

MasakhaNEWS: News Topic Classification for African languages

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Abstract

Despite representing roughly a fifth of the world population, African languages are underrepresented in NLP research, in part due to a lack of datasets. While there are individual language-specific datasets for several tasks, only a handful of tasks (e.g. named entity recognition and machine translation) have datasets covering geographical and typologically-diverse African languages. In this paper, we develop MasakhaNEWS—the largest dataset for news topic classification covering 16 languages widely spoken in Africa. We provide and evaluate a set of baseline models by training classical machine learning models and fine-tuning several language models. Furthermore, we explore several alternatives

to full fine-tuning of language models that are better suited for zero-shot and few-shot learning, such as: cross-lingual parameter-efficient fine-tuning (MAD-X), pattern exploiting training (PET), prompting language models (ChatGPT), and prompt-free sentence transformer fine-tuning (SetFit and the co:here embedding API). Our evaluation in a few-shot setting, shows that with as little as 10 examples per label, we achieve more than 90% (i.e. 86.0 F1 points) of the performance of fully supervised training (92.6 F1 points) leveraging the PET approach. Our work shows that existing supervised approaches work well for all African languages and that language models with only a few supervised samples can reach competitive performance, both findings which demonstrate the applicability of existing NLP techniques for African languages.

* Equal contribution

1 Introduction

News topic classification is a text classification task in NLP that involves categorizing news articles into different categories like sports, business, entertainment, and politics. It has shaped the development of several machine learning algorithms over the years, such as topic modeling (Blei et al., 2001; Ding et al., 2020) and deep learning models (Zhang et al., 2015; Joulin et al., 2017). Similarly, news topic classification is a popular downstream task for evaluating the performance of large language models (LLMs) for both fine-tuning and prompting setups (Yang et al., 2019; Sun et al., 2019; Brown et al., 2020; Liu et al., 2023).

Despite the popularity of the task in benchmarking LMs, most of the evaluation have only been performed on English and a few other high-resource languages. It is *unclear how this approach extends to pre-trained multilingual language models* for low-resource languages. For instance, BLOOM (Scao et al., 2022) was pre-trained on 46 languages, including 22 African languages (mostly from the Niger-Congo family). However, extensive evaluation on these set of African languages was not performed due to lack of evaluation datasets. In general, only a handful of NLP tasks such as machine translation (Adelani et al., 2022a; NLLB-Team et al., 2022), named entity recognition (Adelani et al., 2021, 2022b), and sentiment classification (Muhammad et al., 2023) have standardized benchmark datasets covering several geographical and typologically-diverse African languages. Another popular task that can be used for evaluating the downstream performance of language models is news topic classification, but human-annotated datasets for benchmarking topic classification using language models for African languages are *scarce*.

In this paper, we address two problems: the lack of evaluation datasets and lack of extensive evaluation of LMs for African languages. We create a large-scale **news topic classification** dataset covering 16 typologically-diverse languages widely spoken in Africa, including English and French, with the same label categories across all languages. Our dataset is also suitable for **news headline generation** task (Aralikatte et al., 2023): a special type of text summarization. We provide several baseline models using both classical machine learning approaches and fine-tuning LMs. Furthermore, we explore several alternatives to full fine-tuning of language models that are better suited for

zero-shot and few-shot learning (e.g. 5-examples per label) such as cross-lingual parameter-efficient fine-tuning (MAD-X (Pfeiffer et al., 2020)), pattern exploiting training (PET) (Schick and Schütze, 2021a), prompting ChatGPT LLM, and prompt-free, sentence transformer fine-tuning (SetFit) (Tunstall et al., 2022a), and the co:here embedding API.

Our evaluation in a zero-shot setting shows the potential of prompting ChatGPT for news topic classification for low-resource African languages. We found that GPT-3.5-Turbo has impressive result for languages that make use of Latin script, but *perform poorly for non-Latin based scripts like Amharic and Tigrinya*. However, *GPT-4 was able to overcome this challenge for non-Latin script* with impressive performance matching the result of cross-lingual transfer experiments from a related African language.

In a few-shot setting, we show that with as little as 10 examples per label, we achieved more than 90% (i.e. 86.0 F1 points) of the performance of full supervised training (92.6 F1 points) leveraging the PET approach. We hope this encourages the NLP community to benchmark and evaluate LLMs on more low-resource languages. For reproducibility, we release our data and code under academic license or CC BY-NC 4.0 on Github.¹

2 Related Work

News topic classification, an application of text classification, is a popular task in natural language processing. There are various news topic classification datasets, including BBC News (Greene and Cunningham, 2006), AG News (Zhang et al., 2015), and the multimodal N24News (Wang et al., 2022), all of which are English datasets. In addition, there is the IndicNLP News (Kunchukuttan et al., 2020) which is a multilingual dataset for Indian languages. For African languages, only a handful of human annotated datasets exists, such as the Hausa & Yorùbá dataset (Hedderich et al., 2020) (only covering news headline), KINNEWS & KIRNEWS datasets for Kinyarwanda and Kirundi (Niyongabo et al., 2020), and Tigrinya News (Fesseha et al., 2021). Others are semi-automatically created using predefined topics from news websites like Amharic news (Azime and Mohammed, 2021) and ANTC dataset (Alabi et al., 2022)—that covered five African languages (Lingala, Somali, Naija,

¹<https://github.com/masakhane-io/masakhane-news>

Malagasy, and isiZulu). These datasets, however, have limitations due to the fact that they were created with little or no human supervision and using different labeling schemes. In contrast, in this work we present news topic classification data for 16 typologically diverse African languages with a consistent labeling scheme across all languages.

Prompting Language Models using manually designed prompts to guide text generation has recently been applied to a myriad of NLP tasks, including topic classification. Models such as GPT-3 (Brown et al., 2020) and T5 (Raffel et al., 2020; Sanh et al., 2022) are able to learn more structural and semantic relationships between words and have shown impressive results even in multilingual scenarios when tuned for different tasks (Chung et al., 2022; Muennighoff et al., 2023). One approach to prompt-tuning a language model for topic classification is to design a “template” for classification and insert a sequence of text into template (Gao et al., 2021; Shin et al., 2020).

