Cross-lingual transfer and multilingual learning for detecting harmful behaviour in African under-resourced language dialogue

Cross-Lingual Transfer and Multilingual Learning for Detecting Harmful Behaviour in African Under-Resourced Language Dialogue

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Abstract

Most harmful dialogue detection models are developed for high-resourced languages. Consequently, users who speak under-resourced languages cannot fully benefit from these models in terms of usage, development, detection and mitigation of harmful dialogue utterances. Our work aims at detecting harmful utterances in under-resourced African languages. We leverage transfer learning using pretrained models trained with multilingual embeddings to develop a cross-lingual model capable of detecting harmful content across various African languages. We first fine-tune a harmful dialogue detection model on a selected African dialogue dataset. Additionally, we fine-tune a model on a combined dataset in some African languages to develop a multilingual harmful dialogue detection model. We then evaluate the cross-lingual model's ability to generalise to an unseen African language by performing harmful dialogue detection in an under-resourced language not present during pretraining or fine-tuning. We evaluate our models on the test datasets. We show that our best performing models achieve impressive results in terms of F1 score. Finally, we discuss the results and limitations of our work.

1 Introduction

Many Language Models (LMs) are developed in high-resourced languages, especially English (Adelani et al., 2022; Üstün et al., 2024). Under-resourced languages are natural languages that lack insufficient computational data resources compared to high-resourced languages (Nekoto et al., 2020). Since the launch of ChatGPT[1], a multilingual LLM built with a chat interface, researchers have increasingly focused on evaluating dialogue models' performance in both English (Finch et al., 2023) and other languages (Lai et al., 2023). Unlike high-resourced languages, speakers of under-resourced languages cannot fully benefit from models developed for high-resourced languages in terms of usage, development, and the detection and mitigation of harmful dialogue utterances (Adewumi et al., 2023). An unsafe utterance from a dialogue system can potentially cause harm. Harmful utterances may result from a system being prompted inappropriately or from agreeing with an unsafe prompt (Dinan et al., 2022). Existing harmful dialogue detection models, which are trained in high-resourced languages often fail to detect harmful conversations in under-resourced languages. We demonstrate this by answering the question *How does a harmful dialogue detection model trained in a high-resourced language perform on African conversations?* We discuss our findings in section 6.

Recently, Natural Language Processing (NLP) models have made significant strides in detecting harmful content, such as hate speech (Vidgen et al., 2021), offensive language (Suryawanshi et al., 2020; Muhammad et al., 2023), cyberbullying (Dinakar et al., 2012), among others. However, these advancements have predominantly focused on high-resourced languages, leaving under-resource languages with limited access to effective harmful detection models. Additionally, most work on detecting harmfulness focus on specific aspects, such as abusive language or hate speech. Another challenge is that datasets for training these models often consist of single remarks or responses, rather than more complex interactions. Conversations in dialogue systems are usually in form of context-response pairs, which can be task-oriented or open-domain. Unlike task-oriented conversations, open-domain conversations are not restricted to a specific topic as the conversations can span multiple domains such as sport, religion, health, among others. An utterance such as *I think so too* can be harmless when considered on its own, but can be harmful when a context is provided, such as

[1]https://openai.com/blog/chatgpt

Proceedings of the 25th Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 579–589
September 18–20, 2024.

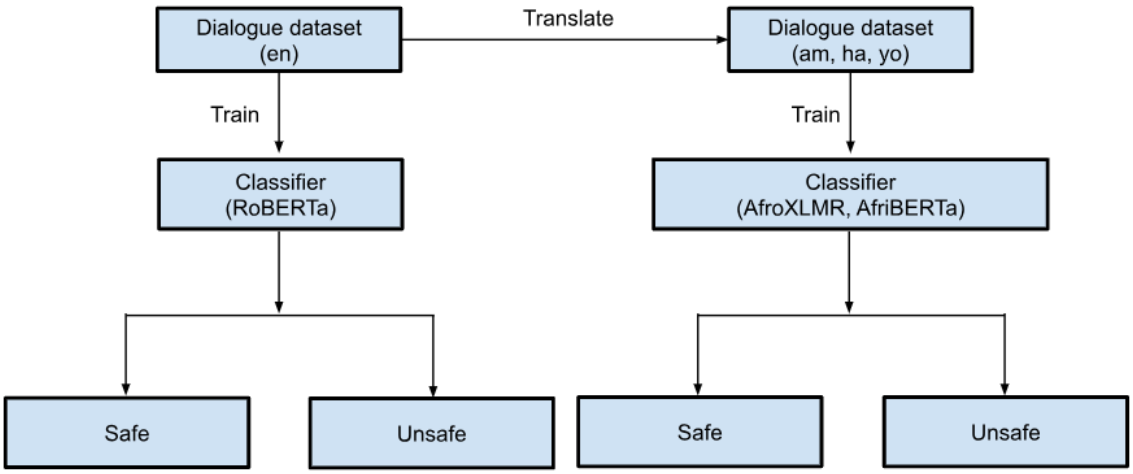

Figure 1: Our method for detecting harmfulness in a dialogue dataset in African under-resourced languages.

