

ENLIVEN-1000: A Comprehensive Revitalization Framework for 1000+ Endangered Languages via Broad-Coverage LID and LLM-Augmented MT

Anonymous submission

Abstract

We present **ENLIVEN-1000**, a unified framework for endangered and low-resource language revitalization that integrates broad-coverage language identification (LID), machine translation (MT), and LLM-generated synthetic data—aimed at expanding safe, equitable NLP support for communities historically excluded from mainstream tools. We compile a text corpus for 1154 languages (1069 endangered or low resource) from public sources and train a fastText-based LID model covering this vast set. The LID system achieves high detection quality with $F1 \approx 0.99$ and $FPR \approx 3 \times 10^{-6}$, substantially broadening reliable coverage beyond existing solutions. Focusing on five diverse endangered languages—Carpathian Romani, Chuj, Sunwar, Kapingamarangi, and Inuktitut—we fine-tune a 600M-parameter NLLB-200 model for translation. Our fine-tuned models outperform zero-shot baselines and even proxy models trained on related, high-resource languages, in both directions (endangered→English and English→endangered). We further use GPT-4o to generate synthetic parallel data, demonstrating that augmenting limited real data with LLM-generated text yields substantial MT improvements. These results illustrate a practical path toward scaling NLP support to hundreds of under-resourced languages. We discuss implications for language revitalization and ethical considerations in working with endangered language communities.

1 Introduction

Thousands of human languages are endangered, with many at risk of extinction by the end of this century (Daily Sabah 2023; UN DESA 2022). Out of over 7,000 living languages, roughly 40–50% are already endangered (Ethnologue 2023). UNESCO predicts that without intervention, we may lose half of today’s languages (or more) by 2100 (Wikipedia 2025). The loss of a language signifies the disappearance of unique cultural knowledge and identity. Recognizing this crisis, global efforts have increased: UNESCO launched an *Atlas of the World’s Languages in Danger* and designated 2022–2032 as the *International Decade of Indigenous Languages* to mobilize revitalization efforts (UN DESA 2022). Collaborative platforms like the Endangered Languages Project (ELP) also connect communities and linguists in documenting and sharing threatened languages.

However, most endangered languages remain underserved by language technology. Fewer than 100 languages

have robust support in widely used tools (e.g., web translators or voice assistants). Even large multilingual models and services cover at best a few hundred languages, leaving the vast majority of endangered languages beyond their scope. This technological gap poses a barrier to revitalization: digital tools (such as text analysis, translation, and educational software) could greatly aid communities, but those tools require data and models for each language.

In this paper, we introduce **ENLIVEN-1000**, a framework for delivering NLP support to 1069 endangered and low-resource languages through three core components: (i) a broad-coverage language identification (LID) system that reliably recognizes and disambiguates more than a thousand languages; (ii) machine translation (MT) systems for those languages; and (iii) a large language model (LLM)–driven synthetic data pipeline that mitigates data scarcity. Together, identification, translation, and augmentation form an end-to-end workflow for corpus creation, information access, and cross-lingual communication in low-resource settings.

Our approach is inspired by recent advances in massively multilingual NLP. On the LID side, reliable identification is “paramount” for building trustworthy datasets (Caswell and Ng 2020). We curate **1,174** languages in total from diverse sources; of these, **1,154** have sufficient and usable data for training and evaluation, which we use to train a fastText-based classifier (Joulin et al. 2017). The remaining languages are included only as candidate labels at inference time to mitigate “out-of-model cousin” errors, and we therefore omit per-language F1/FPR for them (Caswell and Ng 2020; Kreutzer et al. 2022a). On the MT side, we leverage the No Language Left Behind NLLB-200 model from Meta AI (NLLB Team et al. 2022) and fine-tune it on small language-specific corpora. To expand coverage, we generate synthetic parallel data with GPT-4o using few-shot prompts augmented by bilingual lexicons (OpenAI 2023; Yong, Menghini, and Bach 2024), consistent with evidence that synthetic data improves MT quality (Sennrich, Haddow, and Birch 2016; de Gibert et al. 2025).

Contributions.

- **Corpus & LID:** A multilingual corpus spanning 1154 languages and a high-precision fastText-based LID model.
- **MT systems:** Fine-tuned NLLB-200 models for five en-

dangered languages, outperforming zero-shot and proxy baselines.

- **Data scaling case study (Inuktitut):** A controlled scaling study at 31k/62k/93k/124k sentence pairs demonstrating consistent improvements in both directions, underscoring the value of additional real bitext.
- **Synthetic data:** A lexicon-guided GPT-4o few-shot prompting pipeline that boosts MT under data scarcity.
- **Evaluation across data regimes:** We evaluate MT models trained on real-only, synthetic-only, and mixed training regimes, showing that synthetic data can boost performance, especially for the weaker language.
- **Scaling & ethics:** An analysis of how to scale to all 1000+ languages, with guidance for community-centered, ethical deployment.

2 Language Identification (LID)

A first step toward inclusivity in NLP is robust language identification (LID) for low-resource languages. Effective LID allows us to discover, filter, and curate text in target languages from the web or archives, which is crucial for building corpora. Unfortunately, most existing LID systems have limited coverage—many support only a few hundred languages or fewer (Google Research 2016; NLLB Team et al. 2022; Thoma 2018). For example, Google’s compact language detector (CLD3) covers roughly ~ 100 languages (Google Research 2016); fastText-LID and the NLLB LID model target ~ 176 and ~ 200 languages, respectively (Facebook AI Research 2022; NLLB Team et al. 2022). This leaves thousands of languages “in the dark,” including the majority of endangered languages.

Endangerment Status. Because our goal is revitalization for underserved languages, we adopt an inclusive policy on endangerment. Using standard sources (Ethnologue, Glottolog, Endangered Languages Project, UNESCO), and mapping to the Expanded Graded Intergenerational Disruption Scale (EGIDS), we include languages rated **EGIDS 5–9** (Developing $\rightarrow$ Critically Endangered) as well as **EGIDS 10** (Extinct). By contrast, **EGIDS 0–4** (International $\rightarrow$ Educational) denote *institutional* support via schooling and broad functional use; we treat these as *institutional/non-endangered*.

Out-of-Model Cousin Errors. A pervasive failure mode in LID is the *out-of-model cousin* error: when a true language is *absent* from the label set, the classifier systematically assigns it to a *closely related* (“cousin”) language that *is* in the model, inflating false positives and contaminating downstream corpora (Caswell and Ng 2020; Kreutzer et al. 2022b). To mitigate this, we emphasize broad coverage during inference. Concretely, we consider **1,174** languages in total; a small subset could not be processed reliably or lacked sufficient data for training/evaluation. We nevertheless *retain* these languages as candidate labels at inference time to reduce out-of-model cousin confusions, but we *do not* report per-language F1/FPR for them. This design follows best practice observed in prior large-scale audits: keep the label space wide at inference to avoid systematic

misclassification, while restricting quantitative reporting to languages with adequate evidence (Caswell and Ng 2020; Kreutzer et al. 2022b).

Data Compilation. From our inventory, **1,154** languages have sufficient data for training/evaluation; among these, **85** are institutional (EGIDS 0–4) and **1,069** are endangered/low-resource (EGIDS 5–10). We therefore define two evaluation sets: **Full-LID** (*all 1,154* usable languages) and **Endangered-LID** (*the 1,069* endangered/low-resource languages). Unless otherwise noted, metrics (macro-F1, FPR) are reported on these splits; the remaining (non-evaluable) languages are included only as inference-time labels to guard against out-of-model cousin errors. Text data were aggregated from a variety of open sources. A major source was multilingual Bible translations (e.g., the Parallel Bible Corpus), which provide aligned verses in hundreds of languages, often including very low-resource ones (Mayer and Cysouw 2014). While such translations can be stylistically formal or archaic, they offer a starting point for many languages with otherwise scant digital presence. We also used Tatoeba (a crowd-sourced collection of translated sentences) and other public corpora such as UDHR translations and web-scraped datasets to enrich coverage (Tiedemann 2020; Unicode Consortium 2007; Ortiz Suárez, Romary, and Sagot 2020; Wenzek, Lacroix, and Bennoit 2020). Each text line is tagged with its ISO 639-3 code; we verified labels where possible, since mislabeling degrades LID performance (Caswell and Ng 2020).

LID Model. We adopt a supervised `fastText` classifier (Joulin et al. 2017) with character n -grams for short-text LID, an approach that scales well to thousands of labels while remaining fast and lightweight (Facebook AI Research 2022; Kargaran et al. 2023). In line with prior low-resource LID work, we favor `fastText` because it (i) is open-source and easy to deploy across platforms; (ii) delivers calibrated confidence scores that enable thresholded filtering (high-precision corpus creation); (iii) handles broad label sets efficiently, which helps curb *out-of-model cousin* errors when we keep a wide candidate set at inference; and (iv) supports granularity control (e.g., aggregating probabilities for macrolanguages vs. varieties) (Kargaran et al. 2023). Our pipeline (full details in the Appendix) performs Unicode normalization, cross-/within-language de-duplication, stratified splitting (85/5/10 with caps), light temperature upsampling for low-resource classes, and training with standard `fastText` hyperparameters, followed by model quantization for compact deployment.

Evaluation. We report per-language and macro-averaged Precision, Recall, F1, and false positive rate (FPR) under a thresholded decision rule: predict the top label if $\max_l P(l \mid s) \geq \theta$, otherwise output UNDETERMINED. By varying the confidence threshold θ , we control the precision–recall tradeoff: higher θ yields fewer but more reliable labels (higher precision, lower recall), while lower θ yields more coverage at the cost of additional false positives (higher recall, lower precision). This protocol emphasizes high-precision filtering for corpus construction while

Metric	Full (1,128)		Endangered (1,044)	
	$\theta=0.3$	$\theta=0.5$	$\theta=0.3$	$\theta=0.5$
Precision	0.9935	0.9942	0.9909	0.9919
Recall	0.9931	0.9924	0.9910	0.9904
F1	0.9931	0.9931	0.9908	0.9910
FPR↓	0.000004	0.000003	0.000004	0.000004

Table 1: Macro-averaged LID performance at two confidence thresholds. Metrics are computed over languages present in each test split.

improving recall on low-resource classes via light upsampling and calibrated thresholds.

Key Results. As shown in Table 1, the model attains near-perfect macro precision/recall/F1 on both **Full-LID** and **Endangered-LID**. Raising the decision threshold from $\theta=0.3$ to 0.5 yields a modest precision gain and pushes false positives down to only a few per million negatives, with essentially unchanged F1 and a slight drop in recall. This stable trade-off across both evaluation sets lets us operate in a high-precision regime for large-scale corpus filtering while preserving strong recall for low-resource languages. Our LID model greatly outperforms prior open LID systems on low-resource languages (Kargaran et al. 2023; Thoma 2018).

Granularity and Coverage. Some languages in our set are extremely closely related or mutually intelligible dialects, which can challenge fine-grained identification (e.g., closely related Zapotec varieties); occasional confusions are expected and consistent with prior analyses (Caswell and Ng 2020). Nonetheless, the broad coverage and near-perfect performance of our LID (1154 languages) far exceeds that of widely used detectors (Google Research 2016; Facebook AI Research 2022; NLLB Team et al. 2022). In practice, this “opens the pipeline” for endangered languages: one can reliably detect and isolate text in a given endangered language from large multilingual collections. As highlighted by large-scale corpus work (Wenzek, Lacroix, and Benoit 2020; Ortiz Suárez, Romary, and Sagot 2020; Kreutzer et al. 2022b), robust LID and filtering are essential for high-quality datasets in low-resource NLP.

3 Machine Translation (MT)

With a strong LID in hand, we turn to the challenge of machine translation (MT) for endangered languages. MT can facilitate many revitalization activities: it helps speakers translate materials (stories, educational content) into or out of their language, and can assist linguists in deciphering texts. However, building MT systems for endangered languages is daunting due to scarce parallel data. We explore a solution by leveraging a pre-trained multilingual MT model (Meta AI’s NLLB-200) and fine-tuning it on small, language-specific datasets—a strategy shown to be effective for low-resource MT via multilingual pretraining and transfer learning (NLLB Team et al. 2022; Aharoni, Johnson, and Firat 2019; Arivazhagan et al. 2019; Zoph et al. 2016; Neu-

big and Hu 2018). We focus on five languages as case studies, chosen for diversity in geography, family, and script:

- **Carpathian Romani** (ISO 639-3: *rmc*)—An Indo-European (Romani) language spoken in Central/Eastern Europe. It uses Latin-based orthographies that vary by country. It is classified as “At risk” by The Catalogue of Endangered Languages (ElCat) (Campbell et al. 2022).
- **Chuj** (*cac*)—A Mayan language of Guatemala and Mexico. It is spoken mainly in Guatemala’s Huehuetenango highlands—with communities also in nearby Chiapas, Mexico. It is classified as “Vulnerable” by ElCat.
- **Sunwar** (*suz*)—A Sino-Tibetan language of eastern Nepal (Kiranti branch). It is classified as “Threatened” by ElCat. Written in Devanagari.
- **Kapingamarangi** (*kpg*)—A Polynesian outlier language spoken on Kapingamarangi atoll (FSM). It is classified as “Threatened” by ElCat. It represents the Austronesian family and poses interesting challenges due to extremely limited textual data.
- **Inuktitut** (Eastern Canadian Inuktitut, *iku*)—An Eskimo-Aleut language spoken in Arctic Canada. It is classified as “Vulnerable” by ElCat. It uses Canadian Aboriginal Syllabics; we include it because more data are available (e.g., government documents), enabling scaling experiments.

Corpora. For each language, we obtained a small parallel corpus of $\sim 31,000$ sentence pairs (language $\leftrightarrow$ English). Sources included aligned segments from Bible translations (Mayer and Cysouw 2014), community-preserved material from OPUS (Tiedemann 2012), and public government translations for Inuktitut (Joanis et al. 2020). All data were cleaned and deduplicated; we standardized scripts where helpful (e.g., transliterating Kapingamarangi to Latin when unsupported), consistent with practices in multilingual NMT (Aharoni, Johnson, and Firat 2019). We held out 1,000 sentences per language for validation/testing, using the remaining $\sim 30k$ for training.

Model and Fine-Tuning. We used **NLLB-200** as the base system (NLLB Team et al. 2022), specifically the 600M-parameter variant for a balance of capacity and efficiency. Although NLLB-200 was trained many-to-many over 200 languages, our five targets are all absent from its supported languages. We fine-tuned *separately* for each pair and direction ($X \rightarrow \text{En}$ and $\text{En} \rightarrow X$). We initialized from NLLB and continued training on the small parallel corpus for a few thousand updates. We used a learning rate of 5×10^{-5} with linear decay and validated frequently to avoid overfitting (early stopping typically within 5–6 epochs). Following multilingual NMT practice, we employed a *target-language tag* to steer generation: for $X \rightarrow \text{English}$, we prepended `<2eng>` to the source; for $\text{English} \rightarrow X$, we prepended `<2xxx>` (the target code) to the English source (Johnson et al. 2017; NLLB Team et al. 2022). When NLLB lacked a predefined code (e.g., Sunwar, Kapingamarangi), we used a related code or an unused token as a proxy and updated the model’s dictionary accordingly (Aharoni, Johnson, and Firat 2019).

Code	Language	System (NLLB-200-600M)	BLEU	spBLEU	ChrF	TER ↓	COMET
rmc	Carpathian Romani	Fine-tuned	33.99	35.14	53.68	56.35	0.666
		Zero-shot baseline	0.40	0.39	18.65	127.21	0.271
		Best proxy: slk_Latn → eng_Latn	1.25	1.39	18.87	180.79	0.330
		Δ	+32.74	+33.75	+34.81	+70.86	+0.34
cac	Chuj	Fine-tuned	11.42	11.92	33.54	108.47	0.559
		Zero-shot baseline	0.33	0.22	16.87	171.91	0.256
		Best proxy (COMET): por_Latn → eng_Latn	0.17	0.23	13.43	260.20	0.292
		Best proxy (ChrF): grn_Latn → eng_Latn	0.16	0.13	13.72	139.24	0.237
		Δ	+11.09	+11.69	+16.67	+30.77	+0.27
suz	Sunwar	Fine-tuned	13.90	14.69	35.26	93.45	0.645
		Zero-shot baseline	0.27	0.26	17.26	209.71	0.368
		Best proxy (COMET): mai_Deva → eng_Latn	0.43	0.52	13.29	290.85	0.369
		Best proxy (ChrF): dzo_Tibt → eng_Latn	0.33	0.33	13.61	223.89	0.349
		Δ	+13.47	+14.17	+18.00	+116.26	+0.28
kpg	Kapingamarangi	Fine-tuned	28.14	28.90	47.53	66.74	0.668
		Zero-shot baseline	0.25	0.38	16.49	169.75	0.285
		Best proxy (COMET): fij_Latn → eng_Latn	0.52	0.60	13.38	262.06	0.318
		Best proxy (ChrF): smo_Latn → eng_Latn	0.79	0.81	14.62	225.31	0.316
		Δ	+27.35	+28.09	+31.04	+103.01	+0.35
iku	Inuktitut	Fine-tuned	10.92	11.25	24.10	130.80	0.544
		Zero-shot baseline	1.67	0.15	2.91	104.61	0.414
		Best proxy (COMET): tur_Latn → eng_Latn	1.76	0.32	4.06	101.37	0.437
		Best proxy (ChrF): fin_Latn → eng_Latn	1.54	0.50	5.97	108.23	0.435
		Δ	+9.16	+10.75	+18.13	-29.43	+0.11

Table 2: Endangered → English translation results with NLLB-200-600M (fine-tuned on ~31k sentence pairs per language). For each language, the bottom Δ row reports the **absolute improvement of the fine-tuned model over the second-best system in that block**, metric by metric.

Evaluation Setup. We report five complementary metrics, each capturing a different facet of translation quality. We report **BLEU** and **spBLEU** computed case-insensitively with consistent tokenization using SacreBLEU (Papineni et al. 2002; Post 2018); spBLEU applies standardized segmentation to reduce tokenizer variance. We include **ChrF** as a character n-gram F-score (Popović 2015), **TER** as the normalized edit operations required to match the reference (Snover et al. 2006), and **COMET** as a reference-based neural quality estimator aligned with human judgments (Rei et al. 2020).

For each language and direction, we compare:

1. **Zero-Shot Baseline**—off-the-shelf NLLB-200 without fine-tuning (for unsupported languages, effectively near-zero).
2. **Best Proxy Fine-Tuned Baseline**—we screen a panel of ~5 typologically or geographically related high-resource proxies, fine-tune one model per proxy, and report the best dev-set performer. *Example (Sunwar)*: Nepali, Central Tibetan, Maithili, Hindi, Dzongkha, Burmese.
3. **ENLIVEN Fine-Tuned**—our model fine-tuned on the true language’s ~31k parallel pairs.

MT Analysis. Table 2 shows **consistent improvements across all metrics** after fine-tuning on ~31k pairs per language. BLEU and spBLEU jump from near-zero to clearly usable ranges, indicating better n-gram fluency; ChrF rises

substantially, reflecting stronger character-level fidelity and robustness to orthographic variation; COMET increases across the board, confirming gains in semantic adequacy and overall quality; and TER **drops sharply**, meaning far fewer edits would be needed in a post-editing workflow. The Δ rows make this explicit: the fine-tuned system outperforms **both** the zero-shot baseline and the best proxy for language and metric besides one, with the largest gains where the off-the-shelf model struggles most.

We also observe a **script effect**: Latin-script languages show the biggest jumps, Devanagari is close behind, and Canadian Aboriginal Syllabics (Inuktitut) still benefits meaningfully—particularly on COMET and ChrF—even when word-overlap metrics (BLEU/spBLEU) rise more modestly. This pattern aligns with expected tokenization and pretraining coverage differences. Overall, a modest amount of language-specific supervision turns an unreliable zero-shot model into a **reliable endangered→English translator** across multiple quality axes, suitable for corpus growth, data mining, and downstream applications.

