204
OpenBookQA	0.216	**0.218**
Winogrande	0.504	**0.510**
GSM8K	0.016	**0.018**
ARC Easy	0.623	**0.630**
ARC Challenge	0.291	**0.292**
MMLU	**0.252**	0.249
DROP	**0.048**	0.036
Average	**0.279**	**0.279**
Indic Benchmarks		
Indic COPA	0.544	**0.556**
Indic Sentiment	0.524	**0.551**
Indic XNLI	**0.347**	0.346
Indic Paraphrase	0.534	**0.539**
MILU (Indic Multi-turn LU)	**0.261**	0.258
ARC Challenge (Indic)	0.236	**0.244**
TriviaQA (Indic)	**0.268**	0.262
Average	0.388	**0.394**

Table 6: Extrinsic evaluation of MUTANT-Indic vs LLaMA-4 on *English* and *Indic benchmarks*.

	Gemma-3	GPT-OSS	LLaMA-4	Sarvam	Sutra	MUTANT-Indic
Entropy ↓	20.70	20.81	21.09	20.71	20.62	**20.42**
Efficiency ↑	0.22	0.19	0.14	0.21	0.23	**0.28**

Table 7: Rényi's Entropy and Efficiency across top Indic tokenizers. Higher efficiency indicates better balance between vocabulary capacity and token usage.

Model	TTFT (ms) ↓	OTPT (tokens/s) ↑
LLaMA-4	19.17 ± 0.15	117.99
MUTANT-Indic	**18.98 ± 0.36**	**169.42**

Table 8: Inference latency comparison of 1B models trained with LLaMA-4 and MUTANT-Indic tokenizers.

port Bits-per-Character in Appendix C.6, which remains meaningful even near random accuracy. We also trained a model using the Stage-1 tokenizer, which also attains strong downstream performance. Table 26 in Appendix shows that the Stage-1 tokenizer itself constitutes a strong and competitive baseline.

The pretraining corpus (Table 17 in Appendix) balances coverage and domain diversity. It combines web-scale sources (Nemotron CC) for general context with structured data including MegaMath (Zhou et al., 2025), StackV2 (Lozhkov et al., 2024), synthetic generations, and books. Indic-language content constitutes roughly 20% of the corpus, drawn from Indic CC, Wikipedia, and Sangraha Verified (Khan et al., 2024), providing sufficient signal to evaluate cross-lingual and morphologically rich representation quality.

4.3 Impact on latency and throughput

Next, we evaluate how tokenization impacts end-to-end model efficiency. We train two 1B-parameter models under identical conditions: one with our tokenizer and one with the LLaMA tokenizer of similar vocabulary size. We then evaluate inference efficiency over 200 samples spanning Indic languages and English, with varying input lengths. Latency[7] was measured using standard metrics, including Time-To-First-Token (TTFT), Output Throughput (OTPT), and Input Sequence Length (ISL), across 200 instances (See Appendix C.4 for details) with 5 warm-up requests and results averaged over 10 runs. Experiments were done on 8 H100 GPUs using Triton Inference Server as backend, with a maximum generation limit of 256 new tokens. Our tokenizer yields clear efficiency gains (Table 8) which stem from improved compression: shorter token sequences encode more information per token, thereby lowering per-request computation without

Metric	ar	bn	deva	en	gu	ka	ml	pa	ta	te
Data size (MB)	106	396	2200	3590	124	644	580	307	616	617
Percentage	1.12	4.18	23.25	37.94	1.31	6.81	6.13	3.24	6.51	6.52
Vocab %	2.69	6.32	20.89	32.92	2.38	7.82	6.76	4.68	7.04	8.50

Table 9: Script-specific training data size (Total corpus size 9.4 GB) and resulting vocabulary % distribution.

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[7] `https://tinyurl.com/4e7nh7c8`

compromising expressivity. Overall, this demonstrates that tokenizer design directly shapes not only pretraining efficiency but also real-world deployment latency, making it a critical factor for practical model performance.

4.4 Vocabulary Allocation: Explicit vs. Corpus-Driven

We compare explicit vocabulary merging with corpus-driven joint training under script-aware budget constraints. Explicitly merging script-specific tokenizers leads to fragmented segmentation and higher fertility due to cross-script interference (Table 10). In contrast, corpus-driven joint training naturally aligns vocabulary allocation with data distribution (Table 9), achieving lower fertility and outperforming merged and public baselines (Table 3). These results indicate that joint, corpus-driven training is a more effective and scalable strategy.

Tokenizer	as	bn	hi	mai	mr	san	te
Individual	2.05	2.13	**1.21**	**1.35**	1.75	**2.49**	**1.40**
Merged	2.32	2.14	1.55	1.57	1.73	2.79	1.95
MUTANT-Indic	**1.85**	**1.74**	1.23	1.58	**1.63**	2.59	1.88

Table 10: Fertility comparison (↓) between individual script tokenizers and the merged tokenizer across selected Indic languages. Lower values are better.

Dataset	w/ Original LLaMA-4	w/ MUTANT-Indic
English Benchmarks		
Winogrande	0.60	**0.61**
GSM8K	**0.05**	**0.05**
ARC Challenge	**0.40**	0.39
MMLU	**0.32**	0.29
Average	**0.34**	**0.34**
Indic Benchmarks		
Indic COPA	**0.58**	0.56
Indic Sentiment	0.82	**0.85**
Indic XNLI	**0.35**	0.34
Indic Paraphrase	**0.57**	0.53
Average	**0.58**	0.57

Table 11: Performance comparison on English and Indic benchmarks in Continual Pretraining (CPT) setting of LLaMA-3.2 1B model (best scores in bold).

