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Development of a Closed Domain Question Answering System based on Deep Learning

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ABSTRACT

Close Domain Question Answering systems generates answers to questions asked for a specific field of interest like military, health and medicine, economics, education and finance. The process involves information retrieval tasks that automatically extracts answers to the questions asked by humans in natural language using either a pre-structured database or a collection of natural language documents. Deep learning approach was employed in this research to develop a closed Domain Question Answering System for a Nigerian Tertiary institution. The corpus used in training the system was pre-processed using Pandas Library and an end to end comprehension CdQA based on Bidirectional Encoder Representations from Transformers (BERT) was used in pre-training the language representations. The GUI was designed using python tool PyQt5 and the performance of the system was evaluated using Precision, Recall and F-Measure metrics. Results from evaluation with 50 structured questions gave precision score of 88%, Recall rate of 76% and F-Measure rate of 0.82. The results from the evaluation metrics show that the system is efficient and gives a higher accuracy and precise answers to structured questions.

Keywords: Closed Domain, Deep Learning, Encoder, Question Answering

1.0 INTRODUCTION

The rapid increase in massive information storage and the exploration of large amount of data makes finding information a complex and expensive task (Ojokoh and Adebisi. 2018) and this motivated the development of a new adapted research tool known as Question Answering System. Question Answering (QA) systems are automated systems in which a direct answer is expected in response to a submitted query known as question, rather than a set of references that may contain the answers (Pundge et al., 2016). These systems generate answers of questions asked in natural languages (Mishra and Jane, 2016). There are criteria to developing QA systems, they are; (a) Classifications of application domains for which the systems are developed which can be open domain (Unrestricted) or closed domain (Restricted) (Pragisha 2014), (b) Types of questions asked by the users which can be factoid questions (what, who, when, which, how-quantity, quality), list questions, confirmation (is, will etc.), hypothetical (what would happen), causal (how or why) (Wang and Nyberg, 2015), (c) Source and Size of data consulted which could be Structured data source, Semi-structured data source and Un-structured data source. It could also be large scale or small-scale size (d) The forms of answer generated by QA system which could be extracted answer, generated answer and the languages (monolingual, bilingual and cross lingual) (Gupta and Gupta, 2012) (e)Types of techniques used for retrieving answers which could be TF-IDF similarity, Jaccard index, Word embeddings, Deep Learning text similarity algorithms (Tirpude and Alvi, 2015).

Existing QA systems such as YodaQA and QANUS have made a decent progress in text and image classification, but the systems failed to solve the tasks which involve logical reasoning in question answering (Sharma and Mittal, 2017). Search engines like Google present a ranked list of relevant documents in response to users' query based on various aspects such as popularity measures, keyword matching and frequencies of accessing documents but failed to return few relevant and concise sentences as answers along with their related information. These systems do not truly accomplish the task of question answering because users have to examine each document one by one before getting the desired information (Mishra and Jane, 2016). This makes question answering task a time-consuming process.

Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on artificial neural networks. The learning models have obtained a significant success on various natural language processing tasks, such as semantic analysis (Tang, 2015), machine translation (Bahdanau, 2015; Esan et al., 2020) and text summarization. Deep Learning approach has been able to tackle a wide variety of problems in the area reasoning and understanding with an aim to emulate human intelligence (Reddy et al., 2019). This approach helps to solve logical reasoning problem associated with previous QA systems. Therefore, this research developed a closed domain question answering system using deep learning approach.

2.0 RELATED WORKS

The sole aim of question answering systems is to provide concise and accurate answers rather than flooding with documents or even matching passages for users to start searching for answers like the search engines. Closed domain question answering systems have been applied in electronic learning as a learning companion (Pundge, 2016), for learning music (Jibin, 2009). It has also been used in tourism (Anette, 2006) and for answering factual questions. However, several approaches have been employed in developing automatic question answering systems. A domain-restricted question answering system has been developed based on robust semantic analysis in a hybrid NLP system architecture. Question interpretation and answer extraction was carried out in the research by building on a lexical-conceptual structure for question interpretation, which is interfaced with domain-specific concepts and properties in a structured knowledge-base (Sarouti and Ouatik, 2017).

