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INTELLIGENT AI BASED DIALOGUE AGENT TO ENHANCE COMMUNICATION IN ORGAN TRANSPLANT NETWORKS

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Abstract - Organ Transplantation has become a successful mechanism to cure many chronic diseases which otherwise would have been fatal for the patient's life. But, organ transplantation process involves many communication deficiencies that hinder the smooth transplantation process. The process of automation of communication involves adjoining of various hard concepts of Natural language Processing (NLP), Natural Language Understanding (NLU) and Natural Language Generation (NLG). This work proposes an Artificial Intelligence dialogue agent or a Chatbot that can swiftly and accurately manage the communication issues of organ transplantation process by automating the process of providing answers to user's queries, where nature of query can be regarding to authorized transplant centers, legal matters concerning transplantation, general information about transplantation, contact points or Non Governmental organizations working in this domain etc. The dialogue agent functions at two major levels. First level has a trained Long Short Term Memory neural Network to generate answers to user's queries and the second level performs by displaying best matched sentences from the scraped contents from web that best satisfies the user's queries. The results from the experiments proved that the proposed dialog agent was capable of providing accurate and precise answers to user's questions, thereby proving to be an effective communication enhancement agent in organ transplant networks.

Keywords - AI, NLP, NLG, Dialogue agent, Organ Transplantation, Chatbot, LSTM, Glove Encoding.

I. INTRODUCTION

Organ Transplantation is one of the modern day marvels to cure many chronic diseases of patients. Organ transplantation acts as a crucial and sensitive field in Healthcare. There has been a lot of awareness regarding organ transplantation. But in real time to those involved in individual transplant transmission events is challenging due to the complexity of the communication networks among geographically diverse laboratories, Organ procurement organizations, and recipient transplant centers. The delay occurred due to communication gaps is found to be fatal at times.

In spite of several measures, communication gaps occur in many organ transplant cases, so automation of the communication process is needed. At the same time, organ donation is a sensitive field that deals with lives of individuals directly and hence cannot be argued for complete automation. The regions of insensitive areas of communication like query answering, spreading general awareness about organ donation, specifying information about legal authorities involved in organ donation, finding authorized transplant centers near recipients, giving contact details of Non Governmental Organization (NGO) that operate in the organ transplantations etc can be automated. Since there is data availability for insensitive portions of organ transplant communication, it can be used to train an AI agent to reduce the communication gaps. This goal is achieved through dialogue agents or Chatbots, typically used in dialog systems for various practical purposes including customer service or information acquisition.

The recent advancements in text processing domains show that it is possible to leverage the power of Long Short Term Memory (LSTM) Neural network to optimally generate new sentence pattern to answer any of the user based queries. But the limitation of the neural network model is that its efficiency lies within the scope and degree of its training corpus. So to overcome this disadvantage of the system, the user's given query would be searched via Google custom search Application Program Interfaces (API's) and top matched Uniform Resource Locator (URL) links are fetched from it. The contents from the URL are scraped and best 3-5 sentences from its contents that are highly relevant to the user's given query are matched using TF-IDF combined with cosine similarity text retrieval mechanism. By this way, the given user query is always answered even if that was beyond the reach of the custom made corpus. Thus, this work focuses to install a dialogue agent or a Chatbot to remove the communication delay and will further help optimize the process of transplantation by providing safe, reliable, swift, accurate and precise answers to the end users of this system in Organ Transplant networks.

II. LITERATURE SURVEY

Phong Le et.al proposed a new variant of Recurrent Neural Network (RNN) that used the LSTM architecture where memory cells were attributed in the form of parse trees [1]. Authors inferred that their model outperformed the traditional neural networks over Stanford sentiment analysis dataset. The ability of LSTM to effectively capture sentiment in text was inferred from this study. Kai Sheng Tai et.al proposed another variant of RNN, generalization of LSTM to tree topologies, which outperformed existing mythologies in capturing better semantic relation between sentences and sentiment analysis [2]. The ability of LSTM's to capture better semantic relation of the text was taken as an inference from the survey of this paper. Xing xing Zhang et.al proposed a change in the structure of LSTM cells by proposing a new master vector for input and forget gates [3]. This change helped the authors to realize better efficiency in language modeling and made the model to make better logical inference.

