**APoC**

AI Powered Chat-Bot

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**Abstract**

Healthcare technologies are the most evolving domain in current marketplace from providing applications which can predict diseases based on symptoms to more advanced models which can make easier to get the mediclaim based on patients past history and lab reports. Each and every day more and more research are going on in healthcare to make life easy and more comfortable. On keeping this matter of fact as our base, our team has decided to build a project on Artificial Intelligence powered Chat-Bot.

The core implementation of this healthcare Chat-bot includes ‘Deep Learning’, ‘Natural Language Processing’ and ‘Computer Vision’. This chat-bot will be capable to communicate with the user based on the model trained as well as the input dataset which will automatically retrain model after certain interval of time. So as a result a self-learning chat-bot will be developed will which improve its efficiency as per new user input added. The project will be developed as a web application using Deep learning API’s provided by Google TensorFlow. In this chat-bot we are also implementing Optical Character Recognition feature powered by Google ML kit for Report Digitization. The algorithm proposed in this chat-bot will have dynamic nature, which means the application will have the capability of self-training.

**Keywords:** Deep Learning, Artificial intelligence, Machine Learning, Computer vision, Google vision API, Google ML kit, Natural Language Processing.

**Introduction**

Chatbots are programs that imitate human spoken and/or written conversation. They “learn” by discovering patterns in the large amounts of data that are used to train them and the more they interact with humans the better they become. They use artificial intelligence, in the form of machine learning, deep learning and natural language processing.

In recent years chatbot technology has started to gain traction in the healthcare industry with an ever increasing number of bots helping to connect patients with providers as well as offering a host of other services. They can better organize patient pathways, medication management and offer solutions for simpler medical issues.

One of the most widely known chatbots for healthcare use is Florence, named after the Florence Nightingale, the English social reformer and founder of modern nursing. It started life in 2016 as a hobby project of David Hawig, a German entrepreneur, and researcher, and was launched a year later.

This chatbot is a personal health assistant that reminds users to take their medication or birth control pills and helps them keep track of their body weight, mood and other health issues. All users have to do is start chatting with Florence inside a messaging platform, like Skype, Kik or Facebook messenger.

Among the other algorithm-powered chatbots that are helping to make life easier for patients are:

Safedrugbot - a chatbot messaging service for health professionals who need appropriate information about the use of drugs during breastfeeding. It provides informative guides for doctors and others who are working with pregnant and breastfeeding women.

Your.MD - this chatbot is fundamentally a symptom checker powered by artificial intelligence. Users’ type in their symptoms and the chatbot selects the best questions to help define the problem and identify the most relevant health information. If needed it recommends relevant services, products and next steps. Your.MD is not intended as a replacement for doctors, but it can cut down the number of patient visits to practices which most of the time are for minor ailments.

Buoy Health - this is another symptom checker with an algorithm that was trained on clinical data from thousands of medical papers covering five million patients and around 1,700 conditions.

**Related Works**

Health industries are gradually adopting chatbots and are in the easrly phases of implementation. Grand view research, a market research firm estimates that the global chatbot market will reach $1.23 billion by 2025. The majority of these chatbots focus on checking patitnt symptoms.

1. Sensely

Virtual Assistant Molly empowers patients to track their health symptoms using both verbal and non-verbal communication, connected to Bluetooth devices too. Users can share photos and videos with Molly. Using the triage color scheme to indicate the level of emergency, it is highly recommended to take care of you. If the patient's condition is serious, then it can lead to medical help. To address this use case, we have partnered with the Mayo Clinic, which has been providing programmed logical expertise with the use of their nursing facilities for many years. Our assistant integrates Mayo Clinic algorithms to recommend walking care strategies based on the patient's self-reported symptoms.

In the UK, we are partnering with the National Health Service (NHS), the largest healthcare provider in the world. We built a mobile app called Ask NHS, which includes the operation of access to care services, the appointment of doctors to book, and access to a large library of self-care systems. allowing high-profile cases to receive the care they need. There is also a strong financial effect. Specifically, we find that use of the app leads to a double-digit cost reduction, as patients transition their total expenditure from higher costs to lower cost services.