There are some other approaches to few-shot learning without prompting. One of them is SetFit (Tunstall et al., 2022a), which takes advantage of sentence transformers to generate dense representations for input sequences. These representations are then passed through a classifier to predict class labels. The sentence transformers are trained on a few examples using contrastive learning where positive and negative training pairs are sampled by in-class and out-class sampling. Another common approach is Pattern-Exploiting Training also known as PET (Schick and Schütze, 2021a). PET is a semi-supervised training approach that used restructured input sequences to condition language models to better understand a given task, while iPET (Schick and Schütze, 2021b) is an iterative variant of PET that is also shown to perform better.

3 Languages

Table 1 presents the languages covered in along with information on their language families, their primary geographic regions in Africa, and the number of speakers. Our dataset consists of a total of 16 typologically-diverse languages, and they were selected based on the availability of publicly available news corpora in each language, the availability of native-speaking annotators, geographical diversity and most importantly, because they are widely spoken in Africa. English and French are official languages in 42 African countries, Swahili

is native to 12 countries, and Hausa is native to 6 countries. In terms of geographical diversity, we have four languages spoken in West Africa, seven languages spoken in East Africa, two languages spoken in Central Africa (i.e. Lingala and Kiswahili), and two spoken in Southern Africa (i.e. chiShona and isiXhosa). Also, we cover four language families, Niger-Congo (8) Afro-Asiatic (5), Indo-European (2), and English Creole (1). The only English creole language is Nigerian-Pidgin, also known as Naija. Each language is spoken by at least 10 million people, according to Ethnologue (Eberhard et al., 2021).

4 MasakhaNEWS dataset

4.1 Data Source

The data used in this research study were sourced from multiple reputable news outlets. The collection process involved crawling the British Broadcasting Corporation (BBC) and Voice of America (VOA) websites. We crawled between 2k–12k articles depending on the number of articles available on the websites. Some of the websites already have some pre-defined categories, we make use of this to additionally filter articles that do not belong to categories we plan to annotate. We took *inspiration* of news categorization from **BBC English** with six (6) pre-defined and well-defined categories (“*business*”, “*entertainment*”, “*health*”, “*politics*”, “*sports*”, and “*technology*”) with over 500 articles in each category. For English, we only crawled articles belonging to these categories while for the other languages, we crawled all articles. Our target is to have around **3,000** articles for annotation but three languages (Lingala, Rundi, and Somali) have less than that. Table 2 shows the news source per language and the number of articles crawled.

4.2 Data Annotation

We recruited volunteers from the Masakhane community—an African grassroots community focused on advancing NLP for African languages.² The annotators were asked to label 3k articles into eight categories: “*business*”, “*entertainment*”, “*health*”, “*politics*”, “*religion*”, “*sports*”, “*technology*”, and “*uncategorized*”. Six of the categories are based on BBC English major news categories, the “*religion*” label was added since many African

²all annotators are were included as authors of the paper.

Language	Family/branch	Region	# speakers	News Source	# articles
Amharic (amh)	Afro-Asiatic / Ethio-Semitic	East Africa	57M	BBC	8,204
English (eng)	Indo-European / Germanic	Across Africa	1268M	BBC	5,073
French (fra)	Indo-European / Romance	Across Africa	277M	BBC	5,683
Hausa (hau)	Afro-Asiatic / Chadic	West Africa	77M	BBC	6,965
Igbo (ibo)	Niger-Congo / Volta-Niger	West Africa	31M	BBC	4,628
Lingala (lin)	Niger-Congo / Bantu	Central Africa	40M	VOA	2,022
Luganda (lug)	Niger-Congo / Bantu	Central Africa	11M	Gambuuze	2,621
Naija (pcm)	English Creole	West Africa	121M	BBC	7,783
Oromo (orm)	Afro-Asiatic / Cushitic	East Africa	37M	BBC	7,782
Rundi (run)	Niger-Congo / Bantu	East Africa	11M	BBC	2,995
chiShona (sna)	Niger-Congo / Bantu	Southern Africa	11M	VOA & Kwayedza	11,146
Somali (som)	Afro-Asiatic / Cushitic	East Africa	22M	BBC	2,915
Kiswahili (swa)	Niger-Congo / Bantu	East & Central Africa	71M-106M	BBC	6,431
Tigrinya (tig)	Afro-Asiatic / Ethio-Semitic	East Africa	9M	BBC	4,372
isiXhosa (xho)	Niger-Congo / Bantu	Southern Africa	19M	Isolezwe	24,658
Yorùbá (yor)	Niger-Congo / Volta-Niger	West Africa	46M	BBC	6,974

Table 1: **Languages covered in and Data Source:** including language family, region, number of L1 & L2 speakers, and number of articles from each news source.

news websites frequently cover this topic. Other articles that do not belong to the first seven categories, are assigned to the “*uncategorized*” label.

For each language, the annotation followed two stages. In the **first stage**, we randomly shuffled the entire dataset and asked annotators to label the first 200 articles manually. In the **second stage**, we made use of active learning by combining the first 200 annotated articles with articles with pre-defined labels where available, and trained a classifier (i.e. by fine-tuning AfroXLMR-base (Alabi et al., 2022)). We ran predictions on the rest of the articles, and asked annotators to correct the mistakes of the classifier. This approach helped to speed up the annotation process.

Annotation tool We make use of an in-house annotation tool to label the articles. Appendix A shows an example of the interface of the tool. To further simplify the annotator effort, we ask annotators to label articles based on the headlines instead of the entire article. However, since some headlines are not very descriptive, we decided to concatenate the headline and the first two sentences of the news text to provide additional context to annotators.

Inter-agreement score We report Fleiss Kappa score (Fleiss et al., 1971) to measure the agreement of annotation. Table 2 shows that all languages have a moderate to perfect Fleiss Kappa score (i.e. 0.55 - 0.85), which shows a high agreement among the annotators recruited for each language. Languages with only one annotator (i.e. Luganda and Rundi) were excluded in the evaluation.

