HEALTHCARE CHATBOT USING ARTIFICIAL NEURAL NETWORK

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Abstract

The usage of Chatbot is prominent. Recent trends reflect that multinational companies have focused on Artificial Intelligence and developed several Personal Assistant, among them Apple's Siri, Microsoft Cortana, Google Assistant, Facebook Messenger, and Alexa. This motivates the proposed research on Chatbot. Chatbots have effectively reduced human efforts by providing human-like solutions for various business and societal problems. The proposed research is to design and implement a Medical Query Reply Chatbot, which is capable of providing answers to queries related to the field of Medicine and diseases. The appropriate NLP techniques are applied to our Medical Data, developed in the JSON format and the Artificial Neural Network model is used for training this dataset. Artificial Neural Network is a Deep learning technique so that the machine can learn the pattern and response itself and hence we can able to get the accuracy of above 90% during training and testing.

Keywords—Deep Learning, Artificial Neural Network, Chatbot, Natural Language Processing, Personal Assistant.

I - INTRODUCTION

Let's imagine for a minute world where instead of a human being at a customer support center, a chatbot helps us fix our router and the internet starts working again. Such an invention would be of great convenience in this ever-connected world where we cannot afford to wait several hours per year to fix our internet connection, it is the internet. But is it possible? The simple answer is yes. Today's applications and technologies like Apple's Siri, Microsoft Cortana, are at the forefront of highly personalized virtual assistants. They do not do what we have imagined but they are, by no reasonable doubt, a stone's throw away from being able to do so. Now, where do we begin?

The most obvious solution that leads us one step closer to living in our imaginary world is knowing that the chatbot must be able to understand the messages we present and how to respond appropriately. But computers are dumb. For starters, they use numbers raised to the powers of two, which is binary and that is all they know, whilst humans normally use decimal numbers [1], expressed as powers of ten, humans can read, write, and are intelligent. How do we make them understand our natural language when all they know is 0 and 1? Luckily for us, there is a field of computer science called Natural Language Processing (NLP) and linguistics that comes to our rescue. As the name suggests, NLP is a form of artificial intelligence that helps machines "read" text by simulating the human skill to comprehend language. Given the benefit of time, driven by cognitive and semantic technologies, natural language processing will make great strides in the human-like understanding of speech and text, thereby enabling computers to understand what human language input is meant to communicate.

A chatbot is a computer program capable of holding conversations in a single or multiple human languages as if it were human. Applications can range from customer assistance, translation, home automation to name just a few. In the existing system, they use some of the machine learning techniques such as Decision tree, AdaBoost, SVM, random forest, etc to classify the inputs from the user for the Chatbot. These techniques are useful to train small datasets, but when we increase our training datasets its accuracy dropped to very low (<=50%). This paper explores the technologies behind such innovation, implements a simple model, and experiments with the model.

II – RELATED WORK

Oyebode, (2018) explained our research aimed to apply artificial intelligence to improve healthcare delivery in Africa. Specifically, we build an intelligent medical Chatbot called Likita that helps in diagnosing common ailments and recommending appropriate treatments, scheduling doctor's appointments, reminding patients on medication, and answering questions on health-related matters.

Bayu Setiaji, (2016) proposed sentence similarity calculation in this paper using bigram which divides input sentence as two letters of the input sentence. The knowledge of the chatbot is stored in the database. The chatbot consists of a core and interface that is accessing that core in relational database management systems (RDBMS). The database has been employed as knowledge storage and the interpreter has been employed as stored programs of function and procedure sets for a pattern-matching requirement.

Iqbal Muhammad, (2014) proposes a semi-supervised artificially intelligent chatbot framework that can automate parts of primary interaction and customer service. The primary focus of this work is to build a chatbot that can generate contextualized responses in any language without depending much on rich NLP background and a vast number of prior data sets. This system is designed in such a way that with a dictionary of a language and regular customer interaction dataset, it can provide customer services for any business in any language.

