

Bridging Gaps in Natural Language Processing for Yorùbá: A Systematic Review of a Decade of Progress and Prospects

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Abstract

Natural Language Processing (NLP) is becoming a dominant subset of artificial intelligence as the need to help machines understand human language looks indispensable. Several NLP applications are ubiquitous, partly due to the myriads of datasets being churned out daily through mediums like social networking sites. However, the growing development has not been evident in most African languages due to the persisting resource limitation, among other issues. Yorùbá language, a tonal and morphologically rich African language, suffers a similar fate, resulting in limited NLP usage. To encourage further research towards improving this situation, this systematic literature review aims to comprehensively analyse studies addressing NLP development for Yorùbá, identifying challenges, resources, techniques, and applications. A well-defined search string from a structured protocol was employed to search, select, and analyse 105 primary studies between 2014 and 2024 from reputable databases. The review highlights the scarcity of annotated corpora, limited availability of pre-trained language models, and linguistic challenges like tonal complexity and diacritic dependency as significant obstacles. It also revealed the prominent techniques, including rule-based methods, statistical methods, deep learning, and transfer learning, which were implemented alongside datasets of Yorùbá speech corpora, among others. The findings reveal a growing body of multilingual and monolingual resources, even though the field is constrained by socio-cultural factors such as code-switching and desertion of language for digital usage. This review synthesises existing research, providing a foundation for advancing NLP for Yorùbá and in African languages generally. It aims to guide future research by identifying gaps and opportunities, thereby contributing to the broader inclusion of Yorùbá and other under-resourced African languages in global NLP advancements.

Keywords: Natural Language Processing (NLP); Yorùbá language; Systematic review; Low-resource language

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1 Introduction

Natural Language Processing (NLP) is one of the key components of artificial intelligence. It has rapidly gained prominence in recent years as the need to help machines understand human languages grows. NLP involves developing intelligent systems that can converse with humans through natural language [1]. These intelligent systems are products of the two main classes of NLP: natural language understanding and natural language generation. These classes coalesce into the generation of language and understanding its intricacies, respectively [2].

Natural language typically denotes languages spoken and used by humans via various communication channels for day-to-day interactions. In contrast, artificial languages, like computer languages, are those created with certain rules and restrictions [3]. Moreover, unlike artificial language, natural language possesses ambiguity, making its processing often a hard nut to crack. For instance, the statement, “Erik Ten Hag wins his 50th game with Manchester United,” poses a situation where there could be two distinct meanings, depending on if one is saying Erik won his 50th game in charge of the club, or that Erik won his 50th career game with Manchester United. NLP applications have been seen in various exciting domains such as sentiment analysis [4, 5, 6], machine translation [7, 8, 9, 10], named entity recognition [11, 12, 13, 14], parts-of-speech (POS) tagging [15, 16, 17], question answering [18], amongst others, aiming to bridge the communication gap between humans and machines.

NLP techniques have witnessed fascinating evolution with diverse languages worldwide since its inception in the 1950s [19], initially with the rule-based approach. This involves defining linguistic rules for core language concepts, including semantics, pragmatics, morphology and phonology. These techniques have metamorphosed from the rule-based approach to statistical approaches, subsequently incorporating machine learning techniques, which utilise large-scale linguistic resources. Undoubtedly, the explosion of large datasets, mainly through social networking sites, necessitated the implementation of more advanced techniques. This births the introduction of deep learning methods [20], built on neural networks. Interestingly, the field of NLP witnessed revolutionisation through the advancement in deep learning, with notable models like the recurrent neural networks (RNNs), long short-term memory (LSTM), and more recently, the transformer architectures [21]. Moreover, this development has improved NLP performance in machine translation and question-answering tasks. More importantly, it gives way to a better understanding of sequential dependencies in natural language [22].

Furthermore, self-attention mechanisms and bidirectional training in models such as bidirectional encoder representations from transformers (BERT), alongside the generative pre-trained transformer (GPT-3) model developed by OpenAI¹, resulted in remarkable improvement in natural language understanding [23]. This innovation continues to set the pace for the emergence of many improved large language models (LLMs) like the Large Language Model Architecture (LLAMA) [24], Mistral [25], and others. LLMs, usually trained on huge datasets, have been recorded to have achieved state-of-the-art result performance across various tasks, which transitions from task-specific to task-independent architectures [26]. However, the dataset need of these models translates into a boon and bane for NLP in the context of many under-resourced languages in the world. These languages, because they are less digitised, sparingly taught, harbour resource scarcity & low density, are less privileged, among other identifiers, are referred

¹<https://openai.com/>

to as low-resource languages (LRLs) [27, 28].

Despite these significant advancements in NLP for major global languages like English and Chinese, underrepresented languages like Yorùbá—a language spoken by about 50 million people [29, 30] primarily in Nigeria and its diaspora—remain under-explored in computational linguistics research. Yorùbá’s linguistic richness, characterized by tone marking, complex morphology, and extensive oral traditions, presents unique challenges and opportunities for NLP development. Recent studies have underscored the importance of developing NLP resources and techniques for low-resource languages to ensure equitable access to technology, thereby conserving linguistic diversity. For Yorùbá, these early efforts include tasks such as diacritic restoration [31], machine translation [9], sentiment analysis [32], and parts-of-speech tagging [33]. However, the dearth of annotated datasets, tools, and computational models tailored to Yoruba significantly hampers progress in the field.

To promote NLP research involving Yorùbá language, it is essential to access the current status of such research involvement. To the best of our knowledge, no publication has addressed this need. Consequently, this research seeks to provide a systematic literature review (SLR) by synthesising existing research efforts in NLP for Yorùbá language. The study seeks to identify trends, highlight gaps, and propose directions for future research by answering specific research questions on the tasks addressed, methods employed, available resources, and prevailing challenges in NLP research involving Yorùbá language, either as a monolingual or bilingual component or as part of a multilingual study, where it is greatly emphasised. These questions are explicitly outlined in Section 3.2.

Ultimately, the motivation for this study is twofold. Firstly, it aspires to advocate for NLP solutions tailored to African languages, which remain underrepresented in global research. Ultimately, it is intended to bridge the gap between linguistic features unique to Yorùbá and their NLP representations, thereby contributing to linguistic preservation and technological inclusion as part of the Sustainable Development Goals (SDGs) of the United Nations (UN). The outcomes of this review are expected to serve as a comprehensive resource for researchers and practitioners working on Yorùbá language. Moreover, the findings would inform efforts to develop robust NLP systems accounting for the linguistic and cultural needs of Yorùbá while improving cross-lingual applications among other African languages.

2 Background of study

This section briefly introduces the Yorùbá language by discussing its constituents, such as letters and types, and detailing its root regarding its language family.

2.1 Yorùbá language overview

Yorùbá language is one of the largest low-resource African languages with over 47 million speakers, encompassing several dialects with considerable similarities [34, 35]. It is adopted as a native and social language in Western African countries, including Nigeria, Togo, Benin Republic, and other countries like Cuba, Brazil, etc. [36]. Yorùbá uses 25 out of the 26 Latin-script letters, excluding *q*, *z*, *v*, *x* and *c* [37]. Thus, an additional 4 letters—*e*, *ø*, *gb* and *s*—with

the existing 21 makes up the entirety of the Yorùbá alphabets. In addition, it is a tonal language with three primary lexical tones: high, medium, and low [37]. The tones are usually represented by acute (as in ú), grave (as in ù), and an optional macron (as in ū), denoting the high, low and mid-tone, respectively [12]. The three tonal signs and the underdots cater for diacritics, which determine the linguistic meaning of words in the language. Generally, the language is composed of 7 vowels (*a*, *e*, *ɛ*, *i*, *o*, *ø*, and *u*), about 5 nasal vowels, (*an*, *en*, *in*, *ɔn*, and *un*), and 18 consonants (*b*, *d*, *f*, *g*, *gb*, *h*, *j*, *k*, *l*, *m*, *n*, *p*, *r*, *s*, *ʂ*, *t*, *w*, and *y*) [38, 31].

As derived by the Expanded Graded Intergenerational Disruption Scale (EGIDS) categorisation [39], the language currently has the institutional level status. This implies that it has achieved sizable development and is still utilised beyond the community and individual homes. This is evident in its usage and availability of resources through written books, mass media, and various undocumented oral traditions. However, it is still classified as a low-resource language alongside other Nigerian languages due to the dearth of basic computing resources [40]. This indicates that available resources remain untapped for creating natural language corpora and developing technological and NLP tools [41].

2.2 Yorùbá Language Family

The Yorùbá language belongs to the Niger-Congo family [41]. This language family is the most prominent and largest of the four major African linguistic groups: Niger-Congo, Nilo-Saharan, Afro-Asiatic and Khoisan [42]. This language family possesses distinctive noun class systems; nonetheless, they exhibit substantial variations in types, especially in morphological complexity [43]. A substantial part of languages of sub-Saharan Africa—containing Western Africa, Southern Africa, Eastern Africa, and Central Africa—belong to this family, making up about 85% of the entire African language population [44]. Among these are Cape Town, South Africa, in the southern part; Dakar, Senegal, in the western part; and Mombasa, Kenya, in the east of Africa. Figure 1 presents a language tree visualisation showing the connection of these language groups or families. It starts with the Niger-Congo family and shows the groups and subgroups up to the last node, displaying the position of the Yorùbá language, including others in the same class.

At the time of writing this paper, the Niger-Congo language family had 1552 language subgroups, which are classified into three main groups: Atlantic-Congo, Mande, and Kordofanian². In addition to three groups, a language group, *Mbre*, is left unclassified within the Niger-Congo language family. The *Kordofanian* branch is seen to be primarily spoken by the Nuba people of southern Sudan. Unlike the former, the *Mande* languages are commonly spoken in Western African countries, mostly in The Gambia, Burkina Faso, Senegal, and Mali, to mention a few. Similarly, the *Atlantic-Congo* languages are mostly used in a similar demographic as the *Mande* languages. The languages are used mainly in Western African countries like Liberia, Guinea, Guinea-Bissau, Senegal, The Gambia, and Sierra Leone. Moreover, they are documented as the most prominent, diverse, and primary component of the Nigeria-Congo language family [45].

Going down the language tree, it is seen that the Yorùbá language stems from the Atlantic-Congo language group, recognised as the most used in the Niger-Congo language family. Moreover, the *Ijoid*, *Atlantic* and the *Volta-Congo* language groups emerge from this *Atlantic-Congo*