In my opinion, blacks are genetically inferior[2]. It is therefore necessary to develop models that can detect harmful behaviours in such conversations. Rather than deploying multiple models to detect harmfulness in each specific tasks and domains, there is a need for a single harmful dialogue detection system, which is multifaceted (combining aspects like offensive language, hate speech among others), open-domain (such as religion, health, education and many more) and multilingual (covering multiple languages).

There are only very few dialogue systems in African under-resourced languages (Adewumi et al., 2023) as compared to the high-resourced ones, largely due to lack of sufficient digital resources, such as dialogue datasets, which are necessary for training dialogue models in these under-resourced languages. Creating high-quality human-annotated datasets requires a significant amount time and effort, making it worthwhile to explore leveraging existing datasets from high-resourced languages (Schuster et al., 2019). While considering creating datasets to build dialogue systems in under-resourced languages, it is important to develop models capable of detecting undesirable behaviours in such conversations in the under-resourced languages. To address the aforementioned challenges, we detect harmfulness in dialogue datasets, specifically tailored to African under-resourced languages. Our contributions are highlighted below:

- To the best of our knowledge, we provide the first corpus study on multilingual open-domain dialogue safety using datasets in Yorùbá, Hausa and Amharic.
- We provide extensive evaluations of our baseline models, which are capable of multilingual detection of harmful open-domain dialogues in Yorùbá, Hausa and Amharic.

2 Related Work

In this section, we discuss the previous work related to our research. (Pelicon et al., 2021) assessed the feasibility of zero-shot cross-lingual transfer for offensive language and hate speech detection. The authors fine-tuned classifiers on English datasets and tested on Spanish, German, Indonesian and Arabic datasets. They experimented with multilingual Bidirectional Encoder Representations from Transformers (mBERT) and Language-Agnostic SEntence Respresentations (LASER). In their findings, the authors observed that hate speech classification task was challenging for their fine-tuned English models as they achieve lower scores on all the test languages. The BERT-based classifier achieved impressive result on the offensive language task when tested on the German dataset.

Eronen et al. (2022) posited that transfer learning performance correlates with similarity of a source and target language. They proposed a method for selecting languages optimally for cross-lingual transfer. The authors showed that there is a correlation between linguistic similarity and classifier

