Parallel Tokenizers: Rethinking Vocabulary Design for Cross-Lingual Transfer

Anonymous ACL submission

Abstract

Tokenization defines the foundation of multilingual language models by determining how words are represented and shared across languages. However, existing methods often fail to support effective cross-lingual transfer because semantically equivalent words are assigned distinct embeddings. For example, "*I eat rice*" in English and "*Ina cin shinkafa*" in Hausa are typically mapped to different vocabulary indices, preventing shared representations and limiting cross-lingual generalization. We introduce **parallel tokenizers**. This new framework trains tokenizers monolingually and then aligns their vocabularies exhaustively using bilingual dictionaries or word-to-word translation, ensuring consistent indices for semantically equivalent words. This alignment enforces a shared semantic space across languages while naturally improving fertility balance. To assess their effectiveness, we pretrain a transformer encoder from scratch on thirteen low-resource languages and evaluate it on sentiment analysis, hate speech detection, emotion classification, and sentence embedding similarity. Across all tasks, models trained with parallel tokenizers outperform conventional multilingual baselines, confirming that rethinking tokenization is essential for advancing multilingual representation learning–especially in low-resource settings.[1]

1 Introduction

Tokenization is a fundamental component of language models, converting text into discrete units such as words, subwords, or bytes (Sennrich et al., 2016). In multilingual settings (Devlin et al., 2019; Conneau et al., 2020a; Xue et al., 2021), a single tokenizer is typically applied across languages, which disproportionately disadvantages underrepresented languages: the same semantic content is often segmented into longer token sequences compared to high-resource languages (Rust et al., 2021). This imbalance is captured by the fertility score (Rust et al., 2021), which quantifies the number of tokens required to represent a given unit of meaning and exposes systematic inefficiencies in multilingual tokenization.

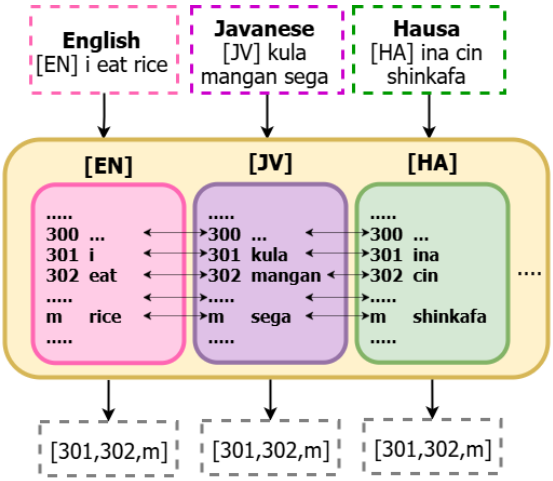

Figure 1: The overview of the parallel tokenizer. Tokens with equivalent meanings across languages are mapped to the same index and thus share the same embedding representation in the model.

Beyond fertility, multilingual tokenizers also fail to align semantics across languages. Semantically equivalent words (e.g., "*eat*" in English, "*ci*" in Hausa, and "食べる" in Japanese) are mapped to entirely distinct vocabulary indices (Devlin et al., 2019; Conneau et al., 2020a; Xue et al., 2021; Achiam et al., 2023; Bai et al., 2023; Dubey et al., 2024), erecting artificial barriers to cross-lingual sharing. This fragmentation undermines the promise of transfer learning in multilingual models and introduces redundancy and inefficiency at the very foundation of representation learning.

Several strategies have been proposed to address these challenges, especially in the pretraining of medium- and low-resource language models. For

[1] Code can be found at anonymous.com

instance, the Sherkala model (Koto et al., 2025)–a multilingual model covering Kazakh, Russian, Turkic, and English–employs vocabulary balancing and data sampling techniques to oversample low-resource languages during tokenizer training, thereby improving fertility scores. However, semantic redundancy remains unresolved. Alternative approaches, such as byte- or character-level tokenizers (Xue et al., 2022; Clark et al., 2022; Cao, 2023), alleviate token length disparities but at the cost of efficiency and semantic interpretability.

We propose a **parallel tokenizer** to address these challenges (Figure 1). Instead of relying on a single multilingual tokenizer, we first train a monolingual tokenizer as a pivot and then align its vocabulary with target languages via word-level mapping, ensuring that token indices correspond to semantically equivalent words across languages. While achieving perfect alignment is inherently difficult, we restrict alignment to exact word forms. To reduce cross-lingual interference, we further incorporate language identity embeddings. (Figure 2), ensuring that token representations remain unique to each language while still enabling cross-lingual semantic sharing. This design yields fairer representations, facilitates more effective transfer, and provides a scalable framework for adding new languages without retraining the entire vocabulary.

Our contributions can be summarized as follows:

- We propose a parallel tokenizer for the multilingual language model that enhances the balance of fertility across individual languages and strengthens cross-lingual transfer. We benchmark pretraining from scratch and continual pretraining strategies, each under three setups: our parallel tokenizer, the traditional multilingual tokenizer, and a pretrained tokenizer from mBERT.
- We demonstrate the effectiveness of parallel tokenizers across diverse downstream tasks, including sentiment analysis, emotion classification, hate speech detection, and sentence embedding, all in low-resource contexts where tokenization quality has a disproportionate impact on performance.
- We present a detailed analysis of training under varying levels of data availability (e.g., 1%, 10%, 50%, 100%), auxiliary languages, and conduct an extensive evaluation of the fertility score to quantify tokenization efficiency.

2 Related Works

The standard practice in multilingual language modeling is to train a single tokenizer on a combined multilingual corpus (Achiam et al., 2023; Devlin et al., 2019; Xue et al., 2021; Dubey et al., 2024; Bai et al., 2023), typically using algorithms such as WordPiece (Devlin et al., 2019), Byte Pair Encoding (BPE) (Sennrich et al., 2016), the Unigram Language Model (Kudo, 2018), or SentencePiece (Kudo and Richardson, 2018). Despite their simplicity and scalability, these approaches face the well-documented *curse of multilinguality* (Conneau et al., 2020a): monolingual tokenizers consistently outperform shared multilingual ones in fertility and segmentation quality (Rust et al., 2021; Petrov et al., 2023), revealing a persistent trade-off between coverage and linguistic specialization. To mitigate these issues, prior studies have proposed balancing vocabulary allocation across languages (Zheng et al., 2021; Chung et al., 2020; Liang et al., 2023; Koto et al., 2025). However, while such methods improve fertility for low-resource languages, they often lead to redundant semantic representations, where tokens with equivalent meanings occupy distinct indices.

Beyond these engineering efforts, several studies have examined the conceptual role of tokenization in multilingual transfer. Conneau et al. (2020b) argue that parameter sharing is the primary factor enabling cross-lingual generalization. However, this line of research has not explored multilingual token embeddings in a parallel setting, where alignment across languages could better capture shared semantics. Limisiewicz et al. (2023) focus on lexical overlap, showing that surface-form similarity alone does not ensure semantic equivalence, leaving open the challenge of designing vocabularies that promote semantic alignment across languages.

Recent theoretical work further highlights the enduring importance of tokenization. Rajaraman et al. (2024) demonstrate that transformers trained on structured distributions struggle to learn effectively without discrete token boundaries, calling into question the feasibility of tokenization-free paradigms (Deiseroth et al., 2024). In this context, our work revisits multilingual tokenization from a new perspective, emphasizing that tokenization remains a foundational component for building semantically aligned and efficient multilingual language models.

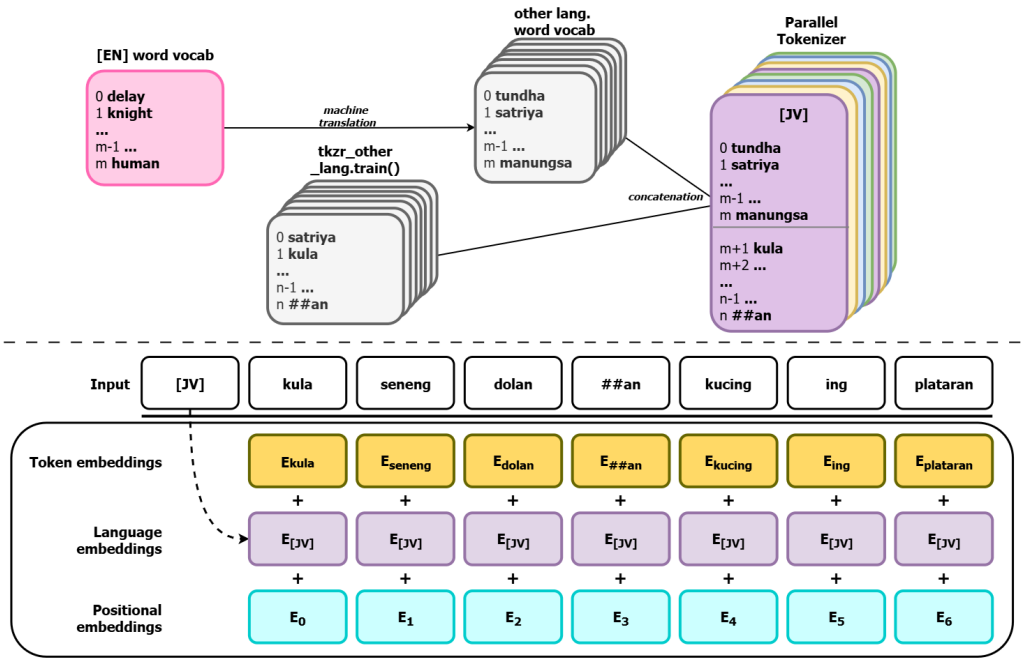

Figure 2: Design of the parallel vocabularies (top) and the model input representation (bottom). The language token (e.g., [JV] in the example) is not used as an explicit input token; instead, it functions as a signal to select the corresponding language identity embedding during input representation.

