# UIO at SemEval-2023 Task 12: Multilingual fine-tuning for sentiment classification in low-resource languages

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#### Abstract

Our contribution to the 2023 AfriSenti-SemEval shared task 12: Sentiment Analysis for African Languages, provides insight into how a multilingual large language model can be a resource for sentiment analysis in languages not seen during pretraining. The shared task provides datasets of a variety of African languages from different language families. The languages are to various degrees related to languages used during pretraining, and the language data contain various degrees of codeswitching. We experiment with both monolingual and multilingual datasets for the final finetuning, and find that with the provided datasets that contain samples in the thousands, monolingual fine-tuning yields the best results.

### 1 Introduction

The 2023 AfriSenti-SemEval Shared Task 12 is the first SemEval shared task for sentiment analysis, targeting African low-resource languages (Muhammad et al., 2023b). It aims to raise awareness for the need of annotated data in languages that receive little attention when it comes to building AI tools for the digital world.

The task is, for each tweet in the dataset, to classify them correctly as conveying a negative, neutral or positive sentiment. This task of classifying sentiment category for microblog statements or individual sentences is a useful component in various Natural Language Processing (NLP) tasks. The problem is well researched for English, where similar tasks are modelled with more than 97% accuracy.<sup>1</sup>

The shared task at hand is split in subtask A, B and C, where subtask A provides training data for 12 African languages, and subtask B provides a joint, multilingual train set for the same languages.

<sup>1</sup>https://paperswithcode.com/task/ sentiment-analysis We did not participate in subtask C which provided test data in two languages for Zero-shot inference.

Our work shares insight to the effect of finetuning a multilingual large language model (llm), for languages not seen during pretraining. We compare the performance of the resulting model with its exposure to similar languages during the various steps of training and fine-tuning. We find that models fine-tuned on larger training sets, and models fine-tuned on languages close to those seen during pretraining and initial fine-tuning, perform the best. We found the "XLM-Twitter-sentiment" model presented in Section 3 to be the best starting point according to our constraints. This model is both adapted to multilingual Twitter data in pretraining, and is initially fine-tuned to sentiment classification on a multilingual Twitter sentiment classification dataset.

We fine-tuned this model on the provided monolingual data, and compared this with alternative models fine-tuned on the the multilingual dataset containing all 12 languages, and also models trained on a concatenation of the training data for the languages in the same language family. This work is presented in Section 5. We found that for the given resources in this task, monolingual finetuning yielded overall best results.

# 2 Background

Sentiment analysis provides insight into opinions and moods held in the population that the authors of the texts represent (Agarwal et al., 2011; Liu, 2017). It may also be an embedded part of a Natural Language Processing (NLP) pipeline, where the end result may be, *e.g.*, a dialogue system or an analysis of customer satisfaction. Sentiment analysis can be performed on various levels, and classifying texts into the categories of "positive", "neutral" or "negative" is not particularly fine-grained. However, this granularity can be modelled with high accuracy, in particular for well-resourced languages. Short texts like Twitter-messages are relatively easy to classify as they are often times opinionated, and may often express only one sentiment.

# 2.1 Previous multilingual sentiment analysis tasks

There has been a number of shared sentiment analysis tasks at SemEval earlier. The data have mainly been on the major languages of the world, and on various European languages. Three recent examples are:

- SemEval 2022 Task 10: Structures sentiment analysis, utilizing Norwegian, Basque, Catalan, Spanish and English data
- SemEval 2020 Task9: SentiMix, English-Hindi and English-Spanish code-mixed data
- SemEval 2017 Task 4: Sentiment Analysis in Twitter, Arabic and English

# **3** Pretrained language models

Fine-tuning an already pretrained llm can be seen as the de-facto standard approach to NLP tasks of sentiment analysis. We decided to search for one multilingual llm that could provide good results for all languages in the competition. We have experienced models based on xlm-Roberta (XLM-R) by Conneau et al. (2020) to be a good starting point for multilingual sentiment analysis. For the low-resource languages in the shared task, we are not aware of any single model that is pretrained on all the languages in the competition, but the AfroXLMR (Alabi et al., 2022) is pretrained on a majority of the included languages. As far as we understand, Hausa, Amharic, Arabic, Swahili and Portugese were present in the training data for both XLM-R and AfroXLMR. Yoruba, Igbo and Kinyarwanda were present in the pretraining of AfroXLMR, but not in XLM-R.

