Improving the Mkulima Repository Content: Utilizing Theses, Dissertations, and LLMs for Agricultural Knowledge Dissemination in Kiswahili

Joseph P. Telemala[1]

[1] Department of Informatics and Information Technology, Sokoine University of Agriculture

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Correspondence concerning this article should be addressed to Joseph P. Telemala, Department of Informatics and Information Technology, Sokoine University of Agriculture, P. O. Box 3038, Morogoro, Tanzania. Email: josephmasamaki@sua.ac.tz

Abstract

The Sokoine National Agricultural Library (SNAL) at the Sokoine University of Agriculture (SUA) faces significant challenges in disseminating agricultural information to Swahili-speaking communities, as most research outputs are predominantly in English. This language barrier hinders the effective transmission of vital agricultural knowledge to key stakeholders in the agriculture-food value chain who use Kiswahili in their daily activities. To address this gap, SNAL established the Mkulima Collection and Repository, dedicated to collecting agricultural content in Kiswahili. Despite these efforts, the Swahili content in the repository remains limited.

This study seeks to enhance the Mkulima Repository by translating abstracts from English-language theses and dissertations using MarianMT, a machine translation (MT) model based on large language models (LLMs). The selected abstracts underwent pre-processing, machine translation, and subsequent quality assessment by multilingual experts.

Our findings reveal significant challenges in using LLMs like MarianMT for low-resource languages such as Kiswahili. While the MT system offers a rapid and scalable method for translating academic content, the accuracy and fluency of the translations were found to be suboptimal, as indicated by the evaluators. Common translation errors, particularly in agriculture-specific terminology and scientific names, highlight the limitations of current MT models in handling specialized agricultural content. These issues underscore the need for a more refined approach, including the development of a curated dataset of Swahili-English pairs that focus on agricultural jargon and the integration of a knowledge base to address the translation of scientific terms.

Keywords: Mkulima collection, SNAL, repository, LLMs, Machine Translation, Kiswahili, Agricultural Information, Thesis, Dissertation

Introduction

Agriculture remains the cornerstone of many economies, especially in developing regions where a significant portion of the population relies on farming for their livelihoods. In Tanzania, agriculture employs the largest share of the labor force (over 60 %) and contributes over three-quarters of the national gross domestic product (URT, 2022). However, the effective dissemination of agricultural knowledge, which is vital for connecting research and innovation with farmers, faces substantial challenges. One of the most critical obstacles in multilingual societies, particularly in Tanzania, is the language barrier (Awili & Kimotho, 2016; Lwoga, 2010; Msuya et al., 2022; Mwalukasa, 2013). The language of instruction, often English, is different from the indigenous languages spoken by local communities (Assefa et al., 2013).

This language disconnect severely hinders the adoption of new agricultural practices, technologies, and innovations, ultimately limiting the impact of research institutions and universities on the farming communities they intend to serve (Martinez, E. P. 2023; Gupta et al, 2020). In many African countries, agricultural extension services and educational materials are typically provided in official languages like English or French, yet most farmers speak only indigenous languages. This situation creates a significant challenge in ensuring that agricultural knowledge is effectively and equitably disseminated (Gupta et al., 2020; Laurett et al., 2021).

The wealth of research knowledge produced by the Sokoine University of Agriculture (SUA) and other agricultural research institutions in Tanzania remain inaccessible to local Tanzanian farmers who primarily speak Kiswahili. The dominance of English in research outputs creates a bottleneck, preventing the practical application of valuable academic findings in the field. In response to this challenge, the Sokoine National Agricultural Library (SNAL) established the Mkulima Collection Section and its digital counterpart, the Mkulima Repository[1], aimed at collecting and providing agricultural content in Kiswahili. While this initiative is a commendable step in addressing the language barrier, the content available remains insufficient to meet the needs of the local Swahili-speaking agricultural community. This is because the available Swahili content on the repository is merely produced by volunteers who translate research outputs from donor funded projects, which is normally produced in English, to Kiswahili.