1. Clarify Health Solutions

It provides insight into the patient journey and the impact of therapies, and uses a variety of analytical methods - including machine learning, neural networks, and deep learning - to enable a system that integrates novel data sets across 200 patient populations. It diversifies its ability to measure analytics across all medical fields with its own set of medical codes, as well as their ability to risk, or control, variability in patients. Both approaches approach machine learning models that continue to gain power and predictability as additional data and observations are added. Together, these capabilities allow us to identify areas of poor medical need, determine the most promising investigators for clinical trials, and understand the effectiveness of treatments in the real world.

With the Therapy Intelligence solution, Clarify's ideal approach provides companies with a comprehensive and segmented view of the market, including information about people (patients), healers, patients on the patient journey, and other market phenomena.

In terms of mapping the disease, Clarify's solution unlocks patient data nationally (e.g., co-morbidities, demographics, Rx history, laboratory results, etc.) and connects each patient to his doctor and his treatment and care centers to create Real-timehotmaps indicate the number of patient-specific patient numbers by the site and the quantitative predictions of trial participation. This helps identify an expanding range of case investigators that may have started the site better.

3) Jvion

Jvion helps healthcare systems prevent patient injuries and the associated costs by enabling clinical staff to focus, resources, and individual interventions on patients whose outcomes can be improved. Unlike traditional AI solutions and technology-based solutions that have neural networks that automatically identify high-risk patients and cause alarm fatigue, Jvion identifies vulnerable patients who can be changed and provide patient-specific recommendations that will deliver better results. Jvion MachineTM is a combination of mathematics -Eigen, a database of over 16 million patients, and software that can be used immediately on any of the 50 potentially harmful neurological disorders (such as sepsis, readmission, falls, ER avoidable visits, and stress injuries) without the need for new models or data perfect. The combined power of the machine brings about the analytical capabilities that providers need to help reduce cognitive load; successfully identify the clinical, social, behavioral, and environmental factors that drive patient risk; and enable future organizational trends. As a leader in preventable injury analytics, Jvion has proven effective in clinical settings for nearly a decade, with hospitals reporting a 30% reduction in potential adverse events and a potential cost savings of $ 6.3 million per year.

4)Riseapps

It's a combination of the mobile app and the web. The mobile app uses a 3D scanner to perform a volumetric scan of the wound, and as part of the AI, we developed a customized algorithm to perform direct wound measurements, recommend treatment, and document documentation.

The web app helps with tracking wound progress and treatment management. All data recorded by the mobile app is automatically uploaded to the cloud storage and then the web app. Here, the expert can look at the wounds with great care and make a clear medical decision based on the data provided by the algorithm. To support AI in this project we created a complex web application with React frontend and Django backend.

5) Vital

Designed to provide a simple and comprehensive view of the emergency department without needing replacement or repair, Vital uses artificial intelligence and natural language to process patients before seeing a physician, making it easier and faster for providers to coordinate care and prioritize patients from room delivery, lab orders, and more . The result is a personalized exchange between patients and provider, and improved departmental procedures throughout. Vital benefits for both patients and physicians. The patient-friendly mobile app allows people to access the ER and provides live-time updates, providing clarity and increasing peace of mind. The cloud-based clinical app provides a variety of patients' perspectives, clear indicators of when workflow is concentrated, allows note taking on mobile devices, and predicts patient dropouts and how they can be accepted overnight.

6) Woebot

Depression is a common cause of mental illness that remains untreated most of the time. Usually the patient feels scared or uncomfortable discussing their pain with another licensed mental health professional or psychiatrist. As a result, they continue to suffer from stressful health problems.

As part of the clinical approach to treating depression, a cleverly designed chatbot has been introduced by Woebot. Using Cognitive-Behavioral Therapy (CBT), the chatbot studies the patient's mood, personality and recommends herbs as a Therapist. Compared to talking with medical therapists, patients find chatbot communication more comfortable. Woebot helps patients cope with depression through CBT.

Stanford University psychologist Alison Darcy is the creator of The Woebot. The app and built-in chatbot aim to help patients cope with emotional challenges such as depression. Woebot introduces CBT-based feedback to your message content.