III - SYSTEM IMPLEMENTATION
1. PROPOSED SYSTEM

In this project, we will be creating a relatively AI chatbot that will be used to answer frequently asked questions. To get high accuracy for a large dataset we propose a deep learning technique called Artificial Neural Network (ANN). By using ANN we can able achieve above 85% accuracy during testing and training. At first, we are extracting the Training data from the JSON file. Then we do some of the text pre-processing works such as changing the data to lower case, stemming, and sorting. In natural language processing, stemming is the text pre-processing normalization task concerned with bluntly removing word affixes (prefixes and suffixes).
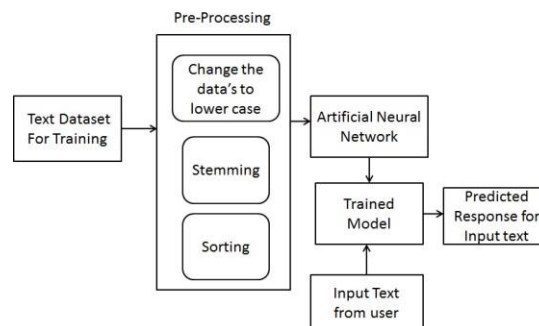

Fig .1 Proposed system architecture

After Pre-processing, we have created a stemmed vocabulary it's time to talk about a bag of words. As we know neural networks and machine learning algorithms require numerical input. So our list of strings won't cut it. We need some way to represent our sentences with numbers and this is where a bag of words comes in. What we are going to do is represent each sentence with a list of the length of the number of words in our model's vocabulary. Each position in the list will represent a word from our vocabulary. If the position in the list is a 1 then that will mean that the word exists in our sentence, if it is a 0 then the word is not present. We call this a bag of words because the order in which the words appear in the sentence is lost, we only know the presence of words in our model's vocabulary. After creating a bag of words are given as input for the Artificial Neural network. The artificial neural network trains the input data and produces a trained model. After training the bot asks for input data from the user, it collects the data and predicts which will be the response that it needs to display and finally it displays the predicted response to the user.

2. DATASET CREATION:

Our dataset comprises various query patterns and their corresponding responses stored in a JSON file. An intent determines the intention of the user to interact with the system. While storing an intent, a tag field defines the intention of that particular intent. The patterns field comprises various types of questions a user having a particular intention may ask the chatbot, and the responses field comprises corresponding relevant answers to those questions as shown in figure 2. If the bot can find a matching pattern for a given user query, it will send the response back to the user. However, if a matching pattern is not found for a given user query, the bot will provide a default

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fallback response, specifying that it cannot interpret the query and will ask the user to be more specific.

```
{"tag": "whyMechatronics",
 "patterns": ["prerequisites for mechatronics engineering",
              "skills required for mechatronics engineering",
              "i am confused if i should take mechatronics",
              "benefits of taking mechatronics"],
"responses": ["Let me help you! If you hold interest in
              Electronic Concepts, Programming, Mathematics
              and Physics, then Mechatronics is for you!"]
},
```

Figure .2 Intent for 'why Mechatronics' tag

3.   DATASET   AND   USER   QUERY PREPROCESSING

Natural language processing is a branch of AI and a machine can perform analysis by understanding the natural language input of the user, processing that input with appropriate NLP techniques, and generating natural language human-like response. The major steps in Natural Language Processing, as shown in Figure .3 are listed below:
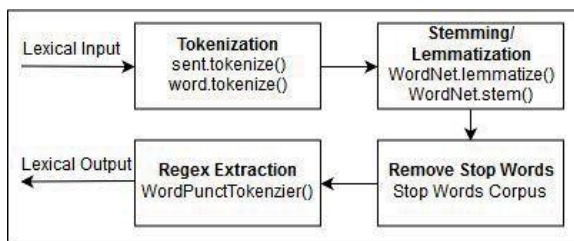
Figure .3 Flow Diagram for Processing Input in NLP

1. *Tokenization:* Tokenization involves converting the character stream into a set of individual tokens. Tokens can be words, numbers, identifiers, special characters, or punctuation.

