Sentiment Analysis Across Multiple African Languages: A Current Benchmark

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Abstract

Sentiment analysis is a fundamental and valuable task in NLP. However, due to limitations in data and technological availability, research into sentiment analysis of African languages has been fragmented and lacking. With the recent release of the AfriSenti-SemEval Shared Task 12, hosted as a part of The 17th International Workshop on Semantic Evaluation, an annotated sentiment analysis of 14 African languages was made available. We benchmarked and compared current state-of-art transformer models across 12 languages and compared the performance of training one-model-per-language versus single-model-all-languages. We also evaluated the performance of standard multilingual models and their ability to learn and transfer cross-lingual representation from non-African to African languages. Our results show that despite work in low resource modeling, more data still produces better models on a per-language basis. Models explicitly developed for African languages outperform other models on all tasks. Additionally, no one-model-fits-all solution exists for a per-language evaluation of the models evaluated. Moreover, for some languages with a smaller sample size, a larger multilingual model may perform better than a dedicated per-language model for sentiment classification.

Introduction

Africa is the second-largest and fastest-growing continent with rich natural resources. However, Africa's adverse climate conditions and geopolitics puts it at a disadvantage in development (Collier and Gunning 1999). After the mass decolonization of Africa, many countries experienced economic crises of varying severity (Wangwe 1995), which served as a hindrance to development. Most African nations are still faced with challenges of "meeting basic needs such as education, energy, food, potable water supply, efficient healthcare delivery" for a significant portion of their population (Akinyede and Adepoju 2010). Although most nations "have national policies and strategies that promote science and technology, but their capacity to implement them remains weak" (Gaillard and Mouton 2022). Consequently, government and industry are yet to prioritize funding for research and development (R&D). (Gaillard and Mouton 2022).

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We can see the effect of less investment on R&D in terms of research output. During 2000–2004, European Union and the USA produced 38.8% and 33.6% of the world publications, respectively. In contrast, Africa produced 1.8% of the world publications (Pouris and Pouris 2009). During the same period, while the rest of the world produced 817,197 patents, Africa produced 633 patents (less than 0.1% of the world's inventions) (Pouris and Pouris 2009). There is a significant limitation provided by the infrastructure as well. As of 2009, African countries had an access rate of 5.4% to the internet despite the global percentage of 23% (Usera 2009), which is made worse by widespread illiteracy. Even when there is access to the internet, the "bandwidth is often too narrow" (Akinyede and Adepoju 2010), which limits the population from accessing information and resources available on the internet. Similarly, there is also a severe and persisting need for more provision for continuing education and training (Akinyede and Adepoju 2010) with the existing education infrastructure. However, in recent days, Africa has been progressing in growing science, technology, and innovation (STI). Africa's share of world publication output more than doubled since 2003 to reach 3% today (Gaillard and Mouton 2022). A vast consumer population has led private sectors to take an interest in the African market (Usera 2009). There has also been increasing foreign funding upon which many medium and small-sized research systems are dependent (Usera 2009).

Sentiment analysis is a part of Natural Language Processing (NLP) that categorizes emotions behind digitalized texts mainly into positive, negative, and neutral. In a digital world, sentiment analysis plays a significant role in providing social impact. NLP can be used as a political tool to help bridge the "informational gaps between decision-makers and citizens in terms of preferred, and eventually winning, outcome. Oftentimes, citizens express their opinions on social media, and user sentiment analysis on these social media posts can be used effectively by the "governments to grasp collective citizens' preferences towards specific negotiation processes..." (Georgiadou, Angelopoulos, and Drake 2020). This approach can help write policies and laws that work to the will and benefit of the citizens. Georgiadou, Angelopoulos, and Drake identify that sentiment analysis can help decision-makers identify different options and help gain additional insights when making decisions and enforcing new laws/policies. Furthermore, Africa is a lucrative market for mobile eCommerce, given that there is a 90% mobile penetration rate for a growing population currently at over 1 billion. However, the growth of the domestic technology industry often needs to catch up. In particular, eCommerce companies can use sentiment analysis to investigate customer issues and address them, which can help make the eCommerce market profitable and more significant.