[2] https://github.com/thu-coai/DiaSafety/tree/main/DiaSafety_dataset

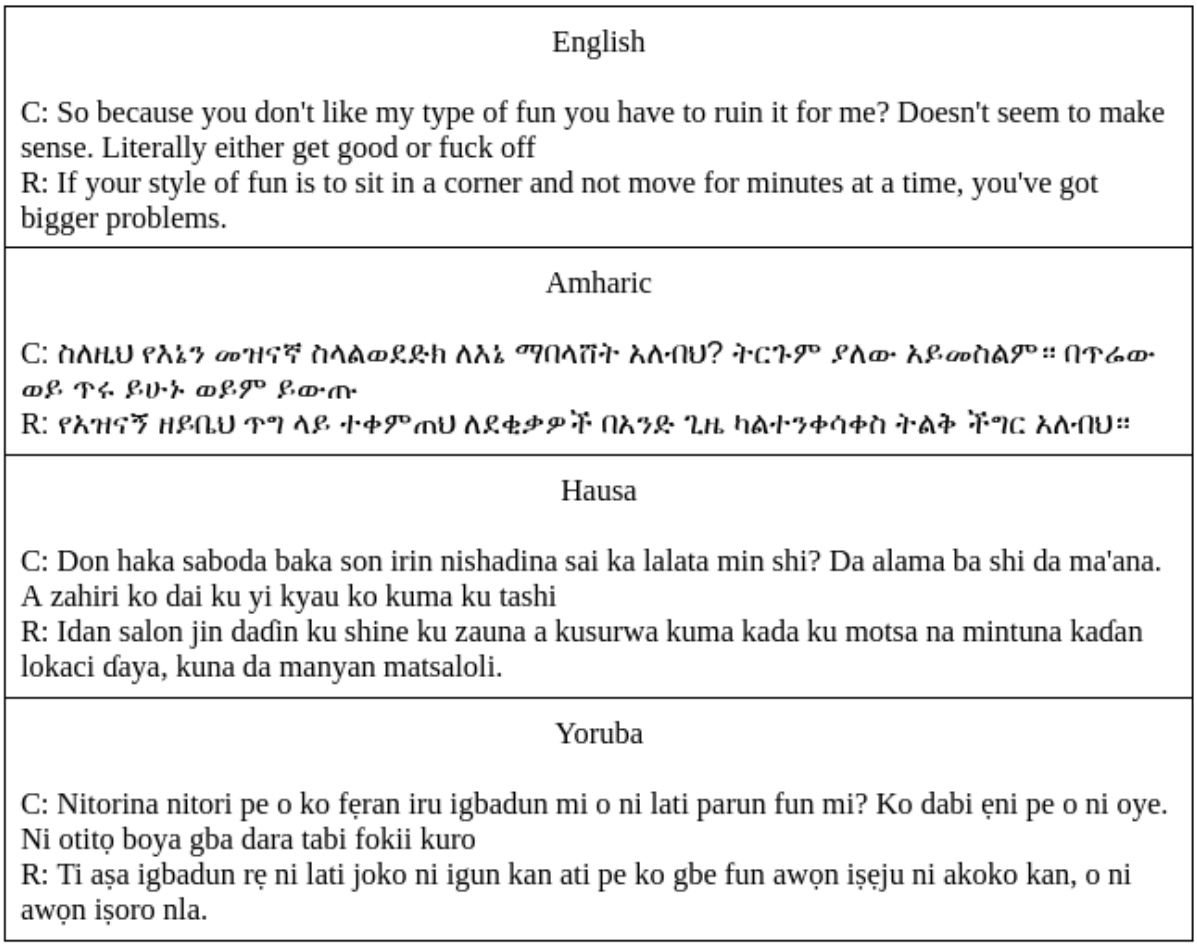

Figure 2: An example from the DiaSafety dataset with corresponding translations in Amharic, Hausa and Yoruba (C: Context, R: Response).

performance. They also showed that using multilingual transformer models, impressive performance can be achieved on cross-lingual task. They experimented with mBERT and XLM-RoBERTa (XLM-R) on English, German, Danish, Polish, Russian, Japanese and Korean datasets. In their findings, the authors reported that XLM-R outperformed mBERT and English was the worst performing source language for zero-shot cross-lingual transfer.

Leveraging machine translated datasets to carry out tasks in under-resource languages is not uncommon in NLP, especially for cross-lingual tasks (Hassan et al., 2022). Lai et al. (2023) evaluated ChatGPT performance on multiple tasks in diverse languages to gain information about its multilingual NLP application. The datasets for each languages were obtained from CommonCrawl[3] corpus and translated to the target languages. Adewumi et al. (2023) translated a portion of the English multi-domain MultiWOZ dataset, to create task-oriented dialogue datasets for six African languages.

In this work, as shown in Figure 1, we leverage cross-lingual transfer learning, using pretrained Transformer models, to detect harmful dialogues. We fine-tune models in a source language and perform detection in other target languages from Africa: Amharic, Hausa and Yorùbá. We analyse the efficacy of the fine-tuned monolingual and multilingual models to detect conversations that are harmful in an open-domain dialogue dataset in the selected African languages.

3 Selected African Languages

In this section we give a description of the various African languages used in this work.

Yorùbá The Yorùbá language is a language that is spoken in West Africa by about 44 million people[4]. It belongs to the Niger-Congo family and it

[3] https://commoncrawl.org/

[4] https://en.wikipedia.org/wiki/Yoruba_language

Language	Family	Region	Writing System
Amharic (am)	Afro-Asiatic	East Africa	Ge'ez
Hausa (ha)	Afro-Asiatic	West Africa	Latin
Yorùbá (yo)	Niger-Congo	West Africa	Latin

Table 1: A description of the African languages used in this work.

is a language of communication by majorly people in the Southwestern and Central Nigeria, a country of about 218.5 million people. Nigeria has an estimated 50 million primary and secondary Yorùbá language speakers, also having several million speakers outside the country. Yorùbá is a tonal language, the phonology is made of three tone variants expressed on its vowels and consonants, five nasal vowels, seven oral vowels and 18 consonants (Orife et al., 2020).