Translating *into* endangered languages (English→X; see Appendix B for the full table) is harder, and BLEU scores are lower on average than X→English, but fine-tuning still makes the task tractable. We obtain **12.72** BLEU for *English→Romani* (vs. 0.12), **12.47** for *English→Kapingamarangi* (vs. 0.22), **3.25** for *English→Chuj* (vs. 0.02), **2.79** for *English→Sunwar* (vs. 0.01), and **5.00**

Size	BLEU	spBLEU	ChrF	TER↓	COMET
31K	10.92	11.25	24.10	130.80	0.544
62K	11.86	10.57	24.80	109.79	0.551
93K	9.04	8.61	24.51	138.79	0.560
124K	14.79	15.41	30.36	123.13	0.586

Table 3: Inuktitut→English with NLLB-600M fine-tuned on one language and increasing data (31K–124K).

for *English→Inuktitut* (vs. 0.68). While one metric (sp-BLEU) for *English→Inuktitut* is slightly lower than baseline—likely an artifact of segmentation—COMET and TER improve substantially (COMET +0.17; TER drops from 439.40 to 97.85).

Overall, across both directions and all five languages, **EN-LIVEN** fine-tuning reliably surpasses zero-shot and proxy baselines. A practical takeaway is that collecting on the order of 30k authentic pairs—via community engagement or targeted mining—suffices to produce usable systems when combined with a pretrained multilingual backbone.

Qualitative Analysis. To concretely illustrate the improvements, consider Sunwar: the zero-shot NLLB (leveraging incidental Hindi/Nepali knowledge) yielded mostly garbled outputs for Sunwar, often mixing Nepali words. The fine-tuned model, by contrast, produces fluent Sunwar closely matching reference translations. For a test sentence meaning “You are strangers in the land” the baseline produced unreadable output, whereas the fine-tuned system generated a similarly-correct Sunwar sentence. This transformation from unusable to reasonably accurate translation is replicated across the five case studies.

Case Study for Data Scaling (Inuktitut). We also investigated data scaling using Inuktitut, where more bitext is available. We created training sets of 31k, 62k, 93k, and 124k Inuktitut–English pairs by adding sentences from government and news sources, and fine-tuned models on each. Table 3 shows a clear upward trend: moving from 31k to 124k steadily strengthens performance for English→Inuktitut and significantly improves Inuktitut→English as well (table in Appendix B), consistent with long-standing observations that additional in-domain parallel data improves NMT quality (Koehn and Knowles 2017). We note a small non-monotonic dip at 93k, likely due to mixed-domain additions and a fixed training schedule; performance rebounds at 124k. This suggests that whenever additional real parallel data can be obtained, it should be incorporated. Nevertheless, for most of the 1000+ languages we target, such large corpora do not exist, motivating synthetic data generation in the next section.

4 Synthetic Data Experiments

While real parallel data is the gold standard for MT, it is scarce for endangered languages. A promising solution is to generate synthetic parallel data using a powerful language model, effectively leveraging high-resource language data (like English texts) to create translations in the low-resource

language (Sennrich, Haddow, and Birch 2016; de Gibert et al. 2025). Recent studies have shown that large LLMs (such as GPT-4o or Claude) can produce surprisingly good translations for languages where they were not explicitly trained (OpenAI 2023; Anthropic 2024). We investigate this approach for two of our languages: Carpathian Romani (rmc) and Inuktitut (iku), chosen as the best- and worst-performing languages in our earlier MT results. Romani had the highest baseline translation quality after fine-tuning (likely due to its linguistic similarity to other languages the model knows, and possibly simpler morphology), whereas Inuktitut remained the most challenging (due to complex morphology and polysynthesis). By testing on both, we gauge the effect of synthetic data in favorable vs. difficult conditions.

Synthetic Data Generation. We generate 1:1 synthetic parallel corpora for *Carpathian Romani* (rmc) and *Inuktitut* (iku) using a lexicon-guided few-shot prompting strategy (Yong, Menghini, and Bach 2024). Concretely, we start from the English side of our real bitext (31k sentences per language) and construct prompts that interleave (i) nearest-neighbor exemplars retrieved by character n -gram similarity from the seed corpus, and (ii) compact bilingual token/phrase lexicons automatically induced from the same seed (token co-occurrence and shallow alignments). A frontier LLM (GPT-4o) translates each English sentence into the target language under style/orthography constraints. For Inuktitut, we request romanized outputs and apply a deterministic romanization→syllabics mapping post hoc to ensure script conformity.

Quality control and de-duplication. We employ a two-stage filter: (1) a semantic gate using LaBSE cosine similarity on small held-out checks (with retry-based selection) to reject low-adequacy generations, and (2) near-duplicate removal with a token-level Levenshtein similarity threshold to discard trivially paraphrastic or repeated items. We also exclude the current source sentence from few-shot blocks (leak-safe exemplars) and enforce basic well-formedness constraints. The pipeline is implemented with strict rate limiting, timeout-aware retries, and periodic checkpoints to enable safe resume.

Downstream MT. Because reference-free quality estimators are unavailable for rmc and iku in our setting, we evaluate the utility of synthetic data via downstream MT performance rather than standalone reference-free metrics. We trained MT models under four regimes for each language (rmc and iku): (1) Real-only 31k – using the original 31k real parallel sentences (same fine-tuned model from early MT); (2) 100% Synthetic 31k – using only the 31k GPT-4o generated pairs for training; (3) Concat-62k – concatenating the real and synthetic data, giving 62k training pairs which mirrors a realistic deployment pattern; (4) 50/50 @31k – mixing real and synthetic but capping the total at 31k (randomly sampled 15.5k from real and 15.5k from synthetic to keep training data size constant at 31k, to isolate data quality effects). We fine-tuned NLLB-200 models for each setting, using the same hyperparameters as before. We then evaluated

Code	Language	System (NLLB-600M)	BLEU	spBLEU	ChrF	TER ↓	COMET
rmc	Carpathian Romani	Real-only (31K)	33.99	35.14	53.68	56.35	0.666
		100% Synthetic (31K)	10.87	14.14	35.62	77.30	0.551
		Concat-62K (31K + 31K)	26.86	38.61	56.38	52.73	0.683
		50/50 @31K (real/synth balanced)	10.87	14.14	35.62	77.30	0.551
iku	Inuktitut	Real-only (31K)	10.92	11.25	24.10	130.80	0.544
		100% Synthetic (31K)	0.75	0.20	4.25	99.56	0.420
		Concat-62K (31K + 31K)	5.47	10.02	23.49	97.30	0.507
		50/50 @31K (real/synth balanced)	4.21	7.07	21.87	102.39	0.491

Table 4: Synthetic augmentation regimes for *rmc*→En and *iku*→En with NLLB-600M fine-tuned per setting. “Real-only” trains on 31K human bitext; “100% Synthetic” uses 31K GPT-4o outputs; “Concat-62K” mixes 31K real + 31K synthetic; “50/50 @31K” balances real/synthetic while keeping the total at 31K. Best per-language scores are bolded.

all models on the same real test set (consisting of genuine translations) and compared metrics for MT.

Results. Table 4 compares real-only, synthetic-only, fixed-budget mixes, and simple concatenation for *rmc* and *iku* (into English). A few themes emerge.

Carpathian Romani (rmc). Synthetic sentences act as strong *augmenters*. Even when trained in isolation they approach the real-only system, and when concatenated with real data they yield the best overall profile: adequacy/fluency improve jointly (ChrF/COMET), while TER drops, indicating fewer edits are needed to reach references. The gains plausibly come from added lexical and constructional coverage that the smaller human set lacks (e.g., rarer inflections and multiword expressions). At a fixed budget (50/50), however, replacing half of the reliable human data with noisier synthetic examples can slightly blunt improvements—suggesting synthetic is most valuable as an *add-on* rather than a substitute for truly low-resource languages.

Inuktitut (iku). Synthetic-only training is weak, and even concatenation produces uneven gains: robustness (TER) improves more consistently than overlap-based or semantic metrics (BLEU/ChrF/COMET). Several factors likely contribute: (i) orthography handling (romanization ↔ syllabics conversion) introduces normalization noise; (ii) domain/style mismatch between GPT outputs and government/news references reduces *n*-gram overlap (hurting BLEU) even when translations are usable; (iii) morphology and compounding create sparse tokenizations that penalize overlap metrics; and (iv) higher LLM noise for *iku* increases the burden on the model to denoise. In short, synthetic data helps *volume* and robustness, but its intrinsic quality matters more for *iku* than for *rmc*.

Metric-level diagnostics. We observe expected divergences across metrics: BLEU/spBLEU (token/segmented overlap) can undervalue acceptable paraphrases and morphological variants that ChrF tolerates; COMET better tracks adequacy/meaning preservation but may be less calibrated for truly low-resource scripts; TER often captures practical editability gains even when overlap metrics move modestly. Reading these together yields a more faithful picture of data utility than any single metric.

Takeaways. (1) LLM-augmented training is best used as an

add-on, not a replacement: when synthetic quality is imperfect, concatenating synthetic with real data outperforms fixed-budget mixes that substitute synthetic for human data and can even surpass the real-only 31k setting—primarily because of increased training size. (2) To raise the floor of synthetic quality, invest in script-aware prompting and post-processing (e.g., romanization/syllabics normalization) plus light filtering, and assess impact with multiple metrics (ChrF, COMET, BLEU, TER), which is especially important for morphologically rich or script-divergent languages. (3) Crucially, these gains appear only when the synthetic data is of reasonable quality: in Inuktitut, where synthetic pairs were noisier, concatenating to 62k with synthetic *reduced* scores relative to the real-only 31k model, showing that added scale cannot compensate for low-quality synthetic data and that augmentation should be applied additively only when the synthetic component is sufficiently good. These conclusions resonate partially with de Gibert et al. (2025), who report improvements from LLM-generated data even when noisy (de Gibert et al. 2025).

Future Outlook. If general-purpose LLMs continue to improve in multilingual grounding, script fidelity, and controllability, we foresee a workflow in which our LID→MT→synthesis pipeline becomes a virtuous loop rather than a one-off bootstrap. LID discovers and filters monolingual text; stronger LLMs then translate or co-generate parallel data directly in community-preferred orthographies and dialects, attach uncertainty and style metadata, self-check via reference-free signals (e.g., round-trip consistency, contrastive probes, QE-like scores), and adapt with small preference datasets from speakers. MT fine-tuned on this higher-quality synthetic+real mix harvests even more usable text, further raising LLM promptability and data quality in the next round. Under community consent and safeguards, this trajectory makes the “translator assistant” role ever more realistic: LLMs augment (not replace) human expertise, turning tiny corpora into sustainable pipelines that can extend practical MT coverage to languages that currently have none.

5 Discussion and Implications

Our study demonstrates a practical framework to scale NLP support to hundreds of endangered languages. By combin-

ing broad LID for data acquisition with LLM-augmented MT training, we address two key bottlenecks: identifying data in the target language and generating enough training material to learn translations. The success on our five case-study languages suggests that similar methods can be applied to many others. In fact, our LID dataset (1154 languages) and project title “ENLIVEN-1000” indicate the ambition to cover over 1000 endangered languages – nearly an order of magnitude more than the languages supported by current translation systems (for context, Google Translate covers 133 languages, and the largest research MT models cover 200) (Google Support 2025; NLLB Team et al. 2022; Fan et al. 2021). Achieving this scale will require careful engineering and community collaboration, but the components presented here lay the groundwork (Caswell and Ng 2020; Sennrich, Haddow, and Birch 2016).

Generalizability: The languages we chose for MT experiments were diverse in family and structure, yet for each we found that a pre-trained model could be adapted with minimal data to produce understandable translations. This bodes well for other languages in our collection. Many endangered languages have at least some related language or similar typology represented in multilingual models (e.g., if a model knows some Algonquian languages, it might help with another Algonquian language). Our results imply that fine-tuning will be effective as long as a small authentic corpus can be obtained. In scenarios where there is sparse parallel data, our synthetic data approach provides a pathway: one can help a starter corpus using LLM-based augmentation and then train an MT model. This approach can be applied iteratively and at scale – for example, generating 10k–20k sentences for each of hundreds of languages and training separate models, or even training one massive multilingual MT model with synthetic data for all those languages (which could leverage transfer across them). We anticipate that integrating human feedback (through community speakers reviewing and correcting some LLM outputs) will further enhance quality, in a loop that involves native speakers in the technology development (Johnson et al. 2017; Aharoni, Johnson, and Firat 2019; Arivazhagan et al. 2019; de Gibert et al. 2025; Nekoto et al. 2020; Bird 2020).

Resource Scaling and Quality: One interesting implication from our Inuktitut data scaling is that more data clearly improves performance, but the returns can diminish if the data is of lower quality (as seen with synthetic vs real). This underlines a trade-off: quantity vs. quality. For many endangered languages, we might be forced to rely on imperfect data (machine-generated or scraped from noisy sources). Our LID model’s high precision can ensure that whatever data we gather is at least in the correct language, reducing one kind of noise (Kreutzer et al. 2022b; Wenzek, Lacroix, and Bennoit 2020; Ortiz Suárez, Romary, and Sagot 2020). As for MT training, techniques like filtering synthetic outputs with back-translation or using agreement between multiple LLMs could improve quality. We view the use of synthetic data not as a one-time shortcut, but as part of a larger pipeline where initial synthetic translations enable a rough MT system, which can then be refined with any new real

data that becomes available (for instance, through crowdsourcing translations of some evaluation texts, or leveraging indigenous language media) (Sennrich, Haddow, and Birch 2016; Wang et al. 2022).

Towards 1000+ Languages: Scaling to 1000 languages also raises engineering challenges: maintaining separate models for each vs. a single unified model, dealing with different scripts and tokenization issues, and evaluating performance when human expertise for many of these languages is limited. Nonetheless, the upside is tremendous – providing even rudimentary translation capability for 1000 endangered languages would dramatically broaden digital inclusion. Consider an indigenous community that currently has no software or online content in their language: an MT system could help translate public health information, educational materials, or allow elders to record stories in their language and translate them for younger generations or outsiders. It also aids linguists in creating bilingual texts and dictionaries. By bridging these languages to a lingua franca (like English), we effectively open a channel of communication that was absent. This contributes to language documentation as well – automatic translation can speed up the processing of field data and creation of translated texts for archival (NLLB Team et al. 2022; Fan et al. 2021).

Our work aligns with the vision of “no language left behind” in NLP and provides a concrete step in that direction focused on endangered languages. Moreover, it complements broader efforts in language technology for low-resource languages, such as speech recognition/synthesis and OCR. A natural next step is to incorporate speech-to-text and text-to-speech for these languages, enabling voice-based translation systems that could be used by non-literate speakers. Another direction is to expand the domain coverage: our experiments used fairly formal texts (Bible, government proceedings). Community use cases might require handling informal speech or dialectal variations; achieving that will require collecting or generating data in those registers, and perhaps fine-tuning models specifically for conversational language.

6 Conclusion

ENLIVEN-1000 shows that a pragmatic combination of broad-coverage LID, targeted fine-tuning of a multilingual MT backbone, and carefully curated LLM-generated data can extend usable NLP support to hundreds of endangered and low-resource languages without bespoke infrastructure for each. Beyond headline scores, the key contribution is a fully-deployable workflow: LID reliably allows for text discovery and filtering; MT adaptation turns small, authentic corpora into functional translation systems in both directions; and synthetic augmentation acts as an *additive* accelerant when quality is high enough, with multi-metric evaluation (BLEU, spBLEU, ChrF, TER, COMET) guiding decisions about when and how to integrate it. Looking forward, we see three immediate fronts for impact: (i) community-centered scaling (consent, orthography/script preferences, dialect labels) and human-in-the-loop post-editing; (ii) robustness work for script-divergent, morphologically rich

languages (prompting, normalization, tokenization) alongside reference-free quality estimation; and (iii) modality expansion to speech (ASR/TTS) and OCR to widen access and documentation. As general-purpose LLMs improve in multilingual grounding and controllability, this LID→MT→synthetic loop can become a virtuous, repeatable pipeline—amplifying, rather than replacing, community expertise—to sustainably broaden language technologies for those most at risk of digital exclusion. Our hope is that this work sparks further research and funding for under-represented languages – aligning with UNESCO’s calls to preserve linguistic diversity as part of our common heritage (UN DESA 2022).

Ethical Statement and Limitations

Working with endangered languages requires careful ethical consideration. These languages often belong to indigenous or marginalized communities who have historically faced oppression, and their linguistic data may carry cultural sensitivities (Bird 2020; Bender and Friedman 2018). We approached the ENLIVEN-1000 project with a mindset of respect, transparency, and inclusivity. We acknowledge the following ethical aspects:

Community Engagement and Consent: Whenever possible, development of language technology for an endangered language should involve the speech community. In this study, we did *not* acquire direct engagement with native speakers due to limited resources and time, and our study exclusively leveraged publicly available texts (e.g., religious translations, governmental proceedings, and other publicly released corpora). We recognize that true revitalization impact comes from community buy-in. In future work, we plan to reach out to native speakers for guidance on our selected languages. For example, we can consult Romani community members about the appropriate orthography and dialect labeling, or discuss with Inuit representatives about the use of Inuktitut syllabics vs romanization. In addition, as we expand to more languages, we plan to establish partnerships with community organizations and obtain consent especially if using any non-public data. We also note that not all communities may want automatic translation of their language; some might fear misuse or loss of control. In such cases, we would refrain from deploying models publicly without community approval (Nekoto et al. 2020; Carroll et al. 2020; United Nations 2007).

Data Transparency and Quality: We only used data from open sources or those with clear usage permissions. Still, much of the data (like Bible translations) was created by missionaries or outside linguists, not the communities themselves. These texts might contain biases or archaic language (Mayer and Cysouw 2014; Hovy and Spruit 2016). We disclose the provenance of our datasets and caution that the MT systems’ outputs may mirror the style of the training data. Users should be informed that these tools are assistive and not a replacement for learning the language or consulting fluent speakers. We also took care to not include any sacred or private texts that we thought communities might not want in a training dataset (beyond widely circulated scrip-

ture translations). All source data and model outputs will be open-sourced, in line with ethical open research practices, so that community members can inspect and audit what has been done with “their” language (Geburu et al. 2021; Bender and Friedman 2018).

Bias and Hallucination in LLM Outputs: For the synthetic data generated by GPT-4, we acknowledge that an LLM might introduce subtle biases or outright errors. GPT-4 is a product of predominantly English internet data; when it produces text in an endangered language, it might inadvertently inject stereotypes (for example, always translating certain words in a way that aligns with colonial-era texts). We attempted to mitigate this by manually checking a sample of outputs and by instructing the model clearly, but some problematic content could slip through. This is an area for improvement – possibly employing multiple LLMs or human reviewers to cross-verify synthetic data. In any case, we emphasize that caution must be used when interpreting translations. Critical decisions (e.g., legal, medical) should not be made solely on automated translations without human verification, especially given the lower reliability in low-resource settings (Bender et al. 2021; Ji et al. 2023; Weidinger et al. 2021).

Cultural Considerations: Language is deeply tied to culture. Automated systems might misinterpret idioms or output phrases that are culturally offensive if used in the wrong context. We did not specifically filter training data for such content beyond basic profanity filters. It’s possible the MT outputs could occasionally produce disrespectful or nonsensical phrases (especially the LLM-synthetic portions). As part of ethical deployment, we advocate for a human-in-the-loop approach in sensitive contexts. That is, use MT to assist, but have native speakers or bilingual experts review and correct important translations. Our ultimate aim is to help preserve and promote the use of these languages, and we strongly believe this must be done with the communities’ leadership. Technology can amplify revitalization efforts, but it cannot succeed without the human element – the desire of people to keep their languages alive (Bird 2020; Nekoto et al. 2020).

In conclusion, we commit to ongoing dialogue with language communities and experts. We will treat any community feedback (e.g., requests to remove data or adjust how a language is represented) with utmost seriousness. This project is driven by a passion for linguistic diversity, and we strive to ensure it remains a force for good in supporting the world’s endangered languages, aligning with ethical standards and the rights of indigenous peoples (United Nations 2007; Carroll et al. 2020).

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A LID Training and Evaluation Details

Preprocessing and De-duplication

Normalization. Each line is normalized with Unicode NFKC, control/format characters are removed, whitespace is collapsed, and lines with fewer than 8 or more than 512 visible characters are discarded. **Two-pass de-duplication.** *Pass 1* computes a SHA-1 hash over every normalized line in every language file and flags hashes that occur in more than one language (cross-language conflicts). *Pass 2* writes per-language cleaned files that (i) drop any cross-language conflicting hashes and (ii) drop within-language duplicates (set semantics).