3 Parallel Tokenizer

To address fertility imbalance and the separation of semantically equivalent words into different token indices (Rust et al., 2021; Bai et al., 2023), we introduce the Parallel Tokenizer. This section outlines (1) the construction of the parallel vocabulary and (2) the design of the model input representation.

3.1 Parallel Vocabulary Design

To construct parallel vocabularies across languages, we first train an English monolingual tokenizer using WordPiece (Devlin et al., 2019) on the English Wikipedia dump as the corpus. We set the vocabulary size to 30,522, which matches the monolingual BERT model (Devlin et al., 2019). The resulting vocabulary entries can be grouped into four categories:

1. `subword`, e.g., *'##ing'*, *'##able'* (28.75% of vocabulary);
2. `short word`, e.g., *'ple'*, *'szo'*, *'rae'*; tokens with a length shorter than four characters (3.28% of vocabulary);
3. `number`, numerical tokens such as *'192'*, *'392'*, etc. (2.10% of vocabulary); and
4. `word`, which encompasses all other tokens, e.g., *'care'*, *'drink'*, *'administration'* (65.87% of vocabulary).

We retain only the English `word`-type vocabulary and expand it into other languages through token-level machine translation (see Figure 2). This filtering is necessary because other token types (`subword`, `short word`, and `number`) often yield unreliable or meaningless translations that rarely correspond to valid equivalents in the target languages. Using this filtered vocabulary as the base, we construct the parallel tokenizer in three steps: (1) translating the `word`-type vocabulary, (2) training a monolingual tokenizer for each target language, and (3) concatenating the resulting vocabularies.

Translating the `word`-type vocabulary. We translate each English `word`-type token into its counterpart in the target language using Google Translate.[2] We initially considered bilingual dictionaries such as PanLex,[3] but found substantial limitations in both coverage and data quality, discussed in Section 6. Machine translation offers broader and more up-to-date lexical coverage. To further ensure quality, we apply back-translation to the invalid outputs, such as multiword or malformed phrases. This process yields semantically aligned vocabularies that form the word-level back-

[2] https://translate.google.com/
[3] https://old.panlex.org/

bone of our parallel tokenizer.

Training a monolingual tokenizer on the target language. Since the English tokenizer contains only 65.87% `word`-type tokens, we expand each parallel tokenizer to the full vocabulary size of 30,052 tokens by training a monolingual tokenizer on its corresponding Wikipedia corpus. The resulting vocabularies serve as sources for additional token types. We also introduce *language identity tokens* (e.g., `[JV]` in Figure 2) to explicitly mark the input language and ensure consistent handling across all languages (see Section 3.2).

Concatenating the vocabulary. For each target language, we concatenate two components: (1) the translated `word`-type tokens and (2) the corresponding monolingual vocabulary. We prioritize the translated `word`-type tokens, special tokens (e.g., `[SEP]`, `[UNK]`, `[CLS]`), language identity tokens,[4] and a 1,000-character-level subset from the English tokenizer. We then append the monolingual vocabulary, remove duplicates, and cap each final vocabulary at 30,522 entries for consistency across languages. On average, across all languages defined in Section 4, we align 82% of `word`-type tokens (slightly below 100% due to back-translation filtering), and 61% of all tokens are aligned in the final parallel tokenizer.

3.2 Model Input Representation

Let $x = (l, x_1, x_2, \ldots, x_i)$ denote an input sequence of length i, where $l \in \mathcal{L}$ represents a language identity token and $\mathcal{L}$ is the set of all such tokens (e.g., `[AM]`, `[HA]`, etc.; see Table 6 in Appendix A), with $|\mathcal{L}| = k$. We define a collection of k parallel tokenizers, each corresponding to a specific language, as

$$\mathcal{T} = \{T_1, T_2, \ldots, T_k\}.$$

Based on Figure 2, the language identity token l determines which tokenizer $T_j \in \mathcal{T}$ is used for tokenization. We then tokenize the remaining sequence $x' = (x_1, x_2, \ldots, x_i)$, excluding l, using T_j to obtain the token IDs $\mathcal{I} = (I_1, I_2, \ldots, I_m)$, where $i \leq m$, along with any auxiliary representations such as attention masks and token type IDs. The final input representation is constructed by summing the token embeddings, segment embeddings, positional embeddings, and a language identity embedding. The language identity embedding is broadcast across all m tokens to provide a unique representation for each language. This additional embedding serves both as a syntactic cue and as a disambiguation signal for unaligned tokens (recall from Section 3.1 that approximately 61% of tokens are aligned across languages).

4 Experimental Setup

4.1 Language Setup

We first define the set of languages considered in this work. English is included as the base language, given its large corpus size and its role in training the base tokenizer. We then select a diverse set of low-resource languages, some represented in mBERT (Devlin et al., 2019) and others absent from it, to evaluate the generalization of our approach in settings where linguistic resources are limited. We use mBERT as a lower-bound baseline, particularly for languages it has not been trained on. The selected languages are as follows:

- Seen by mBERT: Javanese (jav), Minangkabau (min), Sundanese (sun), and Swahili (swa).
- Unseen by mBERT: Acehnese (ace), Amharic (amh), Balinese (ban), Hausa (hau), Igbo (ibo), Kinyarwanda (kin), Oromo (orm), Tigrinya (tir), and Twi (twi).

Most of these languages use the Latin script, while only Amharic and Tigrinya use the Amharic script. The selection is guided by the availability of essential resources, including Wikipedia dumps[5] for tokenizer and transformer pretraining, Google Translate[6] for constructing parallel tokenizers, and FLORES+ (Costa-Jussà et al., 2022) for evaluating tokenization metrics.

4.2 Tokenizers & Models

We adopt the encoder-based transformer mBERT (Multilingual BERT, uncased) (Devlin et al., 2019) as the backbone of our experiments. Focusing on an encoder-only architecture allows us to examine how well cross-lingual transfer generalizes in low-resource settings. mBERT was pretrained on 102 languages using a shared 110K WordPiece vocabulary. As our baseline, we use the original mBERT model and refer to its tokenizer as *Single-102L* (i.e., a single tokenizer vocabulary covering 102 languages), which serves as the reference multilin-

[4] The complete list of language tokens is provided in Appendix A, Table 6, column 'code'.

[5] https://dumps.wikimedia.org/. Resources were downloaded in November 2024.

[6] https://translate.google.com/

gual tokenizer for evaluating our proposed parallel tokenization approach.

To enable a fair comparison, we also train a single tokenizer on the Wikipedia data of the 13 languages listed in Section 4.1 (hereafter referred to as *Single-13L*). Using the same data, we train our proposed parallel tokenizer, denoted as *Parallel-13L*. For both tokenizers, we adopt a pretraining-from-scratch setup, where all model weights are randomly initialized.

4.3 Evaluation Setup

To evaluate the effectiveness of our proposed parallel tokenizer, we conduct three main experiments in low-resource languages: (i) tokenization analysis, (ii) sequence classification, and (iii) cross-lingual representation similarity.

Tokenization Analysis. We use the FLORES+ dataset (Costa-Jussà et al., 2022; Abdulmumin et al., 2024)[7], a parallel corpus covering 200 languages, to evaluate the effectiveness of our parallel tokenizer against both multilingual and monolingual tokenizers in 1,012 parallel texts. All 13 languages studied in our experiments are represented in FLORES+. We report two metrics: (i) Fertility score: the average number of tokens per word, indicating how compact or fragmented the tokenization is; and (ii) Parity score (Petrov et al., 2023): a cross-lingual metric that compares token counts across two languages,[8] assigning the best score when the counts are identical.