Deciding a single label per article After annotation, we assigned the final label to each article by majority voting. Each label of an article needs

to be agreed by a minimum of two annotators to be assigned the label. We only had exceptions for Luganda and Rundi, since they had one annotator. Our final dataset for each language consist of a minimum of 72 articles per topic, and a maximum of 500, except for English language where the classes are roughly balanced. We excluded the infrequent labels so we do not have a highly unbalanced dataset. The choice of a minimum of 72 articles ensures a minimum of 50 articles in the training set.³ Our target is to have at least four topics per language with a minimum of 72 articles. This approach worked smoothly except for two languages: Lingala (“politics”, “health” and “sports”) and chiShona (“business”, “health” and “politics”), where we had only three topics with more than 72 articles. To ensure we have more articles per class, we had to resolve the conflict in annotation between Lingala annotators to ensure we have more labels for the “business” category. This approach still results in infrequent classes for chiShona. We had to crawl additional “sports” articles from a local chiShona website (*Kwayedza*), followed by manual filtering of unrelated sports news.

Data Split Table 2 provides the data split for languages. We also provide the distribution of articles by topics. We divided the annotated data into TRAIN, DEV and TEST split following 70% / 10% / 20% split ratio.

5 Baseline Experiments

We trained baseline text classification models by concatenating the news headline and news text using different approaches.

³since we require 50 instances per class or 50-shots for the few-shot experiments in (§6.2.2)

Language	Train/Dev/Test	# topics	Topics (number of articles per topic)							# Annotator	Fleiss Kappa
			# bus	# ent	# health	# pol	# rel	# sport	# tech		
Amharic (amh)	1311/ 188/ 376	4	404	-	500	500	-	471	-	5	0.81
English (eng)	3309/ 472/ 948	6	799	750	746	821	-	1000	613	7	0.81
French (fra)	1476/ 211/ 422	5	500	-	500	500	-	500	109	3	0.83
Hausa (hau)	2219/ 317/ 637	7	399	500	493	500	493	497	291	5	0.85
Igbo (ibo)	1356/ 194/ 390	6	292	366	424	500	73	285	-	4	0.65
Lingala (lin)	608/ 87/ 175	4	82	-	193	500	-	95	-	2	0.56
Luganda (lug)	771/ 110/ 223	5	169	-	228	500	91	116	-	1	-
Oromo (orm)	1015/ 145/ 292	4	-	119	447	500	-	386	-	3	0.63
Naija (pcm)	1060/ 152/ 305	5	97	460	159	309	-	492	-	4	0.66
Rundi (run)	1117/ 159/ 322	6	76	158	372	500	73	419	-	1	-
chiShona (sna)	1288/ 185/ 369	4	500	-	425	500	-	417	-	3	0.63
Somali (som)	1021/ 148/ 294	7	114	139	354	500	73	148	135	3	0.55
Kiswahili (swa)	1658/ 237/ 476	7	316	98	500	500	292	500	165	4	0.72
Tigrinya (tir)	947/ 137/ 272	6	80	167	395	500	-	125	89	2	0.63
isiXhosa (xho)	1032/ 147/ 297	5	72	500	100	308	-	496	-	3	0.89
Yorùbá (yor)	1433/ 206/ 411	5	-	500	398	500	317	335	-	5	0.80

Table 2: **MasakhaNEWS dataset**. The size of the annotated data, news topics, and number of annotators. Topics are labelled by their prefixes in the table (**topics**): **business**, **entertainment**, **health**, **politics**, **religion**, **sport**, **technology**.

5.1 Baseline Models

We trained three classical ML models: Naive Bayes, multi-layer perceptron, and XGBoost using the popular sklearn tool (Pedregosa et al., 2011). We employed the “CountVectorizer” method to represent the text data, which converts a collection of text documents to a matrix of token counts. This method allows us to convert text data into numerical feature vectors.

Furthermore, we fine-tune nine kinds of multilingual text encoders, seven of them are BERT/RoBERTa-based i.e. XLM-R (base & large) (Conneau et al., 2020), AfriBERTa-large (Ogueji et al., 2021), RemBERT (Chung et al., 2021), AfroXLMR (base & large) (Alabi et al., 2022), and AfroLM (Dossou et al., 2022), the other two are mDeBERTaV3 (He et al., 2021a), and LaBSE (Feng et al., 2022). mDeBERTaV3 pre-trained a DeBERTa-style model (He et al., 2021b) with replaced token detection objective proposed in ELECTRA (Clark et al., 2020). On the other hand, LaBSE is a multilingual sentence transformer model that is popular for mining parallel corpus for machine translation.

Finally, we fine-tuned four multilingual Text-to-Text (T2T) models, mT5-base (Xue et al., 2021), Flan-T5-base (Chung et al., 2022), AfriMT5-base (Adelani et al., 2022a), AfriTeVA-base (Jude Ogundepo et al., 2022). The fine-tuning and evaluation of the multilingual text-encoders and T2T models were performed using HuggingFace Transformers (Wolf et al., 2020) and PyTorch Lightning⁴. The models were fine-tuned on

Nvidia V100 GPU for 20 epochs, batch size of 32, $1e - 5/5e - 5$ lr, and max. sequence length of 256.

The LMs evaluated were both massively multilingual (i.e. typically trained on over 100 languages around the world) and African-centric (i.e. trained mostly on languages spoken in Africa). The African-centric multilingual text encoders are all modeled after XLM-R. AfriBERTa was pre-trained from scratch on 11 African languages, AfroXLMR was adapted to African languages through fine-tuning the original XLM-R model on 17 African languages and 3 languages commonly spoken in Africa, while AfroLM was pre-trained on 23 African languages utilizing active learning. Similar to the multilingual text encoders, the T2T models used in this study were pre-trained on hundreds of languages, and they are all based on the T5 model (Rafael et al., 2020), which is an encoder-decoder model trained with the span-mask denoising objective. mT5 is a multilingual version of T5, and Flan-T5 was fine-tuned on multiple tasks using T5 as a base. The study also included adaptations of the original models, such as AfriMT5-base, as well as AfriTeVA-base, a T5 model pre-trained on 10 African languages.

