PARAMANU: Monolingual LMs for Low-Resource, Morphologically-Rich Indian Languages Trained from Scratch

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Abstract

Multilingual LLMs are very expensive to pretrain, suffer from data and language-dependent imbalance, exhibit English-centric bias, tokenizer's over-segmentation for morphologically rich low-resource languages, and curse of multilinguality. In this work, we study whether we can develop small (sub-400 million parameters) but competitive monolingual generative models from scratch for low-resource morphologically rich Indian languages. One of our primary objectives is affordability, and hence, we impose that the training be done on a *single GPU* and a budget of *less than $1,000*. The PRAMAMANU models we designed outperform all the major, larger multilingual models, under the above training constraints, on the 5 most spoken Indian languages (Bengali, Hindi, Marathi, Tamil and Telugu).

1 Introduction

Despite the existence of over 7,000 languages globally, current NLP and GenAI technologies remain heavily skewed towards English and other high-resource European languages, leaving a significant portion of the world's population, particularly speakers of global south languages, underserved (Schwartz, 2022; Nekoto et al., 2020; Choudhury, 2023). Indian languages, spoken by approximately 1.4 billion people, are among the most neglected, despite the fact that Hindi and Bangla are respectively the 5th and 6th most spoken[1] languages globally. Challenges such as lack of high-quality datasets, poor tokenization, and limited representation in pretraining corpora render Indian languages "low-resource" (Tsvetkov, 2017; Singh, 2008); being morphologically rich further impedes their performance (Joshi et al., 2020; Goyal et al., 2022; Nigatu et al., 2024).

Large language models (LLMs) like LLaMa (Touvron et al., 2023), GPT-NeoX (Black et al., 2022), ChatGPT and PaLM (Chowdhery et al., 2023) are predominantly trained on English and Latin-script languages, showing significantly degraded performance on Indian and other low-resource languages (Bang et al., 2023; Lai et al., 2023a). This disparity persists even in multilingual decoder-only LLMs (e.g., Bloom (Workshop et al., 2023), xGLM (Lin et al., 2022), mGPT (Shliazhko et al., 2024), Aya23 (Aryabumi et al., 2024), Llama-3 (Grattafiori et al., 2024), Llama-3.2). As these models have English-centric bias, and "think in English" (Schut et al., 2025; Guo et al., 2024a) often causes them to perform worse in non-Latin script languages (Shafayat et al., 2024; Shi et al., 2023; Huang et al., 2023; Bang et al., 2023). They also suffer from data and language-dependent imbalance (Dangarikar et al., 2024), a language-fits-all tokenizer resulting in bias, over-segmentation (Ahuja et al., 2023), unfair representation (Pfeiffer et al., 2021), language confusion (Marchisio et al., 2024) and reduced fluency (Guo et al., 2024b). This results in high token fertility for Indian languages, and increased inference and training costs[2].

Adapting existing LLMs to Indian languages through continual pretraining (Zheng et al., 2024a; Ji et al., 2025; Alves et al., 2024) and fine-tuning (Lu et al., 2024; Zheng et al., 2024b) presents multiple challenges, including requirement of large data and compute, vocabulary extension inefficiencies, embedding alignment, and risk of catastrophic forgetting (Zheng et al., 2024a; Ahuja et al., 2023). Moreover, this adaptation pipeline assumes the suitability of English-centric foundations, which may not generalize well to Indian typologies and scripts. Thus, in this work, we address the question: *Is there a space for language-specific models trained under strong constraints*[3]

[1] https://www.babbel.com/en/magazine/the-10-most-spoken-languages-in-the-world

[2] A complete related work section is provided in Appendix A.

[3] Typically, a single GPU and <$1,000 budget for training.

for low-resource, morphologically rich Indian languages?

To answer this question, we propose building dedicated monolingual generative models for five most spoken Indian languages: Bangla (Bengali), Hindi, Marathi, Tamil, and Telugu. By training from scratch using only language-specific Indian data and developing low-fertility tokenizers, we aim to: (i) avoid dataset imbalance across languages, (ii) more easily preprocess and clean smaller datasets, resulting in good-quality data even for low-resource languages, and (iii) benefit from language-specific tokenizers to reduce training, inference cost and latency during inference.

We summarize our contributions as follows:

1. We show that, for the five most spoken Indian languages, under constraints on the compute and budget available, which translate as constraints on the training corpus and model sizes, one should not use as large as possible multilingual models but rather rely on smaller, monolingual models. The models and data used are open-source and pave the way for new studies on language models for Indian languages,
2. We developed morphology-aligned, low-fertility Indian tokenizers combining Unigram tokens into BPE tokenizer,
3. We cleaned the training corpus and developed novel instruction-tuning datasets in Bangla, which were then machine translated and used for Hindi, Marathi, Tamil, and Telugu.

2 Methodology

We pretrain from scratch decoder-only generative language models[4] under 400M parameters on Indian corpora of less than 15GB (25-66B tokens). In this section, we discuss details regarding our novel tokenization, and multilingual instruction dataset creation. The data cleaning step, more standard, is detailed in Appendix B.1.

2.1 Tokenization

To improve morphological alignment for Indian languages, we propose to constructed hybrid tokenizers by fusing vocabularies from independently trained SentencePiece models using BPE (Sennrich et al., 2016) and Unigram LM (Kudo, 2018). This is inspired by Bostrom and Durrett (2020), who found that the unigram LM tokenization (pruning tokens based on unigram LM perplexity) method produces tokens better aligned with morphology. We parse both models into their ModelProto format and augment the BPE model with any tokens from the Unigram model that are not already present. As BPE segmentation is deterministic and does not depend on token probabilities, the added tokens (assigned a neutral score of 0) do not alter segmentation behavior but become available as atomic units for downstream processing. During pre-tokenization, we apply NFC normalization, digit splitting, and byte fallback for unknown UTF-8 characters. Our tokenizers achieve the least fertility scores across all five languages compared to Sarvam 2B (Sarvam2B, 2024), Llama-3.1 (Dubey et al., 2024), Gemma-2 (Team et al., 2024), and GPT-4o as shown in Fig. 1 in Appendix. This hybrid tokenization method improves representation efficiency and reduces training costs by generating fewer tokens per input sequence, crucial under compute constraints.

2.2 Instruction Tuning Datasets

We constructed 23K instructions for Bangla from three sources: 5K human-authored instructions (on culture, literary, practical domain) following guidelines mentioned in Appendix B.3, 15K translated instructions from Dolly (Conover et al., 2023), and 3K self-instruct-generated samples (Wang et al., 2023). These were translated to Hindi, Marathi, Tamil, and Telugu using Google Translate[5] with manual post-editing [6].

3 Experiments

Our monolingual PARAMANU models are based on transformer (Vaswani et al., 2017) causal decoder architecture (Radford et al., 2019). Following Chinchilla (Hoffmann et al., 2022a), LLaMa (Touvron et al., 2023), we used RMSNorm (Zhang and Sennrich, 2019) with norm_epsilon =1e-5, SwiGLU (Shazeer, 2020) activation function, and an activation hidden size of $\sim \frac{8}{3}d$. Following (Chowdhery et al., 2023), we removed all biases from dense layers to improve the training stability. We also used weight tying (Press and Wolf, 2017) to improve the performance of language models by sharing the weights of the embedding and softmax layers. We followed Chinchilla scaling laws and the GPT-2 ratio (a 1.5B model pretrained on 40 GB of text data) (Radford et al., 2019) to esti-

[4]Available at: `anonymous-link-for-review`

[5]https://cloud.google.com/

[6]Available at: `anonymous-link-for-review`.

mate compute optimal model parameter configuration (Table 13 in Appendix.) for our models given the size of the dataset. We used the interpolation method of (Niyogi and Bhattacharya, 2024; Chen et al., 2023) for the position indices of tokens in RoPE based scaling for training longer sequences on a single GPU (see Appendix C).

3.1 Training

We pretrained our models using the AdamW optimizer (Loshchilov and Hutter, 2019), with $\beta_1 = 0.9$, $\beta_2 = 0.95$, eps $= 10^{-5}$. We use a cosine learning rate schedule, with warmup of 1000 steps, and decay final learning rate down to 10% of the peak learning rate. We use a weight decay of 0.1 and gradient clipping of 1.0. To further speedup training, we also used BF16 mixed precision training. We performed hyperparameter tuning on 15M models and used the concept of μP transfer (Yang et al., 2021) to transfer the learned hyperparameters to our bigger models. For instruction-tuning, we followed (Taori et al., 2023). Further details are in Appendix E.

3.2 Evaluation

We evaluate our models on perplexity and downstream tasks including QA, NLI, and commonsense reasoning, across five Indian languages. We also performed human evaluation for Bangla and Hindi as discussed in Appendix D.4. Comparisons are made with 21 multilingual and Indian-adapted LLMs (500M–8B params) such as Bloomz, xGLM, LLaMA-3/3.2, mGPT, Sarvam 2B, Aya23, and fine-tuned models such as OpenHathi, Nemotron-Hindi (Joshi et al., 2025), Airavata (Gala et al., 2024), and Indian-Gemma-Navrasa (Telugu-LLM-Labs, 2025). Models are grouped by size: 500M–1B, 1B–3B, 3B–8B.