²<https://www.ethnologue.com/subgroup/47/>

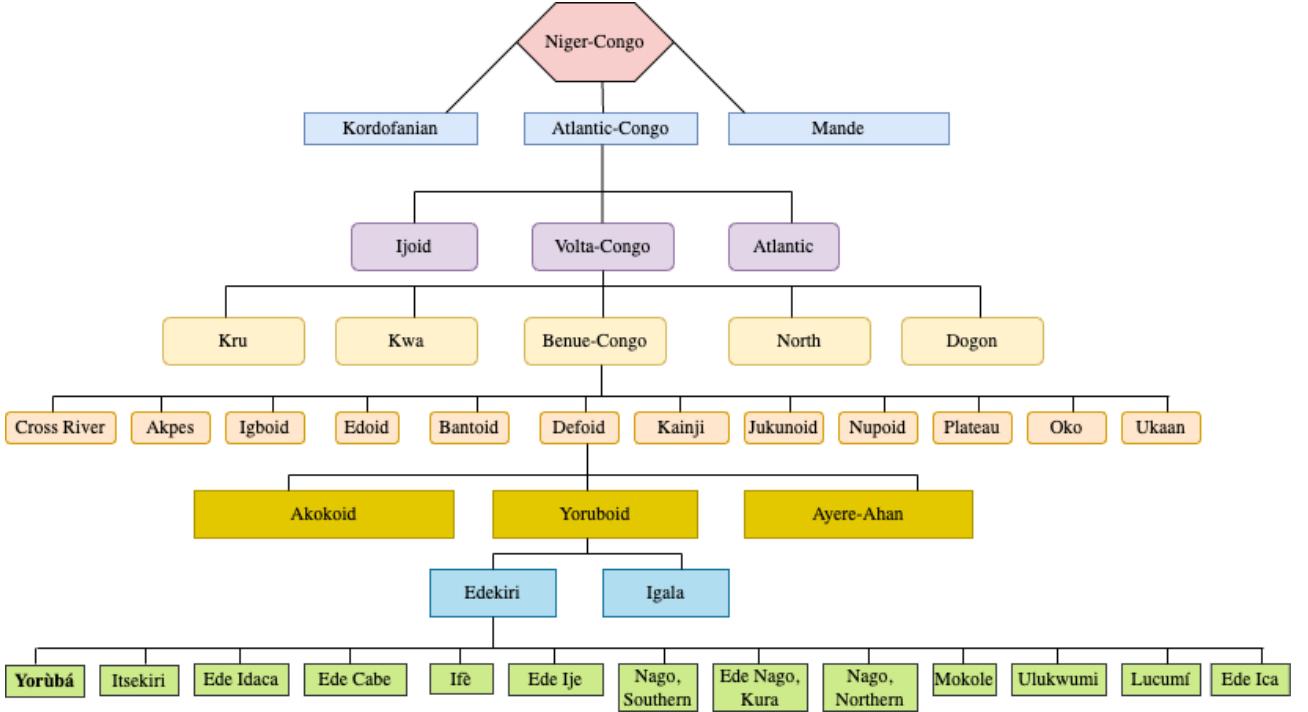


Figure 1: Yorùbá Language Family Tree

group. Among these three branches, the Yoruba follows the path of the *Volta-Congo* subgroup, which was recorded to contain 5 branches: *Kwa*, *Kru*, *Dogon*, *North* and the *Benue-Congo* subgroups. From these, about 12 language family subgroups are documented to be contained in the *Benue-Congo* subgroups, which house the Yorùbá language. However, one language, *Fali of Baissa*, is left unclassified. Furthermore, the *Defoid* subgroup, from the *Benue-Congo* languages begets the *Yoruboid* group, which in turn contains the *Edekiri* and *Igala* language subgroups. Consequently, the Yorùbá language stems from this *Edekiri* branch. Other language in the same class as the Yorùbá language include: *Itsekiri*, *Ede Idaca*, *Ede Cabe*, *Ifè*, *Nago, Southern*, *Ede Ije*, *Ede Nago, Kura*, *Nago, Northern*, *Mokole*, *Ulukwumi (Olùkùmi)*, *Ede Ica*, and *Lucumi*. In summary, the Yorùbá language belongs to the *Niger-Congo* language family, sequentially from *Atlantic-Congo*, *Volta-Congo*, *Benue-Congo*, *Defoid*, *Yoruboid*, with *Edekiri* as its last branch.

3 Materials and Methods

This section details the review processes, from planning to data synthesis. The guidelines comprehensively detailed in [46, 47] were followed to ensure adequacy in the review processes, from the selection of studies to the reporting stage. These guidelines help identify, analyse, and interpret all information from the primary studies considered without bias or prejudice.

3.1 Review Planning

A systematic literature review requires formal planning and conscientiousness. Consequently, a defined protocol was followed to ensure the success of the entire process. The data, in the form of research articles, the review objectives, and defined selection criteria, were managed

using the Covidence³ platform, a software tool for effectively organising systematic reviews. It allows for a sequential flow, following a standard review protocol. Moreover, Zotero⁴ is the reference manager, which ensures optimality and efficiency in the selection and writing process. Combining these tools with Microsoft Excel, the study benefits from tools that ensure flexibility and convenience, minimizing the required rigour of a typical systematic review.

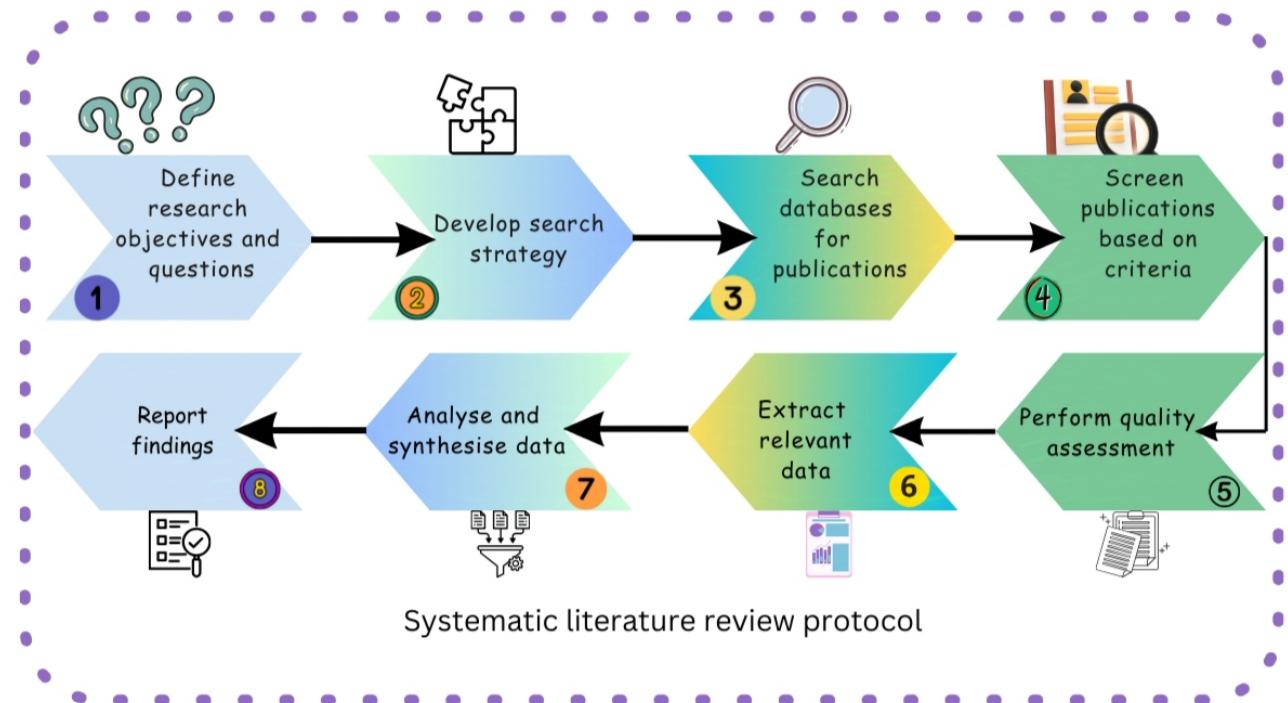


Figure 2: The systematic literature review protocol

Following the review protocol shown in Figure 2, the first task was to define the research objectives and develop the research questions based on the objectives. Thereafter, the search strategy was developed. This includes defining the search string and the scope of the search. Subsequently, potential papers are searched through identified databases and screened based on the selection criteria. A quality assessment is performed on the included paper to ensure standard review and that the relevant data are extracted thereafter. Furthermore, the available data are analysed to obtain meaningful results reported comprehensively afterward. The next sections explained the processes in more detail.

3.2 Research Questions

Research questions were developed to define a precise template for the broad study objectives. Four questions have been carefully defined to cater to all possible domains intertwined with the research objectives by forming a structured set of interrogative statements whose answers are meant to provide insight into the research goal. The questions are motivated by the need to know the current status of Yorùbá language involvement in NLP by investigating the specific

³<https://www.covidence.org/>

⁴<https://www.zotero.org/>

tasks, techniques, resources, and challenges. The research questions are presented sequentially in Table 1 to cater to structure flow and a quick overview.

Table 1: Research questions

S/N	Research Questions
RQ1	What NLP tasks have been addressed for Yorùbá language?
RQ2	What techniques have been employed for Yorùbá NLP?
RQ3	What language resources are available for Yorùbá language?
RQ4	What challenges are associated with NLP development involving Yorùbá language?

3.3 Search Strategy

This section describes the gathering of the vital primary studies and the “systematic” steps toward achieving the goal. It is a crucial phase planned to eliminate potential bias and incorporate randomisation in the studies’ selection and sample size determination. Reputable databases related to the subject matter were painstakingly explored to obtain all relevant studies for the systematic review using a well-defined search strategy. Generally, the central goal of the strategy involves attracting studies that have applied computational NLP approaches involving Yorùbá language, be it as a monolingual, bilingual, or multilingual NLP set-up.

3.3.1 Method and Scope of Search

The strategy initially employed an automated search method to obtain studies relevant to the systematic review. This method involved combing each electronic database with the defined keywords, boolean operators, and wild cards—as and when due. Furthermore, to ensure a representative sample and a higher recall, 9 databases were targeted in total viz: Web of Science⁵, ScienceDirect⁶, Google Scholar⁷, Association for Computing Machinery (ACM) Digital Library⁸, Institute of Electrical and Electronics Engineers (IEEE) Xplore⁹, Semantic Scholar¹⁰, Scopus¹¹, ScienceDirect¹², and Association for Computational Linguistics (ACL) Anthology¹³.

Moreover, with the motive of exploring a decade of the progress of NLP research in the Yorùbá language paradigm, studies between 2014 and 2024 were chosen. This decade range was also established by considering the time of writing this paper, and it is plausible since the studies of 2014 were published towards the year’s end. In addition, to ensure potent quality, only peer-reviewed journal articles and conference papers were included in the search results, with the language of writing exclusively in English. Also, due to the computational requirement of NLP research, studies mainly in Computer Science, Engineering, and Computational Linguistics

⁵<https://www.webofscience.com/>

⁶<https://www.sciencedirect.com/>

⁷<https://scholar.google.com>

⁸<https://dl.acm.org/>

⁹<https://ieeexplore.ieee.org/>

¹⁰<https://www.semanticscholar.org/>

¹¹<https://www.scopus.com/>

¹²<https://www.sciencedirect.com/>

¹³<https://aclanthology.org/>

were considered, further focusing strictly on empirical studies. Figure 3 is a Pareto plot used to show the statistics of the initial search results across the databases, alongside the cumulative percentage. It shows that most papers were from Google Scholar, accounting for about 60% of the search results, while the least was from IEEE Xplore. The curve shows the cumulative percentage of studies from each database. It indicates the percentage contribution of each database, with the least being IEEE Xplore.

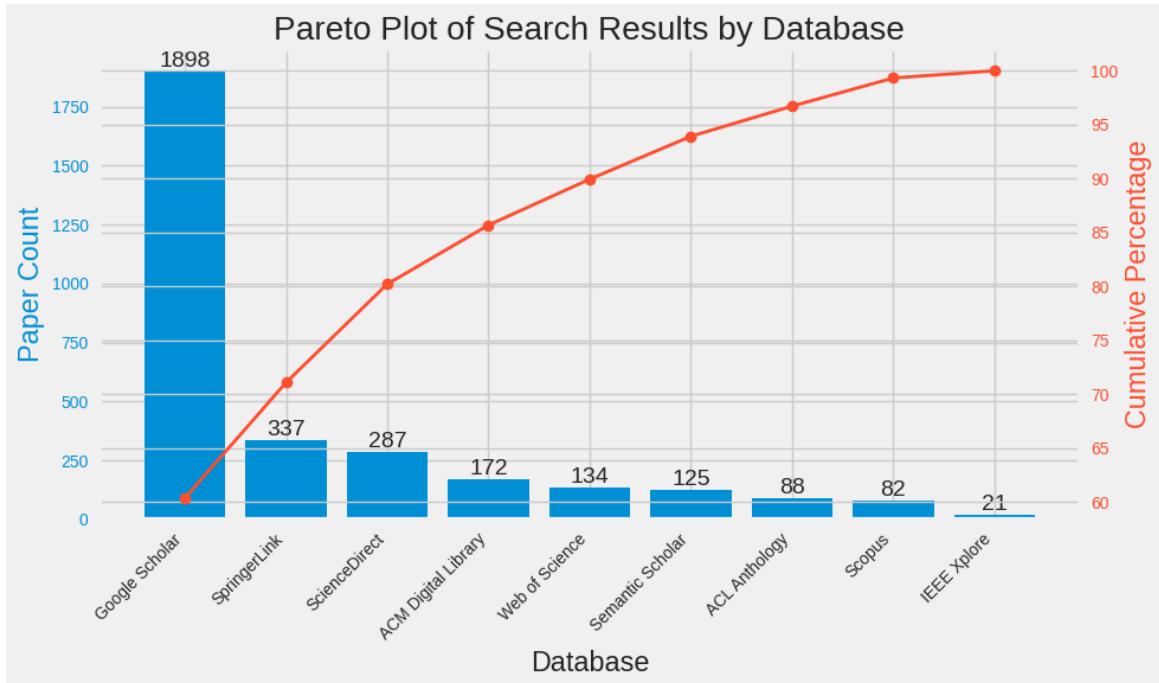


Figure 3: Initial Search Results across Databases

3.3.2 Search Strings

The search strings denote the combination of keywords used in exploring the databases to extract potential primary studies. Potential keywords in the systematic review objectives were identified and combined to build this. However, before the combination, a few related research publications were scanned through to see the usage of the relevant phrases and words. Thus, since the study seeks to synthesize information vis-a-vis NLP research and solutions associated with Yorùbá language, the general search string is formulated based on the three segments and presented as follows:

(“Natural Language Processing” OR NLP OR “Computational linguistics” OR “neural network*” OR statistic* OR “machine learning” OR “artificial intelligence” OR corpus OR dataset* OR “data set*”) AND Yoruba AND (solution OR task OR application)

However, it is pertinent to mention that the search string was modified slightly for different databases based on their unique requirements and search functionalities.

