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A Deep Neural Network-Based Yoruba Intelligent Chatbot System

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ABSTRACT

Two Artificial Intelligence software systems, Bot and Chatbot have recently debuted on the internet. This initiate a communication between the user and a virtual agent. The modeling and performance in deep learning (DL) computation for an Assistant Conversational Agent are presented in this research (Chatbot). The deep neural network (DNN) technique is used to respond to a large number of tokens in an input sentence with more appropriate dialogue. The model was created to do Yoruba-to-Yoruba translations. The major goal of this project is to improve the model's perplexity and learning rate, as well as to find a blue score for translation in the same language. Kares is used to run the experiments, which is written in Python. The data was trained using a deep learning-based algorithm. With the use of training examples, a collection of Yoruba phrases with various intentions was produced. The results demonstrate that the system can communicate in basic Yoruba terms and that it would be able to learn simple Yoruba words. The study result when evaluated showed that the system had 80% accuracy rate.

Keywords: Chatbot, Natural Language Processing, Deep Learning, Artificial Neural Network, Yoruba Language

1. INTRODUCTION

Computers have had a significant impact shift in the way we go about our daily lives in today's environment. A chatbot is a software program that enables operators to be engross with one other in the same manner that they would with a person (Ramesh et al., 2017). Currently, things may take an unanticipated turn toward natural-language (NL) user interfaces, in which users interact with digital systems using a collection of NLP text strings rather than scrolling, button clicks, or swiping (Pardeshi and colleagues, 2020).

This is especially true in recent breakthroughs with chatbot creation (Devakunchari, Agarwal & Agarwal, 2019). Chatbots are computer agents that offer data and service providers with natural-language user interfaces (Dale, 2016). Chatbots are almost as ancient as computers. The chatbot was first developed in 1950 by Alan Turing, generally recognized as the pioneer of theoretical computer science (Hodges, 2009). The Turing Test involves a person, a computer, and a judge. The judge determines if the discussion is between a person and a computer. Both the human and the computers are naturally been asked series question by the judge thereafter, judgement is made based on the users' emotions, tone, and responses (Hodges, 2009).

Joseph Weizenbaum of the Massachusetts Institute of Technology (MIT) artificial intelligent (AI) laboratory created ELIZA which is the initial program to pass the Turing Test (TT) in 1966 (Pham et al., 2018, Paradeshi et al., 2020). In the ELIZA software, the text was comprehended and examined for the existence of a keyword and once a keyword is deduced, the response was changed according to the precedent associated with it. Chatbot programmers have followed the same method since then. While the factual artificial intelligence (AI) is still years, if not decades, away. AI-based messaging systems that can solve real-world issues are already available. Some chatbots are designed just for entertainment and are targeted for a certain audience. Despite the fact that Yoruba is an extensively articulated language in West Africa, with a predictable 30 million utterers, a detailed examination of Chatbot agents reveals that there are few or no Chatbots with whom users may converse in Yoruba. This language is spoken in Nigeria, Togo, and Benin, as well as in parts of Brazil and Ghana (Babatunde et al., 2021). In Sierra Leone, the language is known as Oku, while in Cuba, it is known as Nago (Osunnuga, 2016). Yorùbá is one of the three main dialects articulated in Nigeria, which has over 400 languages (Frances Ayenbi and Oti, 2014, Babatunde et al., 2021).

However, as more individuals and applications begin to utilize chatbots that are multilingual, the need for language-specific chatbots will increase (Mabrouk et al., 2021). The bulk of chatbots have been developed in English. Over the years, there has been an increase in the use of the internet for communication, however there is little support for Hausa and other African languages (Haruna et al., 2021). All of the existing chatbots have certain flaws, but one flaw that they all have is their dearth of assistance for African dialects such as Yoruba (Haruna et al., 2021; Mabrouk et al., 2021). Two major issues arose during the development of language-specific chatbots in the Yoruba language. First, none of the previously deployed African language chatbots have a meaningful lexical area (Mabrouk et al., 2021). Furthermore, for dialects, especially African languages, there are no pre-trained language models (Adelani and colleagues, 2020). As a consequence, it's vital that we work on our domain embedding model.