4.5 Quality Analysis: Undertrained Tokens

We analyze under-trained "Glitch" tokens in our tied-embedding LLaMA-3.2-1B models trained with both the MUTANT-Indic tokenizer and a comparable BPE tokenizer of similar vocabulary size trained on the same corpus. Both tokenizers share the first 90% of the vocabulary. The MUTANT-Indic tokenizer switches to multi-word training for the last 10% whereas the base BPE tokeniser continues standard subword training. Following Land and Bartolo (2024) to construct a reference for unused embeddings, we introduced a small set of dummy tokens into the vocabulary that have zero occurrences in the training data. Their embeddings were averaged to obtain a mean reference vector. We then retrieve the top-K nearest neighbors (cosine distance), which represent potential "glitch" tokens (Geiping et al., 2024). As shown in Figure 6 (in the Appendix C.3), the MUTANT-Indic tokenizer produces far fewer such glitch tokens than the base BPE tokenizer. These results suggest that incorporating multi-words promotes more efficient utilization of the vocabulary, while purely subword-based tokenizers overfit in the long tail, yielding a higher proportion of under-trained tokens.

4.6 Can we replace Opensource model tokenizer with MUTANT-Indic?

Following ReTok (Gu et al., 2024), we replace the tokenizer of a pre-trained LLaMA-3.2-1B model (denoted LLaMA-3.2-ORIG) (Grattafiori et al., 2024) with MUTANT-Indic (referred as LLaMA-3.2-MUTANT-Indic). Let V_{orig} and $V_{\text{MUTANT-Indic}}$ denote their corresponding vocabularies. For a token $t \in V_{\text{MUTANT-Indic}}$, we initialize its embedding $E_{\text{init}}(t)$ as: if $t \in V_{\text{orig}} \cap V_{\text{MUTANT-Indic}}$, then $E_{\text{init}}(t) = E_{\text{orig}}(t)$, its embedding from the pre-trained model, otherwise, if $t \in V_{\text{MUTANT-Indic}} \setminus V_{\text{orig}}$ and decomposes under the original tokenizer into $(t_1, \ldots, t_k)$, then $E_{\text{init}}(t) = \frac{1}{k} \sum_{i=1}^{k} E_{\text{orig}}(t_i)$.

We then continually pretrained the LLaMA-3.2-MUTANT-Indic model, keeping just the embedding and LM head layers trainable, on a 40B-token corpus comprising English, Indic, code, and mathematics (see Appendix for details). As seen in Table 11, the LLaMA-3.2-MUTANT-Indic model performs competitively with the original LLaMA-3.2-ORIG. This suggests that, in addition to pretraining-from-scratch settings, an optimized multilingual tokenizer, such as MUTANT-Indic, could also be leveraged in opensource models through CPT (Continual Pretraining (Chen et al., 2024)) leading to significant throughput gains (see Table 8).

5 Ablation studies

Two-Stage vs. One-Stage: Controlling Vocabulary Recently, BoundlessBPE (Schmidt et al., 2024) also explored a one-stage training paradigm in which pre-tokenization is governed by a fixed regular expression, enabling the direct learning of multiword units in a single pass for English lan-

Tokenizer	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd	Avg
Single-stage (200K)	1.86	1.76	2.05	1.75	1.62	1.37	2.20	1.86	1.39	1.39	2.19	1.61	**2.29**	2.30	1.66	1.67	1.69	1.49	2.68	**3.61**	1.56	2.12	1.88	1.54	1.90
Two-stage (180K/200K)	**1.85**	**1.74**	**2.04**	**1.47**	**1.45**	**1.12**	**2.17**	**1.77**	**1.23**	**1.21**	2.19	**1.58**	2.30	**2.28**	**1.63**	**1.62**	**1.65**	**1.39**	**2.59**	3.72	**1.45**	2.12	1.88	**1.44**	**1.83**

Table 12: Fertility score (↓) for single vs two-stage curriculum training (same evaluation data as Section 3.4).

Parameter	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd	Average
Data size																									
1G	3.02	2.32	2.71	1.62	1.64	1.33	1.97	1.62	1.50	1.43	2.16	1.85	2.83	2.62	1.72	2.13	1.68	1.50	2.46	13.02	1.43	1.92	1.82	1.91	2.42
5G	1.71	1.93	2.58	1.63	1.58	1.33	2.18	1.72	1.40	1.36	2.04	1.57	2.43	2.28	1.68	1.48	1.61	1.57	2.48	4.74	1.30	2.02	1.87	1.43	1.91
10G	1.83	1.74	1.99	1.54	1.56	1.33	2.17	1.83	1.36	1.36	2.15	1.56	2.24	2.27	1.61	1.59	1.65	1.47	2.51	3.60	1.45	2.08	1.83	1.47	**1.80**
25G	1.75	1.84	2.56	1.62	1.57	1.33	2.15	1.78	1.39	1.36	2.04	1.56	2.32	2.23	1.67	1.47	1.63	1.55	2.45	3.92	1.31	2.01	1.86	1.34	1.86
30G	1.76	1.84	2.32	1.62	1.57	1.33	2.13	1.78	1.39	1.36	2.03	1.57	2.31	2.24	1.67	1.47	1.63	1.54	2.45	4.02	1.31	2.00	1.87	1.35	1.86
50G	1.72	1.82	2.25	1.60	1.57	1.34	2.14	1.82	1.39	1.36	2.03	1.58	2.28	2.22	1.69	1.49	1.64	1.52	2.44	4.54	1.31	2.01	1.87	1.34	1.87
Transition point																									
60	1.91	1.80	2.05	1.39	1.38	1.04	2.16	1.77	1.16	1.15	2.17	1.53	2.30	2.29	1.56	1.58	1.68	1.39	2.48	3.89	1.43	2.11	1.86	1.45	1.81
75	1.91	1.79	2.05	1.41	1.38	1.04	2.16	1.77	1.16	1.15	2.16	1.53	2.30	2.28	1.56	1.58	1.68	1.39	2.47	3.91	1.43	2.10	1.86	1.45	1.81
80	1.89	1.78	2.03	1.41	1.38	1.05	2.15	1.77	1.16	1.16	2.14	1.53	2.28	2.26	1.56	1.57	1.67	1.39	2.46	3.83	1.42	2.08	1.83	1.44	1.80
85	1.87	1.77	2.01	1.43	1.39	1.06	2.13	1.76	1.17	1.16	2.13	1.53	2.26	2.25	1.56	1.56	1.66	1.39	2.46	3.78	1.42	2.07	1.82	1.44	1.80
90	1.85	1.74	2.04	1.47	1.45	1.12	2.17	1.77	1.23	1.21	2.19	1.58	2.30	2.28	1.63	1.62	1.65	1.39	2.59	3.72	1.45	2.12	1.88	1.44	1.83
95	1.85	1.75	1.98	1.47	1.42	1.10	2.13	1.74	1.21	1.20	2.12	1.53	2.23	2.24	1.56	1.56	1.66	1.41	2.46	3.68	1.43	2.06	1.81	1.44	1.79
Vocab size																									
162K/180K	1.89	1.78	2.08	1.48	1.47	1.13	2.21	1.80	1.24	1.22	2.22	1.60	2.35	2.27	1.65	1.65	1.68	1.42	2.62	3.84	1.48	2.16	1.91	1.47	1.86
180K/200K	1.85	1.74	2.04	1.47	1.45	1.12	2.17	1.77	1.23	1.21	2.19	1.58	2.30	2.27	1.63	1.62	1.65	1.39	2.59	3.72	1.45	2.12	1.88	1.44	1.82
202K/225K	1.81	1.70	1.99	1.44	1.43	1.10	2.14	1.72	1.20	1.19	2.14	1.55	2.24	2.21	1.59	1.59	1.60	1.36	2.55	3.59	1.41	2.08	1.82	1.41	1.79
225K/250K	1.78	1.67	1.95	1.42	1.42	1.09	2.11	1.69	1.19	1.17	2.10	1.53	2.20	2.17	1.57	1.57	1.57	1.34	2.52	3.45	1.38	2.04	1.77	1.38	1.75