**Proposed Method/ Working Methodology/ Algorithms**

The methodology used in this project is derived from the basic concepts of Natural Language Processing. Some data for this methodology may be easily acquired while others may not be in a machine-readable format or may be unlabeled or of poor quality. Thus, optical character recognition (OCR) is used to convert the data into a machine readable format, clean it, create a labeled data set, and perform exploratory analysis.

In our project, we have used the Tensorflow factorization by which we can transform all the datasets into a standard format, do the preprocessing necessary to get them ready for machine learning pipeline. By this, we can create individual IDs and further these IDs are defined in the dataset. Then, vectorization is applied and this method is optimized to work faster with larger memory footprint. The idea behind this is to semantically launch all the invocations of the inputs in parallel and fuse corresponding operations across all these invocations.

We first use the longest sentence possible and extract maximum features from it. We then form arrays from this sentence and change every incoming sentence based upon that array. We then perform pre-padding and add zeroes to the beginning of the shorter sequences.

We, then, take the input in one particular format and form a numerical relation among the words. The input and output will be the same for a particular index. Our project will then match the ID and the output and convert the labels, which are the outputs from the machine, and train them to make classes of inputs and outputs. Thus, 3 or 4 input layers will be providing us with outputs of around 60 to 70 layers.

After the training of the dataset is complete, the user will input a sentence whose maximum length should be less than or equal to the array length used while training. The IDs in the user-provided sentence input will then be matched with the trained IDs to provide the desired output.

**Implementation**

**CODE:**

**train\_chatbot.py**

import nltk

nltk.download('punkt')

nltk.download('wordnet')

from nltk.stem import WordNetLemmatizer

lemmatizer = WordNetLemmatizer()

import json

import pickle

import numpy as np

from keras.models import Sequential

from keras.layers import Dense, Activation, Dropout

from keras.optimizers import SGD

import random

words=[]

classes = []

documents = []

ignore\_words = ['?', '!']

data\_file = open('intents.json').read()

intents = json.loads(data\_file)

for intent in intents['intents']:

for pattern in intent['patterns']:

w = nltk.word\_tokenize(pattern)

words.extend(w)

# adding documents

documents.append((w, intent['tag']))

if intent['tag'] not in classes:

classes.append(intent['tag'])

words = [lemmatizer.lemmatize(w.lower()) for w in words if w not in ignore\_words]

words = sorted(list(set(words)))

classes = sorted(list(set(classes)))

print (len(documents), "documents")

print (len(classes), "classes", classes)

print (len(words), "unique lemmatized words", words)

pickle.dump(words,open('words.pkl','wb'))

pickle.dump(classes,open('classes.pkl','wb'))

training = []

output\_empty = [0] \* len(classes)

for doc in documents:

bag = []

pattern\_words = doc[0]

pattern\_words = [lemmatizer.lemmatize(word.lower()) for word in pattern\_words]

for w in words:

bag.append(1) if w in pattern\_words else bag.append(0)

output\_row = list(output\_empty)

output\_row[classes.index(doc[1])] = 1

training.append([bag, output\_row])

random.shuffle(training)

training = np.array(training)

train\_x = list(training[:,0])

train\_y = list(training[:,1])

print("Training data created")

model = Sequential()

model.add(Dense(128, input\_shape=(len(train\_x[0]),), activation='relu'))

model.add(Dropout(0.5))

model.add(Dense(64, activation='relu'))

model.add(Dropout(0.5))

model.add(Dense(len(train\_y[0]), activation='softmax'))

sgd = SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)

model.compile(loss='categorical\_crossentropy', optimizer=sgd, metrics=['accuracy'])

#fitting and saving the model

hist = model.fit(np.array(train\_x), np.array(train\_y), epochs=200, batch\_size=5, verbose=1)

model.save('chatbot\_model.h5', hist)

print("model created")