Sequence Classification. We conduct experiments on sentiment analysis, hate speech detection, and emotion classification in low-resource languages by fine-tuning the language model jointly on data from all languages. To analyze cross-lingual transfer, we vary the training size at 1%, 10%, 50%, and 100% of the available data. For sentiment analysis and hate speech detection, we use the NusaX-Senti (Winata et al., 2023) and AfriHate (Muhammad et al., 2025a) datasets, respectively, and evaluate both using macro-F1 over three multi-classes. For emotion classification, we use EthioEmo (Belay et al., 2025) and BRIGHTER (Muhammad et al., 2025b), evaluated with weighted F1 for consistency across six multi-label tasks. A detailed overview of the dataset languages is provided in Table 7 (Appendix B).

Cross-Lingual Representation Similarity. We perform bitext mining (Artetxe and Schwenk, 2019) on FLORES+ using the contextualized representations from the final layer of the language models. Following the setup of Huang et al. (2025), we evaluate all possible language pairs covered by our models. Performance is measured using the error rate of the `xsim` score (Artetxe and Schwenk, 2019). Additionally, we apply Principal Component Analysis (Jolliffe, 2002) to visualize cross-lingual clustering, comparing our parallel tokenizer with the multilingual model that uses a single tokenizer. Representations are considered semantically aligned when sentences from different languages cluster together, rather than being separated by language identity.

4.4 Hyperparameters and Resources

We use an NVIDIA RTX A6000 GPU with 48GB of VRAM for both pretraining and fine-tuning. Pretraining follows the masked language modeling (MLM) setup of Devlin et al. (2019), using a learning rate of 5e-5 for the *Single-13L* model and 1e-4 for our proposed *Parallel-13L* model. Training is performed on 394M tokens per epoch (6M tokens for the development set) for a total of 122,850 steps or 50 epochs. The value is determined empirically based on the convergence of the pretraining loss on the development set.

For evaluation, we set the batch size to 20, the maximum sequence length to 128, and the maximum number of epochs to 100, with early stopping triggered after 5, 2, 3, and 3 epochs for NusaX-senti, AfriHate, EthioEmo, and BRIGHTER, respectively. Learning rates were adopted from the original benchmark recommendations: 1e-5 for NusaX-senti and BRIGHTER, and 5e-5 for AfriHate and EthioEmo. To ensure robustness and fairness, each experiment was repeated three times with different seeds (1, 12, and 123), and we report the mean performance together with the corresponding standard deviations.

5 Results and Analysis

5.1 Tokenization Qualities

Table 1 compares our *Parallel-13L* tokenizer with *Single-102L* (mBERT), *Single-13L*, and the monolingual tokenizers. In terms of fertility score, our method substantially outperforms the multilingual baselines, exceeding the closest one by an average

[7] https://huggingface.co/datasets/openlanguagedata/flores_plus

[8] We select Hausa as the reference language for comparison, as it provides the largest available resource during pretraining.

lang.	tokens/word (fertility score) ↓				parity score ↓			
	Multilingual Tokenizer			Mono-	Multilingual Tokenizer			Mono-
	Single-102L	Single-13L	Parallel-13L	lingual	Single-102L	Single-13L	Parallel-13L	lingual
Seen by mBERT								
jav	1.94	1.65	**1.48**	1.43	1.24	**1.06**	1.13	1.69
min	1.96	1.79	**1.50**	1.46	1.20	**1.05**	1.09	1.68
sun	2.01	1.74	**1.50**	1.44	1.21	**1.01**	1.13	1.74
swa	2.10	1.65	**1.42**	1.38	1.07	**1.01**	1.10	1.63
Unseen by mBERT								
ace	2.27	1.95	**1.54**	1.61	**1.01**	1.20	1.02	1.51
amh	-	2.43	**1.82**	1.66	2.19	1.21	**1.06**	2.33
ban	2.13	1.77	**1.53**	1.48	1.11	**1.03**	1.07	1.63
hau	1.91	1.38	**1.33**	1.30	1.00	1.00	1.00	1.00
ibo	2.16	1.54	**1.50**	1.48	1.12	**1.10**	1.12	1.32
kin	2.78	2.10	**1.70**	1.63	1.16	1.21	**1.03**	1.53
orm	3.01	2.40	**1.82**	1.72	1.23	1.35	**1.07**	1.55
tir	-	2.61	**1.83**	1.85	1.98	1.45	**1.06**	2.14
twi	2.17	1.55	**1.38**	1.35	1.17	1.16	**1.07**	1.42
avg	2.22	1.89	**1.57**	1.52	1.28	1.14	**1.07**	1.63

Table 1: Fertility and parity scores for each tokenizer across all languages. The **bold** scores indicate the best performance for each language. Monolingual tokenizers are also included to provide a comparative perspective between monolingual and multilingual tokenizers. Fertility scores for `amh` and `tir` are marked as N/A for *Single-102L* because mBERT consistently produces `[UNK]` tokens for these languages.

of 0.32 points, indicating more compact segmentation (i.e., fewer tokens per word). The only slight gap (0.05) appears against the monolingual tokenizer, which is expected since monolingual models are optimized for their respective languages.

For the parity score, which quantifies consistency in tokenization across parallel texts and reflects cross-lingual alignment, *Parallel-13L* achieves the best overall performance, outperforming the next-best baseline (*Single-13L*) by 0.07 points on average. The multilingual baselines (*Single-102L* and *Single-13L*) perform notably worse on Amharic-script languages (Amharic and Tigrinya) due to script-specific segmentation differences, while monolingual tokenizers score lowest by design, as parity inherently measures multilingual generalization.

We also analyze the number of `[UNK]` tokens generated when tokenizing FLORES+ inputs, with results shown in Figure 3. Among the languages covered by mBERT, our method produces the fewest `[UNK]` tokens. In contrast, *Parallel-13L* yields slightly more unknown tokens, about eight more on average, than *Single-13L*. The mBERT tokenizer (*Single-102L*) performs worst overall, primarily due to its limited handling of Amharic-script languages.

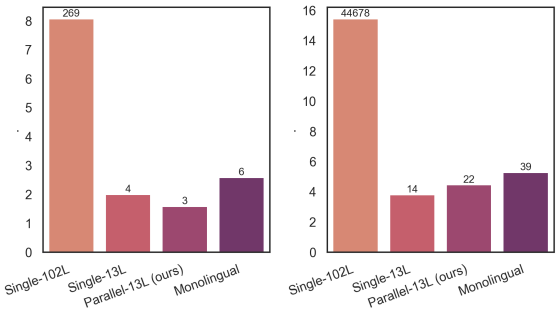

Figure 3: Total number of [UNK] tokens occurs when tokenizing the FLORES+ dataset for each language. Left: languages seen by mBERT (jav, min, sun, swa); Right: languages unseen by mBERT (ace, amh, ban, hau, ibo, kin, orm, tir, twi). Values are plotted on a $\log_2$ scale.

5.2 Sequence Classification

Across three random seeds, Table 2 shows that our parallel tokenizer (*Parallel-13L*) consistently outperforms all baselines across training sizes and evaluation metrics. On average, *Parallel-13L* exceeds the closest baseline by 0.92%, 1.28%, 0.72%, and 1.22% F1 at the 100%, 50%, 10%, and 1% training data levels, respectively. These results demonstrate the effectiveness of a parallelized tokenizer design in enhancing cross-lingual transfer, particularly in low-resource scenarios.

The improvements in our approach are consistent across the NusaX-senti, AfriHate, and BRIGHTER datasets, where *Parallel-13L* outperforms all other baselines regardless of training size. The only exception occurs with EthioEmo, where *Single-13L* achieves higher scores than *Parallel-13L* only at the 10% and 1% settings. Moreover, *Single-102L* performs notably worse on EthioEmo due to its limited coverage of Amharic, Oromo, and Tigrinya, which are languages that rely pre-

#training data	Multilingual Tokenizer	*Sentiment*	*Hate Speech*	*Emotion Classification*		Avg ↑
		NusaX-senti ↑	AfriHate ↑	EthioEmo ↑	BRIGHTER ↑	
100%	Single-102L	73.11 (±1.70)	62.83 (±2.38)	30.10 (±6.97)	48.47 (±1.32)	53.63
	Single-13L	76.09 (±1.27)	69.61 (±1.19)	54.98 (±0.98)	48.26 (±0.94)	62.24
	Parallel-13L (ours)	**76.16 (±1.05)**	**69.80 (±1.20)**	**57.01 (±0.84)**	**49.68 (±1.89)**	**63.16**
50%	Single-102L	69.81 (±1.09)	61.52 (±1.47)	31.96 (±2.20)	44.68 (±1.13)	51.99
	Single-13L	72.47 (±1.36)	67.26 (±1.36)	51.33 (±1.48)	45.77 (±1.46)	59.21
	Parallel-13L (ours)	**73.52 (±1.17)**	**67.40 (±0.94)**	**54.27 (±1.78)**	**46.76 (±1.51)**	**60.49**
10%	Single-102L	59.08 (±2.63)	54.69 (±2.98)	22.07 (±7.47)	36.71 (±1.87)	43.14
	Single-13L	64.76 (±1.84)	59.80 (±2.09)	**42.10 (±2.19)**	36.64 (±2.23)	50.83
	Parallel-13L (ours)	**66.16 (±2.00)**	**60.17 (±1.50)**	41.35 (±2.21)	**38.51 (±1.27)**	**51.55**
1%	Single-102L	27.79 (±7.41)	40.82 (±4.15)	10.73 (±11.17)	0.00 (±0.00)	19.84
	Single-13L	31.54 (±3.87)	44.70 (±4.45)	**27.37 (±1.88)**	17.54 (±2.57)	30.29
	Parallel-13L (ours)	**33.83 (±3.90)**	**46.73 (±2.52)**	26.58 (±1.37)	**18.88 (±3.96)**	**31.51**

Table 2: Performance comparison of tokenizer setups on sentiment analysis, hate speech detection, and emotion classification tasks. Best scores per benchmark setups are highlighted in **bold**.