Stratified Splits

For each language ℓ , lines are shuffled (fixed seed) and split into **train/valid/test** at **85/5/10**. We cap validation and test at ≤ 1000 instances per language (excess is returned to train). The resulting files are concatenated into fastText format with `__label__<iso>` prefixes.

Temperature Upsampling (Train Only)

To mitigate class imbalance, we apply light *temperature upscaling* on the training file. Let p_ℓ be the empirical proportion of language ℓ in train. We draw with weights

$$w_\ell \propto p_\ell^{1/T} \quad (\text{default } 1/T = 0.3, T \approx 3.33),$$

and sample to reach a target of $\approx 2\times$ the original train size. This increases exposure to low-resource classes without overwhelming high-resource ones.

Model and Optimization

We train a supervised fastText classifier (Joulin et al. 2017) over character n -grams with the following settings:

lr	0.8
epoch	2
dim	256
wordNgrams	1
minn/maxn	2/5
loss	softmax
bucket	10^6
minCount/minCountLabel	1000/0

Training uses multi-threading and saves both the standard `.bin` and a quantized `.ftz` model; quantization employs `qnorm` with `dsub=2`.

Thresholded Inference and Metrics

At inference, predict $\hat{l}(s) = \arg \max_{l \in B} P(l | s)$ if $\max_{l \in B} P(l | s) \geq \theta$, otherwise return UNDETERMINED, where B is the base label set (all model labels or only languages present in the benchmark). We report per-language Precision, Recall, F1, and False Positive Rate (FPR), plus macro-averages over languages present in the test set; results are given at $\theta \in \{0.5, 0.3\}$, and we also log top-1/top-3 accuracy on dev/test.

Aggregation and Reporting

For each language ℓ , we aggregate TP_ℓ , FP_ℓ , and FN_ℓ under the decision rule; UNDETERMINED counts toward FN_ℓ for the true label. We compute $Prec_\ell = \frac{TP_\ell}{TP_\ell + FP_\ell}$, $Rec_\ell = \frac{TP_\ell}{TP_\ell + FN_\ell}$, $F1_\ell = \frac{2 \cdot Prec_\ell \cdot Rec_\ell}{Prec_\ell + Rec_\ell}$, and (inline to avoid overflow) $FPR_\ell = \frac{FP_\ell}{FP_\ell + TN_\ell}$. Macro-averages are arithmetic means over languages included in the benchmark split. We export per-language CSVs (metrics, support, and UNDETERMINED counts) and print best/worst languages by F1 for diagnostics.

Reproducibility Notes

We fix the random seed to 13 for shuffling and sampling, and use a single pass of upsampling with the parameters above. The decision threshold(s) and base set B are explicitly reported with each result. All preprocessing, splits, model artifacts, and per-language metrics are saved to disk to facilitate exact reruns.

B Additional MT Results

Synthetic Generation Pipeline

- **Inputs/target:** Load a parallel CSV (SRC_COL, TGT_COL); set TARGET_PAIRS=62k.
- **Chat wrapper:** SDK-compatible chat completions (accepts max_tokens/max_output_tokens), with RPM/TPM limits, timeouts, retries/backoff.
- **Validation (LaBSE):** Small pre-generation check; require mean cosine & hit-rate thresholds or abort/override.
- **Retrieval & hints:** Char n -gram NN over sources; prompts include nearest examples + compact token/phrase lexicon (SimAlign optional).
- **Diverse seeding:** Bin by length/punctuation; round-robin to form a global seed order covering the corpus.
- **Batched creation:** Ask for k new pairs in strict format LRL – English; normalize (NFC) and parse.
- **Dedup/filter:** Maintain a *seen* set; drop near-duplicates via token-level Levenshtein (sliding window); discard malformed rows.
- **Checkpoints/resume:** Every 2k pairs/5 rounds save partial CSV + JSON state (seed pointer/order, rounds); resumable after interrupts.
- **Finalize:** Write the 62k synthetic pairs to CSV and store a brief validation report for audit.

Endangered→English Tables

In the main paper, we reported translation quality for the endangered→English direction for our representative languages. For completeness, this appendix presents the complementary English→endangered results for the same languages, model settings, and training regimes.

Table 5 mirrors the endangered→English results by reporting English→endangered scores for five languages (Carpathian Romani, Chuj, Sunwar, Kapingamarangi, and Inuktitut) with NLLB-200-600M fine-tuned on roughly 31K sentence pairs per language. For each language, we compare the fine-tuned system to the zero-shot baseline across BLEU, spBLEU, ChrF, TER, and COMET, and summarize the absolute metric-wise improvement in the bottom Δ row (for TER, positive Δ indicates a reduction in edits).

Table 6 provides the English→Inuktitut counterpart to our data-scaling analysis, varying the amount of supervised bitext from 31K to 124K sentence pairs while keeping the NLLB-600M architecture fixed.

Finally, Table 7 is the English→endangered analogue of our synthetic augmentation study: it evaluates “Real-only”, “100% Synthetic”, “Concat-62K”, and “50/50 @31K” regimes for English→Carpathian Romani and English→Inuktitut, using the same metrics and experimental conditions as in the endangered→English direction.

After Table 7, the remaining appendix tables report our full LID results, covering all 1,154 languages at both confidence thresholds $\theta = 0.3$ and $\theta = 0.5$.

Code	Language	System (NLLB-200-600M)	BLEU	spBLEU	ChrF	TER ↓	COMET
rmc	Carpathian Romani	Fine-tuned	12.72	18.07	37.98	81.33	0.536
		Zero-shot baseline	0.12	0.12	12.62	130.95	0.271
		Δ	+12.60	+17.95	+25.36	+49.62	+0.27
cac	Chuj	Fine-tuned	3.25	8.09	23.69	136.08	0.511
		Zero-shot baseline	0.02	0.04	9.40	111.20	0.212
		Δ	+3.23	+8.05	+14.29	-24.88	+0.30
suz	Sunwar	Fine-tuned	2.79	10.42	23.57	176.25	0.500
		Zero-shot baseline	0.01	0.00	0.16	118.65	0.167
		Δ	+2.78	+10.42	+23.41	-57.60	+0.33
kpg	Kapingamarangi	Fine-tuned	12.47	16.53	39.50	89.80	0.664
		Zero-shot baseline	0.22	0.28	9.91	112.05	0.222
		Δ	+12.25	+16.25	+29.59	+22.25	+0.44
iku	Inuktitut	Fine-tuned	5.00	0.17	2.20	97.85	0.491
		Zero-shot baseline	0.68	0.21	0.88	439.40	0.325
		Δ	+4.32	-0.04	+1.32	+341.55	+0.17

Table 5: English $\rightarrow$ Endangered translation results with NLLB-200-600M (fine-tuned on $\sim$ 31k sentence pairs per language). For each language, the bottom Δ row reports the **absolute improvement of the fine-tuned model over the zero-shot baseline**, metric by metric (for TER, positive Δ denotes a reduction in edits).

Size	BLEU	spBLEU	ChrF	TER↓	COMET
31K	5.00	0.17	2.20	97.85	0.491
62K	4.40	0.19	2.55	97.70	0.489
93K	2.33	0.04	1.62	99.06	0.481
124K	1.51	0.08	2.65	97.94	0.576

Table 6: English $\rightarrow$ Inuktitut with NLLB-600M fine-tuned on one language and increasing data (31K–124K).

Code	Language	System (NLLB-600M)	BLEU	spBLEU	ChrF	TER ↓	COMET
rmc	Carpathian Romani	Real-only (31K)	12.72	18.07	37.98	81.33	0.536
		100% Synthetic (31K)	5.27	9.27	27.29	93.72	0.497
		Concat-62K (31K + 31K)	16.33	23.86	42.40	73.47	0.556
		50/50 @31K (real/synth balanced)	5.27	9.27	27.29	93.72	0.497
iku	Inuktitut	Real-only (31K)	5.00	0.17	2.20	97.85	0.491
		100% Synthetic (31K)	0.40	0.00	1.21	98.56	0.462
		Concat-62K (31K + 31K)	1.21	0.01	1.82	98.16	0.472
		50/50 @31K (real/synth balanced)	1.06	0.01	1.74	98.42	0.471

Table 7: Synthetic augmentation regimes for $En \rightarrow rmc$ and $En \rightarrow iku$ with NLLB-600M fine-tuned per setting. “Real-only” trains on 31K human bitext; “100% Synthetic” uses 31K GPT-4o outputs; “Concat-62K” mixes 31K real + 31K synthetic; “50/50 @31K” balances real/synthetic while keeping the total at 31K. Best per-language scores are bolded.

Table 8: LID Performance on the Full-LID Set with Thresholds: 0.3 and 0.5.

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
bsp	Bagu Sitemu	47k	448	0.9845814977973570	0.997767871428570	0.9911308203991130	7.69377035414425E-06	0.9911308203991130	0.997767871428570	0.9944382647385980	4.39644020236814E-06
bss	Akone	100k	790	1.0	1.0	1.0	0.0	1.0	0.9987341772151900	0.999366687777074	0.0
buk	Bukawa	9690	777	0.9961538461538460	1.0	0.9980732177263970	3.29852292143578E-06	0.9961538461538460	1.0	0.9980732177263970	3.29852292143578E-06
bus	Bokobaru (Bokobaru)	70k	1000	0.9930139720558880	0.9995	0.994005994005994	7.6984410656842E-06	0.9930139720558880	0.9995	0.994005994005994	7.6984410656842E-06
bvd	Baegu (Baegu)	5.9k	789	0.9874529485570890	0.9974651457541190	0.99242337957124840	1.09952214767462E-05	0.989937106918239	0.9974651457541190	0.9936868686868690	8.79617718139697E-06
bvr	Burara	800	791	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
bxx	Buhutu	1.4k	419	0.9976190476190480	1.0	0.99880810488677	1.09907501846446E-06	0.9976190476190480	1.0	0.99880810488677	1.09907501846446E-06
byx	Qaqet	15k	782	0.9961783439490450	1.0	0.998085513720485	3.29854105529125E-06	0.9961783439490450	1.0	0.998085513720485	3.29854105529125E-06
bzb	Bribri	6k	971	0.9989711934156380	1.0	0.9994853319608850	1.09974222042353E-06	0.9989711934156380	1.0	0.9994853319608850	1.09974222042353E-06
caa	Mapos Buang	10.5k	793	0.9987405541561710	1.0	0.9993698802772530	1.0995269834917E-06	0.9987405541561710	1.0	0.9993698802772530	1.0995269834917E-06
cab	Ch'orti'	55,250	975	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cac	Garifuna	195,800	792	0.9974811083123430	1.0	0.998738965920810	2.19905154906689E-06	0.9974811083123430	1.0	0.998738965920810	2.19905154906689E-06
caf	Chuj	51,200	1000	1.0	0.999	0.999497498749370	1.0	0.999	0.999497498749370	1.0	0.999497498749370
cah	Southern Carrier (Dakelh)	1,039	793	0.9912060201507540	0.9949558638083230	0.9930774071743240	7.69668888444191E-06	0.9924528201886790	0.9949558638083230	0.9937027707808560	6.59716190959021E-06
caj	Kaqch'ik	450,900	790	0.9974715549936790	0.9987341772151900	0.9981024667931690	2.19904671324981E-06	0.9987341772151900	0.9987341772151900	0.9987341772151900	1.0995233566249E-06
cao	Chicobo	550	790	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cav	Chipaya	1200	788	0.998730964467005	0.998730964467005	0.998730964467005	1.099520938727E-06	0.998730964467005	0.998730964467005	1.099520938727E-06	1.099520938727E-06
caw	Carit (Kari'nja)	8,600	789	0.9987341772151900	1.0	0.999366687777074	1.09952214767462E-06	0.9987341772151900	1.0	0.999366687777074	1.09952214767462E-06
cax	Cavineña	601	766	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cay	Chiquitano	5000	793	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cbe	Carapana	650	773	0.9961290322580650	0.9987063389391980	0.9974160206718350	3.29850841449497E-06	0.9961290322580650	0.9987063389391980	0.9974160206718350	3.29850841449497E-06
cbi	Chachi (Cha'palaa)	5,465	1000	0.99803992015968	1.0	0.999009990099990	2.19955459019549E-06	0.99803992015968	1.0	0.999009990099990	2.19955459019549E-06
cbl	Cavie Chavacano	792	792	0.9962168978562420	0.997447474747480	0.996454258675080	3.29857732260433E-06	0.9962168978562420	0.997447474747480	0.996454258675080	3.29857732260433E-06
cbr	Kakataibo-Kashibo (Casilibo-Cacataibo)	2191	930	0.9989258861439310	1.0	0.99462654468335	1.09996263590826E-06	0.9989258861439310	1.0	0.99462654468335	1.09996263590826E-06
cbs	Kashinawa (Huni Kuin)	5,457	739	0.9986468200270640	0.9986468200270640	0.9986468200270640	1.09946170354994E-06	0.9986468200270640	0.9986468200270640	0.9986468200270640	1.09946170354994E-06
cbt	Shawi (Chayahuita)	14k	914	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cby	Kandozi-Chapra	1,586	1000	0.9960159362549800	1.0	0.998003992015968	4.39910918039097E-06	0.9960159362549800	1.0	0.998003992015968	4.39910918039097E-06
cbe	Cacua	400	764	1.0	0.9986910994764400	0.999345211525870	1.0	0.9986910994764400	0.999345211525870	0.999345211525870	1.0
ccc	Comaltepec Chinantec	3,200	785	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
ceb	Cebuano	20m	1000	0.9891089108910890	0.999	0.9940298507462690	1.20975502460752E-05	0.9910714285714290	0.999	0.9950199203187250	9.8979956587969E-06
cek	Eastern Khumi Chin	50k	1000	1.0	0.999	0.999497498749370	1.0	0.999	0.999497498749370	1.0	0.999497498749370
cgc	Kagayanen	30k	782	0.988621997471555	1.0	0.9942784488239030	9.89562316587373E-06	0.9936467598475220	1.0	0.9968132568514980	5.4756842548541E-06
chg	Chamorro	58k	724	0.9986206896551720	1.0	0.999309688750860	1.0994357160841E-06	0.9986206896551720	1.0	0.999309688750860	1.0994357160841E-06
chd	Highland Oaxaca Chontal	3.6k	784	0.9987244897959180	0.9987244897959180	0.9987244897959180	1.09951610296309E-06	0.9987244897959180	0.9987244897959180	0.9987244897959180	1.09951610296309E-06
chf	Tabasco Chontal (Yokot'an)	38k	793	1.0	0.9962168978562420	0.998104864181933	1.0	0.9962168978562420	0.998104864181933	0.998104864181933	1.0
chk	Chukchee	45.9k	1000	1.0	0.997	0.99849774661993	1.0	0.997	0.99849774661993	1.0	0.99849774661993
chl	Quioquepec Chinantec	10,440	789	0.9974715549936790	1.0	0.9987341772151900	2.19904429534924E-06	0.9974715549936790	1.0	0.9987341772151900	2.19904429534924E-06
chz	Ojitalan Chinantec	37,900	792	0.998738965920810	1.0	0.9993698871735020	1.09952577453344E-06	0.998738965920810	1.0	0.9993698871735020	1.09952577453344E-06
cjo	Papuan Asheninka	7870	793	0.9974079794079790	0.997379480209700	0.983116883116880	1.75918514544063E-05	0.9844760672070350	0.997379480209700	0.9988541666666670	1.31938858980407E-05
cjv	Chavne	26k	784	1.0	0.9987244897959180	0.9993618379068280	1.0	0.9987244897959180	0.9993618379068280	0.9993618379068280	1.0
ckb	Central Kurdish (Sorani)	7mm	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cld	Lealaon Chinantec	3.2k	793	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cly	Calyanun	30k	785	0.966707768187423	0.9987261146496820	0.9824504503508770	2.9686967421302E-05	0.9679012345679010	0.9987261146496820	0.9830721003134800	2.8587450109402E-05
cme	Cerna (San)	53.6k	789	0.998693467336630	0.9974651457541190	0.9930599369085170	9.89569932007159E-06	0.9911837909319030	0.9974651457541190	0.994314592545799	7.6966503722344E-06
cni	Ashinka	89.51k	770	0.9961190168175940	1.0	0.99805170355800390	3.29849753437309E-06	0.9974059662775620	0.9987012987012990	0.99805170355800390	2.19989835624873E-06
cnl	Lalana Chinantec	10,700	790	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cnt	Tepejatlal Chinantec	7870	792	0.998738965920810	1.0	0.9993698871735020	1.09952577453344E-06	0.998738965920810	1.0	0.9993698871735020	1.09952577453344E-06
cof	Tsafiki (Colorado)	1,872	792	0.998648865153540	0.998648865153540	0.998648865153540	1.09947379184322E-06	0.998648865153540	0.998648865153540	0.998648865153540	1.09947379184322E-06
con	Cofán (A'í)	1.5k	938	0.99872340254532	1.0	0.9940462169055E-06	1.0	0.99872340254532	1.0	0.9940462169055E-06	1.0
cot	Caquite	500	776	0.9987113402061860	0.9987113402061860	0.9987113402061860	1.09950643156287E-06	0.9987113402061860	0.9987113402061860	0.9987113402061860	1.09950643156287E-06
cpa	Palantla Chinantec	30k	794	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cpb	Ucayali-Yurúa Asheninka	10k	789	0.9836065573770490	0.998591558935360	0.9860935524652340	1.4293789197701E-05	0.9835858585858590	0.9873257287705960	0.9854522454142950	1.4293789197701E-05
cpc	Ajtininka Apurucayali	20k	789	0.9528415961305930	0.9987325728770600	0.9752475274524750	4.28813637593102E-05	0.9551515151515150	0.9987325728770600	0.9682319436961E-05	4.0682319436961E-05
cpu	Pichis Asheninka	17k	790	0.9885786802030460	0.9860759493670890	0.9873257287705960	9.89571020962413E-06	0.9910941475826970	0.9860759493670890	0.9885786802030460	7.6966643637432E-06
cpy	South Ucayali Asheninka	7870	1000	0.993963782696177	0.998	0.9909729187562690	6.59866377058646E-06	0.993963782696177	0.998	0.9909729187562690	6.59866377058646E-06
crn	El Nayar Cera	15k	765	0.9986945169712790	1.0	0.9993468313585990	1.09949313366338E-06	0.9986945169712790	1.0	0.9993468313585990	1.09949313366338E-06
crx	Babine (Northern Carrier)	3,300	946	0.9957627118644070	0.9936575052854120	0.9947089947089950	4.39884794172406E-06	0.9968186638388120	0.9936575052854120	0.9952355743779780	3.29913595629305E-06
cso	Sochiapam Chinantec	3,590	793	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cst	Shin Chin	10k	795	0.998738965920810	0.9962264150943400	0.9974811083123430	1.09952940141619E-06	0.9962264150943400	0.998109640831758	0.998109640831758	1.09952940141619E-06
cta	Tataltepec Chatino	540	786	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
ctp	Western Highland Chatino	12k	788	0.9987325728770600	1.0	0.9993658845909960	1.099520938727E-06	0.9976019184652280	0.9976019184652280	0.9976019184652280	2.19915310613883E-06
cub	Cubé	133.9k	834	0.9976047904191620	0.998800992326140	0.998025164769320	2.19915310613883E-06	0.9976019184652280	0.9976019184652280	0.9976019184652280	2.19915310613883E-06
cuc	Usila Chinantec	7410	790	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cui	Cuiba	2,830	761	0.9986876640419950	1.0	0.9993434011818780	1.09948829814604E-06	1.0	1.0	1.0	0.0
cuk	San Blas Kuna	57.1k	792	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cun	Teutila Cuicatec	3690	783	1.0	0.9987228607918260	0.9993610223642170	1.0	0.9987228607918260	0.9993610223642170	0.9993610223642170	1.0
cux	Tepeuxila Cuicatec	4.2k	795	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cwe	Kwere	150k	1000	0.980980980980981	0.98	0.9804902451225610	2.08957668608751E-05	0.9819458375125380	0.979	0.9804707060590890	1.97959913117594E-05
cya	Nopala Chatino	6k	794	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
dgc	Casiguran Dumagat Agta	580.1k	793								