Benchmarks. We use MMLU (Hendrycks et al., 2021), ARC (Clark et al., 2018), and Belebele (Bandarkar et al., 2024) for all languages, and language-specific datasets: HellaSwag (Hindi), XNLI (Conneau et al., 2018), XStoryCloze (Lin et al., 2022) (Hindi, Telugu), and XCOPA (Ponti et al., 2020) (Tamil) as benchmarks. Evaluation uses datasets from Lai et al. (2023b) and LM Evaluation Harness (LMEval) (Sutawika et al., 2024), with limited HellaSwag support due to tool issues.

3.3 Results

Table 1 summarizes average performance across benchmark tasks in five Indian languages (detailed results are given in Appendix Tables 6, 8, 7, 9, 10). The instruction-tuned Paramanu models outperform, on each language, the 11 LLMs with less than 3B parameters, with the exception of Sarvam 2B which slightly outperforms the Tamil and Telugu Paramanu models; it is however trained on 4T tokens, 50× more than the Paramanu models. The Paramanu models furthermore outperform the larger models OpenHathi-7B and Airavata-7B adapted on Marathi and Hindi through continual pretraining, as well as 6 out of 10 larger (above 3B parameters) language models, including LLMs using up-sampled low-resource data as xGLM which is trained with 30 languages. Although LLaMA-3-8B and Bloomz-7B lead overall due to large-scale instruction tuning on xP3, our models remain competitive with all other models.

3.4 Ablation Studies

Impact of tokenizer and data cleaning. Table 3 in Appendix presents the impact of incorporating Unigram tokens into BPE and of data cleaning across five languages. Our tokenizer improves downstream task average performance over standard BPE by 1.91% (Bangla), 1.41% (Hindi), 1.53% (Marathi), 0.56% (Tamil), and 2.02% (Telugu). Additional data cleaning further boosts scores by 1% (Bangla), 3.5% (Marathi), 1% (Tamil), and 2% (Telugu), with a similar trend observed for BPE tokenizers underscoring the value of data preprocessing irrespective of tokenization strategy.

Impact of shrinking factor for position interpolation context window. Table 4 in Appendix shows the impact of α for position interpolation or downscale the position token indices to accommodate more tokens than max context window possible on limited memory. The average benchmark score monotonically increased with bigger context size for all languages except Telugu. Although we gain on larger sequences, on the flip side, interpolating token position indices to reside in a much narrower region might inject noise which may perturb language modeling benchmark performance.

4 Discussion and Conclusion

Scaling. In our study, smaller Hindi models (e.g., 162M) often outperformed larger ones (e.g., 367M) at fixed training durations, as shown in Appendix Tables 7, 8. With extended training, larger models (e.g., 367M) surpassed smaller counter-

Model	Size	#langs	Bangla	Devanagari		Tamil	Telugu	Training	Context	Pretrained Tokens	
				Marathi	Hindi			Hours	Size	Total	Indian
Paramanu-Bangla	108M	1	25.22	-	-	-	-	42.75	1024	26.21B	26.21B
Paramanu-Bangla-instruct	108M	1	**29.52**	-	-	-	-	+0.5	1024	+3.5M	+3.5M
Paramanu-Marathi	208M	1	-	26.40	30.97	-	-	88	1024	28.83B	28.83B
Paramanu-Marathi-instruct	208M	1	-	**26.93**	30.54	-	-	+0.5	1024	+2.5M	+2.5M
Paramanu-Hindi	367M	1	-	24.20	30.97	-	-	239	1024	66B	66B
Paramanu-Hindi-instruct	367M	1	-	25.54	**40.14**	-	-	+1	1024	+13M	+13M
Paramanu-Tamil	208M	1	-	-	-	33.34	-	112.5	1024	39.32B	39.32B
Paramanu-Tamil-instruct	208M	1	-	-	-	**34.80**	-	+0.5	1024	+3M	+3M
Paramanu-Telugu	208M	1	-	-	-	-	32.22	112.5	1024	39.32B	39.32B
Paramanu-Telugu-instruct	208M	1	-	-	-	-	**34.50**	+0.5	1024	+2.8M	+2.8M
Bloom	560M	45	23.83	24.76	32.84	33.13	31.78	N/A	2048	350B	7.7B
Bloomz (instruction-tuned)	560M	45	24.01	25.29	32.31	33.30	32.25	N/A	2048	+13B	+1.4B
xGLM	564M	30	21.54	22.31	30.69	30.57	30.35	129,024	2048	500B	20B
Llama-3.2	1B	34	24.90	26.06	34.54	32.81	32.13	370,000	128,000	9T	N/A
Bloom	1.1B	45	24.75	25.78	33.87	32.94	33.04	N/A	2048	350B	7.7B
Bloomz (instruction-tuned)	1.1B	45	23.45	23.54	31.87	32.19	30.67	N/A	2048	+13B	+1.4B
mGPT	1.3B	61	22.86	23.30	31.95	29.73	30.96	86,016	2048	400B	15B
xGLM	1.7B	30	22.24	21.69	32.09	30.56	31.12	129,024	2048	500B	20B
Sarvam	2B	11	25.22	26.08	36.27	**35.25**	**34.55**	122,880	8192	4T	2T
Indian-Gemma-Navrasa	2B	16	25.27	26.02	34.40	33.73	33.55	+45	8192	$\geq 2T$	N/A
xGLM	2.9B	30	22.27	21.73	33.18	30.70	33.51	129,024	2048	500B	20B
Llama-3.2	3B	34	**30.17**	**31.36**	40.06	**36.59**	**34.86**	460,000	128,000	9T	N/A
Nemotron-Hindi	4B	15	-	**29.42**	**45.33**	-	-	N/A	4096	8.5T	491.2B
xGLM	4.5B	30	22.88	24.36	32.83	30.77	31.24	129,024	2048	500B	20B
Bloom	7B	45	25.47	25.61	35.92	33.95	33.28	N/A	2048	350B	7.7B
Bloomz (instruction-tuned)	7B	45	**37.77**	**37.68**	**40.80**	**41.41**	**39.71**	N/A	2048	+13B	+1.4B
OpenHathi (CPTLLama-2)	7B	28	-	25.40	35.41	-	-	N/A	4096	$\geq 2T$	$\geq 7B$
Airavata (instruction-tuned)	7B	28	-	26.64	36.93	-	-	N/A	4096	$\geq 2T$	N/A
xGLM	7.5B	30	22.99	22.47	34.16	30.73	31.73	129,024	2048	500B	20B
Llama-3	8B	34	**33.54**	**33.10**	**43.45**	**39.09**	**38.59**	1,300,000	8192	$\geq 15T$	N/A
Aya23	8B	23	25.76	28.69	**43.98**	34.12	31.02	N/A	8192	N/A	N/A

Table 1: Summary of Benchmark Average Scores across Scripts (Bangla, Devanagari, Tamil, Telugu) and Languages. Models that performed better than our models are **underlined and bold**, while the best performance of our model is in **bold**. '-' represents that monolingual and multilingual models are not evaluated on languages of different scripts which were not part of training but languages of same script were evaluated even if it was not part of training. '+' denotes additional tokens/training hours on top of pretrained models for instruction-tuning.

parts (e.g., 162M), underscoring the need for size-appropriate training duration. Hence, we confirm prior findings (Hoffmann et al., 2022b; Kaplan et al., 2020) that larger models require proportionally more training to outperform smaller ones.

Instruction-tuning gains. *Instruction tuning improves downstream performance across all five evaluated languages.* Hindi shows the largest improvement (+9%), followed by Bangla (+4.3%). Gains are smaller for Tamil (+1.46%) and Telugu (+2.28%), likely due to lower-quality machine translation artifacts in instruction tuning datasets.

Cross-lingual Transfer. As one can note form Table 1, the 208M Marathi model matches the 367M Hindi model on Hindi benchmarks (30.97) due to lower perplexity (8.94 vs 11.05), indicating effective cross-lingual transfer between Hindi and Marathi that share the Devanagari script. Instruction tuning however shows asymmetry: Marathi to Hindi reduces performance (-0.43), while Hindi to Marathi improves it ($+1.34$), suggesting reverse transfer from high (Hindi) to low-resource (Marathi) languages (details in Appendix D.1). Thus, these monolingual models are well suited for cross-lingual downstream tasks such as translation and information retrieval.

n-shot Degradation. The experiments and results reported in Appendix D.3 show that performance drops from 0-shot to 25-shot on XNLI-Hindi, XStoryCloze, and XCOPA, echoing trends in GPT models (Valmeekam et al., 2024). This may result from in-context examples acting as soft constraints that hinder generation.

Conclusion. In this paper, we demonstrate that for low-resource Indian languages with rich morphological structures, small language-specific models (under 400M parameters and trained on fewer than 70B tokens) often outperform larger alternatives, unless one employs state-of-the-art multilingual models exceeding 3B parameters and trained on over 1T tokens. *Thus, given constraints on both the model and training set sizes, the best strategy is not necessarily to build a model as large as possible, trained on a corpus as large as possible, but rather to build language-specific models, able to adapt to the richness of each language, and trained on quality data.*

Our work thus contributes to better understanding the role of smaller LMs and enables further research on Indian languages through the models and datasets created during the course of this work.

Limitations

Building generative language models for Indian languages involves several challenges. Each stage such as data collection, pretraining, instruction tuning, and evaluation has its own limitations. Additionally, the societal and cultural implications of deploying AI in underrepresented linguistic communities are complex and beyond the full scope of this section.