3.3.3 Study Selection Criteria

Having obtained a substantial number of studies considered relevant to the study, the criteria to painstakingly select the most essential and directly aligned studies were defined. This

involves a set of defined statements based on the research objectives and scope, making up the inclusion and exclusion criteria. It accounts for the desired year range, publication type, access to full-text documents, etc. Table 2 shows the inclusion and exclusion criteria, which are defined following the PICO criteria: population, intervention, context, and outcome [46]. In addition, *Study Range* and *Publication Type* and *Publication Language* were used to represent the publication years considered for the primary, the type of publication, and the language of publication, respectively. Furthermore, the two classes of criteria—inclusion and exclusion—defined statements to determine if the particular study is to be part of the review or irrelevant to it, respectively. Relevant articles were searched and gathered via the listed databases, bearing in mind the defined criteria.

Initially, 3144 studies were obtained across the 9 databases. The RIS files containing these studies from their respective sources were uploaded on the Covidence software tool. Due to the inevitable intersection across databases, the software detected a total duplicate count of 816, while 50 duplicates were manually detected. Again, following the selection criteria, abstract screening was initially carried out, leaving out a total of 1865 from the unique 2278 studies. Moreover, full-text screening was carried out on the remaining 413 studies, and a total of 308 studies were discarded based on defined reasons. Eventually, 105 primary studies were obtained for inclusion in the review.

Subsequently, backward and forward snowballing techniques were also used to capture studies that might have been missed in database searches due to conflicting terminology, following [48]. For backward snowballing, reference lists of a quarter of the 105 articles were surveyed to check for additional relevant studies. It was observed that the identified publications were part of the initial search results across databases. Additionally, forward snowballing, which involves checking for publications that have cited the potential primary study, was carried out. Here, 5 pre-prints and 1 review publications were discovered; however, they were not included due to the defined exclusion criteria. The snowballing loops were ended after no new studies were obtained. Ultimately, 105 primary studies were included in the SLR after conducting a quality assessment check, presented in Section 3.4. The whole selection process ensures a detailed and comprehensive overview by incorporating the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) framework, which is also presented in Figure 4, following [47].

3.4 Quality Assessment

This section shows further efforts to ensure the credibility of primary studies used in the systematic literature review. Specific quality questions were used for verification to further ascertain the reliability of the primary studies to be eventually included in the SLR. Thus, a quality checklist was created, following the guidelines in [46]. The response associated with each question is defined through a multiple-choice response: Yes, Partially, and No. A “Yes” response shows higher certainty, thus getting a score of 2. Similarly, a “Partially” response is assigned 1, while a “No” response is assigned 0. For this research purpose, a total quality score below the median score is to be excluded. The median is calculated as the value in the $\left(\frac{n+1}{2}\right)^{\text{th}}$ position, where n is the maximum quality score, which equals 16. Thus, for quality scores $S_i = \{1, 2, \dots, 16\}$, the median position, M_p , is derived as follows:

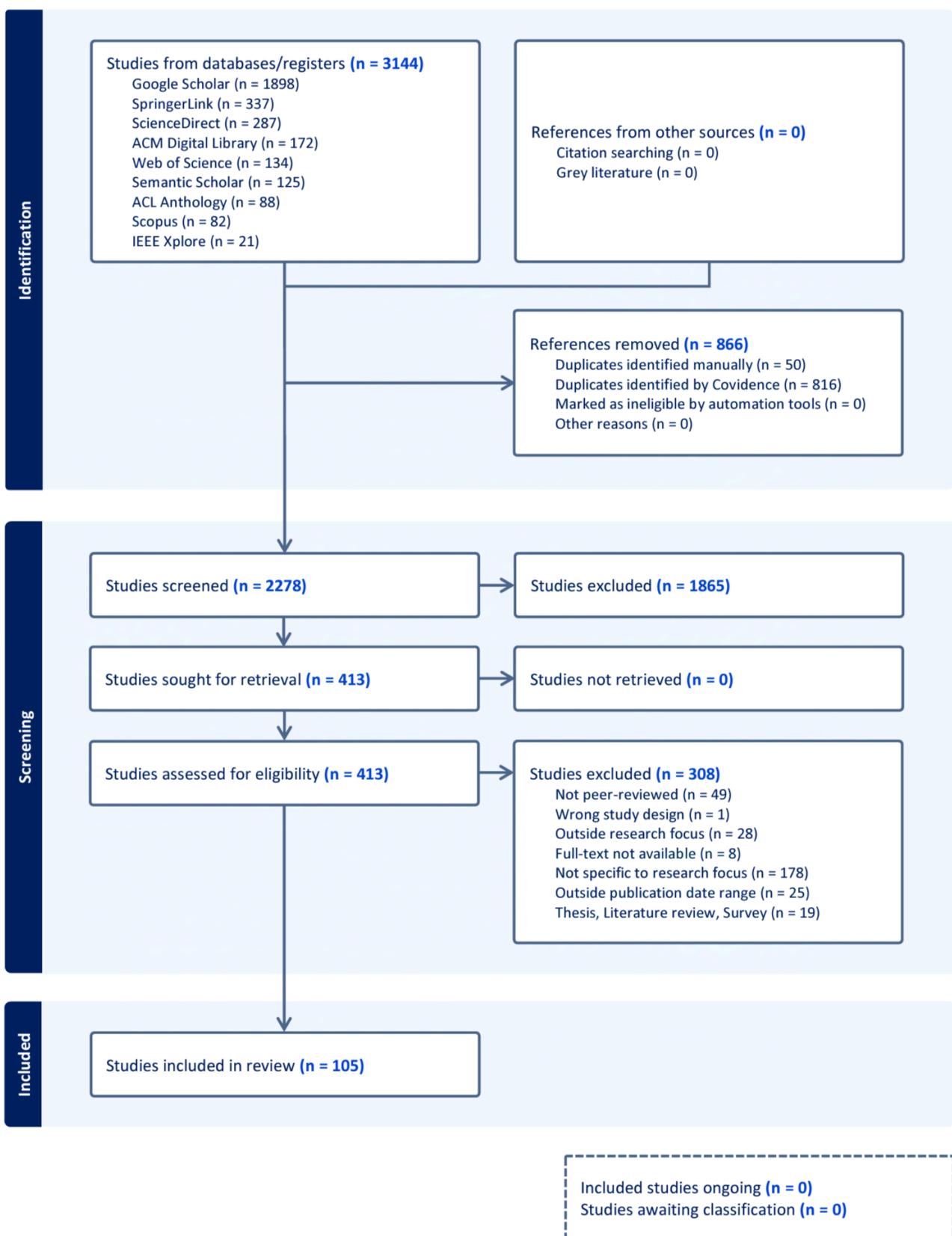


Figure 4: PRISMA diagram of selection process

Table 2: Inclusion and exclusion criteria

S/N	Inclusion	Exclusion
Population	Studies specifically addressing NLP solutions, tasks, or methods for Yorùbá language	Studies not involving Yorùbá language
Comparison	Comparative studies of NLP solutions for low-resource languages, including Yorùbá	Comparative studies not including Yorùbá
Outcome	Studies reporting the performance of NLP solutions involving Yorùbá	Theoretical studies without practical evaluations or results
Intervention	Study involving NLP solutions for Yorùbá language	Study involving NLP solutions for unrelated languages
Study Range	Publications between 2014 & 2024 inclusive	Publications before 2014
Publication type	Peer-review journal articles and conference papers	Non-peer review studies, including thesis, reviews, surveys, etc.
Publication language	Studies published in English language	Studies published in languages other than English

$$M_p = \left(\frac{n+1}{2} \right)^{th} \text{ position} \quad (1)$$

$$M_p = \left(\frac{16+1}{2} \right)^{th} \text{ position}$$

$$\therefore M_p = 8\frac{1}{2}$$

Thus, the median, M , is

$$M = \frac{8+9}{2} = 8.5$$

Consequently, a paper with a score less than 8.5 out of the 16 total score will be excluded. However, no study falls in this range. Hence, the total 105 primary studies are included in the systematic review. Table 3 shows the checklist containing the quality domain and the questions asked for each.

After assessing each potential primary study based on the quality questions, scores were assigned—a maximum of 16 for each. The results are plotted through the histogram in Figure 5. The plot shows that most of the primary studies have a score of 15, followed by 14. Moreover, only a minute quantity of the primary studies has a total score between 9 and 12, with 9 being the minimum total score being 9, while the maximum is 16. This shows high quality in the included primary studies, potentially making this review’s results highly valuable.

3.5 Data Extraction

Data extraction involves collecting information relevant to the SLR from the primary studies. It was carried out by defining an extraction template. This template is structured based on

Table 3: Quality Assessment Checklist

Domain	Question
Research objective	Are the objectives of the study clearly stated?
Methodology and study design	Are the study's methods and experimental design clearly defined?
Research documentation	Are the study's processes comprehensively documented?
Research Question Alignment	Are the research questions answered through the findings?
Study conclusion	Do the conclusions of the study relate to its objectives?
Result evaluation	Does the study validate the results using standard evaluation metrics?
Limitations and bias	Are the limitations of the study acknowledged?
Novelty and contribution	Does the study contribute new tools, resources, insights, or investigate new questions?

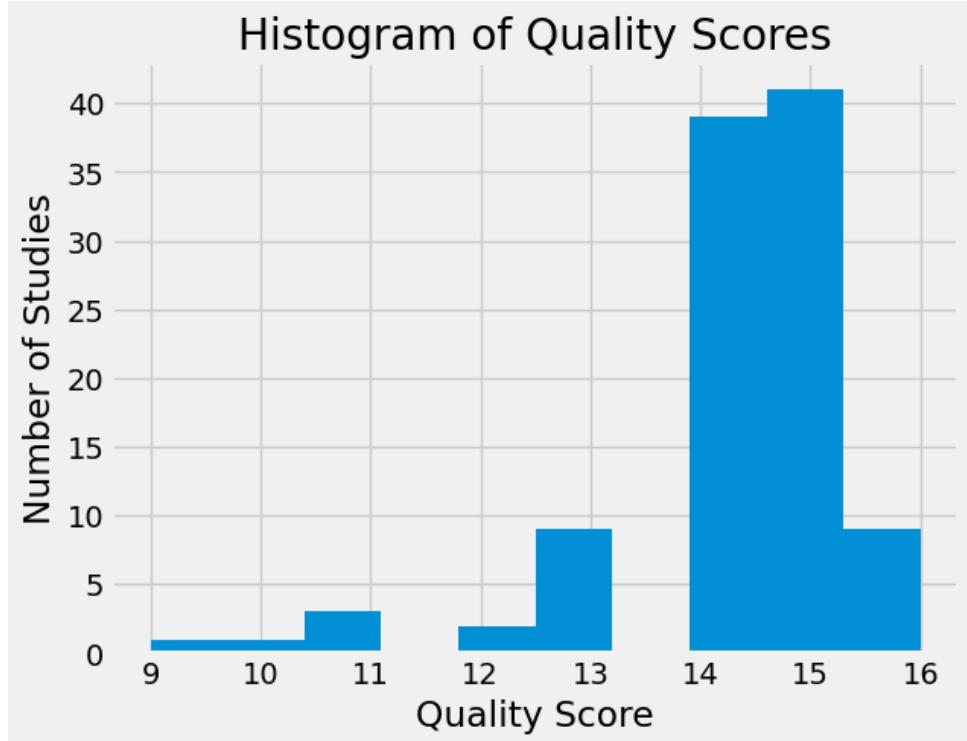


Figure 5: Histogram of total quality score for each study

the following sections: Bibliographic information, research context, NLP focus, language scope, results and evaluation, and contributions. The sections, in turn, contain individual elements that constitute all the extraction items. Pilot extractions were carried out with fewer samples to verify the results and update the form based on the need or irrelevance of variables to be extracted. For this study, the “research country” and “research continent” are taken as the affiliation of the lead author at the time of their research publication. The final extraction template is given in Table 4.