The advent of advanced machine translation (MT) technologies offers a promising solution to this problem (Garcia, 2010; Guerra, 2000). The technology can mainly shorten the process and time required to produce one document by helping translators and interpreters of knowledge from English to Kiswahili. There is enough evidence that the current (neural) MT, powered by large language models (LLMs), can revolutionize the translation process by quickly and accurately translating large volumes of text (Enis and

1 www.mkulima.sua.ac.tz

Hopkins, 2024; Coleman, et al, 2024). In the agricultural context, accurate and fast translation of knowledge makes it possible to produce multilingual educational materials, extension service guides, and instructional manuals at scale (Abdullahi et al., 2016; Morán Vallejo, 2019). By enabling farmers to access critical information in their native languages, they can enhance their ability to understand and implement new agricultural practices (Abdullahi et al., 2016; Chen, 2024).

To that end, this study investigates the possibility of enriching content of the Mkulima repository by utilizing LLM-powered MT. The study specifically focuses on translating abstracts of theses and dissertations produced in English to Kiswahili, a national and the most widely used language in Tanzania and neighboring East African countries. The MT used in this study is based on the OPUS-MT model, which is based on open neural MT. Developed by the Helsinki-NLP group, this model is part of the OPUS-MT project (Tiedemann & Thottingal, 2020), which focuses on multilingual translation using the Marian NMT framework, available on the Hugging Face Transformers[2]. Developers of the model state that it is pre-trained on a diverse range of datasets to ensure high-quality translations across various domains.

Thus, this study provides empirical evidence on the effectiveness of LLM-powered MT for low-resourced languages, alongside insights into common MT challenges in the field of agriculture, which can inform future improvements in the technology and its application in multilingual agricultural contexts. The study is guided by two specific objectives:

i. To evaluate the accuracy and fluency of Kiswahili translations of theses and dissertation abstracts generated by the LLM-based MT model through human assessment.

ii. To analyze common translation errors and challenges encountered by the LLM-based MT model in translating agricultural research abstracts.

The remainder of this paper is structured as follows: it begins with an overview of related literature, followed by a detailed description of the methodology employed in this study. Next, the paper presents the results, which are then analyzed in the discussion section. Finally, the paper concludes with a summary and outlines potential directions for future research.

Literature Review

Machine Translation and Its Role in Bridging Language Gaps

The field of machine translation has seen significant progress with the advent of neural MT (NMT) models, particularly those based on the Transformer architecture. Vaswani et al. (2017) introduced the Transformer model, which has become the foundation for many state-of-the-art NMT

2 Helsinki-NLP/opus-mt-en-sw · Hugging Face

systems. The self-attention mechanism in Transformers allows for better handling of long-range dependencies in text, leading to more accurate translations compared to previous models like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) (Zimerman and Wolf, 2023; Rahali and Akhloufi, 2023).

Hugging Face's Transformers library has played a pivotal role in democratizing access to these advanced models, enabling researchers and practitioners to leverage pre-trained models for various language pairs. Notable among these models are MarianMT (Junczys-Dowmunt et al., 2018) and the multilingual BERT (mBERT) models (Devlin et al., 2019), which have shown promise in producing high-quality translations across multiple languages, including low-resource languages like Kiswahili.

The application of MT in academia is multifaceted, ranging from translating research articles and abstracts to facilitating multilingual education. Recent studies have explored the potential of MT to enhance the accessibility of academic content (Steigerwald et al, 2022; Dabre et al, 2020; Stahlberg, 2020).

Machine Translation Accuracy

Different studies share a common theme in recognizing the significant progress made by MT systems while acknowledging their limitations in achieving human-level accuracy and fluency. MT systems are observed to struggle with errors related to lexical choice, grammatical structures, and semantic nuances, especially when translating between linguistically diverse language pairs (Carl and Báez, 2019; Abdelaal and Alazzawie, 2020). The work of Brazill et al. (2016) suggest that while MT can efficiently produce translations for straightforward texts, human translators excel in handling complex, context-dependent language features. Human oversight remains essential to ensure accuracy, fluency, and cultural relevance (Brazill et al., 2016).

