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DEEP LEARNING MACHINE TRANSLATION TECHNOLOGY IN AFRICAN LANGUAGES TRANSLATION-A REVIEW

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ABSTRACT
Machine translation (MT) is the use of computers to automatically translate one language to another. Machine translation has numerous applications in society, such as ecommerce, tourism and marketing. Africa has approximately 2,000 spoken languages, however, only 30 African languages have been machine translated. The main technical factor for the low-rate adoption of MT in Africa is the poor translation accuracy of existing machine translators. Currently, there are two approaches to MT in Africa. The first approach is the classical approach. This approach utilizes the direct mapping of input texts to produce a translated output. Examples of classical MT approaches include: statistical-based machine translators (SBMT), rule-based machine translators (RBMT) and hybridized machine translators (HMT). Classical approaches are the most widely adopted MT approach for African languages. The main reason for the wide adoption is ease in building and maintenance of classical MT platforms, in addition, the low cost of computing power in utilizing these platforms. However, classical approach has high-levels of inaccuracy due to language structures differentiation. The second approach is the use of Deep learning (DL) MT. Deep learning MT is a field in artificial intelligence concerned with the application of artificial neural networks to mimic the human brain learning process in language translation. Deep learning MT has the advantage of understanding phrases, complex sentence structures, and even slang when compared to classical MT approach. Deep learning has produced results 60-90% more accurate than the classical approach in translating structured languages such as French into English. However, DL has shortcomings in MT, including, high-costs of training and evaluating models, and, DL is data intensive. This review aims to analyze the current status of machine translation approaches in Africa and provide an output recommendation for universalizing applicable MT in African languages translation. The results of this review will be in both graphical and tabular format.

Key Words: Machine Translation, Classical Approach, Deep Learning, Artificial Neural Networks, Deep Learning

INTRODUCTION

Human language has evolved over the last 200,000 years (Baronchelli, 2012).This evolution originated with gesture basis from early humans, then primitive vocalizations and songs from *Homo habilis* humans, and eventually, the use of complex grammatical rules by modern humans. The modern world has over 7,117 languages (Eberhard, 2020) spoken by 7.8 billion people (Worldometer, 2021). The existence of so many spoken languages has led to the rise of a large machine translation (MT) services market valued at $800.0million (Statista Research Department, 2021) and projected to grow to $7.5billion by 2030. However, the vast majority of MT technology is focused on seven languages, namely English, Chinese, Urdu, Farsi, Arabic, French, and Spanish (Siavoshi, 2020). Africa's MT in language translation is underdeveloped, with a size of only $6.0million as of 2015 (Statista Research Department, 2016) despite Africa having 16.72% of the global population (Division, 2019) .The major reasons for Africa's low adoption of in MT in languages translation are, low accuracy in machine translation using classical approaches (Buliva, 2017) and the lack of adequate digitized African language datasets (Knowledge 4 All Foundation Ltd., 2020).

The large language translation services market has attracted a lot of attention from the information technology (IT) industry. This has led to many breakthroughs in the application of IT into human language translations

(Junyoung, 2014). The latest breakthroughs are through the application of artificial intelligence in language MT called Deep learning (DL) MT technology, this technology utilizes artificial neural networks to perform translation, Deep learning MT has shown great promise in solving the challenges of the classical approach by applying machine learning (John, 2019b). Examples of DL MT include: Simple recurrent neural networks frameworks, Gated recurrent Unit frameworks and the Long Short-Term Memory unit frameworks (Rodriguez., & Fonollosa., 2020). However, DL MT adoption in Africa has been slow compared to the rest of the world, this is due to the fact that DL MT are complex to implement and expensive due to the large computing resources required, in addition, DL MT technologies are data-hungry (Mittal, 2019).

AIM OF THE STUDY

Thus, in this review, will seek to understand the current status of MT in Africa and analyze the classical and DL MT approaches adoption in the African languages market. The analysis will be based on verified secondary sources of data gathered from the internet open-sources. The conclusion of the analysis will provide insights into MT trends in Africa and assist researchers interested in pursuing DL-MT technologies research in the African languages translation sector.

METHODOLOGY

1) Data collection: The data gathered for this review is from 25 reputable online peer-reviewed publications, published research articles, open-source research papers that are peer-reviewed, corporate articles (2016-2022). All these papers have different data applications that have been studied and analyzed in this review. The attributes compared were MT used technologies, benefits and challenges in current MT approach, DL MT adoption approach and African continent area MT analysis.