The purpose of this study is to establish an intelligent Yoruba chatbot. This system would handle digital interactions with citizens by using official government language and local dialects, as well as recognizing and replying to users in the appropriate language or dialect. Illiterate and vulnerable communities, including as rural women and those in need of social inclusion and resilience, would have improved access to trustworthy information in Yoruba since services would be digitized. As a consequence, the goal of this research was to fill in the gaps left by prior research. In addition, early chatbot systems relied on pattern matching to classify text, which is difficult (Nursetyo, Setiadi, and Subhiyakto, 2018). A pattern must be provided for each unique input to define a response (Devakunchari, Agarwal, and Agarwal, 2019). This results in a hierarchical pattern structure (Devakunchari, Agarwal, and Agarwal, 2019).

The paper focuses on the design and implementation of a Yoruba intelligent chatbot system by creating an example hand-crafted dataset for rudimentary communications in Yoruba language, developing a python-based application that uses Deep Learning Model for training a chatbot that interacts with users in Yoruba language, and finally testing the system to determine the conversational duration metric and proper functionality of the developed application. The remaining part of the paper is organized as follows: The second section summarizes the extant literature. Our suggested Chatbot technique was outlined in Section Three. The system testing and validation are described in section four. Finally, section five brings the report to a close by highlighting possible future paths for the research.

2. LITERATURE REVIEW

Text and Voice based chatbots are the two main forms of chatbots. ELIZA, the first natural language processing (NLP) software, was created at the MIT AI Test center to demonstrate the triviality of human-computer interaction (Weizenbaum, 1966). To elicit dialogue, the pattern matching and replacement approach was used. This gave users the impression that the computer understood them, but it didn't have or didn't have an incorporated model for contextualizing occurrences. Eliza was the foremost Chatbot, and hence lays the path for additional Natural Language Processing investigation and advancement. It also allowed for effective human-to-human communication. Eliza has a primitive character, and is not a fully smart system since it just repeats the operator's involvement.

ALICE (an abbreviation for Artificial Linguistic Internet Computer Entity), sometimes known as an Alice bot, is an additional text-built Chatbot system (Wallace, 2009). The system is an NLP chatbot with a software that converses with a person using heuristically pattern corresponding instructions applied to the user's involvement. Joseph Weizenbaum also inspired ALICE which is one of the most powerful of its sort at that time. Loebner price has been awarded to it thrice which is given to outstanding humanoid speaking robots in the year 2000, 2001 and 2004. Despite these achievements, the software failed the TT, since even the most unpremeditated operator would frequently reveal the program's mechanical characteristics in brief interactions.

A psychiatrist suggested PARRY, a text-based Chatbot that was developed at Stanford University (Colby, Weber, & Hilf, 1971). This Chatbot was created in the hopes of simulating a person suffering from paranoid schizophrenia. The PARRY program used ideas, conceptualizations, and beliefs to create a basic model of an individual with suspicious schizophrenia's behavior. It also has a conversational technique, making it further thoughtful and mature software than ELIZA. "ELIZA with attitude" is the unsurpassed way to characterize the PARRY Chatbot. In Segura et al., 2019, a Spanish football Chatbot named Chatbot was suggested for the Laliga Football association to deliver information to operators about the Spanish national association. Even though everything is in Spanish, the bot was developed with elements of a standard Eliza and is quite speedy.

A multilingual chatterbot has been suggested that uses the Google Translate infrastructure to deliver interactive conversation in a variety of languages (Vanjani, Aiken & Park, 2019). This chatbot is one of the first to use Google Translate and to be multilingual. The system's user interface, on the other hand, was not very appealing or user-friendly. It also valued existing languages such as English and Arabic over emerging languages like as Hausa, Swahili, and Yoruba, among many others. On the Discord thread, a recommender Chatbot for the programming community was suggested. By providing the finest ideas and suggestions, the Chatbot assists enterprises in recruiting developers.

The bot, on the other hand, is limited in intelligence due to the constrained domain. Furthermore, the DiscordSt library used in the bot's design was not fully standardized, and as a result, the bot may have faulty portions. In, a financial system Chatbot was presented, which was likewise based on text-based bots (Dole, Harekar, and Athalye, 2015). For financial organizations, this Chatbot delivers accurate and timely client support 24 hours a day, 7 days a week. However, since it is based on the Chatbot, the bot suffered from all of ALICE's flaws. A voice assistant is a software agent that can understand and respond to human speech using synthetic voice (Hoy, 2018). To assist people in conversing with computers, several voice chatbots are being created. Siri is one of the voice-based chatbot systems that was suggested in a study.