Another accuracy issue of MT is the quality and clarity of source texts, which is said to significantly affect MT output quality. Well-structured source texts with clear syntax and minimal ambiguity result in more accurate translations, underscoring the importance of optimizing source content for better MT performance (Lee, 2022). MT systems often generate text with less fluency compared to human-written text. Improving fluency involves enhancing the modeling of linguistic structures and context, requiring further advancements in MT algorithms and techniques (Chae and Nenkova, 2009).

Other studies suggest MT systems to incorporate cultural and linguistic knowledge to handle idiomatic expressions, cultural nuances, and morphological complexities, particularly in language pairs with significant differences, such as Arabic-English (Abdelaal and Alazzawie, 2020). Thus, these works highlight the ongoing need for advancements in MT technology, the importance of human involvement in the translation process, and the potential for tailored MT systems that address specific linguistic and cultural challenges.

Evaluation of Machine Translation Accuracy and Challenges

Evaluating machine translation (MT) models involves various methods to assess their accuracy and quality. Automated metrics such as BLEU (Papineni et al., 2002), ROUGE (Lin et al., 2004), METEOR (Banerjee and Lavie, 2007), and TER (Snover et al., 2006) are commonly used for their efficiency and quantitative analysis. BLEU measures n-gram overlap between machine-generated translations and references, ROUGE focuses on recall-oriented measures, METEOR accounts for synonyms and paraphrasing, and TER assesses the number of edits needed to align translations with references. Despite their usefulness, these metrics can struggle with contextual nuances and may not fully capture the quality of translations (Chauhan & Daniel, 2023).

Human evaluations complement automated methods by providing subjective assessments based on fluency, adequacy, and readability (Bojic, et al., 2023). Techniques include post-editing, where experts correct translations to match references, and error analysis, which identifies and categorizes translation errors. Human evaluations also involve ranking or rating translations to offer comparative insights. These methods are more detailed but can be time-consuming and subject to evaluator variability (Han, Wong, & Chao, 2016).

Integrating both automated and human evaluation methods provides a comprehensive view of MT system performance (Chatzikoumi, 2020). Automated metrics offer quick, consistent results, while human assessments add depth by capturing qualitative aspects (Rivera-Trigueros, 2022; Han, et al., 2016). This combined approach addresses the limitations of each method, leading to more accurate evaluations and guiding improvements in MT systems (Chatzikoumi, 2020).

Method

Data Source

The study used ten abstracts extracted from sampled theses and dissertations from the SUA's institutional repository. We selected the latest theses and dissertations from 2020 to 2024 whose topics were on agriculture or allied fields that are directly relevant to the local agricultural community.

Pre-Processing

The sampled abstracts were saved in text files, each abstract in its own file. Pre-processing involved manually removing some information and irrelevant metadata for translation such as names, publication year, author names, images, etc to ensure consistent formatting. The step was necessary in order to not distract the models from focusing on the abstract content.

Machine Translation

We used the MarianMT model (Helsinki-NLP/opus-mt-en-sw), developed by OPUS MT that is specific to the English-Kiswahili pair. Each abstract had between 300 to 500 words. However, due to the token limit of 50 tokens imposed by the MarianMT model, we developed a Python script to handle this constraint. The script segments each abstract into chunks of up to 50 tokens. Once the abstracts are divided into manageable segments, the script sequentially feeds each segment into the MarianMT model for translation. The model processes each segment independently, generating a Swahili translation for the given text. This step is repeated until all segments of the abstract have been translated. After translating all segments, the script concatenates the translated segments to produce the final Kiswahili version of the abstract.

Evaluation and Error Analysis

This study used human evaluators alone to assess the accuracy, accuracy, and error rate of the machine translated abstracts. Particularly, three Master's of Knowledge and Information Management students who are multilingual speakers fluent in both English and Kiswahili evaluated the machine-translated abstracts. We chose this approach over automated methods like BLEU because such metrics provide only quantitative scores without offering insights into the accuracy or fluency of the translated text. In this case, we found it was more appealing to use human evaluators to identify specific issues that need to be addressed to develop a final model capable of producing Kiswahili-translated abstracts suitable for real-world use in the Mkulima repository with minimal human intervention.

