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Development and Evaluation of an English-to Igala Neural Machine Translation System using Deep Learning

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Abstract: Low-resource languages face significant challenges in the digital age due to limited computational tools and data resources. This study presents the development of a neural machine translation (NMT) system for English-to-Igala translation using a Recurrent Neural Network (RNN) model. Igala is one of the under-resourced languages spoken in Nigeria. A bilingual parallel corpus of 1000 English-Igala sentence pairs was compiled and preprocessed to train and evaluate the system. The model achieved high translation accuracy as evidenced by BLEU scores above 0.5 on most test sentences. This research provides a foundational step for the development of computational resources for Igala and supports the broader goal of linguistic inclusivity in artificial intelligence.

***Keyword*: *Neural Machine Translation, Low-Resource Languages, Igala, Deep Learning, Recurrent Neural Network, BLEU Score*.**

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I. INTRODUCTION

The role of language in communication, education, and societal integration cannot be overstated. However, many African languages, including Igala, are underrepresented in digital technologies. English dominates information and communication technologies (ICT), leaving speakers of indigenous languages with limited access to online resources and services. The need to develop language technologies, such as machine translation (MT) systems for indigenous languages, is thus critical (Sani, 2023).

Machine Translation (MT) automates the conversion of text from one language to another. Neural Machine Translation (NMT), a subfield of deep learning, has shown impressive results for high-resource languages (Bahdanau, Cho, & Bengio, 2015). However, low-resource languages such as Igala suffer from data scarcity, linguistic complexity, and limited computational tools. This study addresses these challenges by developing a neural translation model to convert English to Igala, contributing to language preservation, education, and digital equity.

II. RELATED WORKS

Recent advancements in NMT have shown the efficacy of encoder-decoder architectures, particularly when combined with attention mechanisms (Vaswani *et al.*, 2017). However, most of these advancements have been applied to high-resource languages like English, German, or Chinese (Koehn & Knowles, 2017). For low-resource languages, researchers have adopted techniques such as transfer learning, synthetic corpora, and subword modeling (Sennrich, Haddow, & Birch, 2016).

Notably, Currey, Michel, and Heafield (2017) demonstrated how monolingual data could enhance NMT systems for low-resource languages. Similarly, Lample et al. (2018) explored unsupervised MT with promising results. Yet, few studies have focused on African languages. While efforts exist for Yoruba, Hausa, and Igbo (Oyewole & Iwu, 2020), there is limited work on Igala, except for rule-based attempts (Sani, 2016). These gaps highlight the need for dedicated neural translation research for Igala.

III. MATERIALS AND METHOD

- *Review of Existing System*

The goal of the ongoing work is to develop an Igala to English Neural Machine Translation (NMT) system. It is obvious that such a translation system is required, despite the fact that the system is still in development. English and Igala are independent languages with unique linguistic characteristics. Accurate translation between English speakers and the Igala-speaking population has the potential to open up new channels for communication, instruction, and cultural exchange. There aren't many translation resources and tools accessible for Igala, and the ones that are frequently

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focus on widely used tongues. It is crucial to build an NMT system specifically designed for English to Igala translation in order to bridge the gap in communication and promote better understanding and interaction between English- and Igala-speaking people. By harnessing the advancements in NMT and training models on parallel English-Igala datasets, researchers can work toward creating a reliable and accurate translation system. As part of the evaluation and improvement of the NMT models, a number of designs, optimization procedures, and training approaches will be contrasted in order to decide which is the most effective way to translate from English to Igala.

A successful English to Igala NMT program will have a significant impact on culture, education, and society. It can facilitate communication, information sharing, and knowledge access between the Igala and English-speaking communities. The possible benefits of this research include advancing language diversity, preserving cultural heritage, and fostering inter-linguistic understanding. Even though specific references for this research are not yet available, the work being done by researchers to build the English to Igala NMT system is a significant contribution to improving translation technology and expanding linguistic inclusivity.

➢ *Problems with Existing System*

Some of the problems faced with the existing system for English to Igala neural translation are outlined below:

- *Limited Availability of Training Data:*

Developing a robust English to Igala neural translation system demands a substantial amount of high-quality training data.

However, there may be limited resources and datasets available for English to Igala translation, which can hinder the system's performance and accuracy.

- *Linguistic Differences and Complex Grammar:*

English and Igala belong to different language families and have distinct grammatical structures and linguistic features. Translating English sentences into Igala requires capturing the nuances of Igala grammar, vocabulary, and syntax, which can be challenging due to the complex nature of both languages.