2) Data inclusion criteria: To evaluate the data inclusion criteria a comparison table was drawn to include as the following attributes: Author, Sub vertical, Data collection measurements, Technologies, Benefits, Challenges, Solutions and Drivers of MT in Africa. Articles were excluded when selected attributes were not present. In our analysis, the number of classical MT approach, amount of DL MT approach, underlying technologies adoption was included since no information can find with all the peer-reviewed publications (2016-2022).

3) Data analysis: Oversampling method is utilized to analyze the 25 peer-reviewed articles, Oversampling is applicable due to the small size of available data on African MT. A higher sample selection of DL MT based data will be utilized.
The two metrics for analysis are:

i. BLEU (Bilingual Evaluation Understudy). BLEU score is a metric for automatically evaluating machine translated texts.

Table 1 Bleu Score Interpretation Guideline from 0 to 100

BLEU SCORE	MACHINE TRANSLATION ACCURACY
< 10	Poor translation
10 – 19	Low quality translation
20 – 29	The translation is clear, but has significant grammatical errors
30 – 40	Understandable to good translations
40 – 50	High accuracy translations
50 – 60	Very high accuracy, adequate, and fluent translations
> 60	Machine translation accuracy is better

ii. Discussion and Conclusion from the peer-reviewed articles that provide analytical data terms such as adoption rates of MT technologies (high, low and medium).

4) Data Results

Results of analysis will be presented in Graphs and charts using the following parameters:

i. Market share of various MT approaches in the African Market 2016-2022
ii. DL MT growth rate in the African MT market 2016-2022

iii. Adoption level of DL MT vs Classical MT in Africa in 2021/22
iv. Translation accuracy of DL MT vs Classical MT in African languages translation (using BLEU mean score of 0-100)
v. Future application preference between DL MT and Classical MT

PRESENTATION AND DISCUSSION OF FINDINGS

Table 2 summarizes the findings of reviewing 25 up to date peer reviewed research papers in MT. The review was done to establish the uptake of DL ML in language translation in the African continent and the world. Findings from each research paper were presented using the following table format. The MT technology approach, the MT technology application geographical zone, the MT Technology current status, the percentage of MT technology applied in the MT market, the Benefits of utilizing the MT Technology, the challenges in utilizing the MT Technology approach and the Future trends in adoption of the MT Technology approach.

Table 2 Machine Translation Analysis from 25 Peer Reviewed Scientific Articles of 2016-2022

No	Article Citation	MT Technology Approach	MT Technology Application Geographical Zone	MT Technology Current Status as of 2022	Benefits of MT Technology	Challenges of MT Technology Approach	Future of trends of MT Technology Approach
1	(Research, 2022)	Classical MT and DL MT	Global	-Classical MT-70% world market share -DL NMT-15% world market share -Other MT approaches-15%	**Benefits of Classical MT:** -Easy to implement -Cheap to maintain -Open-source resources -Well-tested Technology **Benefits of DL MT:** -Higher accuracy in translation -Ability to capture language differentiation nuances -Ability to self-learn and improve, hence easier to update with higher automation over classical (Siminyu, 2018)MT	Challenges of Classical MT: -Low-accuracy in translation compared to DL MT -Labor intensive in maintenance and updates -Low language structures differentiation capacity Challenges of DL MT: -High costs of resources such as cloud computing -Complex technical requirements in developing frameworks -Data hungry	-DL MT has higher investments than classical MT, thus, higher adoption rate in the future
2	(Ben Goertzel, 2021)	DL MT in Africa	-Sub-Sahara Africa	-Low-adoption	-Higher accuracy in Sub-Saharan African Languages Translation -	-High input costs of cloud computing and training frameworks -Lack of adequate Digitized datasets-Most Sub-Saharan languages (80%) have no written form	-DL MT has High potential for adoption
3	(Siminyu, 2018)	DL MT	Sub-Sahara Africa	-Bilingual DL MT development for ChiChewa and Kiswahili translation to English	-Higher accuracy	-High costs of framework -Inadequate digital dataset	-DL MT has High adoption for other African languages translation
4	(Agbolo, 2022)	-DL MT called OB Translate version 1.9.6 released in 2022 -Classical MT called OB Translate 1.1.1 released in 2020	-Sub-Sahara Africa	-OB Translate 1.1.1 cancelled BLEU score of 25 -OB Translate 1.9.6 in early adoption BLEU score of 51	-Version 1.9.6 is 60% more accurate in translating Igbo compared to version 1.1.0	-Version 1.9.6 is 200% more expensive in cloud computing costs compared to version 1.1.0 -Version 1.9.6 is taking 12 months longer to train, test and validate compared to version 1.1.0	-DL MT has High adoption potential with 20% greater market participation
5	(Masakhane open source project, 2019)	DL MT using Transformers neural network	Sub-Sahara Africa	-Pidgin dialect to English DL MT translator under development BLEU score of 60	-High accuracy compared to Classical MT translators of Pidgin dialect in Nigeria	-Lack of funding -Inadequate sized digital datasets	-DL MT has High adoption rate