Table 4: Data Extraction Template

Variable	Extraction Item
V1	Study ID
V2	Article Title
V3	Publication Year
V4	Research Country
V5	Research Continent
V6	Publication Type
V7	Publication Source
V8	NLP Task
V9	NLP Technique
V10	Language Scope
V11	Dataset
V12	Citation Count

3.6 Data Synthesis

This section involves integrating and interpreting information extracted from the selected studies. Initially, data were obtained from individual databases and combined to form the primary studies after excluding required studies based on the selection criteria. Findings were obtained from the primary studies across diverse domains, including the NLP tasks, techniques, resources, and challenges. Moreover, the process was carried out using Microsoft Excel and the Covidence platform, mentioned explicitly in Section 3.1. The ultimate goal at this stage is to identify patterns, trends, and knowledge gaps to inform future research directions in Yorùbá NLP.

4 Results and Interpretations

This section discusses the results obtained from the primary studies included in the systematic review through the data synthesis. It helps answer the research questions and provides visual illustrations of every component of the primary studies.

4.1 General Statistics

The primary studies included in the research, totalling 105, were synthesized for relevant data. They consist only of journal articles and conference papers based on the selection criteria specified in the systematic review protocol. Figure 6 reveals the frequency of the sample—included

primary studies—over the years. It attests that the Yorùbá NLP research has grown over the years, with an apparent upward trend after the break in year 2017. In addition, 2023 and 2024 have the highest number of primary studies, even though the latter year is yet to end at the time of this review. Subsequently, the publications are assessed based on the type. Figure 7 shows the distribution of article type, in which there are more conference papers (62.9%) than journal articles (37.1%). This observation is plausible as most researchers in this domain are primarily involved in conferences.

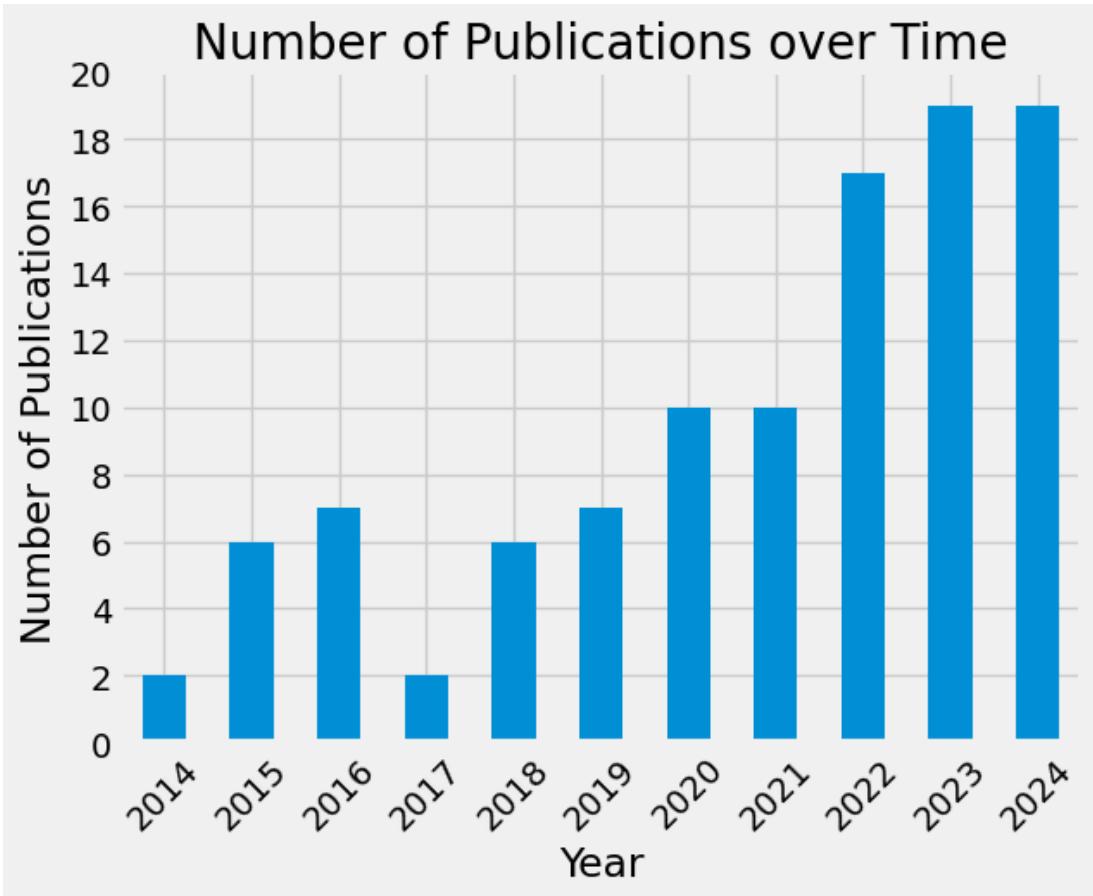


Figure 6: Distribution of publication per year

Furthermore, accessing the authors contributing to this field shows an informative trend, as depicted in Figure 8. Figure 8b shows the top 20 authors in this field based on the primary studies. The top author, David Adelani, has about 18 included publications in total. Moreover, there have been observable collaborations among the top 7 authors, including Dossou, BFP; and Osei, S. Similarly, significant collaborations exist among Lin, J; Oladipo, A; and Ogundepo, OJ, among other notable collaborations. In addition, even though the top 20 authors in the field were represented, the minimum number of publications on the chart in Figure 8b being 5, left out authors with publications between 2 and 4. Hence, Figure 8a ensures a representative visualization by revealing famous authors in the research domain.

Finally, Figure 9 shows the first authors' geographical locations at the publication's time. It reveals an interesting insight, making it known that most publishers were based in Nigeria at the time of publishing, while a considerable number were also in the United States, Canada, South

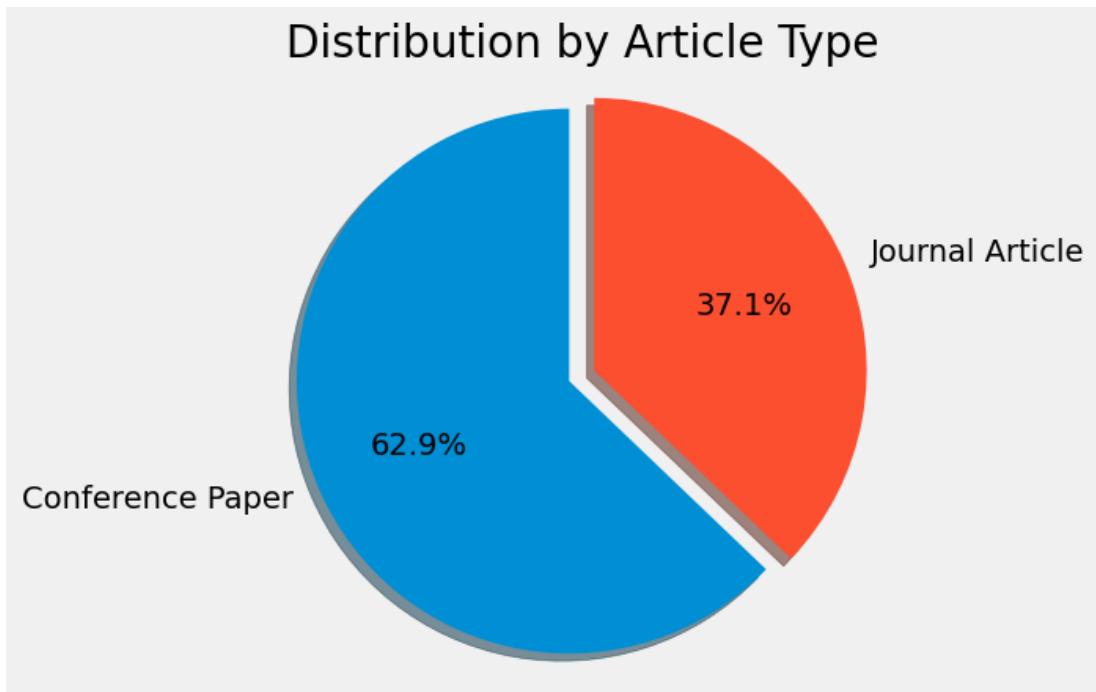


Figure 7: Distribution of publication types

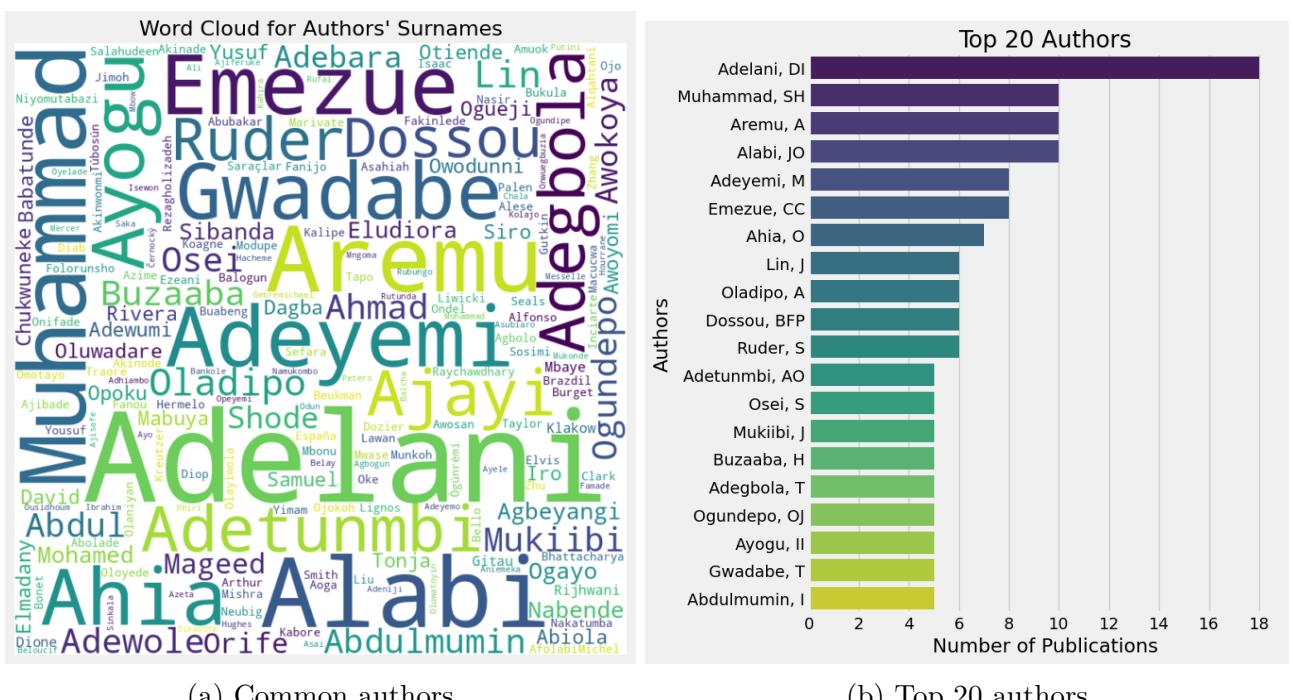


Figure 8: Popular authors by publication number

Africa, Germany, and the Benin Republic. This tells that research in this domain extends beyond the dominant speaking country of the Language—Nigeria. It also shows promising outcomes due to visible collaborations taking place among researchers across the world.

