

The Current State of the NLP in Sub-Saharan Africa - A Position Paper

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Abstract

001 In this study, we present our position on the
002 current state of the NLP in Sub-Saharan Africa.
003 Our position comes from surveys of litera-
004 ture we conducted on NLP activities (research
005 and publications) in Sub-Saharan African lan-
006 guages. We discussed issues of NLP research
007 outcomes for Sub-Saharan Africa based on the
008 results of the survey. Some of these issues in-
009 clude low-quality results of NLP studies, insuf-
010 ficient access to research funding, and lack of
011 an interdisciplinary approach to NLP research
012 in the region’s languages. Results of the study
013 reveal that most of the NLP work done for Sub-
014 Saharan African languages from 2020-2023
015 was centered around corpus development, lan-
016 guage modeling, and sentiment analysis. About
017 61% of the NLP work in sub-Saharan Africa
018 does not have access to funding. Funding
019 sources are mainly NGO-driven with 66.7%
020 of work that received funding being multilin-
021 gual studies. However, 64% of NLP activities
022 in the region are monolingual. We finalize our
023 position by providing recommendations on ad-
024 dressing issues raised and discovered based on
025 the survey.

026 1 Introduction

027 Natural Language Processing (NLP) has emerged
028 as a transformative field in artificial intelligence,
029 revolutionizing how humans interact with machines
030 and systems. NLP, a subfield of artificial intel-
031 ligence, involves the development of algorithms
032 and models that enable computers to understand,
033 interpret, and generate human language. As the
034 applications of NLP continue to increase globally,
035 it is crucial to assess the state of this technology in
036 different languages and geographical contexts. In
037 this position paper, we look into the current state of
038 NLP in Sub-Saharan Africa. We aim to highlight
039 the challenges and opportunities in harnessing this
040 technology for the region’s linguistic diversity.

041 Sub-Saharan Africa, a region rich in cultural
042 and linguistic diversity, presents a unique set of
043 challenges and opportunities for adopting and de-
044 veloping NLP technologies. With a rich tradition of
045 storytelling, poems, songs, and literature, in recent
046 years it has seen a proliferation of communication
047 in through digital and social media. One of the
048 distinctive characteristics of the region is its low-
049 resource nature, marked by limited access to digi-
050 tal data, computing resources, and research infras-
051 tructure. The low-resource nature of Sub-Saharan
052 Africa poses a significant hurdle to the applica-
053 tion of NLP technologies. Different from well-
054 resourced languages with extensive datasets and
055 models, many African languages, have a scarcity
056 of linguistic resources. Despite these challenges,
057 there is a growing recognition of the potential of
058 NLP to address linguistic diversity, promote lo-
059 cal language preservation, and contribute to the
060 region’s socio-economic development.

061 This paper aims to explore the current landscape
062 of NLP in Sub-Saharan Africa, from the Horn of
063 Africa in the east to the Westernmost of Africa in
064 the west, down to the Southernmost of Africa in
065 the south. We present the breadth and depth of
066 NLP activities in Sub-Saharan Africa. Discuss the
067 current challenges, areas of strength and weakness,
068 and propose recommendations.

069 Our discussion is within the context of NLP Al-
070 gorithms, fundamental applications, corpora, and
071 sources of NLP research funding. By examining
072 these, we seek to identify opportunities for the
073 integration of NLP technologies to address soci-
074 etal needs and linguistic preservation. Also, to
075 contribute to the overall development of the Sub-
076 Saharan African region and its inclusion in the
077 ever-rapid growth of information and communica-
078 tion technology usage. As we navigate through the
079 nuances of NLP in Sub-Saharan Africa, we hope
080 to present our position on collaborative efforts that
081 harness the potential of technology to uplift com-

082 munities, preserve languages, and foster inclusive
083 development.