As llms may suffer not only from language barriers, but also from domain barriers (Aue and Gamon, 2005), we found a recent version of XLM-R to be of particular interest; the **XLM-Twitter** (XLM-T) model by Barbieri et al. (2022). The model is a result of further pretraining of XLM-R models on twitter data (198M tweets, 12G of uncompressed text). The twitter data were not filtered according to language. English, Portugese and Arabic are all among the top four best represented languages. Amharic is within the top 30 best represented languages in their additional pretraining

on Twitter data. Further details on this model are presented in Section 5.1, where we also present the **XLM-Twitter-sentiment**  $(XLMT-sentiment)^2$  model which comes already fine-tuned on a multi-lingual Twitter sentiment dataset.

We included an **mpnet-model** (Reimers and Gurevych, 2019) for comparison, since we consider the concept of sentence-transformers to be relevant to this task. Its performance was on par with the competition for some languages, and is an interesting approach worthy of further studies. The model was the best for Nigerian Pidgin, but had not strong enough overall performance across the languages.

The above mentioned models were fine-tuned and evaluated on the shared task data for each language in subtask A. The results are reported in Table 1, and we decided to use the XLMT-sentiment model as the pretrained llm for all our further experiments.

# 4 Dataset

We trained our model on only the data provided by the shared task. The twelve languages in the training dataset are represented with annotated tweets counting from 804 to 14172 in the training split, as can be seen in Table 2. The dataset by Muhammad et al. (2023a) builds on the work of Muhammad et al. (2022) and Yimam et al. (2020). The dataset includes two Creole languages, Nigerian Pidgin and Mozambican Portuguese, and two arabic languages, Algerian Arabic and Moroccan Arabic / Darija. In addition there is an amount of codeswitching in the data (Muhammad et al., 2022). The languages have therefore various levels of similarity, shared vocabulary or closeness to larger languages that our llm was pretrained on.

In addition to the training data for each language, the task includes a pre-shuffled dataset containing data from all the individual language datasets, for the multilingual Task B.

# 5 Our submission

Our self-imposed constraints on the experiments have been:

- Use no language data outside the provided datasets
- Use no pretrained llm larger than "base" size

<sup>2</sup>cardiffnlp/twitter-xlm-roberta-base-sentiment

Model Language	afro-xlmr- mini	mpnet- base-v2	XLM-Twitter- base	XLMT-sentiment- base
Amharic	58.5%	45.0%	58.5%	63.5%
Algerian Arabic	64.0%	57.5%	66.5%	68.0%
Hausa	74.5%	71.5%	75.0%	71.5%
Igbo	74.0%	72.5%	74.5%	75.0%
Kinyarwanda	60.0%	59.0%	63.5%	63.0%
Moroccan Arabic(Darija),	75.5%	70.0%	81.5%	78.0%
Nigerian Pidgin	72.0%	78.0%	77.0%	74.0%
Mozambican Portuguese	62.0%	59.5%	72.0%	70.0%
Swahili	57.0%	57.5%	58.5%	58.5%
Xitsonga	49.5%	47.5%	55.0%	58.5%
Twi	62.0%	65.0%	65.5%	68.0%
Yoruba	73.5%	74.0%	79.0%	75.5%
Mean	65.2%	63.1%	68.9%	68.6%
Lowest	49.5%	45.0%	55.0%	58.5%

Table 1: Initial results  $(F_1)$  from fine-tuning four pretrained llms on each language individually, and testing on a dev split created from the initial training data. Although XLM-Twitter had the highest average scores, we chose XLMT-sentiment for our contribution, since it was noticeably better on the weakest language.