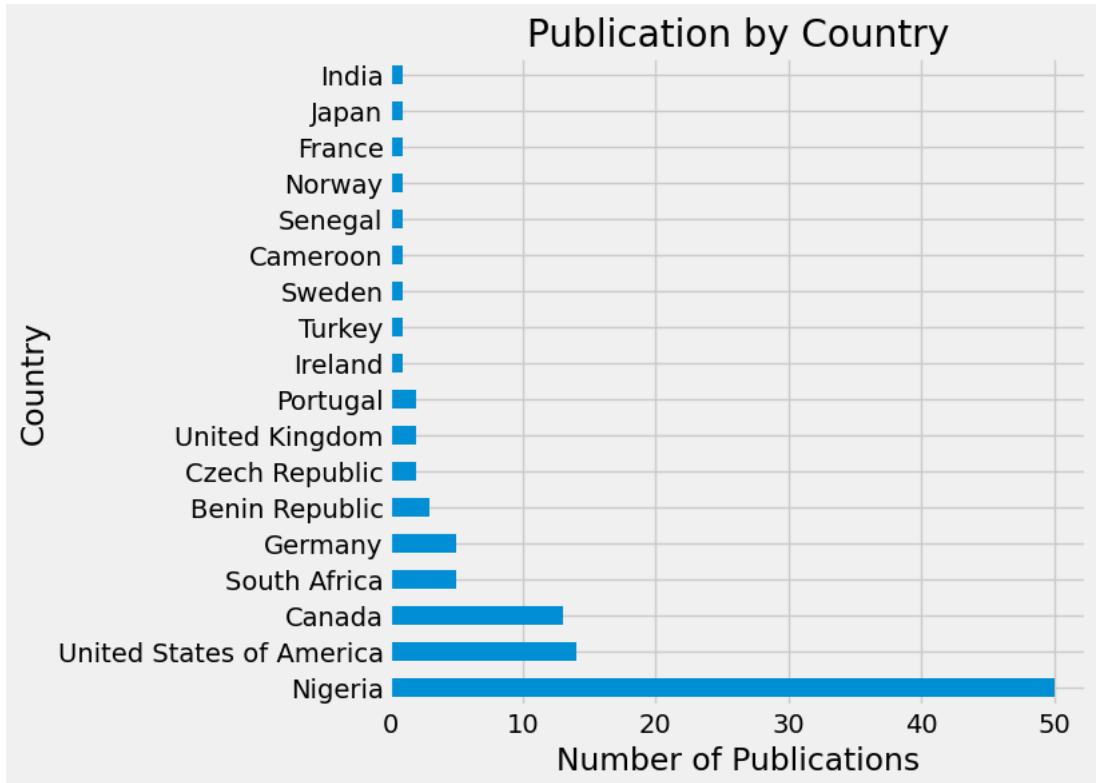


Figure 9: Publications by geographical location

4.2 Research Question Analysis

This section contains pertinent responses to specific research questions outlined by the systematic literature review objectives. The analysis presented herein represents a key contribution to the review. It summarises the inquiry findings through structured responses to each question, making it an essential tool for answering similar questions for future researchers.

4.2.1 RQ1: What NLP tasks have been addressed for the Yorùbá language?

Investigating the various NLP tasks involved with applying Yorùbá language has revealed improved and promising results over the years. These NLP tasks or solutions synthesis considered the application of the language either as a monolingual NLP research or as part of a bilingual or multilingual task—only considered when there is a vivid emphasis on the language.

Efforts have been made to democratize the numbering system of Yorùbá language through NLP with an earlier study [49], which tried to develop a computational system for converting cardinal numbers into their Yorùbá number names in a number-to-text conversion task. Similarly, [50] develops a machine translation system for translating English number text into Yorùbá text, considering the context. While the former focused on the text normalization task, a core

foundational NLP task required in this research domain, the latter focused on machine translation. Moreover, diacritic restoration, an important component of text normalization tasks, has been given considerable research efforts, as seen from [31, 51, 52, 53] studies. Ultimately, three studies [54, 55, 56] have made efforts toward improving spell-checking and correction in the Yorùbá texts. These tasks are crucial for accurately representing texts in the language, thereby improving the availability of quality data.

The need to understand sentence structure due to its importance for the syntactic parsing of text has also made parts-of-speech tagging essential research towards improving Yorùbá NLP. This involves assigning grammatical categories, such as nouns, adjectives, adverbs, etc., to words based on the meaning or context. Four studies [17, 15, 33, 16] worked on this task, whereas [17] involved 20 typologically diverse African languages, in which Yorùbá was a key subset of. Similarly, NLP tasks involving morphological induction [57] and analysis [58, 59] were explored as these are essential for breaking words into their roots and affixes. In addition, two studies [60, 61] investigated syllabification tasks, which involve breaking words into their syllables. These tasks are essential for ensuring precise semantic and syntactic parsing in texts.

Furthermore, identifying entities, such as names of people, organizations and places, in texts is crucial to advancing Yorùbá NLP. This involves the named entity recognition aspect of NLP and has been investigated in a significant number of studies, including [11, 62, 12, 14, 13]. These studies are essential for identifying specific entities, such as cultural components and personal names in Yorùbá, and are, in turn, vital for downstream tasks. A study [63] also developed a dependency parsing multi-task model in a multilingual approach by considering Wolof, Bambara, and Yorùbá language as core components. The study is crucial for analyzing grammatical relationships among words in a sentence, and it involves syntactic knowledge transfer from high-resource to the extremely low-resource languages referenced.

Many studies also explored the crucial task involving automatic translation of text data between Yorùbá and other languages. About 18 studies explored the machine translation (MT) tasks, cutting across rule-based machine translation (RBMT) [30, 64, 65, 66, 67, 50, 9], statistical machine translation (SMT) [8, 68], neural machine translation (NMT) [28, 10, 69, 70, 71, 72], and a few hybrid MT methods involving SMT and RBMT [29]; RBMT and example-based machine translation (EBMT) [73]; SMT and NMT [7]. Moreover, a similar task on sentence alignment, which is crucial to NMT, was explored in [74], considering a bilingual approach involving English-Yorùbá pair.

Language modelling is also an indispensable task, as it is often necessary to predict the likelihood of word sequences to capture linguistic patterns in languages. Only a handful of studies have been seen to work in this domain; the related studies of [75, 76] specifically involve multilingual language model pre-training, which were developed for African languages, with significant emphasis on Yorùbá language. Moreover, to verify the effectiveness of a modest amount of data for multilingual language modelling, [77] introduced the AfriBERTa model, while [78] also introduced AfriTeVa, to further extend language modelling with limited training data to sequence-to-sequence modelling. Furthermore, the semantic modelling task was explored in [38]. It involves the construction of a Yorùbá language ontology meant to characterise the semantic relationships between the words, among which are antonyms, synonyms, hyponyms, hypernyms, holonyms and meronyms.

Understanding sentiment-bearing phrases or words in text and speech is equally essential to Yorùbá NLP for determining the language users' emotional undertone. Research in sentiment analysis has also been explored across a few studies, with most using a multilingual approach. [79, 80] strictly investigate sentiment analysis while [5, 6, 81, 4] includes language resource development alongside the sentiment analysis tasks addressed. In addition, research which solely involves text [65, 82, 77] or topic classification [83, 84] was also explored in five studies altogether. Moreover, under these broader classification categories, the language identification or detection task was also carried out in two studies [85, 86].

Even though most studies tend to involve text processing, quite a substantial number of studies also investigated speech processing in Yorùbá NLP. This ranges from text-to-speech synthesis [87, 88, 89, 90], tone recognition for continuous speech [91], speech recognition [92, 93, 94], text-to-speech analysis [95], speech-based gender recognition [96] and multi-tasks involving both text-to-speech and speech-to-text [97], text-to-speech and language speech resource development [98, 99, 36, 100, 101], speech synthesis and language pitch modelling [102], and two studies exclusively focusing on speech corpus development [103, 104]. Whereas, [35] differs as it is based on corpus development for visually grounded speech. Furthermore, to optimize modelling in speech recognition, acoustic unit discovery tasks [105, 106, 107] are essential in learning speech sounds embedding to retain the linguistically relevant acoustic information and discard the irrelevant ones.

Ultimately, increased usage of social networking sites and websites, among others, has undoubtedly exploded the extent of information available in recent years. Thus, developing effective methods of accessing and retrieving information is indispensable. Few studies also explored this, including tasks on dense information retrieval [108], monolingual retrieval tasks [109], and cross-lingual information retrieval tasks [18, 110, 111].

These insights show considerable progress with the involvement of Yorùbá language in various NLP tasks, culminating in invaluable efforts at solution development in the research domain. Table 5 is used to summarize the various NLP tasks involving Yorùbá as presented by the primary studies.

Table 5: Summary of NLP Tasks and Corresponding Studies

NLP Task	Studies Addressing Task	Popular Techniques	Dataset used
Acoustic unit discovery	[106], [107], [105]	Statistical modelling	Yorùbá Speech Corpus; Custom data
Automatic speech recognition	[101], [103], [94], [92]	Statistical modelling	ÍròyìnSpeech; Custom data
Diacritic restoration	[51], [53], [52]	Neural networks	Lagos-NWU Yorùbá Speech Corpus; Custom data

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NLP Task	Studies Addressing the Task	Popular Techniques	Dataset used
Language modelling	[38], [75], [77], [76]	Multilingual training	WÚRÀ; Common Crawl Corpus; Custom data
Information retrieval	[110], [109], [108], [111], [18]	Multilingual language modelling	AFRIQA; MIRACL; CIRAL; Custom data
Machine translation	[8], [29], [30], [28], [71], [9], [64], [70], [69], [65], [7], [73], [66], [67], [74], [50], [68], [72], [10], [34], [112], [37]	Rule-based; statistical modelling; multilingual pre-training	WebCrawl African; YORULECT; IkiniYorùbá; MENYO-20k; Custom data
Named Entity Recognition	[11], [62], [12], [14], [113], [13], [77], [84]	Transfer learning; Pre-training multilingual embeddings	MasakhaNER; Common Crawl Corpus; Custom data
Part-of-speech tagging	[17], [16], [33], [15]	Statistical modelling; cross-lingual transfer	MasakhaPOS; Lagos-NWU Yorùbá Speech Corpus; Custom data
Sentiment analysis	[4], [5], [6], [81], [80], [79]	Deep learning; transfer learning	AfriSenti; NaijaSenti; NollySenti; Custom data
Speech-based gender recognition	[114], [96]	Neural networks	Lagos-NWU Yorùbá Speech Corpus
Spell checking & correction	[54], [55], [56]	Statistical modelling	Custom data
Syllabification	[61], [60]	Rule-based	Custom data
Speech-to-Text	[97], [106]	Statistical modelling	Yorùbá Speech Corpus; Custom data
Text and topic classification	[115], [83], [82], [77], [84], [85], [86]	Machine learning; multilingual language pre-training	MasakhaNEWS; Common Crawl Corpus; Custom data
Text-to-Speech	[87], [88], [97], [101], [98], [99], [36], [100], [104], [89], [90]	Rule-based	IròyìnSpeech; Prosodic Read Speech Corpus; BibleTTS; Antenatal Orientation Speech Dataset; Yorùbá Speech Corpus; Custom data
Tone identification and recognition	[91], [93], [95]	Machine learning; neural networks	Yorùbá Speech Corpus; Custom data

4.2.2 RQ2: What techniques have been employed for *Yorùbá* NLP?

The metamorphosis of NLP techniques involving Yorùbá language is observed to not necessarily lag behind the general trend of accomplishment in the NLP community. Most of the earlier research works are seen to be limited to implementing rule-based techniques [87, 30, 64, 55] be-

fore the advancement, leading to incorporating statistical modelling [103, 86, 8, 116], and sometimes, a combination of both techniques [81]. Furthermore, recent studies have incorporated supervised machine learning [11, 51, 82, 93] and unsupervised learning [117, 107, 57, 105, 59] techniques in this research domain, and a few times, the hybrid of statistics and machine learning techniques [33, 116]. Lately, deep learning architectures [80, 79, 52, 31, 28], as well as a hybrid of machine and deep learning methods [115] are being utilised for various tasks as well.

Also, due to the low-resource nature of Yorùbá language, NLP research works in its domain have benefitted from transfer learning by pre-training on a high-resource language and fine-tuning on specific tasks in this language. Transfer learning of this nature over the years has been mainly composed of leveraging multilingual pre-training [71, 118, 119, 120, 63, 77] and cross-lingual transfer [121, 18, 17, 111]. Figure 10 shows word clouds of both the employed techniques 10b and the NLP tasks 10a carried out in the primary studies involved in the review.