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
ghs	Gulu-Samane	13k	745	0.9986559139784950	0.9973154362416110	0.9979852249832100	1.09946895649401E-06	1.0	0.9973154362416110	0.9986559139784950	0.0
glk	Gilaki	2.8m	88	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
gmv	Gamo	2.1m	780	0.9873257287705960	0.9987179487179490	0.9972891650732950	1.09951126724171E-06	0.98856416772554	0.9974358974358970	0.9929802169751120	9.8956014051754E-06
gng	Ngangam	250k	790	0.9962168978562420	1.0	0.998104864181933	3.29857006987471E-06	0.9962168978562420	1.0	0.998104864181933	3.29857006987471E-06
gnw	Guniya	450	1000	0.9990999099999999	1.0	0.9990999099999999	1.09977220599774E-06	0.9990999099999999	1.0	0.9990999099999999	1.09977220599774E-06
gof	Western Bolivian Guarani	9.7k	780	0.9948320413436690	0.9871794871794870	0.9909909909909910	4.39804506866684E-06	0.9948253557562920	0.985897435897436	0.9903412749517070	4.39804506866684E-06
gub	Gofa	392k	790	0.9923664122137400	0.9873417721518990	0.9898477157360410	6.59714013974942E-06	0.99616858235754790	0.9873417721518990	0.9917355371900830	3.29857006987471E-06
guh	Guajajara (Tenetehára)	15k	1000	1.0	1.0	1.0	1.0	1.0	0.999	0.999497498749370	1.0
guh	Guaibito (Hiwi)	34.2k	738	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
gui	Eastern Bolivian Guarani	33.670	780	0.9847715736040610	0.9948717948717950	0.9897959183673470	1.39141352069005E-05	0.9860228716645490	0.9948717948717950	0.990427568602425	1.20946239396588E-05
gum	Gumabiano (Misak)	23.500	946	0.9989429175475690	0.9989429175475690	0.9991198543102E-06	0.9989429175475690	0.9989429175475690	0.9989429175475690	0.9989429175475690	1.09971198543102E-06
gun	Mbyá Guarani	25.450	1000	0.998	0.998	0.998	2.19955459019549E-06	0.998	0.998	0.998	2.19955459019549E-06
guo	Guayabero (Jiw)	1.118	776	0.9974293059125960	1.0	0.9987129987129990	2.19901286312574E-06	0.9987129987129990	1.0	0.9993560849967800	1.0995064136287E-06
gux	Goumanchéma	1.5m	794	0.9974779319041620	0.9962216624685140	0.9968494013862630	2.19905638490524E-06	0.9974747474747480	0.9949622166246850	0.9962168978562420	2.19905638490524E-06
gvc	Guamano (Wanama)	2.045	774	0.9974160206718350	0.9974160206718350	0.9974160206718350	2.1990080274788E-06	0.9987063389391980	0.9974160206718350	0.9987063389391980	1.09950404137394E-06
gvf	Golin	51.1k	789	1.0	0.9987325728770600	0.9993658845909960	1.0	1.0	0.9987325728770600	0.9993658845909960	1.0
gvn	Kuku-Yalanji	240	807	0.9987608426270140	0.9987608426270140	0.9987608426270140	1.09954390918647E-06	0.9987608426270140	0.9987608426270140	0.9987608426270140	1.09954390918647E-06
gvs	Gumawana	470	1000	0.9950149551345960	0.998	0.9960562421367950	5.49888647548871E-06	0.99603996003996	0.997	0.99605017254370	4.39910918039097E-06
gwi	Gwich'in	800	783	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
gym	Ngäbere (Guaymí)	5.090	774	0.9974226804123710	1.0	0.9987096774193550	2.1990080274788E-06	0.9974226804123710	1.0	0.9987096774193550	2.1990080274788E-06
gyr	Guarayu	5k	787	1.0	1.0	1.0	0.0	1.0	0.9987293519695040	0.9993642720915450	1.0
haw	Hawaiian	2k	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
hbo	Ancient Hebrew	0 (n/a)	1000	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
hch	Wixárika (Huichol)	20k	791	0.9987373737373740	1.0	0.9993682880606440	1.0995256557784E-06	0.9987373737373740	1.0	0.9993682880606440	1.0995256557784E-06
heb	Hebrew	10m	768	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
heg	Heling	14k	903	0.9955849889624720	0.9988925802879290	0.9972360420121610	4.39963894053039E-06	0.9966814159292040	0.997785176585880	0.9972329828444940	3.2989799539779E-06
hix	Hikaryana	60k	759	0.9986824769433470	0.9986824769433470	0.9986824769433470	1.09986824769433470	0.9986824769433470	0.9986824769433470	1.09986824769433470	1.09986824769433470
hla	Halia	25k	770	0.9961190168175940	1.0	0.998055735800390	3.29849753473309E-06	0.9987029831387810	1.0	0.9993510707332900	1.0994917812436E-06
hlt	Matu Chin	40k	1000	1.0	0.998	0.998	0.998	0.998	0.998	0.998	0.0
hmo	Hiri Motu	95k	1000	0.9950199203187250	0.999	0.9970059880239520	5.49888647548871E-06	0.9970059880239520	0.999	0.998001998001998	3.29933188529323E-06
hnu	Caribbean Hindustani	300k	782	0.9974452715836530	0.9987212276214830	0.9980830670926520	2.199087237019416E-06	0.9974452715836530	0.9987212276214830	0.9980830670926520	2.19902737019416E-06
hop	Hopi	5.260	790	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
hot	Malci	2.3k	764	0.9960886571056060	1.0	0.9980404964075770	3.29847577434468E-06	0.9960886571056060	1.0	0.9980404964075770	3.29847577434468E-06
hto	Minica Huitoto	6.800	791	1.0	0.9974715549936790	0.9987341772151900	0.0	0.9974715549936790	0.9987341772151900	0.9987341772151900	0.0
hub	Wampra (Elaumbisa)	9330	772	0.99740459662775620	0.996113896373060	0.9967595593000650	2.19900319185313E-06	0.99740459662775620	0.996113896373060	0.9967595593000650	2.19900319185313E-06
huf	Hufi	80k	1000	0.9960159362549800	1.0	0.998003992015968	1.09900918039097E-06	0.9970089730807580	1.0	0.9993238852630050	3.2993238852630050
hun	Hungarian	13m	794	0.9924812030075190	0.9974811083123430	0.9949748743718590	6.59716915471571E-06	0.9937264742785450	0.9974811083123430	0.9956002514412050	5.49746096226309E-06
hus	Huastec (Wastek)	121.750	792	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
huv	Murui Huitoto	1.130	766	0.9960988296488950	1.0	0.9980456026058630	3.29848302765558E-06	0.9960988296488950	1.0	0.9980456026058630	3.29848302765558E-06
huv	San Mateo del Mar Huave	12k	795	0.9974905897114180	1.0	0.9987437185929630	2.1990588283239E-06	0.9987437185929630	1.0	0.9993714644478470	1.09952940146119E-06
hvn	Hawu	100k	65	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
ian	Iatmul	46k	763	0.9973856209150330	0.9973856209150330	0.9973856209150330	2.19898626730376E-06	0.9986910994764400	0.9973856209150330	0.9980379332897320	1.09949313366538E-06
ign	Ignaciano (Mojeño-Ignaciano)	4.5k	736	0.9986431478968790	1.0	0.9993211133740670	1.09945807711379E-06	0.9986431478968790	1.0	0.9993211133740670	1.09945807711379E-06
ikk	Ika	100k	795	1.0	0.9987421383647800	0.9993706733948440	0.0	0.9987421383647800	0.9993706733948440	0.9987421383647800	0.0
ikw	Ikwere	28m	793	0.9974747474747480	0.9962168978562420	0.9968454258755080	2.1990339669834E-06	0.9987357747968390	0.9962168978562420	0.9974747474747480	1.0995266834917E-06
ilo	Ilocano	11m	1000	0.998003992015968	1.0	0.9990099900999990	2.19955459019549E-06	0.998003992015968	1.0	0.9990099900999990	2.19955459019549E-06
imo	Imbongu	42.5k	765	0.9947984395318600	1.0	0.9973243807004090	4.999797253466152E-06	0.99609375	0.9980430528357370	3.298479400996132E-06	1.09951489402875E-06
inb	Inga (Jungle Kichwa)	11.200	783	0.9987228607918260	0.9987228607918260	0.9987228607918260	1.09951489402875E-06	0.9987228607918260	0.9987228607918260	0.9987228607918260	1.09951489402875E-06
ino	Indonesian	275m	1000	0.9928294573643110	0.958	0.94291338587233E-05	1.3893159837323E-05	0.9300291545189600	0.957	0.9432218334154760	7.97182625470375E-05
ino	Inoke-Yate	10k	743	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
iou	Tuma-Irumu	2.200	1000	0.9970059880239520	0.999	0.998001998001998	3.29933188529323E-06	0.998001998001998	0.999	0.99800507496251870	2.19955459019549E-06
ipi	Ipili	26k	584	0.9982905982905980	1.0	0.9991445680068440	1.09927436898903E-06	0.9982905982905980	1.0	0.9991445680068440	1.09927436898903E-06
isn	Isanzu	32.400	794	0.9790123456790120	0.9987405541561710	0.9987780548628430	1.099619792716945E-05	0.9814126394052050	0.9974811083123430	0.998161364772020	1.649229228687893E-06
ita	Italian	68m	1000	1.0	0.994	0.9969909729187560	0.0	0.994	0.994	0.9969909729187560	0.0
iws	Sepik Iwam	2.500	781	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
ixl	Isil	69k	792	0.9987389659520810	1.0	0.9993690851735020	1.09952577453344E-06	0.9987389659520810	1.0	0.9993690851735020	1.09952577453344E-06
jac	Eastern Jacaeco (Popti')	50k	791	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
jae	Yabem	2k	1000	1.0	0.999	0.9994997498749370	0.0	0.998	0.998	0.9998998989898999	0.0
jao	Yanyuwa	52	71	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
jic	Tol (Cicaque)	550	789	0.9974715549936790	1.0	0.9987341772151900	2.19904429534924E-06	0.9987325728770600	0.9987325728770600	0.9987325728770600	1.09952214767462E-06
jid	Bu (Jidda)	6k	794	0.9937027707808560	0.9937027707808560	0.9937027707808560	5.4976406226309E-06	0.9936948297604040	0.992443249370280	0.9936948297604040	5.4976406226309E-06
jiv	Shuar	50k	779	0.9987080103359170	0.9922978177150190	0.9954925949774630	1.09951005831801E-06	0.9987080103359170	0.9922978177150190	0.9954925949774630	1.09951005831801E-06
jni	Janji	1.150	794	0.9924337957124840	0.9911838790931990	0.9918084436042850	6.59716915471571E-06	0.9924337957124840	0.9911838790931990	0.9918084436042850	6.59716915471571E-06
jpn	Japanese	130m	3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
jvn	Caribbean Javanese	77k	773	0.9987080015959170	1.0	0.9993538578888820	1.099502804883166E-06	0.9987080015959170	1.0	0.9993538578888820	1.099502804883166E-06
kan	Kanada	59m	1000	0.9910802775024780	1.0	0.9955201592832260	1.09959565587969E-06	0.9920634920634920	1.0	0.9960159362549800	8.79821836078194E-06
kaa	Capanahua	400	791	0.9974779319041620	1.0	0.9987373737373740	2.19909491315569E-06	0.9987373737373740	1.0	0.9993682880606440	1.0995256557784E-06
kbc	Kadiwéu	1590	782	0.9987228607918260	1.0	0.9993610223642170	1.09951368509708E-06	0.9987228607918260	1.0	0.9993610223642170	1.09951368509708E-06
kbi	Camsá (Kamsá/Biatá)	4773	783	1.0	1.0						

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
kaw	Kandas	480	309	0.9871794871794870	0.9967637540453080	0.9919484702093400	4.39578663311376E-06	0.9967637540453080	0.9967637540453080	0.9967637540453080	1.09894215827844E-06
ksd	Kaama (Tolai)	61k	1000	0.999	0.999	0.999	1.0997729509774E-06	0.999	0.999	0.999	1.0997729509774E-06
ksj	Uare	1.3k	420	0.9976133651551310	0.9952380952380950	0.9964243146603100	1.09907622643168E-06	1.0	0.9952380952380950	0.9976133651551310	1.0
ksr	Borong	2070	954	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
ktm	Kurti	3k	242	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
kto	Kuot	2.4k	779	0.9987179487179490	1.0	0.9993585631815270	1.09951005831801E-06	1.0	1.0	1.0	0.0
kud	'Auhelawa	1.2k	789	0.9987341772151900	1.0	0.999366687777074	1.0995221476462E-06	1.0	0.9987325728770600	0.999366687777074	0.0
kue	Kuman	115k	794	0.997487431871859300	1.0	0.9987421383647800	2.19905638490524E-06	0.9987421383647800	1.0	0.9993706373948400	1.09952819245262E-06
kup	Kunimaipia	8.2k	749	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
kvg	Kuni-Bouzi	4.5k	801	0.9987531172069830	1.0	0.9993761696818470	1.0995366525348E-06	0.9987515605493130	0.9987515605493130	0.9987515605493130	1.0995366525348E-06
kvn	Border Kuna (Guna)	700	791	0.997479319041620	1.0	0.999366687777074	1.0995221476462E-06	1.0	0.999366687777074	1.0	0.0
kwd	Kwaio	13.2k	787	0.998730644677005	1.0	0.999366687777074	1.0995221476462E-06	1.0	1.0	1.0	0.0
kwf	Kwara'ae	32.4k	932	0.9978540772532190	0.9978540772532190	0.9978540772532190	2.19939010912274E-06	0.9978540772532190	0.9978540772532190	0.9978540772532190	2.19939010912274E-06
kwi	Awa-Cusique (Awa Pit)	17.46k	791	1.0	0.9987357774968390	0.9993674889310560	1.0	0.9987357774968390	0.9993674889310560	1.0	0.0
kwy	Kwanga	7.52k	793	1.0	0.9974779319041620	0.9987373737373740	0.0	1.0	0.9974779319041620	0.9987373737373740	1.0
kyc	Kyaka	15.4k	1000	0.9970059880239520	0.999	0.998001988001998	3.29933188529323E-06	0.998001988001998	0.999	0.9985007496251870	2.19955459019549E-06
kyf	Kouya	10.1k	785	0.9924146649810370	1.0	0.9961928934010150	6.59710387140046E-06	0.9924146649810370	1.0	0.9961928934010150	6.59710387140046E-06
kyg	Keyagana	12.3k	950	0.9958071278826000	1.0	0.9978991596638660	4.3988672916724E-06	0.9958071278826000	1.0	0.9978991596638660	4.3988672916724E-06
kyz	Kenga	40k	790	0.9987357774968390	1.0	0.9993674889310560	1.0995233566249E-06	0.9987357774968390	1.0	0.9993674889310560	1.0995233566249E-06
kyz	Kayabi	1,000	727	1.0	0.9986244841815680	0.9993117687543020	1.0	0.9986244841815680	0.9993117687543020	1.0	0.0
kze	Kosena	2,000	766	0.9947984395318660	0.9986945169712790	0.996742671009772	4.39797737027404E-06	0.996909375	0.9986945169712790	0.9973924380700400	3.29848302765558E-06
lac	Lacandon	1,000	790	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
lbb	Label	140	798	0.9949367088607600	0.9974619289340100	0.9961977186311790	4.39808375490799E-06	0.9961977186311790	0.9974619289340100	0.9968294229549780	3.2985628168099E-06
lbk	Central Bontok (Bontoc)	26k	938	0.9978609625668450	0.9946695095948830	0.996262680192205	2.19944062116905E-06	0.9989293361884370	0.9946695095948830	0.9967948717948720	1.09970231058452E-06
lcm	Tungga (Lavongla)	12k	954	0.997901364113260	0.9968553459119500	0.99734780807551130	1.09944332089548E-06	1.0	0.9968553459119500	0.998425196803940	1.0
leu	Kara	5k	786	0.9987212276214830	0.99363867684447840	0.996173469387755	1.09951852083972E-06	0.9987212276214830	0.99363867684447840	0.996173469387755	1.09951852083972E-06
lex	Luang	18k	961	0.995846313603323	0.9979188345473470	0.9968814968814970	4.398920549081E-06	0.9968814968814970	0.9979188345473470	0.995846313603323	1.09977939597810E-06
lgl	Wala	6.98k	787	0.997465145754190	0.997309644670050	2.1990349564060E-06	1.0	0.997465145754190	0.997309644670050	1.0	0.0
lid	Nyindro	4.2k	950	0.9978925184404640	0.9968421052631580	0.9973607352817270	2.1994336458362E-06	0.9978925184404640	0.9968421052631580	0.9973607352817270	2.1994336458362E-06
lif	Limbu	334k	783	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
lin	Lingla	2.04mm	1000	0.9940357852882700	1.0	0.9970089730807580	6.59866377058646E-06	0.9950248756218910	1.0	0.9975062344139650	5.49888647548871E-06
llg	Lole	20k	900	0.9856035347340790	0.9888888888888890	0.9872434830817490	1.42955326460481E-05	0.9889888765294770	0.9888888888888890	0.989438576987215	9.89609721649485E-06
llo	Ganda (Luganda)	4.13mm	1000	0.9891196348130790	0.9924530084530570	0.99734830817490	1.20975502460752E-05	0.9924530084530570	0.9924530084530570	0.9924530084530570	8.79821836078194E-06
luo	Dholuo	4.27mm	1000	0.999	0.999	0.999	1.099729509774E-06	0.999	0.999	0.999	1.099729509774E-06
lhw	Lewo	2.2k	777	0.9948783610755440	1.0	0.9974326059050070	4.39803056191438E-06	0.9948783610755440	1.0	0.9974326059050070	4.39803056191438E-06
maa	San Jerónimo Tecúlti Mazatec	21,100	791	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
maj	Jalapa de Díaz Mazatec	24,200	788	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mam	Mam	842,000	793	0.9974811083123430	0.9987389659520810	0.9981096408317580	2.1990539669834E-06	0.9974811083123430	0.9987389659520810	0.9981096408317580	2.1990539669834E-06
maq	Chiquihuitlán Mazatec	169,400	793	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mav	Sateré-Mawé	7,134	742	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
maw	Central Mazahua	350k	782	0.9974457215836530	0.9987212276214830	0.9980830670926520	2.19902737019416E-06	0.998719590268886	0.9974457215836530	0.9980830670926520	1.09951368509708E-06
mhb	Western Bukidnon Manobo	19k	1000	0.9950149551345960	0.998	0.9965052421367950	5.49888647548871E-06	0.998	0.998	0.998	2.19955459019549E-06
mhc	Makushi	29,100	784	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mhb	Mangseni	2,500	789	0.9987325728770600	0.9987325728770600	0.9987325728770600	1.0995221476462E-06	0.9987325728770600	0.9987325728770600	0.9987325728770600	1.0995221476462E-06
mhj	Nadëb	300	784	0.9961880559085130	1.0	0.9980903882877150	3.2985483088926E-06	0.9961880559085130	1.0	0.9980903882877150	3.2985483088926E-06
mbl	Makaká	800	790	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mbs	Sarangani Manobo	58k	932	0.9957264957264960	1.0	0.997858672368740	4.39878021824548E-06	0.9989281886388000	1.0	0.9994638069705100	1.09969505456137E-06
mbt	Matigsalug Manobo	30k	789	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mca	Maca (Enxet-Maca)	1,500	793	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mcb	Machiguenga (Matsigenka)	10,100	766	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mcd	Sharanahua	438	735	1.0	0.998639455782313	0.9993192648059900	1.0	0.998639455782313	0.9993192648059900	1.0	0.0
mcf	Matís (Mayoruna)	4,000	776	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mco	Coatlán Mixe	5,000	784	0.9987261146496820	1.0	0.9993626513703000	1.09951610296309E-06	0.9987261146496820	1.0	0.9993626513703000	1.09951610296309E-06
mcp	Makaa	80k	792	1.0	0.9974747474747480	0.9987357774968400	1.0	0.9974747474747480	0.9987357774968400	1.0	0.0
mcr	Ese	10k	792	0.99494748743718590	1.0	0.9974811083123430	4.3981039813378E-06	0.9962216624685140	0.9974747474747480	0.9974747474747480	3.29857773260033E-06
mer	Menya	20k	761	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mdy	Maale (Malé)	53,800	1000	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
med	Melpa	130k	750	0.9960159362549800	1.0	0.998003992015968	3.29842500260152E-06	0.9960159362549800	1.0	0.998003992015968	3.29842500260152E-06
mee	Mengen	8,400	787	0.9974651457541190	1.0	0.9987309644670050	2.19903945956406E-06	0.9987293519695040	0.9987293519695040	0.9987293519695040	1.09951972978203E-06
meq	Mekeo	19,000	777	1.0	0.9987129987129990	0.9993560849967800	1.0	0.9987129987129990	0.9993560849967800	1.0	0.0
met	Merey	10k	790	0.9974715549936790	0.9987341772151900	0.9981024667931690	1.0990471324981E-06	0.9987341772151900	0.9987341772151900	0.9987341772151900	1.0995233566249E-06
meu	Mare	1,250	937	0.9989316239316240	0.9978655282817500	0.998386929150945	2.1990710124068E-06	0.9989308412834220	0.9978655282817500	0.998386929150945	1.099701124068E-06
meu	Motu	39k	1000	0.9969909729187560	0.994	0.9954932398597900	3.29933188529323E-06	0.9979899497487440	0.993	0.9954887218045110	2.19955459019549E-06
mge	Morokodo	3,400	382	0.9973753280839900	0.9947643979057590	0.9960681520314550	1.09903303254377E-06	1.0	0.9947643979057590	0.9973753280839900	1.0
mgh	Makhuwa-Meetto	2.4m	794	1.0	0.9987405541561710	0.9986988027725230	1.0	0.9987405541561710	0.9987405541561710	0.9987405541561710	1.0
mhw	Matimbu	7.82k	791	0.963963963963964	0.9953488372093020	0.99740503429430	8.79062918928422E-06	0.9683257918552040	0.9953488372093020	0.99740503429430	7.69180646237E-06
mib	Atatláhuca Mixtec	12,000	788	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mie	Mi'kmaq (Micmac)	8,145	789	0.9987341772151900	1.0	0.999366687777074	1.0995221476462E-06	1.0	1.0	1.0	0.0
mif	Ocotapee Mixtec	6,500	790	0.9974747474747480	1.0	0.9987357774968400	1.0995233566249E-06	0.9987357774968400	1.0	0.9993674889310560	1.0995233566249E-06
mig	San Miguel El Grande Mixtec	5,600	794	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mih	Chayuco Mixtec	10k	790	0.9987357774968390	1.0	0.9993674889310560	1.0995233566249E-06	0.9987357774968390	1.0	0.9993674889310560	1.0995233566249E-06
mil	Peñoles Mixtec	7.3k	788	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mio	Pinotepa Nacional Mixtec	20k	791	1.0	1.0	1.0	1.0	1.0	1		