The following section reviews relevant research on sentiment analysis for African Languages. This paper seeks to help advance and contribute to the NLP and sentiment analysis literature for African languages by evaluating the performance of current state-of-the-art transformer models and methods across 12 African languages. We end with a presentation of our results and a brief discussion of limitations and future work.

Relevant Works

There are over 2000 languages spoken across African nations. However, many of these languages are explicitly oral with limited written texts. Moreover, the generational impact of colonialism has devastated African languages' support, preservation, and integration (Alexander 2009). These factors and more have contributed to a technological space that does not equitably represent African languages and results in limited datasets and corpora available for research using NLP and sentiment analysis for these languages (Martinus and Abbott 2019). However, with recent advancements in NLP and growing interest in Africa, some current and relevant work, albeit limited, in modeling language representations and sentiment classification will be covered in the following subsections.

Multilingual Models

Some researchers suggest that about 30% of all current day languages are African-derived Languages (Robinson 2003). There have been large multilingual models covering 100 plus languages such as XLM-R(Conneau et al. 2019) less than 5 of the languages which were officially African. This phenomenon is not tied to XLM-R; it applies to almost all multilingual models, except those specifically targeted at African Languages. Thus, this section will focus on the three models that are aiming to change the lack of Large Scale NLP Models for African Languages, which are AfriBERTa(Ogueji, Zhu, and Lin 2021), AfroXLMR(Alabi et al. 2022), and AfroLM(Dossou et al. 2022). Each of these models, detailed below, is the top Performing Multilingual model for African Languages based on a literature review and to the best of our knowledge. For future reference, you can find the languages supported by or pre-trained on each of the models in Table 3.

AfriBERTa AfriBERTa (Ogueji, Zhu, and Lin 2021) was one of the first of its kind; of Multilingual Models focused on primarily African Languages. It demonstrated that creating high-performing multilingual models trained on only low-resource languages is more than possible. It comprises 11 African languages, and the total training data used amounts to less than 1 gigabyte of text. Compared to mainstream multilingual high resource language models such as XLM-R(Conneau et al. 2019), which was trained on 2.5 Terabytes of data, AfriBERTa beat XLM-R and mBERT in Named Entity Recognition (NER) and Text Classification Tasks across most African languages.

AfroXLMR AfroXLMR (Alabi et al. 2022) followed AfriBERTa (Ogueji, Zhu, and Lin 2021) in its development but took a different approach than it. Where AfroXLMR followed multilingual adaptive fine-tuning (MAFT) on XLM-R(Conneau et al. 2019) to add support of 17 of the highest resourced African languages and three other languages that are widely spoken on the continent of Africa. To further their modeling, they also removed all vocabulary tokens from the embedding layer that are non-African writing scripts (Ogueji, Zhu, and Lin 2021). This adaptation allowed them to create a high-performing multilingual African Language model that is 50% smaller than XLM-R and is competitive when evaluated in NER, news topic classification, and sentiment classification.

AfroLM AfroLM (Dossou et al. 2022) is the most recent in the lineage from AfroXLMR (Alabi et al. 2022), and AfriBERTa (Ogueji, Zhu, and Lin 2021) of top Performing Multilingual model for African Languages. AfroLM provides a unique approach to the problem of Low Resource African Multilingual model problem; they developed and trained their model from scratch utilizing an Active Learning approach to the problem. While active learning is excellent at addressing low-resource problems, it receives minimal attention in NLP since it requires expert annotations and labeling. While BERT performs well, it still leaves much to be desired in low-resource language problems. With AfroLM active learning approach, the authors were able to outperform AfriBERTa (Ogueji, Zhu, and Lin 2021), AfroXLMR (Alabi et al. 2022), and XLM-R(Conneau et al. 2019) in downstream tasks such as NER, topic classification, and sentiment classification. They demonstrated that the performance needed for African languages can be found outside BERT-based models and can be discovered in other approaches.