2. *Lemmatization:* Lemmatization involves reducing word variations into simpler forms. Lemmatization uses a language dictionary to perform an accurate reduction to root words Lemmatization was found to be better than stemming which uses simple pattern matching to remove suffixes of tokens.

3. *Removal of stop words:* Stop words like 'is', 'are', 'the', etc. do not add value to the meaning of the sentence. They are not as important as the keywords, hence they can be removed from the text for better processing.

4. *Regex Extraction:* Words such as 'can't', 'don't', 'b.tech', 'm.tech' can be specified in different ways; therefore, they should be normalized and tagged. Therefore, using a regular

expression such words are converted to one standard form.

4. ARTIFICIAL NEURAL NETWORKS:

Artificial neurons are a set of linked units or nodes in an ANN that loosely resemble the neurons in a biological brain. Each link, like synapses in a highly biological brain, has the ability to send a signal to other neurons. a synthetic neuron that receives and analyses a symptom before signalling neurons attached to it Because the "signal" at a link might be a complex variable, each neuron's output is calculated using a non-linear function of the sum of its inputs. Edges are the terms for the connections. It changes the signal intensity at a link by increasing or decreasing the signal strength. Neurons may have a threshold set, and if the mixed signal surpasses that threshold, a symbol is sent. Neurons are normally found in clusters.
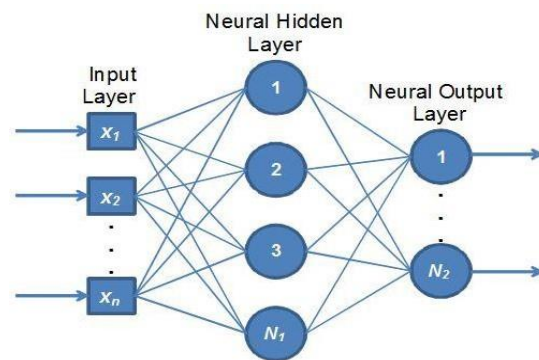

Fig .4 Artificial Neural Network

The neural network structure is made up of an input layer, hidden neural layers, and an output neural layer, as shown in Fig.4. A set of weights, represented by a matrix of synaptic weights, is also present between the layers and will be changed throughout the training phase. It's also worth noting that activation functions must be implemented for each of the neurons (hidden neural layers and output neural layer) in order to restrict their output.

ANN Training

The training which is to be passed to the ANN model is designed such that it is a combination of the encoded distinct lemmatized words and tags as shown in (1).

Training Set = {encoded(different lemmatized list) +encoded(tag list)}   (1)
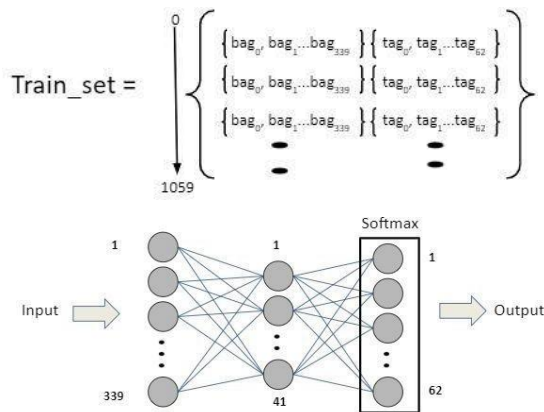
Figure .5 Neural Network created for the project

Figure .5 depicts an intended Neural Network-specific for our model. The first layer in our Neural net is the input layer, which consists of 339 neurons, which are the unique lemmatized words. The output shape of the input layer is approximately 2/3rd of the number of output possibilities ie. 62 Tags (⅔ of 62 = 41). Thus the middle hidden layer consists of 41 neurons. The Softmax activation function is used for the output layer, which comprises 62 neurons that correspond to the 62 intent classes. The main advantage of using Softmax is the output probabilities range, as it helps to map the non-normalized output to a

probability distribution over predicted output classes as seen from the mathematical equation (2). The range is between 0 to 1, and the sum of all the probabilities will be equal to one.

$$softmax(z_i) = \frac{exp(z_i)}{\sum_j exp(z_j)} \qquad (2)$$

After specifying the number of layers for the model, we configure the learning process using the compile method wherein we specify an optimizer, a loss function, and a list of metrics.