6	(Knowledge 4 All Foundation Ltd., 2020)	DL MT vs Classical MT in Africa	Africa	-Classical MT 90% adoption -DL MT less than 9% adoption -Other MT 1% adoption	Classical MT has lower barriers of entry such as: -Low-cost -Easy to implement -open-source resources DL MT has higher accuracy	-Classical MT has low accuracy and is labour intensive -DL MT is resource expensive and has high data consumption rate	-High interest in DL MT in Africa
7	(Adepetun, 2022)	DL-MT	Sub-Sahara Africa	-High adoption in 55 African languages translation	-High accuracy -Digitized datasets availability	-Non-open source	DL MT has High adoption through Meta social media platforms
8	(Odoje, 2013)	-Classical MT -DL MT	-Nigeria	-Classical MT dominant adoption -DL MT nil adoption	Classical MT: -Low cost -Easy to implement DL MT: -High accuracy	Classical MT: -Low accuracy -Labour intensive DL MT: -Untested technology -High costs	DL MT has high possibility of future adoption
9	(Albarino, 2020)	DL-MT	Sub-Sahara Africa	-DL MT adoption	-High accuracy -Digitized datasets availability of 16 languages	-High costs of input resources	DL MT has High adoption
10	(Marivate, 2020)	DL-MT	Africa	-DL MT adoption	-High accuracy -Digitized datasets availability	-High costs of input resources	Resolving high costs to lead to high adoption of DL-MT in Africa
11	(INDABAX, 2021)	DL MT in Africa	Sub-Sahara Africa	-Low-adoption	-Higher accuracy in Sub-Saharan African Languages Translation -	-High input costs of cloud computing and training frameworks -Lack of adequate Digitized datasets-Most Sub-Saharan languages (80%) have no written form	-DL MT has High potential for adoption
12	(Burg Translations, 2022)	-DL MT vs Classical MT in Africa	-Africa	-Classical MT 90% adoption -DL MT less than 9% adoption -Other MT 1% adoption	Classical MT has lower barriers of entry such as: -Low-cost -Easy to implement -open-source resources DL MT has higher accuracy	-Classical MT has low accuracy and is labour intensive -DL MT is resource expensive and has high data consumption rate	-High interest in DL MT in Africa
13	(Quartz Africa, 2022)	DL-MT	-Sub-Sahara Africa	-High adoption in 65 African languages translation BLEU score 65	-High accuracy -Digitized datasets availability	-Non-open source	High adoption through Meta social media platforms
14	(LionBridge, 2022)	MT market size, share and trends	Africa	-Classical MT-90% Africa market adoption -DL NMT-9% Africa market adoption -Other MT approaches-1% adoption	Benefits of Classical MT: -Easy to implement -Cheap to maintain -Open-source resources -Well-tested Technology Benefits of DL MT: -Higher accuracy in translation -Ability to capture language differentiation nuances -Ability to self-learn and improve, hence easier to update with higher automation over classical	Challenges of Classical MT: -Low-accuracy in translation compared to DL MT -Labor intensive in maintenance and updates -Low language structures differentiation capacity Challenges of DL MT: -High costs of resources such as cloud computing -Complex technical requirements in developing frameworks -Data hungry	-DL MT has higher investments than classical MT, thus, higher adoption rate in the future
15	(Lim, 2022)	MT market size, share and trends	Global	-Classical MT-65% world market adoption -DL NMT-25% world market adoption -Other MT approaches-10% adoption	Benefits of Classical MT: -Easy to implement -Cheap to maintain -Open-source resources -Well-tested Technology Benefits of DL MT: -Higher accuracy in translation -language differentiation nuances capacity -self-learning capacity and improve, hence easier to update with higher automation over classical MT	Challenges of Classical MT: -Low-accuracy in translation compared to DL MT -Labor intensive in maintenance and updates -Low language structures differentiation capacity Challenges of DL MT: -High costs of resources such as cloud computing -Complex technical requirements in	-DL MT has higher investments than classical MT, thus, higher adoption rate in the future