In addition, a QA system was developed using a random walk-based learning method with recurrent neural networks for ranking metric network embedding (Zhao et al., 2016). Research revealed that the method achieved better performance than several state of-the-art QA systems. Wang and Nyberg (2015) proposed an approach that addressed the answer sentence selection problem for question answering with a method that uses a stacked bidirectional Long-Short Term Memory (BLSTM) network that sequentially read words from question and answer sentences, and then outputs their relevance scores. Compared to prior works, this approach does not require any syntactic parsing or external knowledge resources like WordNet. The experimental result gotten shows that the system outperforms previous work which requires syntactic features and external knowledge resources (Wang and Nyberg 2015).

R-NET, an end-to-end neural networks model was introduced for reading comprehension style question answering, which aims to answer questions from a given passage (Ojokoh and Adebisi 2018). The question and passage were first matched with gated attention-based recurrent networks to obtain the question-aware passage representation, then a self-matching attention mechanism was proposed to refine the representation by matching the passage against itself, which effectively encodes information from the whole passage. Pointer network was employed to locate the positions of answers from the passages. Sharma and Mittal (2017) built a dictionary-based query translation system with queries using N-gram technique and out of vocabulary (OOV) terms were transliterated using the proposed OOVTTM technique. The target documents were retrieved using vector space retrieval model. Research showed that the approach achieved better results.

Deep learning approach has also been used in developing QA systems. Tang (2016) developed a deep learning (DL) framework for answering selection task which does not depend on manually defined features or linguistic tools. An improvement to the system was carried out by combining two or more approaches (Stroh and Mathur, 2017). Research show that the method outperformed the baseline with relatively fast training and fewer parameters than other memory networks. A deep learning question-answering framework was developed by exploring a generic framework to systematically build the question-answering systems (Carvalho and Barbosa, 2019). The framework enables the deployment of turnkey systems directly from already existing collections of documents so that the systems can be used to provide a question-answering communication channel.

Cohen et al., (2018) studied the effectiveness of adversarial learning as a cross domain regularize in the context of the ranking task. An adversarial discriminator was used and neural ranking model was trained on a small set of domains. The adversarial approach proposed showed a consistent improved performance under the two evaluation settings used and over two other different deep neural baselines. QA models were developed to tackle the visual and numeric reasoning tasks by using modular components. The model addressed the reasoning task of question-answering on categorical plots like bar graphs and pie charts (Reddy et al., 2019). The research formulated supervised pre-training tasks to train simpler modules and then combined these modules to solve the question answering task using Figure Net novel architecture. Various research revealed the importance of question answering system and the need for improvement on the efficiency of question answering systems to meet up requirements of various domains where question answering systems function.

3.0 METHODOLOGY

3.1 Design of the Question Answering System

The main tools utilized for designing the Question Answering system are: Windows Operating System, Python programming language, CdQA Model, Keras and TensorFlow, Jupyter Notebook, PyQt5, py2exe as shown in Figure 1. The system was designed using an End-To-End Closed Domain Question Answering System CdQA model (a deep learning model that uses BERT Hugging face transformer library on python programming environment). Corpus for training the system was obtained from Federal University, Oye-Ekiti's official website (www.fuoye.edu.ng) using web scraping as shown in Figure 2. The scraped data was later cleaned to remove unwanted data and then stored into a single folder where it is converted to a structured data frame using python pandas library data-frame code snippet as shown in Figure 3.

The architecture of the system as shown in Figure 1 contains three main components which include; input module, CdQA Module and output module. The Input (query) module allow users ask question to be answered by the system. The CdQA Module involves the major question processing, passage retrieval and answer extraction process in the system. This is the main functional aspect of the system. It involves all the deep learning process algorithm engaged in the system. It involves: question processing where questions are processed and analyzed, retriever which selects a list of documents in form of articles in the dataset (database) that are the most likely to contain the answer (creates TF-IDF features based on uni-grams and bi-grams and compute the cosine similarity between the question sentence and each document of the database) and the Answer Extraction (Reader) divides each document into paragraphs and send them with the question to the Reader, which is basically the trained Deep Learning model using BERT End to End Transformer algorithm model. The Reader outputs the most probable answer it can find in each paragraph. The Ranker compares the answers by using an internal score function and outputs the most likely one according to the scores. This layer selects the scored paragraph and the answer can be extracted from the top ranked sentences based on the trained model. The database is attached to the retrieval and reader modules and it consists the corpus of the domain data and information in form of articles arranged in paragraphs and stored as .csv file extension, this is where the search for the possible answer is carried out. The Database can be updated from time to time whenever there are new entries from the domain. The last module is the Output module which displays answers to the questions asked.

