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LEVERAGING DEEP LEARNING TO DEVELOP AN INTELLIGENT CHATBOT

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ABSTRACT

The evaluation of an intelligent Humanoid Robot system is not very common. These intelligent robots answer the query without the interference of human.

This research proposes a Humanoid Robot with oneself learning ability to acknowledge and react to individuals dependent on Deep Learning and enormous information from the web. These types of robot generally used in hotels and resorts, educational institution and the public sector. The Humanoid Robot ought to think about the style of inquiries and close the appropriate response through discussion among robot and client. In our condition, the robot will recognize the client's face and acknowledge orders from the client to do an activity. The inquiry from the client will be handled utilizing profound learning and will contrast the outcome and information on the framework.

Our research used GRU/LSTM, CNN and BiDAF with massive SQUAD data set in Deep Learning methods for training purposes. Our research shows that implementing BIDAF with GRU/LSTM encoder gives higher accuracy matching and F1 Score than the BIDAF model with CNN.

1. INTRODUCTION

The developing interest and need for UI age among framework and client lead to the advancement of discussion specialists. A discussion specialist is utilized as an interface between the framework and client for data change. The framework is client started correspondence with the Conversation specialist by the common language, signals, discourse with liberated from cost, access whenever, anyplace. The framework handles the Natural language question utilizing NLP steps, for example, parsing, tokenization, stemming, watchword extraction and so on [2] [16]. A portion of the NLP Question noting frameworks are ASK JEEVES, START, ANSWER BUS, and so on are instances of discussion specialists. Discussion specialist go about as chatterbots for giving an exact answer utilizing design coordinating, straightforward predefined rules, static information bases, information base and so on

In the client Question Answering System (QAS), steps, for example, question characterization, Information recovery and data extraction are utilized for exact answer extraction. QAS frameworks have required supporting different territories from scholastics to corporate for demanding, exact data.

The cycle is very agreeable however ought to make up for reaction time and precision. As of late, profound learning is perhaps the most required exploration fields in software engineering. To defeat this, profound learning works with responding to complex inquiries utilizing outside information, a neural organization for preparing and use classifier to seal the appropriate responses. The appropriate response age, profound learning is utilized for simple recovery with a legitimate preparing and approval set.

2. FRAMEWORK ARCHITECTURE

The proposed framework design describes different stages associated with complex QA framework advancement, for example, question preparing, question type distinguishing proof like who, when, what, how, why, and so forth. The distinguished inquiry type as unpredictable the appropriate response age is finished with the assistance of profound learning ideas, as demonstrated in Fig.1.

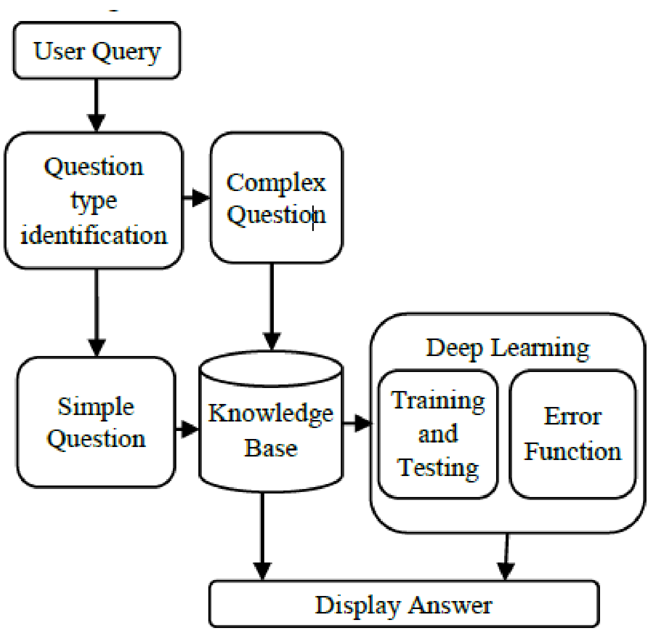

Fig.1. QASArchitecture with Deep Learning

The questioning preparation stage gets the question contribution to everyday language through an interface. The users question variations, and the previous chronicled QA sets kept up in an information base to reduce competitor answers' reaction time. The question is pre-prepared utilizing tokenization, stop words removal and originating from separating keywords. Question classifier prepares with design layout framed by POS-tagger to distinguish the questioning types [15]. The question classifier of the framework determines the query types, for example, WH question (Factoid) and complex query utilizing question design. Answers choice is made by keywords coordinating with client inquiry if question coordinating with found in information base answer displays from the information base.

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The unpredictable inquiry needs a definitive answer by joining numerous sentences outline from related records. Complex searches are different from the unstable and nonvolatile memory (investigation question); who is mother Teresa? When was he conceived? (Various sentence question) and so on

Large numbers of the current summary strategies don't utilize the semantics of terms. A profound learning procedure helps in the deep examination of the answer outline framework with minimal error.