5.2 Baseline Results

Table 3 shows the result of training several models on TRAIN split and evaluation on the TEST split for each language. Our evaluation shows that classical ML models are worse in general than fine-tuning multilingual LMs on average, however, the drop in performance is sometimes comparable to LMs if the language was not covered during the pre-training. For example, MLP, NaiveBayes and

⁴[https://pytorch-lightning/](https://pytorch-lightning.org/)

Model	size	amh	eng	fra	hau	ibo	lin	lug	orm	pcm	run	sna	som	swa	tir	xho	yor	AVG
<i>classical ML</i>																		
MLP	<20K	92.0	88.2	84.6	86.7	80.1	84.3	82.2	86.7	93.5	85.9	92.6	71.1	77.9	81.9	94.5	89.3	85.7
NaiveBayes	<20K	91.8	83.7	84.3	85.3	79.8	82.8	84.0	85.6	92.8	79.9	91.5	74.8	76.6	71.4	91.0	84.0	83.7
XGBoost	<20K	90.1	86.0	81.2	84.7	78.6	74.8	83.8	83.2	93.3	79.2	94.3	68.5	74.9	75.2	91.1	85.2	82.8
<i>multilingual text encoders</i>																		
AfriBERTa	126M	90.6	88.9	76.4	89.2	87.3	87.0	85.1	89.4	98.1	91.3	89.3	83.9	83.3	87.0	86.9	90.3	87.8
XLM-R-base	270M	90.9	90.6	90.4	88.4	82.5	87.9	65.3	82.2	97.8	85.9	88.9	73.8	85.6	54.6	78.6	84.5	83.0
AfroXLMR-base	270M	94.2	92.2	92.5	91.0	90.7	93.0	89.4	92.1	98.2	91.4	95.4	85.2	88.2	86.5	94.7	93.0	91.7
AfroLM	270M	90.3	87.7	77.5	88.3	85.4	85.7	88.0	83.5	95.9	86.8	92.5	72.0	83.2	83.5	91.4	86.5	86.1
mDeBERTa	276M	91.7	90.8	89.2	88.6	88.3	81.6	65.7	84.7	96.8	89.4	93.9	72.0	84.6	78.7	90.5	89.3	86.0
LABSE	471M	92.5	91.6	90.9	90.0	91.6	89.6	86.8	86.7	98.4	91.1	94.6	82.1	87.6	83.8	94.7	92.1	90.3
XLM-R-large	550M	93.1	92.2	91.4	90.6	84.2	91.8	73.9	88.4	98.4	87.0	88.9	76.1	85.6	62.7	89.2	84.5	86.1
AfroXLMR-large	550M	94.4	93.1	91.1	92.2	93.4	93.7	89.9	92.1	98.8	92.7	95.4	86.9	87.7	89.5	97.3	94.0	92.6
RemBERT	559M	92.4	92.4	90.8	90.5	91.1	91.5	86.7	88.7	98.2	90.6	93.9	75.9	86.7	69.9	92.5	93.0	89.1
<i>multilingual text-to-text LMs</i>																		
AfriTeVa-base	229M	87.0	80.3	71.9	85.8	79.9	82.8	60.2	82.9	95.2	80.0	84.4	58.0	80.7	55.2	69.4	86.4	77.5
mT5-base	580M	78.2	89.8	59.0	82.7	76.8	80.8	75.0	79.2	96.1	85.7	90.4	75.0	76.1	65.1	71.8	86.2	80.0
Flan-T5-base	580M	54.5	92.4	88.9	84.5	86.6	90.6	84.1	85.8	97.8	87.3	90.6	76.0	79.0	41.5	90.8	88.0	82.4
AfriMT5-base	580M	90.2	90.3	87.4	87.9	88.0	88.6	84.8	83.9	96.6	91.0	91.5	77.8	84.4	80.8	91.6	88.8	87.7

Table 3: **Baseline results on** . We compare several ML approaches using both classical ML and LMs. Average is over 5 runs. Evaluation is based on weighted F1-score. Africa-centric models are in gray color

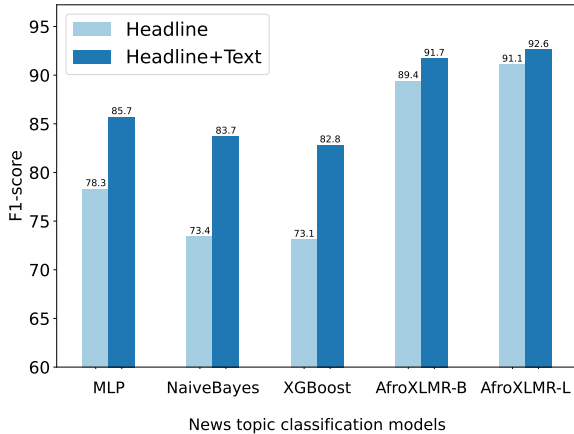


Figure 1: **Comparison of article content type used for training news topic classification models.** We report the average across all languages when either headline or headline+text is used

XGBoost have better performance than AfriBERTa on fra and sna since they were not seen during pre-training of the LM. Similarly, AfroLM had worse result for fra for the same reason. On average, XLM-R-base, AfroLM, mDeBERTaV3, XLM-R-large gave 83.0 F1, 86.1 F1, 86.0 F1, and 86.1 F1 respectively, with worse performance compared to the other LMs (87.8 – 92.6 F1) because they do not cover some of the African languages during pre-training (see Table 6) or they have been pre-trained on a small data (e.g. AfroLM pretrained on less than 0.8GB despite seeing 23 African languages during pre-training). Larger models such as LABSE and RemBERT that cover more languages performed better than the smaller models, for example, LABSE achieved over of 2.5 F1 points over AfriBERTa.

The best result achieved is by AfroXLMR-base/large with over 4.0 F1 improvement over AfriBERTa. The larger variant gave the overall best result due to the size. AfroXLMR models benefited from being pre-trained on most of the languages we evaluated on. We also tried multilingual T2T models, but none of the models reach the performance of AfroXLMR-large despite their larger sizes. We observe the same trend that the adapted mT5 model (i.e. AfriMT5) gave better result compared to mT5 similar to how AfroXLMR gave better result than XLM-R. We found *FlanT5-base to be competitive to AfriMT5* despite seeing few African languages, however, *the performance was very low for languages that uses the Ge’ez script* like amh and tir since the model do not support Ge’ez.