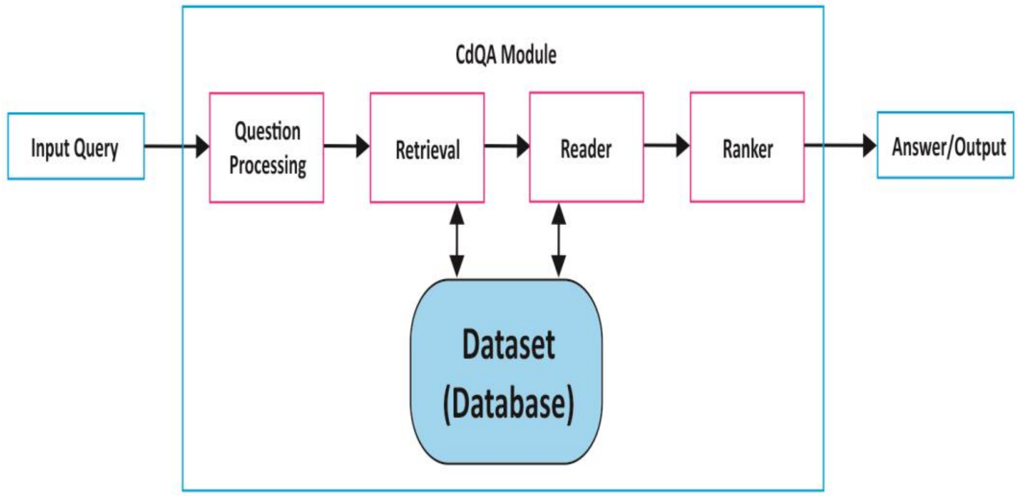
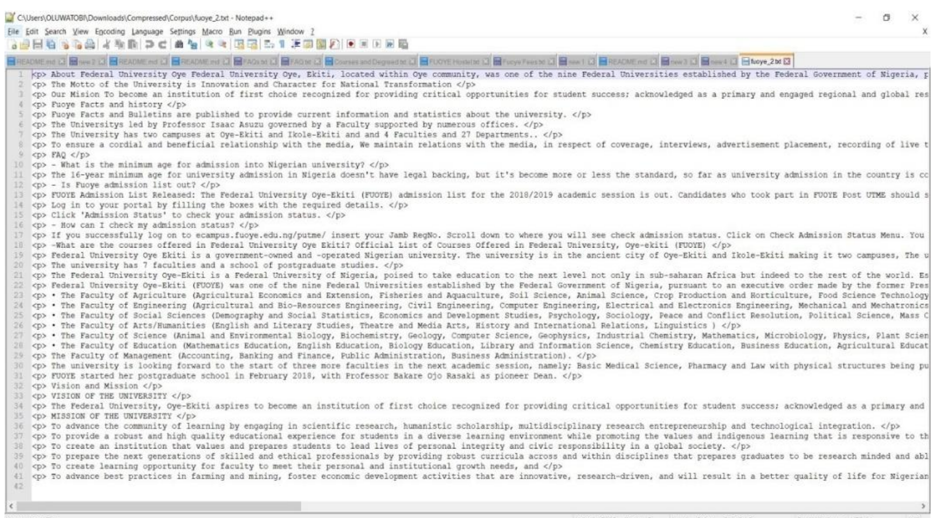