**chatgui.py:**

import nltk

from nltk.stem import WordNetLemmatizer

lemmatizer = WordNetLemmatizer()

import pickle

import numpy as np

from keras.models import load\_model

model = load\_model('chatbot\_model.h5')

import json

import random

intents = json.loads(open('intents.json').read())

words = pickle.load(open('words.pkl','rb'))

classes = pickle.load(open('classes.pkl','rb'))

def clean\_up\_sentence(sentence):

sentence\_words = nltk.word\_tokenize(sentence)

sentence\_words = [lemmatizer.lemmatize(word.lower()) for word in sentence\_words]

return sentence\_words

def bow(sentence, words, show\_details=True):

sentence\_words = clean\_up\_sentence(sentence)

bag = [0]\*len(words)

for s in sentence\_words:

for i,w in enumerate(words):

if w == s:

bag[i] = 1

if show\_details:

print ("found in bag: %s" % w)

return(np.array(bag))

def predict\_class(sentence, model):

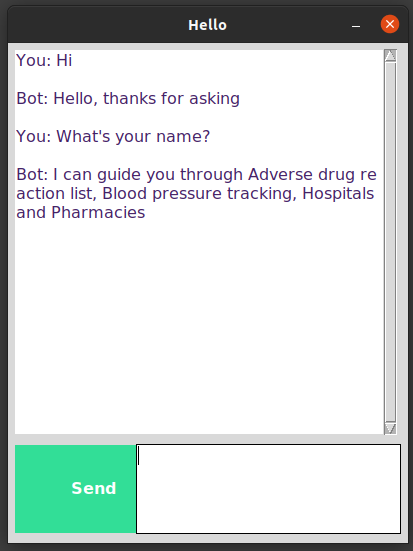
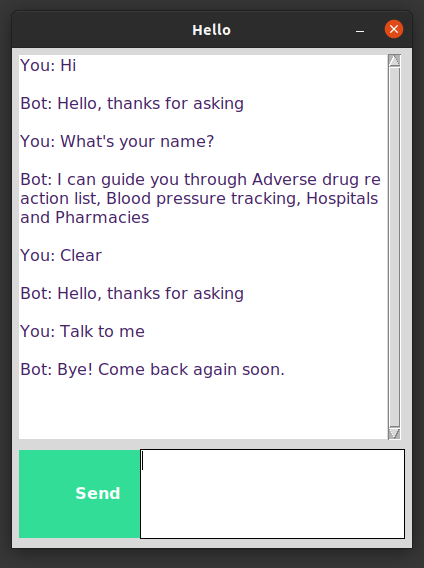
p = bow(sentence, words,show\_details=False)

res = model.predict(np.array([p]))[0]

ERROR\_THRESHOLD = 0.25

results = [[i,r] for i,r in enumerate(res) if r>ERROR\_THRESHOLD]

**OUTPUT:**

**Result & Discussion**

The model used in this project is Sequential Neural Network which is a part of Convolutional Neural Network which contains 3 hidden layers. We have use ‘WordNetLemmitizer’ to convert the input sequence of words into token and then finding the sequence based on this.

The model is trained with SDG optimizer with decay as 1e-6, momentum as 0.9 and the categorical cross entropy loss function is used to calculate the loss and reduce it for next repetition. Then the model is saved in a graph file with extension as ‘.h5’.

The User interface is created in for easy interaction with the models with the functionality of chat with bot. The overall accuracy of the model is 96% which is quite good for this type of problems as the machine are incapable of understanding the emotions and due to this reason the there is a semantic loss of 4%.

**Conclusion and Future Work**

Health care is a major field of research in our present generation. If light is thrown upon our present COVID-19 condition, it can be realized that health care is a major concern and at high alert all over the world. Therefore, our Sequential Neural Network based Health Care chat bot can be of great use and will be in demand if brought into the market.

However, the domains that are touched in this project are limited to: adverse drug reaction. Blood pressure tracking, hospitals and pharmacies. Multiple other domains could be added to this list, which would require large volumes of training as well as testing data in order to train the bot to give more accurate results in a wide range of health-care-oriented domains.

Also, our model has a semantic loss of 4% which can be used by deriving structured data from a variety of hospitals and health care facilities to train our AI powered Health Care chat bot.

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