Data

Our models are trained on a limited corpus consisting mainly of news articles, Wikipedia, and other structured sources in Indian languages, totaling only a few billion tokens. The dataset lacks diversity across key domains such as law, science, education, and general world knowledge. As a result, the models perform sub-optimally on benchmarks like MMLU, which test broad academic and professional understanding. As with any LLM, the data it is trained on determines the range and quality of its capabilities.

Furthermore, the models were not exposed to any English language data, including Indian English. This restricts their knowledge in domains like governance, legal discourse, and policy, where English is commonly used in India.

Training

Due to resource constraints, models were trained over multiple epochs on repeated tokens. Although this helps to reinforce learning in low-resource settings, it increases the risk of overfitting and can reduce generalization. Furthermore, our models were pretrained using a single A100 GPU, which significantly restricted training duration, batch size, and overall scale. As a result, the models may not have reached full convergence. The lack of compute and open-source infrastructure for Indian language models continues to be a major bottleneck. Detailed training logs are omitted due to space limitations.

Instruction Tuning and Safety

We instruction-tuned the models using 15,000 machine-translated instructions generated via Google Translate. This may introduce grammatical errors or semantic inconsistencies, as machine translation quality for Indic languages remains below human-level accuracy.

No safety mechanisms such as prompt filtering, fact-checking, or toxicity detection were applied. The outputs shown in this paper are raw model responses, without post-processing. As a result, models may generate factually incorrect, biased, or inappropriate content. We emphasize the need for responsible use and future work on safety and alignment.

Evaluation

Evaluation was conducted in a zero-shot setting without task-specific fine-tuning. This limits performance, especially on complex or domain-specific tasks. Benchmarks like MMLU highlight the impact of limited training data and the absence of instruction tuning aligned with task objectives. Future improvements can be expected through more diverse data and supervised fine-tuning.

Ethical Considerations

In this work, we advocate for greater openness in developing generative language models, especially for low-resource morphologically rich Indian languages serving more than 1 billion speakers. Open access is crucial for deepening our scientific understanding of these models and ensuring that communities beyond the Global North can actively participate in their advancement. Training on openly available datasets not only supports transparency but also helps bridge the gap for languages and regions that have historically been underrepresented in AI research.

By releasing our models and tokenizers openly, we empower researchers, developers, and communities to build upon existing work rather than starting from scratch saving resources and reducing environmental impact. While we acknowledge the risks of misuse, we believe that broader access enables more diverse efforts to identify, study, and mitigate potential harms. We recognize that openness comes with risks these models could be misused. However, we believe open access also helps researchers identify and reduce such risks more effectively by encouraging diverse solutions.

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Appendix

A Related Work

Despite the rise of multilingual decoder-only LLMs like Bloom (Workshop et al., 2023), xGLM (Lin et al., 2022), Sarvam 2B (Sarvam2B, 2024), which uses 40%-50% English data, many models remain English-biased such as Llama-3.2 (Dubey et al., 2024) with only 8% non English tokens out of 15T tokens. A key issue is neuron sparsitystudies show that in models like OPT-66B (Zhang et al., 2022), over 70% of feed-forward network (FFN) neurons in some layers remain inactive across diverse inputs (Voita et al., 2024). This high sparsity limits models's learning capacity and generalization, particularly for non-English languages, revealing a critical flaw in current multilingual LLM design. Recent efforts to adapt English-centric models like Llama for Indian languages (Airavata (Gala et al., 2024), OpenHathi (SarvamAI, 2023) for Hindi, Nemotron-Hindi (Joshi et al., 2025) for Hindi, TamilLlama for Tamil) have involved extending vocabulary and fine-tuning techniques such as LoRA (Hu et al., 2022) and QLoRA (Dettmers et al., 2023). Aya23 8B (Aryabumi et al., 2024), mGPT (Shliazhko et al., 2024) and Sarvam 2B (Sarvam2B, 2024) are Indian languages dedicated LLMs trained from scratch but with English as dominant language. However, these models still exhibit a strong English bias and struggle to generate high-quality text in Indian languages. Massively multilingual models (MMTs) (Devlin et al., 2019), (Conneau et al., 2020), (Xue et al., 2021) are pretrained on large corpora but often lack alignment between languages, leading to poor transfer performance for distant languages (Lauscher et al., 2020). (Rust et al., 2021) find that this curse of multilinguality may simply be a result of lower quality tokenization per language in multilingual models. (Chang et al., 2024) find that adding multilingual data in similar languages improves performance for low-resource languages, but improvements decrease as models reach capacity limitations and multilingual data consistently hurts high-resource language performance. IndianNLP generally suffers from lack of adequate cultural and linguistics relevant datasets for Indian languages. There have been efforts (Doddapaneni et al., 2023; Khan et al., 2024) to develop large scale datasets to develop deep learning language models. However,

the existing datasets for supervised learning are mostly translated from English to various Indian languages including benchmark.

B Data

B.1 Data Cleaning

Following prior work (Doddapaneni et al., 2023; Abadji et al., 2022), we perform regex-based filtering of HTML/XML tags, emails, links, emojis, personal info, and remove non-literal and foreign-script characters. Language identification is done using `cld3`[7] and IndianLID-FTN (Madhani et al., 2023) to discard non-target languages. We filter toxic content using Team et al. (2022), normalize whitespace and Unicode, and deduplicate paragraphs using 128-bit MurmurHash[8]. For Indian scripts (Bengali, Devanagari, Tamil, and Telugu), sentence splitting uses language-specific punctuation (danda "।" for Bengali and Devanagari scripts).

B.2 Dataset for Pretraining

The pretrained data of 54.6 GB UTF-8 bytes for 5 major Indian languages was split into 95% training and 5% validation to retain as much data as possible, since the goal is to take a step toward developing effective pretrained generative language models from scratch for 5 major Indian languages. The pretraining corpus primarily consists of web-scraped news, blogs, and Wikipedia from IndianCorp v2 (Doddapaneni et al., 2023) for Marathi, Tamil, and Telugu, which was used to train IndianBERT-v2, and Bangla literature from Vacaspati (Bhattacharyya et al., 2023), used in training Bangla Electra. IndianCorp v2 also includes Indian language data from Wikipedia and OSCAR (Ortiz Su'arez et al., 2019). Our pretraining corpora have no source code, scientific journals/articles, scientific books, legal & constitutional documents, etc. Dataset details can be found in Table 2.

B.3 Annotators Guidelines to design Bengali Instruction-Tuning Dataset

We construct a manually curated dataset of 5,000 high-quality instructionresponse pairs in Bengali, focusing on cultural, literary, and practical domains relevant to Bengali-speaking users in India. Below, we outline the core annotation guidelines used to ensure consistency, linguistic accuracy, and cultural relevance.

Annotation Protocol

Each data point consists of:

- **Instruction:** A natural prompt in Bengali, emulating user queries or tasks.
- **Response:** A helpful, accurate, and contextually appropriate answer in Bengali.
- **Category (optional):** Domain label (e.g., Literature, Daily Life).

Domain Coverage.

To promote diversity, we target a balanced distribution across ten culturally salient domains: literature, culture/tradition, history/politics, religion, education, health and daily life, technology, ethics, creative writing, and casual conversation.

Instruction Types.

We include a variety of prompt formats, including:

- Informational Q&A (e.g., historical facts, literary interpretation)
- How-to and procedural instructions
- Creative writing prompts (e.g., poem, story)
- Comparative and opinion-based prompts
- Grammar correction and translation tasks

Language Guidelines.

Instructions and responses are written in standard colloquial Bengali. Annotators avoid code-switching and maintain gender neutrality unless contextually necessary. All content is free of offensive, biased, or politically sensitive material.

Quality Control

All samples undergo dual-stage validation:

1. Peer review for factual correctness, fluency, and clarity.
2. Final check for linguistic naturalness and domain balance.

This dataset aims to support instruction-tuning of LLMs in Bengali by providing diverse, culturally grounded, and linguistically accurate examples.

C Context Scaling with RoPE Embeddings for Efficient Pretraining

We employ a scaled variant of Rotary Positional Embeddings (RoPE; Su et al., 2022) with a base value of $\theta = 10{,}000$. To support pretraining with large context lengths on hardware-constrained settings (e.g., a single A100 40GB GPU), we introduce a *shrinking factor* that scales the input token position ids before the RoPE methodology is ap-

[7] https://github.com/google/cld3
[8] https://pypi.org/project/mmh3/

Language	Family	Script	Corpus Source	Corpus Size (GB)	#Sentences	#Speakers
Bangla	Indo-European	Bangla	Vacasapati	3.6	22,533,608	300 M
Hindi	Indo-European	Devanagari	IITB monolingual	15.8	52,124,643	692 M
Marathi	Indo-European	Devanagari	Indian Corp v2	12.5	34,567,839	99 M
Tamil	Indo-Dravidian	Tamil	Indian Corp v2	10.7	27,872,768	77 M
Telugu	Indo-Dravidian	Telugu	Indian Corp v2	13.5	40,241,847	95 M

Table 2: Pretraining Data details after data cleaning along with language families, scripts, and speaker estimates. Speaker data is from the Indian Census 2011.

plied. This *shrinking factor* is defined as the ratio of the target context length y to a fixed *permissible_context_size_length* L, which corresponds to the maximum context length that the available hardware can accommodate. All other training hyperparameters such as batch size, vocabulary size, and model dimensions remain unchanged. Formally, for each token position p, we compute a scaled position p' as:

$$p' = \frac{p}{\alpha} = \frac{p \cdot L}{y}$$

For example, with a target context length of $y = 4096$ and a permissible length of $L = 256$, the shrinking factor is $\alpha = \frac{4096}{256} = 16$. A token at position $p = 4000$ is mapped to $p' = \frac{4000}{16} = 250.00$, and its neighbor at $p = 4001$ maps to $p' \approx 250.06$. This ensures all scaled positions lie within the permissible range $[0, L]$ This is how we can capture higher context size during pretraining outside the *permissible_context_size_length*. Further, exploiting the fact that positional embeddings can be applied to non-integer positions as using RoPE, the self-attention score is only dependent on the relative position of the tokens through trigonometric functions. This scaling preserves the models ability to learn long-range dependencies.