3. PROPOSED METHOD

Our examination focuses on the question, remarking on the Deep Learning approach. The contrast between our Robot with Pepper [10] robot is, Pepper covers Human Recognition, Object Recognition and Speech Recognition subject to NAOqisoftware [11]. We use Google API Speech Recognition using Python language to detect the voice [12]. To comprehend and discover the appropriate response, we use Deep learning innovation created utilizing Python. After the successful response, Google text to speech API will be implemented to reply to the users' query.

Our previous research proposed face and speech recognition using preprocessing like stemming and tokenization forthe educational Robot. The outcome is terrific as youngster learn best during their free time. They can dramatically learn a different technique and become more focused. To enhance the previous work, we make the humanoid Robot more effective and efficient by crawling and training the Robot through web, text, and other data collection.

To accomplish the difficult action of the Robot, it is essential to have comprehensive and exhaustive collections of abilities, particularly in light of the inquiries [14]. Our past research addresses number balancing word issues in the deduction or expansion activity shown inArabic Language by utilizing different NLP standards and essential self-learning ability [15].

Our algorithm for this Robot appears in 1:

```
function QueryReply(userQuery), do
merge user_question sentence
encode embed query_ sentence
compare encoded user_question and encoded context to find answer
return answer
function addtodataset(newquery), do
append newquery to addtodataset
get newadded_status
return newadded_status
if the camera detects the face, show
greeting msg
while true, do
startlisteningusermsg
if queryexist, do
processthequery
```

```
extract answer from QueryReply(userQuery)
if answer not null, do
say answer
else, do
say "no query found"
else if clientwantstoadddata, do
listen data from user
addtodataset(knowledge)
if add to knowledge success, do
say "successfully insert knowledge"
else, do
say "append knowledge process failed"
else if user say goodbye, do
say "god bye"
break
```

SQuADwill we used[16] for the machine learning dataset for the preparation. This dataset is dependent on Wikipedia articles with different themes. This dataset has approx. 88.000 preparing questions (train dataset) and a 10.000 improvement dataset (dev set). The appropriate responses' sentences in every case some portion of the section article.

We convert each word from the dataset to the training set in the initial layer.Word transformation is the Meta description of the word in the vector-matrix, a word which similar significance will have a relative depiction. We use 100 segments of GloVe[17] word introducing.

$$\beta = softmax(m) \in R^N$$

$$c' = \sum_{i=1}^{N} \beta_i c_i \in R^{2h}$$

At last, for every setting position c I, we consolidate the output from C2Q consideration and Q2C consideration as portrayed in the condition below

$$b_i = [c_i; a_i; c_i \circ a_i; c_i \circ c'] \in R^{8h} \, \forall i \in \{1, \dots, N\}$$

The last layer is a softmax output layer that assists us with choosing the beginning and end lists for the appropriate response range. We consolidate the setting of concealed states and the consideration vector from the last layer to make mixed reps. These mixed reps become the contribution to a completely associated layer that utilizes softmax to make a p_start vector with the likelihood for start list and a p_end vector with the likelihood for end record. We can search for start and end list that augment p_start * p_end [21][22].

4. RESULTS AND DISCUSSION

For the examinations, we attempt to test utilizing the RNN encoder and CNN encoder. We operate 150 secret encoders, 150 secret models, with 0.15 dropout and 33 clump size. We have used NvidiaGeforce with 8GB Ram with 16GB dedicated memory for training purpose.

We analyzed frequency score and precision from the enhanced dataset. After the successfultraining of the model, we test it,Which results in 100% of the preparation dataset.

Table 1.Output of our research

Method	Dev (em /f1)	Test (em / f1)
RNN Encoder	51.69 / 67.24	68.87 / 82.43
CNN Encoder	46.35 / 61.34	53.99 / 69.55

When comparing RNN Encoder with CNN encoder in our model, CNN gives a perfect outcome of 43.000th cycle, whereas RNN provides an output of 93.000th. We find that the result of EM and F1 score of RNN encoder is better in two different methodologies. The score of EM and F1 in the training and testing dataset has better result while using 10% of the training set and testing set. Our proposed model effectively analyses the user input and reply to the user more efficiently. In light of

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investigations we have done commonly, our framework has demonstrated to be very practical and plausible for simple applications.

5. CONCLUSION

Our model effectively gets information employing massive information discovery and answers the client's inquiries using deep learning. From our trial using RNN and CNN as an encoder layer, we tracked down that model with encoder based on RNN and BiDAF consideration layer to get higher EM, and F1 scores than the CNN encoder with the purpose of the model can deal with question replying between Humanoid Robot and human.
The encoder based on RNN in terms of EM/F1 gives more accuracy thanthe CNN encoder.
We will execute the data set to save information for future advancement to store more data and oversee it without any problem. Using SQUAD 2.0 We will improve the algorithm to investigate better and improve to deal with unanswerable questions.

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