AfriSenti-SemEval / NaijaSenti

Annotated datasets for Sentiment Analysis derived from African Languages are vastly limited. This paucity has vastly impeded the development of this task. While there have been previous initiatives to expand data access and availability, the AfriSenti-SemEval Shared Task 12, hosted as a part of The 17th International Workshop on Semantic Evaluation, is a concentrated effort and shared a collection of Twitter datasets in 14 African languages for sentiment classification (Muhammad et al. 2022a; Yimam et al. 2020). At the time of writing, monolingual sentiment annotated datasets of 12 languages are made available. The task is co-created by the creators of NaijaSenti (Muhammad et al. 2022b) and expands on NaijaSenti. They provided 13 datasets comprising 12 different languages, each being a dataset and a dataset composed of all the languages. The 12 African Languages covered are Hausa(HA), Yoruba(YO), Igbo(IG), Nigerian Pigdin(PCM), Amharic(AM), Algerian Arabic(DZ), Moroccan Arabic/-Darija(MA), Swahili(SW), Kinyarwanda(KR), Twi(TWI), Mozambican Portuguese(PT), and Xitsonga(Mozambique Dialect) (TS). These languages are derived from a diverse range of African Countries Nigeria, Ethiopia, Kenya, Tanzania, Algeria, Rwanda, Ghana, Mozambique, South Africa, and Morocco, all in different regions of Africa. The data was gathered from Twitter composed of 3 sentiment labels positive, negative, and neutral, with some of the tweets being code-mixed. While most of these languages have a limited amount of corpus, to our knowledge, some languages, such as Xitsonga, have labeled sentiment analysis datasets created for the first time.

Methodology

This section details the Datasets, Pre-Processing, Modeling, and Evaluation for this work.

Datasets

We utilized all thirteen datasets from the AfriSenti-SemEval Task comprising Hausa(HA), Yoruba(YO), Igbo(IG), Nigerian Pidgin (PCM), Amharic(AM), Algerian Arabic(DZ), Moroccan Arabic/Darija(MA), Swahili(SW), Kinyarwanda(KR), Twi(TWI), Mozambican Portuguese(PT), Xitsonga(Mozambique Dialect) (TS), and a combination of all the 12 language datasets for a multilingual task(ALL). With the sourcing of all the datasets coming from Twitter, it allows us to claim that the performance of these models should mirror their use in a real-world setting. The dataset makeup is seen below in Table 1.

Langs	Neg	Neu	Pos	Total
HA	5467	5808	5574	16849
YO	2315	3871	4426	10612
IG	3070	5319	3644	12033
PCM	4054	93	2255	6402
AM	1936	3880	1665	7481
DZ	1115	428	522	2065
MA	1802	2350	1925	6077
SW	239	1340	684	2263
KR	1433	1572	1124	4129
TWI	1462	580	1827	3869
PT	978	2000	852	3830
TS	356	171	480	1007
ALL	24449	27693	25196	77338

Table 1: Sentence Labels of Each Dataset

Langs	Train	Val	Test	Total
HA	12754	1418	2677	16849
YO	7669	853	2090	10612
IG	9172	1020	1841	12033
PCM	4608	513	1281	6402
AM	5385	599	1497	7481
DZ	1485	166	414	2065
MA	5024	559	494	6077
SW	1629	181	453	2263
KR	2971	331	827	4129
TWI	3132	349	388	3869
PT	2756	307	767	3830
TS	723	81	203	1007
ALL	57316	6369	13653	77338

Table 2: Sample Sizes by Each Dataset

The dataset is roughly balanced by labels outside of PCM (Nigerian Pigdin), DZ (Algerian Arabic), SW (Swahili), TWI, PT(Mozambican Portuguese), and TS(Xitsonga).

Pre-Processing

At the time of writing and experimentation, the official test set of the datasets had not been made available. We utilized the development set in lieu of the Test Set and performed a 90/10 random stratified split on the official training set for our training and validation sets. The sample size of each split utilized can be seen in Table 2. Then, we cleaned the data by removing the English stop-words, punctuation, and digits from the sentences and denoising the social media text. After cleaning, the cleaned sentences passed through the model-specific tokenizer (Wolf et al. 2019). We set the max sentence token value to 20 using the average number of tokens in a sentence across all languages; the sentences with fewer than 20 tokens were padded with zeros. After tokenization, we finetune and evaluate the chosen models as detailed in the following subsection.