D Added Evaluation

D.1 Cross-Lingual Transfer across same languages of Devanagari Script.

To test how languages of Devanagari script generalize to unseen languages, we trained Sanskrit monolingual model and a multilingual model, mPARAMANU-162M on languages of Indo-European family (Assamese, Bangla, Devanagari script (Sanskrit, Konkani, Maithili), Odia). We intentionally kept out Hindi and Marathi from the training of our multilingual model to test its generalization to languages of Devanagari script. Table 5 shows strong zero-shot transfer within languages that share the same script, Devanagari.

For example, PARAMANU-SANSKRIT 139M, trained without Hindi, achieves 31.05 avg on Hindi, outperforming xGLM 564M and approaching BLOOM 560M. mPARAMANU-162M also generalizes well to Hindi and Marathi. This implies that both monolingual and multilingual small language models of shared script can be further used for downstream cross-lingual NLP, information retrieval and translation tasks.

D.2 Language Specific Evaluation

In this subsection, we discuss language-specific benchmarks for five Indian languages: Bengali, Hindi, Marathi, Tamil, and Telugu. Tables 6, 7, 8, 9, 10 shows the respective languauge specific quantitative benchmark results.

Bangla. From Table 6, we see that Paramanu-Bangla 108M outperformed 8 of 11 LLMs in the range of 500M and 3B, tying with Llama-3.2 1B, rivaling Sarvam 2B despite being smaller in size by 20×. While it trails 5 of 7 LLMs above 3B, it exceeds xGLM 7.5B and Bloom 1.1B in average score across MMLU, ARC, and Belebele benchmarks, despite being smaller by 70 times than xGLM 7.5B and pretrained on only 26.21 billon tokens. Trained solely on Bangla literature, its limited domain coverage explains weaker MMLU results. Instruction-tuning on 27k Bangla instructions yields PARAMANU-BANGLA-INSTRUCT 108M, which surpasses all 11 LLMs in the 500M-3B range and 3 of 7 above 3B, including xGLM 4.5B, Bloom 7B, and xGLM 7.5B. On ARC, it outperforms all models. The multilingual variant (mPARAMANU) underperforms its monolingual counterpart, reflecting the multilinguality trade-off. Notably, Bloom 1.1-Instruct also shows a 1.3% drop in Bangla performance.

Devanagari. Table 8 and Table 7 show

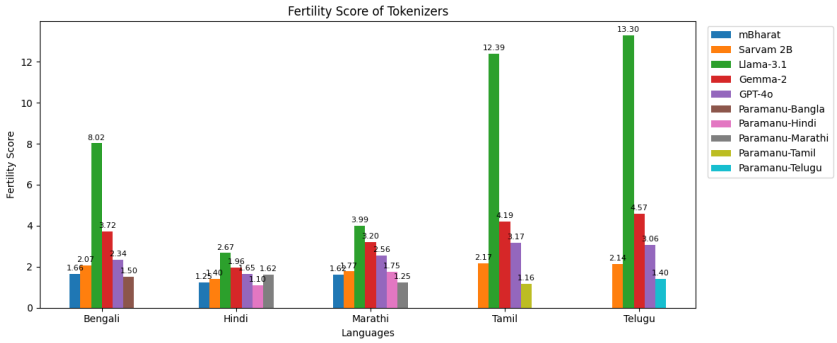


Figure 1: Fertility score of our tokenizer v/s LLMs across languages of 4 scripts (Bengali, Devanagari, Tamil, and Telugu). LLMs score are reported from (Sarvam2B, 2024)

Test input indic multilingual text in 7 languages: ভাৰত মোৰ মাতৃভূমি ভারत आमार मातृभूमि साडा देश भारत है भारत हो म्हजो देश भारत हमर देश अछि ভাৰত হেউছি মোর মাতৃভূমি अस्माकं देशः भारतवर्षः

Tokenized by LLaMA-2 32k tokenizer:['▁', '<0xE0>', '<0xA6>', '<0xAD>', 'া', '<0xE0>', '<0xA7>', '<0xB0>', 'ত', '▁', 'ম', 'োৰ', '<0xE0>', '<0xA7>', '<0xB0>', '▁', 'ম', 'া', 'ত', '<0xE0>', '<0xA7>', '<0x83>', '<0xE0>', '<0xA6>', '<0xAD>', '<0xE0>', '<0xA7>', '<0x82>', 'ম', 'ি', '▁', '<0xE0>', '<0xA6>', '<0xAD>', 'া', 'র', 'ত', '▁', '<0xE0>', '<0xA6>', '<0x86>', 'ম', 'া', 'র', '▁', 'ম', 'া', 'ত', '<0xE0>', '<0xA7>', '<0x83>', '<0xE0>', '<0xA6>', '<0xAD>', '<0xE0>', '<0xA7>', '<0x82>', 'ম', 'ি', '▁', 'স', 'া', 'ড', 'া', '▁', 'द', 'े', 'श', '▁', 'भ', 'ा', 'र', 'त', '▁', 'ह', 'ै', '▁', 'भ', 'ा', 'र', 'त', '▁', 'ह', 'ो', '▁', 'म', '् ', 'ह', 'ज', 'ो', '▁', 'द', 'े', 'श', '▁', 'भ', 'ा', 'र', 'त', '▁', 'ह', 'म', 'र', '▁', 'द', 'े', 'श', '▁', 'अ', '<0xE0>', '<0xA4>', '<0x9B>', 'ि', '▁', '<0xE0>', '<0xAC>', '<0xAD>', '<0xE0>', '<0xAC>', '<0xBE>', '<0xE0>', '<0xAC>', '<0xB0>', '<0xE0>', '<0xAC>', '<0xA4>', '▁', '<0xE0>', '<0xAC>', '<0xB9>', '<0xE0>', '<0xAD>', '<0x87>', '<0xE0>', '<0xAC>', '<0x89>', '<0xE0>', '<0xAC>', '<0x9B>', '<0xE0>', '<0xAC>', '<0xBF>', '▁', '<0xE0>', '<0xAC>', '<0xAE>', '<0xE0>', '<0xAD>', '<0x8B>', '<0xE0>', '<0xAC>', '<0xB0>', '▁', '<0xE0>', '<0xAC>', '<0xAE>', '<0xE0>', '<0xAC>', '<0xBE>', '<0xE0>', '<0xAC>', '<0xA4>', '<0xE0>', '<0xAD>', '<0x83>', '<0xE0>', '<0xAC>', '<0xAD>', '<0xE0>', '<0xAD>', '<0x82>', '<0xE0>', '<0xAC>', '<0xAE>', '<0xE0>', '<0xAC>', '<0xBF>', '▁', 'অ', 'স', 'ৃ', 'ম', 'া', 'ক', 'ং', '▁', 'द', 'े', 'श', '<0xE0>', '<0xA4>', '<0x83>', '▁', 'भ', 'ा', 'र', 'त', 'व', 'र', 'ष', '<0xE0>', '<0xA4>', '<0x83>']

Tokenized by mBharat tokenizer:['▁ভাৰত', '▁মোৰ', '▁মাতৃ', 'ভূ', 'মি', '▁ভারत', '▁आमार', '▁मातृ', 'भू', 'मि', '▁सा', 'डा', '▁देश', '▁भारत', '▁है', '▁भारत', '▁हो', '▁म्ह', 'जो', '▁देश', '▁भारत', '▁हम', 'र', '▁देश', '▁अछि', '▁ভাৰত', '▁হেউছি', '▁মোৰ', '▁মা', 'ত', 'ৃ', 'ভূমি', '▁अ', 'स्मा', 'कं', '▁देश', 'ः', '▁भारत', 'वर्ष', 'ः']

Figure 2: mBharat Tokenizer v/s LLaMa-2 tokenizer for input in 7 Indian languages.