Evaluators were presented with six pairs of abstracts, consisting of the original English version and its Swahili translation, one pair at a time. For each pair, evaluators were asked a series of Likert-scale questions designed to assess various aspects of the translation and capture specific themes related to translation quality, including comprehension, accuracy, grammar, and naturalness. Table 1 details the breakdown of the questions, grouped by theme. Apart from the evaluations made by the evaluators, we conducted a thorough error analysis for one of the abstracts.

Table 1: Questions used to evaluate the translated text.

Theme	**Question**

Comprehension and Meaning	*Q1: To what extent does the translation capture the main ideas of the source text?*
	Q2: How much of the meaning from the source text is preserved in the translation?
	Q3: How accurately does the translation reflect the nuances and details of the source text?
Grammaticality and Naturalness	*Q4: How grammatically correct is the translation?*
	Q5: How natural does the translation read, as if written by a native speaker?
Errors and Omissions	*Q6: To what extent are there mistranslations that change the meaning?*
	Q7: How often are there omissions in the translation?

The analysis on the quantitative evaluation by our evaluators were mainly descriptive statistics. To ensure that there was consistency and reliability of evaluators' ratings among the evaluators, we used Cohen's Kappa and Fleiss' Kappa inter-rater metrics. Cohen's Kappa evaluates the agreement between two raters whereas Fleiss' Kappa is designed for multiple evaluators. These measures provide an objective assessment of agreement, accounting for chance, which is crucial when dealing with subjective evaluations like translations.

Results

Translation Quality

Out of the 10 translated abstracts, we selected 6 abstracts for evaluation. Table 2 presents the inter-rater agreement score using Cohen's Kappa and Fleiss' Kappa for the first abstract. Based on the Cohen's Kappa, the first (R1) and second (R2) rater had poor agreement about the quality of the translations, whereas the first (R1) and third (R3) rater as well as R2 and R3 showed an overall slight agreement about the quality of translation. Based on the Fleiss' Kappa, raters were in poor agreement.

Table 2: Inter-rater agreement for the first abstract.

	Metric		**Value**
Abstract 1	Cohen's Kappa	R1 – R2	-0.166667
		R1 – R3	0.125000
		R2 – R3	0.176471
	Fleiss' Kappa		-0.040541

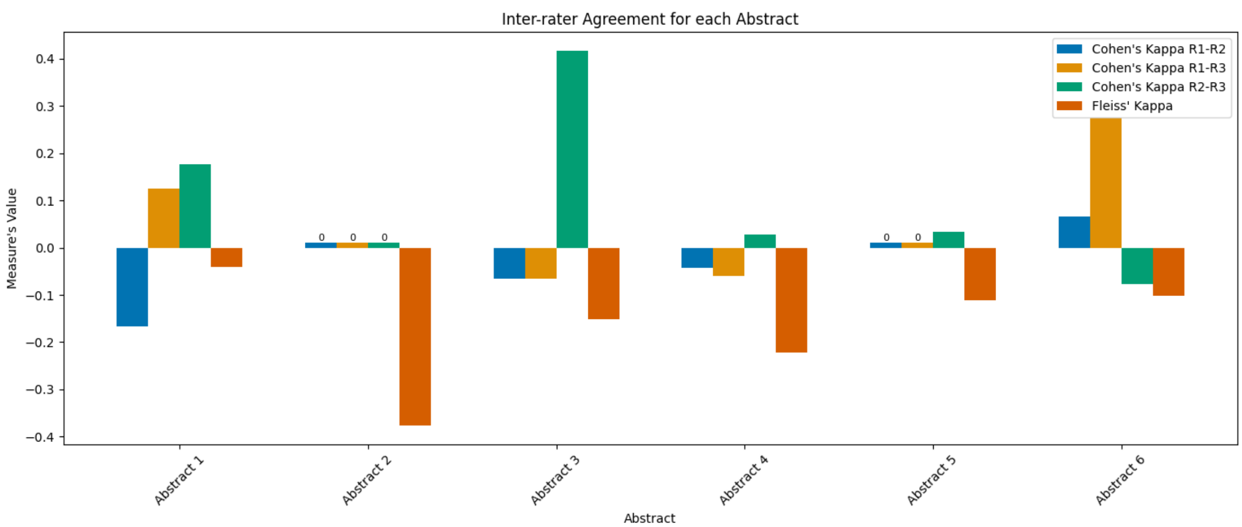

Figure 1: Inter-rater agreement for all the six abstracts.