Table 13: Ablation of tokenizer training data size (in GB), transition point (as a % of vocab size 200K), vocab size ($t = 90\%$) and its impact on fertility score (↓). We use the same evaluation data as described in Section 3.4.

guage. Our approach instead introduces a two-stage procedure. We replicate the one-stage setup of BoundlessBPE using its released regex and compare against our strategy. Our method consistently achieves lower fertility across the top 10 Indic languages and English (Table 12). Overall, the comparison highlights a clear trade-off: while one-stage methods capture surface-level patterns indiscriminately, our two-stage design balances efficiency and linguistic integrity by decoupling subword and multiword learning.

Dataset Size Similar to Reddy et al. (2025), we study the effects of scaling training data in Stage 1 of our training. Table 13 shows that the performance plateaus after 10G of data.

Transition Point We ablate the transition point t (Section 3.2) at which training shifts from subword to cross-word merges. Varying t reveals a clear trade-off: early transitions favor frequent multiword expressions but weaken morphological coverage, while late transitions preserve subwords at the cost of longer sequences. Across Indic and non-Indic languages, intermediate values of 85-90% t yields the best balance, improving token efficiency and cross-lingual consistency (Table 13).

Vocabulary Size Vocabulary size strongly influences tokenization-model efficiency with trade-offs. Smaller vocabularies yield finer subword units that generalize well to unseen words but with increased compute costs. Larger vocabularies shorten sequences by encoding frequent forms as single tokens, but waste capacity on rare items, inflate embeddings and softmax layers (Shazeer et al., 2017), and have bias toward high-resource languages, hurting multilingual balance. With the same transition point at 90%, we found no significant impact on fertility scores beyond 200K (Table 13).

Effect of Normalization Prior works show that unicode normalization is crucial for multilingual settings (Karthika et al., 2025b), which reduces token fragmentation and inflated vocabulary size. Table 25 (in Appendix) shows that NFKC yielded marginal but consistent gains by unifying character forms. Accordingly, we adopt NFKC to reduce variability and improve tokenizer robustness.

6 Conclusion

In this work, we revisit tokenization as a central design choice for multilingual LLMs and introduce MUTANT, a principled and general recipe for multilingual tokenizer training. We demonstrate the effectiveness of this framework with MUTANT-Indic, which achieves SOTA performance across Indic languages through systematic analyses of vocabulary size, data distribution, language-specific pre-tokenization, and multi-stage learning. Extensive evaluation across intrinsic efficiency metrics, downstream tasks, ablations, and inference latency, in both pretraining-from-scratch and continual pretraining settings, highlights consistent gains in efficiency and deployment cost. We will additionally publicly release our evaluation framework to support reproducibility and future research.

Limitations

While MUTANT-Indic achieves strong intrinsic efficiency gains and practical throughput improvements, our study has several limitations. First, although we evaluate across 22 Indic languages, English, and code, the analysis is restricted to these language families, and extending the framework to other low-resource or non-Indic languages remains future work. Second, downstream evaluations are limited to models up to 1B parameters due to compute constraints; while prior scaling-law results suggest these gains extrapolate to larger models, we do not validate this empirically. Third, although we analyze morphology-aware pre-tokenization, we do not integrate it into the final tokenizer due to its high inference latency, leaving efficient implementations to future work. Finally, while our evaluation framework standardizes intrinsic metrics, it does not capture all linguistic dimensions relevant to downstream tasks.

Ethical Considerations

Ethics Statement This work focuses on the responsible development of multilingual tokenization methods for Indian languages. We did not collect or utilize any sensitive or Personally Identifiable Information (PII). AI tools (like ChatGPT) were used to refine text writing and section phrasing in the paper. All external datasets, libraries, and tools employed in this work are appropriately acknowledged through citations. Since the study did not involve personal, medical, or otherwise sensitive information, formal IRB approval was not required. Throughout the process, we aimed to minimize biases that could disadvantage low-resource languages. We provide our exhaustive study to advance the development of inclusive and efficient multilingual language models.