Language	Configuration	MMLU	ARC	Belebele	XCOPA	XStoryCloze	HellaSwag	XNLI	Average
Bangla	full (ours)	**24.82**	**25.75**	**25.11**	-	-	-	-	**25.22**
	full w/o Unigram	22.66	23.61	23.67	-	-	-	-	23.31
	full w/o cleaning	23.67	24.21	25.00	-	-	-	-	24.29
	full w/o Unigram w/o cleaning	20.55	21.56	23.33	-	-	-	-	21.81
Hindi	full (ours)	**25.18**	**27.14**	**26.22**	-	**48.78**	**25.02**	**33.49**	**30.97**
	full w/o Unigram	23.35	25.54	25.22	-	46.78	24.89	**33.49**	29.87
	full w/o cleaning	24.72	22.25	25.44	-	48.16	24.06	32.34	29.49
	full w/o Unigram w/o cleaning	22.75	21.83	23.56	-	44.96	24.02	33.21	28.38
Marathi	full (ours)	**25.39**	**26.49**	**27.33**	-	-	-	-	**26.40**
	full w/o Unigram	25.31	23.20	26.11	-	-	-	-	24.87
	full w/o cleaning	22.47	22.42	24.00	-	-	-	-	22.96
	full w/o Unigram w/o cleaning	23.17	21.82	21.78	-	-	-	-	22.26
Tamil	full (ours)	**24.37**	**24.51**	**26.88**	**57.60**	-	-	-	**33.34**
	full w/o Unigram	23.87	24.08	26.11	57.00	-	-	-	32.76
	full w/o cleaning	23.25	23.38	26.56	56.20	-	-	-	32.35
	full w/o Unigram w/o cleaning	22.47	22.50	24.00	54.80	-	-	-	30.94
Telugu	full (ours)	**25.26**	**26.32**	**26.00**	-	**54.20**	-	-	**32.95**
	full w/o Unigram	25.12	21.75	24.44	-	52.42	-	-	30.93
	full w/o cleaning	24.16	22.68	23.11	-	53.73	-	-	30.92
	full w/o Unigram w/o cleaning	22.95	17.81	23.22	-	51.72	-	-	28.92

Table 3: Ablation study across Bangla (108M), Marathi (208M), Tamil (208M), Telugu (208M), and Hindi (367M) models. Evaluates the impact of tokenizer type and data cleaning. All scores are reported as zero-shot Accuracy (%). Dash (-) indicates benchmark not applicable or not available on LM-Eval.

that PARAMANU models achieve strong results on Devanagari benchmarks despite their small size and limited pretraining. PARAMANU-MARATHI 208M outperforms all LLMs in the 500M-3B range and 4 of 10 models above 3B on Marathi. MPARAMANU 162M and monolingual PARAMANU-SANSKRIT, despite not being trained on Hindi and Marathi data, surpass the random baseline and 8 of 21 LLMs via cross-lingual transfer. PARAMANU-HINDI-INSTRUCT 367M, tuned on 27k Hindi instructions and 52k synthetic Alpaca dataset, exceeds 18 of 21 LLMs on Marathi, and outperforms 8 models (500M–3B) and 6 of 10 above 3B on Hindi. Though Nemotron-Hindi 4B and Aya23 8B lead in Hindi, our models are significantly more efficient. Unlike costly continual pretraining and fine-tuning of LLMs (e.g., OpenHathi 7B, Airavata 7B, Indian-Gemma 2B), our pretrain from scratch approach of tiny monolingual models for low-resource languages with language-specific tokenization yields competitive results using just 240 GPU-hours.

Tamil. From Table 9, our model, Paramanu-Tamil (208M), outperformed 9 of 11 in range 500M-3B including Bloom, Llama-3.2, mGPT, xGLM) across four benchmarks in Tamil, coming close to Sarvam (2B) despite being 10 times smaller and trained on 76 times less Indian tokens compared to Sarvam 2B. However, its performance on MMLU is lower than the random baseline like many LLMs including Sarvam 2B in comparison as shown in the table as the model is mostly trained on Tamil news corpora. Paramanu-Tamil-instruct which is instruction-tuned on our translated 23,000 instructions dataset performed better than all models except Sarvam 2B in the range between 500M-3B and 4 LLMs out of 7 in the range of 3B and 8B.

Telugu. From Table 10, Paramanu-Telugu 208M outperformed 6 models out of 11 and 3 models (XGLM 4.5B, 7.5B, Aya23 8B) between 3B and 8B despite being trained Telugu pretrained on 39.32 billion tokens. After instruction-tuning on 23,000 machine translated instructions, Paramanu-Telugu-instruct (208M) outperformed all models between 500M and 3B except Sarvam 2B in the range of 500M and 3B and underperformed than 3 models of 7 in the range of 3B and 8B. On ARC benchmark, our models peformed better than all models except Bloomz 7B. The improvements in metric scores for Tamil and Telugu instruction-tuned models were modest, likely due to lower-quality machine translations from Bangla compared to Hindi.

D.3 n-shot degradation

In this subsection, we present Table 11, which shows n-shot performance (0-shot, 5-shot, and 25-

Language	Configuration	MMLU	ARC	Belebele	XCOPA	XStoryCloze	HellaSwag	XNLI	Average
Bangla	α =1, ctx=256	22.62	24.04	23.00	-	-	-	-	23.22
	α =2, ctx=512	**25.84**	23.52	**25.44**	-	-	-	-	24.93
	α =3, ctx=768	23.39	**25.75**	25.33	-	-	-	-	24.82
	α =4, ctx=1024	24.82	**25.75**	25.22	-	-	-	-	**25.22**
Hindi	α =2, ctx=512	25.43	25.34	27.56	-	48.78	25.14	33.17	30.90
	α =3, ctx=768	25.36	25.86	26.44	-	47.78	25.13	33.29	30.64
	α =4, ctx=1024	25.18	27.14	26.22	-	48.78	25.02	33.49	30.97
Marathi	α =1, ctx=256	22.96	**28.48**	22.33	-	-	-	-	24.59
	α =2, ctx=512	24.45	26.06	25.89	-	-	-	-	25.46
	α =3, ctx=768	24.58	24.66	**27.78**	-	-	-	-	25.67
	α =4, ctx=1024	**25.39**	26.94	27.33	-	-	-	-	**26.55**
Tamil	α =1, ctx=256	22.72	**25.04**	23.22	53.20	-	-	-	31.04
	α =2, ctx=512	23.40	22.94	23.89	53.80	-	-	-	31.00
	α =3, ctx=768	**25.30**	23.91	23.33	54.80	-	-	-	31.84
	α =4, ctx=1024	24.37	24.51	**26.88**	**57.60**	-	-	-	**33.34**
Telugu	α =1, ctx=256	**26.83**	25.26	21.89	-	53.01	-	-	31.75
	α =2, ctx=512	25.06	**25.61**	**28.89**	-	53.34	-	-	**33.22**
	α =3, ctx=768	25.40	26.32	22.67	-	53.08	-	-	31.87
	α =4, ctx=1024	25.26	26.32	26.00	-	**54.20**	-	-	32.95

Table 4: Ablation study for shrinking factor α of position interpolation for varying context size (ctx) pretraining across Bangla (108M), Marathi (208M), Tamil (208M), Telugu (208M), and Hindi (367M) models for . All scores are reported as zero-shot Accuracy (%). Dash(-) indicates benchmark not applicable or not available on LM-Eval.

Model	Size	#langs	Devanagari	
			Marathi	Hindi
Paramanu-Sanskrit	139M	1	25.26	31.05
mParamanu	162M	6	25.28	30.07
Paramanu-Marathi	208M	1	26.40	30.97
Paramanu-Marathi-instruct	208M	1	26.93	30.54
Paramanu-Hindi	367M	1	24.20	30.97
Paramanu-Hindi-instruct	367M	1	25.54	40.14

Table 5: Cross-lingual transfer among languages with Devanagari script (Hindi, Marathi, Sanskrit)of Indo-European family. Both Sanskrit and mParamanu model was not trained on Hindi.

shot) on language benchmarks.

D.4 Human Evaluation

Automated evaluation metrics may overlook significant qualitative enhancements, especially when model outputs align well with particular linguistic or cultural contexts (Barnett et al., 2024). Figure 3 shows average human ratings for models text generation across grammar, coherence, creativity, and factuality. We perform human evaluation for Bangla and Hindi for all pretrained models. For human evaluation, we asked 10 annotators to evaluate top-3 responses for 10 prompts on a scale of 0 (worst) to 5 (best). We reached inter-annotator kappa score of 0.85 for Bengali, 0.79 for Hindi, and 0.72 for Sanskrit. Figure 4 shows the bar chart for inter-annotator agreement's Fleiss Kappa score.

D.5 Perplexity, MFU, CPU Inference Speed

Table 12 lists the test perplexity, MFU metric during pretraining and CPU inference speed of our various pretrained models. In terms of quantitative evaluation of language modeling, the lower the perplexity, the better is the language model.

Model	CPU Inference Speed	Perplexity	MFU
Bangla 87.25M	42.327	5.069	35.36
Bangla 108.5M	37.351	4.102	22.57
Hindi 162M	34.492	16.992	39.45
Hindi 367.5M	12.906	11.052	39.87
mParamanu 92.63M	39.459	8.443	39.57
mParamanu 162M	34.711	6.924	39.93
Marathi 207.73M	24.875	8.943	19.50
Sanskrit 139.33M	38.676	1.748	37.81
Tamil 207.84M	24.535	7.618	18.77
Telugu 208.25M	24.125	5.400	40.07

Table 12: CPU Inference speed (tokens/sec, FP32), perplexity of our models and MFU metric during training. MFU is Model FLOPs Utilization metric.