						developing frameworks -Data hungry	
16	(Microsoft News Center, 2022)	DL MT	South Africa	-Launched in April 1,2022 for Zulu language translation BLEU score 58	-Higher translation accuracy compared to classical MT for Zulu language -Higher language differentiation fluency compared to classical MT	-Complexity in technology -Inadequate digitized Zulu data for model training, validation and testing	-High adoption
17	(Tomedes, 2022)	DL MT vs Classical MT	Africa	Analysis of 2022 Africa MT -Adoption rate 11% for DL MT And 88% for classical MT	DL MT advantages over classical MT in Africa: -High accuracy -Cost Efficiency -Scalability -Flexibility	Challenges of DL MT over classical MT in Africa: -Cost -Complexity -Lack of open-source framework shells	-High adoption rate
18	(Diden, 2022)	DL MT	West Africa	10 West African languages under Google translate DL MT for translation to French BLEU score 53	-Higher translation accuracy -Ability to capture language differentiation nuances	- Lack of open-sources -Cost	-High adoption rate
19	(Kevin Duh, 2020)	DL MT vs classical MT(SBMT)	Africa	-Swahili and Somali BLEU test scores show DL MT to be 75% and 50% more accurate than classical MT of the SBMT variant	--Higher translation accuracy -Better algorithm tuning, i.e., DL MT is better at updates to source code efficiency than SBMT	-Digitized Data inadequacy for African languages -	-High Adoption rate
20	(Allahsera Auguste Tapo, 2020)	DL MT	-Sahel region -DL MT in translating Bambara language in Mali into French	-DL MT applied to Bambara into French translation BLEU score 45	-Higher translation accuracy	-Training data scarcity -Training data pre-processing is costly -Lack of Smartphones to utilize the framework in Bambara	-Low adoption rate
21	(Muscleh, 2016)	DL MT	Sahara region	-Applied DL MT in medical translation for migrants from the Sahel heading to EU	-High accuracy -Flexibility	-Scarcity in training data -Low adoption due to low skills in utilizing technology by the migrants	-Medium adoption
22	(Liu, 2018)	DL MT vs Classical MT in 3 African languages	Sub-Sahara Africa	DL MT and Classical MT(SBMT) applied to Shona, Oromo and Burj translation to English BLEU Score of DL MT is 55,57 and 59 respectively, compared to SBMT at BLEU score of 17,27,40	-Higher accuracy of DL MT	Challenges of DL MT over classical MT in sub-Sahara Africa: -Cost -Complexity -Lack of open-source framework shells	-High adoption rate
23	(Maiei, 2020)	DL MT in Afrikaans, isiZulu, N.Sotho, Setswana and Xitsonga	South Africa	DL MT applications in five South African languages to English translation BLEU score of 33.3 for DL MT isiZulu translation	-Higher accuracy		Low adoption
24	(Martinus, 2020)	DL MT	South Africa	BLEU Scores for 10 South Africa languages translated by a DL MT platform to English: -Afrikaans-59 -Ndebele-24 -Xhosa-37 -Zulu-44	-Higher accuracy of DL MT	-High costs of implementation	-High adoption

				-Northern Sotho- 45 -Sesotho-42 -Setswana-47 -Swati-36 -Tshiveni-52 -Xitsonga-46			
25	(Z.Abbott, 2022)	DL MT	South Africa	DL MT application to translating English-to-Setswana BLEU score higher by 5 points above previous classical MT(SBMT) approach	DL MT has higher accuracy	DL MT is resource expensive and has high data consumption rate	-High interest in DL MT in South Africa

Note: All BLEU scores are rounded off to whole numbers.

Table 3 shows the growth rate of DL MT in the African MT market from 2016 to 2022. The growth rate increased from 5% in 2016 to 15% in 2022. This indicates that DL MT is becoming more popular in the African MT market. This is due to higher accuracy in translation, the ability to capture language differentiation nuances and the ability to self-learn and improve. In addition, DL MT is Flexible to related languages. Furthermore, DL MT is more cost Efficient due to automation in updates and scalable compared to classical MT.