Headline-only training We compare our results using headline+text (as shown in Table 3) with training on the article headline—with shorter content, we find out that fine-tuned LMs gave impressive performance with only headlines while classical ML methods struggle due to shorter content. Figure 1 shows the result of our comparison. AfroXLMR-base and AfroXLMR-large both improve by (2.3) and (1.5) F1 points respectively if we use headline+text instead of headline. Classical ML models improve the most when we make use of headline+text instead of headline; MLP, NaiveBayes and XGBoost improve by large F1 points (i.e. 7.4 – 9.7). Thus, for the remainder of this paper, we make use of headline+text. Appendix B provides the breakdown of the result by languages for the comparison of headline and headline+text.

SRC LANG	amh	eng	fra	hau	ibo	lin	lug	orm	pcm	run	sna	som	swa	tir	xho	yor	AVG	AVG ^{src}
<i>Fine-tune (AfroXLMR-base)</i>																		
hau	81.8	78.8	72.9	91.5	83.2	74.4	57.5	63.3	93.2	81.6	85.5	63.3	80.7	73.2	77.4	80.4	77.4	76.2
swa	89.5	82.4	86.7	80.8	81.5	74.5	66.5	63.8	92.7	86.2	83.6	74.7	87.3	71.8	72.6	80.4	79.7	79.1
<i>MAD-X</i>																		
hau	81.0	79.5	72.2	90.3	87.4	82.6	84.4	80.2	91.2	76.0	89.9	66.5	81.2	72.6	82.8	87.4	81.6	81.0
swa	91.0	80.9	86.1	81.2	83.0	85.0	75.1	82.6	94.2	86.9	90.1	74.6	88.4	77.6	80.7	88.8	84.1	84.0
<i>PET</i>																		
None	67.2	53.3	51.7	42.1	50.4	28.6	27.0	43.9	63.1	57.9	62.2	39.2	53.8	45.2	56.0	49.7	49.5	49.7
<i>SETFIT</i>																		
None	75.8	61.6	60.1	53.3	53.1	59.6	40.1	38.9	72.0	55.1	66.6	49.4	55.2	37.8	49.3	63.7	55.7	55.9
<i>ChatGPT (GPT 3.5 Turbo) - Mar 23 version</i>																		
None	33.3	79.3	67.6	59.4	65.0	62.3	59.4	62.9	93.2	73.6	73.0	62.0	69.3	41.4	73.9	80.1	66.0	66.2
<i>ChatGPT (GPT 3.5 Turbo) - May 24 version</i>																		
None	36.1	79.5	69.6	70.1	78.3	75.1	64.7	72.0	93.1	82.2	84.5	72.3	75.9	45.0	78.0	81.7	72.4	72.3
<i>GPT 4 - May 24 version</i>																		
None	88.5	79.1	77.3	76.5	84.0	82.6	77.9	70.0	96.2	88.6	90.8	77.3	75.0	76.7	83.1	83.7	81.7	82.5

Table 4: **Zero-shot learning on** . We compare several approaches such as using MAD-X, PET and SetFit. We excluded the source languages hau and swa from the average (AVG^{src}).

6 Zero-shot and Few-shot transfer

6.1 Methods

Here, we compare different zero-shot and few-shot methods:

Fine-tune (Fine-tune on a *source language*, and evaluate on a *target language*) using AfroXLMR-base. This is only used in the **zero-shot setting**.

MAD-X (Pfeiffer et al., 2020, 2021) - a parameter efficient approach for cross-lingual transfer leveraging the modularity, and portability of adapters (Houlsby et al., 2019). We followed the same **zero-shot** setup as Alabi et al. (2022), however, we make use of hau and swa as source languages since they cover all the news topics used by all languages. The setup is as follows: (1) We train language adapters using monolingual news corpora of our focus languages. We perform language adaptation on the *news* corpus to match the domain of our dataset, similar to (Alabi et al., 2022). (2) We train a task adapter on the source language labelled data using source language adapter. (3) We substitute the source language adapter with the target language to run prediction on the target language test set, while retaining the task adapter.

PET/iPET (Schick and Schütze, 2021a,b), also known as (Iterative) **P**attern **E**xploiting **T**raining is a semi-supervised approach that makes use of few labelled examples and a prompt/pattern to a LM for few-shot learning. It involves three steps. (1) designing of a prompt/pattern and a verbalizer (that maps each label to a word from LM vocabulary). (2) train an LM on each pattern based on few labelled examples (3) distill the knowledge

of the LM on unlabelled data. Therefore, PET leverages unlabelled examples to improve few-shot learning. iPET on the other hand, repeats step 2 and 3 iteratively. We make use of the same set of patterns used for AGNEWS English dataset (Zhang et al., 2015) provided by the PET/iPET authors. The patterns are (1) $P_1(x) = ____ : a, b$ (2) $P_2(x) = a(____)b$ (3) $P_3(x) = ____ - ab$ (4) $P_4(x) = ab(____)$ (5) $P_5(x) = ____ News : ab$ (6) $P_6(x) = [Category : ____]ab$, where a is the news headline and b is the news text. In evaluation, we take average over all patterns.

SetFit (Tunstall et al., 2022b) is a few-shot learning framework based on sentence transformer models (Reimers and Gurevych, 2019) like LaBSE following two steps. **Step 1** fine-tunes the sentence transformer model using a few labelled examples with contrastive learning—where positive examples, are K -examples from a class c , and negative examples pairs are labelled examples with random labels from other classes. Contrastive learning approach enlarges the size of training data in few-shot scenarios. In **Step 2**, the fine-tuned sentence transformer model is used to extract rich sentence representation for each labelled example, followed by logistic regression for classification. The advantage of this approach is that it is faster and requires no prompt unlike PET. We use this in both **zero- and few-shot setting**. For the zero-shot setting, SetFit creates dummy example N -times (we set $N = 8$, similar to the SetFit paper) like “**this sentence is { }**” where { } can be any news topic like “sports”.

Co:here multilingual sentence transformer co:here introduced a multilingual embedding

model *multilingual-22-12*⁵, which supports over a hundred languages, including most of the languages included in . This is only for the few-shot setting.