Figure 1: Architecture of the Question Answering System



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<p> The Motto of the University is Innovation and Character for National Transformation </p>
<p> Our Mision To become an institution of first choice recognized for providing critical opportunities for student success; acknowledged as a primary and engaged regional and global res
<p> Fuoye Facts and history </p>
<p> Fuoye Facts and Bulletins are published to provide current information and statistics about the university. </p>
<p> The Universitys led by Professor Isaac Asuzu governed by a Faculty supported by numerous offices. </p>
<p> The University has two campuses at Oye-Ekiti and Ikole-Ekiti and and 4 Faculties and 27 Departments.. </p>
<p> To ensure a cordial and beneficial relationship with the media, We maintain relations with the media, in respect of coverage, interviews, advertisement placement, recording of live t
<p> FAQ </p>
<p> - What is the minimum age for admission into Nigerian university? </p>
<p> The 16-year minimum age for university admission in Nigeria doesn't have legal backing, but it's become more or less the standard, so far as university admission in the country is cc
<p> - Is Fuoye admission list out? </p>
<p> FUOYE Admission List Released: The Federal University Oye-Ekiti (FUOYE) admission list for the 2018/2019 academic session is out. Candidates who took part in FUOYE Post UTME should s
<p> Log in to your portal by filling the boxes with the required details. </p>
<p> Click 'Admission Status' to check your admission status. </p>
<p> - How can I check my admission status? </p>
<p> If you successfully log on to ecampus.fuoye.edu.ng/putme/ insert your Jamb RegNo. Scroll down to where you will see check admission status. Click on Check Admission Status Menu. You
<p> -What are the courses offered in Federal University Oye Ekiti? Official List of Courses Offered in Federal University, Oye-ekiti (FUOYE) </p>
<p> Federal University Oye Ekiti is a government-owned and -operated Nigerian university. The university is in the ancient city of Oye-Ekiti and Ikole-Ekiti making it two campuses, The u
<p> The university has 7 faculties and a school of postgraduate studies. </p>
<p> The Federal University Oye-Ekiti is a Federal University of Nigeria, poised to take education to the next level not only in sub-saharan Africa but indeed to the rest of the world. Es
<p> Federal University Oye-Ekiti (FUOYE) was one of the nine Federal Universities established by the Federal Government of Nigeria, pursuant to an executive order made by the former Pres
<p> • The Faculty of Agriculture (Agricultural Economics and Extension, Fisheries and Aquaculture, Soil Science, Animal Science, Crop Production and Horticulture, Food Science Technology
<p> • The Faculty of Engineering (Agricultural and Bio-Resources Engineering, Civil Engineering, Computer Engineering, Electrical and Electronics Engineering, Mechanical and Mechatronics
<p> • The Faculty of Social Sciences (Demography and Social Statistics, Economics and Development Studies, Psychology, Sociology, Peace and Conflict Resolution, Political Science, Mass C
<p> • The Faculty of Arts/Humanities (English and Literary Studies, Theatre and Media Arts, History and International Relations, Linguistics ) </p>
<p> • The Faculty of Science (Animal and Environmental Biology, Biochemistry, Geology, Computer Science, Geophysics, Industrial Chemistry, Mathematics, Microbiology, Physics, Plant Scien
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<p> The Faculty of Management (Accounting, Banking and Finance, Public Administration, Business Administration). </p>
<p> The university is looking forward to the start of three more faculties in the next academic session, namely; Basic Medical Science, Pharmacy and Law with physical structures being pu
<p> FUOYE started her postgraduate school in February 2018, with Professor Bakare Ojo Rasaki as pioneer Dean. </p>
<p> Vision and Mission </p>
<p> VISION OF THE UNIVERSITY </p>
<p> The Federal University, Oye-Ekiti aspires to become an institution of first choice recognized for providing critical opportunities for student success; acknowledged as a primary and
<p> MISSION OF THE UNIVERSITY </p>
<p> To advance the community of learning by engaging in scientific research, humanistic scholarship, multidisciplinary research entrepreneurship and technological integration. </p>
<p> To provide a robust and high quality educational experience for students in a diverse learning environment while promoting the values and indigenous learning that is responsive to th
<p> To create an institution that values and prepares students to lead lives of personal integrity and civic responsibility in a global society. </p>
<p> To prepare the next generations of skilled and ethical professionals by providing robust curricula across and within disciplines that prepares graduates to be research minded and abl
<p> To create learning opportunity for faculty to meet their personal and institutional growth needs, and </p>
<p> To advance best practices in farming and mining, foster economic development activities that are innovative, research-driven, and will result in a better quality of life for Nigerian
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Figure 2: Web Scraped Data from Domain Website