The purpose of gates in the LSTM cells and their modification was duly noted from the study of this paper. Iulian Vlad Serban et.al carried out the survey of wide public datasets for dialogue systems and inferred the chief characteristics, uses and modification strategies of those corpuses [4]. The above study aided our work by specifying how to create a text data corpus from the scratch. Petr Baudis et.al proposed a question answering system YodaQA by integrating many different question answering task definitions across different knowledge bases [5]. This work helped the proposed dialogue agent on how to successfully build a Q&A system that manages data from multiple domains. Antoine Bordes et.al proposed transfer learning techniques for question answering mechanism for their custom created dataset of 100k questions [6]. Their study aided our work by showing the performance enhancement achieved by LSTM for large datasets and proving the answering ability of LSTM. Eric Brill et.al proposed AskMSR, question answering system based on linguistic analyses of each and every question [7].

This study helped our work by presenting various prediction methodologies for LSTM answering mechanism which were incorporated to our work. Soren Auer et.al proposed a methodology to extract structured information from Wikipedia by introducing system called DBpedia which was capable of querying against multiple datasets retrieved from Wikipedia [8]. This study helped our work by the illustration of scraping data from web and the process of linking it with existing data sources. General study of literature pertained to the domain of NLP, NLG and answering systems [9][10] facilitated in helping to conclude that LSTM was the best possible choice for constructing a dialogue agent and the same was implemented in the work. Thus, study for various literature aided in finalization of LSTM model, word embedding techniques and answer retrieval strategies needed for the dialogue agent.

III. ARCHITECTURE OF THE PROPOSED DIALOGUE AGENT FOR ORGAN TRANSPLANTATION NETWORKS

Dialogue agent architecture is composed of 2 main functionalities: to generate an answer for user's query through LSTM trained model and to display top matched sentences from text content of URL's extracted from custom Google search of the user's query. The purpose of having 2 explicit layers is that if the user's query is in the out of the context of text corpus used for text generation, LSTM model will fail. On such cases to add robustness to the system, as well as to add additional support to the generated answers from the model, web scraping functionality is incorporated. The combined architecture composing of these two layers is described in Fig 1. These 2 layers together form the proposed dialogue agent.

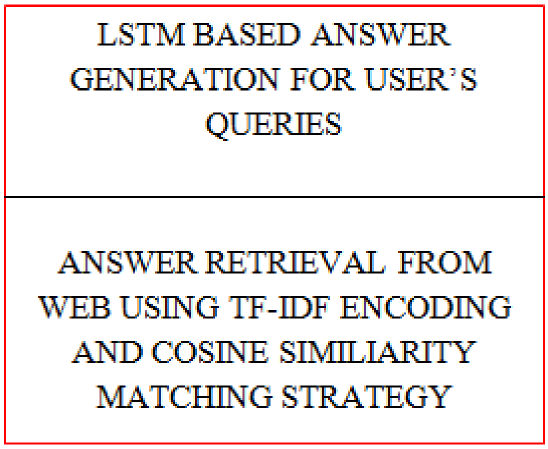

Figure 1: Dialogue agent architecture layers

3.1 LSTM BASED ANSWER GENERATION FOR USER'S QUERIES

The users of the dialogue agent system can be any unclassified group ranging from the general public, donor or associates of donors, recipients or associates of recipients, legal agencies, NGO associates etc. Hence the text corpus must contain necessary details of question and answers pertaining to the views and needs of all the mentioned stakeholders. The intention of the text corpus is to provide simple, accurate and precise answers to user's questions. The corpus used for query answering Chatbot is named as 'Organ transplantation Q&A corpus' .The corpus is custom created suited to the various information domains of organ transplantation conditions, taken from the legitimate data sources like TNOS (Tamil Nadu organ sharing), Mohan foundation (NGO organization), Wikipedia (for general awareness)etc. The text corpus is created only to suite for organ transplantation scenario of Tamil Nadu, because authentic data sources for organ transplant network of Tamil Nadu were alone studied for this data collection process.