084 **2 Fundamental Algorithms and tools for** 085 **NLP**

086 NLP algorithmic tools are as diverse as corpora
087 (texts) used to model algorithms to achieve a spe-
088 cific NLP application. Algorithms are better uti-
089 lized when they are applied across multiple lan-
090 guages (Daniel and H. Martin, 2020). Africa has
091 over 1000 languages (at the minimum) grouped
092 into four categories based on their ethnological ori-
093 gin. Language properties differ within and across
094 these groups, most of the NLP work in Sub-Saharan
095 Africa in the past is monolingual and tested on a sin-
096 gle language only (C. S. and R., 2020; M. A. et al.,
097 2019; M.A. et al., 2019; Mahloane and Trausan-
098 Matu, 2015; Eckart et al., 2020; Malema et al.,
099 2020; Suleiman et al., 2019; Zakari et al., 2021;
100 Zandam et al., 2023; Rakhmanov and Schlippe,
101 2022; Ibrahim et al., 2022a,b; Chukwunke et al.,
102 2022; Awwalu et al., 2021; Ogbuju and Onyesolu,
103 2019; Abdulmumin and Galadanci, 2019; Tukur
104 et al., 2019; Onyenwe et al., 2018; Ezeani et al.,
105 2018; Rozaimie et al., 2017; Sèmiyou et al., 2013;
106 Afolabi et al., 2013; Mohammed and Prasad, 2024;
107 Bashir et al., 2015; Ralethe, 2020; Augustinus et al.,
108 2016; Augustinus and Dirix, 2013; Gaustad and
109 Eiselen, 2022; Matthew, 2015; Brokensha et al.,
110 2023). However, this is changing, with over 45%
111 of the recent NLP work in Sub-Saharan Africa be-
112 ing multilingual. (Akeru et al., 2022; Alabi et al.,
113 2022b,a; Z. et al., 2021; Muhammad et al., 2023;
114 N. et al., 2022; Gaim et al., 2022; Gaustad and
115 Puttkammer, 2022; Adebara and Abdul-Mageed,
116 2022; Adelani et al.; et 'al., 2022; Mabokela and
117 Schlippe, 2022; Nekoto et al., 2020; Nyoni and Bas-
118 sett, 2021; Moses et al., 2022; Griesel and Bosch,
119 2020; Marivate et al., 2020; Ogueji et al., 2021;
120 Oladipo et al., 2022; E. and P., 2014; Mboning
121 et al., 2020; Rajab, 2022; Nakatumba-Nabende
122 et al., 2024; Tonja et al., 2024; Oyewusi et al., 2021;
123 Dossou and Emezue, 2021; Adelani et al., 2020;
124 Mohammed and Prasad, 2023; Van Zaanen et al.,
125 2014; Eiselen and Gaustad, 2023). (See Figure 6
126 in Appendix A: 6.)

127 NLP algorithmic tools used for language pre-
128 processing and modeling can be divided into clas-
129 sical and modern tools. Tokenization and pre-
130 processing techniques, useful algorithms such as
131 Minimum Edit Distance, statistical Hidden Markov

Model (HMM), N-gram Language Models, Naive
Bayes, and Logistic regression, etc. are classical
tools that integrate well with language grammatical
structures and variations (Daniel and H. Martin,
2020; Dale, 2010). These have worked well with
languages with NLP research history to provide
fundamental NLP resource tools and are suitable
for developing quality NLP resource tools for low-
resource languages. Modern algorithmic tools are
a suite of Neural networks and Neural language
models. Modern NLP tools are data-driven and
machine-learning approaches to language model-
ing and processing, responsible for the huge suc-
cess of NLP applications among languages with
NLP research history and better language resources.
Most work in Africa NLP in recent times utilizes
modern approaches. Even though, with the techno-
logical advancement of the Internet and social me-
dia technologies, there is sufficient raw data (texts,
images, videos, and audio) for the Sub-Saharan
African languages, the results of NLP research are
significantly low when compared with the rich NLP
resource languages and languages with a long his-
tory of NLP research.