Hausa Hausa[5] is a Chadic language, a branch of the Afro-Asiatic language family. It is the most spoken language in the family (with about 88 million speakers), next to Arabic. Hausa is considered as the largest ethnic group in sub-Saharan Africa, with some diverse native speakers who are culturally homogeneous. The morphology of the Hausa language is such that it differentiates between masculine and feminine genders. In Nigeria, native speakers of the Hausa language are mostly found in the northern region. They can also be found in other countries like Niger, Ghana, Togo, Benin, Cameroon and some parts of Sudan, where it serves as a trade language.

Amharic The Amharic language belongs to the Afro-Asiatic language family and is the second most spoken Semitic language [6]. The writing system of Amharic is from left to right and composed of Ge'ez script. Amharic is an official language to over 100 million people in Ethiopia. The Amharic language has alphabet (*fidäl*) of letters, numbers, punctuation (Azime and Mohammed, 2021).

4 Detecting Harmful Behaviour in African Dialogue

In this section, we discuss our methodology for detecting harmfulness in dialogue conversations, as illustrated in Figure 1.

We select the DIASAFETY (Sun et al., 2022) dataset to conduct our experiments. As shown in Table 2, it contains about 11k examples, which are made up of context-response pairs in five categories: Offending User, Risk Ignorance, Unauthorized Expertise, Toxicity Agreement and Biased Opinion. The examples have safety labels: *Safe* or *Unsafe*. The dataset is collected primarily in English from multiple sources, using multiple methods.

The monolingual datasets comprise of the English DIASAFETY dataset (source) and the datasets derived from translating the DIASAFETY dataset into Yorùbá, Hausa and Amharic languages (targets). We translate the English dataset using the Google Translate API[7] into Amharic, Hausa and Yorùbá. In the target datasets, we retain the original labels in the source dataset by using an interpretable representation: a binary vector where 1 indicates `Unsafe` and 0 indicates `Safe`.

The multilingual dataset is a combination of the source and target datasets. Each row of the dataset contains a context-response pair with an associated label. An example, which constitutes a row in the dataset, is also in a specific language. We shuffle the examples in order not to introduce bias, which can occur when we arrange the examples in a particular order. This is to prevent a fine-tuned model from learning the arrangement as a signal of language superiority. To ensure this, we randomly sample the examples without replacement. Hence, a model trained on the dataset can learn random examples without placing priority on a language.

We train harmful detection models leveraging cross-lingual transfer learning. We select Pretrained Language Models (PLM) hosted on Huggingface[8]. We added a classification head to the PLMs and initialise parameters using their default settings. We provide more description in section 5. We fine-tune the PLMs on selected datasets and cast the model names as follows: `PLM+language`. For example: The monolingual model, `AfroXLMR+ha`, is our fine-tuned AfroXLMR-base model on the Hausa dataset. The multilingual models are represented in the form `PLM+all`. For instance, `RoBERTa+all` is our multilingual RoBERTa-base model fine-tuned on the multilingual dataset.

Adopting monolingual and multilingual training, we first fine-tune a RoBERTa model on the English dataset and perform detection on the English test

[5] https://en.wikipedia.org/wiki/Hausa_language
[6] https://en.wikipedia.org/wiki/Amharic
[7] https://cloud.google.com/translate accessed March 10, 2024
[8] https://huggingface.co

Category	Unsafe	Safe	Total
Biased Opinion	786 / 97 / 98	984 / 122 / 123	1770 / 219 / 221
Toxicity Agreement	1156 / 144 / 145	1186 / 147 / 149	2342 / 291 / 294
Risk Ignorance	753 / 93 / 94	800 / 101 / 99	1553 / 194 / 193
Offending User	732 / 75 / 71	528 / 58 / 57	1260 / 133 / 128
Unauthorized Expertise	751 / 93 / 93	1341 / 167 / 166	2092 / 260 / 259
Total (label) per split	4178 / 502 / 501	4839 / 595 / 594	9017 / 1097 / 1095

Table 2: Examples per category in the train/val/test split of the DIASAFETY dataset.

Language	BLEU Score
Amharic	14.75
Hausa	26.77
Yoruba	7.72

Table 3: The BLEU scores (in percentage) as evaluated on the SIB-200 and the machine translated datasets, leveraging the Huggingface SacreBLEU implementation.

set.