3.1.1 DATASET DESCRIPTION – ORGAN TRANSPLANT Q&A CORPUS

There is no pre existing Question and Answers corpus for the organ transplantation processes available in the public domain. So a dataset was needed to be compiled from the scratch. The text corpus for dialogue agent in the arena of organ transplantation was aimed to support queries ranging from wide variety of topics like authorized hospitals from the region of Tamil Nadu, contacts of authorized NGO's, legal regulations for organ transplant, TN government regulations, general awareness for organ transplantation, the medical procedure of transplantation of organs etc. Since each of the above mentioned topics are extrinsic to each other, there is no single data source that could be used to create the entire Q&A text corpus. So, separate data sources were explored for each topic in above mentioned list. In order to have authentic and original information, a question answering dataset was formed only from legitimate government websites like tnos.org, where the list of government authorized transplant centers in Tamil Nadu was referred. To gather information about NGO working in the organ transplantation field, the external authentic reference site of mohanfoundation.org was used because over the years Mohan Foundation played the role as leading NGO in organ transplantation. The cumulative information about various NGO's working in this field was acquired from here. Regarding the legal procedures for organ transplantation and penalties associated with malpractices in organ transplantation, the law of human organ transplant act, 1991 was studied and questions and answer patterns were framed. With all these external references we could form a question answering dataset which contained about 1500 pairs of questions and answers corpus associated with organ transplantation, more specific to liver and kidney transplants. Table 1 gives the summary of topics considered for Q&A and their corresponding data sources.

S.NO	TOPIC DOMAIN	DATASOURCE
1	Authorized organ transplant centers in TN	www.tnos.org
2	Legal regulations for Organ Transplant	The transplantation of Human Organs Act,1994
3	NGO's for Organ transplant and general awareness for Organ Transplant	www.mohanfoundation.org

Table 1
Data sources for Organ transplant Q&A corpus

3.1.2 FUNCTIONAL DESCRIPTION OF THE LSTM BASED ANSWER GENERATION MODEL

There are many deep learning variants of Recurrent Neural Networks (RNN) for text or sequence data generation. LSTM, one such deep learning RNN model is used for the dialogue agent. The main advantage of LSTM over RNN is that, RNN were found to solve the problem of exploding and vanishing gradient problems encountered in RNN by the effective implementation of input, output and forget gates present at each cell of LSTM. Instead of implementing a LSTM model from scratch, proposed model was built using Seq2Seq architecture, which is a LSTM based deep learning framework built by Google to facilitate easy coding strategy for NLG problems. It was initially to tackle machine translation. The specialty of Seq2Seq LSTM models is that they offer dedicated encoder-decoder networks, to train the corpus. For this dialogue agent, encoder portion of model was fed with questions and decoder portion of the model was fed with its corresponding answers.

The other advantage of using Seq2Seq model is the ability to offer attention mechanism (prevents information loss by optimally changing the weights between encoder and decoder to capture relevancy and context from different time series), beam search (ability to pick the word with highest probability score by constructing a tree of top results) etc. 'Organ Transplant Q&A corpus' is first subjected to pre processing which results in cleaned corpus. The pre processing techniques used were lowercasing, stop word removal, Tokenization, lemmatization etc. From all the unique words in corpus a vocabulary dictionary is created where each unique word is identified with an id number. This id number is crucial to perform encoding decoding operations of Seq2Seq. All deep learning models work only with numerical entities and not with textual entities. So feature extraction is process of converting the words to vectors capturing its sequential and contextual value of the word. The study used Glove word embedding strategy. The Glove embedding is preferred for the study because of its ability to combine global matrix factorization methods as well as local context window analysis.

The Glove encoding vector size for each word in this work is of 50. The pre-trained Glove vectors of Stanford University for 6 Billion Tokens each of 50 dimensions size was used for the study. The cleaned and encoded corpus has 2 parts question part and its corresponding answers part. Once the model is trained it can tested by giving random questions to the system and we can check the degree of accuracy for the questions with profanity or support score generated by seq2seq model itself. This is an easy way to validate the answer accuracy and reliability. Thus, a Seq2Seq LSTM based dialogue agent model with attention and beam search components was constructed. The Seq2Seq model was trained with the Organ transplant Q&A corpus and after the training phase, the test portion of the text corpus was used to test the relevancy and accuracy of answers generated by the system. The architecture of the proposed LSTM model for answer generation is illustrated in Fig 2.