Reproducibility Statement To promote transparency and reproducibility, we will release the artifacts publicly to benchmark performance of Indian tokenizers, along with detailed documentation. Detailed records of experimental setups, hyperparameters, and evaluation protocols are maintained to allow replication of our results with the implementation details in the Appendix. In addition, we provide ablation studies to facilitate fair benchmarking and enable future research on Indian and multilingual tokenization.

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Appendix

A Language Details

We provide more details about the 22 languages and corresponding scripts considered in our work in Table 14. Additionally, ISO code mapping is also provided in Table 15.

B Implementation

B.1 Tokenizer implementation

Our training code for the tokenizer is based on the open implementation of SuperBPE[8] using HuggingFace library (Jain, 2022). We first curate a multilingual corpus of ∼50G from OLMo (OLMo et al., 2025), Wikipedia[9], books, PDFs, Common Crawl, and the Sangraha dataset (Khan et al., 2024) where we sample our tokenizer training data from varied sources to get enough representation of the different languages individually. English data was mostly sampled from OLMo and code data from Stackv2 (Lozhkov et al., 2024). The common crawl corpus was language-identified using fastText LID, deduplicated using MinHash, filtered for boilerplate and HTML artifacts, normalized using Unicode NFKC and script-validated to reduce cross-script contamination, similar to FineWeb (Penedo et al., 2024). The final MUTANT-Indic tokenizer uses a shared vocabulary of 200K tokens, distributed across language scripts and is trained on 10GB of multilingual high quality data.

In our work, we also explored merging tokenizers based on the default priority based BPE in SentencePiece[10]. While we explored implementing the multi-word two stage curriculum in the SentencePiece, we found that it was not trivial. On the other hand, HuggingFace showed issues with the merging strategy. We thus relied on different implementations for different approaches.

B.2 Training details

We provide more details about our training setup as discussed in Section 4.2. Each model was trained for 50B tokens under matched hyperparameters (learning rate, batch size, training steps), aligning FLOPs to isolate tokenizer effects. The evaluation was performed using `lm-eval-harness` (Gao et al., 2024) across standard English benchmarks

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[8] `https://github.com/PythonNut/superbpe/tree/main`

[9] `https://en.wikipedia.org/wiki/`

[10] `https://github.com/google/sentencepiece`

Family	Script	Languages
Indo-Aryan	Devanagari	Hindi, Marathi, Maithili, Dogri, Konkani, Sanskrit, Nepali, Kashmiri
	Bengali (bn)	Assamese, Bengali
	Gurmukhi (pa)	Punjabi
	Arabic (ar)	Urdu, Sindhi
Dravidian	Kannada (kn)	Kannada
	Malayalam (ml)	Malayalam
	Tamil (ta)	Tamil
	Telugu (te)	Telugu
Tibeto-Burman	Devanagari	Bodo
	Meitei Mayek	Manipuri (Meitei Mayek script)
Austroasiatic	Ol Chiki (sat)	Santali

Table 14: Linguistic composition of the 22 scheduled Indian languages analyzed in this work, with their corresponding scripts.

Code	Language	Code	Language	Code	Language
as	Assamese	bn	Bengali	brx	Bodo
doi	Dogri	gu	Gujarati	hi	Hindi
kn	Kannada	ks	Kashmiri	gom	Konkani
mai	Maithili	ml	Malayalam	mni	Manipuri
mr	Marathi	ne	Nepali	or	Odia
pa	Punjabi	san	Sanskrit	sat	Santali
snd	Sindhi	ta	Tamil	te	Telugu
ur	Urdu				

Table 15: Mapping of ISO codes to corresponding 22 Indic languages.

(MMLU, GSM8K, Winogrande, TriviaQA, HellaSwag, ARC, OpenBookQA, CommonsenseQA, DROP) and Indic benchmarks (IndicCOPA, IndicSentiment, IndicXParaphrase, IndicXNLI (Doddapaneni et al., 2023), ARC Challenge Indic (Sarvam AI, 2025), and MILU (Verma et al., 2024)). We report EM for GSM8K and TriviaQA, F1 for DROP, and Accuracy for other benchmarks. Shot settings were fixed per task: 25-shot for ARC/ARC Challenge Indic, 10-shot for HellaSwag, 5-shot for MMLU, GSM8K, and TriviaQA, and zero-shot for the remainder. This setup allows a direct assessment of how tokenizer design influences pretraining efficiency, semantic representation, and generalization across English and Indic tasks.

C Additional Discussion

C.1 Mismatch Between Loss and Task Performance

Although toknizers, incorporating multi-word often show slightly higher loss (Liu et al., 2025b) during training compared to models using traditional atomic tokenizers like SentencePiece/BPE, this does not necessarily translate to worse downstream performance. We hypothesize that this is due to two complementary factors. First, the introduction of longer or multi-word tokens such as “to the" or “as well as" increases the number of semantically overlapping candidates, making the model’s prediction space less sharply peaked. This means the model may distribute probability across several plausible completions (e.g., “to", “to the", “to be"), thereby lowering the maximum assigned probability to the correct token and inflating the cross-entropy loss. In contrast, other BPE tokenizers often yield only one atomic candidate for such function words, allowing sharper predictions with lower loss. Second, MUTANT-Indic tokenizes text into fewer, more meaningful units, so when computing the average loss per token, each mistake contributes more heavily to the total. As a result, although the model learns more compact and generalizable representations, its token-level loss appears higher. This creates a divergence between model loss and real-world task accuracy, indicating that traditional loss curves may underrepresent the representational efficiency and practical utility of compositional tokenizers like MUTANT-Indic.