IV - RESULTS AND DISCUSSION

1. CREATED DATASET

The created dataset consists of tags, patterns, and responses, tags represent the category of patterns and responses. Patterns consist of medical-related questions for example "can you suggest some drugs to cure acne", I have anxiety", "can you suggest some medicines to cure asthma". Responses consist of the answers for the particular questions for example "Take, doxycycline or minocycline, it will cure acne", "Singulair is a better choice to cure asthma". The following fig represents the structure of the input dataset.

Figure .6 Dataset for training

2. MODEL TRAINING

The training is done by using ANN Model, we coded the machine to train itself with the epoch of 1000, which means it trains itself by using the pre-processed input dataset 1000 times

and so we can get the accuracy of 99%. If the epoch is high we can able to get high accuracy. If the epoch is low then the accuracy also low and so we trained the model 1000 times to get high accuracy. The following figure 5.2 represents the loss and accuracy during training.

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```
Training Step: 3999 | total loss: 0.12799 | time: 0.013s
| Adam | epoch: 1000 | loss: 0.12799 - acc: 0.9989 -- iter: 24/26
Training Step: 4000 | total loss: 0.12405 | time: 0.018s
| Adam | epoch: 1000 | loss: 0.12405 - acc: 0.9990 -- iter: 26/26
--
```

Figure .7 Training Output

3. TESTING

After training, we test the chatbot by raising questions to the chatbot. We give a typed text as input to the chatbot. The chatbot gets the input data from us and pre-processes it and predicts the responses for the given questions and prints it on the command window. The following figure 5.3 represents the chat output between the user and the chatbot. At first, the user asked the question "clobetasol is used for what?" which means he got a medicine which is named clobetasol but he didn't know the use of this medicine and

hence asked the chatbot about that medicine. The chatbot collects the question from the user and by using its trained knowledge the bot predicts the tag of that particular question, and then it picks the response for that particular tag and prints it on the output window. As a result of conducting the training 1000 times, we can able to get 99% accurate predictions during testing also.

