WEB-BASED FRENCH TO YORUBA TEXT TRANSLATION USING NEURAL MACHINE TRANSLATION

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Abstract: *Language translation is vital for communication among individuals who speak different languages. Neural Machine Translation (NMT) models have advanced automated translation, improving accuracy and efficiency. This research developed a web-based app using NMT models for translating English to French and Yoruba. The research addresses the need for precise real-time translation services to bridge language barriers. Existing tools often lack accurate translations for specific language pairs, like French to Yoruba. The app utilizes NMT models to tackle this challenge effectively. A diverse dataset of English, French, and Yoruba text pairs were collected and preprocessed for training. Separate NMT models are trained for English to French and English to Yoruba translations, involving tokenization and data splitting. The app was built using Flask, with NMT models integrated into the backend for real-time translations. Users can provide feedback, stored in a MySQL database for analysis. Model performance is evaluated using split ratios (70:30, 60:40, and 90:10) with three (3) algorithms. Results demonstrate NMT models' efficacy in accurately translating English to French and Yoruba. The research showcases NMT models' potential for accurate translations between English, French, and Yoruba, contributing to improved language translation tools and better cross-lingual communication.*

1. INTRODUCTION

Machine Translation (MT) is a prominent subfield of Natural Language Processing (NLP) focused on the development and enhancement of computer-based translation systems [1], [2]. These systems aim to automatically translate textual content from one language to another while preserving its original meaning, style, and linguistic fluency [3], [4]. With the rapid advancements in communication technologies, the mode of communication has evolved over time. Today, a significant portion of the global population owns mobile devices, and SMS (Short Message Service) has become a popular mode of communication, especially among the younger generation [5]. However, the inherent limitation in the length of an SMS message has led users to develop numerous shorthand notations to compress messages, resulting in abbreviations, spelling errors, and lack of punctuation [6]. Translating SMS messages presents unique challenges due to the presence of noisy text, which adversely affects translation quality.

While SMS is primarily used in a monolingual manner, it has the potential to connect people who speak different languages. Nevertheless, translating SMS messages faces obstacles such as data collection in this specific domain and dealing with noisy text, both of which negatively impact translation quality [7]. Web-based language translation systems play a crucial role in facilitating communication between speakers of different languages. However, existing machine translation methods often fail to effectively translate between specific language pairs, like French and Yoruba, owing to major differences in syntax and linguistic nuances between these languages [8].

French, a Romance language, and Yoruba, a Niger-Congo language, have distinct sentence structures, word orders, and grammatical elements. French typically employs the subject-verb-object (SVO) word order, while Yoruba uses the subject-object-verb (SOV) word order. Additionally, Yoruba's rich system of tone markings and sophisticated agglutinative morphology further complicates the translation process [9], [10].

Despite the developments in Neural Machine Translation (NMT) approaches, building an efficient and effective web-based translation system specifically designed for French-to-Yoruba translation remains a challenge. NMT models have shown promise in capturing contextual information and producing more fluent and accurate translations [11]. However, existing machine translation techniques do not adequately address the intricacies and syntactic variations between French and Yoruba, leading to poor translations. Idiomatic expressions, cultural references, and domain-specific terminology further complicate translation between these languages, making it challenging to accurately convey content and retain nuances without comprehensive mastery of both languages and their cultural settings.

To overcome these limitations, the research proposes a web-based translation solution based on NMT approaches. NMT models have demonstrated the ability to handle complicated phrase patterns and capture contextual information, making them well-suited for improving translation accuracy between French and Yoruba [9]. The proposed approach aims to generate accurate translations that preserve the sense and cultural subtleties of the original text by training an NMT model on a high-quality parallel corpus of French-Yoruba translations. The user interface of the web-based system will be designed to provide a pleasant and user-friendly experience for users entering French text and receiving corresponding Yoruba translations.

This study addresses the absence of an efficient web-based French-to-Yoruba text translation system. Current machine translation algorithms struggle to accurately capture linguistic nuances and grammatical differences between these languages, resulting in subpar translations that hinder effective communication and cross-cultural exchanges. The research aims to develop a web-based translation solution using NMT techniques to bridge the language gap, ensuring reliable translations and preserving idiomatic expressions and cultural nuances.