OpenAI ChatGPT API⁶ is an LLM trained on a large chunk of texts to predict the next word like GPT-3 (Brown et al., 2020), followed by a set of instructions in a prompt based on human feedback. It leverages Reinforcement Learning from Human Feedback (RLHF), similar to InstructGPT (Ouyang et al., 2022) to make the LLM to interact in a conversational way. We prompt the OpenAI API based on GPT-3.5 Turbo and GPT-4 to categorize articles into news topics. For the prompting, we make use of a simple template from Sanh et al. (2022): *'Is this a piece of news regarding {"business, entertainment, health, politics, religion, sports or technology"}? {INPUT}'*. We make use of the first 100 tokens of headline+text as {INPUT}. The completion of the LLM can be a single word, a sentence, or multiple sentences. We check if a descriptive word relating to any of the news topics has been predicted. For example, "economy", "economic", "finance" is mapped to "business" news. We provide more details on the ChatGPT evaluation in Appendix C.

For all few-shot settings, we tried K samples/shots per class where $K = 5, 10, 20, 50$. We make use of LaBSE as the sentence transformer for SetFit, and AfroXLMR-large as the LM for PET.

6.2 Results

6.2.1 Zero-shot evaluation

GPT-3.5-Turbo performs poorly on non-Latin scripts Table 4 shows the result of zero-shot evaluation using FINE-TUNE, MAD-X, PET, SETFIT and GPT-3.5-TURBO (March 2023 version). Our result shows that cross-lingual zero-shot transfer from a source language with same domain and task (i.e FINE-TUNE & MAD-X), gives superior result (+11 F1) than PET, SetFit, and GPT-3.5-TURBO. GPT-3.5-TURBO gave better results with over +9.0 F1 point better than SETFIT and PET showing that capabilities of instruction-tuned LLMs over smaller LMs. However, the results of CHATGPT were poor (< 42.0) for non-Latin based languages like Amharic and Tigrinya which makes use of the Ge'ez script. The languages that make use of

Latin script have over 59.0%. Surprisingly, some results of GPT-3.5-TURBO are comparable to the FINE-TUNE approach for some languages (English, Luganda, Oromo, Naija, Somali, isiXhosa, and Yorùbá), without leveraging any additional technique apart from prompting the LLM.

GPT-3.5-Turbo evaluation improves with newer versions We repeated GPT-3.5-TURBO evaluation using a newer version (May 23, 2023 version), our results suggest a significant improvement of the result for 14 (out of 16) languages in our evaluation. This implies that the newer version of the model seems to be better than older versions for the news topic classification task.

GPT-4 overcomes the limited non-Latin capabilities of GPT-3.5-Turbo We also evaluated on GPT-4 on the 16 languages in zero-shot setting. Our results shows a significant improvement in performance over GPT-3.5-TURBO by over +9 points. Surprisingly, GPT-4 was able to overcome the limitation of GPT-3.5-TURBO for languages with non-Latin script (i.e Amharic and Tigrinya) with impressive performance, matching the performance of cross-lingual transfer experiment from a related African language (i.e. FINE-TUNE hau/swa → xx and MAX-X hau → xx).

The large performance gap between GPT-3.5-Turbo and GPT-4 may be due to either the former being a distilled version of a more powerful model created to reduce inference cost, which also significantly affected its performance on non-Latin scripts.^{7 8} Alternatively, GPT-4 may just be a bigger and better model with more multilingual and non-Latin capabilities.

Leveraging labelled data from other languages is more effective In general, it may be advantageous to consider leveraging knowledge from other languages with available training data when no labelled data is available for the target language. Also, we observe that Swahili (swa) achieves better result as a source language than Hausa (hau) especially when transferring to fra (+13.8), lug (+9.0), and eng (+3.6). The reason for the impressive performance from Swahili to Luganda might be due to both languages belonging to the same Greater Lake Bantu language sub-group, but it is

⁵<https://docs.cohere.ai/docs/text-classification-with-classify>

⁶<https://openai.com/blog/chatgpt>

⁷<https://arstechnica.com/information-technology/2023/07/is-chatgpt-getting-worse-over-time-study-claims-yes-but-others-arent-sure/>

⁸<https://platform.openai.com/docs/models/gpt-3-5>

Model	amh	eng	fra	hau	ibo	lin	lug	orm	pcm	run	sna	som	swa	tir	xho	yor	AVG
<i>Fine-tune (AfroXLMR-large)</i>																	
5-shots	68.4	55.1	58.0	35.8	71.3	52.7	29.2	39.2	92.5	71.2	70.2	18.1	42.5	30.2	46.5	62.7	52.7
10-shots	75.5	75.2	65.9	64.6	86.1	72.6	31.3	56.8	95.8	87.3	80.8	38.9	73.8	36.3	61.7	69.4	67.0
20-shots	88.5	85.6	78.3	85.2	90.4	80.8	48.4	41.1	97.4	90.0	92.3	63.6	82.9	67.3	83.1	84.3	78.7
50-shots	91.4	87.5	86.9	88.8	87.3	91.0	75.2	71.3	96.4	89.8	95.5	85.3	86.6	86.2	94.1	90.2	87.7
<i>Fine-tune (LaBSE)</i>																	
5-shots	71.6	67.4	61.3	60.7	63.6	65.9	59.5	43.3	86.5	65.6	83.1	25.4	49.1	36.1	46.0	71.2	59.7
10-shots	79.0	77.1	76.8	79.7	77.1	70.2	68.3	58.5	94.5	81.9	84.8	44.8	77.2	51.8	69.9	79.8	73.2
20-shots	90.3	84.7	83.1	85.1	82.0	82.2	70.4	72.3	95.5	86.0	90.6	66.6	84.3	69.0	80.5	86.0	81.8
50-shots	89.6	86.3	85.6	87.1	86.4	88.4	80.6	77.8	96.7	87.9	93.0	80.1	85.3	79.6	87.4	88.6	86.3
<i>PET</i>																	
5-shots	89.9	80.8	72.3	82.6	85.0	82.9	79.0	89.2	94.5	87.7	88.9	69.5	79.6	59.7	84.3	84.0	81.9
10-shots	91.1	81.7	83.3	86.6	86.1	87.6	84.0	91.8	96.6	90.8	91.4	74.9	81.1	69.2	88.9	90.5	86.0
20-shots	92.7	86.4	82.8	89.1	88.6	89.2	83.8	94.9	96.7	88.7	93.3	81.6	83.5	72.4	91.5	91.0	87.9
50-shots	92.9	89.2	89.1	90.9	90.6	89.6	86.7	96.0	97.2	90.9	94.8	84.2	84.2	76.4	93.5	92.4	89.9
<i>SetFit</i>																	
5-shots	68.3	69.6	64.3	76.0	78.9	48.3	28.9	38.8	91.2	74.8	85.8	68.9	76.8	73.1	84.0	60.2	68.0
10-shots	84.8	82.0	80.5	79.4	71.4	77.8	49.5	57.3	92.8	83.8	89.2	65.1	81.2	64.9	83.6	76.5	76.2
20-shots	87.9	78.5	83.9	83.3	81.8	86.6	71.7	61.0	97.4	87.0	83.2	69.4	79.2	64.9	78.4	85.0	80.0
50-shots	88.6	76.6	83.8	83.0	77.3	81.9	60.8	63.6	93.6	85.6	90.6	67.9	76.5	69.8	83.8	86.0	79.3
<i>Cohere sentence embedding API</i>																	
5-shots	66.0	65.9	60.2	74.2	72.0	69.8	50.2	50.0	74.0	61.2	78.1	52.8	67.7	60.1	68.3	71.9	65.2
10-shots	80.1	72.5	71.4	80.4	75.7	78.4	65.5	57.2	84.9	78.2	85.0	60.4	73.8	59.8	83.2	80.1	74.2
20-shots	87.6	78.0	78.4	82.9	77.7	86.9	70.2	63.9	88.7	82.7	86.6	65.3	79.0	64.8	88.2	83.9	79.1
50-shots	90.2	80.9	83.2	85.6	81.9	87.7	78.0	70.6	94.9	84.1	90.5	68.9	77.6	72.8	90.4	88.4	82.9