Figure 1 shows the level of agreements between raters across the 6 evaluated abstracts. Based on Cohen's Kappa, the figure indicates that there was a moderate agreement between R2 and R3 for Abstract 3 and a fair agreement for R1 and R3 for Abstract 6, whereas for the rest of the abstracts, raters had poor agreements on the quality of translation. The Fleiss' Kappa also shows poor agreement among evaluators regarding the quality of translation.

Since Cohen's and Fleiss' Kappa can only indicate agreement or disagreement, they do not tell how exactly evaluators agreed or disagree. That is, the scores do not indicate whether, for example, the translation was good or bad, even if all raters had a perfect agreement. In other words, evaluators can all agree that the translation was of poor or good quality. But they can also disagree about the quality where some could be suggesting that the translation was good while others see it as poor. Thus, to have a clear view of what our evaluators rated, Figure 2 shows the evaluators scores aggregated per abstract. Even though the Cohen' and Fleiss Kappa indicate poor or low agreement, which could imply that the translations were viewed by others as good, others saw them as poor, these scores generally suggest a low quality of translated texts.

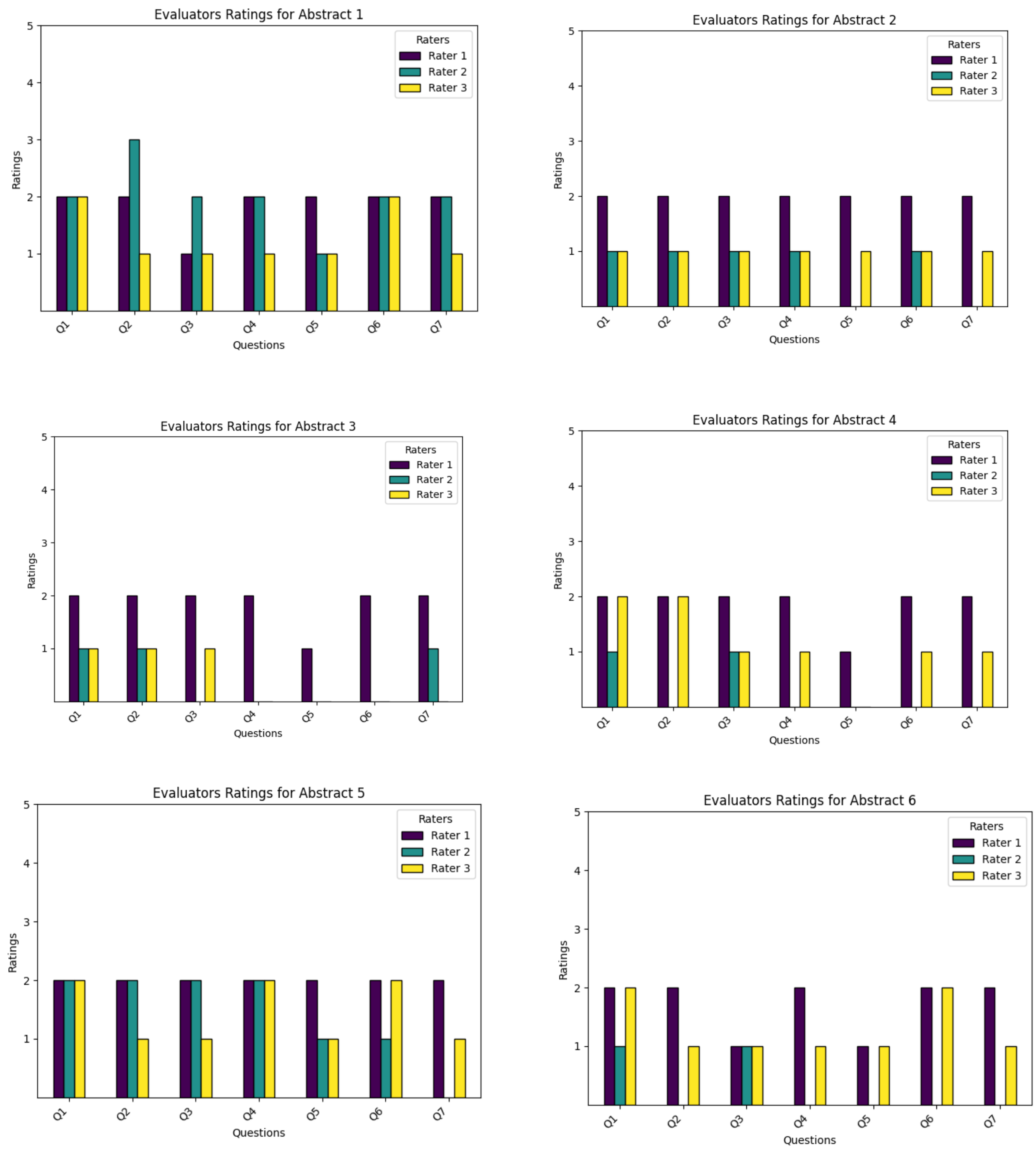

Figure 2: Evaluation scores across the six abstracts

Qualitative Error Analysis

We took the first abstract to have a closer qualitative look to identify errors related to terminology, grammar, coherence, and other linguistic challenges encountered by the model. Some of the observations are summarized in Table 3.

Table 3: Key observations from the qualitative error analysis.

Category	Original Text	Translated Text	Error Description
Terminology	"Rodents belong to the order Rodentia."	"Rodents ni ya jamii ya Rodntina."	"Rodentia" is a scientific term that should remain unchanged.
	"Mastomys natalensis"	"Mastomys thtalisis"	The scientific name is mistranslated and should remain as "Mastomys natalensis."