C.2 Morphologically grounded token splitting

We investigate the impact of incorporating morphological information into tokenization for Indic languages (Brahma et al., 2025). The approach involves pre-processing text with a morphology analyzer to segment words into morphemes prior to training. This experiment focuses on languages in the Devanagari script.

Tokenizer	Architecture	Parameters	Data Size (B)	Learning Rate	Train Steps	Context Length	Batch Size	Vocab Size
LLaMA-4	LLaMA-3.2	1B	53.24	5×10^{-5}	68000	4096	192	201134
MUTANT-Indic	LLaMA-3.2	1B	53.18	5×10^{-5}	68000	4096	192	200008

Table 16: Pretraining configuration for different tokenizers.

Category	**Sources**	**Percentage (%)**	**Token Count (B)**
Web	Nemotron CC	30	15
Math	MegaMath	15	7.5
Code	StackV2	15	7.5
Synthetic	New Generations	10	5
Books	Archive	10	5
Indic	Indic CC	8	4
Indic	Indic Wiki	4	2
Indic	Sangraha Verified	8	4
Total		100	50

Table 17: Pretraining corpus distribution across domains and token count. Indic content is emphasized to reflect multilingual objectives.

We compare two variants: Tokenizer A, trained on raw text, and Tokenizer B, trained on morphologically segmented text using morphology analyzer (Kunchukuttan, 2020). At inference time, Tokenizer B requires the same pre-processing for consistency. Tokenizer B exhibits more semantically coherent multi-words, reflecting meaningful morpheme combinations (Figure 4, 5). This promotes better generalization across related forms and reduces the raw token-to-word ratio, as morpheme-based units are more compressible. Sample outputs (Figures 4, 5) illustrate the contrast between surface-level splits and linguistically aligned segmentations.

Despite these gains, we do not adopt this approach in our final tokenizer. The primary limitation is latency, as the pipeline requires both language identification and morphological analysis. For completeness, we evaluated a Hindi morphology-aware tokenizer augmented with a morphological analyzer (Kunchukuttan, 2020) combined with language identification (LID)[11]. We performed inference on approximately 4-5 MB of Hindi text and measured throughput over 10 runs (with 5 warm-up runs), comparing against our MUTANT-Indic tokenizer. Our tokenizer achieved 194K tokens/sec, whereas the morphology-aware tokenizer achieved 90K tokens/sec, representing a 53.28% reduction in throughput. This slowdown arises entirely from the additional LID and morphology-analysis stages, underscoring the efficiency advantages of our approach even when compared to linguistically informed baselines. Extending robust analyzers across all Indic languages also introduces engineering overhead and brittle dependencies. Nevertheless, morphology-aware tokenization remains a promising direction if fast, reliable analyzers become widely available.

C.3 More on Glitch tokens

For each tokenizer, we vary $K \in \{10, 50, 100, 150, \ldots, 400\}$ to select the top-K embeddings closest to a reference vector derived from artificially unused tokens in the vocabulary (Land and Bartolo, 2024; Geiping et al., 2024). For the MUTANT-Indic tokenizer, we count the number of multi-word tokens within the top-K. For the BPE variant, we count tokens with IDs $>$ 180,000, which corresponds to the upper 20K of the vocabulary. Both tokenizers share the first 180K IDs; the difference lies in how the final 20K IDs are utilized: MUTANT-Indic allocates this space for frequent multi-word tokens, while the BPE tokenizer continues learning subwords. This design choice allows MUTANT-Indic to more effectively utilize the tail of the vocabulary for meaningful units, whereas the BPE tokenizer exhibits overfitting in low-frequency subwords. The trend of these counts across different top-K values is visualized in Figure 6. As K increases, the fraction of multi-word tokens in MUTANT-Indic remains low but stable, while the BPE variant consistently shows a higher fraction of under-trained subwords, indicating overfitting in the residual vocabulary space.

C.4 More on Latency and Throughput Evaluation

To obtain reliable latency and throughput measurements, we constructed a 200-example multilingual inference set intended to approximate realistic LLM workloads. The set contains diverse sentence-completion style prompts representative of common generation patterns. We include 20 inputs per language across English and nine major Indic languages, ensuring balanced coverage of script diversity, lexical variation, and syntactic complexity. Table 18 presents the token-length distribution of these examples under both the LLaMA-4 tokenizer and our MUTANT-Indic, allowing a con-

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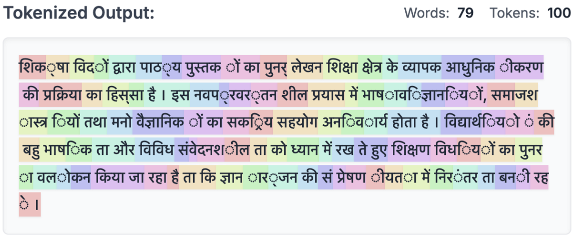
[11] `https://pypi.org/project/langdetect/`



शिक◌्षा विद◌ों द्वारा पाठ◌्य पुस्तक ◌ों का पुनर् लेखन शिक्षा क्षेत्र के व्यापक आधुनिक ◌ीकरण की प्रक्रिया का हिस्सा है । इस नवप◌्रवर◌्तन शील प्रयास में भाष◌ाव◌िज्ञान◌िय◌ों, समाजश ◌ास्त्र ◌ियों तथा मनो वैज्ञानिक ◌ों का सक्रिय सहयोग अन◌िव◌ार्य होता है । विद्यार्थ◌िय◌ो ◌ं की बहु भाष◌िक ता और विविध संवेदनश◌ील ता को ध्यान में रख ते हुए शिक्षण विध◌िय◌ों का पुनर ◌ा वल◌ोकन किया जा रहा है ता कि ज्ञान ◌ार◌्जन की सं प्रेषण ◌ीयत◌ा में निर◌ंतर ता बन◌ी रह ◌े ।

Figure 4: Tokenized output of morph-aware tokenizer

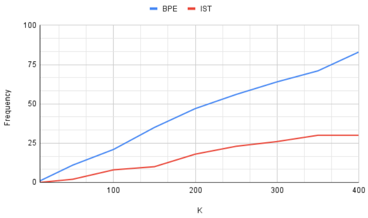


Figure 6: Trend of potential glitch tokens in upper 20K of vocabulary for different K.

trolled comparison of inference efficiency across tokenization schemes.