Table 5: **Few-shot learning on** . We compare several few-shot learning approaches: PET, SetFit and Cohere Embedding API.

unclear why Hausa gave worse results than Swahili when adapting to English or French. However, with few examples, PET and SetFit methods are powerful without leveraging training data and models from other languages.

6.2.2 Few-shot evaluation

Table 5 shows the result of the few-shot learning approaches. With only 5-shots, we find all the few-shot approaches to be better than the usual FINE-TUNE baselines for most languages. However, as the number of shots increases, they have comparable results with SETFIT and CO:HERE API especially for $K = 20, 50$ shots. However, we found that PET achieved very impressive results with 5-shots (81.9 on average), matching the performance of SETFIT/CO:HERE API with 50-shots. The results are even better with more shots i.e ($k = 10, 86.0$ F1), ($k = 20, 87.9$ F1), and ($k = 50, 89.9$ F1). Surprisingly, with 50-shots, PET gave competitive result to the full-supervised setting (i.e. fine-tuning all TRAIN data) that achieved (92.6 F1) (see Table 3). It’s important to note that PET make use of additional unlabelled data while SetFit and Cohere API do not. In general, our result highlight the importance of getting few labelled examples for a new language we are adapting to, even if it is as little as 10 examples per class—which is typically not time-consuming to annotate (Lauscher et al., 2020; Hedderich et al., 2020).

7 Conclusion

In this paper, we created the largest news topic classification dataset for 16 typologically diverse languages spoken in Africa. We provide an extensive evaluation using both full-supervised and few-shot learning settings. Furthermore, we study different techniques of adapting prompt-based tuning and non-prompt methods of LMs to African languages. Our experimental results shows that prompting LLMs like ChatGPT perform poorly on the simple task of text classification for several under-resourced African languages especially for non-Latin based scripts. Furthermore, we showed the potential of prompt-based few-shot learning approaches like PET (based on smaller LMs) for African languages. Our work shows that existing supervised approaches work well for all African languages and that language models with only a few supervised samples can reach competitive performance, both findings which demonstrate the applicability of existing NLP techniques for African languages.

In the future, we plan to extend this dataset to more African languages, include the evaluation of other multilingual LLMs like BLOOM, mT0 (Muennighoff et al., 2022) and XGLM (Lin et al., 2022), and extend analysis to other text classification tasks like sentiment classification (Shode et al., 2022, 2023; Muhammad et al., 2023).

8 Limitations

One major limitation of our work is that we did not evaluate extensively the performance of ChatGPT LLM on several African languages and tasks such as question answering, and text generation tasks. Our evaluation is only limited to text classification and may not generalize to many tasks. However, we feel that if it perform poorly on text classification, the result may even be worse on more difficult NLP tasks. Also, there is a challenge that our result may not be fully reproducible since we use the ChatGPT API where the underlining LLM are often updated or improved with time. It might be that the support for non-Latin based script may improve significantly in few months. This limitation also applied to the co:here embedding API.

9 Ethics Statement

Our work aims to provide benchmark dataset for African languages, we do not see any potential harms when using our news topic classification datasets and models to train ML models, the annotated dataset is based on the news domain, and the articles are publicly available, and we believe the dataset and news topic annotation is unlikely to cause unintended harm. Also, we do not see any privacy risks in using our dataset and models because it is based on news domain.

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A Annotation Tool

Figure 2 provides an example of the interface of our in-house annotation tool.

B Comparing different article content types

Table 7 provides the comparison between using only news headline and headline+text for training. We find significantly improvement on average when we make use of headline+text for training across all models and languages especially for classical ML methods (MLP, NaiveBayes, and XGBoost).

C ChatGPT Evaluation

We prompted ChatGPT for news topic classification using the following template: *'Is this a piece of news regarding {"business, entertainment, health, politics, religion, sports or technology"}? {{INPUT}}'*. The completion may take different forms e.g. a single word, sentence or multiple sentences. Examples of such predictions are:

1. sports
2. This is a piece of news regarding sports.
3. This is a piece of sports news regarding the CHAN 2021 football tournament in Cameroon. It reports that the Mali national football team has advanced to the semi-finals after defeating the Congo national team in a match that ended in a penalty shootout.
4. This is a piece of news regarding sports. It talks about the recent match between Tunisia and Angola in the African Cup of Nations. Both teams scored a goal, and the article mentions some of the details of the game, such as the penalty and missed chances.
5. I'm sorry, but I'm having trouble understanding this piece of news as it appears to be in a language I don't recognize. Can you please provide me with news in English so I can assist you better?