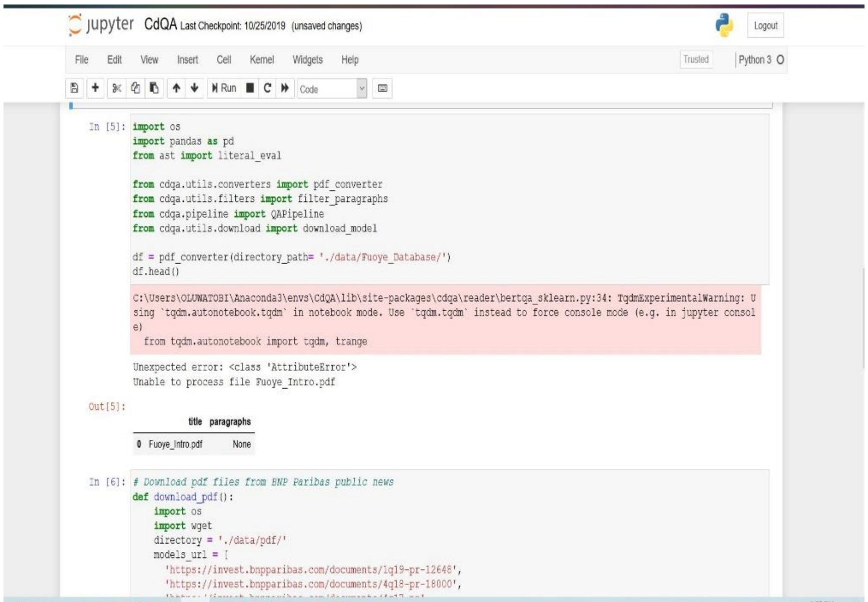

Figure 3: Creating Structured Dataframe From Database.

3.2 Model Training

The designed QA model was trained to obtain optimum accuracy in prediction and functionalities of the model. The model was trained using the datasets available as a supervised classification problem to study similar questions, frequent questions, frequent answers and similar answers so as to familiarize with the database and to minimize error of the answer sequence. The first step carried out was to fit the CdQA pipeline model with created corpus using the pre-trained python reader snippet code:

```
“import pandas as pd
from ast import literal_eval
from cdqa.pipeline import QAPipeline
df = pd.read_csv('FuoyeDataset.csv', converters={'paragraphs': literal_eval})
cdqa_pipeline = QAPipeline(reader='bert_qa_vCPU-sklearn.joblib')
cdqa_pipeline.fit_retriever(df=df)
cdqa_pipeline.dump_reader(‘directory to save model.joblib')”
```

The above code snippet imports the pandas library and other CdQA libraries required to train the model, the fourth line code fits the dataset arranged in paragraphs per articles according to the created dataframe with the model, it then aligns it to the reader from CdQA pipeline in background for the model to get accustomed to the dataset corpus which is what is called model training.

3.3 System Implementation

The internal working mechanism of the CdQA module as stated in the architecture of the system involves the sequential processes taken by the system to work on any input query. The input query module sends an initiation to the question processing module to acquire the question. The Retriever module receives the query and searches through the database which contains pools of articles to access the paragraphs that contains the keyword processed from the input query using tf-idf matrix to determine the top highest score paragraph that like contains the best answer. The Reader receives the top ranged paragraphs to extract the answer from the best suitable paragraph, the answer is then sent out to the output module in form of prediction. This process is then repeated for subsequent queries. The internal mechanism of the CdQA Module is shown in Figure 4.