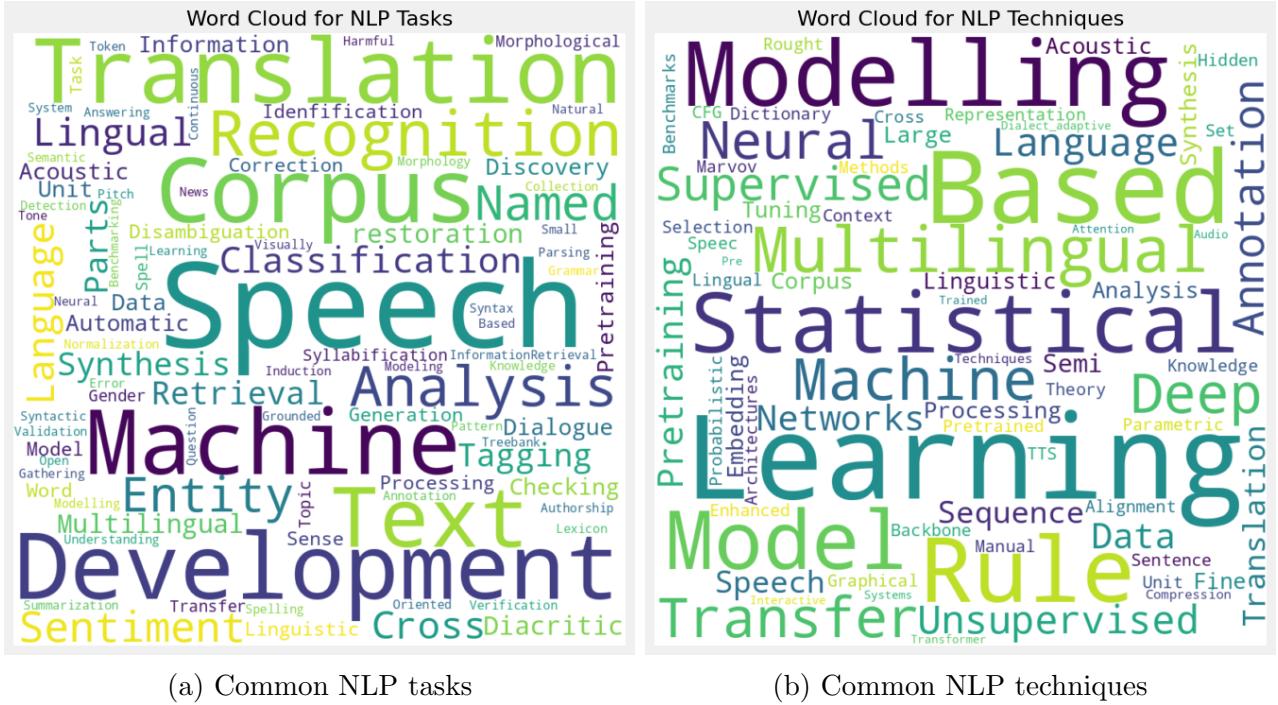


Figure 10: Word clouds of NLP tasks and techniques

Table 6 shows a cross-tabulation of the specific NLP tasks involving Yorùbá language together with the NLP techniques utilised in each task. It reveals that only studies involving sentiment analysis and TTS tasks utilised all the techniques as classified. The MT task closely followed the previous two tasks vis-a-vis the varieties of techniques involved in their studies; all the techniques classes were utilised in the MT studies, except for the machine learning technique. Moreover, other tasks have studies utilising most of the classes of techniques; however, acoustic unit discovery, ASR, spell checking & correction, speech-to-text, and tone identification & recognition tasks include studies using only two different techniques. In addition, only the speech-based gender recognition task has studies involving only a single technique—deep learning technique.

Table 6: Cross Tabulation of NLP Tasks and Techniques

NLP Task	Techniques					
	Rule-Based	Statistical Modelling	Machine Learning	Deep Learning	Transfer Learning	Multilingual Pre-training & Cross-Lingual Transfer
Acoustic unit discovery	-	✓	✓	-	-	-
Automatic speech recognition	-	✓	-	-	✓	-
Diacritic restoration	-	✓	✓	✓	-	-
Language modelling	-	-	-	✓	✓	✓
Information retrieval	-	-	-	-	✓	✓
Machine translation	✓	✓	-	✓	✓	✓
Named Entity Recognition	-	-	✓	-	✓	✓
Part-of-speech tagging	-	✓	✓	-	✓	✓
Sentiment analysis	✓	✓	✓	✓	✓	✓
Speech-based gender recognition	-	-	-	✓	-	-
Spell checking & correction	✓	✓	-	-	-	-
Syllabification	✓	-	✓	✓	-	-
Speech-to-Text	-	✓	-	-	✓	-
Text and topic classification	-	-	✓	✓	✓	✓
Text-to-Speech	✓	✓	✓	✓	✓	✓
Tone identification and recognition	-	-	✓	✓	-	-

4.2.3 RQ3: What language resources are available for Yorùbá language?

Many low-resource languages experience stunted growth in their language development due to the flaw associated with their lack of substantial datasets required for various NLP tasks amidst recent data-hungry models. This factor has undoubtedly prompted significant efforts at developing various language resources for Yorùbá language to further improve the performance of various NLP tasks in the language. The developed resources have been seen to cut across different domains; while some studies solely focused on resource development, others utilised the datasets or corpora on specific tasks. The summary of the corpora, which contains Yorùbá either as a monolingual, bilingual, or as an important part of a multilingual dataset, is presented in Table 7. Furthermore, for detail purposes, specific datasets or corpora with assigned names are briefly outlined individually as follows, while others are listed as part of the general descriptions:

AFRIQA: AFRIQA [18] pioneers among cross-lingual question-answering (QA) corpus devel-

opment for African languages. It is the first cross-lingual open retrieval question-answering (XOR QA) dataset focused on African languages, bridging the gap in resource availability and paving the way for more equitable and inclusive question-answering technologies. More importantly, Yorùbá language is a core component among the languages in the dataset, as it comprises about 12,239 XOR QA examples for 10 African languages across the southern, western, eastern and central African regions, viz: Bemba, Fon, Hausa, Igbo, Kinyarwanda, Swahili, Twi, Wolof, Yorùbá and Zulu. Specifically, for Yorùbá language, the training, dev, and testing examples are 360, 261, and 332, respectively. Furthermore, experiments to evaluate the performance of state-of-the-art models on the dataset were carried out, and this mainly involved automatic translation, which entails translating questions or retrieved documents in preparation for processing, and multilingual retrieval, involving carrying out direct retrieval through the aid of multilingual embeddings.

AfriSenti: AfriSenti [4] focuses on providing a high-quality, large-scale dataset to address the lack of resources for sentiment analysis in underrepresented African languages. This benchmark contains over 110,000 posts involving 14 African languages across four language families—Niger-Congo, Afro-Asiatic, English Creole and Indo-European—in which Yorùbá is a core part. The languages featured in the dataset are namely: Amharic, Algerian Arabic, Hausa, Igbo, Kinyarwanda, Moroccan Arabic, Mozambican Portuguese, Nigerian Pidgin, Oromo, Swahili, Tigrinya, Twi, Xitsonga, and Yorùbá. The sentiment categories captured in the corpus include positive, negative and neutral. Furthermore, baseline traditional machine learning and pre-trained multilingual language models were trained to facilitate empirical analysis. Moreover, evaluation metrics include accuracy, F1 score, and precision/recall. Overall, it established a benchmark for sentiment analysis in Yorùbá language, also enabling comparisons of models and techniques for African languages.

AfriWOZ: AfriWOZ [122] also pioneers in resource development involving dialogue generation for low-resource African languages. It presents a high-quality dialogue generation dataset for 6 African languages, emphasising the Yorùbá language as a subset. Other five languages include Hausa, Kinyarwanda, Nigerian Pidgin English, Swahili, and Wolof; all languages spread across three language families—Afro-Asiatic, Niger-Congo, and English Creole. The dialogue dataset for the included languages was developed from the MultiWoz dataset [123], and experiments were performed to avail empirical analysis for related tasks using transfer learning approaches.

Antenatal Orientation Speech Dataset: This dataset contains multilingual speech datasets in English, Nigerian Pidgin English, and Yorùbá languages, basically for antenatal orientation in Nigeria, being the main geographical source of the languages. The dataset [100] is composed of a word count of 2,639 for English, 3,202 for Yorùbá, and 2,521 for Pidgin. Moreover, the corresponding speech datasets had 59,880 seconds for English, 70,380 seconds for Yorùbá, and 69,840 seconds for Pidgin, both showing a dominant percentage for Yorùbá language. The size of the speech datasets was 15.6 KB for English, 17.9 KB for Yorùbá, and 18.3 KB for Pidgin. This dataset will be valuable for antenatal orientation in Nigeria and contribute to the currently low-resource status of Yorùbá language by improving its availability for NLP tasks.

BibleTTS: BibleTTS [98] is an open speech multilingual dataset containing ten languages of sub-Saharan Africa, viz: Akuapem Twi, Asante Twi, Chichewa, Ewe, Hausa, Kikuyu, Lingala, Luganda, Luo, and Yorùbá. The corpus emanates from Bible recordings provided by

the Open-Bible project of Biblica and contains high-quality $48kHz$ studio recordings for single speakers, with up to 86 hours of data per language. Furthermore, TTS models were developed by leveraging the dataset, which ascertains its usability and quality for speech synthesis. The dataset is openly available for commercial and non-commercial use as it's licensed CC-BY-SA License, promoting accessibility and further research in text-to-speech for Yorùbá, among other languages captured.

CIRAL: CIRAL[111] presents a cross-lingual information retrieval (CLIR) in four languages—Hausa, Somali, Swahili, and Yorùbá—with great emphasis on Yorùbá language. The corpus comprises over 2.5 million in passages curated from indigenous African websites. The data annotation involved native speakers annotating over 1,600 queries and 30,000 binary relevance judgments, ensuring high-quality data for evaluation. Furthermore, reproducible baselines involving translation-based and embedding-based CLIR were further developed to support empirical analysis for related tasks. The dataset is relevant for retrieving relevant documents or passages in one language, e.g., Hausa, Swahili, Yorùbá, or Somali, based on queries expressed in another language.

IkiniYorùbá: IkiniYorùbá[37] is a dataset focusing on the cultural aspect of Yorùbá, intending to investigate how well MT models can translate greetings in the language into English. This dataset comprises 960 parallel sentences of Yorùbá greetings and their English translations. Moreover, it also incorporates the movie transcript subset of the MENYO-20k dataset[72], which contains conversational Yorùbá-English data. The performance of MT models was evaluated on the datasets to enable empirical analysis for related studies in future. The introduction of the IkiniYorùbá dataset is a valuable contribution to the research community working on Yorùbá NLP.

IròyìnSpeech: IròyìnSpeech [101] presents high-quality speech corpus exclusively in Yorùbá language, which allows for multipurpose usage involving Automatic Speech Recognition(ASR) and Text-to-Speech (TTS) tasks. The data collection involves curating 23,000 sentences from news and creative writing domains under an open license (CC-BY-4.0). Also, it included 5,000 sentences on the Mozilla Common Voice platform to crowdsource recordings and validations. The data contributions include 42 hours of in-house recorded speech data by 80 volunteers and an additional 6 hours of validated recordings on Mozilla Common Voice. Ultimately, a high-fidelity single-speaker Yorùbá TTS system was evaluated on the curated speech data, including a baseline word error rate (WER) of 23.8 for ASR purposes.

Lagos-NWU Yorùbá Speech Corpus: To promote research voice recognition, a speech corpus including 16 female and 17 male speakers was recorded in Lagos, Nigeria [16]. A total of 130 utterances read from brief texts chosen for phonetic coverage were recorded by each speaker. Moreover, recordings were made using a microphone attached to a laptop computer in a peaceful office setting to ensure quality in the corpus. Ultimately, this corpus will be relevant for various NLP tasks in Yorùbá, such as TTS, ASR, etc.

MasakhaNER: MaskhaNER [12] boasts as the first largest high-quality dataset for named entity recognition tasks focused on African languages, in which Yorùbá was greatly emphasised. The dataset scope extends to 10 African languages and across four language families, and they include Yorùbá, Amharic, Hausa, Igbo, Kinyarwanda, Wolof, Nigerian-Pidgin, Luo,

and Swahili.