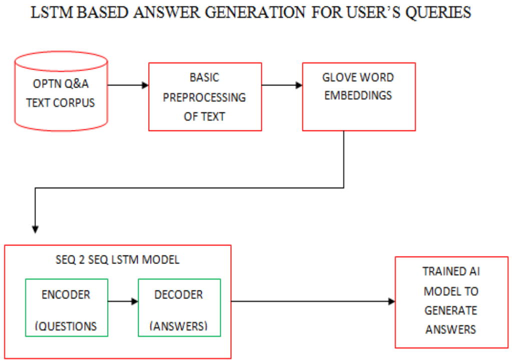

Figure 2: LSTM architecture for Answer generation

The algorithm for the proposed LSTM model is explained below.

Input: Text corpus with questions and answers for Organ Transplantation domain

Output: A LSTM Learning model that can automatically generate answers for given questions

1. Basic preprocessing of text corpus (lower casing, stop word removal)
2. Creating a word dictionary for corpus and giving unique word id for each word
3. For each word in word dictionary create word vector (word encoding)
4. Create the neuron and LSTM cell architecture of Seq2Seq model
5. Convert all words in questions and answers list into their corresponding id's
6. Feed the question words id's to context part of Seq2seq
7. Feed the answer words id's to target part of Seq2seq
8. Train the model for predefined number of epochs
9. Return the trained model

The working methodology of the system is relatively simple. Once the Seq2Seq LSTM **is** trained, the user's test query is captured and it is fed to encoder portion of network. The Seq2Seq predicts the answer through the learned weights of the neural network and gives a probability score (Markov chain Probability) to certify its authenticity. The working methodology is illustrated in the Fig 3.

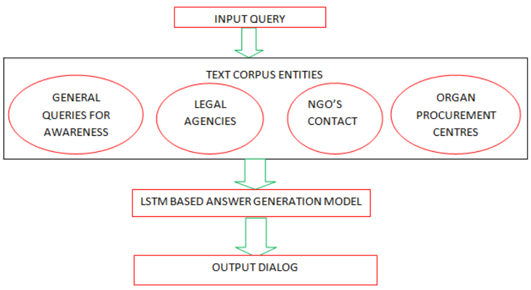

Figure 3: Answer generation Workflow or methodology

The neural network architecture of the Seq2Seq model is illustrated in Table 2. Table 2 gives the account of architecture details of Seq2Seq LSTM model used in the study. The Table shows use of many constant numerical entities like max_length_sentence which denotes maximum length of longest sentence in corpus. In the study, max_length_sentence is encountered as 114. For sentences, that have less than 114 words, the rest of the words are padded with word id 0 / -1.The constant word_vec_size denotes the size of each word vector. The study used word_vec_size as 50. Both context and target portions will have their memory networks consisting of LSTM cells. The study used 300 LSTM cells. Finally to reduce the loss in training, dense layer is used for which a constant called word_dic_size is used denoting the size of word dictionary formed with words from text corpus. The study had word_dic_size has 2059.

Layer name	**Neuron count**	**Connected to**
Input context (questions)	(None,max_length_sentence)	-
Input Target (answers)	(None, max_length_sentence)	-
Embedding layer	(None, max_length_sentence , word_vec_size)	Input context & Input Target
Context LSTM cells	300 cells	Embedding layer after Input context
Target LSTM cells	300 cells	Embedding layer after Input Target