3 NLP Applications for Sub-Saharan African Languages

The Fundamental fields of NLP applications are
divided into five groups namely, Information ex-
traction/retrieval (e.g. Name entity recognition,
relation detection & classification, etc.), Question
answering & Summarization (Question process-
ing & question answering, and summarization),
Speech recognition (Automatic speech recognition
and text-to-speech), Machine translation and Dia-
logue system & Conversational agents (Basic di-
alogue system and chatbot) Daniel and H. Martin
(2020). Within these areas of NLP applications
are numerous applications or tools such as Chat-
bots, Sentiment Analysis, Grammar Checker, Spam
Detection, Smart Assistant, Market Intelligence,
Targeted Advertising, machine translation, speech
recognition, automatic summarization, email filter-
ing, social media analytics, etc. Most of the NLP
work done for Sub-Sahara African languages in
2020 - 2023 centered around corpus development,
language modeling, and sentiment analysis (See
Figure 1 in Appendix A: 1), with little work on
name entity recognition, speech recognition, part
of speech tagging, machine translation, and speech
recognition. Despite these efforts, the results of

most studies are of low quality and lack standardization and benchmarking. However, 2023 ended with a more collaborative effort across the globe involving numerous Sub-Saharan African NLP research communities that improvised a Name Entity Recognition tool as a benchmark that works for 10 African languages [Adelani et al.](#).

4 NLP Datasets (Corpora) for Sub-Saharan African Languages

NLP datasets are known as corpora. Corpus is a linguistic term that refers to the language electronic text in its natural communicative forms without necessarily regard to the language it contains [Suleiman et al. \(2019\)](#). For example, text from newspapers, fiction or non-fiction books, and spoken genres like telephone conversations, and business meetings. Words are products of our conversations. Every text in its natural form is a derivative of one or more speakers or writers, using a specific dialect of a specific language, at a specific time and place for a specific function [Daniel and H. Martin \(2020\)](#). Language models depend on quality corpus and suitable algorithms. Many NLP applications perform better when modeled with large corpus and modern deep learning algorithms. Applications such as machine translation require large parallel corpora for good performance. Only very recently we started having a benchmark corpus for Sub-Sahara Africa NLP tasks. Except for fewer public datasets developed by individual Africa NLP researchers, most existing platforms for Africa Datasets curation are NGOs deriving, with their sources from International organizations. Notable among them are Lacuna funds and AI4D. Despite the efforts in acquiring original Sub-Saharan Africa datasets, most of the datasets have issues of access, proper documentation, and presentation format. While there are several corpora for African languages, you hardly see parallel corpora for two or more Sub-Saharan African languages. The common thing is to have parallel corpora of an African language and English or French, and most of them are lexicon-based parallel corpora curated from online multilingual dictionaries. For example Hausa - English or Kiswahili-English parallel corpora. And most of the time, they are specialized forms of parallel corpus.

5 Issues and Recommendation

1. Sub-Saharan African language NLP has a long way to catch up with global NLP research communities, particularly countries with a long history of NLP research activities. The problem of Sub-Saharan African language NLP ranges from low-quality research resources with interchangeability and interoperability issues, to the absence of multidisciplinary collaborative research involving linguistics and computational linguistics, to the issue of funding NLP research activities in universities.

To address the issue of low-quality tools, standards, interoperability, and interchangeability, we recommend adherence to the principles of software design and software engineering best practices in language modeling. This will help with developing a standard African language resources tool that is largely independent of a specific language and can easily be adapted for a large category of Sub-Saharan language families with interoperability.

2. Another big issue with Sub-Saharan African language NLP is the disconnect between NLP researchers and linguistic domain experts. Sub-Saharan African language linguistics uses methodologies different from NLP-based computing approaches for language processing. Even though, the modern machine learning approach to NLP does not require an understanding of a language's grammatical structures; origin, formation, and derivations, such knowledge is needed to produce reliable educational basic language resource tools. These tools are fundamentals in developing NLP applications that are acceptable, reusable, and deployable.