	"zoonotic pathogens"	"virusi vinavyoibuka vya wanyama"	The translation changes the meaning, as it refers only to viruses ("virusi") instead of the broader "pathogens," which include bacteria and parasites.
	"One Health" approach	"njia moja ya mawasiliano"	"One Health" is a specific health approach and is mistranslated as "njia moja ya mawasiliano" (one way of communication), which is not accurate.
Grammar & Syntax	"They were anaesthetized using Isoflurane."	"Hizo ziliundwa kwa kutumia Isoflurane."	The verb "ziliundwa" (were formed) is incorrect; should be "walilevya"/"walileweshwa…" (were anesthetized).
	"Rodents were captured in Kibondo, Kyerwa and Uvinza."	"Rodents walinaswa katika Kibondo, Kyerwa na Uvinza."	The translation maintains the plural agreement, which is correct in this instance.
Sentence structure	"Since there is constant interaction between humans, animals and	"Kwa kuwa kuna uhusiano wa daima kati ya wanadamu,	The translation accurately retains the sentence structure.

	rodents..."	wanyama na panya..."	
Coherence	"Rodent-borne diseases are transmitted either directly or indirectly..."	"Maradhi yanayoenezwa hupitishwa ama moja kwa moja ama..."	The translation does not clearly communicate the indirect transmission modes.
	"There were eleven pools of oral-pharyngeal swabs and a single pool of rectal swabs."	"Kulikuwa na vidimbwi kumi na viwili vya kufumwa kwa mdomo na sawa."	The translation misses the distinction between the types of swabs ("oral-pharyngeal" vs. "rectal"), causing ambiguity.
Consistency	"Hantavirus, Lassa fever, Lymphocytic choriomeningitis"	"Hantavirus, Lassa homa, Lymphocytic choriomenititis"	Inconsistent translation of disease names, with "Lassa fever" translated as "Lassa homa" but "Lymphocytic choriomeningitis" retained incorrectly.
Additional Observations	"This study presents the first reports of natural infection of rodents with Helicobacter pylori..."	"Uchunguzi huu unatoa taarifa za kwanza za ambukizo la kiasili la panya na..."	The translation conveys the general idea but lacks the nuanced emphasis on the significance of these first reports, potentially affecting the interpretation of the study's importance.