This Chatbot is a virtual assistant that was initially introduced in October 2011 on Apple Inc.'s iOS, iPad OS, watch OS, macOS, and tv OS operating systems. Before Apple purchased Siri Inc and made the product part of its suite of services, the bot creators were part of a business named Siri Inc. ((206) How did Siri get her start? - Quora, no date). It uses voice queries and a natural-language user interface to react to human inquiries, offer suggestions, and carry out tasks by delegating requests to a variety of Internet services. The programming agent adapts to users' language selections, searches, and preferences over time. Individualized outcomes are attained. One of Siri's key flaws is its inability to recognize certain words.

Cortana is a voice Chatbot for Microsoft Windows that leverages the Bing Search engine to do things such as creating reminders and answering user inquiries (Paul, Bhat, and lone, 2017; Hoy, 2018). The Chatbot offers a user-friendly graphical interface and is simple to use. The system, however, is only accessible in the following languages: English, French, Chinese, German, Italian, Japanese, and Spanish. Another voice-based intelligent Chatbot (Du Preez, Lall, and Sinha, 2009) was presented to enable users to converse with the system using their voices. The system was created using the Java Programming Language, which is a distributed programming language.

The Chatbot, on the other hand, suffers from the slowness associated with Java programs. Lisa is another voice-based Chatbot that was created to help students with their everyday activities on campus by providing information and services (Dibitonto et al., 2018). The emphasis was on how the bot affects the user's experience and engagement, as well as what amount of intelligence should be conceived and executed. One of the system's advantages is that it enables users to understand both their needs and their behavior when using the tool. However, this method may only be utilized on the university's campus.

Amazon Alexa, sometimes known as Alexa, is a voice-activated chatbot created by Amazon workers Rohit Prasad and others in 2014 (Lopatovska et al., 2019). This Chatbot's features include voice interaction, music playback, composing to-do lists, setting alarms, streaming podcasts, playing audiobooks, and weather, traffic, sports, and other activities that require real-time information, such as news. Alexa may also be utilized as a home automation system to operate a variety of smart gadgets. There is a known security flaw in Amazon Alexa that enables third-party attackers to get access to the device and listen in on users' conversations. BOTTA, the first Arabic dialect chatbot, was created in 2016 and employs the Egyptian Arabic dialect in communication (Ali and Habash, 2016). It portrays a female figure that entertains users by conversing with them. BOTTA was created using AIML and released on the Pandorabots platform.

The writers of (Al-Ghadhban and Al-Twairesh, 2020) created a social chatbot that can facilitate communication with students of King Saud University's (KSU) information technology (IT) department utilizing the Saudi Arabic dialect. They gathered 248 inputs/outputs from KSU IT students, then preprocessed and categorized the information into several text files to create the conversation dataset. Haruna et al. (2021) created an intelligent Hausa language web-based chatbot that interacts with Hausa language users using a pattern matching algorithm. Users may also teach the Hausa Chatbot certain Hausa words.

Pattern matching, on the other hand, is a brute-force approach that is difficult to master: a pattern must be provided for each unique input in order to describe a response (Devakunchari, Agarwal, and Agarwal, 2019; Pardeshi et al., 2020). This results in a hierarchical pattern structure. After a thorough and critical examination of both types of chatbot agents, it is clear that no Yoruba-language chatbot has been developed, whereas Haruna et al. (2021) developed a Hausa-language chatbot. As a result, the catalyst for this research and development is to fill the gap left by other studies and developments.