MasakhaPOS: MasakhaPOS [17] presents a huge POS dataset available for 20 diverse African languages, of which Yorùbá language was greatly emphasised. Other languages featured in the dataset include Bambara, Fon, Hausa, Igbo, Luo, Luganda, Akan/Twi, Wolof, isiZulu, isiXhosa, Setswana, Kiswahili, Nigerian Pidgin English, Mossi, Kinyarwanda, Ghomálá, Éwé, chiShona, and Chichewa. Moreover, Yorùbá data was jointly obtained from Voice of Nigeria and Asejere online newspapers, containing a 43,601 token with an average sentence length of 24.4. Moreover, baseline models using conditional random fields (CRF) and multilingual pre-trained language models such as mBERT and XLM-R were developed to support empirical analysis for related tasks.

MENYO-20k: MENYO-20k [72] presents a multi-domain parallel corpus of Yorùbá-English with clean orthography and standardized train-test splits, with focus on improving the evaluations of MT models on low-resource language. The dataset’s domain includes texts from news articles, radio and movie transcripts, TED talks, etc. In addition, special attention was given to the diacritization of Yorùbá texts in the corpus, as it plays an essential role in intelligibility and translation quality in MT NLP tasks. Neural MT models are benchmarked to enable future empirical analysis in similar studies. The dataset is available through a CC BY-NC 4.0 licence.

NaijaSenti: NaijaSenti [6] is a sentiment classification corpus for four prominent languages used as a medium of communication in Nigeria: Yorùbá, Hausa, Nigerian Pidgin English and Igbo. The dataset was obtained from X—formerly Twitter—and comprises roughly 30,000 tweets for each language, including code-mixed tweets. Benchmarks were also developed on monolingual sentiment analysis tasks for each language, and the dataset and model codes are publicly available online.

NollySenti: NollySenti [5] is a parallel multilingual corpus for sentiment classification in five languages spoken in Nigeria, including Yorùbá, Nigerian Pidgin English, Hausa, Igbo and English. The dataset source reviews from Nollywood movies—movies primarily made in Nigeria—initially in English, with translations into the four Nigerian languages involved. Moreover, the initial collection for the dataset comprises 882 negative reviews and 1,018 positive reviews, with an average word length of 20.7 and 35.0, respectively, making up two sentiment classification categories. Benchmarks were also developed through traditional machine-learning techniques and pre-trained language modelling to enable empirical analysis for future research in the domain.

Prosodic Read Speech Corpus: This corpus contains a high-quality speech corpus [104] of 7,376 phrases and sentences in Standard Yorùbá language. A TTS system was developed on the corpus and evaluated using the mean open score and semantically unpredictable sentence (SUS) test score to support empirical analysis for future related studies. The developed corpus can be used as valuable research material for future studies on Yorùbá speech processing, synthesis, and recognition

TATA: TATA [119] dataset is a large and high-quality multilingual dataset focused on African languages, created from Demographic and Health Surveys (DHS) Program bilingual reports. It consists of 8,700 examples in nine languages, with Russian as a zero-shot test language. Yorùbá

is a core component of these languages; other languages in the dataset include Arabic, English, French, Hausa, Igbo, Portuguese, and Swahili. A transformer-based multilingual pre-trained language model was evaluated on the dataset, supporting empirical analysis in future related studies.

TTS Yorùbá Speech Corpus: A comprehensive Yorùbá speech corpus was designed primarily for TTS synthesis research and development in the language [99]. The Yorùbá speech corpus contains 2,415 sentences with 46,117 words and 148,823 phonemes. The corpus has a good balance of sentence types—affirmative, interrogative, and exclamatory—and phoneme distribution. Furthermore, the Yorùbá speech corpus was also integrated into the MaryTTS¹⁴ open-source multilingual text-to-speech (TTS) synthesis platform, which achieved a Mean Opinion Score (MOS) of 2.9 out of 5 for the quality of the synthesized speech.

WebCrawl African: WebCrawl African [112] contains multilingual parallel corpora for diverse African languages. It was gathered to build resources for machine translation tasks in low-resource and extremely low-resource African languages. The parallel corpus spans 74 language pairs, which includes 15 African languages, of which Yorùbá language was greatly emphasised. For empirical analysis purposes, two multilingual models were trained on behalf of 24 African languages, including Yorùbá language, using the dataset and evaluated using FLORES-200 [124] benchmarks. The dataset will be useful for multilingual and cross-lingual machine translation tasks involving Yorùbá language.

WÚRÀ: WÚRÀ [76] presents a new high-quality multilingual pre-training corpus for African languages, with Yorùbá greatly emphasised. The dataset is \approx 30GB for all languages and \approx 19GB for African languages. Downstream tasks ranging from MT, summarization, cross-lingual question answering, and text classification were built on the corpora to enable empirical analysis for related future studies.

YFACC: YFACC [35] connected speech with visual representations in the dataset comprising spoken captions in Yorùbá language for 6,000 Flickr¹⁵ images. The audio captions also utilised single-speaker recording to ensure consistency in the audio data. Moreover, it includes cross-lingual pairing, whereby images are tagged with English visual labels and paired with Yorùbá speech, permitting cross-lingual applications. The empirical analysis is also catered for by developing a baseline cross-lingual model. Ultimately, this dataset addressed the dearth of visually-grounded speech datasets in low-resource languages, essentially focusing on Yorùbá language. Furthermore, it provides a new benchmark for visually-grounded speech models in low-resource language settings.

Yorùbá Speech Corpus: An open-source speech dataset exclusively for Yorùbá developed in [36]. This corpus comprises over 4 hours of 48kHz recordings from 36 male and female volunteers. It also includes transcriptions with disfluency annotations and full diacritization, essential for pronunciation and lexical disambiguation. Moreover, the dataset was tested in a statistical parametric speech synthesis (SPSS) for evaluation purposes and compared with related corpora in the same domain. The corpus will support TTS, ASR, and speech-to-speech translation, contributing to West African corpus linguistics.

¹⁴<https://marytts.github.io/>

¹⁵<https://www.flickr.com>

Yorùbá Treebank (YTB): YTB [41] boasts of the first-tree bank in Yorùbá language. It contains manually annotated Yorùbá Bible sections and is relevant for investigating dependency analysis in the language.

YORÙLECT: YORÙLECT [34] introduces a high-quality parallel text and speech corpus specifically in Yorùbá language, across three domains—machine translation, automatic speech recognition, and speech-to-text translation—and four Yorùbá dialects—Standard Yorùbá, Ifè, Ìjèbú, and Ìlaje. The Ifè dialect is spoken primarily among the people of Ṗsun state, Ìjèbú among people of Ṗgún state, and Ìlaje, among the people of Ondó state—all states located in the South West geopolitical zone of Nigeria. Text data from various sources were obtained and localised into the three Yorùbá dialects for the corpus development. Similarly, high-quality speech data in standard Yorùbá, Ifè, and Ìlaje were recorded. The text portion contains about 1506 parallel sentences for each dialect, totalling 6024, and the speech part contains ≈ 3 hours of audio for the trio of standard Yorùbá, Ifè, and Ìlaje. Furthermore, to aid empirical analysis, experiments involving the domain of text MT, ASR and speech-to Yorùbá were carried out, and the dataset and models were published under an open licence, making it relevant for Yorùbá NLP tasks.

Table 7 is used to summarize the available language resources relevant for NLP development involving Yorùbá language.

Table 7: Summary of Resources Available for Yorùbá NLP Development

Resource	Type	Use Case	Language Frequency	Study Used
AFRIQA	Annotated corpus	Cross-lingual retrieval	open-question answering	Multilingual [18]
AfriSenti	Annotated corpus	Sentiment analysis	Multilingual	[4]
AfriWOZ	Dialogue dataset	Dialogue generation	Multilingual	[122]
Antenatal orientation	Speech corpus, text corpus	Speech recognition, machine translation	Multilingual	[100]
BibleTTS	Speech corpus	Text-to-speech	Multilingual	[98]
CIRAL	Annotated corpus	Cross-lingual information retrieval	Multilingual	[111]
IkiniYorùbá	Parallel corpus	Machine translation	Bilingual	[37]
IròyìnSpeech	Speech corpus	Automatic speech recognition, text-to-speech	Monolingual	[101]
Lagos NWU Yorùbá Speech Corpus	Speech corpus	Automatic speech recognition	Monolingual	[16], [53], [52], [31]
MasakhaNER	Annotated corpus	Named entity recognition	Multilingual	[12]
MasakhaPOS	POS dataset	Part-of-speech tagging	Multilingual	[17]

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Resource	Type	Use Case	Language Frequency	Study Used
MIRACL	Annotated corpus	Monolingual information retrieval	Multilingual	[109], [108]
MENYO-20k	Parallel corpus	Machine translation	Bilingual	[72], [28], [74]
NaijaSenti	Annotated corpus	Sentiment analysis	Multilingual	[6]
NollySenti	Parallel corpus	Sentiment classification, machine translation	Multilingual	[5]
Prosodic Speech	Read Speech corpus	Text-to-speech	Monolingual	[104]
TATA	Parallel corpus	Data-to-text generation, multilingual generation	Multilingual	[119]
TTS Speech Corpus	Yorùbá Speech corpus	Text-to-speech	Monolingual	[99]
Webcrawl African	Parallel corpora	Machine translation	Multilingual	[112]
WÚRÀ	Parallel corpus	Cross-lingual question answering; text classification; summarization; & machine translation	Multilingual	[76]
YFACC	Speech-image dataset	Cross-lingual keyword localisation	Monolingual	[35]
Yorùbá Speech Corpus	Speech corpus	Text-to-speech; automatic speech recognition; speech-to-speech translation	Monolingual	[36, 91], [105], [107]
Yorùbá Treebank	Dependency treebank	Dependency parsing and analysis	Monolingual	[41]
YORULECT	Parallel text and speech corpus	Machine translation; automatic speech recognition; & speech-to-text translation	Monolingual	[34]

4.2.4 RQ4: What are the major challenges in developing NLP solutions for Yorùbá?

Natural language solution development for Yorùbá faces multiple challenges limiting its growth as a low-resource language. Data synthesis in this study has helped identify five primary challenges, including linguistic, technical, resource, cultural and societal factors, and evaluation and benchmarking challenges.

Linguistic challenges: Yorùbá language exhibits several linguistic properties that make NLP

development in it an exigent task. These linguistic features of the language often complicate its NLP development, and they mainly account for its tone dependency, morphology, diacritic demand, and code-switching demerits, which are summarised briefly below:

- **Tonal complexity:** Yorùbá language implicit pitch contours, denoting tonal components, in communicating emphasis and other para-linguistic expressions. Thus, they usually determine the semantic property of the message conveyed in the language. For instance, *Ògún* (a deity associated with iron) is different from either of *ogun* (war) and *ogún* (twenty). This distinction in linguistic meaning complicates various NLP tasks even though the words belong to the same phonetic sequence. For instance, one of the main challenges for speech recognition in Yorùbá is determining the tone associated with a syllable [91]. Similarly, utilising context-dependent phone units to capture long-term spectrum dependencies of tone in Yorùbá is typically less successful and oftentimes requires a different means of acoustic modelling [93]. Furthermore, in bilingual English-Yorùbá MT tasks, tone-changing verbs [66] also present challenges as they frequently alter the semantic properties of the sentence they are used in by shifting from a low-tone to a mid-tone. Consequently, accurate representation and processing of tones are essential for NLP tasks like diacritic restoration, TTS synthesis, and MT.
- **Diacritic dependency:** Similar to the tonal feature of Yorùbá language, it also requires appropriate assignment of accent property to characters in a segment. This task is usually referred to as diacritic restoration, and it's essential to fully decipher the linguistic meaning of words. Diacritic marks are usually placed above, below, or between characters to indicate pronunciation and may change the meaning of the composed words [53]. Like most languages involving diacritic, Yorùbá language users often omit them in electronic texts, increasing lexical ambiguity and also posing challenges to NLP systems as a result of mislaying the accompanying syntactic, grammatical, or semantic information, partially or totally [51]. This omission is sometimes due to the unavailability of supporting applications and devices [31] or lack of knowledge by most users [90], resulting in a drawback towards improving NLP representation in the language.
- **Morphological Complexity:** Carrying out analysis of word formation and structure in Yorùbá language tends to be oftentimes complex due to its plenitude in terms of rules involving noun and verb inflection patterns [58]. Handling agglutinative morphology and word compounding has also been stated to require advanced morphological analysis tools [59]. The deficiency in this regard frequently creates ambiguity in unsophisticated NLP systems due to issues like affixes of words and the required rules to correctly programme the system for effective analysis. Efforts towards addressing this have incorporated automatic morphological induction [57] to ensure compatibility, producing a more accurate representation in the NLP domain.
- **Code-Switching:** This is common for most Nigerian languages, and Yorùbá is not spared of the growing ‘civilization’. Despite initiatives towards sustaining native languages, it is evident that the younger generation finds it difficult to carry on lengthy conversations or even to form lengthy sentences without interspersing the conversation with terms frequently borrowed from the English language [30]. This phenomenon introduces additional complexity in NLP tasks like language identification, sentiment analysis, and machine translation, as they reduce data availability purely in the language. This is evident in the dataset obtained for NaijaSenti [6], which aimed to conduct monolingual sentiment

analysis for four languages through a curated corpus from X, as a certain proportion of the corpus had to cater for the phenomenon.