We recommend that African NLP research communities should focus on the provision of basic language resource toolkits that comprise language pre-processing techniques such as tokenization, word normalization, lemmatization/word form, and word stemming. The toolkits should also include morphological tagging, language model N-grams, and maximum likelihood estimator. Such a toolkit will enhance the rapid prototyping of essential requirements for a new language. Furthermore, there is a need to engage in multidisciplinary research involving Sub-Saharan African language linguistics,

278	computational linguistics, domain-specific experts,	A: 7). This has a negative setback towards	327
279	and NLP researchers.	achieving interoperable and interchangeable	328
280		NLP resources for Sub-Saharan African lan-	329
281	3. On the issue of corpora, the study indicated a	guages. The few available sources of fund-	330
282	growing dataset development for Sub-Saharan	ing come from either institution of the gov-	331
283	African Languages. We have started to see	ernment of some African countries (such as	332
284	benchmark work done. While this is a wel-	the South African Centre for Digital Lan-	333
285	come development, more is still needed for	guage Resources (SADiLaR), the National	334
286	sub-Saharan African languages to grow from	Research Foundation (NRF), and the Tertiary	335
287	low-resource language to rich-resource lan-	Education Trust Fund (TetFund) of Nigeria,	336
288	guage. Our study has indicated the complete	etc.) or International organizations interven-	337
289	absence of languages in the Central Africa re-	tion with the NGOs model (such as Lacuna	338
290	gion of Sub-Saharan Africa in NLP research	Fund, the Deutsche Forschungsgemeinschaft	339
291	visibility. In short, less than 4% of Sub-	(DFG, German Research Foundation), and	340
292	Saharan African languages are currently cov-	The AI4D Africa Initiative among others). Ei-	341
293	ered in NLP research radar. This indicates the	ther of the two sources of funding research	342
294	level of work that needs to be done to bring as	comes with too many bureaucratic protocols	343
295	many languages as possible.	that tend to limit the fund amount, scope, and	344
296		direction of research for optimal research out-	345
297	We recommend a deliberate effort to be made to	puts.	346
298	develop datasets for underrepresented languages of		
299	Sub-Saharan Africa. This means that more than the	We advocate for more funding from African gov-	347
300	availability of online text is required to cover all	ernment institutions, local stakeholders corporate	348
301	kinds of text needed for NLP, specifically for lan-	organizations, foreign agencies, and governments	349
302	guages that are not visible online. Spoken genres	with less bureaucracy to enable access for Sub-	350
303	from conversations, interviews, and transcription	Saharan African NLP research communities.	351
304	of stories from late-night storytellers will provide		
305	our algorithms with text to process.	6 Conclusion	352
306			
307	4. Another dimension regarding corpora is the	This study surveyed more than 100 articles writ-	353
308	lack of parallel corpora for inter-languages	ten between 2013 and 2023 containing works on	354
309	of Sub-Saharan African languages. Parallel	Sub-Saharan African Language NLP. We have re-	355
310	corpora are required for machine translation	viewed and extracted fewer than 70 relevant arti-	356
311	applications.	cles on NLP activities in languages that cut across	357
312		all four regions of Sub-Saharan Africa. Based on	358
313	We advocate for the collection of parallel corpora	these surveys, we established our position on the	359
314	for inter-language or intra-language families of	thought-provoking NLP research issues of Sub-	360
315	Sub-Saharan African Languages. Doing so will	Saharan African languages. Finally, we provide	361
316	set a new narrative for African NLP in the area	recommendations on ways to address issues in the	362
317	of machine translation application. Finally, we	current state of NLP in Sub-Saharan Africa.	363
318	recommend the use of a datasheet to provide de-		
319	tailed properties of dataset development. Propert-	7 Limitation	364
320	ies such as motivation, situation, language varie-		
321	ties, speaker demographics, collection process, an-	Our position comes from surveys of literature we	365
322	notation process, and distribution Daniel and H. Martin	conducted on NLP activities (research and publica-	366
323	(2020) will provide answers to who produced the	tions) for Sub-Saharan African languages. While	367
324	language dataset, in what context, and for what	we have covered several major publications on sub-	368
325	purpose Daniel and H. Martin (2020) .	Saharan African languages, this is by no means	369
326		exhaustive.	370
	5. Finally, the problem of funding NLP research		
	efforts for Sub-Saharan African languages.	References	371
	Our study indicated that more than 60% of		
	NLP research for Sub-Saharan African lan-	I. Abdulmumin and B. S. Galadanci. 2019. hauwe:	372
	guages is not funded (see Figure 7, Appendix	Hausa words embedding for natural language pro-	373