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
mwp	Kala Lagaw Ya	700	575	0.9948096885813150	1.0	0.997398091934085	3.29779048037815E-06	0.9982638888888890	1.0	0.999131190269331	1.09926349345938E-06
mxb	Tezoatlán Mixtec	5,080	793	0.9962311557788940	1.0	0.9981120201384520	3.2985809504751E-06	0.9962311557788940	1.0	0.9981120201384520	3.2985809504751E-06
mnp	Tlahuilopec Mixe	132k	792	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
mxq	Jaquila Mixe	8k	792	0.9987389659520810	1.0	0.9993600851733020	1.09952577453344E-06	1.0	1.0	1.0	0.0
mxt	Jamiltepec Mixtec	10k	791	0.9987373737373740	1.0	0.9993682880606440	1.09952456557784E-06	1.0	1.0	1.0	0.0
mya	Burmese	43m	1000	1.0	0.999	0.9994997498749370	1.0	0.999	0.999	0.9994997498749370	1.0
myk	Mamara Senoufo	738k	805	0.9877300613496930	1.0	0.9938271604938270	1.09954149119817E-05	0.990159901599016	1.0	0.9950556242274410	8.79633192958536E-06
myu	Mundurukú	10,100	759	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
myw	Muyuw (Murua)	4,700	671	0.9985096870342770	0.9985096870342770	0.9985096870342770	1.09937951020444E-06	0.9985096870342770	0.9985096870342770	0.9985096870342770	1.09937951020444E-06
mzc	Macuna	1,110	782	0.9961734693877550	0.9987212276214830	0.9974457215836530	3.29854105529125E-06	0.9961734693877550	0.9987212276214830	0.9974457215836530	3.29854105529125E-06
mzz	Maidjodonu	730	65	0.9848484848484850	1.0	0.9923664122137400	1.09864756484767E-06	1.0	1.0	1.0	0.0
nab	Southern Nambikura	720	682	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
naf	Nabak	16k	767	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nak	Nakanai	13k	786	0.9987293519695040	1.0	0.9993642720915450	1.09951852083972E-06	0.9987293519695040	1.0	0.9993642720915450	1.09951852083972E-06
nas	Naasioi	45k	798	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nay	Ngarindjeri	0	39	0.975	1.0	0.9873417721518990	1.09861618305582E-06	1.0	1.0	1.0	0.0
nbc	Negem	4,400	369	0.994579945799458	0.994579945799458	0.994579945799458	2.19802924697716E-06	0.994579945799458	0.994579945799458	0.994579945799458	2.19802924697716E-06
nca	Iyo	6,900	786	0.9949367088607600	1.0	0.9974619289340100	4.3980740833589E-06	0.9961977186311790	1.0	0.9980952380952380	3.2985556251917E-06
nch	Central Huasteca Nahuatl	200k	1000	0.9851924975320830	0.998	0.9951548931042370	1.6469659464661E-05	0.9871414441473800	0.998	0.9925410243659870	1.4297048362707E-05
ncj	Northern Puebla Nahuatl	40k	792	0.9949622166246850	0.9974747474747480	0.9962168978562420	4.39810309813378E-06	0.994958638083230	0.9962121212121210	0.99585396214511	4.39810309813378E-06
ncm	Michoacán Nahuatl	4.7k	780	0.9974163029525030	0.9974358974358970	0.9987163029525030	1.0995167264711E-06	0.9974358974358970	0.9987163029525030	1.0995167264711E-06	4.39810309813378E-06
ncu	Chumungur	69k	763	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
ndg	Ndengereko	72k	791	0.9750312109862670	0.9873577749683940	0.9811557788944720	2.19904913115569E-05	0.982367758186398	0.9860935524652340	0.9842271293375390	1.53933439180898E-05
ndj	Ndambu	155k	795	0.9874843554443050	0.9924528301886790	0.9899623588456710	2.19802924697716E-06	0.9899623588456710	0.9924528301886790	0.9912060301307540	8.7962352132955E-06
ngp	Ngulu	131k	791	0.982412063015080	0.984886498740550	0.9836477987421380	1.5393409494337E-05	0.984886498740550	0.984886498740550	1.3194383094314E-05	0.0
ngr	Guerrero Nahuatl	550k	799	0.9974715549936790	0.9974715549936790	1.0990491115569E-06	2.1990491115569E-06	0.9974715549936790	0.9974715549936790	0.9981234772151900	1.09952456557784E-06
nhe	Eastern Huasteca Nahuatl	450k	772	0.9738903394255870	0.966321243523316	0.9700910273081920	2.19900319185313E-05	0.9738562091503270	0.965029067357510	0.9694209499024070	2.19900319185313E-05
nbg	Tetelcingo Nahuatl	3,500	790	0.9949367088607600	0.9974619289340100	0.0	1.0	0.9949367088607600	0.9974619289340100	0.0	1.0
nbi	Zacatlán-Ahuacatlán-Tepetztlán Nahuatl	17,100	790	0.9974715549936790	0.9987341772151900	0.9981024667931690	2.19904671324981E-06	0.9974683544303800	0.9974683544303800	0.9974683544303800	2.19904671324981E-06
nbo	Takuu	1,750	791	0.9669926803667510	0.9832193909260410	0.96871632706018E-05	0.9669926803667510	0.9669926803667510	0.9832193909260410	0.96871632706018E-05	0.9669926803667510
nhr	Naro	14k	790	0.9962168978562420	1.0	0.998104864181933	3.29857006987471E-06	0.9974747474747480	1.0	0.998735774968400	2.19904671324981E-06
nhs	Noome	25k	792	0.992481203075190	1.0	0.9962264150943600	6.59715464720066E-06	0.992481203075190	1.0	0.99715464720066E-06	6.59715464720066E-06
nhw	Western Huasteca Nahuatl	400k	1000	0.9719157472417250	0.969	0.970455635232880	3.0793742627368E-05	0.9745490945674040	0.969	0.9719157472417250	2.7404432774434E-05
nhy	Northern Oaxaca Nahuatl	12k	792	0.9974683544303800	0.9949494949494950	0.9962073324905180	2.19905154906689E-06	0.9974683544303800	0.9949494949494950	0.9962073324905180	2.19905154906689E-06
nif	Nek	2k	371	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nii	Nii	12k	778	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nin	Ninzo	35k	794	0.99125	0.9987405541561710	0.9949811794228360	7.69669734716833E-06	0.9924906132665830	0.9987405541561710	0.9956057752667920	6.59716915471571E-06
nko	Nkonya	28k	782	0.991128010139417	1.0	0.9955442393380010	7.6965979567957E-06	0.9949109414758270	1.0	0.9974489795918730	4.3980547038833E-06
nlg	Gela	11,876	1000	0.9979959991983968	0.996	0.9969969699696970	2.19955450919549E-06	0.9979919678714860	0.994	0.9959919636979360	2.19955450919549E-06
nmw	Rifaa	120	229	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nna	Nyangumarta	22k	799	0.9952380952380950	1.0	0.9976133651551310	1.0988214041619E-06	0.9952380952380950	1.0	0.9976133651551310	1.0988214041619E-06
ngd	Ngindo	220k	793	0.98252417690387	0.9924337957124840	0.9874529845570890	1.539377768838E-05	0.9849812265331660	0.9924337957124840	0.9886934673366310	3.19432380190046E-05
noa	Wauana (Noanamá)	8,177	784	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nop	Numanggang	2,300	1000	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
not	Nomatsiguenga	6,500	778	0.9974326059006000	0.9987146529562980	0.9980732177263970	2.19901769879395E-06	0.9987146529562980	0.9987146529562980	0.9987146529562980	2.19901769879395E-06
nou	EWage-Toni	12,900	775	0.998711202018680	1.0	0.999352546744040	1.0995052264981E-06	0.9987096774193550	0.9987096774193550	0.9987096774193550	1.0995052264981E-06
npi	Nepali	20m	1000	0.999009990099999	1.0	0.999502498750630	1.0997729509774E-06	0.999009990099999	1.0	0.999502498750630	1.0997729509774E-06
nps	Southeastern Puebla Nahuatl	135k	794	0.9924906132668520	0.9987405541561710	0.99745752667920	6.59716915471571E-06	0.9987405541561710	0.99745752667920	0.9987405541561710	6.59716915471571E-06
npu	Nechan	6,500	788	0.99873252770600	1.0	0.9993658849950960	1.099520938727E-06	0.99873252770600	1.0	0.9993658849950960	1.099520938727E-06
nss	Nali	2,900	688	0.998546511627907	0.998546511627907	0.998546511627907	1.09940005738868E-06	0.998546511627907	0.998546511627907	0.998546511627907	1.09940005738868E-06
ntj	Nganyajarra	990	1000	0.997005980239520	0.999	0.99900198001998	3.29933188529323E-06	0.997005980239520	0.999	0.99900198001998	3.29933188529323E-06
ntp	Northern Tephuian	6,200	772	1.0	0.9987046632124350	0.9993519118600310	1.0	0.9987046632124350	0.9993519118600310	1.0	0.9987046632124350
ntu	Natigui	4,280	995	0.996993987975952	1.0	0.9984947315604620	3.29931374274151E-06	0.996993987975952	1.0	0.9984947315604620	3.29931374274151E-06
nuy	Nungubuy (Wubuy)	360	795	1.0	0.9987421383647800	0.9993706733794840	1.0	1.0	0.9974842767295600	0.9987405541561710	0.0
nvu	Namia	72k	794	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nwi	Southwest Nana	4,500	783	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nya	Chewa (Nyanja)	15m	1000	0.9930209371884350	0.996	0.9945082376433550	7.6984410656842E-06	0.9940119760479040	0.996	0.99504995004995	6.5986673758864E-06
nys	Nonong	0	116	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
nzo	Obo Manobo	60k	788	0.9924433249370280	1.0	0.9962073324905180	5.9712563236198E-06	0.9924337957124840	0.998730964467005	0.9955724225173940	6.59712563236198E-06
oko	Orokua	47k	777	0.9987129987129990	0.9993560849967800	0.9993560849967800	0.9993560849967800	0.9974259974259980	0.9987134020618000	0.9987134020618000	0.9993560849967800
ong	Olo	13,700	786	0.9974619289340100	1.0	0.9987293519695050	2.19903704167945E-06	0.9974619289340100	1.0	0.9987293519695050	2.19903704167945E-06
ons	Olo	5,500	794	0.9987405541561710	0.9993698802772530	0.9993698802772530	1.0	0.9987405541561710	0.9993698802772530	0.9993698802772530	1.0
ood	Tobono O'odham	752	1000	0.996010632978720	0.998001324450370	0.996010632978720	1.0	0.996010632978720	0.998001324450370	0.996010632978720	1.0
opm	Okapamin	8,000	759	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
ory	Odia (Oriya)	50m	1000	0.999	0.999	0.999	1.0997729509774E-06	0.999	0.999	0.999	1.0997729509774E-06
ote	Mezquital Otomi	100k	794	0.9974811083123430	0.9974811083123430	0.9974811083123430	2.19905638490524E-06	0.9974811083123430	0.9974811083123430	0.9974811083123430	2.19905638490524E-06
otm	Eastern Highland Otomi	70k	787	0.9987293519695040	0.9993642720915450	0.9987293519695040	1.0	0.9987293519695040	0.9993642720915450	0.9987293519695040	1.0
otn	Querétaro Otomi	16k	786	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0
otq	Querétaro Otomi	33k	794	0.99873252770600	0.99873252770600	0.99873252770600	1.099520938727E-06	0.99873252770600	0.99873252770600	0.99873252770600	1.099520938727E-06
ots	Estado de México Otomi	780k	793	0.9974811083123430	0.99						

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
qxh	Panao Quechua	64k	770	0.9758576874205850	0.9974025974025970	0.9865125240847780	2.08094843843629E-05	0.9795918367346940	0.9974025974025970	0.9884169884169880	1.75919668499898E-05
qxh	Northern Conchucos Ancash Quechua	250k	792	0.9726708074534160	0.9886363636363640	0.9805886036318100	2.41895670397358E-05	0.9750933997399734	0.9886363636363640	0.9818181818181820	2.1905154966899E-05
rai	Southern Conchucos Ancash Quechua	250k	739	0.9613848202396800	0.976995404660810	0.9691275167783240	3.18843894029483E-05	0.9639037433115508	0.9756427604871450	0.9697377269670480	2.968546598484E-05
reg	Ramouaina	10,300	783	0.9974457215836530	0.9974457215836530	0.9974457215836530	2.19902278085751E-06	0.9987212276214830	0.9974457215836530	0.9980830670926520	1.09951489402875E-06
rgu	Kara	100k	793	0.9850931677018630	1.0	0.9924906132665830	1.13943238019004E-05	0.9863013698630100	0.9987389659520810	0.9924812030075190	1.0204768184087E-06
rkb	Ringgou (Rikou)	12,000	817	0.9938873505623470	0.9951040391676870	0.994945128440370	5.49777999643744E-06	0.9938650306748470	0.9914320685343520	0.9926470588235290	5.49777999643744E-06
rmc	Rikbaktsä	910	765	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
rmy	Carpathian Romani	472,470	114	0.991304347826087	1.0	0.9956331877729260	1.09870671232892E-06	0.9912280701754390	0.9912280701754390	0.9912280701754390	1.09870671232892E-06
row	Vlax Romani	885,970	228	0.991304347826087	1.0	0.9956331877729260	2.19768869080388E-06	0.9956331877729260	1.0	0.9978118161925600	1.0985443450194E-06
rop	Rotokas	4,320	786	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
row	Kriol	7,500	1000	0.9970089738007580	1.0	0.9985022466300550	3.2993138529323E-06	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06
roo	Dela-Oenale	7,000	902	0.9944258639910810	0.9889135254988910	0.9916203446339190	4.9892837940922E-06	0.9953571426857140	0.9889135254988910	0.9922135706340380	4.39863510352738E-06
rro	Waima	15k	794	0.9987405541561710	0.9987405541561710	0.9987405541561710	1.09952819245262E-06	0.9987405541561710	0.9987405541561710	0.9987405541561710	1.09952819245262E-06
rug	Lagari	692k	794	0.992462311557789	0.9949622166246850	0.9937106918238990	6.59716915471571E-06	0.9962168978562420	0.9949622166246850	0.9955896119407690	3.29858457735786E-06
rub	Roviana	9,870	1000	0.9950149551345960	0.998	0.9965052421367950	5.49886647548871E-06	0.996003996003996	0.997	0.9965017491254370	4.39910918039907E-06
sab	Buglere (Bocotä)	2,500	724	1.0	1.0	1.0	0.0	1.0	0.9986187845303870	0.9993089149965450	0.0
sbe	Saliba	2,500	788	0.9961977118631170	0.997461928340100	0.9968264229549780	2.9856281618099E-06	0.9961977118631170	0.997461928340100	0.9968264229549780	3.9968264229549780
sbk	Safwa	158,000	792	0.9788557213030350	0.9938686868686860	0.9862153384718240	3.26919381670683E-05	0.9800747198007470	0.9938686868686860	0.9968355579937370	1.75924123295351E-05
sbs	Subiya (Kuhane)	35,000	792	0.9738805970149250	0.9886363636363640	0.981203007518797	2.30900412652032E-05	0.9811320754716980	0.9848484848484850	0.982986764858220	1.6492886180017E-06
seh	Sena	2.8m	196	0.9848484848484850	0.9948979591836740	0.9898477157360410	3.296417212422768E-06	0.9898477157360410	0.9948979591836740	0.9923664122137400	2.19761141615178E-06
sey	Secoya (Paicoica)	1,174	791	1.0	1.0	1.0	0.0	1.0	0.9987357774968390	0.9993674889310560	0.0
sfb	Mag-antsi Aytä	4,200	785	0.9727385377943000	1.0	0.986180945226130	2.4189380618017E-05	0.9800249687890140	1.0	0.9899117276166460	1.75922769904012E-05
sgz	Sursurunga	3,000	773	0.998708010359170	1.0	0.9993535875888820	1.099502808483166E-06	0.998708010359170	1.0	0.9993535875888820	1.099502808483166E-06
shj	Shatt	30k	115	1.0	0.991304347826087	0.9956331877729260	0.0	1.0	0.991304347826087	0.9956331877729260	0.0
shp	Shipibo-Konibo	97k	66	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
sim	Mende	3,180	778	1.0	0.9987146529562980	0.9993569131832800	1.0	0.9974293059125960	0.9987129987129990	0.9987129987129990	0.0
sja	Epena (Sajja)	3,550	786	0.998727733689570	0.998727733689570	0.998727733689570	1.09951852083972E-06	1.0	0.9974554707370140	0.9987261146468020	0.0
sll	Salt-Yui (Yui)	6,500	786	1.0	0.998727733689570	0.9993569126757270	1.0	1.0	0.998727733689570	0.9993569126757270	0.0
smk	Bolnago	50k	787	0.987437185926480	0.9987293519695040	0.9930511686670880	1.09951972978203E-05	0.9899244332493700	0.9987293519695040	0.9943074003795070	8.79615783825625E-06
smn	Sinauogro	15k	792	0.9974747474747480	0.9974747474747480	0.9974747474747480	2.19905154906689E-06	0.9987357774968390	0.9974747474747480	0.9981048641819330	1.0995257473344E-06
snn	Siona	200	786	0.9987293519695040	1.0	0.9993642720915450	1.09951852083972E-06	1.0	1.0	1.0	0.0
snp	Siiane	29k	783	0.9987248975959180	1.0	0.9993618379068280	1.09951489402875E-06	1.0	1.0	1.0	0.0
snr	Sam	780	66	0.9696969696969700	0.9846153846153850	0.9846153846153850	0.0	0.9696969696969700	0.9846153846153850	0.9846153846153850	0.0
snr	Saniyo-Hiyewe	644	776	0.9974293059125960	1.0	0.9987129987129990	2.19901286312574E-06	0.9974293059125960	1.0	0.9987129987129990	2.19901286312574E-06
som	Somali	24m	1000	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06	0.999	0.999	0.999	0.0
soq	Kanasi	2,400	1000	0.9970089738007580	1.0	0.9985022466300550	3.2993138529323E-06	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06
sox	Miyobe	8,700	792	0.9949748743718590	1.0	0.9974811083123430	3.9810309813378E-06	0.9949748743718590	1.0	0.9974811083123430	3.9810309813378E-06
spl	Scelept	7,200	687	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
spm	Akumen (Sepen)	409	162	0.9938650306748470	1.0	0.9969230769230770	1.09876465889401E-06	0.9938650306748470	1.0	0.9969230769230770	1.09876465889401E-06
spp	Supyire Senufo	99k	814	0.9963121041727266	0.99431357272666	0.9953460186828100	3.2993138529323E-06	0.99431357272666	0.99431357272666	0.99431357272666	3.2993138529323E-06
sps	Sapona	3,100	814	0.9975460122699300	0.9987714987714990	0.9981583793738490	2.19910474445853E-06	0.9975460122699300	0.9987714987714990	0.9981583793738490	2.19910474445853E-06
spr	Sabot	279,000	780	0.9987179487179490	0.9987179487179490	0.9987179487179490	1.09951126724171E-06	0.9987179487179490	0.9987179487179490	0.9987179487179490	1.09951126724171E-06
spr	Siriano	217	780	0.9987179487179490	0.9987179487179490	0.9987179487179490	1.09951126724171E-06	0.9987179487179490	0.9987179487179490	0.9987179487179490	1.09951126724171E-06
sra	Saramaccan	23k	774	0.9987096774193550	1.0	0.9993544220787660	1.0995040137394E-06	0.9987096774193550	1.0	0.9993544220787660	1.0995040137394E-06
srn	Sranan Tongo	519,600	789	0.9962121212121210	1.0	0.9981024667931690	3.298566420386E-06	0.9987341772151900	1.0	0.999366687777074	1.09952214767462E-06
srq	Sirionö	400	781	0.998719590268886	0.998719590268886	0.998719590268886	1.09951247616807E-06	1.0	0.998719590268886	0.9993593850069090	0.0
ssd	Sisi	1,310	1000	0.996	0.996	0.996	4.39910918039907E-06	0.996	0.996	0.996	4.39910918039907E-06
ssg	Seimat	1,400	789	0.9924242424242420	0.9961977186311790	0.9943074003795070	6.59716915471571E-06	0.9961977186311790	0.9961977186311790	0.9961977186311790	3.29856644302586E-06
ssx	Sambirigi	3,130	940	1.0	0.9968085106382980	0.9984017048481620	0.0	0.9968085106382980	0.9984017048481620	0.9984017048481620	0.0
stp	Southwestern Tepehuan	36,543	785	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
sua	Sulka	2,500	738	0.9986468200270640	1.0	0.9993229519295870	1.09946049473523E-06	1.0	1.0	1.0	0.0
sue	Suena	3,000	788	0.9962073324905180	1.0	0.9981000633312220	3.29856281618099E-06	0.9974683544303800	1.0	0.9987325728770600	2.19904187745399E-06
sus	Susu	2.4m	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
suz	Sunwar	32,708	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
swb	Swahili	200m	1000	0.9850894632206760	0.991	0.988053882320310	1.6496659526466E-05	0.988011088011988	0.999	0.9994997498749370	0.0
swp	Sium	20k	1000	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06	0.998	0.998	0.998	0.0
stb	Suba	174k	790	0.9875	1.0	0.9937106918238990	1.099523566249E-05	0.9962168978562420	1.0	0.9981048641819330	3.29857006987471E-06
tac	Lowland Tarahumara (Western Tarahumara)	39,800	785	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
taj	Eastern Tamang	759k	788	0.986232799887836	1.0	0.9930686830497800	1.2094730325997E-05	0.9886934673366830	0.998730964467005	0.9936868686868690	9.89568844854297E-06
tam	Tamil	80m	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
tav	Tatuyo	331	756	0.9973579920739760	0.9986772486772490	0.9980171844018510	2.19896450761337E-06	0.9986754966887420	0.9973544973544970	0.9980145598941100	1.09948225380668E-06
tay	Tai (Tay)	900	767	0.9986979166666670	1.0	0.9993485342019550	1.099495551441E-06	0.9986979166666670	1.0	0.9993485342019550	1.099495551441E-06
tba	Takia	400	780	0.9974522242993630	0.9987244897959180	0.9987244897959180	2.19902278085751E-06	0.9987244897959180	0.9987244897959180	0.9987244897959180	2.19902278085751E-06
tbf	Mandara	4,000	792	0.9987389659520810	1.0	0.9993690851735020	1.0995257453344E-06	0.9987389659520810	1.0	0.9993690851735020	1.0995257453344E-06
tbi	Tboli	95,300	1007	0.9724770642207600	0.9906542056074770	0.9814814814814820	3.29609476809649E-06	0.9906542056074770	0.9906542056074770	0.9906542056074770	2.19739652493766E-06
tbo	Tawala	20k	789	0.9987325728770600	0.9987325728770600	0.9987325728770600	1.09952214767462E-06	0.9987325728770600	0.9987325728770600	0.9987325728770600	1.