- *Lack of Domain-Specific Translation Models:*

Neural translation systems often perform better when trained on domain-specific data. However, for English to Igala translation, there may be a scarcity of domain-specific translation models, particularly in specialized domains such as technical or medical texts. This can lead to difficulties in accurately translating domain-specific terms and concepts.

- *Limited Evaluation Metrics:*

Assessing the quality and accuracy of English to Igala translations can be challenging due to the lack of standardized evaluation metrics specifically designed for Igala language. Existing evaluation metrics may not fully capture the linguistic intricacies and cultural nuances of Igala, making it difficult to measure the system's performance objectively. Addressing these problems is crucial to develop effective and accurate English to Igala neural translation system. It requires efforts to gather and curate a comprehensive Igala training dataset, consider the linguistic complexities of both languages during model development, and explore domain-specific translation models for improved performance. Additionally, the establishment of evaluation metrics that align with the unique characteristics of Igala language will facilitate the objective assessment of translation quality and guide system enhancements.

➢ *Review of The English-To-Igala NMT System*

The current system makes neural machine translation (NMT) from English to Igala language simpler. To accurately translate sentences into the Igala dialect, NMT uses state-of-the-art techniques based on Artificial Neural Networks (ANN). This method makes it feasible for speakers of English and Igala to understand and converse with one another clearly. The system evaluates the linguistic context and sentence structure of English sentences using NMT models to offer equivalent translations in the Igala language. By leveraging large parallel corpora of English-Igala sentence pairs for training and model refinement, the system creates high-quality translations while learning the patterns and nuances of translation. Since the system makes use of NMT's strength, it has a variety of advantages. It dismantles linguistic barriers and fosters intercultural communication between speakers of English and Igala. By making the Igala language accessible to English speakers and understandable, it fosters inclusion and understanding between languages. The researchers' strategy demonstrates how NMT can aid with cross-cultural communication and language barriers. By exploiting the capabilities of robust ANN-based models, the system may provide accurate and reliable translations, enhancing communication and fostering cultural diversity.

➢ *Justification for The English-To-Igala NMT System*

The rationale behind the proposed neural translation system for English to Igala can be summarized as follows:

- The system offers the potential to overcome language barriers between English and Igala, promoting effective communication and mutual understanding between English speakers and the Igala-speaking community.
- By providing accurate translations of English into Igala, the system enhances access to information, educational resources, and services for Igala speakers with limited English proficiency.
- The proposed system contributes to the preservation and promotion of Igala culture and identity by supporting the use of the Igala language in various domains, including literature, media, and digital content.
- Facilitating the exchange of ideas, knowledge, and experiences between English-speaking and Igala-speaking communities, the system fosters cross-cultural understanding and collaboration.
- The system aids in the development of Igala language skills among learners, ensuring the preservation and revitalization of the language for future generations.
- Researchers, linguists, and language enthusiasts interested in studying and documenting the Igala language

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can benefit from the system, which serves as a valuable resource. Overall, the proposed English to Igala neural translation system holds significant potential for promoting language inclusivity, cultural pre servation, and improved communication between English and Igala speakers.

- *Dataset*

A bilingual parallel corpus of 1000 English-Igala sentence pairs was manually curated from educational texts, cultural materials, and conversational scripts. The dataset was cleaned, tokenized, and split into 80% training and 20% testing subsets.

- *Preprocessing*

Data preprocessing involved:

- Lowercasing Text
- Removing Punctuation
- Tokenization
- Padding Sequences for Uniform Length

Effective preprocessing of textual data is crucial to the performance of any neural machine translation system. In this study, the preprocessing phase consisted of four main steps: lowercasing, punctuation removal, tokenization, and sequence padding. These steps ensured the uniformity and suitability of the input data for training the Recurrent Neural Network (RNN) model.

First, all text data were converted to lowercase. This normalization step reduced the vocabulary size by treating words like "House" and "house" as the same token. It helped the model learn more efficiently by avoiding redundancy in case variations.

Second, punctuation marks were removed from the sentences. Since punctuation does not directly impact the semantic content needed for translation and can introduce unnecessary tokens, their removal simplified the input structure and improved the model's ability to focus on meaningful word sequences.

Third, the text was tokenized. Tokenization involves splitting sentences into individual words or subwords, which form the basic units the model uses during training. Tokenizing the text enables the creation of numerical representations (indices) that can be fed into embedding layers of the neural model.