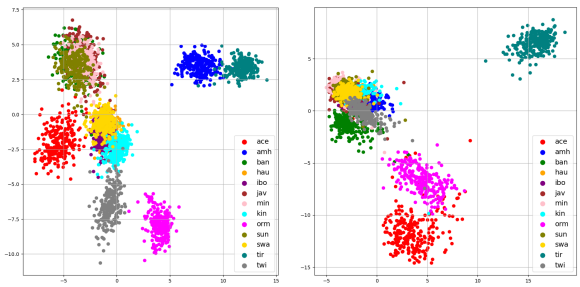

Figure 4: PCA visualization of the last hidden states from *Single-13L* (left) and *Parallel-13L* (right) models on the FLORES+ dataset.

	Single-102L	Single-13L	Parallel-13L
Avg. err. `xsim` ↓	91.33	83.56	**74.08**
# of best `xsim` ↑	3	12	**63**

Table 3: Bitext mining metric meta-scores on pretrained models under different setups.

#data in tgt language		S-102L	S-13L	P-13L (ours)
50%	NusaX-senti	71.76	75.22	**75.42**
	AfriHate	61.45	**67.06**	67.00
	EthioEmo	29.75	51.73	**53.63**
	BRIGHTER	44.11	45.00	**47.11**
0%	NusaX-senti	68.80	71.83	**72.70**
	AfriHate	33.72	37.27	**40.67**
	EthioEmo	9.73	**23.75**	23.20
	BRIGHTER	15.66	15.04	**19.73**

Table 4: Benchmarking results under limited target-language data. S-102L, S-13L, and P-13L denote *Single-102L*, *Single-13L*, and *Parallel-13L*, respectively.

dominantly on the Amharic script. Detailed per-language benchmark results are provided in Appendix C (Tables 8, 9, 10, and 11 for NusaX-senti, AfriHate, EthioEmo, and BRIGHTER, respectively).

5.3 Cross-Lingual Representation Similarity

Using the parallel FLORES+ corpus, we visualize cross-lingual representation similarity for each model by extracting the final hidden states of 250 sampled parallel sentences. If a model learns shared representations across languages, PCA should reveal clusters based on semantic similarity rather than language identity. Figure 4 compares *Single-13L* and *Parallel-13L* in 2D space. *Single-13L* tends to cluster representations by language family, for example, Indonesian languages (Sundanese, Minangkabau, Balinese, and Javanese) group together, while African languages form a separate cluster. In contrast, *Parallel-13L* yields more compact cross-lingual clusters, indicating stronger semantic alignment, with only Acehnese, Oromo, and Tigrinya appearing as outliers for both due to limited data.

We further evaluate cross-lingual similarity through bitext mining. As shown in Table 3, *Parallel-13L* achieves the lowest `xsim` error rate and the highest number of best scores across language pairs (details in Appendix D). These results confirm that *Parallel-13L* learns more semantically consistent representations across languages than *Single-13L*, reinforcing its advantage for cross-lingual tasks.

5.4 Cross-Lingual Transfer under Limited Target-Language Data

While our main experiments use data from all languages during training, we further analyze the model's behavior when the target-language data is scarce or unavailable–a common scenario in low-resource settings. To simulate this condition, we exclude the target language from the training corpus and evaluate two setups: (i) 0% target-language data (zero-shot) and (ii) 50% target-language data (partial-shot). Table 4 shows that our method consistently achieves the highest F1 scores in both

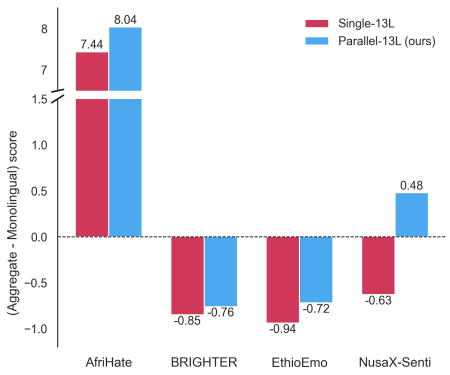

Figure 5: Performance differences across benchmarks on both cross-lingual and monolingual finetuning data for models pretrained with different tokenizer setups.

settings. The only exceptions are a slight decrease of 0.06% on AfriHate with 50% target data and 0.55% on EthioEmo with 0% target train data. Overall, *Parallel-13L* outperforms the baselines, demonstrating stronger cross-lingual transfer than the traditional single tokenizer. The detailed results are presented in Appendix E in Table 15, 16, 17, and 18.

5.5 How Much Does Multilingual Training Improve Over Single-Language Training?

This analysis compares fine-tuning on concatenated multilingual datasets with training solely on a target language's data. As shown in Figure 5, both baselines and our method benefit from multilingual training in the AfriHate benchmark, with average gains of 7-8%. In contrast, improvements are smaller for BRIGHTER and EthioEmo, while in NusaX-senti, our method still achieves a modest 0.48% increase. Between *Single-13L* and *Parallel-13L*, the latter benefits more consistently from multilingual concatenation, suggesting that it leverages shared cross-lingual information more effectively. Detailed results for monolingual fine-tuning are provided in Appendix F, showing that overall performance is comparable, though *Parallel-13L* maintains slightly higher scores on average.

5.6 Continual Pre-Training Experiments

We perform continual pretraining (CPT) from mBERT by adapting its vocabulary and tokenizer to our parallel setup. Newly introduced token embeddings are initialized by averaging the mBERT embeddings of their constituent subwords, as determined by the original mBERT tokenizer (Koto et al., 2021). Unlike pretraining from scratch, this approach retains all mBERT parameters while updating the token embedding layer to accommodate the new vocabularies. In *Single-13L*, each token in the new vocabulary is mapped to its corresponding English subwords in mBERT, and its embedding is initialized by averaging the associated subword embeddings. In *Parallel-13L*, each token is tokenized into subwords across all 13 languages, and its embedding is initialized by averaging the pooled subword embeddings across languages.

#data	S-102L*	S-13L*	P-13L* (ours)
NusaX-senti	73.1 (±1.7)	78.3 (±1.0)	**78.6** (±1.2)
Afrihate	62.8 (±2.4)	**71.3** (±1.9)	70.1 (±0.9)
EthioEmo	30.1 (±7.0)	56.7 (±0.9)	**57.4** (±0.8)
BRIGHTER	48.5 (±1.3)	**50.5** (±0.9)	50.3 (±1.2)

Table 5: Benchmarking results under the continual pretraining setting. S-102L*, S-13L*, and P-13L* denote *Single-102L*, *Single-13L*, and *Parallel-13L*, respectively, which have been continually pretrained from the mBERT model.

Table 5 shows that *Single-13L* and *Parallel-13L* achieve similar performance under continual pretraining (CPT). However, as detailed in Appendix G, our method yields stronger cross-lingual alignment, languages cluster by meaning rather than family, and bitext mining confirms more consistent representations. This indicates that even when task scores converge, *Parallel-13L* maintains a structural advantage in preserving cross-lingual coherence.

6 Conclusion

We introduce parallel tokenizers, constructed by first training a monolingual tokenizer as a pivot and then aligning its word vocabulary with other languages using machine translation, ensuring that semantically equivalent words across languages share the same representation. We evaluate this approach along three dimensions. In terms of tokenization quality, it yields the lowest fertility and parity scores, indicating more efficient tokenization while reducing disparities across languages. In sequence classification,our method shows improvements over the baselines, yielding higher average F1 scores across benchmarks. Finally, in cross-lingual sentence representation, our approach produces stronger cross-lingual alignment representation than ordinary tokenization methods, making it especially beneficial for cross-lingual training and for incorporating auxiliary languages into multilingual models.