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
tte	Tektiteko	5,900	795	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
tte	Bwanabwana	2,400	704	0.9929378531073450	0.9985795454545450	0.9957507082152970	5.49709698308323E-06	0.9929278642149930	0.9971590909090910	0.9950389794472010	5.49709698308323E-06
tue	Tuyuca	1442	779	0.9974391805377220	1.0	0.9987179487179490	2.19902116630630E-06	0.9987163029525030	0.9987163029525030	0.9987163029525030	1.09951005831801E-06
tuf	Central Tumbeko (U'wa)	3,550	786	0.9974619289340100	1.0	0.9987293519695050	2.19903704167945E-06	0.9974619289340100	1.0	0.9987293519695050	2.19903704167945E-06
tuo	Tucano	13,996	1000	1.0	0.998	0.9989898989898990	0.0	1.0	0.998	0.9989898989898990	0.0
tur	Turkish	90m	1000	0.9930348258706470	0.998	0.9955112219451370	7.6984410656842E-06	0.9950149551345960	0.998	0.9965052421367950	5.49888647548871E-06
tvk	Southeast Ambrym (Vatlongos)	3,700	800	1.0	0.99875	0.9993746091307070	0.0	0.9975	0.99875	0.9987484355444310	0.0
twi	Twi	20m	1000	0.992992992992993	0.992	0.9924962481240620	7.6984410656842E-06	0.9949748743718590	0.99	0.9924812030075190	5.49888647548871E-06
tsq	Ti	20,000	898	0.9844961240310080	0.9899777282850780	0.9872293170460860	1.5395155144676E-05	0.9877643324249170	0.9888641425389760	0.9883138564273790	1.20961933279597E-05
tsu	Kayapo (Mekêngökre)	7,100	750	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
tzj	Tz'utujil	83,800	782	0.9974489795918370	1.0	0.9987228607918260	2.19902737019416E-06	0.9974489795918370	1.0	0.9987228607918260	2.19902737019416E-06
tzo	Tzotzil	260k	776	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
tbr	Ubir	2,560	902	0.9957627118644070	0.9978768577494690	0.996818663888120	4.39882859194597E-06	0.9978746014877790	0.9968152866242040	0.9973446627721272	2.19941429597298E-06
udu	Uduk	22k	1000	0.999000999000999	1.0	0.9995002498750630	1.09977729509774E-06	1.0	1.0	1.0	0.0
uig	Uyghur	13m	1000	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06	0.999	0.999	0.999	1.09977729509774E-06
ukr	Ukrainian	51m	962	0.998960498960499	0.998960498960499	0.998960498960499	1.099731356347E-06	0.998960498960499	0.998960498960499	0.998960498960499	1.099731356347E-06
uli	Ulithian	3,075	790	0.9962168978562420	1.0	0.998104864181933	0.9957006987471E-06	0.9974747474747480	1.0	0.998737774968400	2.19904671324981E-06
uli	Merian Mir	320	377	0.9973474801061010	0.9973474801061010	0.9973474801061010	1.0990242862388E-06	1.0	0.9973474801061010	0.99867197875166	0.0
urp	Uripiv-Wala-Rano-Atchin	9,000	791	0.9962216624685140	1.0	0.998107255205050	0.99832736967333E-06	0.9962216624685140	1.0	0.998107255205050	3.2985736967333E-06
ura	Urarina	3,000	722	0.9987046632124350	0.9987046632124350	0.9987046632124350	1.09950159592657E-06	0.9987046632124350	0.9987046632124350	1.09950159592657E-06	0.9987046632124350
urb	Urubú-Ka'apor (Ka'apor)	800	767	0.9960988296488950	0.9986962190352020	0.9973958333333330	3.298486654323E-06	0.9986962190352020	0.9993476842791910	0.9993476842791910	1.098896970262388E-06
uri	Urim	3,740	249	0.996	0.996	0.997959919839680	1.09886970262388E-06	0.996	0.996	0.996	1.098896970262388E-06
urt	Urat	6,280	782	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
urw	Sob (Sop)	2,500	118	0.9915254237288140	0.9915254237288140	0.9915254237288140	1.0987115409759E-06	0.9915254237288140	0.9915254237288140	0.9915254237288140	1.0987115409759E-06
usa	Usafua	1,300	812	0.996319018404908	1.0	0.9981561155500920	3.29864986261123E-06	0.996319018404908	1.0	0.9981561155500920	3.29864986261123E-06
usp	Uspanteko	3,000	789	0.9987325728770600	0.9987325728770600	0.9987325728770600	1.09952214767462E-06	0.9987325728770600	0.9987325728770600	1.09952214767462E-06	0.9987325728770600
uvh	Uri	2,500	749	0.9986666666666670	1.0	0.999332885923950	1.09947379184322E-06	0.9986666666666670	1.0	0.999332885923950	1.09947379184322E-06
uvl	Ute	6,000	790	0.9987341772151900	0.9987341772151900	0.9987341772151900	1.09952335662349E-06	1.0	0.9987341772151900	0.9987341772151900	1.09952335662349E-06
vid	Viaduna	32,000	1000	0.9919839679358720	0.99	0.990990990990991	8.79821836078194E-06	0.9939698492462310	0.989	0.9914786967418550	6.59866377058646E-06
vie	Vietnamese	86m	1000	0.999000999000999	1.0	0.9990002498750630	1.09977729509774E-06	0.999000999000999	1.0	0.9990002498750630	1.09977729509774E-06
viv	Iduna	5,560	744	1.0	0.9973118279569890	0.998541049798120	0.0	0.9973118279569890	0.998541049798120	0.998541049798120	0.0
vmy	Ayautla Mazatec	3,700	794	0.9974874371859300	1.0	0.9987421383647800	2.199053638490524E-06	0.9974874371859300	1.0	0.9987421383647800	2.199053638490524E-06
waj	Wafra	1,990	783	0.9974522292993630	1.0	0.9987244897959180	2.19902737019416E-06	0.9974522292993630	1.0	0.9987244897959180	2.19902737019416E-06
wal	Walaita	2.7m	1000	0.997997997997998	0.997	0.9974987493746870	2.19955459019549E-06	0.997997997997998	0.997	0.9974987493746870	2.19955459019549E-06
wap	Wapishana	10,900	788	0.9987325728770600	1.0	0.9993658845909960	1.099520938727E-06	0.9987325728770600	1.0	0.9993658845909960	1.099520938727E-06
wat	Kanimuwa	26,000	259	0.9810606060606060	1.0	0.9904397705544930	4.9440888951403E-06	0.9810606060606060	1.0	0.9904397705544930	4.9440888951403E-06
wbi	Vwarij	39,000	793	0.987468671691980	0.9936948297604040	0.9905719673161530	1.099526949917E-05	0.9924433749370280	0.9936948297604040	0.9936948297604040	6.5971619095103E-06
wbp	Warpi	2,670	932	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
wed	Wedau	2,200	408	0.9975490196078430	0.9975490196078430	0.9975490196078430	1.09906173100025E-06	1.0	0.9975490196078430	0.9987730061349690	0.0
wer	Weri	4,160	785	1.0	0.9987261146496820	0.9993626513703000	0.0	0.9987261146496820	0.9993626513703000	0.9993626513703000	0.0
wim	Wik-Mungkan	840	748	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
wir	Wiru	15,300	781	0.9974457215836530	1.0	0.9987212276214830	2.1990495233613E-06	0.9974457215836530	1.0	0.9987212276214830	2.1990495233613E-06
wiv	Vitu	7,000	792	0.9937106918238990	0.9974747474747480	0.9955891610497690	5.49762887266722E-06	0.9949622166246850	0.9974747474747480	0.9962168978562420	4.3981030981378E-06
wmt	Walmajirari	860	997	0.9979797979797980	1.0	0.989795918367347	2.1973732810548E-06	0.9979797979797980	1.0	0.989795918367347	2.1973732810548E-06
wmw	Mwani	167,150	793	0.9986155388471180	0.9924337957124840	0.9893148962916400	1.20947968184087E-05	0.9899244332493700	0.9911726166465650	0.9905482041587900	8.7962158679362E-06
wnc	Wanotat	8,200	1000	0.9970089730807580	1.0	0.9985022466300550	3.29933188529323E-06	0.9970089730807580	1.0	0.9985022466300550	3.29933188529323E-06
wnu	Wun	1,400	792	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
wol	Wolof	18m	1000	0.9979899497487440	0.993	0.9954887218045110	2.19955459019549E-06	0.997989975653920	0.992	0.9949849548645940	2.19955459019549E-06
wos	Hang'a Hundu	7,200	782	0.9974489795918370	1.0	0.9987228607918260	2.19902737019416E-06	0.9974489795918370	1.0	0.9987228607918260	2.19902737019416E-06
wrk	Garwa	110	411	0.9975728155339810	1.0	0.9987849331713240	1.09906653482226E-06	1.0	1.0	1.0	0.0
wro	Worrora	20	182	1.0	0.9945054945054950	0.9972451790633610	0.0	0.9945054945054950	0.9972451790633610	0.9972451790633610	0.0
wrs	Waris	2,500	895	0.9988839285714290	1.0	0.9994416527097840	1.09965031120104E-06	0.9988839285714290	1.0	0.9994416527097840	1.09965031120104E-06
wsk	Waskia	20,000	1000	0.9960159362549800	1.0	0.998003992015968	4.39910918039097E-06	0.9970089730807580	1.0	0.998003992015968	4.39910918039097E-06
wuv	Wuvulu-Aua	1,600	793	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
xav	Xavante	13,303	699	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
xcd	Hdi	29,000	794	0.9962264150943400	0.9974811083123430	0.996833668974200	3.29858457378786E-06	0.9962264150943400	0.9974811083123430	0.996833668974200	3.29858457378786E-06
xla	Kamula	800	962	0.998960498960499	1.0	0.99947997919168	1.0997301262702E-06	0.998960498960499	1.0	0.99947997919168	1.0997301262702E-06
xnn	Northern Kanakanay	70,000	721	0.9834183673469390	0.9987046632124350	0.9910025706940870	4.2935207470454E-05	0.9834183673469390	0.9987046632124350	0.9910025706940870	4.2935207470454E-05
xon	Konkomba	920,000	786	0.9886792452830190	1.0	0.9943074003795070	8.9956666755752E-06	0.9924242424242420	1.0	0.9961977186311790	6.59711112503835E-06
xis	Sio	3,500	1000	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06	0.999	0.999	0.999	1.099497498749370
xtl	Diuxi-Tilantongo Mixtec	4,220	788	1.0	0.9974619289340100	0.9987293519695050	0.0	1.0	0.9974619289340100	0.9987293519695050	0.0
xtm	Magdalena Peñasco Mixtec	7,350	792	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
yaa	Yaminahua	1,390	756	0.9986789960369880	1.0	0.9953390614672840	1.09948225380668E-06	0.9986789960369880	1.0	0.9953390614672840	1.09948225380668E-06
yad	Yagua	4,297	741	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
yai	Yalunka	1,000	1000	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06
yap	Yapese	6,590	1000	1.0	0.999	0.9994997498749370	0.0	0.999	0.999	0.9994997498749370	0.0
yap	Yaqui	16,000	793	0.993734335839599	1.0	0.9968573224387100	5.49763491745851E-06	0.9987405541561710	1.0	0.993698802772530	0.995269834917E-06
yby	Yaweyuha	4,600	787	0.9974587039390090	0.9974587039390090	0.9974587039390090	2.1990394596406E-06	0.998727353689570	0.9974587039390090		