Modeling and Evaluation

This section contains our steps for Per Language and Multilingual Modeling. We selected to train four models including XLM-R (Conneau et al. 2019), AfriBERTa (Ogueji, Zhu, and Lin 2021), AfroXLMR (Alabi et al. 2022), and AfroLM (Dossou et al. 2022). XLM-R sets a baseline since it is pretrained on the least number of African languages.; it is a large model and provides a baseline for comparison of cross-lingual transfer to African languages. The other models were chosen for their proven track record performance on NLP tasks for disparate African languages.

Lang	XLM-R	AfriBERTa	AfroXLMR	AfroLM
HA	YES	YES	YES	YES
YO	NO	YES	YES	YES
IG	NO	YES	YES	YES
PCM	NO	YES	YES	YES
AM	YES	YES	YES	YES
DZ	*YES	NO	NO	NO
MA	*YES	NO	NO	NO
SW	YES	YES	YES	YES
KR	NO	NO	YES	YES
TWI	NO	NO	YES	NO
PT	*YES	NO	NO	NO
TS	NO	NO	NO	NO

Table 3: Models Language Support *Means that the model Supports the Language but not the African Variant such as XLM-R supports Portuguese but not explicitly Mozambican Portuguese

Per Language Modeling Although some languages share similar origins and roots, modern languages are distinct. To evaluate if a dedicated model better supported the uniqueness of each language, we fine-tuned each of the four models individually on each of the 12 languages. This process resulted in 48 models(4 models x 12 languages); we repeated the process with another 48 on a different seed value to ensure the evaluation was standard and not seed-specific. Each model maintained identical hyperparameters of 5 epochs and a training batch size of 256. The held-out validation set was used while fine-tuning to mitigate over-fitting as much as possible due to the nature of small data sets.

Multilingual Modeling While language-specific models are justifiable, the number of models and sample size required grows linearly with the number of languages. Additionally, multilingual models can capture interdependencies between languages to better represent multiple languages with a single model. Since only 1 dataset is utilized for training each model, we only developed four models and an additional four for evaluation confirmation at a different seed value. Then each model had the identical parameters of 5 epochs and train batch size of 256. Each model maintained identical hyperparameters of 5 epochs and a training batch size of 256. The held-out validation set was used while fine-tuning to mitigate over-fitting.

Model training and inference were performed on a late 2021 Lambda Tensorbook with 16 GB Nvidia GeForce 3080. To enable the reproducibility of our work and help other works in the field, we have made our open-sourced access to our code which involves the entire process from pre-processing to modeling, and evaluation. Readers are encouraged to look at the source code at the URL *http://bit.ly/40yvilf* and reach out to the authors for any further questions they might have regarding the work performed in this paper.

Evaluation Evaluation for Per-Language and Multilingual modeling was done on the test set. Standard, weighted average classification metrics: F1, Precision, Recall, and Accuracy are reported in the following Results section. Since the two different seeds provided nearly identical predictions, we only report the scores from the better of the two models. We further use precision-recall curves to compare the performance of each class for the multilingual model.

Results

Per Language Performance

Lang	Model	F1	Precision	Recall	Accuracy
HA	AfriBERTa	.76	.76	.76	.76
YO	AfriBERTa	.71	.71	.70	.70
IG	AfriBERTa	.78	.79	.78	.76
PCM	AfroXLMR	.71	.70	.72	.72
AM	AfroLM	.59	.60	.61	.61
DZ	AfroXLMR	.58	.66	.63	.63
MA	AfroXLMR	.77	.78	.76	.76
SW	AfriBERTa	.62	.63	.64	.64
KR	AfroXLMR	.57	.58	.57	.57
TWI	AfroXLMR	.58	.58	.60	.60
PT	AfroLM	.53	.53	.55	.55
TS	AfriBERTa	.54	.56	.58	.58

Table 4: Best Performing Models (Highest Weighted-F1) Per-Language

Upon comparing Tables 2 and 3 with the average performance of Per-language models' performance in Table 4, we first observe that the performance is proportional to training size. Furthermore, we see that the models originally pretrained on more African languages have higher generalized performance on African languages than their counterparts, as seen by the superior performance of AfriBERTa, AfroLM, and AfroXLMR. Results also show that no one-model-fit-all solution works across different languages for per-language modeling. Unsurprisingly, none of the languages performed best using a generic XLM-R model. Out of all the models, XLM-R was most affected by overfitting since the validation error was much lower than the test error. These results further support the necessity of further research into African Languages since the general efforts are insufficient, and specialization may be needed.