```
Start talking with the bot (type quit to stop)!
You: clobetasol is used for what?
clobetasol is used to treat psoriasis
You: clobetasol uses
clobetasol is used in the treatement of psoriasis
You: plavix is used for what?
Plavix is used in the treatement of stroke
You: losartan is used for what?
losartan is used to treat high blood pressure
You: i have insomnia
Use Ambien, This drug have the ability to cure insomnia
You: can you suggest drugs to reduce high blood pressure
For High Blood Pressure treatment you need to take lisinopril or amlodipine or losartan consistantly
You: hi
Hello!
You: how are you
Good to see you again!
You: can you suggest some medicines to cure cholestrol
No problem Take atorvastatin, it will reduce cholestrol level
You: Doctor said, i have bipolar disorder
Lamictal is a better choice to cure bipolar disorder
You: acne medicines
doxycycline is a better choice to cure acne
You: hey bot, i want to ask you something, what is your aim
Plavix or clopidogrel is a best choice to cure stroke
```

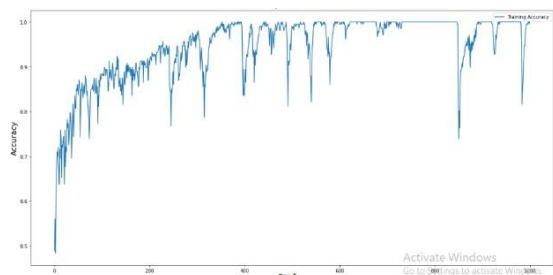**Fig .8 chatting with Chatbot**

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Fig.8 Accuracy vs Epoch graph

The above figure.8 shows the Accuracy vs Epoch graph of the trained model. In the above graph, the accuracy increases with an increase in the   epoch.
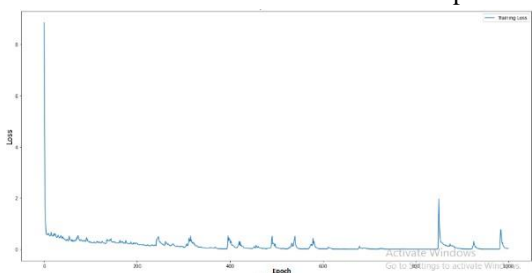

Fig .9 Loss vs Epoch

The above figure.9 shows the Loss vs Epoch graph of the trained model. In the above graph, the loss decreases with an increase in the epoch.

CONCLUSION

        Our Chatbot was capable of solving user queries related to the university to a great extent as observed in the test results obtained. To optimize the model used in the implementation, several hyper-parameter adjustments were made until the most effective values to minimize the cost function and to maximize the accuracy were found. The end-user testing was done in two phases, the number of correct responses was improved in the second phase exhibiting a probability score of 0.72 after devising additional training phrases and keywords. The introduction of artificial intelligence in the field of education and counseling through application-based Chatbots as one discussed in our project will give rise to more personalized, efficient, and faster query solutions leading to increased user engagement and saving resources such as time and money shortly.

REFERENCES

[1] Tin Kam Ho. Random decision forests. In Document analysis and recognition, 1995., proceedings of the third international conference on, volume 1, pages 278–282. IEEE, 1995.

[2] Xu, Shuo & Li, Yan & Zheng, Wang. (2017). Bayesian Multinomial Naïve Bayes Classifier to Text Classification. 347-352. 10.1007/978- 981-10-5041.

[3] Evgeniou, Theodoros & Pontil, Massimiliano. (2001). Support Vector Machines: Theory and Applications. 2049. 249-257. 10.1007/3-540-44673.

[4] Robert E Schapire. The boosting approach to machine learning: An overview. In Nonlinear estimation and classification, pages 149–171. Springer, 2003.

[5] Mehryar Mohri, Afshin Rostamizadeh, and Ameet Talwalkar. Foundations of machine learning. MIT press, 2012.

[6] Qaiser, Shahzad & Ali, Ramsha. (2018). Text Mining: Use of TF-IDF to Examine the Relevance of Words to Documents. International Journal of Computer Applications. 181. 10.5120/ijca2018917395.

[7] Rahutomo, Faisal & Kitasuka, Teruaki & Aritsugi, Masayoshi. "Semantic Cosine Similarity". The 7th International Student Conference on Advanced Science and Technology ICAST (2012).

[8] Chowdhury, Shammur & Alam, Firoj & Khan, Naira. (2018). Towards Bangla Named Entity Recognition. 10.1109/ICCITECHN.2018.8631931.

[9] Dozier, Christopher & Kondadadi, Ravikumar & Light, Marc & Vachher, Arun & Veeramachaneni, Sriharsha & Wudali, Ramdev. (2010). Named Entity Recognition and Resolution in Legal Text. 27-43 10.1007/978-3-642-12837-2.

[10] "Blood Pressure Chart." Blood Pressure: Blood Pressure Chart, www.bloodpressureuk.org/BloodPressureandyou/Thebasics/Bloodpressure chart.

[11] "Disease Prediction Using Machine Learning With GUI",https://www.kaggle.com/neelima98/disease-prediction-usingmachine-learning

[12] "Cloud Translation API Documentation | Cloud Translation API Google Cloud." Google, Google, cloud.google.com/translate/docs/.

[13] Fabian Pedregosa, Ga¨el Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikitlearn: Machine learning in python. Journal of Machine Learning Research, 12(Oct):2825–2830, 2011