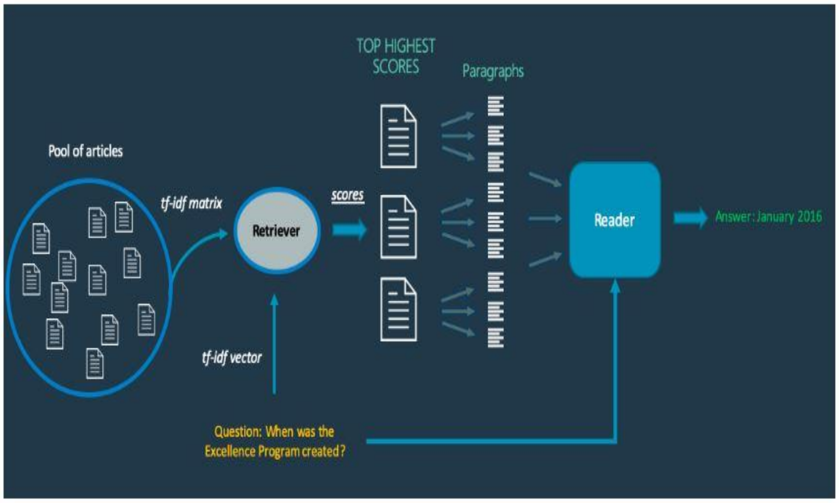

Figure 4: Internal Mechanism of the CdQA Module

Figure 5 shows the interactive interface that connects the user and the whole background system process. The GUI has the input and output interface, the input interface takes in the queries (Question) while the output interface displays the response as answer. On entering the input query, the system begins to execute the code from query processing module to the retriever module and the reader module, to the ranking layer to get the best suitable answer to the output layer. The graphic user interface showing Query and Answer is shown in Figure 6.

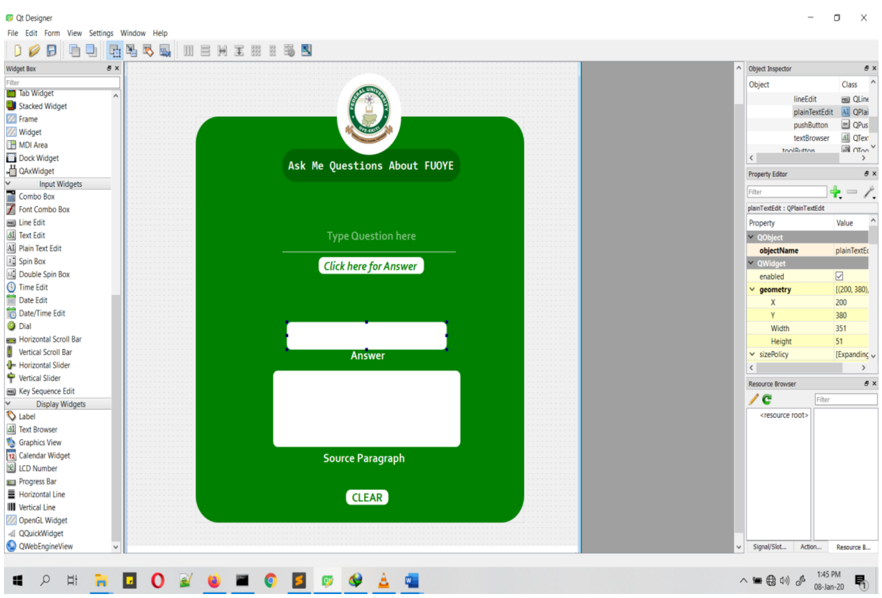

Figure 5: GUI Design using PyQt5 tool (Qt Designer)