3. METHODOLOGY

3.1 Dataset

The dataset is a hand-crafted collection of commonly used Yoruba phrases. It's a straightforward dataset with 14 distinct tags, each with its own set of patterns and replies. These patterns and replies are presented in the form of a question and answer. A dictionary mapping of dictionaries is included in the dataset. Intents are first mapped to tags, patterns, context, and replies, and then each one is mapped to its queries and keywords. Because this is a short dataset, training it with a deep neural networks model leads to overfitting the model, suitable care must be made when developing the model to discover the ideal learning rate**.**

```
{"intents": [
    {"tag": "greeting",
     "patterns": ["Ẹn lẹ", "Ṣe ẹnikẹni wa nibẹ?", "Bawo ni", "Ẹn lẹ", "Bawo ni o se wa"],
     "responses": ["Ẹn lẹ", "E se", "Ẹn lẹ"]
    },
{"tag": "goodbye",
     "patterns": ["O dabọ", "Ma a ri e laipe", "O dabọ"],
     "responses": ["Ma a ri e laipe", "gbadun ọjọ rẹ", "O dabọ! Pada lẹẹkansi"]
    },
{"tag": "thanks",
     "patterns": ["O ṣeun", "adupe", "Iyẹn wulo", "O ṣeun fun iranlọwọ"],
     "responses": ["Idunnu mi ni lati ṣe iranlọwọ!", "Nigbakugba!", "O gbadun mọ mi", "kaabọ!"]
    },
{"tag": "about",
     "patterns": ["Tani e?", "Iru ki ni o je?", "Tani iwọ?" ],
     "responses": ["Emi ni Adisa, oluranlọwọ bot rẹ", "Emi ni Adisa, ọlọgbọn atọwọda"]
    },
    {"tag": "name",
    "patterns": ["Ki 'ni oruko re", "kini o yẹ ki n pe ọ", "kini orukọ Ẹ?"],
    "responses": ["O le pe mi ni Adisa.", "Emi ni Adisa!", "Kan pe mi bi Adisa"]
    },
    {"tag": "help",
    "patterns": ["Ṣe o le ran mi lọwọ?", "ran mi ni ọwọ jọwọ", "Ṣe o le ṣe iranlọwọ?", "Kini o le ṣe fun mi?", "Mo nilo ati
    "responses": ["Sọ fun mi bi MO ṣe le ṣe iranlọwọ fun ọ", "Sọ fun mi iṣoro rẹ lati ran ọ lọwọ", "Bẹẹni Daju, Bawo ni MO
    },
    {"tag": "createaccount",
    "patterns": ["Mo nilo lati ṣẹda iwe apamọ tuntun kan", "bi o ṣe le ṣii iwe apamọ tuntun kan", "Mo fẹ ṣẹda iwe ipamọ kan
    "responses": ["O le ni rọọrun ṣẹda iwe apamọ tuntun lati oju opo wẹẹbu wa", "Kan lọ si oju opo wẹẹbu wa ki o tẹle awọn
    },
```


Figure 1. Sample Dataset

Text data with 14 tags and numerous patterns and replies for each tag is included in this dataset. Before constructing a machine learning or deep learning model, various preparation activities must be undertaken when working with text data. Tokenization is the most fundamental and fundamental process that can be applied to text data. It's a simple process for splitting down text material into smaller components called words. Natural Language Processing is used to tokenize the patterns. The NLTK module in Python allows for natural language processing. Each word is then lemmatized, and any duplicates are removed from the word list. Lemmatizing is the process of converting words to lemma form and storing the python objects required for prediction in a pickle file.

A sample collection of Yoruba phrases, intentions, patterns, and replies is shown in Figure 1. The process of translating the application from English to Yoruba. Different intents were created in the example JSON file shown in figure 4.2, and training samples for those intents were used to train your chatbot model, using those training sample data as model training data (X) and intents as model training categories (Y). The user may speak with the Yoruba chatbot after successfully training the Yoruba dataset, as demonstrated in figure 1.

3.2 Architecture

The training data, which comprises both input and output data, is now produced. The pattern will be the input, and the pattern's class will be the output. The user's input is first tokenized, then lemmatized, so that strings can be matched against the chatbot database, which contains all of the responses, and the user can receive a suitable message. The computer, on the other hand, is unable to comprehend the words, therefore they are converted to numbers. This is similar to one-hot encoding for categorical data. The result of this operation is sent into the neural network as input. The whole technique is shown in Figure 1. There are two kinds of training and testing datasets. The training and testing datasets are 80 percent and 20 percent separated, respectively. The model is trained using training data, and the model's accuracy is verified using testing data.