E Model & Training Configuration

In this section, we provide details on the various model architecture and pretraining hyperparameters used in our experiments. Tables 13 and 14 list these configurations. Figure 5 shows GPU utilization during the pretraining of the Hindi model on

Models	Size	MMLU-Bangla	ARC-Bangla	Belebele-Bangla	Average (Bangla)	Belebele-Assamese
Paramanu-Bangla (ours)	108M	24.82	25.75	25.11	25.22	25.33
Paramanu-Bangla-instruct (ours)	108M	**27.60**	**28.50**	**32.45**	**29.52**	**30.54**
mParamanu (ours)	92M*	25.78	26.18	22.44	24.80	22.44
mParamanu (ours)	162M	25.29	26.01	27.44	26.24	29.00
mParamanu (ours)	237M*	22.52	25.92	24.44	24.29	24.28
Bloom	560M	22.61	26.00	22.89	23.83	22.78
Bloomz (instruction-tuned)	560M	25.82	23.43	22.77	24.01	25.11
xGLM	564M	22.61	18.47	23.55	21.54	22.77
Llama-3.2	1B	25.83	20.44	28.44	24.90	28.33
Bloom	1.1B	23.90	24.37	26.00	24.75	26.89
Bloomz	1.1B	25.19	20.61	24.55	23.45	22.33
mGPT	1.3B	24.12	18.90	25.55	22.86	24.88
xGLM	1.7B	24.46	19.50	22.77	22.24	22.55
Sarvam	2B	24.05	28.40	23.22	25.22	27.78
Indian-Gemma-Navrasa (instruction-tuned)	2B	**29.07**	20.87	25.88	25.27	24.44
xGLM	2.9B	23.75	19.85	23.22	22.27	22.66
Llama-3.2	3B	**32.51**	21.47	**36.55**	**30.17**	**33.88**
xGLM	4.5B	25.74	21.04	21.88	22.88	22.44
Bloom	7B	27.10	26.09	23.22	25.47	23.11
Bloomz (instruction-tuned)	7B	**32.46**	27.20	**53.67**	**37.77**	**48.00**
xGLM	7.5B	24.69	19.41	24.88	22.99	24.44
Llama-3	8B	**35.77**	23.86	**41.00**	**33.54**	**35.77**
Aya23	8B	26.94	18.81	31.55	25.76	**31.22**

* Trained for the same number of steps.

Table 6: Zero-shot evaluation of LLMs across translated benchmarks of MMLU, HellaSwag, ARC datasets, and Belebele in Bengali script. All benchmarks report Accuracy. Models that performed better than our models have been **underlined and bold**, the best performance of our model has been **bold**.

Models	Size	MMLU-Hindi	HellaSwag-Hindi	ARC-Hindi	XStoryCloze-Hindi	XNLI-Hindi	Belebele-Hindi	Average
Paramanu-Sanskrit (ours)	139M	25.16	25.64	25.17	50.23	34.46	25.66	31.05
mParamanu (ours)	92M*	23.94	25.31	26.28	47.05	33.45	24.44	30.07
mParamanu (ours)	162M*	24.84	24.87	22.35	49.24	33.70	25.44	30.07
mParamanu (ours)	237M*	22.78	25.17	27.57	46.79	33.13	21.89	29.55
Paramanu-Marathi (ours)	208M	25.49	26.59	23.97	48.71	33.73	27.33	30.97
Paramanu-Marathi-instruct (ours)	208M	23.71	27.78	23.89	50.89	34.10	22.89	30.54
Paramanu-Hindi (ours)	162M*	23.15	25.37	27.31	48.91	33.17	22.67	30.09
Paramanu-Hindi (ours)	367M*	24.38	24.83	27.05	47.92	32.00	23.33	29.92
Paramanu-Hindi (ours)	367M	25.18	25.02	27.14	48.78	33.49	26.22	30.97
Paramanu-Hindi-instruct (ours)	367M	**30.25**	**29.42**	**30.23**	**58.00**	**40.25**	**42.78**	**40.14**
Bloom	560M	23.67	27.50	23.88	54.79	40.80	26.44	32.84
Bloomz (instruction-tuned)	560M	25.87	26.48	24.40	55.53	35.58	26.00	32.31
xGLM	564M	22.70	26.96	20.20	52.00	38.31	24.00	30.69
Llama-3.2	1B	28.22	28.95	23.97	56.25	40.08	29.77	34.54
Bloom	1.1B	23.86	28.28	24.74	55.59	**42.77**	28.00	33.87
Bloomz	1.1B	24.90	28.54	21.06	56.65	37.87	22.22	31.87
mGPT	1.3B	24.26	27.42	19.86	52.74	**41.32**	26.11	31.95
xGLM	1.7B	24.70	28.46	20.63	55.79	38.99	24.00	32.09
Sarvam	2B	24.54	**33.66**	28.00	**60.29**	**46.74**	24.44	36.27
Indian-Gemma-Navrasa (instruction-tuned)	2B	29.63	**30.31**	22.43	**60.62**	37.22	26.22	34.40
xGLM	2.9B	24.47	29.19	21.23	57.57	**42.65**	24.00	33.18
Llama-3.2	3B	**34.88**	**32.78**	24.65	**60.75**	**43.45**	**43.88**	40.06
Nemotron-Hindi	4B	**41.64**	**37.86**	**31.93**	**65.91**	**40.92**	**53.77**	**45.33**
xGLM	4.5B	25.93	28.44	21.06	56.84	**41.28**	23.44	32.83
Bloom	7B	27.04	**31.39**	26.36	**60.55**	**47.18**	23.00	35.92
Bloomz (instruction-tuned)	7B	**35.55**	28.57	29.36	57.71	**40.52**	**53.11**	**40.80**
OpenHathi (Llama-2 CPT)	7B	27.69	**30.54**	25.51	57.04	39.03	32.66	35.41
Airavata (instruction-tuned OpenHathi)	7B	**30.43**	**29.53**	25.60	55.59	39.04	41.44	36.93
xGLM	7.5B	26.27	**30.52**	21.40	**58.70**	**45.74**	22.33	34.16
Llama-3	8B	**40.05**	**35.48**	27.48	**63.07**	**45.30**	**49.33**	**43.45**
Aya23	8B	**33.68**	**36.24**	29.88	**64.39**	**47.18**	**52.55**	**43.98**

* Trained for the same number of steps.

Table 7: Zero-shot evaluation of LLMs for cross-lingual language transfer in Hindi. All benchmarks report Accuracy. Models that performed better than our models have been underlined and bold, the best performance of our model has been **bold**.

Models	Size	MMLU-Marathi	ARC-Marathi	Belebele-Marathi	Average
Paramanu-Sanskrit (ours)	139M	24.96	26.49	24.33	25.26
mParamanu (ours)	92M*	23.37	27.53	25.22	25.37
mParamanu (ours)	162M	25.68	22.16	**28.00**	25.28
mParamanu (ours)	237M*	22.73	24.16	23.67	23.52
Paramanu-Marathi (ours)	208M	25.39	26.49	27.33	26.40
Paramanu-Marathi-instruct (ours)	208M	**25.97**	**26.94**	27.87	**26.93**
Paramanu-Hindi (ours)	162M	22.83	24.76	22.78	23.45
Paramanu-Hindi (ours)	367M	23.78	24.16	24.66	24.20
Paramanu-Hindi-instruct (ours)	367M	24.54	25.63	26.44	25.54
Bloom	560M	22.78	24.50	27.00	24.76
Bloomz (instruction-tuned)	560M	26.20	24.24	25.44	25.29
xGLM	564M	22.53	21.29	23.11	22.31
Llama-3.2	1B	26.37	23.72	**28.11**	26.06
Bloom	1.1B	23.93	25.10	**28.33**	25.78
Bloomz (instruction-tuned)	1.1B	24.82	21.81	24.0	23.54
mGPT	1.3B	23.26	22.33	24.33	23.30
xGLM	1.7B	22.54	20.43	22.11	21.69
Sarvam	2B	23.96	27.53	26.77	26.08
Indian-Gemma-Navrasa (instruction-tuned)	2B	28.29	22.77	27.00	26.02
xGLM	2.9B	23.10	19.56	22.55	21.73
Llama-3.2	3B	**31.83**	24.93	**37.33**	**31.36**
Nemotron-Hindi	4B	**32.32**	23.72	**32.22**	29.42
xGLM	4.5B	25.59	23.29	24.22	24.36
Bloom	7B	27.30	25.54	24.00	25.61
Bloomz (instruction-tuned)	7B	**32.62**	**27.44**	**53.00**	**37.68**
OpenHathi (Llama-2 CPT))	7B	26.09	24.24	25.88	25.40
Airavata (instruction-tuned of OpenHathi)	7B	26.15	23.90	**29.89**	26.64
xGLM	7.5B	23.73	21.91	21.77	22.47
Llama-3	8B	**35.47**	25.19	**38.66**	**33.10**
Aya23	8B	27.80	22.94	**35.33**	28.69

* Trained for the same number of steps.

Table 8: Zero-shot evaluation of LLMs for cross-lingual language transfer in Marathi. All benchmarks report Accuracy. Models that performed better than our models have been underlined and bold, the best performance of our model has been **bold**.