To extract the right category, we make use of a simple verbalizer that maps the news topic to several indicative words (capitalization ignored) for the category like:

- (a) 'business': { 'business', 'finance', 'economy', 'economics' }

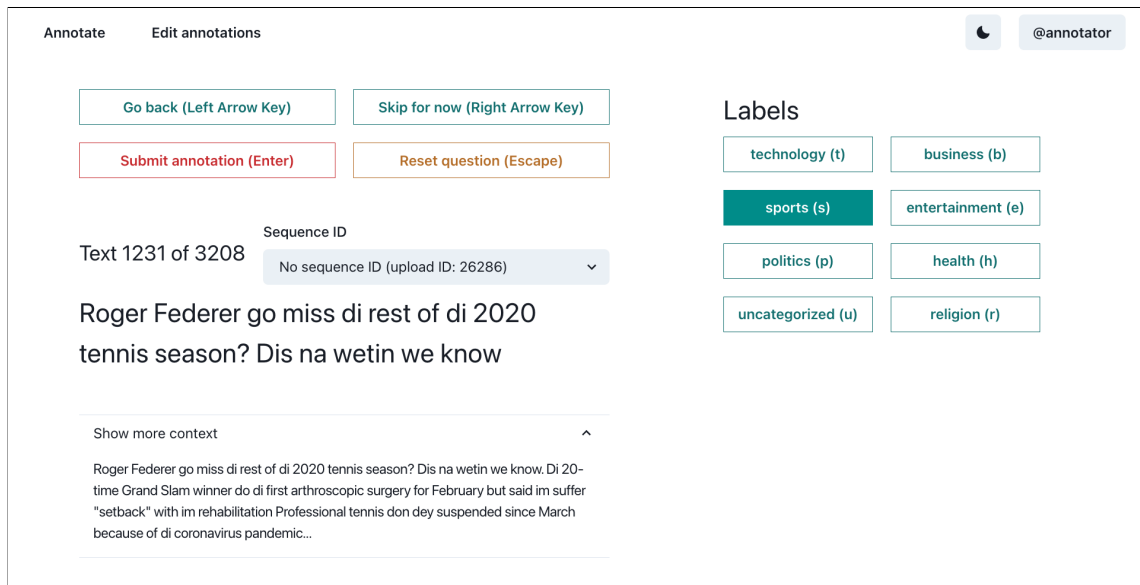


Figure 2: **Interface of our in-house Annotation tool.** Annotators can correct the pre-defined category assigned and also edit their annotation

- (b) 'entertainment': { 'entertainment', 'music' }
- (c) 'health': { 'health' }
- (d) 'politics': { 'politics', 'political' }
- (e) 'religion': { 'religion' }
- (f) 'sports': { 'sports', 'sport' }
- (g) 'technology': { 'technology' }

When the right category is not obvious, like (5 : “I’m sorry, but I’m having trouble understanding this piece of news as it appears to be in a language I don’t recognize. ”), we choose a random category before computing F1-score.

LLM	LLM size	# Lang.	# African Lang.	Focus languages covered
XLM-R-base/large	270M/550M	100	8	amh, eng, fra, hau, orm, som, swa, xho
AfriBERTa-large	126M	11	11	amh, hau, ibo, orm, pcm, run, swa, tir, yor
mDeBERTa	276M	110	8	amh, eng, fra, hau, orm, swa, xho
RemBERT	575M	110	12	amh, eng, fra, hau, ibo, sna, swa, xho, yor
AfriTeVa-base	229M	11	11	amh, run, hau, ibo, orm, pcm, swa, tir, yor
AfroXLMR-base/large	270M/550M	20	17	amh, eng, fra, hau, ibo, orm, pcm, run, sna, swa, xho, yor
AfriMT5-base	580M	20	17	amh, eng, fra, hau, ibo, orm, pcm, run, sna, swa, xho, yor
FlanT5-base	580M	60	5	eng, fra, ibo, swa, yor

Table 6: Languages covered by different multilingual Models and their sizes

Model	size	amh	eng	fra	hau	ibo	lin	lug	orm	pcm	run	sna	som	swa	tir	xho	yor	AVG
<i>Headline</i>																		
MLP	<20K	86.7	72.6	69.8	80.4	77.8	79.4	74.6	81.9	87.5	73.8	84.9	71.4	69.3	80.7	79.1	83.0	78.3
NaiveBayes	<20K	88.8	71.6	70.0	76.6	75.8	74.0	74.6	74.2	82.6	64.3	79.5	61.7	60.6	66.0	72.5	81.4	73.4
XGBoost	<20K	83.6	71.3	67.8	77.4	71.3	76.7	68.7	77.7	80.8	71.3	84.6	63.4	66.4	62.1	69.4	77.5	73.1
AfroXLMR-base	270M	91.8	87.0	92.0	89.2	87.8	89.0	87.4	87.4	97.4	87.8	94.5	85.9	85.0	85.7	93.5	88.6	89.4
AfroXLMR-large	550M	93.0	89.3	91.8	91.0	90.7	91.4	87.7	90.9	98.2	89.3	95.9	87.1	86.6	88.5	96.2	90.3	91.1
<i>Headline+Text</i>																		
MLP	<20K	92.0	88.2	84.6	86.7	80.1	84.3	82.2	86.7	93.5	85.9	92.6	71.1	77.9	81.9	94.5	89.3	85.7
NaiveBayes	<20K	91.8	83.7	84.3	85.3	79.8	82.8	84.0	85.6	92.8	79.9	91.5	74.8	76.6	71.4	91.0	84.0	83.7
XGBoost	<20K	90.1	86.0	81.2	84.7	78.6	74.8	83.8	83.2	93.3	79.2	94.3	68.5	74.9	75.2	91.1	85.2	82.8
AfroXLMR-base	270M	94.2	92.2	92.5	91.0	90.7	93.0	89.4	92.1	98.2	91.4	95.4	85.2	88.2	86.5	94.7	93.0	91.7
AfroXLMR-large	550M	94.4	93.1	91.1	92.2	93.4	93.7	89.9	92.1	98.8	92.7	95.4	86.9	87.7	89.5	97.3	94.0	92.6

Table 7: **Baseline results on** . We compare different article content types (i.e headline and headline+text) used to train news topic classification models. Average is over 5 runs. Evaluation is based on weighted F1-score.