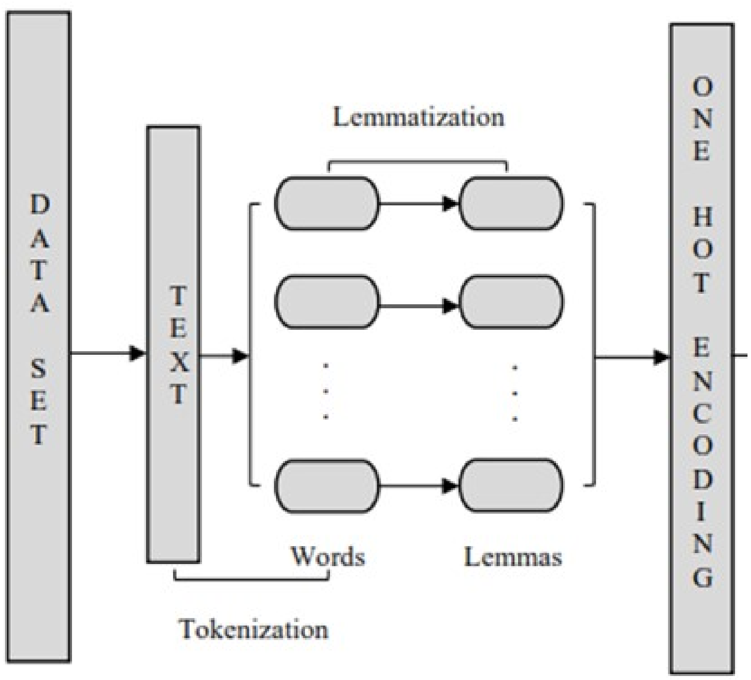

Figure 2. The architecture of the System

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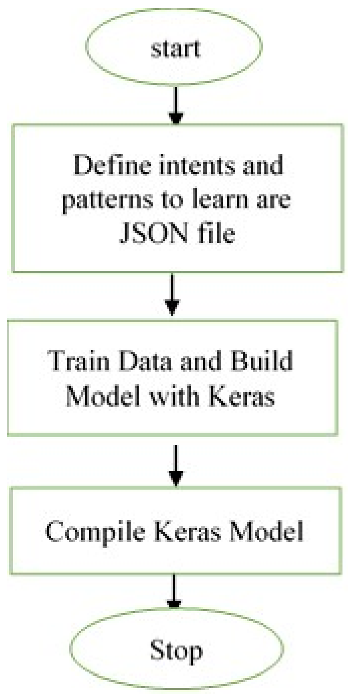

Figure 3. Program flow of the working of the chatbot

3.3 Proposed Algorithm

This model is created via a feed-forward neural network design, in which data is only passed forward in the network. The input is changed in each hidden layer, and the output is passed on to the next levels. The DNN model was mathematically interpreted in the following equations:

$$Z^n = a^{(n-1)}w^n + b^n$$
$$a^n = g\left(Z^{(n)}\right) \qquad (1)$$

4. RESULTS AND DISCUSSION

A DNN is used to evaluate the dataset's analysis. A Python-based machine learning toolkit called 'Keras' is used to evaluate the performance depending on the analysis. For input and the buried layer, ReLu is the activation function. The output's softmax function is used to activate it. The creation of this model is carried out in a sequential manner. The chatbot's output is displayed on the terminal of Visual Studio Code when the user interacts with the chatbot.