Discussion, Challenges and Opportunities

This study addresses the scarcity of Swahili content within the agricultural sector in Swahili-speaking countries of East Africa by leveraging the electronic theses and dissertations available in the institutional repository at Sokoine University of Agriculture (SUA). This work aims to benefit Swahili speakers by expanding the content accessible in their language. We set out to achieve two primary objectives, as outlined in the introduction, and here we explore the discussion around these objectives and the potential for integrating translated texts into the Mkulima repository.

Accuracy and fluency of LLM-Translated Abstracts

The findings reveal that the accuracy of the translated abstracts was generally low, as assessed by our evaluators, who represent typical end-users of this knowledge. The evaluators' differing opinions on translation quality, reflected in their scores, highlight the need for careful consideration when using LLM-powered MT for a low-resource language like Kiswahili. These insights suggest that more rigorous measures must be implemented before deploying these MT texts and documents in practical applications, such as the Mkulima repository.

Common Translation Errors

Our qualitative analysis of translation errors exposed several issues that can beattributed to the low ratings by evaluators. We identified obvious mistranslations and grammatical mistakes, as well as issues with maintaining the logical flow of the text. However, of particular interest are the errors related to domain-specific terminology. Given that our abstracts predominantly pertain to agriculture, the MarianMT model faced challenges in accurately translating agricultural jargon into Kiswahili.

To develop a fully functional and automatic MT model for this task, it is crucial to create a carefully curated dataset of Swahili-English pairs, particularly focusing on agricultural terminology. Another critical challenge is the translation of scientific names, which are typically not supposed to be translated. There is an opportunity to build a knowledge base for terms that can provide local context without altering the scientific names. Understanding the patterns of these translation errors is vital for enhancing machine translation systems and tailoring them to specific languages and contexts, as noted by Carl and Báez (2019) and Abdelaal and Alazzawie (2020).

Given the complexity of gathering contextually relevant agricultural information in Kiswahili, after the MT process, we propose a review process involving student volunteers with expertise in agriculture. These volunteers can review and correct translated abstracts, focusing on the accurate translation of scientific names and agricultural jargon. Consequently, the final review and editing must be performed by human experts who are native Swahili speakers. This study underscores the importance of human oversight in ensuring accuracy, fluency, and cultural relevance, aligning with observations made by Brazill et al. (2016). This work underscores the challenges and opportunities in enhancing machine translation for low-resource languages, highlighting the importance of collaboration between technology and human expertise. Technology alone, even with the advancements of LLMs, which are touted for their superior performance in NLP applications like machine translation, cannot deliver optimal results without well-curated data.

Conclusion

This study demonstrates the potential of leveraging large language models (LLMs) for machine translation to address the significant language barriers in the dissemination of agricultural knowledge in Tanzania. Given the importance of agriculture to the Tanzanian economy and the predominantly Swahili-speaking population, overcoming these barriers is crucial for enhancing the impact of research and innovation on local farming practices.

By translating the abstracts of theses and dissertations from English to Kiswahili, our work aims to enrich the content available in the Mkulima repository, thus facilitating access to vital agricultural knowledge for Swahili-speaking communities. While the OPUS-MT model, developed by the Helsinki-NLP group, shows promise in supporting these translation efforts, our findings highlight key challenges, such as translating domain-specific jargon and scientific names, which affect translation accuracy and fluency.

The results underline the necessity of human oversight and collaboration in refining machine translation outputs. Involving native Kiswahili speakers and agricultural experts in the translation review process ensures that translated materials maintain cultural relevance and accuracy. This collaboration between technology and human expertise is essential for creating effective language tools that can meet the needs of low-resource language communities.

Overall, this study provides empirical insights into the effectiveness of LLM-powered machine translation for low-resource languages and highlights areas for improvement. By addressing these challenges, we can advance the development of multilingual educational materials and extension services, ultimately empowering farmers to adopt innovative agricultural practices. This research lays the groundwork for future initiatives aiming to bridge language gaps and promote sustainable agricultural development in multilingual societies.

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