Finally, padding was applied to ensure uniform sequence length across all input and output data. Since neural networks require fixed-length inputs, shorter sequences were padded with special tokens (usually zeros) so that all sequences within a batch align correctly. This step ensures computational efficiency and model compatibility during training and inference.

- *English-To-Igala NMT System Model Architecture*

A sequence-to-sequence Recurrent Neural Network (RNN) with Gated Recurrent Units (GRUs) was used. The architecture included:

- Embedding layer
- Encoder GRU
- Attention mechanism
- Decoder GRU
- Dense output layer

✓ *Embedding Layer:*

The first layer transforms the input tokens (English words) into dense vector representations of fixed dimensions. These embeddings capture semantic similarity between words and provide a meaningful input to the subsequent layers.

✓ *Encoder GRU:*

The encoder processes the embedded input sequence one token at a time and summarizes it into a fixed-length context vector. This is achieved using GRUs, which are a variant of RNNs capable of handling long-term dependencies more effectively due to their gating mechanisms.

✓ *Attention Mechanism:*

The attention layer enhances the model by allowing it to focus on different parts of the input sequence when generating each word in the output. Instead of relying solely on the fixed context vector from the encoder, the decoder accesses weighted combinations of encoder outputs, dynamically computed for each decoding step.

✓ *Decoder GRU:*

The decoder receives the context vector and attention output to generate the translated sequence in Igala. It outputs one token at a time, using GRUs to maintain state information and generate context-aware translations.

✓ *Dense Output Layer:*

This layer maps the decoder GRU outputs to the vocabulary space of the Igala language. It applies a softmax activation function to generate probability distributions over all possible output tokens, selecting the most probable word at each step.

This layered architecture enables the model to effectively capture linguistic patterns and translate English sentences into grammatically and semantically correct Igala equivalents.