Limitations

To develop a robust parallel tokenizer, each stage of designing the parallel vocabulary and model input representation required careful consideration. For mapping the English vocabulary in the tokenizer, we employed machine translation (MT). Although bilingual dictionaries can potentially provide more precise word-level mappings due to their predefined vocabularies, our attempt to utilize the PanLex bilingual dictionary (as discussed in Section 3.1) revealed substantial limitations in both coverage and data quality, particularly for lower-resource languages. While MT enabled us to align approximately 61% of tokens, the bilingual dictionary achieved only about 21.5%. Therefore, we adopted MT for our final approach.

This choice, however, introduces a minor limitation related to the quality of the machine translation itself, as several mapping errors were observed, including invalid outputs such as multiword or malformed phrases. Consequently, there remains potential to improve token alignment through more refined resources or hybrid methods. Furthermore, there is room to enhance the model's input representation, as detailed in Appendix H, which we plan to investigate further in future work.

Our current study focuses on sequence classification, aligning with our focus on low-resource languages that have limited data. In future research, as more diverse datasets become available, we aim to expand the benchmarking to additional tasks and languages, ensuring that the parallel tokenizer can effectively scale and maintain performance across a broader linguistic spectrum.

Ethical Consideration

All datasets used in this work are publicly available and comply with their respective licenses, including Wikipedia, FLORES+, and established benchmarks for sentiment, hate speech, and emotion classification. No personally identifiable or sensitive information was collected or used. Our study aims to improve multilingual representation quality, particularly for low-resource languages. However, since the underlying data may contain cultural or societal biases, we recommend that future work include bias analysis and community engagement when extending models to additional linguistic or cultural contexts.

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A Language Resource Availability Details

Table 6 presents the availability of language resources under study in the Wikipedia dumps. English is highlighted in lime, as it serves both as the reference for comparison to other lower-resource languages and the pivot language when constructing the parallel tokenizers, due to its large corpus size and richer vocabulary coverage.

Lang.	iso	code	Script	Resource
English	eng	[EN]	Latin	10.7GB
Acehnese	ace	[AC]	Latin	2.52MB
Amharic	amh	[AM]	Amharic	18MB
Balinese	ban	[BA]	Latin	14.24MB
Hausa	hau	[HA]	Latin	108MB
Igbo	ibo	[IG]	Latin	104MB
Javanese	jav	[JV]	Latin	50.7MB
Kinyarwanda	kin	[RW]	Latin	12.25MB
Minangkabau	min	[MI]	Latin	85.4MB
Oromo	orm	[OR]	Latin	3.71MB
Sundanese	sun	[SU]	Latin	34.1MB
Swahili	swa	[SW]	Latin	54.4MB
Tigrinya	tir	[TI]	Amharic	1.1MB
Twi	twi	[TW]	Latin	8.6MB

Table 6: Language resource availability. The 'iso' column lists language codes following the ISO 639-3 convention, while the 'code' column specifies the language identifiers used to determine the language embeddings in the model's input representation.

B Benchmark Language Coverage

Table 7 reports the language coverage of each benchmark included in our study. For brevity, we use the abbreviations NusaX, Afri, Ethio, and BRIGHT to refer to the NusaX-senti, AfriHate, EthioEmo, and BRIGHTER datasets, respectively. The numbers next to the checkmarks indicate the number of instances used in the benchmarking process.

lang.	NusaX	Afri	Ethio	BRIGHT
ace	✓(1K)			
amh		✓(4.96K)	✓(5.92K)	
ban	✓(1K)			
hau		✓(6.64K)		✓(5.02K)
ibo		✓(5K)		✓(6.73K)
jav	✓(1K)			
min	✓(1K)			
kin		✓(4.72K)		✓(5.73K)
orm		✓(5.03K)	✓(5.74K)	
sun	✓(1K)			✓(3.17K)
swa		✓(21.1K)		✓(7.72K)
tir		✓(5.07K)	✓(6.14K)	
twi		✓(3.9K)		

Table 7: Benchmark language coverage.

C Benchmarking Result Details

Tables 8, 9, 10, and 11 present the benchmarking results for NusaX-senti, AfriHate, EthioEmo, and BRIGHTER, respectively. Results are reported for each language in the benchmark under training data settings of 100%, 50%, 10%, and 1%. To ensure stability and reliability, each experiment was run three times with different random seeds, and the reported results include the corresponding standard deviations. Based on the average results, our method yields better results than the other baselines, highlighting the performance of our method in cross-lingual settings.

D Bitext Mining Details

Tables 12, 13, and 14 present the bitext mining performance of each model using their corresponding tokenizers: *Single-102L*, *Single-13L*, and *Parallel-13L*. Performance is evaluated using the `xsim` error rate, which measures how accurately a model selects the equivalent sentence across languages based on the FLORES+ parallel data. A lower error rate indicates better cross-lingual alignment, making this metric an effective indicator of a model's ability to capture cross-lingual representations.

E Cross-Lingual Transfer under Limited Target-Language Data Details

Similar to Appendix C, we report benchmarking results under a limited target-language data setting, where the auxiliary languages are fully utilized (100% of the data) during training, while the target language is limited to 50% or 0% of its data. This setup highlights cross-lingual transfer from the auxiliary languages to the target language. Tables 15, 16, 17, and 18 present the results for NusaX-senti, AfriHate, EthioEmo, and BRIGHTER, respectively. For each language, we repeat the experiments three times with different seeds to ensure robustness.

F Monolingual Benchmarking Details

The benchmarking results using monolingual training data are shown in Tables 19, 20, 21, and 22. Each experiment was repeated three times with preselected seeds, and we report the averages along with the standard deviations for each language. Overall, the results are comparable: *Single-13L* performs better on the NusaX-senti and AfriHate benchmarks, while *Parallel-13L* performs better on emotion classification tasks such as EthioEmo and

#data	Tokenizer	ace	ban	jav	min	sun	**avg**
100%	Single-102L	72.02 (±4.04)	71.02 (±0.43)	76.20 (±0.99)	74.96 (±1.39)	71.32 (±1.67)	73.11 (±1.70)
	Single-13L	**76.61 (±1.31)**	**73.23 (±1.00)**	77.43 (±1.45)	76.48 (±1.37)	76.68 (±1.19)	76.09 (±1.27)
	Parallel-13L (ours)	74.22 (±1.91)	72.62 (±1.22)	**78.26 (±0.50)**	**78.43 (±0.42)**	**77.26 (±1.22)**	**76.16 (±1.05)**
50%	Single-102L	67.86 (±0.57)	68.24 (±2.08)	71.56 (±1.11)	71.76 (±0.62)	69.62 (±1.09)	69.81 (±1.09)
	Single-13L	**73.44 (±1.41)**	69.68 (±1.76)	71.86 (±2.03)	73.14 (±1.01)	74.22 (±0.61)	72.47 (±1.36)
	Parallel-13L (ours)	71.53 (±0.52)	**72.83 (±2.03)**	**74.34 (±0.86)**	**74.38 (±2.15)**	**74.52 (±0.31)**	**73.52 (±1.17)**
10%	Single-102L	56.95 (±2.34)	55.81 (±0.60)	57.59 (±6.97)	64.25 (±1.65)	60.80 (±1.57)	59.08 (±2.63)
	Single-13L	63.63 (±2.35)	63.02 (±1.92)	**66.59 (±1.86)**	65.06 (±1.60)	65.51 (±1.46)	64.76 (±1.84)
	Parallel-13L (ours)	**65.38 (±0.47)**	**65.07 (±1.38)**	65.65 (±5.20)	**68.62 (±1.19)**	**66.07 (±1.77)**	**66.16 (±2.00)**
1%	Single-102L	30.56 (±6.21)	27.26 (±8.12)	27.53 (±8.04)	30.42 (±7.12)	23.17 (±7.53)	27.79 (±7.41)
	Single-13L	**32.98 (±3.42)**	30.46 (±5.47)	28.12 (±4.77)	34.90 (±2.78)	31.26 (±2.93)	31.54 (±3.87)
	Parallel-13L (ours)	24.78 (±6.28)	**33.14 (±2.55)**	**39.18 (±6.41)**	**37.75 (±2.91)**	**34.29 (±1.34)**	**33.83 (±3.90)**

Table 8: NusaX-senti benchmarking results. 'ace', 'ban', 'jav', 'min', and 'sun' denote Acehnese, Balinese, Javanese, Minangkabau, and Sundanese, respectively.