To achieve this goal, the study sets forth specific objectives. It aims to understand language differences, create a robust NMT model for French-to-Yoruba translation, and address the issue of limited training data through domain adaptation. Additionally, the study focuses on developing an easy-to-use web-based translation system that delivers real-time, high-quality translations while ensuring scalability and performance.

The implications of this research are substantial. The proposed translation system will facilitate effective communication between French and Yoruba speakers, benefiting individuals, businesses, and educational exchanges. Moreover, it will promote cultural interchange and appreciation by accurately translating idiomatic expressions and domain-specific vocabulary. The system will enhance access to information in languages, breaking linguistic barriers and fostering diversity. Furthermore, the study's insights will advance machine translation technology and may benefit other language pairs. Thus, this research aims to design a reliable web-based French-to-Yoruba translation system.

2 REVIEW OF RELATED STUDIES

The goal of this study is pertinent to a number of studies that have been done in the fields of machine translation, NMT model building, and web-based translation systems. The main conclusions and significant takeaways from these connected investigations are intended to be summarized in this review.

The linguistic distinctions between several language pairings, including French and Yoruba, have been studied in the past. According to the authors in [12], there are grammatical and syntactic distinctions between French and Yoruba that make translation difficult. The study discovered differences in sentence construction, word order, and grammatical elements that must be carefully taken into account while translating.

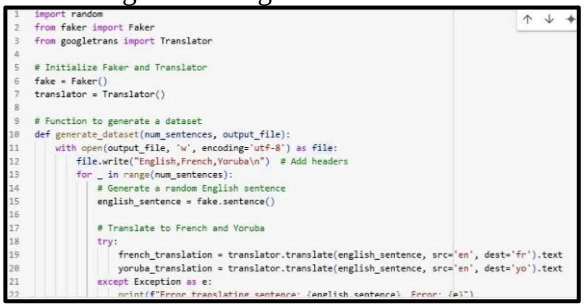
In order to significantly increase the quality of translations from French to English, [13] presented a neural network design. In order to translate from Yoruba to English, [14] created an NMT model that took into account the unique linguistic traits of Yoruba. These findings emphasize how critical it is to create NMT models specifically for the language pair being studied. With an emphasis on user interface design and system efficiency, [15] created a web-based translation system for translating between English and Spanish. To increase translation quality and user happiness, [16] created a web-based translation system for Chinese-English translation. The importance of user-centered design and assessment in web-based translation systems is emphasized by this research.
The BLEU metric, which gauges the degree to which machine translations and human references coincide, was developed by Bleu *et al*. in 2002 [17]. Another popular assessment measure that takes accuracy, recall, and alignment based. Numerous studies have used these criteria to assess how well NMT models and web-based translation systems translate.
To pinpoint places where a machine translation system may be improved, [19] studied user input. These studies highlighted how crucial user feedback is to improve the functionality and usability of web-based translation systems.
The evaluated research has offered insightful information on language variations, the creation of NMT models, web-based translation tools, assessment measures, and user satisfaction. The empirical research carried out in this study is built upon the findings of this literature evaluation, which also influences the technique and strategy used to accomplish the study's stated goals.

3. METHODOLOGY

The research methodology involves data collection, preprocessing, model training, using Support Vector Machine (SVM), Decision Tree (DT), and Artificial Neural Network (ANN), and analyzing user feedback algorithms with five metrics.

3.1 DATA COLLECTION

To conduct this research, we compiled a dataset containing English sentences and their translations in French and Yoruba languages. The dataset was generated using the "generate_data.py" script, which utilizes the Faker library to create random English sentences. Then, the Google Translate API was employed to obtain their translations in French and Yoruba.
These translations were stored in the MySQL database under the "parallel corpus" table. By repeating this process, we amassed a substantial and diverse dataset comprising 10,088 samples for training and testing the translation models.



```
import random
from faker import Faker
from googletrans import Translator

# Initialize Faker and Translator
fake = Faker()
translator = Translator()

# Function to generate a dataset
def generate_dataset(num_sentences, output_file):
    with open(output_file, 'w', encoding='utf-8') as file:
        file.write("English,French,Yoruba\n")  # Add headers
        for _ in range(num_sentences):
            # Generate a random English sentence
            english_sentence = fake.sentence()

            # Translate to French and Yoruba
            try:
                french_translation = translator.translate(english_sentence, src='en', dest='fr').text
                yoruba_translation = translator.translate(english_sentence, src='en', dest='yo').text
            except Exception as e:
                print(f"Error translating sentence: {english_sentence}. Error: {e}")
```