374	cessing. <i>In Proceedings of the 2019 2nd International Conference of the IEEE Nigeria Computer Chapter.</i>	Shikali C. S. and Mokhosi R. 2020. Enhancing african low-resource languages: Swahili data for language modeling. <i>Data in Brief</i> , 31.	428
375			429
376			430
377	I. Adebara and M. Abdul-Mageed. 2022. Towards afro-centric nlp for african languages: Where we are and where we can go. <i>Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)</i> :3814–3841.	C. Chukwunke, I. Ezeani, P. Rayson, and M. El-Haj. 2022. gboBERT models: Building and training transformer models for the igbo language. <i>n Proceedings of the Thirteenth Language Resources and Evaluation Conference.</i>	431
378			432
379			433
380			434
381			435
382	D. I. Adelani, M. A. Hedderich, D. Zhu, E. Van den Berg, and D. Klakow. 2020. Distant supervision and noisy label learning for low resource named entity recognition: A study on hausa and yorùbá. <i>In Proceedings of the ICLR 2020 Workshop.</i>	R Dale. 2010. Classical approaches to natural language processing. <i>In Indurkha, F. J. Damerou (Eds.), Handbook of natural language processing, second edition(pp. 3-7). (Chapman Hall: CRC machine learning pattern recognition series).</i>	436
383			437
384			438
385			439
386			440
387	D. I. Adelani, G. Neubig, S. Ruder, S. Rijhwani, M. Beukman, C. Palen-Michel, and et ‘al. [link] .	Jurafsky Daniel and James H. Martin. 2020. <i>Speech and Language Processing An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition</i> , volume 3rd edition draft.	441
388			442
389	A. Afolabi, E. Omidiora, and T. Arulogun. 2013. Development of text to speech system for yoruba language. <i>2nd International Conference on Engineering and Technology Research.</i>		443
390			444
391			
392			
393	B. Akera, J. Mukiiibi, L. S. Naggayi, C. Babirye, I. Owomugisha, S. Nsumba, and et ‘al. 2022. Machine translation for african languages: Community creation of datasets and models in uganda. <i>AfricaNLP workshop at ICLR 2022.</i>	B. F. P. Dossou and C. C. Emezue. 2021. Okwugbé: End-to-end speech recognition for fon and igbo. <i>In Proceedings of the African NLP Workshop, EACL 2021.</i>	445
394			446
395			447
396			448
397			
398	J. O. Alabi, D. I. Adelani, M. Mosbach, and D. Klakow. 2022a. Adapting pre-trained language models to african languages via multilingual adaptive fine-tuning. <i>arXiv:2204.06487v3.</i>	Roald E. and Martin J. P. 2014. Developing text resources for ten south african languages. <i>Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC’14).</i>	449
399			450
400			451
401			452
402	J. O. Alabi, D. I. Adelani, M. Mosbach, and D. Klakow. 2022b. Multilingual language model adaptive fine-tuning: A study on african languages. <i>AfricaNLP workshop at ICLR 2022.</i>	T. Eckart, S. Bosch, U. Quasthoff, E. Körner, D. Goldhahn, and S. Kaleschke. 2020. Usability and accessibility of bantu language dictionaries in the digital age: Mobile access in an open environment. <i>Proceedings of the First Workshops on Resources for African Indigenous Languages (RAIL).</i>	453
403			454
404			455
405			456
406	L. Augustinus and P. Dirix. 2013. The ipp effect in afrikaans: A corpus analysis. <i>In Proceedings of the 19th Nordic Conference of Computational Linguistics (NODALIDA 2013).</i>	R. Eiselen and T. Gaustad. 2023. eep learning and low-resource languages: How much data is enough? a case study of three linguistically distinct south african languages. <i>n Proceedings of the Fourth Workshop on Resources for African Indigenous Languages (RAIL 2023).</i>	459
407			460
408			461
409			462
410	L. Augustinus, P. Dirix, D. Van Niekerk, I. Schuurman, V. Vandeghinste, F. Van Eynde, and G. Van Huyssteen. 2016. Afribooms: An online treebank for afrikaans. <i>In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16).</i>		463
411			464
412			
413			
414			
415			
416	J. Awwalu, S. E. Abdullahi, and A. E. Ewwiekpaefe. 2021. A corpus-based transformation-based learning for hausa text parts of speech tagging. <i>International Journal of Computing and Digital Systems</i> , 10.	Barack et ‘al. 2022. Kencorpus: A kenyan language corpus of swahili, dholuo, and luhya for natural language processing tasks.	465
417			466
418			467
419			
420	M. Bashir, A. Rozaimée, and W. M. Wan Isa. 2015. A word stemming algorithm for hausa language. <i>IOSR Journal of Computer Engineering</i> , 17.	I. Ezeani, M. Hepple, I. Onyenwe, and E. Chioma. 2018. Igbo diacritic restoration using embedding models. <i>In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Student Research Workshop.</i>	468
421			469
422			470
423	S. Brokensha, E. Kotzé, and B. Senekal. 2023. Machine learning for document classification in an archive of the national afrikaans literary museum and research centre. <i>Journal of the South African Society of Archivists</i> , 56.	F. Gaim, W. Yang, and J. C. Park. 2022. Geezswitch: Language identification in typologically related low-resourced east african languages. <i>IREC 2022.</i>	471
424			472
425			473
426			474
427			475
		T. Gaustad and R. Eiselen. 2022. Exploring afrikaans word embeddings with analogies and nearest neighbors. <i>Proceedings of the 3rd Workshop on Resources for African Indigenous Languages (RAIL)</i> , 4.	476
			477
			478
			479