#data	Tokenizer	amh	hau	ibo	kin	orm	swa	tir	twi	**avg**
100%	Single-102L	32.78 (±5.06)	69.25 (±0.61)	86.33 (±1.59)	69.93 (±1.95)	62.11 (±3.26)	90.28 (±0.31)	36.39 (±4.05)	55.58 (±2.27)	62.83 (±2.38)
	Single-13L	59.72 (±1.80)	69.51 (±1.94)	85.36 (±0.74)	72.96 (±1.54)	**62.21 (±0.73)**	**90.29 (±0.39)**	60.91 (±1.09)	**55.91 (±1.27)**	69.61 (±1.19)
	Parallel-13L (ours)	**59.91 (±0.35)**	**70.93 (±2.19)**	**87.62 (±0.85)**	**73.44 (±1.56)**	61.45 (±0.59)	89.94 (±0.22)	**61.61 (±1.07)**	53.47 (±2.77)	**69.80 (±1.20)**
50%	Single-102L	34.47 (±2.34)	67.86 (±0.28)	83.70 (±1.90)	67.68 (±1.98)	59.34 (±2.45)	88.50 (±0.37)	37.96 (±0.18)	52.66 (±2.24)	61.52 (±1.47)
	Single-13L	55.15 (±1.98)	66.23 (±1.76)	84.30 (±0.20)	**71.21 (±1.57)**	59.44 (±0.77)	87.41 (±0.46)	**61.33 (±1.21)**	**53.01 (±2.95)**	67.26 (±1.36)
	Parallel-13L (ours)	**57.23 (±0.65)**	**67.89 (±2.15)**	**85.47 (±0.67)**	69.39 (±1.45)	**60.16 (±0.86)**	**88.60 (±0.08)**	59.50 (±0.76)	50.96 (±0.92)	**67.40 (±0.94)**
10%	Single-102L	32.07 (±6.33)	58.86 (±1.08)	74.01 (±1.08)	58.65 (±4.15)	48.25 (±5.85)	**85.12 (±0.72)**	35.44 (±3.44)	45.15 (±1.17)	54.69 (±2.98)
	Single-13L	50.83 (±0.29)	61.34 (±0.87)	77.39 (±1.80)	56.89 (±1.52)	50.49 (±6.57)	82.78 (±1.13)	**51.52 (±2.53)**	**47.13 (±1.98)**	59.80 (±2.09)
	Parallel-13L (ours)	**51.27 (±2.07)**	**62.50 (±1.78)**	**79.93 (±1.09)**	**63.93 (±0.15)**	**51.08 (±0.38)**	84.24 (±1.19)	49.10 (±1.47)	39.29 (±3.87)	**60.17 (±1.50)**
1%	Single-102L	38.30 (±2.98)	40.12 (±5.33)	33.43 (±5.68)	37.84 (±1.97)	**42.42 (±7.43)**	70.75 (±0.55)	35.88 (±9.04)	27.81 (±0.22)	40.82 (±4.15)
	Single-13L	41.41 (±2.79)	**43.31 (±7.82)**	47.25 (±6.60)	42.37 (±3.92)	41.98 (±4.11)	69.11 (±2.53)	**41.49 (±4.06)**	30.70 (±3.79)	44.70 (±4.45)
	Parallel-13L (ours)	**42.70 (±1.03)**	43.09 (±3.84)	**55.44 (±3.25)**	**48.10 (±1.81)**	42.35 (±3.00)	**71.33 (±2.22)**	39.56 (±2.28)	**31.26 (±2.74)**	**46.73 (±2.52)**

Table 9: AfriHate benchmarking results. 'amh', 'hau', 'ibo', 'kin', 'orm', 'swh', 'tir', and 'twi' denote Amharic, Hausa, Igbo, Kinyarwanda, Oromo, Swahili, Tigrinya, and Twi, respectively.

#data	Tokenizer	amh	orm	tir	**avg**
100%	Single-102L	12.06 (±10.55)	**60.80 (±0.73)**	17.43 (±9.62)	30.10 (±6.97)
	Single-13L	55.07 (±1.01)	58.96 (±1.18)	50.92 (±0.75)	54.98 (±0.98)
	Parallel-13L (ours)	**60.22 (±0.32)**	59.59 (±1.18)	**51.21 (±1.03)**	**57.01 (±0.84)**
50%	Single-102L	18.16 (±2.62)	**58.22 (±0.29)**	19.49 (±3.68)	31.96 (±2.20)
	Single-13L	52.98 (±2.09)	55.53 (±1.06)	45.48 (±1.31)	51.33 (±1.48)
	Parallel-13L (ours)	**58.33 (±1.12)**	55.64 (±1.78)	**48.86 (±2.44)**	**54.27 (±1.78)**
10%	Single-102L	12.51 (±5.24)	39.85 (±5.11)	13.84 (±12.06)	22.07 (±7.47)
	Single-13L	**44.32 (±2.86)**	43.18 (±1.03)	**38.79 (±2.66)**	**42.10 (±2.19)**
	Parallel-13L (ours)	44.00 (±2.86)	**43.36 (±1.73)**	36.68 (±2.04)	41.35 (±2.21)
1%	Single-102L	10.97 (±9.50)	6.45 (±11.17)	14.78 (±12.85)	10.73 (±11.17)
	Single-13L	**34.85 (±0.34)**	24.37 (±3.50)	**22.91 (±1.81)**	**27.37 (±1.88)**
	Parallel-13L (ours)	33.77 (±1.83)	**24.42 (±1.67)**	21.55 (±0.62)	26.58 (±1.37)

Table 10: EthioEmo benchmarking results. 'amh', 'orm', and 'tir' denote Amharic, Oromo, and Tigrinya, respectively.

#data	Tokenizer	hau	ibo	kin	sun	swa	avg
100%	Single-102L	56.84 (±1.34)	57.71 (±1.16)	41.42 (±1.79)	**61.01 (±1.39)**	**25.37 (±0.94)**	48.47 (±1.32)
	Single-13L	58.66 (±0.16)	**58.72 (±0.63)**	41.65 (±0.58)	60.11 (±0.61)	22.16 (±2.71)	48.26 (±0.94)
	Parallel-13L (ours)	**60.20 (±1.96)**	58.37 (±1.57)	**45.41 (±2.10)**	60.49 (±1.05)	23.95 (±2.76)	**49.68 (±1.89)**
50%	Single-102L	51.34 (±0.63)	54.09 (±0.91)	37.82 (±1.16)	58.25 (±2.64)	**21.89 (±0.33)**	44.68 (±1.13)
	Single-13L	53.89 (±1.29)	**55.08 (±0.58)**	39.36 (±1.83)	**59.77 (±1.05)**	20.76 (±2.52)	45.77 (±1.46)
	Parallel-13L (ours)	**56.65 (±0.81)**	55.05 (±1.65)	**43.42 (±0.81)**	57.56 (±2.02)	21.13 (±2.26)	**46.76 (±1.51)**
10%	Single-102L	39.67 (±1.50)	42.25 (±1.83)	28.33 (±1.57)	**55.10 (±3.32)**	**18.21 (±1.13)**	36.71 (±1.87)
	Single-13L	43.03 (±1.65)	**45.12 (±2.80)**	27.62 (±0.60)	50.63 (±4.83)	16.78 (±1.25)	36.64 (±2.23)
	Parallel-13L (ours)	**45.73 (±0.70)**	45.00 (±2.27)	**33.12 (±0.68)**	51.95 (±2.11)	16.74 (±0.58)	**38.51 (±1.27)**
1%	Single-102L	0.00 (±0.00)	0.00 (±0.00)	0.00 (±0.00)	0.00 (±0.00)	0.00 (±0.00)	0.00 (±0.00)
	Single-13L	9.02 (±8.00)	**21.28 (±3.23)**	14.89 (±0.76)	42.50 (±0.84)	0.00 (±0.00)	17.54 (±2.57)
	Parallel-13L (ours)	**14.91 (±3.24)**	15.97 (±13.91)	**17.20 (±1.93)**	**46.30 (±0.72)**	0.00 (±0.00)	**18.88 (±3.96)**

Table 11: BRIGHTER benchmarking results. 'hau', 'ibo', 'kin', 'sun', and 'swa' denote Hausa, Igbo, Kinyarwanda, Sundanese, and Swahili, respectively.

	ace	amh	ban	hau	ibo	jav	min	kin	orm	sun	swa	tir	twi
ace		98.81	**79.74**	93.58	93.87	79.35	83.70	95.06	**96.15**	82.61	90.22	98.91	91.70
amh			99.11	99.90	99.80	99.41	99.31	99.80	99.60	98.62	99.51	**88.34**	99.80
ban				93.28	93.68	56.52	72.33	95.16	96.15	61.96	80.24	98.81	90.71
hau					93.48	93.48	94.96	95.16	96.44	95.65	96.34	98.91	94.37
ibo						94.17	95.45	96.15	97.92	96.44	95.95	99.41	96.84
jav							59.88	94.47	96.25	36.56	57.11	99.31	91.21
min								96.15	96.74	55.93	75.89	99.21	92.98
kin									98.52	96.15	95.65	99.21	97.33
orm										98.02	98.42	99.11	97.83
sun											68.28	99.31	92.59
swa												99.41	95.65
tir													99.90
twi													

Table 12: *Single-102L* bitext mining scores, calculated using `xsim` error rate score.