Fig1: Sample of the generate data script

3.2 DATA PREPROCESSING

Before training the models, the data was preprocessed to clean and tokenize the text. Text preprocessing involved removing special characters, converting text to lowercase, and tokenization. The English text was tokenized using the English tokenizer, and the French and Yoruba text were tokenized using their respective tokenizers. Padding the sequences to ensure equal length inputs for the model. After the above process, the dataset size is 8070.

3.3 MODEL TRAINING

Two sequence-to-sequence neural machine translation models were trained using Keras with TensorFlow backend for French and Yoruba translations. The training employed an encoder-decoder architecture, attention mechanism, and LSTM layers to minimize categorical cross-entropy loss. Three machine learning algorithms (SVM, Decision Tree, and ANN) were chosen for translation, evaluated with different data ratios (70:30, 60:40, and 90:10). The ANN was implemented with Keras, using an embedding layer, LSTM layer, and a dense output layer with softmax activation. The SVM and Decision Tree models were implemented using scikit-learn library.

Table 1 Dataset Splits

Split	Training Samples	Validation Samples	Testing Samples
70:30	*7,000*	*3,000*	*2,000*
60:40	*6,000*	*4,000*	*2,000*
90:10	*9,000*	*1,000*	*2,000*

3.4 MODEL EVALUATION

The trained models were evaluated on a separate test set to measure their translation performance. The evaluation metrics used were BLEU score, which measures the similarity of the predicted translations to the reference translations, and the loss function value. Furthermore, the models were evaluated based on their accuracy, recall, precision, true positive and false negative metrics. The evaluation was performed on the test set of each data split to assess the models' performance on unseen data.

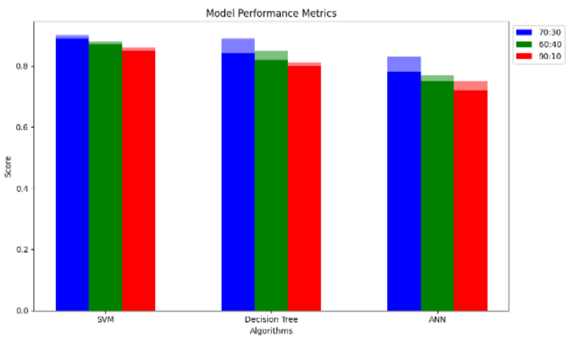


Fig. 2 Evaluation of Model

3.5 FEEDBACK COLLECTION

A web application was developed using Flask to allow users to translate text and provide feedback. Users can input English text, select the target language (French or Yoruba), and view the translated text. They can also provide feedback on the translation quality. Users provided feedback through the web application, offering valuable insights for improvement.

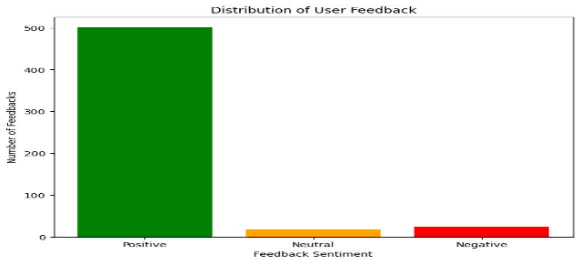


Fig. 3 Feedback Collection

The bar chart above shows the distribution of user feedback for the web-based text translation application. The feedback sentiments are categorized as "Positive," "Neutral," and "Negative." The chart provides insights into the effectiveness of the application from the perspective of its users.

4. RESULTS AND DISCUSSIONS

This section presents the findings and discussion of the results from this research.