Models	Size	Belebele-Tamil	XCOPA-Tamil	MMLU-Tamil	ARC-Tamil	Average
Paramanu-Tamil (ours)	208M	26.88	**57.60**	24.37	24.51	33.34
Paramanu-Tamil-instruct (ours)	208M	**30.22**	56.00	**26.95**	**26.04**	**34.80**
Bloom	560M	27.22	55.80	23.95	25.57	33.13
Bloomz (instruction-tuned)	560M	23.55	**58.60**	25.78	25.30	33.30
xGLM	564M	22.77	56.20	22.74	20.57	30.57
Llama-3.2	1B	28.44	55.60	25.95	21.27	32.81
Bloom	1.1B	25.77	57.00	24.67	24.34	32.94
Bloomz	1.1B	22.66	57.40	26.10	22.59	32.19
mGPT	1.3B	20.88	53.20	23.50	21.36	29.73
xGLM	1.7B	21.88	55.00	23.66	21.71	30.56
Sarvam	2B	27.44	**63.00**	24.06	**26.53**	**35.25**
Indian-Gemma-Navrasa (instruction-tuned)	2B	25.44	**59.00**	**27.84**	22.67	33.73
xGLM	2.9B	23.44	54.20	24.33	20.84	30.70
Llama-3.2	3B	**34.00**	**59.00**	**29.47**	23.90	**36.59**
xGLM	4.5B	22.66	55.20	24.03	21.19	30.77
Bloom	7B	25.55	**59.20**	26.39	24.69	33.95
Bloomz (instruction-tuned)	7B	**50.66**	57.40	**29.48**	**28.10**	**41.41**
xGLM	7.5B	22.44	54.40	24.39	21.71	30.73
Llama-3	8B	**38.55**	**59.80**	**31.66**	**26.35**	**39.09**
Aya23	8B	**33.55**	55.60	26.14	21.19	34.12

Table 9: Zero-shot evaluation of LLMs in Tamil script models. All benchmarks report Accuracy. Models that performed better than our models have been underlined and bold, the best performance of our model has been **bold**.

Models	Size	Belebele-Telugu	XStoryCloze-Telugu	MMLU-Telugu	ARC-Telugu	Average
Paramanu-Telugu (ours)	208M	26.00	51.42	25.12	**26.32**	32.22
Paramanu-Telugu-instruct (ours)	208M	**27.50**	**58.00**	**26.75**	25.75	**34.50**
Bloom	560M	23.55	55.65	24.10	23.85	31.78
Bloomz (instruction-tuned)	560M	22.44	54.86	**26.82**	24.91	32.25
xGLM	564M	25.11	55.85	22.91	17.54	30.35
Llama-3.2	1B	**28.44**	54.86	25.40	19.82	32.13
Bloom	1.1B	26.88	56.38	24.53	24.38	33.04
Bloomz (instruction-tuned)	1.1B	23.11	55.32	25.49	18.77	30.67
mGPT	1.3B	22.88	57.25	25.85	17.89	30.96
xGLM	1.7B	23.66	**58.23**	24.34	18.24	31.12
Sarvam	2B	**27.66**	**60.09**	24.67	25.78	**34.55**
Indian-Gemma-Navrasa (instruction-tuned)	2B	26.55	**58.57**	**28.58**	20.52	33.55
xGLM	2.9B	22.66	**60.09**	23.45	18.85	33.51
Llama-3.2	3B	**31.55**	**58.17**	**29.47**	20.26	**34.86**
xGLM	4.5B	23.66	57.04	24.87	19.38	31.24
Bloom	7B	24.66	57.37	26.62	24.47	33.28
Bloomz (instruction-tuned)	7B	**43.11**	**58.23**	**29.55**	**27.98**	**39.71**
xGLM	7.5B	24.66	**60.22**	23.90	18.15	31.73
Llama-3	8B	**36.88**	**63.53**	**32.74**	21.22	**38.59**
Aya23	8B	**28.55**	54.07	19.91	21.57	31.02

Table 10: Zero-shot evaluation of LLMs in Telugu script models. All benchmarks report Accuracy. Models that performed better than our models have been underlined and bold, the best performance of our model has been **bold**.

N-shot	XNLI-Hindi	XStoryCloze-Hindi	XStoryCloze-Telugu	XCOPA-Tamil
0	33.49	**52.42**	**56.06**	**54.00**
5	**34.04**	51.49	54.67	52.40
25	33.23	52.02	55.92	49.80

Table 11: N-shot evaluation of pretrained Paramanu models across various benchmarks.

a single GPU. Figure 6 presents plots of training loss versus training steps and training loss versus training tokens for several of our pretrained models.

n_params	d_model	n_layers	n_heads	n_kv_heads	Seq Len
108M	768	12	12	12	1024
139M	896	14	14	14	1024
162M	1024	12	16	16	1024
208M	1024	16	16	16	1024
237M	1024	18	18	18	1024
367M	1280	18	10	10	1024

Table 13: Model size configuration.

Model	Params	Batch	Grad Acc.	Seq Len	LR
Bangla	87.25M	32	8	1024	0.002
Bangla	108.5M	32	8	1024	0.003
Hindi	162M	32	8	1024	0.002
Hindi	367.5M	32	16	1024	0.003
Marathi	207.73M	32	8	1024	0.003
mParamanu	92.63M	32	16	1024	0.002
mParamanu	162M	32	8	1024	0.002
Sanskrit	139.3M	64	8	1024	0.003
Tamil	207.84M	32	8	1024	0.002
Telugu	208.25M	16	16	1024	0.003

Table 14: Training hyperparameters for various Paramanu models. All models are pretrained for 100K training steps except Hindi 365M (150K).

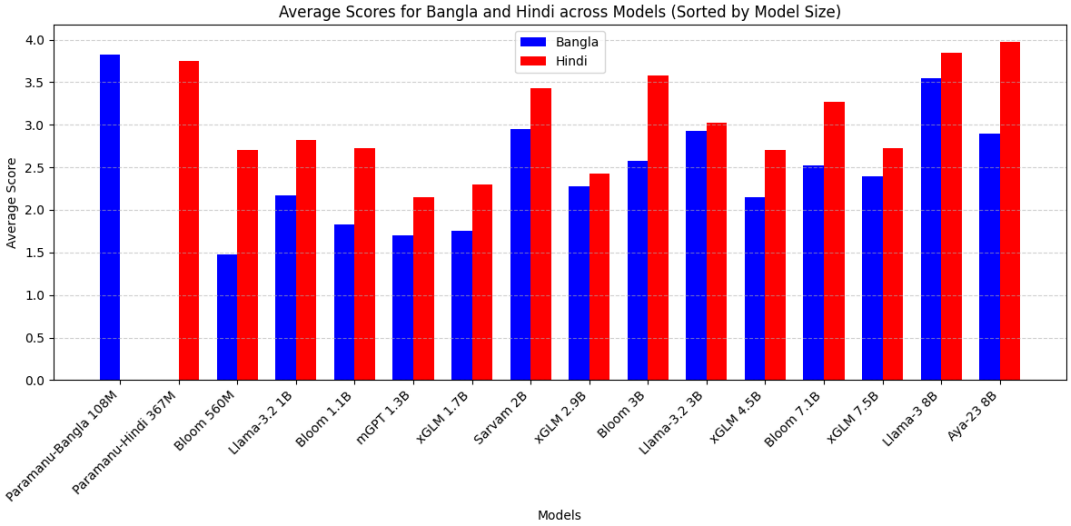


Figure 3: Human evaluation of LLMs. Average score across Grammar, Coherence, Creativity, Factuality.

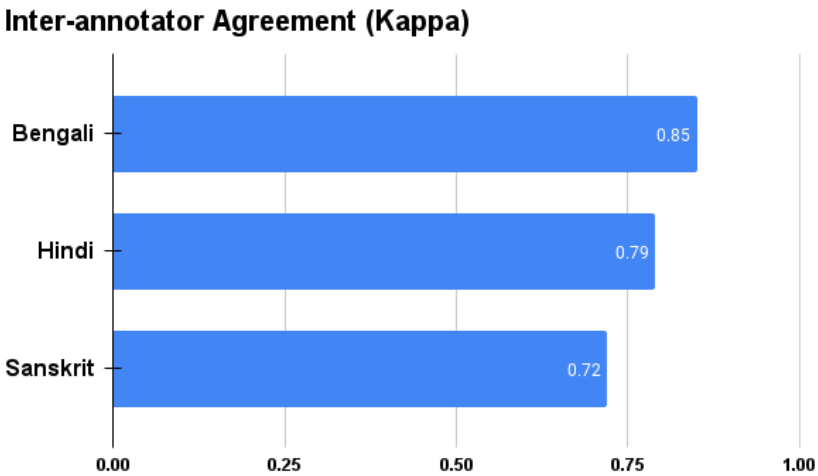


Figure 4: Inter-Annotator Agreement (Kappa)

Language	Input Prompt	Text Generation
Assamese	ভাৰত মোৰ মাতৃভূমি	মোৰ দেশ ভাৰত বিশ্বৰ বিভিন্ন ঠাইৰ সংস্কৃতিকলৈয়ে গঢ় লৈ উঠিছে। মোৰ দেশ ভাৰত এখন সাংস্কৃতিক কেন্দ্ৰ।
Bangla	ভারত আমার মাতৃভূমি	আমার দেশ ভারতবর্ষ আমাদের দেশ । আমার দেশ ভারতবর্ষের বিরাট অংশ এক সময় বঙ্গদেশের মত ছিল।
Dogri	साडा देश भारत है	साडा देश भारत है हाँ आज के समय से आने वाला उत्तर भारतीय है जहां धीरूभाई अम्बानी फॉर युवा का मुजफ्फरपुर का लोग है वहां के बावजूद बिग बॉस नाम की तरफ से भी कुछ लकी।
Konkani	भारत हो म्हजो देश	भारत हो म्हजो देश ह्या राष्ट्राची वाट लायल्या भारत हो म्हजो देश भारत म्हज्या इतिहासांत देव म्हज्या इतिहासांत आस्पावता आदलें पैकूच आसा त्या इतिहासाचो आदलो काळ आशिल्लो हाका इतिहासाचो चवथो भाग म्हण्टा।
Maithili	भारत हमर देश अछि	भारत हमर देश अछि और ओ देशक सर्वोच्च पदसँ ओतप्रोत अछि भारत हो म्हजो देश हो मोलांत।
Odia	ଭାରତ ହେଉଛି ମୋର ମାତୃଭୂମି	ଭାରତ ହେଉଛି ମୋର ମାତୃଭୂମି ଜାତିର ଏକତ୍ରୀକରଣ ହୋଇଛି ଭାରତ ହେଉଛି ମୋର ମାତୃଭୂମି ଓ ମୋ ନିଜସ୍ୱତା
Sanskrit	अस्माकं देशः भारतवर्षः	अस्माकं देशः भारतवर्षः सर्वातिशायी। अस्माकं देशः भारतवर्षः इति ख्यातः।