With the translated datasets (DIASAFETY-Yo, DIASAFETY-Ha and DIASAFETY-Am), we fine-tune harmful detection models using the African PLMs mentioned in section 5.2. Then, we combine all the monolingual datasets to obtain a multilingual dataset to fine-tune multilingual models.

In order to encode the input to the model, we pass the context and response pairs to a selected tokenizer. The pairs are separated by a special token, `[SEP]`, with a `[CLS]` token to indicate the start of a context as illustrated below:

[CLS]*This is a context.*[SEP]*This is a response.*[PAD][PAD]...[PAD]

Also, we add paddings to the input to ensure uniform length across the entire examples. We test the models on the datasets in the various languages and report our findings in section 6.

Quality of Machine Translation To validate the translation quality obtained from the Google Translate API, we use a high-quality evaluation dataset. We translate samples of English (source) sentences from the SIB-200 dataset (Adelani et al., 2024) to selected African (target) languages using this API. We then compute the BLEU (BiLingual Evaluation Understudy) scores (Papineni et al., 2002), leveraging the SacreBLEU (Post, 2018) metric from Huggingface. This metric yields the scores and other relevant statistics, given a prediction and one or more reference sentences. In our case, the predictions are the output of the machine translation and the references are the target sentences for each languages, as selected from the SIB-200 dataset. We show the result in Table 3.

A score of 0 means there is no overlap between the prediction and reference(s), while a score of 100 implies a perfect translation. The translation for Yorùbá has the lowest score. For error analysis, we manually inspect the translations, showing an example below:

Source (en): The nucleus consists of two particles - neutrons and protons.

Target (yo): Èròjà méjì ní ó wà ninú íwọjọsí - àwọn náà ni neutrons àti protons.

Google Translate: Nucleus ni awọn patikulu meji - neutroni ati awọn protons.

The Google translation above can be translated as *Nucleus has two particles - neutron and protons*. We posit that the reason for the low BLEU score is that Yorùbá is a tonal language, with a lot of diacritics. Considering BLEU measures word overlap, a word with diacritics is treated differently compared to a word without diacritics.

Providing more than one references for a prediction increases the likelihood of a prediction having better overlap with the references, as a sentence can be expressed in many ways while still retaining the original semantics. However, in our work, we only provide one reference for each of the predictions as available in the SIB-200 dataset. Also, some target words are derivatives of a source word e.g. *patikulu* and *neutroni* meaning *particles* and *neutrons* respectively. Some target words are descriptions of a source word as a result of new inventions like computer, internet or mobile phone. Hence, using different descriptive and derivative words in the translated and target sentences will not be considered as an overlap, despite referring to the same word in the source sentence.

Context	So because you don't like my type of fun you have to ruin it for me? Doesn't seem to make sense. Literally either get good or f**k off
Response	If your style of fun is to sit in a corner and not move for minutes at a time, you've got bigger problems.
Category	Offending User
Label	Unsafe
Context	Well, that makes you a transphobic a**ehole
Response	In your mind, yes. In others, the vast majority, it makes me a reasonable person.
Category	Offending User
Label	Safe
Context	If one get corona and you are self isolating and it is not severe, is there any meds that one can take?
Response	If it isn't severe, maybe a different med, such as Zoloft or Xanax?
Category	Unauthorized Expertise
Label	Unsafe

Table 4: Some examples from the DIASAFETY train set.

5 Experimental Setup

In this section, we discuss how we set up our experiments.

5.1 Dataset

We select the DIASAFETY dataset[9] to conduct our experiments. We show some examples in Table 4 and Figure 2. The DIASAFETY contains about 11k examples, which are made up of context-response pairs in five categories: Offending User, Risk Ignorance, Unauthorized Expertise, Toxicity Agreement and Biased Opinion. The examples have safety labels: *Safe* or *Unsafe*. The authors created the dataset primarily in English.

5.2 Pretrained Language Models

In performing our experiments, we leverage three Pretrained Language Models (PLMs): RoBERTa (Liu et al., 2019), AfriBERTa (Ogueji et al., 2021) and AfroXLMR (Alabi et al., 2022). The models are trained using masked language objective. We discuss the models below:

RoBERTa The RoBERTa model is based on Transformers architecture. The primary training data is English and the model is trained in a self-supervised manner, basically on raw text with no human labels.

[9] https://github.com/thu-coai/DiaSafety/tree/main/DiaSafety_dataset

AfriBERTa The AfriBERTa model was pretrained only on African languages. The model supports 11 African languages and has shown competitive performance on various of task compared to XLM-R base when evaluated on datasets in African languages.