Table 3: Deep learning growth rate in the African Market

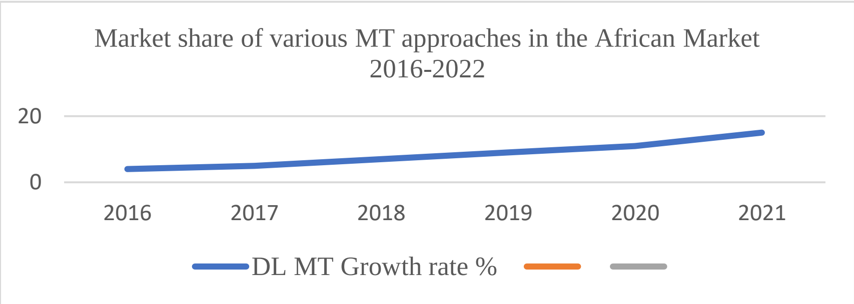

Table 4 shows the growth rate of DL MT in the global market from 2016 to 2022. The growth rate increased from 4% to 15% in 2022. This indicates that the world MT market is increasingly adopting DL MT due to its higher translation accuracy, ability to capture language nuances, self-learning and improvement capabilities, flexibility to related languages, cost efficiency, and scalability compared to classical MT.

Table 4: Deep Learning growth rate globally

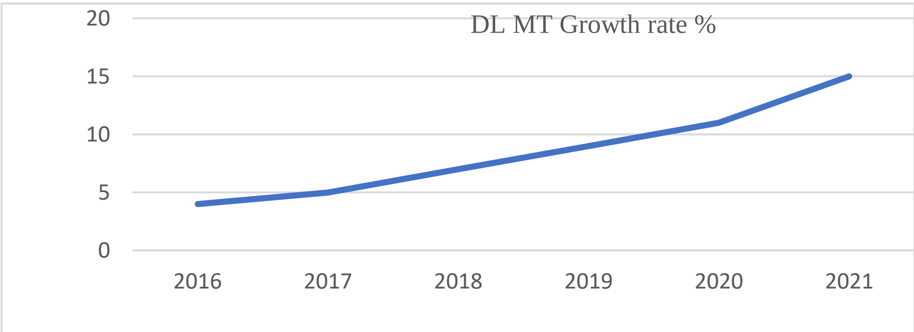

Figure 1 is a pie graph, which shows the level of MT adoption by type in 2021/2022, classical machine translation (MT) has the highest level of adoption at 70%, followed by DL MT at 15%, and other MT at 15%. This indicates that classical MT is still the most widely adopted MT approach in the African languages market. The reasons for this are that classical MT is easy to implement, cheap to maintain, and uses open-source resources. Additionally, it is a well-tested technology that is low-cost and easy to implement due to its open-source resources.

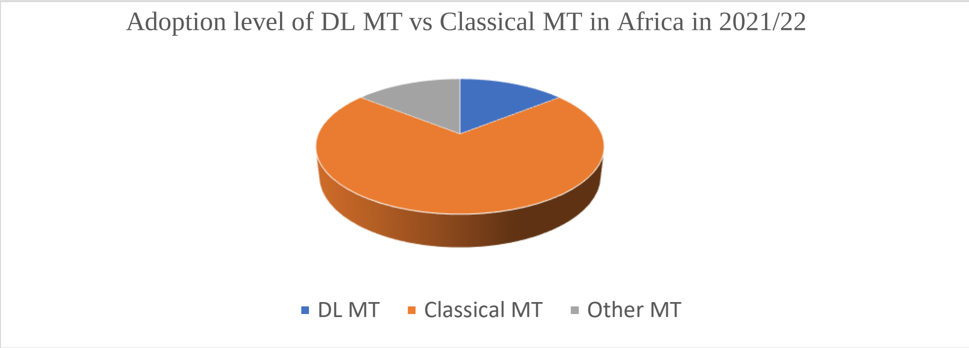

Figure 1: Pie graph for Level of MT adoption by

Figure 2 is a bar graph that shows the translation accuracy comparison for DL MT vs classical MT. The graph shows that DL MT had a BLEU score average of 60 plus, while classical MT BLEU score average was 22. This indicates that DL MT has higher translation accuracy than classical MT. This is due to the fact that DL MT has self-learning and memorization capacity, thus DL MT can adapt to new sentences translation with a higher precision compared to classical MT.