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
acf	Saint Lucian Creole French	357,000	792	0.9974811083123430	1.0	0.998738965920810	2.19905154906689E-06	0.9974811083123430	1.0	0.998738965920810	2.19905154906689E-06
bel	Belarusian	10m	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
ben	Bengali	270m	1000	0.9960159362549800	1.0	0.998003992015968	4.39910918039097E-06	0.9960159362549800	1.0	0.998003992015968	4.39910918039097E-06
bjj	Belize Kriol English	200,000	779	1.0	1.0	1.0	0.0	1.0	0.9987163029525030	0.999377392421320	0.0
ces	Czech	12m	791	0.9801734820322180	1.0	0.9899874843554440	1.75923930492455E-05	0.9801734820322180	1.0	0.9899874843554440	1.75923930492455E-05
cop	Coptic	0	792	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
cth	Thaiphum Chin	1,000	1000	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06	0.999	0.999	0.999	0.999
daa	Danglalet	60,000	784	0.9961880559085130	1.0	0.9980903882877150	3.2985483088926E-06	0.9961880559085130	1.0	0.9980903882877150	3.2985483088926E-06
dad	Marik	3,500	792	0.9962264150943400	1.0	0.998109640831758	3.29857732360033E-06	0.9962264150943400	1.0	0.998109640831758	3.29857732360033E-06
dah	Gwahatle	1,570	768	0.9961089494163420	1.0	0.9980506822612090	3.2984902809839E-06	0.9961089494163420	1.0	0.9980506822612090	3.2984902809839E-06
dan	Danish	5.6m	1000	1.0	0.999	0.9994997498749370	0.0	1.0	0.998	0.998989898989899	0.0
ded	Deda	6,500	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
deu	German	155m	1000	0.996011964107677	0.999	0.9975037443834250	4.39910918039097E-06	0.996011964107677	0.999	0.9985007496251870	2.19955459019549E-06
djk	Aukan (Ndjuka)	67,000	786	0.9961928934010150	0.9987277353689570	0.9974587039390090	3.29855556251917E-06	0.9961928934010150	0.9987277353689570	0.9974587039390090	3.29855556251917E-06
eng	English	1.46bn	1000	0.99700559880239520	0.999	0.998001998001998	3.29933188529323E-06	0.99700559880239520	0.999	0.9975012493753120	3.29933188529323E-06
epo	Esperanto	100,000	1000	0.997002997002997	0.998	0.9975012493753120	3.29933188529323E-06	0.997	0.997	0.997	0.997
fra	French	321m	1000	0.997997997997998	0.997	0.9974987493746870	2.19955459019549E-06	0.997997997997998	0.996	0.9969696969696970	2.19955459019549E-06
gre	Ancient Greek	0	791	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
guj	Gujarati	62m	1000	0.9950248756218910	1.0	0.9975062344139650	5.49888647548871E-06	0.9950248756218910	1.0	0.9975062344139650	5.49888647548871E-06
gul	Gullah (Sea Island Creole English)	300	794	0.996253845671270	1.0	0.9981143914632310	3.29885845775786E-06	0.996253845671270	1.0	0.998747371859300	1.21995638490524E-06
hat	Haitian Creole	13m	1000	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
hau	Hausa	94m	796	0.980246913580247	0.9974874371859300	0.9887920298879200	1.75924897661188E-05	0.980246913580247	0.9974874371859300	0.9887920298879200	1.75924897661188E-05
hin	Hindi	610m	1000	0.978473581213070	1.0	0.9891196834817010	2.41951004921503E-05	0.978473581213070	0.999	0.989598112927190	2.19955459019549E-06
hrv	Croatian	6.0m	1000	0.9737373737373740	0.964	0.9688442211055280	2.096296725413E-05	0.9737373737373740	0.964	0.9693312322724990	2.7494432374436E-05
kbq	Kamano	63,000	1000	0.999000999000999	1.0	0.9995002498750630	1.0997729509774E-06	1.0	1.0	1.0	0.0
lat	Latin	0	1000	1.0	0.998	0.998989898989899	0.0	1.0	0.998	0.998989898989899	0.0
lit	Lithuanian	3.1m	703	0.9957507082152970	1.0	0.9978708303761530	3.2982545636849E-06	0.9957507082152970	1.0	0.9987595454545450	2.19883637578993E-06
mal	Malayalam	39m	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
mar	Marathi	84m	1000	0.991080275024780	1.0	0.9955201592832260	9.89799565587969E-06	0.991080275024780	1.0	0.9965122027745390	7.6984410656842E-06
mpx	Huastla-Panacati Mixima-Panacati	74,600	793	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
nfa	Dhao	5,000	903	0.9988938053097350	1.0	0.9994465965888990	1.0996599851326E-06	0.9988938053097350	0.9988925802879290	0.9988925802879290	1.0996599851326E-06
nld	Dutch	250m	1000	0.998998989898999	0.998	0.9984992496248120	1.0997729509774E-06	0.998998989898999	0.997	0.997997997997998	0.997799799799798
por	Portuguese	279m	786	0.9949367088607600	1.0	0.994619289340100	4.3980740833589E-06	0.9949367088607600	1.0	0.9980952380592380	3.29855556251917E-06
rom	Romanian	28m	114	0.991304347826087	1.0	0.995631877292960	1.09870671232892E-06	0.991304347826087	1.0	0.995631877292960	1.09870671232892E-06
rus	Russian	260m	1000	1.0	0.999	0.9994997498749370	0.0	1.0	0.999	0.9994997498749370	0.0
san	Sanskrit	24,821	791	0.9949685534591200	1.0	0.9974779319041620	4.39809862621138E-06	0.9949685534591200	1.0	0.9993682880606440	1.0995245657784E-06
spa	Spanish	460m	1000	0.9930343870647070	0.998	0.9955112219451370	7.6984410656842E-06	0.9930343870647070	0.998	0.9960079840310260	6.5986617075864E-06
srp	Serbian	12m	1000	0.9635108481262330	0.977	0.9702085402184710	4.06917599186165E-05	0.9635108481262330	0.977	0.971129622266400	3.8492205328421E-05
swe	Swedish	11m	1000	1.0	0.997	0.99849774661993	0.0	1.0	0.997	0.99849774661993	0.0
urd	Urdu	246m	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
zaj	Zaramo	293,000	792	0.947565543071161	0.9583333333333330	0.9529190207156310	4.61800825304046E-05	0.947565543071161	0.9583333333333330	0.9529190207156310	4.61800825304046E-05
zyp	Zyphie Chin	21,000	793	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
mgj	Abureni	4k	563	1.0	0.9928952042628780	0.9964349376114080	0.0	1.0	0.9928952042628780	0.9964349376114080	0.0
aca	Achagua	250	515	1.0	0.9883495145631070	0.9941406250000000	0.0	1.0	0.9883495145631070	0.9941406250000000	0.0
adj	Adioukrou	160k	1000	0.99899195483871	0.991	0.9949799168787150	1.0997729509774E-06	0.99899195483871	0.999	0.9949748743718590	1.0997729509774E-06
adi	Adnyamthanha	262	2	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
duo	Agta, Dupaninan	1,400	1000	0.997654120040960	0.981	0.9894099848714070	2.19955459019549E-06	0.997654120040960	0.978	0.988377968671046	1.0997729509774E-06
esg	Aheri Gong	3,000	844	0.99644128113879	0.995260663507109	0.99850622406639	3.2987659316496E-06	0.99644128113879	0.995260663507109	0.99850622406639	3.2987659316496E-06
ahg	Ahirani	150,000	1000	0.9881306537982200	0.999	0.9935355450522020	1.3197327511729E-05	0.9881306537982200	0.999	0.9945246391239420	1.0997729509774E-06
alw	Alaba-K'abeena	1.6 million	174	0.9885714285714290	0.9942528735632180	0.991404011461318	2.1975829290867E-06	0.9885714285714290	0.9942528735632180	0.991404011461318	2.1975829290867E-06
mim	Alacatzala Mixtec	204,000	906	1.0	0.9900662251655630	0.99508323194675540	0.0	1.0	0.9989624724061810	0.9944506104328520	0.0
omb	Ambae, East	34,000	1000	0.9989949748743720	0.994	0.9984912280701750	1.0997729509774E-06	0.9989949748743720	0.994	0.9964912280701750	1.0997729509774E-06
abc	Ambala Atya	5,000	122	0.9918032786885250	0.9918032786885250	0.9918032786885250	0.9918032786885250	0.9918032786885250	0.9918032786885250	0.9918032786885250	0.9918032786885250
anh	Amharic	2.9m	187	0.988764049438200	0.9411764705882350	0.9643835616438360	2.1975898436349E-06	0.988764049438200	0.9411764705882350	0.9643835616438360	2.1975898436349E-06
akc	Angal Heneng	32 million	776	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
kko	Anufo	91,000	1000	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
any	Anyin	180,000	943	0.9968017057569300	0.991512046369034990	0.9941520463783260	3.2991250720309E-06	0.9968017057569300	0.991512046369034990	0.9941520463783260	3.2991250720309E-06
apy	Apalai	1.45 million	1000	1.0	0.995	0.9974937343358400	0.0	1.0	0.994	0.9969999729187560	0.0
app	Apma	450	1000	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
arb	Arabic, Algerian	7,800	1.0	0.9909090909090900	1.0	0.9952380952380950	1.09858118240293E-06	0.9909090909090900	1.0	0.9952380952380950	1.09858118240293E-06
aeb	Arabic, Tunisian	42 million	497	0.9959919839679360	1.0	0.9979919678714860	2.1983389657649E-06	0.9959919839679360	1.0	0.9979919678714860	2.1983389657649E-06
luc	Atinga	13 million	854	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
prq	Asheninka Perené	495,000	1.0	0.998003992015968	1.0	0.9990009990009990	2.19955459019549E-06	0.998003992015968	1.0	0.9990009990009990	2.19955459019549E-06
auu	Auye	7,200	1000	0.957	0.957	0.9780275932549820	0.0	0.957	0.954	0.9780275932549820	0.0
avu	Avokaya	5,350	1000	0.997	0.997	0.997	0.997	0.997	0.996	0.9964982491245620	3.29933188529323E-06
avt	Avokaya	40,000	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
abx	Ayta, Abellen	4,400	1000	0.997695431472080	0.983	0.9904282115860920	2.19955459019549E-06	0.997695431472080	0.983	0.9989901826437940	1.0997729509774E-06
blx	Ayta, Mag-Indi	5,000	1000	0.9835902536051720	0.989	0.9835902536051720	0.9851004921503E-05	0.9835902536051720	0.989	0.9851004921503E-05	0.9835902536051720
miy	Ayutla Mixtec	5,000	1000	1.0	0.998	0.998989898989899	0.0	1.0	0.998	0.998989898989899	0.0
bfd	Bafut	105,000	1000	0.9989775051124740	0.977	0.987866318503540	1.0997729509774E-06	0.9989775051124740	0.977	0.987866318503540	1.0997729509774E-06
bsw	Baisi	3,500	286	0.9761092150170650	1.0	0.9879101899827290	7.69240067737083E-06	0.9761092150170650	0.979381443298969	0.9965034965034970	7.69240067737083E-06
bcc	Southern Baluchi	8,600m	1000	0.997	0.997	0.99849774661993	0.0	0.997	0.997	0.99849774661993	0.0
bno	Bambalang	29,000	875	0.99885231100							

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
asm	Cishingini	100,000	1000	0.9979529170931420	0.975	0.9863429438534250	2.19955459019549E-06	0.9979508196721310	0.974	0.98582995951417	2.19955459019549E-06
mta	Cotabato Manobo	30,000	1000	0.99898949748743720	0.994	0.9964912280701750	1.09977729509774E-06	0.9989939637826960	0.993	0.995897963891675	1.09977729509774E-06
crf	Cree, Northern East	6,870	27	1.0	0.92529259292952960	0.9615384615384620	0.0	1.0	0.92592592592952960	0.9615384615384620	0.0
cul	Culina	1000	1000	1.0	0.996	0.9979509198396880	0.0	1.0	0.996	0.9979509198396880	0.0
cug	Cung	2,000	1000	0.998991935483871	0.991	0.9949799196787150	1.09977729509774E-06	0.9989909182643800	0.99	0.9944751381215470	1.09977729509774E-06
dny	Dan	1.58 million	1000	1.0	0.999	0.999497498749370	0.0	1.0	0.999	0.999497498749370	0.0
dnu	Danu	100,000	793	0.9987405541561710	1.0	0.99936980272350	1.0995269834917E-06	0.9987389659520810	0.9987389659520810	0.9987389659520810	1.0995269834917E-06
dnt	Delo	10,900	1000	0.997	0.997	0.99732393188529323E-06	0.9979979979797998	0.997	0.997	0.9974987493746870	2.19955459019549E-06
des	Desano	2,460	1000	0.987	0.9934574735782590	0.0	1.0	0.986	0.9929506545820750	0.0	1.0
dso	Desiya	50,000	795	0.9962406015037590	1.0	0.9981167608286250	3.29858820424858E-06	0.9987437185929650	1.0	0.9993714644877440	1.09952940141619E-06
dhn	Dhanki	163,000	1000	0.9959266802443990	0.978	0.9868819374369320	4.39910918039097E-06	0.9969293756397130	0.974	0.985331100657560	3.29933188529323E-06
div	Maldivian	356,000	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
mbd	Dibabawen Manobo	10,000	1000	0.9989816700611000	0.981	0.9899091826437940	1.09977729509774E-06	0.9989785495403470	0.978	0.988377968671046	1.09977729509774E-06
dig	Digo	88,000	1000	0.993455095862770	0.985	0.9894525364138620	6.59866377058646E-06	0.9959473150962510	0.983	0.9894313034725720	4.39910918039097E-06
dji	Djeebbana	100	6	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
dyl	Djimini Senoufo	95,500	1000	0.997002997002997	0.998	0.9975012493753120	3.29933188529323E-06	0.997002997002997	0.998	0.9975012493753120	3.29933188529323E-06
sce	Dongxiang	250,000	1000	0.982	0.9909182643794150	0.0	1.0	0.977	0.9883662114314620	0.0	1.0
bru	Eastern Bru	69,000	1000	0.995995995995996	0.995	0.9954977488744370	4.39910918039097E-06	0.995995995995996	0.995	0.9954977488744370	4.39910918039097E-06
xrb	Eastern Karahoro	35,000	1000	1.0	0.995	0.9974937343358400	0.0	0.998	0.9969909729187560	0.0	1.0
eka	Ekajuk	30,000	1000	0.9968796869049790	0.961	0.9786150712830960	3.29933188529323E-06	0.9968717413972890	0.956	0.9760081674323630	3.29933188529323E-06
ekk	Estonian, Standard	953,000	419	0.9881235154394300	0.9928400954653940	0.9875350923232E-06	0.9880952380952380	0.9904534606205250	0.9887294390809300	5.4953750923232E-06	0.0
utr	Etulo	10,000	1000	1.0	0.986	0.992506545820750	0.0	0.984	0.9919354838709680	0.0	1.0
fnn	Finnish	4,700,000	1000	0.9979508196721310	0.974	0.98582995951417	2.19955459019549E-06	0.9989733059548260	0.973	0.9858156028367890	1.09977729509774E-06
fag	Finongan	1,300	162	0.9876543209876540	0.997	0.99378881978857760	0.0	0.9876543209876540	0.99378881978857760	0.0	1.0
frd	Fordata	50,000	1000	0.998949748743720	0.994	0.9964912280701750	1.09977729509774E-06	0.991	0.9954796584630840	0.0	1.0
flr	Fuliru	300,000	1000	0.9940179461615160	0.997	0.9955067398901650	6.59866377058646E-06	0.995004995004995	0.996	0.995502488755620	5.49888647548871E-06
gdg	Ga'dang	6,000	1000	0.9890547263681590	0.994	0.9915211970074810	1.09977729509774E-06	0.991991991991992	0.991	0.991495747873937	8.3977550923232E-06
gbl	Gamit	400,000	922	1.0	0.9945770065075920	0.9927181130494830	0.0	1.0	0.9945770065075920	0.9927181130494830	0.0
gaq	Gata'	3,060	795	0.9924906132665830	0.9949811794228360	6.59717640849716E-06	0.9924906132665830	0.9974842767295600	0.9949811794228360	6.59717640849716E-06	0.0
gyl	Gayil	55,700	912	1.0	0.9901315789473690	0.9950413223140500	0.0	1.0	0.9890350877192980	0.9944873208379270	0.0
ghn	Ghanongga	2,510	1000	0.9909638554216870	0.987	0.9979795574729720	9.89799565587960E-06	0.9909547738693470	0.986	0.99541779448620	9.89799565587960E-06
grt	Ghari	12,100	1000	0.998	0.998	0.99877959118240	2.19955459019549E-06	0.9989898989898999	0.998	0.9984992406214820	1.09977729509774E-06
acd	Gikyode	10,400	1000	0.99603996003996	0.997	0.9965017491254370	4.39910918039097E-06	0.997	0.997	0.997	0.0
nyf	Giyana	623,000	1000	0.9949849548645940	0.992	0.9934902353530300	5.49888647548871E-06	0.9949748743718590	0.999	0.9924812003075190	5.49888647548871E-06
glw	Glyada	28,500	453	0.9955947136563880	0.9977924944812360	0.9966923925027560	2.19823218167949E-06	0.9955947136563880	0.9977924944812360	0.9966923925027560	2.19823218167949E-06
gqr	Gore	87,000	1000	0.9989868287740630	0.986	0.992450931051837	1.09977729509774E-06	0.9989847715736040	0.984	0.9914573682619650	1.09977729509774E-06
goj	Gowlan	20,200	1000	0.9878296146044630	0.974	0.9808660624370590	1.31973275411729E-05	0.9897959183673470	0.97	0.9797979797979800	1.09977729509774E-06
gok	Gowli	35,000	1000	0.998995983935743	0.995	0.9969939879759520	1.09977729509774E-06	0.998995983935743	0.995	0.9969939879759520	1.09977729509774E-06
gde	Gude	68,000	1000	1.0	0.987	0.9934574735782590	0.0	1.0	0.986	0.992506545820750	0.0
gdf	Guduf-Gava	55,900	312	0.9967320261437910	0.9775641025641030	1.09894578131199E-06	0.9967320261437910	0.9775641025641030	0.9870550161812300	1.09894578131199E-06	0.0
rub	Gungu	49,000	1000	0.9979818365287590	0.989	0.99347061778001	2.19955459019549E-06	0.997979797979798	0.988	0.9929648241206030	2.19955459019549E-06
guf	Gupapuyngu	450	2	1.0	0.5	0.6666666666666670	0.0	1.0	0.5	0.6666666666666670	0.0
gge	Guragone	20	1	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
gue	Gurinj	540	31	1.0	0.967741935483871	0.9836065573770490	0.0	1.0	0.967741935483871	0.9836065573770490	0.0
gvr	Gurung	325,622	1000	1.0	0.992	0.995939357429720	0.0	1.0	0.992	0.9954796584630840	0.0
gwr	Gwore	409,000	1000	0.993006993006993	0.992	0.993503248375812	7.6984410656842E-06	0.9959919839679360	0.994	0.994994994994995	4.39910918039097E-06
hnb	Halti	500,000	1000	0.9807497467071940	0.968	0.9743331655762460	2.08957668608571E-05	0.9847094801232340	0.966	0.9752501176678450	1.64966594264661E-05
bge	Haryanni	13m	790	0.98625	0.9987341772151900	0.9924528301886790	1.20947569228739E-05	0.987483554443030	0.9987341772151900	0.9930774071743240	1.0995233566249E-05
mey	Hassaniya	2.7m	91	1.0	0.978021978021978	0.9888888888888890	0.0	1.0	0.978021978021978	0.9888888888888890	0.0
hav	Havu	506,000	351	0.997093023255814	0.9772079772079770	0.9870503597122300	1.0989928622209E-06	0.9970760233918130	0.9715099715099720	0.9841269941269840	1.0989928622209E-06
hoy	Hoyi	500	795	0.9949937421777220	1.0	0.9974905897114180	4.39811760682624E-06	0.9962406015037590	1.0	0.9981167608286250	3.29858820424858E-06
hre	Hre	113,000	1000	0.9969879518072290	0.993	0.9940899799599290	3.29933188529323E-06	0.9969849246231160	0.992	0.9944862155388470	3.29933188529323E-06
hru	Hruso	4,000	135	1.0	0.9851851851851850	0.9925373134328360	0.0	1.0	0.9851851851851850	0.9925373134328360	0.0
var	Huarjio	2,840	1000	1.0	0.999	0.9994997498749370	0.0	1.0	0.997	0.99849774661993	0.0
dud	Huon-Saare	73,000	1000	0.996969696969697	0.996	0.9964982491245620	3.29933188529323E-06	0.996969696969697	0.996	0.9964982491245620	3.29933188529323E-06
hwo	Hwana	32,000	1000	0.9979736575481260	0.985	0.9914443885254150	2.19955459019549E-06	0.9989847715736040	0.984	0.9914357682619650	1.09977729509774E-06
ihl	Ihaloi	11,000	1000	1.0	0.995	0.9974937343358400	0.0	1.0	0.995	0.9974937343358400	0.0
ivb	Ihantai	1,350	1000	0.9826707441386340	0.964	0.973245835466480	1.86962140166616E-05	0.9856262833675560	0.96	0.972644376899966	1.53968821313684E-05
isl	Icelandic	230,000	989	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
ifa	Ifuga, Angenad	27,000	1000	0.9736070381231670	0.996	0.9846762243054990	2.9693869676391E-05	0.9764474975466140	0.995	0.9856326358099460	2.63946550823458E-05
ifu	Ifuga, Mayoyao	30,000	1000	0.9989989898989899	0.998	0.9984992496248120	1.09977729509774E-06	0.998996909729190	0.996	0.9974962436655000	1.09977729509774E-06
itk	Ifuga, Tawali	30,000	1000	0.9870259481037920	0.989	0.988011988011988	1.42971048362707E-05	0.9896969097291890	0.987	0.9884827240861290	1.09977729509774E-06
ibo	Igbo	18m	1000	0.9950199203187250	0.999	0.9970059880239520	5.49888647548871E-06	0.996011964107677	0.999	0.997503743834250	4.39910918039097E-06
ikz	Ikizu	132,000	1000	0.9969669696969697	0.987	0.9919579898949750	3.29933188529323E-06	0.9969666329625890	0.986	0.9954529914529920	3.29933188529323E-06
iqw	Ikwo	260,000	1000	0.9673267326732670	0.977	0.9921393034825870	3.62926507382255E-05	0.9672619047619050	0.975	0.9711155378486060	3.62926507382255E-05
isd	Isnag	30,000	1000	0.995979894974870	0.991	0.993483709273183	4.39910918039097E-06	0.995979894974870	0.991	0.993483709273183	4.39910918039097E-06
ivz	Ivatan	35,000	997	0.989010989010989	0.9929789368104310	0.9909909909909910	1.20975103323736E-05	0.9909819639278560	0.9919759277833500	0.9914786967418550	9.89796299921476E-06
izz	Izii	540,000	1000	0.9787878787878790	0.969	0.9738693467336680	2.30953231970526E-05	0.9787878787878790	0.969	0.9836934	