587 W. Oyewusi, O. Adekanmbi, I. Okoh, V. Onuigwe,
588 M. Salami, O. Osakuade, S. Ibejih, and U. Musa.
589 2021. Comprehensive named entity recognition for 5
590 nigerian languages. *In Proceedings of the AfricaNLP
591 Workshop, EAACL 2021.*

592 J. Rajab. 2022. Effect of tokenisation strategies for low-
593 resourced southern african languages. *In ICLR 2022
594 Workshop AfricaNLP.*

595 O. Rakhmanov and T. Schlippe. 2022. Sentiment
596 analysis for hausa: Classifying students' comments.
597 *In Proceedings of the 1st Annual Meeting
598 of the ELRA/ISCA Special Interest Group on Under-
599 Resourced Languages.*

600 S. Ralethe. 2020. Adaptation of deep bidirectional trans-
601 formers for afrikaans language. *In Proceedings of
602 the Twelfth Language Resources and Evaluation Con-
603 ference.*

604 A. Rozaimée, M. Bashir, and W. Malini. 2017. Auto-
605 matic hausa language text summarization based on
606 feature extraction using naïve bayes model. *World
607 Applied Sciences Journal*, 35.

608 M. A. Suleiman, M. M. Aliyu, and S. I. Zimit. 2019.
609 Towards the development of hausa language corpus.
610 *International Journal of Scientific Engineering Re-
611 search*, 10.

612 A. A. Sèmiyou, J. O. R. Aoga, and M. A. Igue. 2013.
613 Part-of-speech tagging of yoruba standard, language
614 of niger-congo family. *Research Journal of Com-
615 puter and Information Technology Sciences*, 1.