	ace	amh	ban	hau	ibo	jav	min	kin	orm	sun	swa	tir	twi
ace		**97.83**	82.21	85.67	88.34	73.12	**72.83**	**91.01**	97.04	**77.57**	86.26	**98.52**	**89.62**
amh			96.74	96.34	96.94	96.44	96.74	97.53	97.73	96.94	96.54	90.51	98.02
ban				72.83	77.87	**35.97**	48.02	84.19	96.34	47.43	71.54	98.22	85.28
hau					64.43	62.15	72.13	82.91	95.26	68.38	63.54	97.63	81.72
ibo						70.95	78.46	87.15	96.84	75.69	71.05	98.02	85.97
jav							43.58	85.38	96.44	**34.88**	63.64	98.42	83.70
min								84.19	96.34	**42.89**	69.76	98.32	84.09
kin									97.04	**84.68**	78.36	98.32	88.54
orm										97.23	96.64	**98.12**	**96.84**
sun											67.29	98.62	84.58
swa												98.52	82.11
tir													98.91
twi													

Table 13: *Single-13L* bitext mining scores, calculated using `xsim` error rate score.

	ace	amh	ban	hau	ibo	jav	min	kin	orm	sun	swa	tir	twi
ace		98.32	88.04	**76.98**	**85.77**	**71.34**	81.23	98.62	97.92	82.31	**70.36**	98.81	98.22
amh			**77.87**	**73.62**	**85.08**	**69.96**	**72.43**	**83.30**	**95.45**	**81.92**	**65.61**	97.33	**86.96**
ban				**57.11**	**68.18**	50.79	**46.25**	**70.95**	**85.87**	**46.25**	**47.73**	**95.45**	**76.48**
hau					**52.87**	**35.57**	**41.40**	**60.18**	**82.91**	**57.11**	**30.93**	**89.43**	**70.55**
ibo						**58.10**	**68.28**	**78.36**	**87.35**	**72.53**	**54.25**	**97.23**	**77.27**
jav							**22.92**	**56.92**	**79.84**	44.27	**24.51**	**92.98**	**75.30**
min								**60.77**	**79.45**	87.15	**29.74**	**95.16**	**71.44**
kin									**92.29**	89.03	**59.19**	**96.15**	**81.92**
orm										**93.08**	**83.70**	98.62	97.23
sun											**47.33**	**92.89**	**72.92**
swa												**87.65**	**70.36**
tir													**98.62**
twi													

Table 14: *Parallel-13L* bitext mining scores, calculated using `xsim` error rate score.

#data	Tokenizer	ace	ban	jav	min	sun	avg
50%	Single-102L	71.15 (±1.11)	68.03 (±1.24)	74.70 (±1.05)	71.64 (±1.93)	71.83 (±0.98)	71.76 (±1.26)
	Single-13L	**75.99 (±0.88)**	70.69 (±2.97)	**78.00 (±0.82)**	74.92 (±2.56)	**76.50 (±0.72)**	75.22 (±1.59)
	Parallel-13L (ours)	73.75 (±0.62)	**71.94 (±1.05)**	77.01 (±1.52)	**78.15 (±0.70)**	76.22 (±2.10)	**75.42 (±1.20)**
0%	Single-102L	63.10 (±1.92)	67.80 (±2.28)	72.52 (±1.66)	68.41 (±0.97)	70.44 (±1.28)	68.80 (±1.62)
	Single-13L	66.77 (±2.59)	**69.76 (±2.20)**	73.93 (±2.37)	74.09 (±1.85)	**74.60 (±0.95)**	71.83 (±1.99)
	Parallel-13L (ours)	**69.44 (±1.94)**	67.43 (±1.27)	**76.66 (±0.71)**	**75.87 (±2.05)**	74.12 (±1.50)	**72.70 (±1.49)**

Table 15: NusaX-senti benchmarking results under a limited target-language data setting. 'ace', 'ban', 'jav', 'min', and 'sun' denote Acehnese, Balinese, Javanese, Minangkabau, and Sundanese, respectively.

#data	Tokenizer	amh	hau	ibo	kin	orm	swh	tir	twi	avg
50%	Single-102L	34.81 (±1.71)	**67.85 (±0.83)**	83.68 (±0.67)	58.28 (±3.41)	69.06 (±1.60)	88.58 (±0.33)	34.69 (±3.07)	**54.65 (±2.64)**	61.45 (±1.78)
	Single-13L	**57.92 (±0.69)**	65.35 (±1.71)	84.20 (±0.43)	59.20 (±1.52)	69.23 (±0.80)	88.22 (±0.55)	57.75 (±3.59)	54.63 (±2.30)	**67.06 (±1.45)**
	Parallel-13L (ours)	57.01 (±0.13)	66.18 (±1.73)	**85.27 (±1.52)**	**59.35 (±2.04)**	**70.77 (±0.62)**	**88.73 (±0.11)**	**58.57 (±1.41)**	50.13 (±3.01)	67.00 (±1.32)
0%	Single-102L	31.74 (±3.35)	38.28 (±0.81)	34.82 (±1.71)	28.28 (±1.67)	34.10 (±1.50)	37.58 (±2.75)	**39.93 (±2.01)**	25.01 (±1.15)	33.72 (±1.87)
	Single-13L	42.32 (±2.74)	39.32 (±3.11)	38.91 (±1.91)	36.86 (±0.78)	40.06 (±4.86)	42.06 (±0.67)	35.27 (±2.89)	23.37 (±4.55)	37.27 (±2.69)
	Parallel-13L (ours)	**46.38 (±2.74)**	**45.13 (±3.04)**	**45.13 (±4.18)**	**41.32 (±1.07)**	**44.78 (±4.19)**	**44.11 (±5.10)**	32.45 (±2.41)	**26.08 (±1.68)**	**40.67 (±3.05)**

Table 16: AfriHate benchmarking results under a limited target-language data setting. 'amh', 'hau', 'ibo', 'kin', 'orm', 'swh', 'tir', and 'twi' denote Amharic, Hausa, Igbo, Kinyarwanda, Oromo, Swahili, Tigrinya, and Twi, respectively.

#data	Tokenizer	amh	orm	tir	avg
50%	Single-102L	14.89 (±1.15)	53.83 (±4.11)	20.53 (±7.24)	29.75 (±4.17)
	Single-13L	53.96 (±1.26)	54.65 (±1.48)	46.60 (±0.91)	51.73 (±1.22)
	Parallel-13L (ours)	**58.39 (±0.51)**	**55.77 (±0.82)**	**46.74 (±3.27)**	**53.63 (±1.53)**
0%	Single-102L	11.04 (±6.25)	0.00 (±0.00)	18.15 (±5.83)	9.73 (±4.03)
	Single-13L	**32.58 (±4.21)**	12.10 (±4.66)	**26.55 (±0.65)**	**23.75 (±3.17)**
	Parallel-13L (ours)	27.46 (±3.60)	**18.61 (±0.27)**	23.53 (±4.77)	23.20 (±2.88)

Table 17: EthioEmo benchmarking results under a limited target-language data setting. 'amh', 'orm', and 'tir' denote Amharic, Oromo, and Tigrinya, respectively.

BRIGHTER. On average across all benchmarks, however, *Parallel-13L* outperforms *Single-13L* by 0.42%.

G Continual Pre-Training: Representation Similarity

As discussed in Section 5.6, although the benchmarking performance of *Single-13L* and *Parallel-13L* after CPT is comparable, the cross-lingual representation similarity is stronger in *Parallel-13L*. This is illustrated in Figure 6, where we visualize the embedding spaces of FLORES+ (Costa-Jussà et al., 2022) sentences for each language in two dimensions using PCA. In *Single-13L*, inputs from the same language family remain clustered. For instance, Indonesian local languages (Acehnese, Minangkabau, Sundanese, etc.) cluster together, African languages cluster together, and Amharic-script languages (Amharic and Tigrinya) are separated into distinct clusters. In contrast, *Parallel-13L* shows tighter cross-lingual clustering, with languages grouped more uniformly, including Amharic. The main outliers are Tigrinya and Twi, which remain separated in both models, likely due to limited pretraining resources.

These observations are further supported by our bitext mining analysis on the models after CPT. As shown in Table 23, *Parallel-13L* consistently achieves the lowest error rates and the highest number of best `xsim` scores, outperforming the other models, although the gains are smaller than those observed when pretraining from scratch. Tables 24 and 25 provide the detailed `xsim` scores for each language pair in both *Single-13L* and *Parallel-13L*.