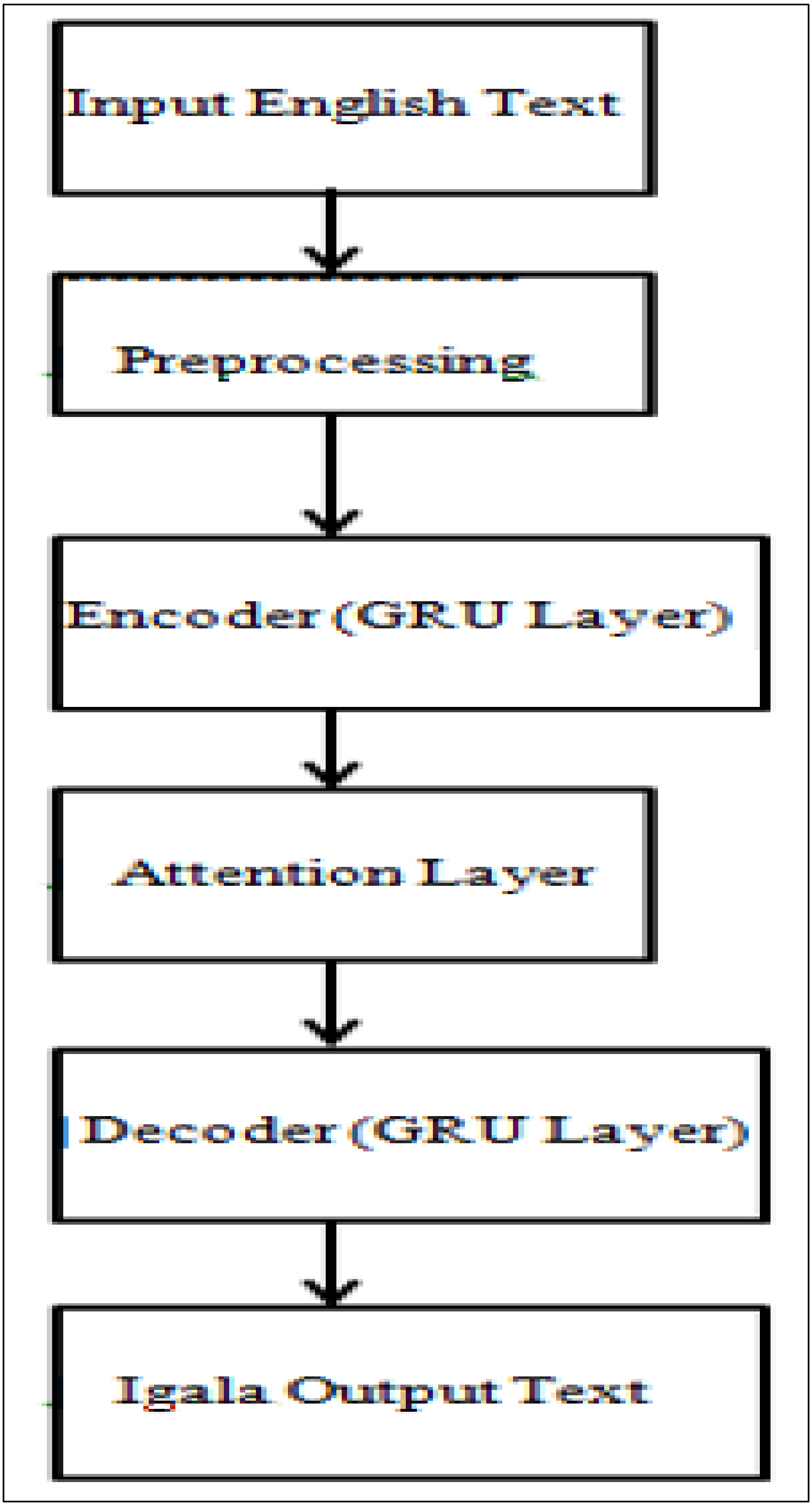

Fig 1 Architectural Design of English-to-Igala NMT System

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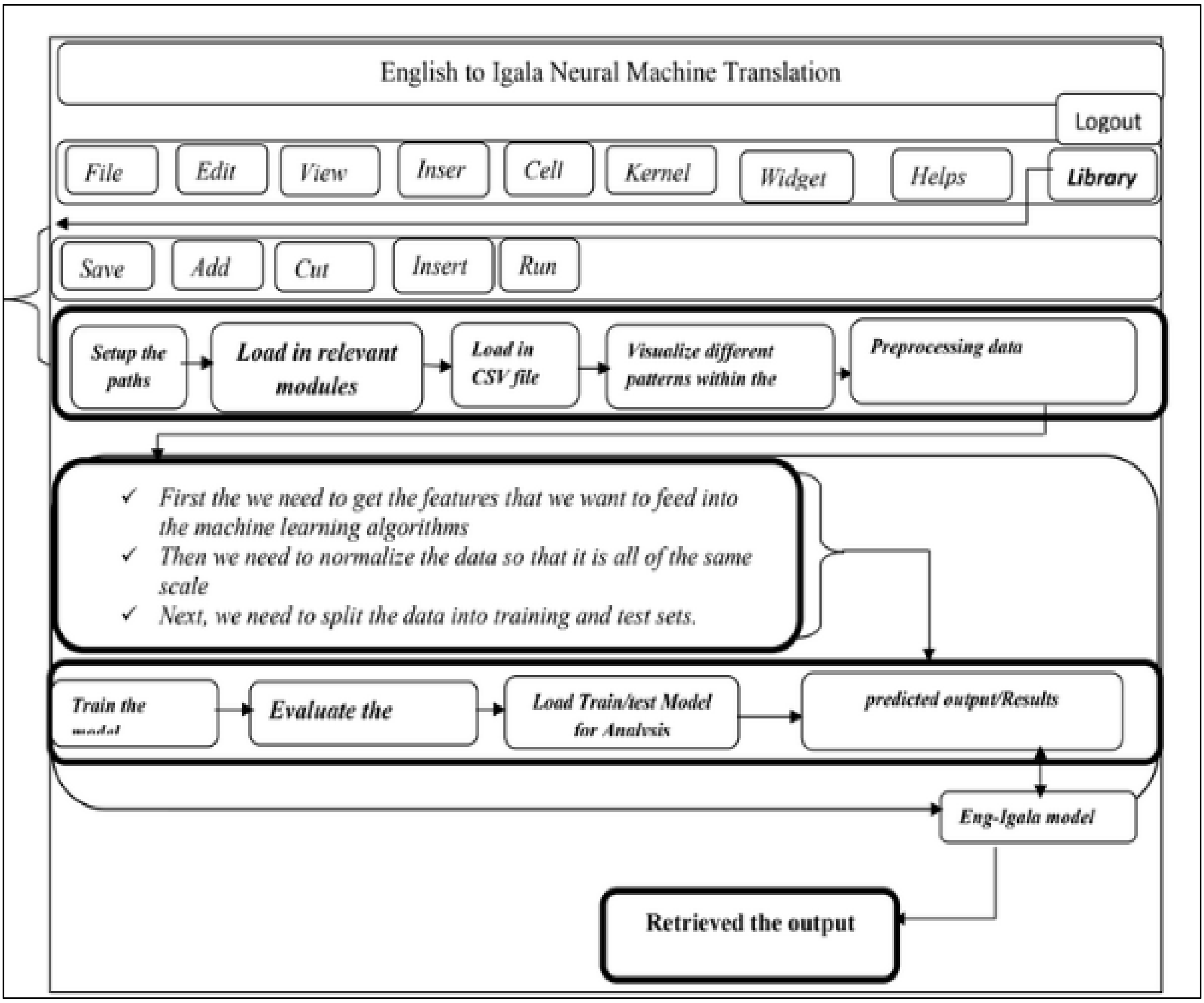