616 A. L. Tonja, O. Kolesnikova, A. Gelbukh, and J. Kalita.
617 2024. Parallel corpus for low-resource ethiopian
618 languages. *In Proceedings of the Fifth Workshop on
619 Resources for African Indigenous Languages (RAIL).*

620 A. Tukur, K. Umar, and A. S. Muhammad. 2019. Tag-
621 ging part of speech in hausa sentences. *In Proceed-
622 ings of the 2019 15th International Conference on
623 Electronics, Computer and Computation (ICECCO).*

624 M. M. Van Zaanen, G. Van Huyssteen, S. Aussems,
625 C. Emmerly, and R. Eiselen. 2014. The development
626 of dutch and afrikaans language resources for com-
627 pound boundary analysis. *Proceedings of the Ninth
628 International Conference on Language Resources
629 and Evaluation (LREC 2014).*

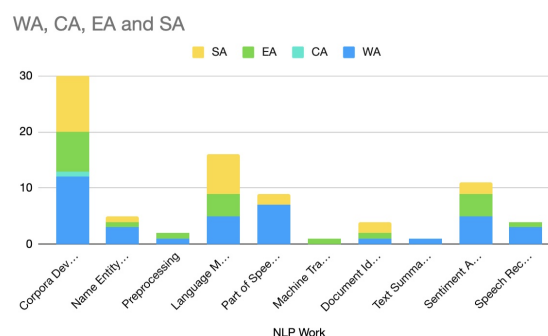
630 Andrew Z., Evan C., and Sandy R. 2021. [Text nor-
631 malization for low-resource languages of africa.](#)
632 *AfricaNLP2021.*

633 R. Y. Zakari, Z. K. Lawal, and I. Abdulmumin. 2021. A
634 systematic literature review of hausa natural language
635 processing. *International Journal of Computer and
636 Information Technology*, 10.

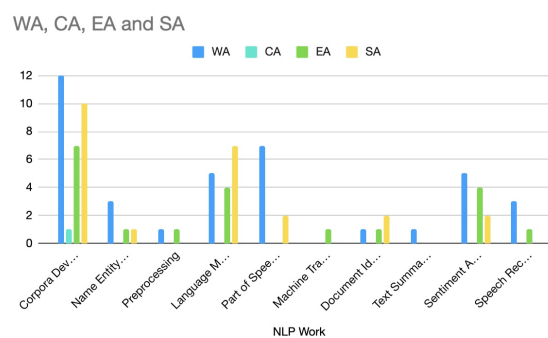
637 A. Y. Zandam, F. M. Adam, and I. Inuwa-Dutse. 2023.
638 Online threat detection in hausa language. *In Pro-
639 ceedings of the 2023 AfricaNLP Workshop at ICLR.*

640 A Appendix

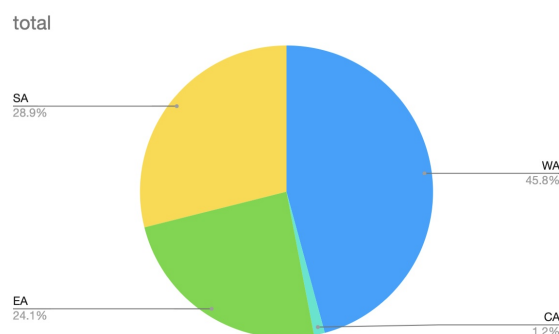
641 NLP Activities Across Sub-Sahara African Re- 642 gions.



642 Figure 1: NLP Activities of Sub-Saharan Africa Across different NLP application areas.



642 Figure 2: NLP Activities based on Regions in Sub-Saharan Africa. WA - West Africa, CA- Central Africa, EA - East Africa, and SA - South Africa regions.



642 Figure 3: Percentage of NLP activities across Sub-Saharan African Regions

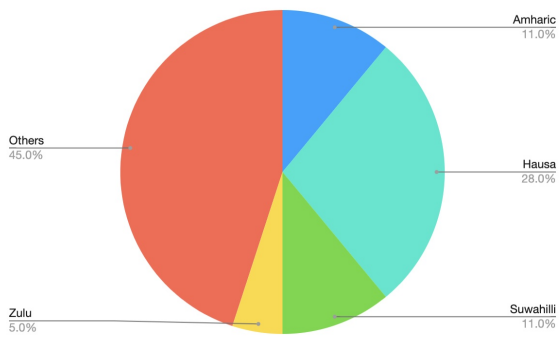


Figure 4: Percentage of NLP Activities based on the Language with the highest population in each region of Sub-Saharan Africa. Others - represent NLP activities for other languages in all four regions.