Table 18: Token-length statistics for the 200-example inference set. We report min, p75, p90, p99, maximum, and average token lengths.

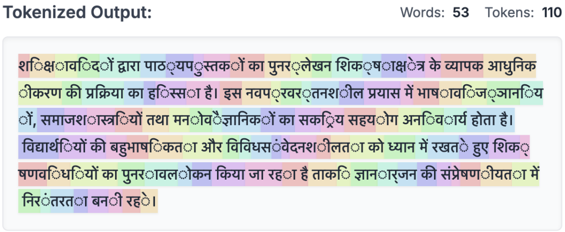
Tokenizer	**min**	**p75**	**p90**	**p99**	**max**	**avg**
Llama-4	288	805	1157	2583	2869	784
MUTANT-Indic	178	440	541	654	676	379

C.5 Details About Baseline Tokenizers

Tokenizer fertility is shaped by multiple factors including training data distribution, vocabulary construction, and underlying algorithmic choices, yet publicly available documentation on these aspects is often limited. Table 19 summarizes the vocabulary sizes, training methodologies, and any disclosed data distributions for all baseline tokenizers considered in our study.

Tokenizer	**Vocab Size**	**Training Algorithm / Framework**	**Data Distribution**
DeepSeek-R1	128K	BPE (undisclosed variant)	Not publicly disclosed
Gemma-3	262K	SentencePiece	140+ languages
GPT-OSS	200K	o200k_harmony (TikToken variant)	Not publicly disclosed
LLaMA-3.2-1B	128K	BPE / SentencePiece-based	Not publicly disclosed
LLaMA-4	200K	BPE	Not fully disclosed
Mistral-Nemo	131K	Tekken tokenizer (TikToken-based)	100+ languages; multilingual + code
Qwen-3	151K	Byte-level BPE	Not publicly disclosed
Sarvam	68K	Not publicly disclosed	Not publicly disclosed
Sutra	256K	SentencePiece (unigram/BPE hybrid)	Balanced multilingual; uniform sampling

Table 19: Summary of baseline tokenizers and publicly available training details.



श◌िक्ष◌ाव◌िद◌ों द्वारा पाठ◌्यप◌ुस्तक◌ों का पुनर◌्लेखन शिक◌्ष◌ाक्ष◌ेत्र के व्यापक आधुनिक ◌ीकरण की प्रक्रिया का ह◌िस्स◌ा है। इस नवप◌्रवर◌्तनश◌ील प्रयास में भाष◌ाव◌िज◌्ञान◌िय ◌ों, समाजश◌ास्त्र◌ियों तथा मन◌ोव◌ैज्ञानिक◌ों का सक्रिय सहय◌ोग अन◌िव◌ार्य होता है। विद्यार्थ◌ियों की बहुभाष◌िकत◌ा और विविधस◌ंवेदनश◌ीलत◌ा को ध्यान में रखत◌े हुए शिक◌् षणव◌िध◌ियों का पुनर◌ावल◌ोकन किया जा रह◌ा है ताक◌ि ज्ञान◌ार्जन की संप्रेषण◌ीयत◌ा में निर◌ंतरत◌ा बन◌ी रह◌े।

Figure 5: Tokenized output of non morph-aware tokenizer

C.6 Bits-per-Character Evaluation on Multiple Choice Benchmarks

In addition to task-level accuracy, we evaluate the language modeling quality of the models using *bits-per-character* (BPC) measured on the gold answer continuations of benchmark examples. Following Heineman et al. (2025), we compute BPC as:

$$\mathrm{BPC}(y|x) = -\frac{1}{|y|\log 2}\sum_{t=1}^{|y|}\log P(y_t \mid x, y_{<t}), \tag{1}$$

where x denotes the prompt, y is the gold continuation (correct answer text), and $|y|$ is the number of character in the continuation. Lower values indicate better modeling of the target continuation.

This metric provides a continuous measure of modeling quality that is independent of the discrete multiple-choice selection. It allows comparison of tokenizers through the likelihood assigned to the correct answers in benchmark datasets, where accuracy is near chance.

English Benchmarks Table 20 reports BPC values on several English multiple-choice benchmarks. Across these tasks, the model trained with the MUTANT-Indic tokenizer consistently achieves lower BPC compared to the model trained with the LLaMA-4 tokenizer, indicating improved likelihood modeling of the correct answer continuations.

Tokenizer	**ARC-C**	**ARC-E**	**OBQA**	**HellaSwag**	**CSQA**
MUTANT-Indic	**1.0284**	**1.2368**	**1.5774**	**0.9867**	**2.3445**
LLaMA-4	1.2575	1.6037	1.8345	0.9983	2.7398

Table 20: Bits-per-character (lower is better) on English multiple-choice benchmarks. ARC-C: ARC-Challenge, ARC-E: ARC-Easy, OBQA: OpenBookQA, CSQA: CommonsenseQA.

Indic Benchmark We further evaluate BPC on translated ARC-Challenge benchmarks across ten

Tokenizer	bn	gu	hi	kn	ml	mr	or	pa	ta	te
MUTANT-Indic	1.2747	1.3480	1.3066	1.2113	1.0298	1.3205	1.1975	1.2054	0.9317	1.1535
LLaMA-4	1.2756	1.4275	1.3254	1.3193	1.2264	1.4368	1.3694	1.3935	1.0508	1.2889

Table 21: Bits-per-character (lower is better) on ARC-Challenge across Indic languages.