Table 15: mParamanu 162 M pretrained model text generation

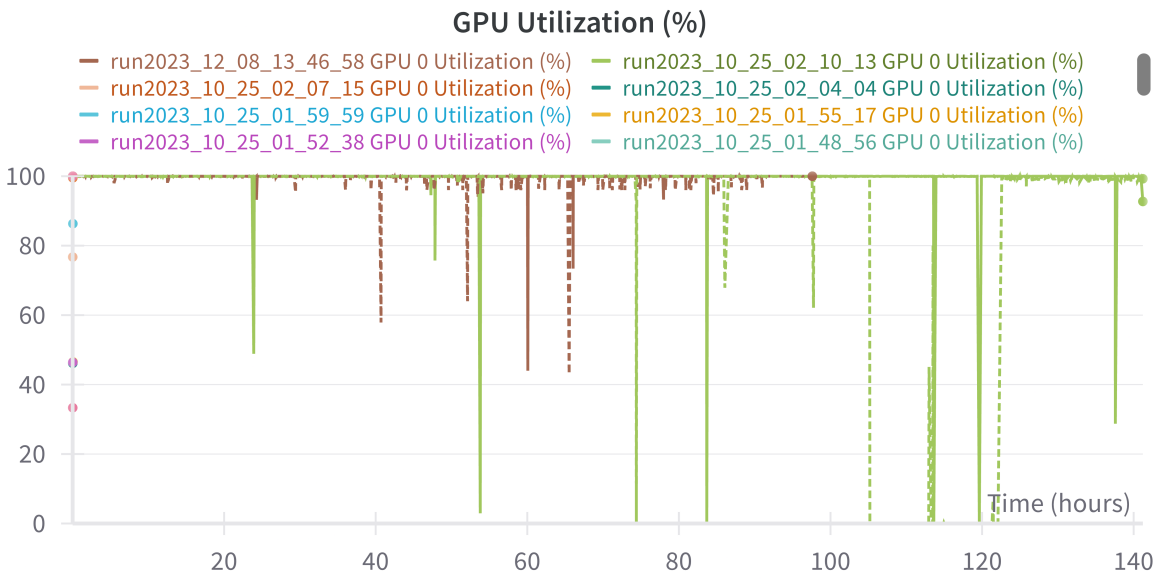
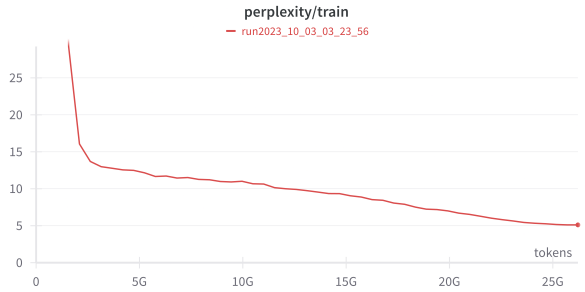
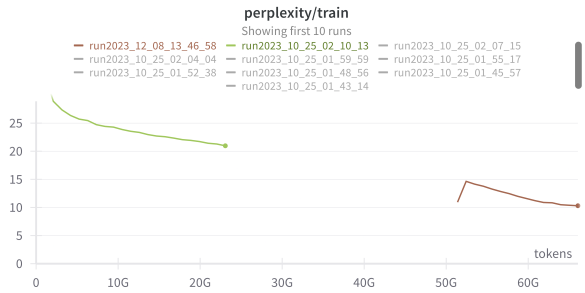


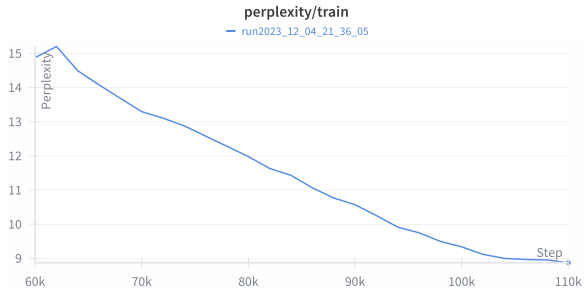
Figure 5: GPU Utilization (%) for pretraining Hindi language model from scratch. Each color indicates a run, resumed after an interruption.



(a) Training Perplexity for Paramanu-Bangla v/s Tokens in Billion (G=billion). Each color indicates a run, resumed after an interruption.



(b) Training Perplexity for Paramanu-Hindi v/s Tokens in Billion (G=billion). Each color indicates a run, resumed after an interruption.



(c) Training Perplexity of Paramanu-Marathi v/s training steps. Each color indicates a run, resumed after an interruption.

(d) Training Perplexity of Paramanu-Sanskrit v/s training steps. Each color indicates a run, resumed after an interruption.

Figure 6: Training Perplexity v/s Tokens and Training Perplexity v/s training steps for Paramanu pretrained models. Each color indicates a run, resumed after an interruption.

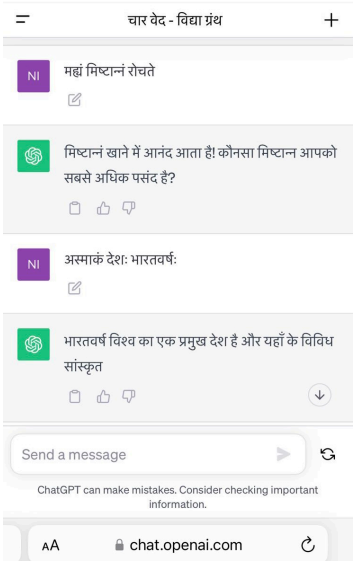


Figure 7: GPT-3.5 Turbo response to Sanskrit prompt: अस्माकं देशः भारतवर्षः (asmākaṁ dēśaḥ bhāratavarṣaḥ), मह्यं मिष्टान्नं रोचते (mahyaṁ miṣṭānnaṁ rōcatē.) Accessed in October 2023.

Figure 8: GPT-3.5 Turbo response to Sanskrit prompt: वेदः चत्वारः सन्ति (vēdaḥ catvāraḥ santi), किमर्थं त्वं गच्छसि (kimarthaṁ tvaṁ gacchasi.) Accessed in October 2023.

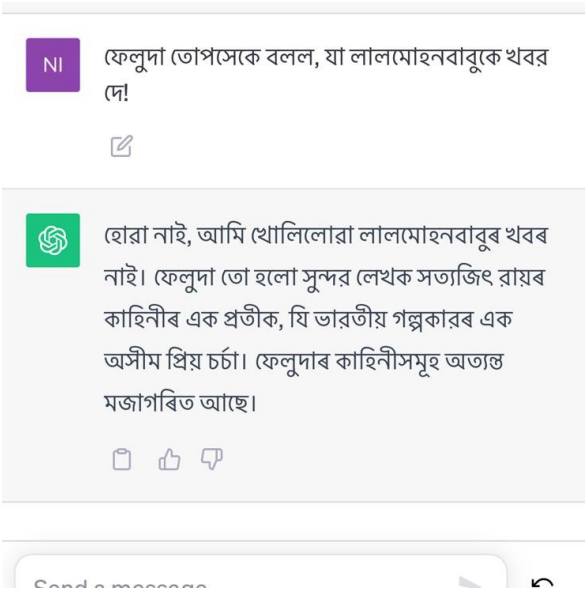


Figure 9: GPT-3.5 Turbo response to Bangla prompt ফেলুদা তোপসেকে বলল, যা লালমোহনবাবুকে খবর দে! Accessed in October 2023.

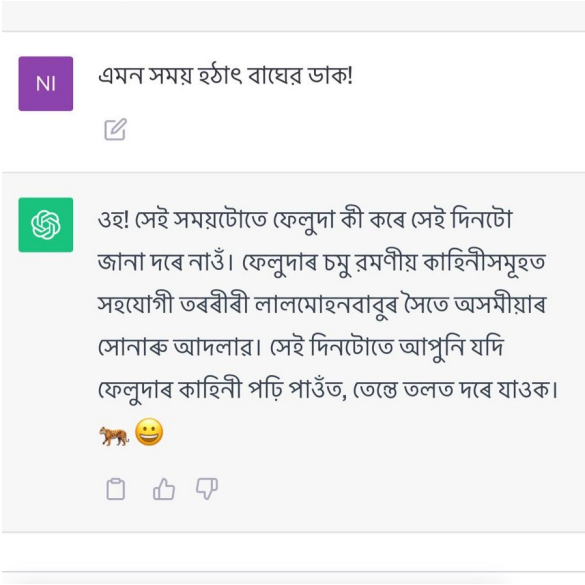


Figure 10: GPT-3.5 Turbo response to Bangla prompt এমন সময় হঠাৎ বাঘের ডাক! Acessed in October 2023.