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
loq	Lobala	60,000	1000	0.9969818913480890	0.991	0.9939819458375130	3.29933188529323E-06	0.9969788519637460	0.99	0.9934771700953340	3.29933188529323E-06
lhm	Lotho	25,000	795	0.9718482252141980	0.9987421383647800	0.9851116625310180	2.52891762325725E-05	0.9754299754299750	0.9987421383647800	0.99869484151646990	2.19905880283239E-05
log	LoDoghi	210,000	1000	1.0	1.0	1.0	0.0	1.0	0.998	0.9989789899898999	0.0
zip	Loxicha Zapotec	75,000	1000	0.9989517819706500	0.9553	0.9754350051177070	1.09977729509774E-06	1.0	0.9945	0.971223650385610	0.0
knh	Lubugang Kalinga	14,000	1000	1.0	0.67	0.8023952095808380	0.0	1.0	0.669	0.8016776512881970	0.0
lmd	Lumun	45,000	833	1.0	0.9903961584633850	0.9951749095295540	0.0	1.0	0.9891956782713090	0.945684972842490	0.0
lga	Lungga	2,770	1000	0.9888888888888890	0.979	0.9839195978099500	1.20975502460752E-05	0.9908814589665650	0.978	0.984398590840463	9.8979956587969E-06
two	Luwu	80,000	1000	0.9969849246231160	0.992	0.9944862155388470	3.29933188529323E-06	0.9979879275653920	0.992	0.9949849548645940	2.19955459019549E-06
lyn	Luyana	222,000	1000	1.0	0.972	0.9858012170385400	0.0	1.0	0.97	0.9847715736040610	0.0
ayz	Mai Brat	20,000	1000	1.0	0.985	0.992433249370280	0.0	1.0	0.983	0.9914271306101870	0.0
mai	Maithili	31.9m	967	0.9989669421487600	1.0	0.999483204134367	1.09973738271301E-06	0.9989669421487600	1.0	0.999483204134367	1.09973738271301E-06
pmv	Malay, Papuan	500,000	1000	0.9989615784008310	0.962	0.9801324503311260	1.09977729509774E-06	0.9989572471324300	0.958	0.9780500255232660	1.09977729509774E-06
mgq	Malila	65,000	1000	0.9979899497487440	0.993	0.9954887218045110	2.19955459019549E-06	0.9979899497487440	0.993	0.9954887218045110	2.19955459019549E-06
mmn	Mamanwa	5,150	1000	0.9979818365287590	0.989	0.993470617780011	2.19955459019549E-06	0.9979818365287590	0.989	0.993470617780011	2.19955459019549E-06
kby	Manga Kanuri	280,000	1000	1.0	0.992	0.9959839357429720	0.0	1.0	0.99	0.9949748743718590	0.0
mge	Mango	52,200	996	1.0	0.9909638554216870	0.9954614220877460	0.0	1.0	0.9909638554216870	0.9954614220877460	0.0
mhi	Manobo, Ilianen	14,600	1000	0.997	0.997	0.997	3.29933188529323E-06	0.996969696969697	0.996	0.9964982491245620	3.29933188529323E-06
mfm	Marathi South	166,000	872	0.997709049255441	0.9988532110091740	0.9982808022922640	2.199244999919178E-06	0.9988518943742830	0.9977064220183490	0.998278266041310	1.09962249959589E-06
mth	Matla	18,000	1000	0.998969909729190	0.996	0.9974062443665500	1.09977729509774E-06	1.0	0.994	0.9969909729187560	0.0
mvy	Matengo	150,000	1000	0.9938650306748470	0.972	0.9828109201213350	6.59866377058646E-06	0.9958974538974360	0.971	0.9832911392405060	4.39910918039077E-06
mfy	Mayo	40,000	1000	1.0	0.991	0.995476584630840	0.0	1.0	0.99	0.9940748743718590	0.0
mdm	Mayogo	100,000	1000	0.998997995991984	0.997	0.9979979979979979	1.09977729509774E-06	0.998997995991984	0.997	0.9979979979979979	1.09977729509774E-06
mfo	Mbe	14,300	1000	1.0	0.987	0.9934574735782590	0.0	1.0	0.986	0.9929506545820750	0.0
mbu	Mbula-Bwazza	40,600	1000	1.0	0.989	0.9944695827048770	0.0	1.0	0.988	0.993963782696177	0.0
mfx	Melo	20,200	322	0.9487179487179490	0.9192546583850930	0.9337359432176660	1.75833257322081E-05	0.9516129032258070	0.9161490683229810	0.9335443037974680	1.64843673873945E-05
mxm	Meramera	2,000	1000	0.9969818913480890	0.991	0.9939819458375130	3.29933188529323E-06	0.9979757085020240	0.986	0.9919517102615700	2.19955459019549E-06
mxx	Metlatónoc Mixtec	46,600	1000	1.0	0.997	0.99849774661993	0.0	1.0	0.997	0.99849774661993	0.0
mif	Mofu-Gudur	60,000	1000	0.998969909729190	0.996	0.9974962443665500	1.09977729509774E-06	0.99895983935743	0.995	0.996939879759520	1.09977729509774E-06
mzq	Mori Atas	16,100	190	0.9578947368421050	0.9578947368421050	0.97897847368421050	8.79038771103798E-06	0.9574468085106380	0.9473684210526320	0.9523809523809520	8.79038771103798E-06
mpa	Mpoti	80,000	1000	0.9959473150962510	0.983	0.9894313034725720	4.39910918039097E-06	0.9979654120040600	0.981	0.9894099848714070	2.19955459019549E-06
mox	Mukulu	12,000	1000	0.99892950654582	0.992	0.9954841946813850	1.09977729509774E-06	0.998991935483871	0.991	0.9949799196787150	1.09977729509774E-06
unx	Munda	519,000	792	0.9949748743718590	1.0	0.99647811083123430	4.39810309813378E-06	0.9974811083123430	1.0	0.9987389659520810	2.1990515496689E-06
tur	Murle	60,000	1000	0.9989949748743720	0.994	0.9969412280701750	1.09977729509774E-06	0.998991935483871	0.991	0.9949799196787150	1.09977729509774E-06
sur	Mwaghavul	295,000	667	0.9850075962518740	0.997	0.992471290933660	0.0	0.9850075962518740	0.996	0.992471290933660	0.0
mso	Mwan	17,000	1000	0.998997995991984	0.997	0.9979979979979979	1.09977729509774E-06	0.998969909729190	0.996	0.9974962443665500	1.09977729509774E-06
muh	Mündli	23,000	1000	0.9979939819458380	0.995	0.9964947421131700	2.19955459019549E-06	0.9979939819458380	0.995	0.9964947421131700	2.19955459019549E-06
nag	Naga Pidgin	3,000	795	0.9987405541561710	0.9974842767295600	0.9981120201384520	1.099529401619E-06	0.9987405541561710	0.9974842767295600	0.9981120201384520	1.099529401619E-06
kfw	Naga, Kharam	14,000	795	0.9962358845671270	0.9974842731859300	0.9974847371859300	3.29858820424858E-06	0.9962358845671270	0.9974847371859300	0.9974847371859300	3.29858820424858E-06
trt	Naga, Tutsa	25,000	791	0.9962168978562420	0.9987357774968390	0.9974747474747470	3.29857369673353E-06	0.9962168978562420	0.9987357774968390	0.9974747474747470	3.29857369673353E-06
neck	Nakara	75	2	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
nal	Nalik	5,140	792	0.9962264150943400	1.0	0.998109640831758	3.29857732360033E-06	0.9962264150943400	1.0	0.998109640831758	3.29857732360033E-06
naw	Nawuri	14,000	1000	1.0	0.997	0.99849774661993	0.0	0.997959919839680	0.996	0.997959919839680	0.0
ncr	Ncane	15,500	1000	0.9979919678714860	0.994	0.9959919839679360	2.19955459019549E-06	0.9989949748743720	0.994	0.9964912280701750	1.09977729509774E-06
ndh	Ndali	150,000	1000	0.993006993006993	0.994	0.993503248375812	7.6984410656842E-06	0.9949899799599200	0.993	0.993939393939394	5.49888647548871E-06
dne	Ndendele	100,000	1000	0.9989785495043470	0.978	0.988377968671046	1.09977729509774E-06	1.0	0.978	0.9888776541961580	0.0
ndz	Ndogo	48,000	1000	1.0	0.998	0.998989898989899	0.0	1.0	0.998	0.998989898989899	0.0
njd	Ndondé Hamba	10,000	144	0.9470198675496690	0.9930555555555560	0.9604915254237290	8.7899434257266E-06	0.9466666666666670	0.9861111111111110	0.9659863945578230	8.7899434257266E-06
ndv	Ndut	38,600	1000	0.989076464767730	0.996	0.992526138445441	1.20975502460752E-05	0.99005964214771170	0.996	0.9930209371884530	1.09977729509774E-06
nny	Ngiti	100,000	1000	0.999009990990999	1.0	0.9995024987570630	1.09977729509774E-06	0.999009990999999	1.0	0.9995024987570630	1.09977729509774E-06
xnj	Ngoni	170,000	795	0.9925	0.9987421383647800	0.995611285264580	6.59717640849716E-06	0.992490613265830	0.9974842767295600	0.9949811794228360	6.59717640849716E-06
pcn	Nigerian Pidgin	120m	1000	0.998969909729190	0.996	0.9974962443665500	1.09977729509774E-06	0.998969909729190	0.996	0.9974962443665500	1.09977729509774E-06
num	Niufo'o	690	785	0.9987244897959180	0.9974522292993630	0.9989789541108990	1.09951513190008E-06	1.0	0.9961783439490450	0.998085513720485	0.0
nkn	Nkangala	22,300	886	1.0	0.97855304704060	0.9901614375356530	0.0	1.0	0.9974847474747470	0.9885844748858450	0.0
snf	Noon	32,900	1000	0.9979919678714860	0.994	0.9959919839679360	2.19955459019549E-06	0.9979899497487440	0.993	0.9954887218045110	2.19955459019549E-06
stb	Northern Subanen	10,000	1000	0.99892950654582	0.992	0.9954841946813850	1.09977729509774E-06	0.9989909182643800	0.99	0.994475138125470	1.09977729509774E-06
nob	Norwegian	4,640	772	0.9922779922779920	0.9987046632124350	0.995480955451320	6.5970095755594E-06	0.993556010309280	0.9987046632124350	0.9961240310077520	5.49750797963283E-06
ncf	Notsi	1,48m	1000	0.996926229081970	0.973	0.9848178137651820	3.29933188529323E-06	0.9979338842975210	0.966	0.9817031707317010	2.19955459019549E-06
nxl	Nuaulu, South	1,500	1000	1.0	0.976	0.9878542501021460	0.0	1.0	0.972	0.9858012170385400	0.0
nuq	Nukumanu	700	1000	0.9979253112033200	0.962	0.9976334012219660	2.19955459019549E-06	0.9979144942648590	0.957	0.9770209064777950	2.19955459019549E-06
nkr	Nukuro	860	1000	0.997997997997998	0.997	0.9974987493746870	2.19955459019549E-06	0.998997995991984	0.997	0.997997997997998	1.09977729509774E-06
naw	Nuni, Southern	168,000	1000	1.0	0.998	0.998989898989899	0.0	1.0	0.998	0.998989898989899	0.0
nwb	Nyabwa	42,700	1000	1.0	0.989	0.9944695827048770	0.0	1.0	0.989	0.9944695827048770	0.0
nyy	Nyakuya-Ngondé	805,000	1000	0.999	0.999	0.999	1.09977729509774E-06	1.0	0.999	0.999497498749370	0.0
nij	Nyole	34,000	1000	0.9861111111111110	0.994	0.99003980408374500	1.53968821313684E-05	0.9890547263681590	0.994	0.99152119704074810	1.20975502460752E-05
gaz	Oromo, West Central	8,92m	1000	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06
ury	Orya	1,600	1000	0.990009900099999	0.991	0.9905047476261870	1.09977729509774E-06	0.991	0.991	0.991	9.8979956587969E-06
oyd	Oyda	16,600	272	0.9325842696629210	0.9154411764705880	0.9239332096474950	1.97801545709				

Code (ISO-639-3)	Name	Speakers	Support ($\theta = 0.3$)	Precision ($\theta = 0.3$)	Recall ($\theta = 0.3$)	F1 ($\theta = 0.3$)	FPR ($\theta = 0.3$)	Precision ($\theta = 0.5$)	Recall ($\theta = 0.5$)	F1 ($\theta = 0.5$)	FPR ($\theta = 0.5$)
thv	Tahaggart Tamahaq	25,000	395	1.0	0.979746835443038	0.989769820971867	0.0	1.0	0.979746835443038	0.989769820971867	0.0
blt	Tai Dam	699,000	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
tlj	Talinga-Bwisi	68,500	1000	0.9970059880239520	0.999	0.998001998001998	3.29933188529323E-06	0.998001998001998	0.999	0.9985007496251870	2.19955459019549E-06
ttq	Tamajaq, Tawallammat	450,000	913	1.0	0.9956188389923330	0.9978946103183320	0.0	1.0	0.9934282584885000	0.9967032967032970	0.0
taq	Tamasheq	250,000	702	1.0	0.9971509971509970	0.9985734664764620	0.0	1.0	0.9971509971509970	0.9985734664764620	0.0
tpu	Tampuan	31,100	84	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
rif	Tarifit	1.5m	1000	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
yer	Tarok	300,000	1000	1.0	0.992	0.9959839357429720	0.0	1.0	0.99	0.9949748743718590	0.0
tsq	Tausug	900,000	1000	0.9959919839679360	0.994	0.994994994994995	4.39910918039097E-06	0.9979899497487440	0.993	0.9954887218045110	2.19955459019549E-06
tvn	Tavoyan	400,000	822	1.0	0.9975669099756690	0.9987819732034110	0.0	1.0	0.9975669099756690	0.9987819732034110	0.0
tyx	Teke-Tyee	14,400	1000	1.0	0.977	0.9883662114314620	0.0	1.0	0.976	0.9878542510121460	0.0
kdh	Tem	204,000	1000	1.0	0.995	0.9974937343358400	0.0	1.0	0.995	0.9974937343358400	0.0
ted	Tepo Krumen	28,300	1000	0.9969788519637460	0.99	0.9934771700953340	3.29933188529323E-06	0.9969758064516130	0.989	0.9929718875502010	3.29933188529323E-06
nod	Thai, Northern	6m	50	1.0	0.94	0.9690721649484540	0.0	1.0	0.94	0.9690721649484540	0.0
thr	Tharu, Rana	336,000	1000	0.9867751780264500	0.97	0.97813568308119	1.42971048362707E-05	0.9907786885245900	0.967	0.9787449392712550	9.89799565587969E-06
bod	Central Tibetan	1.07m	947	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
tcn	Tichurong	2,420	269	0.9924812030075190	0.9814126394052050	0.9869158878504670	2.19778770689424E-06	0.9962264150943400	0.9887640449438200	1.09889385344712E-06	0.0
tkr	Tsakhur	13,000	618	0.9983844911147010	1.0	0.9991915925626520	1.09931545626538E-06	0.9983818770226540	0.9983818770226540	1.09931545626538E-06	0.0
tsn	Tswana	3.41m	758	0.9986807387862800	0.9986807387862800	0.9986807387862800	1.09948467153445E-06	0.9986807387862800	0.9986807387862800	1.09948467153445E-06	0.0
bov	Tuwuli	11,400	1000	0.994	0.994	0.994	6.59866377058646E-06	0.9959839357429720	0.992	0.993987959519040	4.39910918039097E-06
udi	Udi	4,200	1000	0.9989837398373980	0.983	0.9909274193548390	1.09977729509774E-06	0.9989806320081550	0.98	0.989399293286219	1.09977729509774E-06
vaa	Vaagri Booli	9,300	1000	0.9979939819458380	0.995	0.9964947421131700	2.19955459019549E-06	0.9979939819458380	0.995	0.9964947421131700	2.19955459019549E-06
vgr	Vaghri	10,000	1000	0.9979899497487440	0.993	0.9954887218045110	2.19955459019549E-06	0.9979838709677420	0.99	0.9939759036144580	2.19955459019549E-06
wbq	Waddar	1.93m	510	0.9863013698630140	0.9882352941176470	0.987263849167480	7.69429468049441E-06	0.9921259842519690	0.9882352941176470	0.9901768172888020	4.39673981742538E-06
fad	Wagi	3,380	224	1.0	0.9419642857142860	0.9701149425287360	0.0	1.0	0.9419642857142860	0.9701149425287360	0.0
wja	Waja	60,000	252	1.0	0.9880952380952380	0.9940119760479040	0.0	1.0	0.9880952380952380	0.9940119760479040	0.0
cou	Wamey	18,400	1000	1.0	0.99	0.9949748743718590	0.0	1.0	0.99	0.9949748743718590	0.0
mfi	Wandala	23,500	1000	0.9989898989898989	0.989	0.9939698492462310	1.09977729509774E-06	1.0	0.988	0.993963782696177	0.0
hrw	Warwar Feni	4,200	1000	1.0	0.971	0.9852866565195330	0.0	1.0	0.968	0.983739837398374	0.0
guc	Wayuu	170,000	1000	1.0	0.999	0.999497498749370	0.0	1.0	0.999	0.999497498749370	0.0
kyu	Western Kayah	100,000	1000	1.0	0.999	0.999497498749370	0.0	1.0	0.999	0.999497498749370	0.0
suc	Western Subanon	75,000	1000	0.996	0.996	0.996	4.39910918039097E-06	0.9979919678714860	0.994	0.9959919839679360	2.19955459019549E-06
wlo	Wolio	65,000	1000	0.9989764585465710	0.976	0.9873545776428930	1.09977729509774E-06	0.9989754098360660	0.975	0.9868421052631580	1.09977729509774E-06
wob	Wé Northern	156,000	1000	1.0	0.993	0.9964877069744110	0.0	1.0	0.993	0.9964877069744110	0.0
nce	Yale	600	350	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
ymp	Yamap	1,580	502	0.9979959919839680	0.9920318725099600	0.9950049950049950	1.09917528878083E-06	0.9979959919839680	0.9920318725099600	0.9950049950049950	1.09917528878083E-06
yam	Yamba	40,800	1000	1.0	0.993	0.9964877069744110	0.0	1.0	0.993	0.9964877069744110	0.0
yns	Yansi	100,000	1000	1.0	0.99	0.9949748743718590	0.0	1.0	0.99	0.9949748743718590	0.0
zae	Yareni Zapotec	2,900	1000	1.0	0.993	0.9964877069744110	0.0	1.0	0.992	0.9959839357429720	0.0
jni	Yemsa	81,600	147	0.9931972789115650	0.9931972789115650	0.9931972789115650	1.09874654993583E-06	1.0	0.9931972789115650	0.996807307167240	0.0
yij	Yindjibarndi	330	5	1.0	1.0	1.0	0.0	1.0	0.8	0.888888888888889	0.0
zak	Zanaki	100,000	1000	0.9919597989949750	0.987	0.9894736842105260	8.79821836078194E-06	0.9919436052366570	0.985	0.9884596086302060	8.79821836078194E-06
zin	Zinza	138,000	1000	1.0	0.984	0.9919354838709680	0.0	1.0	0.983	0.9914271306101870	0.0
gel	ut-Ma'in	36,000	869	0.9976798143851510	0.9896432681242810	0.9936452917388790	2.19923774419786E-06	0.9976798143851510	0.9896432681242810	0.9936452917388790	2.19923774419786E-06
bwo	Borna	19,900	794	0.9987421383647800	1.0	0.9993706733794840	1.09952819245262E-06	1.0	1.0	1.0	0.0
ena	Apal	980	990	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
mni	Meitei	1.37m	790	0.9987341772151900	0.9987341772151900	0.9987341772151900	1.0995233566249E-06	0.9987341772151900	0.9987341772151900	1.0995233566249E-06	0.0
nde	Ndebele	1.55m	1000	0.998	0.998	0.998	2.19955459019549E-06	0.9989898989898989	0.998	0.9984992496248120	1.09977729509774E-06
nlx	Nahali	15,000	794	0.9924812030075190	0.9974811083123430	0.9949748743718590	6.59716915471571E-06	0.9949748743718590	0.9974811083123430	0.9962264150943400	4.39811276981047E-06
sna	Shona	10,700	1000	0.994035785282700	1.0	0.9970089730807580	6.59866377058646E-06	0.9970089880239520	0.999	0.998001998001998	3.29933188529323E-06
tdk	Malagasy, Tandroy-Mahafaly	1m	1000	0.998003992015968	1.0	0.999009990009990	2.19955459019549E-06	0.999009990009990	1.0	0.9995002498750630	1.09977729509774E-06
uro	Ura	19,900	789	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0
yao	Yao	1m	794	0.9900124843945070	0.9987405541561710	0.9943573667711600	8.79622553962095E-06	0.9912390488110140	0.9974811083123430	0.9943502824858760	7.69669734716833E-06
yom	Kiyombe	1.47m	1000	0.9920634920634920	1.0	0.9960159362549800	8.79821836078194E-06	0.9930417495029820	0.999	0.9960119641076770	7.6984410656842E-06

Table 18: LID Performance on the Full-LID Set with Thresholds: 0.3 and 0.5.