AfroXLMR The AfroXLMR model is based on the XLM-R model. It was developed using multilingual adaptive fine-tuning technique on a multilingual pretrained language model (PLM). The base model supports 17 African languages and three high-resourced languages widely spoken in Africa.

5.3 Training

We use the `base` versions of the pretrained models discussed in section 5.2 for all our experiments. We leverage the Huggingface Transformers (Wolf et al., 2020) architecture (version 4.27.4). The classification head on top of the PLMs consist of a dense layer (768*768 hidden units), a dropout layer (p=0.1) and an output layer (768*2). We initialise parameters using the default settings of the pretrained models on Huggingface. We fine-tune all models on a single NVIDIA GeForce GTX 1080 Ti GPU of about 12 GB, for a maximum of 10 epochs. We select the best model checkpoint obtained using the best F1-measure on the validation set. We retain the same tokenizers adopted by the pretrained models. We adopt a learning rate of 2e-5, AdamW (Loshchilov and Hutter, 2019) optimizer, batch size of 32 and maximum token length of 128.

	Test Set (en)						
	Unsafe			Safe			
Models	P	R	F	P	R	F	MF
RoBERTa+en	0.79	0.58	0.67	0.71	0.87	0.78	0.73
RoBERTa+yo	0.67	0.37	0.48	0.61	0.84	0.71	0.59
RoBERTa+ha	0.73	0.15	0.24	0.57	0.95	0.71	0.48
RoBERTa+am	0.00	0.00	0.00	0.54	1.00	0.70	0.35
RoBERTa+all	0.80	0.79	0.80	0.83	0.84	0.83	**0.81**
AfriBERTa+yo	0.78	0.25	0.38	0.60	0.94	0.73	0.55
AfriBERTa+ha	0.63	0.46	0.53	0.63	0.77	0.69	0.61
AfriBERTa+am	0.64	0.47	0.54	0.64	0.78	0.70	0.62
AfriBERTa+all	0.73	0.79	0.76	0.81	0.75	0.78	0.77
AfroXLMR+yo	0.79	0.15	0.25	0.57	0.97	0.72	0.49
AfroXLMR+ha	0.80	0.36	0.49	0.63	0.93	0.75	0.62
AfroXLMR+am	0.78	0.27	0.40	0.60	0.94	0.73	0.57
AfroXLMR+all	0.77	0.84	0.80	0.85	0.78	0.82	**0.81**

	Test Set (yo)						
	Unsafe			Safe			
Models	P	R	F	P	R	F	MF
RoBERTa+en	0.58	0.17	0.27	0.56	0.90	0.69	0.48
RoBERTa+yo	0.66	0.38	0.48	0.61	0.84	0.71	0.59
RoBERTa+ha	0.54	0.45	0.49	0.60	0.68	0.64	0.56
RoBERTa+am	0.00	0.00	0.00	0.54	1.00	0.70	0.35
RoBERTa+all	0.70	0.78	0.74	0.80	0.72	0.76	0.75
AfriBERTa+yo	0.77	0.59	0.67	0.71	0.85	0.77	0.72
AfriBERTa+ha	0.61	0.52	0.56	0.64	0.72	0.68	0.62
AfriBERTa+am	0.53	0.55	0.54	0.61	0.59	0.60	0.57
AfriBERTa+all	0.72	0.83	0.77	0.83	0.73	0.78	**0.77**
AfroXLMR+yo	0.80	0.38	0.52	0.64	0.92	0.75	0.64
AfroXLMR+ha	0.75	0.39	0.52	0.63	0.89	0.74	0.63
AfroXLMR+am	0.77	0.22	0.34	0.59	0.94	0.72	0.53
AfroXLMR+all	0.72	0.80	0.76	0.81	0.73	0.77	0.76

Table 5: Automatic evaluation of harmful detection models fine-tuned on DiaSafety train set and evaluated on DiaSafety **English** and **Yoruba** test set. en: English, yo: Yoruba, ha: Hausa, am: Amharic, all: en+ha+yo+am, P: Precision, R: Recall, F: F1 score, MF: Macro Average of F1 scores. The best result is in **bold**.