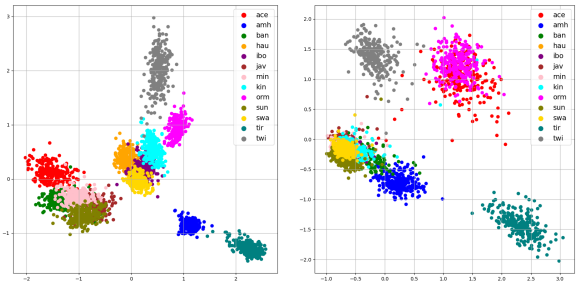

Figure 6: Principal Component Analysis (PCA) of continual pretrained model embeddings, comparing the *Single-13L* (left) and the *Parallel-13L* (right) on the parallel data FLORES+ dataset.

H Model Input Representation Design

Since we require a 'language token' to select the appropriate tokenizer for a given input, our input representation differs slightly from the conventional approach. During the model design phase, as presented in Figure 7, we explored several alternatives and ultimately selected the most effective method. Specifically, we considered three designs: (1) placing the language token at the beginning of every input sequence, requiring the model to process it as the first token; (2) the *Parallel-13L* approach, where the language token serves as a signal that is added to each token embedding, effectively combining token and language embeddings; and (3) augmenting only the embeddings of unaligned vocabulary items (i.e., tokens not belonging to the `word`-type category[9]).

We pretrained models with each of these meth-

[9]We store unaligned vocabulary items at the end of the vocabulary indices

#data	Tokenizer	hau	ibo	kin	sun	swa	avg
50%	Single-102L	50.75 (±0.85)	54.30 (±0.95)	35.29 (±0.75)	**58.34 (±0.80)**	21.89 (±1.51)	44.11 (±0.97)
	Single-13L	52.92 (±1.09)	55.41 (±0.32)	39.57 (±2.08)	58.18 (±1.78)	18.95 (±1.33)	45.00 (±1.32)
	Parallel-13L (ours)	**57.36 (±0.62)**	**56.64 (±0.95)**	**41.72 (±0.83)**	57.89 (±1.38)	**21.96 (±1.39)**	**47.11 (±1.04)**
0%	Single-102L	13.71 (±2.70)	13.02 (±2.54)	19.47 (±2.37)	15.41 (±1.41)	**16.70 (±2.54)**	15.66 (±2.31)
	Single-3L	15.13 (±3.30)	**16.31 (±0.61)**	9.72 (±0.59)	**18.93 (±2.24)**	15.13 (±1.45)	15.04 (±1.64)
	Parallel-13L (ours)	**26.92 (±2.65)**	16.08 (±2.15)	**23.37 (±0.32)**	15.90 (±0.96)	16.38 (±3.31)	**19.73 (±1.88)**

Table 18: BRIGHTER benchmarking results under a limited target-language data setting. 'hau', 'ibo', 'kin', 'sun', and 'swa' denote Hausa, Igbo, Kinyarwanda, Sundanese, and Swahili, respectively.

Tokenizer	ace	ban	jav	min	sun	avg
Single-13L	**74.86 (±1.02)**	**77.01 (±0.80)**	**77.92 (±1.62)**	77.14 (±1.00)	**76.65 (±2.51)**	**76.72 (±1.39)**
Parallel-13L (ours)	73.27 (±1.18)	73.76 (±0.43)	77.75 (±0.44)	**77.85 (±0.43)**	75.76 (±2.70)	75.68 (±1.04)

Table 19: NusaX-senti benchmarking results under monolingual setting. 'ace', 'ban', 'jav', 'min', and 'sun' denote Acehnese, Balinese, Javanese, Minangkabau, and Sundanese, respectively.

Tokenizer	amh	hau	ibo	kin	orm	swh	tir	twi	avg
Single-13L	**60.92 (±2.41)**	74.39 (±0.65)	84.96 (±0.83)	**63.82 (±1.20)**	**73.60 (±1.29)**	90.13 (±0.18)	61.76 (±1.66)	**56.49 (±3.00)**	**62.17 (±1.75)**
Parallel-13L (ours)	60.39 (±0.89)	**75.35 (±1.52)**	**87.70 (±0.26)**	62.94 (±1.54)	73.59 (±0.41)	**90.30 (±0.42)**	**61.94 (±2.77)**	55.20 (±1.15)	61.76 (±1.73)

Table 20: AfriHate benchmarking results under monolingual setting. 'amh', 'hau', 'ibo', 'kin', 'orm', 'swh', 'tir', and 'twi' denote Amharic, Hausa, Igbo, Kinyarwanda, Oromo, Swahili, Tigrinya, and Twi, respectively.

Tokenizer	amh	orm	tir	avg
Single-13L	58.70 (±1.32)	**60.15 (±0.75)**	48.92 (±1.24)	55.92 (±1.10)
Parallel-13L (ours)	**60.98 (±1.09)**	59.63 (±1.63)	**52.58 (±0.20)**	**57.73 (±0.97)**

Table 21: EthioEmo benchmarking results under monolingual setting. 'amh', 'orm', and 'tir' denote Amharic, Oromo, and Tigrinya, respectively.

Tokenizer	hau	ibo	kin	sun	swa	avg
Single-13L	57.90 (±1.40)	58.89 (±1.53)	43.89 (±0.20)	**61.05 (±0.93)**	23.81 (±1.14)	49.11 (±1.04)
Parallel-13L (ours)	**60.23 (±0.35)**	**59.23 (±0.71)**	**47.74 (±2.45)**	60.97 (±0.79)	**24.04 (±2.15)**	**50.44 (±1.29)**

Table 22: BRIGHTER benchmarking results under monolingual setting. 'hau', 'ibo', 'kin', 'sun', and 'swa', denote Hausa, Igbo, Kinyarwanda, Sundanese, and Swahili, respectively.

	Single-102L	Single-13L	Parallel-13L
Avg. `xsim` ↓	91.33	72.18	**69.34**
# of best `xsim` ↑	1	29	**48**

Table 23: Bitext mining metric meta-scores on CPT models.

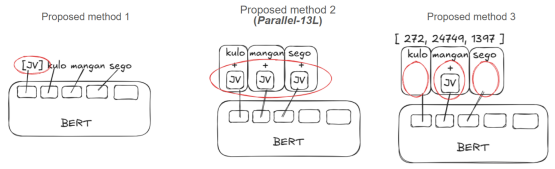

Figure 7: The design of the model input representation. We adopt the second method and refer to it as *Parallel-13L*.

ods from scratch using the same dataset (Wikipedia dumps for the 13 languages studied in this paper). The first and third approaches did not converge as quickly or effectively as *Parallel-13L*, which therefore became our chosen design for the experiments reported in Section 5 and beyond.

	ace	amh	ban	hau	ibo	jav	min	kin	orm	sun	swa	tir	twi
ace		**91.01**	**65.42**	68.28	**76.09**	**55.83**	**67.59**	**82.61**	**93.68**	79.05	68.28	**97.73**	**82.51**
amh			93.48	90.42	89.72	88.24	90.51	91.90	**94.96**	89.92	90.81	92.29	94.76
ban				**40.02**	**50.40**	**27.96**	**44.86**	74.51	91.40	50.59	38.54	97.33	77.08
hau					36.26	29.25	41.80	67.00	90.61	**40.32**	24.90	95.55	69.76
ibo						**43.68**	**55.14**	74.11	92.59	**53.56**	40.51	**96.44**	76.38
jav							24.41	70.85	91.70	**28.06**	29.05	95.65	75.30
min								**69.96**	90.51	**28.36**	38.14	96.54	75.30
kin									94.37	**73.62**	66.21	**96.84**	85.57
orm										**91.11**	90.81	**97.43**	**93.08**
sun											**33.10**	96.05	**75.79**
swa												95.16	73.22
tir													98.02
twi													

Table 24: Bitext mining metric scores on CPT models trained with *Single-13L* tokenizer.

	ace	amh	ban	hau	ibo	jav	min	kin	orm	sun	swa	tir	twi
ace		98.02	77.37	**62.55**	80.53	57.41	90.32	98.62	97.83	**68.58**	**59.98**	98.52	89.43
amh			**74.90**	**62.65**	**78.46**	**63.54**	**64.62**	**76.88**	95.06	**71.15**	**59.49**	97.33	**86.07**
ban				41.01	61.07	30.43	56.82	**63.34**	**85.18**	**37.06**	**34.19**	**92.98**	**76.68**
hau					**31.82**	**20.06**	**28.75**	**47.92**	**79.15**	53.56	**17.39**	**90.61**	**63.24**
ibo						43.97	69.86	**66.60**	**85.18**	62.35	**36.76**	97.04	**72.63**
jav							**22.43**	**50.79**	**76.98**	52.87	**22.13**	**92.69**	**69.57**
min								76.98	**89.53**	57.21	**25.10**	**92.79**	**72.23**
kin									**91.70**	83.60	**54.64**	97.04	**78.56**
orm										96.34	**80.53**	98.81	98.22
sun											40.32	**90.12**	85.28
swa												**91.21**	**68.08**
tir													**97.92**
twi													

Table 25: Bitext mining metric scores on CPT models trained with *Parallel-13L* tokenizer.