Table 2
Seq2Seq neural network architecture

3.2 ANSWER RETRIEVAL FROM WEB USING AND COSINE SIMILIARITY MATCHING STATERGY

The information retrieval system is a network of algorithms, which facilitate the search of relevant data/documents as per the user requirement. It not only provides the relevant information to the user but also tracks the utility of the displayed data as per user behavior, i.e. giving the user the most relevant information sources. This objective can be performed by cosine similarity strategy where word vector of question is compared to word vector of each sentence in the text file and cosine score is obtained. The given question is searched through the web with Google search API (which can be obtained from Google cloud console either as paid or trail version basis) and top 10 URL links that are given by search result is collected. It is to be noted that not all the links will be useful; some may raise exceptions like fetched link might have only video content, fetched link might have extremely less text content etc. Hence an exception check becomes essential. Each link is then web-scraped and textual contents from URL link are stored inside a list. The preliminary need for the web scraping is the need to pre understands the HTML web structure of the page. But, in real time it is not possible to know the web structure in advance. The study tried to extract text only from known or pre existing HTML tags like paragraph, heading, table tags etc. In certain cases due to nested HTML tag structure extracted text may not form a proper sentence. There are many libraries to check if a sentence is grammatically valid or not in many host programming languages. With the help of those libraries, sentences extracted that are ill formed can be rejected. The extracted text from each URL is made as a text corpus. The other main challenge in this functionality is to extract best sentence as answer from a corpus (text from web) that might possibly contain thousands of sentences. From the 1000 sentences we need to pick top 3 best matched sentences that accurately answer the question posted by user. This objective can be performed by cosine similarity strategy where word vector of question is compared to word vector of each sentence in the text file and cosine score is obtained. The sentences with best highest cosine scores will be chosen as answer. In order to compare two words using cosine similarity, it is essential that words are encoded to numerical entities or vectors for each sentence in corpus using TF-IDF strategy. The user's query is appended at the end of text corpus to manipulate encoding process. The TF-IDF vector of the given query is then compared to TF-IDF vectors of rest of the sentences in corpus using cosine similarity, the sentence in corpus with top 3 highest cosine similarity score is displayed as output dialogue. The architecture of Answer retrieval mechanism is illustrated in Fig 4.

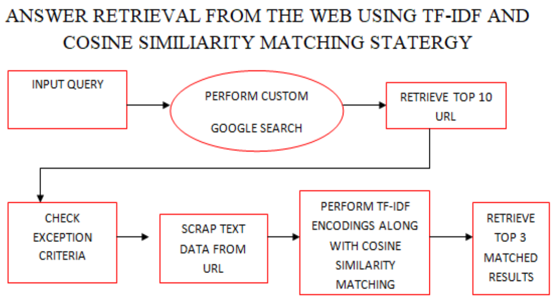

Figure 4: Architecture of best answer retrieval from web

The working methodology is illustrated in Fig 5. The given query is first performed the Google search and web links are obtained. Each link is then web scraped and text corpus is formed. Then, the answer retrieval methodology using TF-IDF and cosine similarity is applied to get the desired result. The Fig 5 illustrates this workflow model.

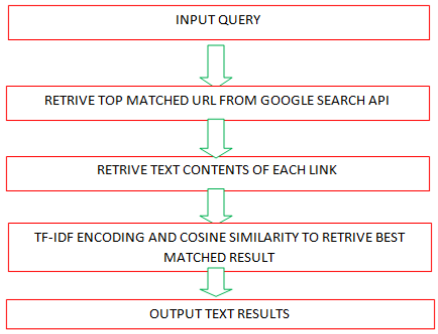

Figure 5: Workflow of best answer retrieval from web

IV. IMPLEMENTATION AND RESULT ANALYSIS

This section deals with nature of implementation environment and results conducted after various experiments to prove the efficiency of the dialogue agent.

The experiment was conducted in python 2 Jupyter notebook of Google Colab environment. Google Colab offers free GPU powered environment and 16 RAM cloud computing node for free usage for up to 12 hours. Following packages were used in python xlrd, Tensorflow and Keras. Jupyter notebooks in Google cloud environment. The GPU power offered by Colab is Tesla K80. For building the LSTM model for text generation the seq2seq framework written in python by Google was used as an abstraction. Further, in order to scrap the web, Beautiful soap library in python was used.