Symbol	Language	Family	Train
am	Amharic	Afro-Asiatic, Semitic, South, Ethiopian	5984
dz	Algerian Arabic	Afro-Asiatic, Semitic, Arabic	1651
ha	Hausa	Afro-Asiatic, Chadic, West	14172
ig	Igbo	Niger-Congo, Atlantic-Congo, Volta-Congo	10192
kr	Kinyarwanda	Niger-Congo, Atlantic-Congo, Volta-Congo	3302
ma	Moroccan Arabic / Darija,	Afro-Asiatic, Semitic, Arabic	5583
pcm	Nigerian Pidgin	Creole, English based	5121
pt	Mozambican Portuguese	Creole, Portuguese based	3063
SW	Swahili	Niger-Congo, Atlantic-Congo, Volta-Congo	1810
ts	Xitsonga	Niger-Congo, Atlantic-Congo, Volta-Congo	804
twi	Twi	Niger-Congo, Atlantic-Congo, Volta-Congo	3481
yo	Yoruba	Niger-Congo, Atlantic-Congo, Volta-Congo	8522

Table 2: The languages in the training dataset, with language families and length of training splits in the dataset. The family classification is our abbreviation of data gathered from the Ethnologue dataset (Ethnologue) and from Wikipedia. This classification is merely a functional grouping to apply to the task at hand, and not assumed to be authoritative.

train-category test-language	in-language	language-cat	multilingual	Comment
MoroccanArabic/Darija,	97.5%	96.2%	96.7%	Arabic
Igbo	78.8%	77.6%	78.5%	Train size
Hausa	77.7%	NA	76.2%	Train size
Yoruba	71.3%	71.4%	70.0%	Train size
Mozambican Portuguese	71.0%	71.0%	68.8%	Portuguese
Algerian Arabic	68.1%	66.4%	61.2%	Arabic
Kinyarwanda	60.9%	57.1%	55.6%	
Amharic	59.9%	56.2%	57.1%	
Twi	58.7%	56.8%	56.7%	
Xitsonga	54.9%	50.1%	45.9%	
Nigerian Pidgin	51.1%	51.8%	50.1%	
Swahili	50.5%	49.4%	46.0%	

Table 3:  $F_1$ -scores from subsequent experiments after submission. The *XLMT-sentiment* model was fine-tuned on either the one language tested only (In-language), the combined training data from the languages in the target model's language family (language-cat), or on the complete multilingual dataset. We find that the best performing models are either trained on the languages with the largest training dataset, or on languages related to languages that were seen both during model pretraining and initial fine-tuning. Best result for each language is printed in boldface.

- No additional pretraining of the llm
- Use the same llm for fine-tuning on all languages

Our experiments have sought to answer two questions:

- a) What pretrained llm can be a good base for sentiment analysis in the provided lowresource languages?
- b) Can we combine data for the provided languages to provide a training set that performs better than the single-language dataset?

**Our answer to question a)** is found in Section 3 and Table 1 where we conclude that XLMT-sentiment is our best model to fine-tune for these languages.

**To answer b)** we test all languages on the model fine-tuned on the multilingual dataset prepared for subtask B. We also create subsets of languages based on language families or classifications. We decide on the subsets of Afro-Asiatic-Semitic, Volta-Congo, and Creole. the groupings were derived from information in the Ethnologue dataset (Ethnologue) and from Wikipedia.<sup>3</sup>. Hausa was the only Chadic language in the training data, and was not evaluated against any language family dataset. Our reasoning for evaluating each language against multilingual training data, is that since some of the languages are poorly related to data used in the pretraining of the llm, more data may be better. But due to the "curse of multilinguality" (Conneau et al., 2020) where it is observed that adding more and more languages comes at a cost, we also speculate that training only on languages within the same language family might help.

During the initial experiments that lead to our choices for the competition submission, we found that only for Swahili did the model perform better when being fine-tuned on the multilingual dataset, than when being fine-tuned on its own language's training data. Our submission for Swahili is therefore based on a model fine-tuned on the multilingual dataset, while for all the other languages, their monolingual datasets were used.