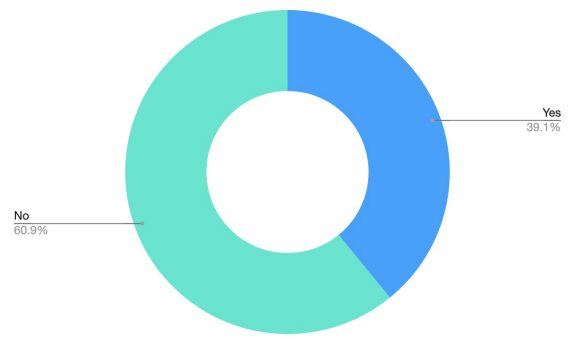


Figure 7: Percentage of NLP Activities with or without access to funding.

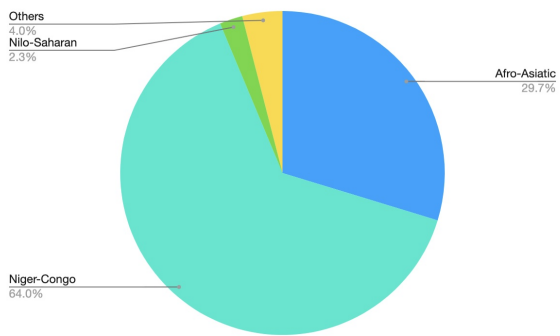


Figure 5: Percentage of NLP Activities of Sub-Saharan African Languages based on the large language family categories they belong to. Others - represent other language families with origins outside of the African Continent.

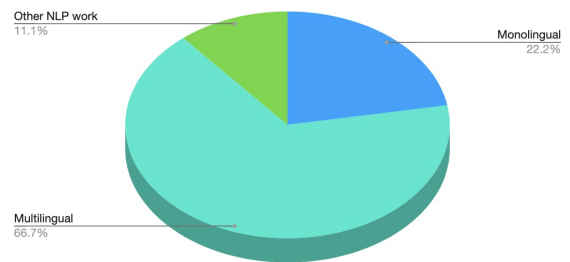


Figure 8: Percentage of NLP Activities based on single or multiple languages with access to funding. Other NLP work - represents other NLP activities in the form of a survey or review with access to funding.

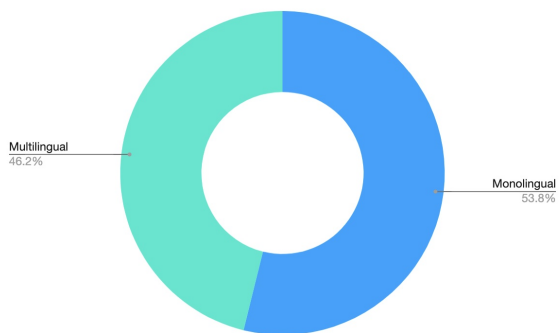


Figure 6: Percentage of NLP Activities based on single or multiple languages of Sub-Saharan Africa.

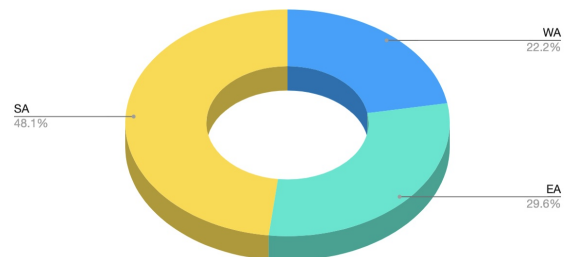


Figure 9: Percentage of NLP Activities based on regions in Sub-Saharan Africa with access to funding.