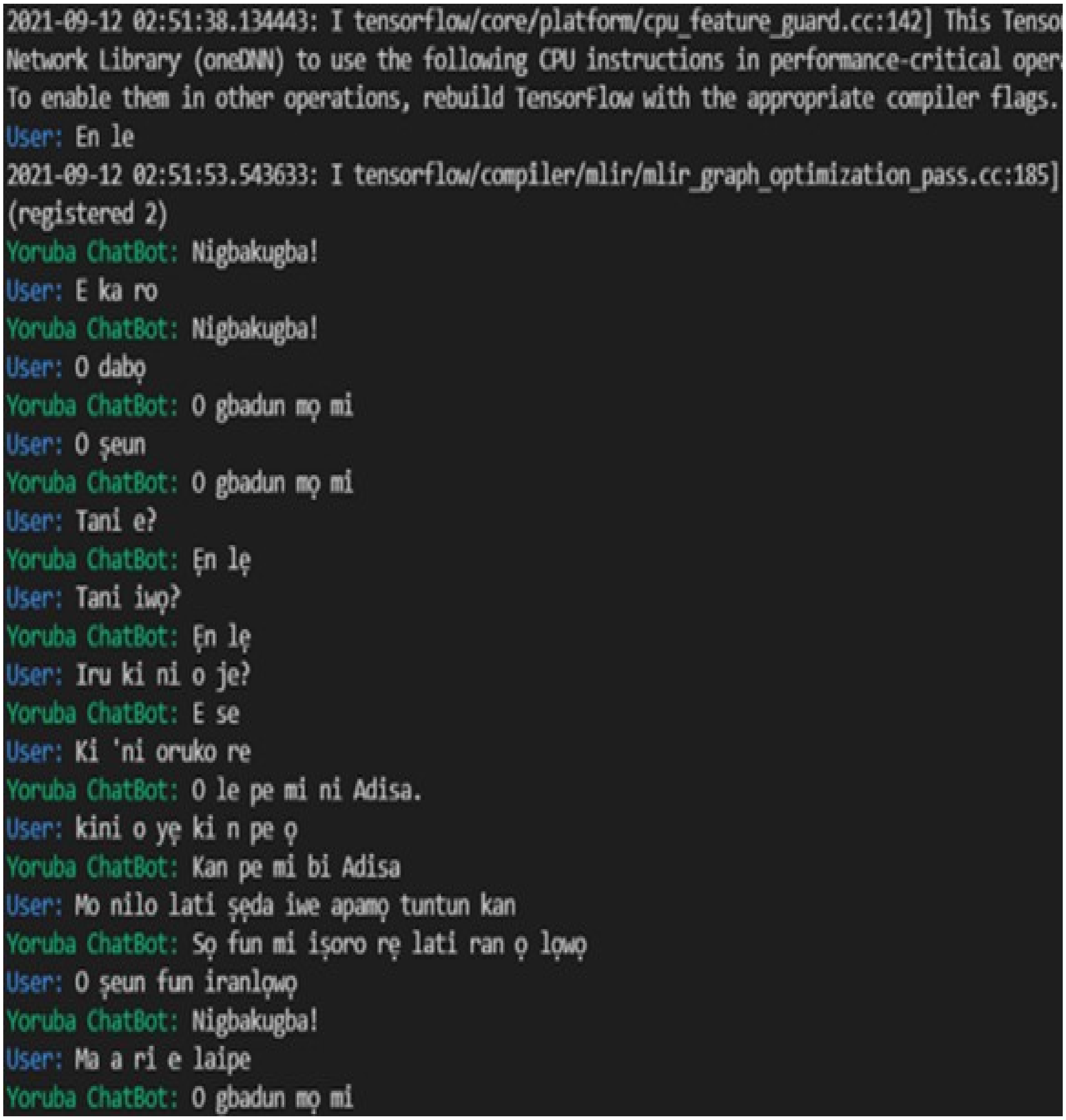

Figure 4. System Interface showing Yoruba Chatbot and User

The difficulty in evaluating derives from the fact that each topic has an impact on the others, and the same conversation will not happen more than once; one slightly different response will result in an entirely new dialogue. As a result, we compared our chatbot system to other current chatbots in order to enhance the chatbot's performance. Our chatbot system gave 800 valid answers when it checked the 1000 most frequently asked queries on the input corpus. That's an 80 percent accuracy rate.

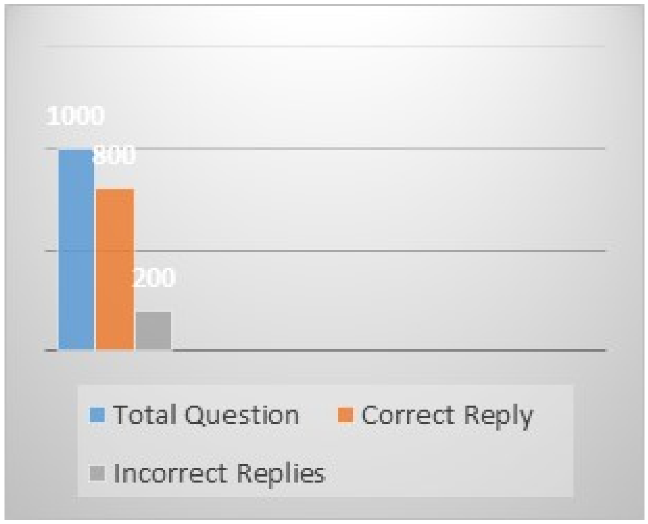

Figure 5. Evaluation of the result

4. CONCLUSION

Keras has been used to create a Yoruba-to-Yoruba language translation Chatbot that uses a deep learning NMT model. The DNN and attention mechanisms were used to create the Chatbot architecture. The Chatbot Knowledge Base is public, and it uses a Text data with 14 tags to provide authentic responses. In the future, the model will be awarded for responses that are both relevant and sentimentally acceptable. The Deep Reinforcement Learning (DRL) technique will be used. The methods used to build and train the chatbot can also be applied to specific domain chatbots, such as scientific, healthcare, security, banking, e-commerce, and educational chatbots. This approach will make it easier to construct chatbots in any domain, and it can improve current chatbots based on simple other neural networks architecture by employing the attention mechanism described above.

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