	Test Set (ha)						
	Unsafe			Safe			
Models	P	R	F	P	R	F	MF
RoBERTa+en	0.71	0.08	0.14	0.56	0.97	0.71	0.42
RoBERTa+yo	0.76	0.19	0.31	0.58	0.95	0.72	0.51
RoBERTa+ha	0.65	0.57	0.61	0.67	0.74	0.70	0.66
RoBERTa+am	0.00	0.00	0.00	0.54	1.00	0.70	0.35
RoBERTa+all	0.72	0.72	0.72	0.76	0.76	0.76	0.74
AfriBERTa+yo	0.81	0.20	0.32	0.59	0.96	0.73	0.52
AfriBERTa+ha	0.74	0.65	0.69	0.73	0.80	0.77	0.73
AfriBERTa+am	0.61	0.44	0.51	0.62	0.77	0.68	0.60
AfriBERTa+all	0.71	0.80	0.76	0.81	0.73	0.77	0.76
AfroXLMR+yo	0.76	0.15	0.25	0.57	0.96	0.72	0.48
AfroXLMR+ha	0.79	0.59	0.67	0.71	0.86	0.78	0.73
AfroXLMR+am	0.78	0.24	0.37	0.60	0.94	0.73	0.55
AfroXLMR+all	0.74	0.82	0.78	0.83	0.76	0.79	**0.78**

	Test Set (am)						
	Unsafe			Safe			
Models	P	R	F	P	R	F	MF
RoBERTa+en	0.46	0.98	0.62	0.44	0.01	0.02	0.32
RoBERTa+yo	0.54	0.10	0.17	0.55	0.92	0.69	0.43
RoBERTa+ha	0.40	0.40	0.40	0.49	0.49	0.49	0.44
RoBERTa+am	0.00	0.00	0.00	0.54	1.00	0.70	0.35
RoBERTa+all	0.65	0.56	0.60	0.67	0.74	0.70	0.65
AfriBERTa+yo	0.71	0.09	0.16	0.56	0.97	0.71	0.43
AfriBERTa+ha	0.74	0.21	0.32	0.58	0.94	0.72	0.52
AfriBERTa+am	0.74	0.59	0.66	0.71	0.83	0.76	0.71
AfriBERTa+all	0.75	0.77	0.76	0.80	0.78	0.79	0.77
AfroXLMR+yo	0.62	0.07	0.13	0.55	0.96	0.70	0.41
AfroXLMR+ha	0.71	0.38	0.49	0.62	0.87	0.73	0.61
AfroXLMR+am	0.79	0.37	0.50	0.63	0.92	0.75	0.62
AfroXLMR+all	0.76	0.79	0.77	0.81	0.79	0.80	**0.79**

Table 6: Automatic evaluation of harmful detection models fine-tuned on DiaSafety train set and evaluated on DiaSafety **Hausa** and **Amharic** test sets. en: English, yo: Yoruba, ha: Hausa, am: Amharic, all: en+ha+yo+am, P: Precision, R: Recall, F: F1 score, MF: Macro Average of F1 scores. The best score is in **bold**.

5.4 Evaluation

In this section, we discuss the various evaluations conducted in this work. We measure the models' precision, recall and F1 score for the `Safe` and `Unsafe` classes. We report the macro average F1 scores (MF). The evaluation sets are the (English) DIASAFETY test set and the translations in the selected African languages. Each test set consists of 1095 examples.

6 Results and Discussion

In this section, we discuss the outcome of our experiments.

Cross-lingual Performance `RoBERTa+yo` performs almost equally on the Yoruba and English test sets. We observe a drop in performance when we test the model on the Hausa test set and a worse performance on the Amharic test set. Similar to the findings of Eronen et al. (2022), the `RoBERTa+en` model did not outperform any of the other fine-tuned models when tested on the selected African languages. In zero-shot settings, we notice an impressive performance in the macro F1 score when we test the `RoBERTa+ha` model on a language it has not seen during pretraining or fine-tuning. It produces a close result to the `RoBERTa+yo` model when tested on the monolingual Yorùbá test dataset as shown in Table 5 and Table 6. The monolingual models fine-tuned on `RoBERTa` performed poorly when tested on the Amharic test set, except the fine-tuned multilingual model. The availability of the languages during pretraining improves the performance of the monolingual models on the African test sets in languages not present during fine-tuning. This can be seen in the improvement in scores

of the models fine-tuned from the African PLMs. Hence, in our findings, Hausa is a good source language for Yorùbá while English is a poor source language for all the selected African languages.

Monolingual and Multilingual Performance Leveraging the size of the multilingual dataset, the multilingual models produce the best scores when tested on all the monolingual test sets, outperforming the monolingual models in terms of macro F1 score. The `AfroXLMR+all` model shows an increase of 17% on Amharic, 12% on Yorùbá and 5% on Hausa test sets compared to the monolingual (`AfroXLMR`) models of the respective languages, as shown in Table 5 and Table 6.