Multilingual Performance

	F1	Precision	Recall	Accuracy
XLM-R	.19	.13	.36	.36
AfriBERTa	.66	.66	.66	.66
AfroXLMR	**.67**	**.68**	**.67**	**.67**
AfroLM	.63	.64	.63	.63

Table 5: Performance of Models for the Multilingual Dataset

As seen in Table 5, while the three African language-customized models have similar performance capabilities, XLM-R is outperformed by the three African language-customized models in overall performance. This discrepancy further confirms what is seen in Table 4 that a generic XLM-R performs subpar compared to the three African language-customized models at a per-language level. Finally, despite the models' difference in size and approaches, they perform similarly on average, with AfroXLMR slightly outperforming the rest.

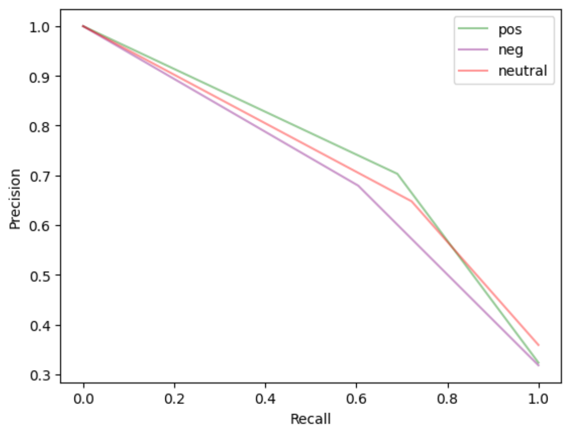

Figure 1: PR curve for best performing model from Table 5

As seen in Figure 1, we see that for the best performing from Table 5 the model performs better in the order: of positive, neutral, and negative. This result is an interesting observation because classification models usually struggle with neutral classes since the difference between positive and negative classes tends to be apparent. Perhaps more research is warranted on the polarity of expression across African languages.

Conclusion

With the recent release of the AfriSenti-SemEval Shared Task 12, hosted as a part of The 17th International Workshop on Semantic Evaluation, an annotated sentiment analysis of 14 African languages was made available. We benchmarked and compared current state-of-art transformer models across 12 languages and compared the performance of training one-model-per-language versus single-model-all-languages. We also evaluated the performance of standard multilingual models and their ability to learn and transfer cross-lingual representation from non-African to African languages. Our results show that despite work in low resource modeling, more data still produces better models on a per-language basis. Models explicitly developed for African languages outperform other models on all tasks. Additionally, no one-model-fits-all solution exists for a per-language evaluation of the models evaluated. Moreover, for some languages with a smaller sample size, a larger multilingual model may perform better than a dedicated per-language model for sentiment classification. However, our work is not comprehensive; we implore future researchers and readers to peruse the limitations and future work below.

Limitations & Future Work

While sentiment analysis is a fundamental and valuable task in NLP, the potential for abuse of sentiments persists. Mass surveillance, suppression of free speech, and monitoring of dissidents by tyrannical governmental or invasive corporate institutions are potential abuses of these technologies. With the promise of Africa, we can utilize these technologies appropriately and avoid misuse such as the Cambridge Analytica scandal (Isaak and Hanna 2018).

In terms of limitations of our work, more data would improve performance across the board, so we implore more partnerships with native speakers to expand data access and availability from African academic institutions. In addition, we did not experiment with any hyperparameter optimization which may result in improved performance. Moreover, our approach provides a performance benchmark across multiple languages; the reliance on pre-existing models is limiting and carries pre-existing performance issues and bias. Future work can be to make adaptations suited to African language tokens. We must add that while we had sufficient computing power for this task, this is a privilege not available to all. Additionally, we cleaned the data by removing the English stop-words, punctuation, and digits from the sentences and denoising the social media text. This approach causes a loss of information, such as emoticons or transliterated text which may provide further information for the task at hand. We utilized an average token size for tokenizing each sentence; however, this also limits texts with tokens larger than average. Finally, the authors of this work are not experts or speakers of these languages, so further qualitative analysis of the results is complicated.

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