Indic languages. Results are shown in Table 21. The MUTANT-Indic tokenizer generally produces lower BPC values across the evaluated languages, suggesting improved modeling efficiency for the gold answer continuations.

C.7 Stage-2 Regex Boundary Constraints

Stage 1 pre-tokenization relies on established regex-based segmentation strategies commonly used in multilingual tokenizers (e.g., GPT-2 and LLaMA-style rules). These patterns separate punctuation, normalize whitespace boundaries, and produce stable token units prior to subword learning.

Stage 2 instead applies additional regex constraints that regulate subword merges during tokenizer training. The objective is to enable learning of frequent multi-word expressions while preventing unstable token formations.

Specifically, the Stage 2 regex enforces: (i) sentence boundary preservation, preventing merges across sentence delimiters; (ii) explicit handling of Indic punctuation such as the Devanagari markers ‘।” and ‘॥” as hard boundaries; and (iii) controlled segmentation of numeric sequences.

D Metrics Definitions

Here, we discuss the different intrinsic metrics used in our evaluation framework.

D.1 Token-to-Word Ratio

The Token-to-word ratio measures the average number of tokens required to represent a single word. It captures the degree of segmentation induced by a tokenizer and is particularly informative for morphologically rich languages where excessive fragmentation increases sequence length. We report this metric to evaluate whether tokenizers balance compact representations with sufficient linguistic coverage.

D.2 Bytes-per-token

Bytes-per-token quantifies the average number of raw text bytes contained in a token. Since scripts differ substantially in character set size and encoding, this metric provides a language-agnostic measure of efficiency. Higher values indicate that tokens encode more information per unit, which reduces sequence length. We include this metric to enable direct comparison of tokenizers across writing systems.

D.3 Normalized Sequence Length

Normalized sequence length measures the average length of tokenized sequences relative to a chosen base tokenizer. Instead of reporting absolute sequence lengths, this metric highlights how much longer or shorter sequences become when compared to an established reference. It enables fairer cross-tokenizer comparisons since raw lengths can vary significantly across languages and corpora. A normalized value greater than one indicates that the tokenizer produces longer sequences than the baseline, while a value less than one reflects more compact tokenization. We include this metric to directly assess relative efficiency in sequence compression.

D.4 Reyni’s Efficiency

Rényi’s entropy measures the uncertainty of token distributions induced by a tokenizer, extending Shannon entropy by allowing different orders to emphasize frequent or rare tokens. A tokenizer with a very large vocabulary may contain many infrequent tokens that are poorly utilized, while a very small vocabulary forces overuse of common tokens. Entropy therefore reflects how effectively the vocabulary is allocated. To complement this, Rényi’s efficiency normalizes entropy with respect to vocabulary size, providing a scale-invariant view of how well the vocabulary capacity is utilized. Together, these metrics characterize both the distributional balance of tokens and the comparative efficiency of different vocabulary scales.

E Extended Results

In the main paper, due to space constraints, we limited the number of tokenizers presented. Here, we provide an extended list including all of our baseline tokenizers. Table 22 and 23 provides the NSL scores and fertility scores of the other tokenizers considered in our work. Table 25 shows the fertility scores for different normalization techniques in our MUTANT-Indic tokenizer. Additionally, we also compare the performance of two models trained with only Stage-1 and the 2-stage curriculum tokenizer in Table 26.

Table 22: Comparison of NSL scores (Base LLaMA-4) for different tokenizers across all languages.

Tokenizer (↓)	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
DeepSeek-R1	0.83	0.97	1.25	1.03	1.29	0.98	1.28	1.48	1.59	1.29	1.41	1.34	1.52	0.99	1.49	1.61	0.67	1.41	1.19	0.69	1.34	0.82	1.34	1.21
Gemma-3	0.63	0.59	0.87	1.31	0.91	1.06	0.94	0.76	0.83	0.93	0.81	0.89	0.73	0.81	0.76	0.83	0.44	0.89	0.84	0.59	0.99	0.45	0.67	0.85
GPT-OSS	0.63	0.83	0.95	1.03	0.96	1.00	0.96	0.71	0.94	0.95	0.79	0.90	0.72	0.89	0.94	0.85	0.60	0.85	0.94	1.43	0.83	0.56	0.71	0.88
LLaMA-3.2-1B	1.90	2.71	1.08	1.02	1.36	0.99	1.22	2.91	1.47	1.36	3.30	1.16	3.25	1.92	1.41	1.44	1.48	2.45	1.19	1.34	1.33	2.11	3.01	1.58
LLaMA-4	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mistral-Nemo	1.00	0.95	1.06	1.15	1.07	1.06	1.09	1.09	1.12	1.08	0.91	1.08	0.95	0.95	1.13	1.21	1.57	0.98	1.04	1.34	1.20	0.63	0.64	0.95
Qwen-3	1.68	2.37	1.78	1.11	1.85	1.03	1.72	2.59	2.65	2.16	2.69	1.97	2.57	1.72	2.35	2.47	1.19	2.37	1.92	0.96	1.37	1.63	2.45	1.63
Sutra	0.55	0.74	0.93	2.09	0.92	0.89	0.96	0.68	0.92	0.91	0.67	0.94	0.65	0.92	0.84	0.82	0.24	0.51	0.91	0.26	1.10	0.47	0.59	0.90
Sarvam	0.99	0.66	0.91	1.50	1.00	1.27	1.13	0.64	0.85	1.19	0.62	0.99	0.65	2.19	0.72	0.96	0.24	0.54	0.93	1.45	3.63	0.45	0.56	4.25
MUTANT-Indic	0.45	0.60	0.65	0.94	0.78	0.85	0.82	0.54	0.68	0.80	0.53	0.76	0.50	0.91	0.61	0.67	0.18	0.45	0.66	0.45	0.72	0.38	0.44	0.86

Table 23: Fertility scores across tokenizers and languages. Lower is better.