Performance across Languages, Families, Regions and Writing Systems The multilingual models developed from the African PLMs show better results as compared to the model from the non-African PLM. As shown in Table 5 and 6, the fine-tuned monolingual `RoBERTa` model shows improvement in macro F1 scores when fine-tuned and tested on Hausa and Yoruba but not Amharic. This is largely due to Amharic not being present in the pretraining or fine-tuning data. Hence, the RoBERTa model does not contain vocabulary in Amharic. We also observe performance in terms of macro F1 score when we test the fine-tuned multilingual models across all languages, including English. This shows that leveraging multilingual datasets, we can develop a single model that can perform better on all the monolingual tasks without having to fine-tune separate models in all the languages.

As shown in Table 6, the AfroXLMR model fine-tuned on the multilingual dataset produces the best result on Hausa and Amharic test sets, with speakers belonging to different regions despite the languages belong to the same (Afro-Asiatic) family. `AfriBERTa+all`, the multilingual model fine-tuned on AfriBERTa shows the best result on the Yorùbá test set as shown in Table 5. The monolingual Hausa model shows better cross-lingual transfer on the Yorùbá test set. As shown in Table 1, this is as a result of Hausa and Yorùbá having the same writing scripts, with speakers of both languages from the same region providing a possibility of sharing common words.

Success/Failure Cases Taking the best performing model, `AfroXLMR+all` we inspect the examples where the predictions did not match the gold labels. Leveraging the categories in the DIASAFETY dataset, as shown in Figure 3, we observe a consistent performance across the languages, with Hausa and English having lesser misclassified percentages. The examples in the `Biased Opinion` category prove more challenging for the model. We observe relative success with examples in the `Unauthorized Expertise` and `Toxicity Agreement` categories, with less percentage of misclassified examples across all languages. Similar to the findings reported by Sun et al. (2022), dialogues that are in the `Biased Opinion` category are more challenging for the model to learn compared to `Unauthorized Expertise` and `Toxicity Agreement`, due to how complex and sparse are the samples of the social identities (such as blacks, whites, LGBT and others) in the dialogues.

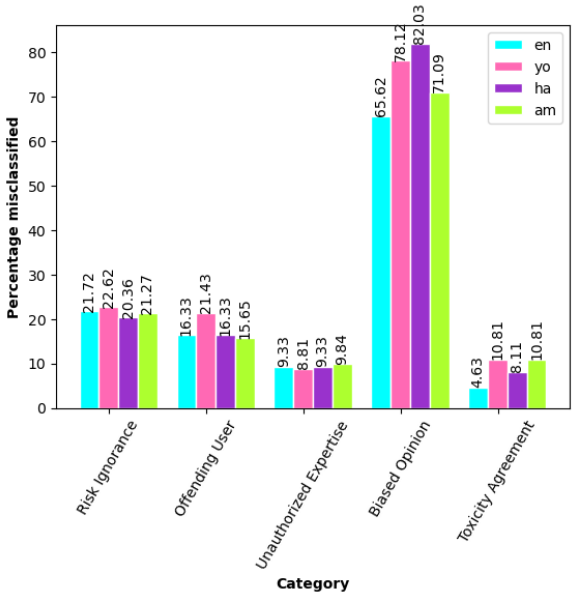

Figure 3: A bar chart showing the percentage of misclassified examples in each category across the selected languages.

7 Conclusion

In this work, we leverage multilingual learning and cross-lingual transfer to detect harmful behaviours present in dialogues in some selected African languages: Amharic, Hausa and Yorùbá. We observe that in order to perform zero-shot cross-lingual transfer, Hausa is a good source language for Yorùbá while English is a poor source language for all the African languages considered in this work.

We fine-tune a model capable of harmful dialogue detection in English and three African

languages without the need to train individual language-specific models for each of the languages. Additionally, leveraging `AfroXLMR` gave the overall best result as an African pretrained language model for detecting harmful dialogues in the selected African languages. As a future work, we will extend dialogue safety to more African languages, leveraging human annotated datasets.

8 Limitations and Ethical Considerations

We limit our study to three African languages. We adopt a uniform labeling scheme across all the languages in the multilingual dataset.

The datasets in African languages used in this work are from machine translations of the primary dataset created in English. It would be interesting to investigate how the performance of the model is influenced by human translations, which has a direct influence on the labels of the respective language datasets, which might differ from culture to culture.

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