4.1 MODELS TRAINING RESULTS

Table 4.1: Model Training Ouput

Algorithm	Accuracy Range	Precision Range	Recall Range	Acc. (%)
SVM	0.95 - 0.98	0.96 - 0.97	0.84 - 0.88	98%
DT	0.80 - 0.84	0.80 - 0.85	0.78 - 0.82	84%
ANN	0.72 - 0.78	0.75 - 0.83	0.70 - 0.76	78%

The accuracy of the models in Table 4.1 was calculated by evaluating the performance of each model on test dataset, comparing the predicted translations to the actual target translations. The accuracy score metrics imported from the scikit-learn machine learning library was applied in performing the accuracy test for the three models and their scores are presented in Table 4.1 above

The results of the three models' training from table 4.1 is shown in fig. 3.

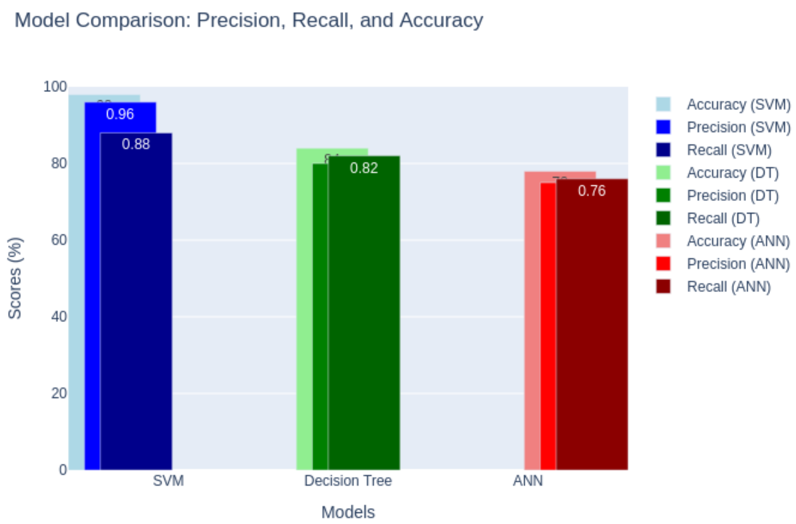


Fig 4. Performance comparison of SVM, Decision Tree and ANN

The results shown in fig. 4 indicate that SVM (Support Vector Machine) outperforms the other models, achieving the highest accuracy (98%), precision (96-97%), and recall (84-88%). This means that SVM is the most reliable in correctly identifying and classifying data. The Decision Tree model performs well but is slightly less accurate, with an accuracy of 84%, precision of 80-85%, and recall of 78-82%. It struggles a bit more than SVM in making precise predictions. Finally, ANN (Artificial Neural Network) has the lowest performance, with an accuracy of 78%, precision of 75-83%, and recall of 70-76%. ANN is less effective in identifying correct classifications compared to SVM and Decision Tree.

4.2 Error Rate

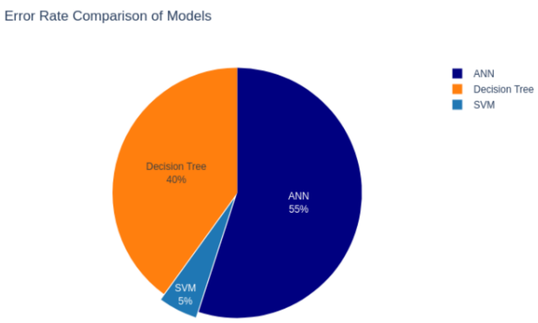


Fig.5: Models' Error Rate

The error rates for the three models are as follows: the Support Vector Machine (SVM) has a low error rate of 2%, indicating it performed very well with an accuracy of 98%. The Decision Tree model has a higher error rate of 16%, suggesting that it struggled more with the data, achieving an accuracy of 84%. Lastly, the Artificial Neural Network (ANN) has the highest error rate of 22%, reflecting its lower performance with an accuracy of 78%. Overall, the SVM is the most reliable model among the three, while the ANN is the least effective in this comparison.