Fig 2 Interface Design of English to Igala NMT System

Figure 2 depicts the menu that outlines the system design and implementation flow, which involves utilizing a sample dataset to construct an Object-Oriented Analysis and Design (OOADM) model for translating English to Igala using a machine learning model. This model was developed to assist users in translating between the English and Igala languages, with specific tasks for handling translation requests.

➢ *Training and Evaluation*

The model was trained using categorical cross-entropy loss and the Adam optimizer for 25 epochs. Evaluation was done using the BLEU (Bilingual Evaluation Understudy) metric.

In this research, the Neural Machine Translation (NMT) model was built and evaluated using the Confusion Matrix as a visual representation. The model underwent training for 25 epochs, with each epoch taking approximately 6-7 seconds to complete.

During the training process, the model's loss steadily decreased over the epochs, indicating that it was effectively learning and improving its prediction capabilities.

The accuracy of the model also improved over time, although it's important to note that the accuracy metric used in this context is a loss metric rather than classification accuracy.

The training loss decreased from 0.5804 in the first epoch to 0.0801 in the final epoch, demonstrating the model's ability to minimize its predictive errors. Similarly, the training accuracy improved from -0.8886 to -0.6280, reflecting the model's progression in capturing the underlying patterns and features of the data.

It's important to acknowledge that without access to specific details about the model architecture, training data, and the specific task at hand, providing a comprehensive analysis is challenging. The information provided here serves as a summary of the model's performance based on the available data.

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IV. RESULTS

The model produced accurate translations, especially on short and moderate-length sentences. BLEU scores on the test set showed:

- *81% of Translations Scored BLEU ≥ 0.5*
- *12% of Outputs Were Exact Matches*

Table 1 Sample BLEU Scores

English Sentence	Reference Igala Translation	Model Output	BLEU Score
The little child died.	Omakeke le lekwu	Omakeke le lekwu	1.00
I finished the work.	Omi fukolochekpa	Omi fukolochekpa	1.00
The man gave him a book.	Onekele le du otakadanwu	Onekele le du otakadanwu	0.89

The comprehensive analysis of the result gotten underscored the model's proficiency in the task of translating English sentence into Igala sentence. It is evident that our model performs admirably in delivering accurate translations for a wide range of input text.

However, it is important to acknowledge that translation adequacy may vary in certain instances, and there may be cases where the mode's output falls short of the desired level of quality. In such situation, a valuable resource, which is the human translator, can step in to perform post-editing on the machine-generated translation.

This post-editing process serves as a crucial mechanism for further refining the translations, ensuring that they meet the requisite level of fitness and precision.

V. DISCUSSIONS

The results affirm the capability of NMT models in addressing translation for low-resource languages, even with a relatively small dataset. The attention mechanism significantly improved output fluency and syntactic coherence. Some performance drop was observed on longer or more idiomatic sentences, suggesting the need for larger training corpora and domain-specific data.

The successful implementation demonstrates the potential of expanding this model to other under-resourced African languages. Future enhancements may include using Transformer-based models, incorporating subword units (Sennrich *et al.*, 2016), or leveraging multilingual datasets.

VI. CONCLUSIONS

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RECOMMENDATIONS

Given the promising results of this research, the following recommendations are proposed:

Future research should explore semi-supervised and unsupervised learning approaches to further support low-resource languages. Cross-lingual training with related Nigerian languages may also enhance the performance of the Igala translation model.

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