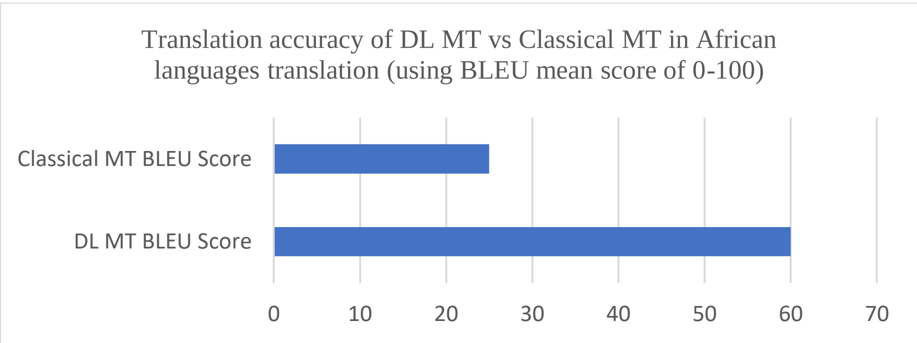

Figure 2: Bar graph for Translation accuracy comparison

Figure 3 shows the future application preference between DL MT versus classical MT. The graph shows that 75% of respondents prefer DL MT, while classical MT was 20%, and other MT was 5%. This indicates that DL MT is preferred for future applications.

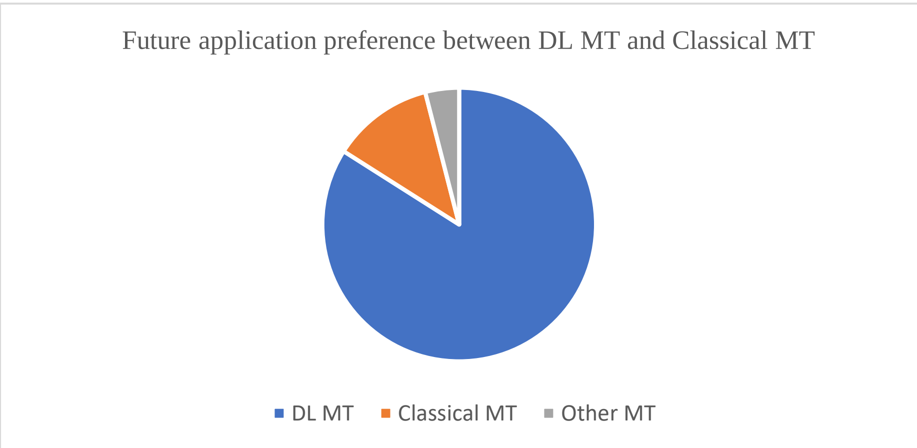

Figure 3: Future application preference between DL MT versus Classical MT

CONCLUSION AND RECOMMENDATION

This research review sought to understand the current status of machine translation (MT) in Africa by analyzing the current status of MT approaches in Africa and the adoption of classical and deep learning (DL) MT approaches in the African languages market. The analysis was based on verified secondary sources of data gathered from the internet open-sources publications.

Overall, the graphs provide valuable insights into the current status of MT approaches in Africa and the adoption of classical and DL MT approaches in the African languages market. The graphs show that DL MT is growing in popularity in both the African and global markets and has higher translation accuracy than classical MT. The graphs also show that classical MT has the highest level of adoption in the African languages market, but DL MT is preferred for future applications.

From the analysis of 25 peer-reviewed publications (2016–2022), it was found that classical MT approach was the most widely utilized in the African continent, however, DL MT has the fastest growth rate. In addition, DL MT approach demonstrates a much higher translation accuracy of 60% plus for African languages. However, classical approach MT remains dominant in application. Finally, this analysis indicates DL MT approach has the higher future application preference to classical MT.

From this study a number of recommendations can be made. The African Union, African Universities and other concerned funding organizations should establish an African MT working group to coordinate wide scale adoption of DL MT technologies in the African continent. Consequently, worldwide organizations should establish more funding bodies to fund creation of more datasets in different languages to facilitate more training of DL MT in various languages. This will improve language translations not only in Africa, but the entire world and lead to less language barriers.

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