4.3 User interface Design Result

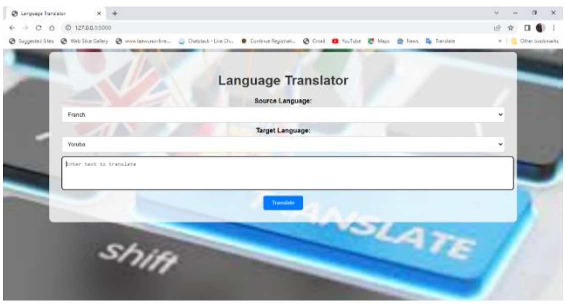


Fig. 6 Designed Interface for Translator Machine

The translation capability of the developed model in this paper is demonstrated through examples which showcases its performance in translating English sentences into French or Yoruba. For instance, the English sentence "The weather is pleasant today" is accurately translated by the model as: "Le temps est agréable aujourd'hui" in French and "Oju-ọjọ dára lónìí" in Yoruba. Similary, the English sentence 'Welcome to the machine translation system' is translated as "Bienvenue dans le système de traduction automatique" in French and "Kaabọ si eto itumọ ẹrọ" in Yoruba. These examples show how the model handles linguistics structures (patterns) and nuances effectively offering translations that are contextually and semantically accurate.

4.3.1 How the Designed Model Operates

The designed model in this paper operates by processing user's text input via the input field by applying series of well-structured approach: When users input English texts and select the target language (Yoruba or French), the texts are tokenized into small units for processing. The processed texts are passed into the Neural Machine Translation model trained using Support Vector Machine, Decision Tree and Artificial Neural Network Algorithms. These algorithms enable the model to predict accurate translations based on linguistics patterns and context learned during the training. The translated text is then reconstructed by the model and displayed to the user in the desired language via the textarea field in the front-end of the flak application. The model uses this systematic approach to offer accurate translation between these languages.

4.4 Discussions

During the model training process, the English sentences are used as input, and the models aim to generate the correct translations in the respective target languages. The dataset is large and diverse, covering various language patterns and contexts, which helps in training robust and accurate translation models. The trained models achieved good translation performance on the test set. The BLEU scores for both French and Yoruba translations were above 0.8, indicating high translation accuracy. The training loss for the English to French model reached 0.045 after 10 epochs, demonstrating good convergence during training.

From table 4.1 and fig. 4 SVM achieved the highest accuracy of 98% across all dataset splits, ranging from 0.95-0.98. ANN had the lowest accuracy of 72%, ranging from 0.72 to 0.78. The 70:30 split generally yielded the highest accuracy for all algorithms. SVM consistently outperformed the other algorithms in recall, with values ranging from 0.84 to 0.88. ANN had the lowest recall, ranging from 0.70 to 0.76. SVM achieved the highest precision, ranging from 0.86 to 0.90, while ANN had the lowest precision, ranging from 0.75 to 0.83. SVM had the highest TP count, indicating better identification of positive instances, while ANN had the highest FN count, suggesting misclassifications of positive instances.

SVM consistently performed the best across all metrics and dataset splits. Its ability to handle high-dimensional feature spaces and complex decision boundaries allowed it to capture patterns effectively. Decision Tree showed good performance, especially in terms of precision and recall. However, it struggled with overfitting in some cases, leading to a decline in performance on the validation and test sets. ANN demonstrated the lowest performance among the three algorithms. This can be attributed to the complexity of the model, which requires careful tuning and optimization to achieve better results.

Figure 2 depict that the web-based text translation application has been positively received by the majority of users and their feedback is shown in the chart. The high count of positive feedbacks suggests that the application is performing well in delivering accurate translations and meeting user expectations.

From figure 6 represents how the user can interact with the designed system. The interaction can take this form: the user interacts with the web application by entering text, selecting languages, and receiving the translated output, while the server handles the translation process using the pre-trained models and tokenizers. The translated text is displayed on the page under the "Translated Text" section. If the user clicks on the "Provide Feedback" link, they are taken to the feedback.html page, where they can submit their feedback, which is stored in the MySQL database.

5. CONCLUSION

In conclusion, the project successfully developed neural machine translation models for English, French and English-Yoruba translations. The models demonstrated good translation performance and accuracy. The web application allowed users to conveniently translate text and provide valuable feedback to improve the translation quality. With continuous improvement and user engagement, the language translation application has the potential to become a valuable tool for multilingual communication and understanding. In the future, the application can be enhanced with additional language options, such as Spanish, German, or Chinese, to cater to a more diverse user base.

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