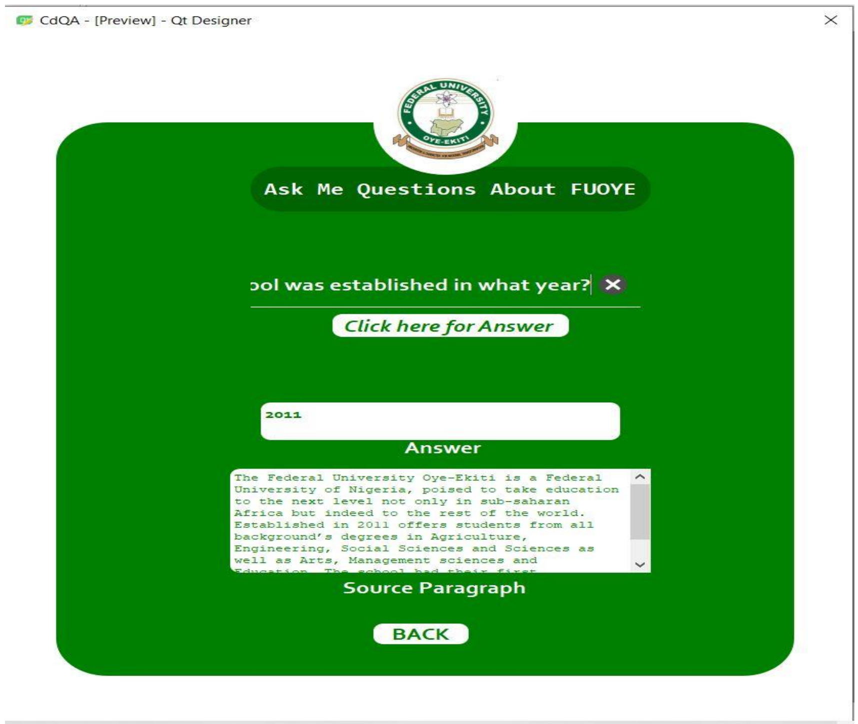

Figure 6: GUI Interface Showing Query and Answer

3.4 Evaluation of System

The developed system was evaluated using three combined evaluation metrics based on the expected answers from the system. The evaluation metrics used for this system are: the Precision, Recall and F-measure (Derici et al. 2015).

The metrics are given by:

- Precision= $\frac{Number\ of\ Correct\ Answers}{Number\ of\ Questions\ Answered}$
- Recall= $\frac{Number\ of\ Correct\ Answers}{Number\ of\ Questions\ to\ be\ Answered}$
- F-Measure = $\frac{2(Precision \times Recall)}{Precision \times Recall}$

4.0 RESULT AND DISCUSSION

The developed system was tested with 50 different questions which are in structured question format. About 25 of the questions were related to the history of the school, 10 of the total questions describe the school, 10 questions involved list answers while about 5 questions are of yes or no type. For these 50 questions, system produces correct output with great accuracy as the queries are structured. The accuracy of the answers was very low when tested with unstructured questions compared to the structured questions. Also, most questions for yes or no answer have no accurate response during testing because while dealing with keywords the "yes" or "no" answer cannot be retrieved within the paragraphs, this is a limitation of yes or no related questions. The results obtained from the evaluation of the developed system are shown in Table 4.1. From the Table, of the 50 questions tested, 43 questions were answered which gives percentage score of answered questions to be

83% with about 38 questions answered correctly giving a percentage score of correctly answered questions to be 76%. The Precision score obtained was 0.88, Recall score obtained is 0.76 and the F-measure score obtained is 0.82.

The approach used in this research yielded better results than previous approach because it answered less incorrect questions than the open-ended QA approach. In comparison with past systems (Sarrouti and Ouatik, 2017), the developed QA system has a higher percentage of precision, recall and F-measure score for structured questions and show that the system developed has higher accuracy. The success rate of the developed system exceeds that of Google in the domain covered because of the closed domain QA approach used in designing the model. Results also indicate that the closed domain QA framework has a practical implication of being adapted in an educational setting to support a teaching-learning process (Derici et al. 2018).

Table 1: Results from Evaluation of the developed QA system

S/N	**REFERENCE**	**SCORE**
1	TOTAL QUESTIONS TESTED	50
2	ANSWERED QUESTIONS	43
3	CORRECT ANSWER	38
4	PRECISION	0.88
5	RECALL	0.76
5	F-MEASURE	0.82

5.0 CONCLUSION

A closed domain question answering system was developed in this research using the Deep Learning approach. The developed system has a high percentage of precision, recall and F-measure score for structured questions. The system also yielded higher accuracy than previous open-domain QA systems because it answered less incorrect questions and results show that the success rate of the developed system exceeds that of Google in the domain covered. The closed domain QA framework used in developing the model enables the it to be used in an educational setting for teaching and learning. Future works can consider training the developed model on a high memory GPU based microprocessor and with a larger and well-structured Dataset.

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