Tokenizer (↓)	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
DeepSeek-R1	3.54	2.88	4.23	1.53	2.66	1.34	3.68	4.92	3.02	2.49	6.01	3.21	7.95	2.67	4.17	3.97	7.13	4.48	5.07	6.12	2.82	4.92	6.13	2.17
Gemma3	2.65	1.69	2.84	1.79	1.69	1.39	2.60	2.50	1.47	1.48	3.34	1.91	3.45	2.07	2.03	2.03	4.42	2.83	3.37	5.16	2.03	2.50	2.94	1.44
GPT-OSS	2.66	2.41	3.17	1.51	1.89	1.33	2.73	2.37	1.72	1.58	3.34	2.01	3.51	2.41	2.61	2.10	6.26	2.71	3.89	13.01	1.76	3.18	3.13	1.51
Llama-3.2-1B	8.44	8.08	3.64	1.51	2.92	1.35	3.46	9.95	2.74	2.70	14.44	2.79	16.26	5.31	3.90	3.52	15.68	7.88	4.86	12.15	2.85	12.25	13.68	2.73
LLaMA-4	4.40	2.93	3.34	1.46	2.00	1.34	2.84	3.37	1.83	1.72	4.23	2.28	4.95	2.73	2.79	2.46	10.51	3.23	4.12	9.04	2.13	5.87	4.53	1.76
Mistral-Nemo	4.28	2.82	3.52	1.75	2.12	1.41	3.08	3.63	2.05	1.82	3.84	2.48	4.82	2.67	3.10	2.97	16.92	3.04	4.34	12.16	2.51	3.67	3.71	1.65
Qwen3-32B	7.47	7.11	6.10	1.68	4.05	1.41	5.08	8.87	4.86	3.70	11.48	4.53	12.77	4.76	6.56	6.10	12.37	7.60	8.04	8.81	2.95	9.69	11.10	2.90
Sarvam-2B	4.24	1.91	2.92	2.14	1.85	1.66	3.01	2.11	1.53	1.91	2.53	2.11	3.19	4.60	1.94	2.35	2.43	1.67	3.78	13.07	7.62	2.49	2.63	7.93
Sutra	2.12	2.07	3.06	2.12	1.78	1.17	2.68	2.15	1.62	1.48	2.71	2.08	3.10	2.40	2.18	2.01	2.24	1.50	3.76	2.03	2.23	2.58	2.77	1.55
MUTANT-Indic	1.85	1.74	2.04	1.47	1.45	1.12	2.17	1.77	1.23	1.21	2.19	1.58	2.30	2.28	1.63	1.62	1.65	1.39	2.59	3.72	1.45	2.12	1.88	1.44

Regex	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
MUTANT-Indic (Stage-1)	1.83	1.74	1.99	1.54	1.56	1.33	2.17	1.83	1.36	1.36	2.15	1.56	2.24	2.27	1.61	1.59	1.65	1.47	2.51	3.60	1.45	2.07	1.83	1.47
MUTANT-Indic (Stage-2)	1.85	1.74	2.04	1.47	1.45	1.12	2.17	1.77	1.23	1.21	2.19	1.58	2.30	2.28	1.63	1.62	1.65	1.39	2.59	3.72	1.45	2.12	1.88	1.44

Table 24: Fertility scores (↓) comparing our tokenizer after Stage 1 and Stage 2 curriculum. Stage-1 tokenizer corresponds to: cleaned corpus, standard BPE, LLaMA-4 regex, identical vocabulary and data size. The only difference between this baseline and our final MUTANT-Indic is the Stage-2 curriculum phase.

Tokenizer	as	bn	brx	code	doi	eng	gom	gu	hi	kas	kn	mai	ml	mni	mr	nep	or	pa	san	sat	snd	ta	te	urd
NFC	1.8520	1.7449	2.0412	1.4658	1.4520	1.1167	2.1741	1.7664	1.2250	1.2042	2.1845	1.5761	2.3025	2.2421	1.6273	1.6241	1.6464	1.3915	2.5859	3.7170	1.4515	2.1226	1.8754	1.4371
NFD	1.8518	1.7454	2.0413	1.4665	1.4521	1.1168	2.1661	1.7667	1.2252	1.2044	2.1905	1.5765	2.3019	2.2487	1.6274	1.6246	1.6465	1.3917	2.5864	3.7170	1.4523	2.1227	1.8757	1.4377
NFKC	1.8512	1.7430	2.0409	1.4647	1.4520	1.1155	2.1738	1.7644	1.2239	1.2041	2.1812	1.5762	2.2991	2.2327	1.6258	1.6234	1.6420	1.3884	2.5855	3.7172	1.4505	2.1200	1.8724	1.4369

Table 25: Fertility scores with NFC, NFD, NFKC normalization for all languages.

Table 26: Comparison of downstream performance between MUTANT-Indic (Stage-1) and MUTANT-Indic (Stage-2).

English Benchmarks			Indic Benchmarks		
Dataset	MUTANT-Indic-Stage-1	MUTANT-Indic-Stage-2	Dataset	MUTANT-Indic-Stage-1	MUTANT-Indic-Stage-1
HellaSwag	0.348	0.357	Indic COPA	0.556	0.556
CommonsenseQA	0.193	0.204	Indic Sentiment	0.557	0.551
OpenBookQA	0.214	0.218	Indic XNLI	0.366	0.346
Winogrande	0.515	0.510	Indic Paraphrase	0.562	0.539
GSM8K	0.021	0.018	MILU (Indic Multi-turn LU)	0.265	0.258
ARC Easy	0.625	0.630	ARC Challenge (Indic)	0.247	0.244
ARC Challenge	0.279	0.292	TriviaQA (Indic)	0.268	0.262
MMLU	0.255	0.249			
DROP	0.042	0.036			
Average	0.277	0.279	Average	0.403	**0.394**