Result analysis

The experiments to prove efficiency of the proposed LSTM models was aimed in 3 major analyses: First analysis was aimed to monitor the accuracy and loss patterns of LSTM during training phase, second analysis was to prove functional efficiency of Glove encoding and third analysis was to prove the accuracy of the answers predicted by the system.

The decline of loss and growth of accuracy of the trained LSTM model for 1000 epochs for Organ Transplant Q&A corpus is shown in Fig 6. From the diagram we can infer that as epochs increases the loss in prediction gradually decreases and the accuracy of the model gradually increases.

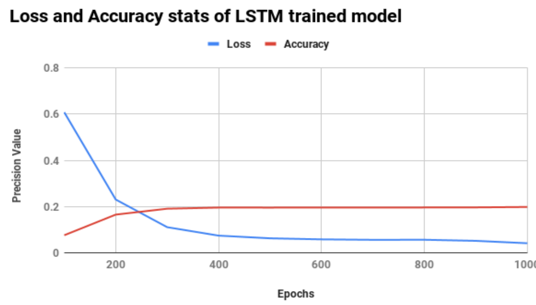

Fig 6: Loss and accuracy of the LSTM trained model

In order to understand the role of word embedding vectors, top 40 most commonly used words in corpus were chosen. Their word vectors whose size is 50 were subjected to Principal Component Analysis and their dimension was reduced to 2, so that they can be projected in 2D plane. On plotting all these 40 words in XY plane, the similarity between 2 words is given by Euclidean distance between them, smaller the distance, better is the similarity. The Fig 7 shows 2D projection of word vectors and it was inferred from the graph that Glove captures better contextual meaning of the corpus, as words that come in the same context tend to have shorter Euclidean distance.

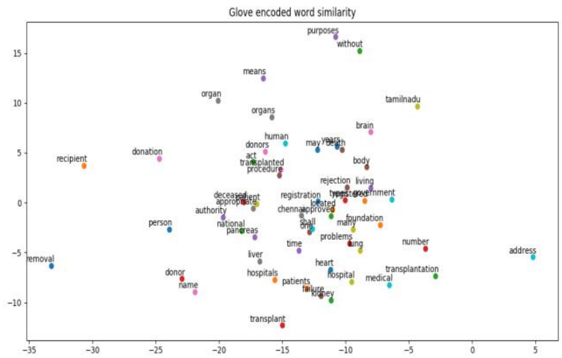

Fig 7: Two dimensional projection of word vectors

The ability of the model to give accurate answers to the question is measured in Fig 8. From the testing portion of the test corpus, 15 random questions from testing questions which were not trained before were fed as input to the dialogue agent. The confidence score or probability score indicating the correctness of answer for all these questions proved that nearly 75 percent of test questions had confidence score above 0.50 making the system reliable.

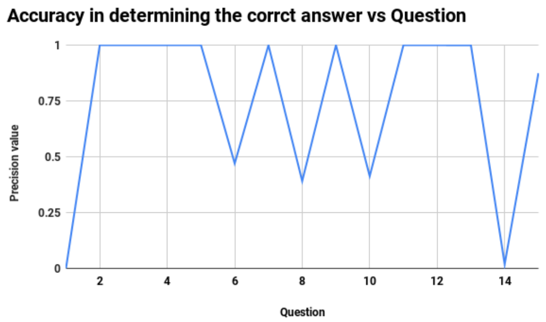

Fig 8: Accuracy of the model to give correct answers to questions

V. CONCLUSION

The proposed dialogue agent for organ transplant network was successfully built and aims of the agent to provide simple, reliable, accurate communication enhancement feature to the information sensitive filed of organ transplant networks through a smart AI based dialogue agent were achieved. The results from experiments proved that the dialogue agent was successfully trained to capture semantic and contextual details of text corpus through Glove word embedding and precision analysis to determine the accuracy of the generated answers by the agent also proved to be satisfactory. The ability to provide answers precise answers gathered after filtering and elimination of text sentences scraped from web search, proved the dialogue agent is robust, fault tolerant, ubiquitous, consistent and conformable to user's queries. Thus, the proposed dialogue agent can serve as an effective communication enhancement feature in Organ transplant networks.

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