#### 5.1 Our chosen pretrained language model

The XLMT-sentiment language model was introduced in Section 3. The XLMT-sentiment language model was fine-tuned on a dataset for sentiment classification on eight different languages, including Arabic, English and Portugese. Thus, the model was already fine-tuned for the task at hand. Our fine-tuning is therefore a subsequent fine-tuning for the same task, but with data from other languages. Due to resource constraints, we used the base version of all models, no large version. XLMT-

<sup>&</sup>lt;sup>3</sup>https://www.wikipedia.org/

sentiment<sub>base</sub> is, apart from the classification head, a further trained version of XLM-Roberta<sub>base</sub>. The XLM-Roberta models were trained with a Sentence Piece (SPM) tokenizer. A few other details on the architecture are presented in Table 4:

Detail	Value	
Languages	100	
Vocabulary	250K	
Layers	12	
Parameters	270M	

Table 4: A few details on the XLM-Roberta<sub>base</sub> llm (Conneau et al., 2020). This model was further trained and fine-tuned into XLMT-sentiment, the model chosen for our contribution.

#### 5.2 Hyperparmaters for fine-tuning

All fine-tuning experiments are performed with a Huggingface AutoModelForSequenceClassification wrapper around the pretrained llm. For the competition contribution, we concatenated the labelled train- and dev-data for each language and for the multilingual dataset.

The only hyperparameters we searched for, were the amount of epochs to train, within the maximum of seven epochs. The epochs selected for each single-language model were:

dz:7, am:5, yo:6, twi:4, pcm:6,pt:7 ma:7, ha:4, ig:6, ts:5, kr:7

The symbol for each language is found in Table 2. A few other hyperparameters are found in Table 5:

Value	
2e-5	
100	
0.01	
32	

Table 5: A few details on our hyper-parameters for finetuning our llms on the Afrisenti datsets.

#### 5.3 Competition results

Our results in the competition were around average or lower. Taking into account our constraint on llm size and on the fact that no other target language resources were applied, we find the results reasonable. Our code will be available on github.<sup>4</sup>

<sup>4</sup>https://github.com/egilron/ AfriSenti-SemEval-2023

#### 5.4 Subsequent analysis

After our submission to the competition, we re-ran the experiments, fine-tuning on the training split, and evaluating on the labelled development split. Table 3 reports the findings from these experiments, where we allowed the model to train for up to 14 epochs. Under these new conditions we see that Swahili would also benefited from inference on a model fine-tuned on its own training data only.

Table 3 shows that nearly all languages had better results fine-tuning only on their own language. We believe that the fact that virtually all languages hava training samples in the thousands, gives the model enough in-language signal, and that the added data from other languages adds too much noise. This is in line with our earlier findings where we for a lower-resourced language, found that adding related English data was mostly beneficial only when the in-language samples were less than 500 (Rønningstad, 2020).

# 6 Conclusion

We have shown how the *Twitter-xlmr-sentiment* model can be a helpful resource and starting point for sentiment analysis in low-resource languages. We have seen that fine-tuning with a multilingual dataset was in general not helpful for these language data, with training samples in the thousands. A suggestion for further work is to fine-tune models with only ten, or a hundred in-language training samples, and measure the value of adding multilingual data in those few-shot situations.

We have found that best results were achieved for languages that either have the largest training set, or what we assume are languages close to higher resourced languages that have been seen during training and initial fine-tuning. We find that Nigerian Pidgin performed second to worst. We were expecting this language to perform better due to its supposedly relatedness to English. We have not attempted to quantify any language similarities, and have no explanation why Nigerian Pidgin performed so poorly.

# 7 Ethical considerations

In this work we are performing experiments on several low-resource African languages. Our intent is to learn from this language diversity, and contribute towards a stronger digital presence for these languages. This can be viewed as giving people stuff they have not asked for, as we do not know to what degree this is a felt need among the actual language communities. But we also consider all languages to be worth studying and learning from, whether or not this study is of immediate experienced benefit to the language users or not. We are therefore thankful to the organizers for allowing us to work on these languages, and we do not assume that our work is of direct benefit to others than ourselves. We have only conducted work that we ourselves appreciate, when others conduct similar work on our own not-so-highly resourced native language.

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