Resource challenges: The challenges in obtaining substantial or quality resources for training NLP models involving Yorùbá language is the ultimate pitfall for their NLP development, just like in many other low-resource languages [76, 72]. The existence of a comprehensive lexicon for most high-resource languages makes their pre-processing task less taxing, unlike a low-resource language like Yorùbá. The unavailability often leads to applying manual data cleaning, hence the task of token validation for corpus development [125].

In addition, limited corpora pose significant challenges in various NLP tasks. For instance, a comparatively short corpus of speech recordings and minimal language-specific development can automatically build acoustic models for an elementary speech synthesiser in a new language; however, tonal languages like Yorùbá require additional resources [102] which is usually not readily available. Also, word-level and character-level models are especially common for most diacritic restoration tasks [53]. However, they require significant training data to prevent sparsity in the models. Similarly, out-of-vocabulary word translation is a significant issue for low-resource languages that lack parallel training data [70]. This phenomenon is considered a stumbling block to NLP development in these different domains, albeit recent efforts have been directed towards implementing other viable methods requiring lower resources for a handful of tasks supporting such.

Generally, limited available corpora for developing NLP tools have been a consistent challenge in NLP development involving Yorùbá and under low-resource languages. Studies have also shown the presence of quality issues for existing corpora and models [76], which limits the reliability of findings from using such corpus. Consequently, efforts towards creating readily available corpora for specific NLP tasks are sacrosanct since better results mostly require high-quality and large data [51].

Technological challenges: Limited availability of pre-processing tools is also a phenomenon constituting a major setback for most low-resource African languages, as the tool suitable for a language tends not to suit another, such as Yorùbá, owing to its morphological complexity and diacritic dependency. For instance, English word punctuation segmentation will not necessarily work for *Arabizi*, the Arabic chat language, since these marks define its own orthography [126]. Furthermore, research on pre-processing tools for different languages within the same family collectively suggests that while some can work across related languages, optimal results often require language-specific adjustments and careful consideration of the target domain and linguistic features [127].

Other language tools, including the syntactic parser and POS tagger, have also been reported to mostly fail in accounting for Yorùbá language linguistic nuances [15], thereby constituting a challenge requiring the development of language-specific tools for these specific tasks. Similarly, an essential NLP task such as effective spell-checking development in Yorùbá is still at the early development [56] due to non-consideration of diacritic necessity in earlier studies [55], resulting in their limitation. A limited number of studies [17, 54, 56] involving computational NLP have been seen to include Yorùbá language in these domains. Furthermore, the majority of Yorùbá texts are also seen to be typed using the plain ASCII Character Set, without diacritics [31], perhaps due to limited tools supporting their full implementation. This situation also induces

lower quality translation between Yorùbá language and most European languages due to lack of adequate elision resolution tool [30]. Thus, there is a growing need for flexible, multilingual pre-processing solutions.

Cultural and Societal Factors: An African language, such as Yorùbá, is not only a mirror into the mind of its users but also a mirror into their culture and history [38]. This emphasises the richness of the culture and language. However, younger generations of Yorùbá speakers increasingly favour English for formal and digital communication, while the parents also decide not to teach their infants many times [90]. This shift reduces the volume of contemporary Yorùbá texts and contributes to the decline of the language in digital contexts. Moreover, despite the evident progress in MT tasks for low-resource languages, NMT models still lag in accurately carrying out automatic translation involving cultures [72] for Yorùbá language. Consequently, cultural and societal challenges of Yorùbá in NLP development require considerable attention, as they could potentially endanger the language in the face of westernization, globalization, and inter-ethnic communication [38].

Table 8 summarizes the challenges of NLP development involving Yorùbá language and some of the highlighted solutions.

Table 8: Summary of Challenges in Yorùbá NLP Development

Challenge category	Specific challenge	Primary studies	Proposed solutions
Linguistic	Tonal complexity, diacritic dependency, morphological complexity, & code-switching	[66], [91], [102], [93], [31], [51], [52], [53]	Diacritic-aware models; Automatic morphological induction
Technological	Limited pre-trained models and lack of language-specific tools	[77], [29], [30]	Fine-tuning multilingual models; Developing elision resolution tool
Resource scarcity	Limited annotated corpora for specific tasks	[11],[76], [122], [30]	Collaborative corpus development across various NLP tasks; Multilingual corpus development
Socio-cultural	Adopting foreign language as first language	[90], [38]	Implementing iterative learning systems for Yorùbá language

5 Discussion

This systematic review was intended to capture the growth and current stage of NLP participation for Yorùbá language over a decade. Through the information synthesised from the primary studies, it is obvious that significant progress has been made in notable areas of NLP involving Yorùbá language. MT has particularly received more attention through the inclusion of the language primarily in bilingual MT research [64, 68, 74, 69, 28, 67, 50] involving translation between two languages. Related studies investigating the inherent prerequisite towards enhancing translation qualities in MT model qualities, the development of MT tools, such as vowel elision resolution [30], and the application of rough set theory [29] in translation have been explored. Moreover, the need to create better quality data [76] has also led towards improved research in this domain through the development of additional parallel corpora and leveraging multilingual language pre-training to improve the model training capability in the presence of large high-quality datasets.

Similar to MT research, significant efforts have been made in TTS synthesis, with considerable efforts towards corpus development, as evidenced by publicly available datasets, most of which are speech corpora. Even though it is the primary focus in most research investigating the task, some of the studies have included ASR and speech-to-text [101, 97, 34] in their experiments contributing to the entire research. Furthermore, sentiment analysis and information retrieval tasks involving Yorùbá have also benefited significantly from multilingual corpus development through the need to develop language resources for low-resource African languages. Most have been through the works in [4] and [111].

Generally, NLP tasks such as sentiment analysis, machine translation, text-to-speech synthesis, automatic speech recognition, named entity recognition, information retrieval, parts-of-speech tagging, and language modelling have received considerable research efforts, with at least four studies each addressing them. In addition, innovative approaches, transfer learning, and diacritic-aware systems have demonstrated promising results, showcasing the adaptability of state-of-the-art techniques to Yorùbá NLP, albeit earlier studies have depended mostly on the rule-based methods. Resources like Yorùbá speech corpus [36], MENYO-20k [72], Lagos NWU Yorùbá Speech Corpus [16] among others, have also been pivotal in advancing the field by providing foundational datasets, as they have been used in more than one study.

Furthermore, recent studies have showcased the importance of multilingual and cross-lingual techniques, as they help to promote language availability for many African languages simultaneously. This is evident from named entity recognition [12, 14], sentiment analysis [6, 4, 5], and information retrieval tasks [18, 111, 109]. Also, models pre-trained on multilingual datasets have been seen to be beneficial for a low-resource language like Yorùbá. Ultimately, it is also evident that collaborative, open-source and community initiatives have greatly improved research and availability of resources in the bid to overcome resource scarcity whilst fostering knowledge-sharing among these resource-scarce African languages.

However, in the context of constraints stunting the rapid growth of NLP in Yorùbá language, studies have highlighted mainly linguistic complexity such as diacritic dependency [31] and tonal variation [66]. Other challenges involving cultural and societal factors were also highlighted, including the primary hindrance, which has always been a limitation in available corpora or

the quality of such available corpora.

5.1 Limitation of study

While this systematic literature review investigates the progress and status of NLP involving Yorùbá, it is noteworthy to mention that “Yorùbá” in this case is not specific to a certain dialect of the language, such as Yorùbá of Ifè, Ìjèbú, or Ilàje. The study recognised Yorùbá language as one encompassing several dialects across different countries. Even though certain sections of it specifically highlighted NLP research and resources involving Yorùbá dialects [34], this study might not be sufficient when dialects of the language are the sole focus in the NLP research.

Furthermore, the last date for retrieving information for the study was October 2024. Hence, publications emerging afterwards would not have been included in the synthesis. Similarly, only peer-reviewed studies were included to ensure high quality and reliability in findings. This might limit a recently published relevant study undergoing a peer-review process during the period the databases were searched. Nevertheless, the systematic review ensures a substantial representation of information from various primary studies by considering a decade of publication years.

6 Conclusion and Future Directions

This section summarises the study and process involved and aims to inform readers of possible research areas towards improving Yorùbá language involvement in NLP research.

6.1 Conclusion

This SLR explores NLP progress involving Yorùbá language. It involves surveying studies between 2014 and 2024, which have used Yorùbá language in their NLP research, and those with great emphasis on the language, in case of a multilingual setting. Moreover, data were synthesized from these primary studies to deduce findings, thereby procuring answers to the established four research questions, which form the core objectives of the research.

The research questions explore the tasks, techniques, language resources, and challenges involved in Yorùbá NLP over a decade. Established protocols and guidelines were followed systematically to ensure maximum formal inundation, eliminating possible bias. Moreover, the information synthesised from the 105 primary studies has been carefully reported, encapsulating the relevant findings from the systematic review.

Ultimately, with this study, language researchers will be abreast of the current progress in Yorùbá NLP, thereby equipping them with the necessary ideas to preserve the language through NLP tool representation—this is crucial as it is a widely spoken language with abundant cultural richness and linguistic features. Similarly, it is required to guide future researchers plying this route to eliminate or limit possible odyssey in their research journey.

6.2 Future Directions

Even though the findings show promising results for NLP research involving Yorùbá language, it is pertinent to outline the current absence of significant efforts in some domains, which are equally important towards improving NLP in the language. For instance, research efforts involving the identification of abusive, offensive, hate speech or cyberbullying, which are all regarded as harmful language usage, have not been explored. This could be due to a lack of or limited annotated corpus in this domain. Such research tasks are essential for ameliorating the usage rate of sensitive words, phrases, and sentences on social media, as they could potentially endanger other users. Consequently, future research efforts can be directed toward building relevant corpora to address these NLP challenges and creating relevant benchmarks to facilitate empirical analysis and continuous research.

Sarcasm detection is another fascinating realm that remains untapped yet for Yorùbá and most under-resource languages. Sarcasm is used to mask the true emotion in a state, mostly by exuding positivity or a seeming positive demeanour. This phenomenon of saying what is not meant or meaning what is not said by natural language users poses challenges for NLP. However, it is essential to accurately detect users' real emotions for different purposes, including product reviews, feedback analysis, politics & governance, among others. Consequently, developing relevant sarcasm corpora and benchmarks that will potentially birth advanced sarcasm detection models is crucial. Future research can be focused on this domain to promote certainty in natural language usage.

Moreover, general resource development tasks are essential to limit the paucity of Yorùbá language resources. This could be achieved through continuous collaboration, open-source, and community initiatives, such as the one carried out through Maskhane¹⁶. Moreover, more priority can be given to developing Yorùbá-specific pre-trained models and fine-tuning existing multilingual models for better performance in under-resourced settings.

Furthermore, more research should be directed towards solving linguistic challenges such as tonal variations, morphology complexities, and diacritic restoration, as these are essential for decoding the nuances in the language. Developing pre-processing tools and models that cater to and integrate linguistic knowledge or incorporate phonological features in the language could significantly improve performance.

Finally, addressing the drawbacks associated with cultural and social challenges will require developing context-aware models that can adapt to real-world changes. Continuous language usage would also benefit from exploring new cases, such as LLM conversational agents, and developing healthcare and educational tools incorporating NLP. These innovations can aid in bridging the digital gaps among the Yorùbá-speaking communities.

Declaration of Conflict of Interest

The authors attest that no conflict of interest is involved in the publication.

¹⁶<https://www.masakhane.io/>

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Data Availability

No data was used for this research task. However, datasheets that record the different stages in the SLR can be found in the GitHub repository¹⁷ for reference.

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¹⁷<https://github.com/toheebadura/SLR>

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