An Approach to Medical Diagnosis Using Smart Chatbot

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Abstract. People avoid initial hospital treatment that could turn into a major disease in the future. With rapid changes, remote or home-stationed diagnosis systems are becoming exponentially popular, featuring ample number of advantages like cost-efficiency, quick and authentic decision support for medical diagnostics, treatment and prevention of any physical or mental damages. Our proposed idea is to create an affordable and accessible all-day chatbot- *DiagZone* for people to check on their health in contrast to the conventional way of higher time investments. Since it is free and provides mobility with the capability of being accessible anywhere irrespective of the user's location, it encourages practical utilization. It saves on unnecessary time required in specialist consultations. With the help of AWS Lex, AWS Lambda and channel Twilio, we have integrated our Flask based Chatbot to Whatsapp. Text entered by the user is processed with the pivotal implementation of NLP. After DiagZone has gathered adequate keywords from the original messages, it will start to lead the conversation by interrogating the user and trying to list a few diseases that the user may suffer from. Once the Chatbot has detected the probable disease, it works effectively by suggesting redressal measures and medications to the user or by referring them to a doctor.

Keywords: AWS Lex · Lambda · Twilio · NLP · Flask · Whatsapp

1 Introduction

A medical chatbot system has a profound influence on state health culture. It has exponentially advanced and is less susceptible to any possibility of a manual error. People today are at a greater risk of becoming addicted to the Internet but are devoid of the concern of having good mental and physical health. They try not to go for hospital treatment for trivial matters which in turn could cost them a major disease in the future. Our proposed bot methodology aims to solve this problem, to create an affordable and accessible all-day chatbot. The fact that chatbot is free and remotely accessible encourages the user to own and use it. This makes it effective to save on the essence of consultation with specialist doctors. After the Chatbot has collected enough keywords from the original messages, it will now start to lead the conversation by interrogating the user and thereby exerts to list a few diseases that the user may suffer from. As soon as it receives enough

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data, it discerns a disease or an injury that the user might be suffering from. This works out once the Chatbot has detected a user or by referring the user to a doctor if the rate strikes a preset limit number. Working out on these lines, we have named the Chatbot as DiagZone, a person's complete zone for diagnostic purposes.

There are several methods to make medical diagnosis. These are in various directions and with different technology. Using rough set theory [14] and formal concept analysis in [15, 17] using hybrid models of fuzzy set and soft set in [16]. This paper aims to introduce the design of our Chatbot which can be used in the fields of medical diagnosis by providing diagnostics and remediate measures based on the indicators provided in the application. Natural Language Processing (NLP) techniques such as Python NLTK can be used to analyze speech, and clever answers can be obtained by designing an appropriate human response engine. Health care negotiations have a high potential for medical communication by improvising and bridging the clinic-patient and physician-patient gap. It can assist in meeting the need for health services through remote testing, vigil and swift medication, or even telephonic consultation. The idea has been devised in lieu of the current prevailing pandemic times wherein a remote consultation can help people to avoid the risks they might have to endure while visiting a hospital.

2 Literature Review

Using AI based concepts, a diagnosis confined Chatbot was devised to help users identify illness based on their symptoms and was proposed by Fernandes et al. [1]. It was fed with a knowledge base that had diseases and NLP made it capable to transform the user-fed inputs as a part of their queries and ultimately gave their desired response. The response time for this was 10-20ms. These retrieve knowledge from databases consisting of approximately 150 diseases to develop the diagnostic chatbot. Results show that it can be used for retrieving information in devices like Alexa and Siri.

A generic chatbot called 'Diabot' – a (DIA)gnostic chat (BOT) was proposed by Sahoo et al. [2]. Using NLU, chatbot has a direct conversation with the patient to get personalized predictions using the dataset stored based on the symptoms taken as inputs from the user. It was then used for specialized Diabetes prediction using Pima Indian diabetes dataset. Its front-end was made using RASA NLU based text pre-processing to understand what the patient wants, React UI and undertook quantitative performance comparison of an ample number of machine learning algorithms. Among asthenic learners, the accuracy of the model showed counterbalanced results and prediction showed that diabetes prediction was above par.

To show the use of chatbots which can be used in the diagnosis of Achluophobia a chatbot was introduced by Belfin et al. [3]. It is based on the fact that it can diagnose the severity of disease based on the patient's inputs. It performs NLP for extraction of the meaning and uses DT to sort down to its classifications to be able to characterize and classify a user in terms of a likely disease. The NLP unit retrieves the meaning of keywords to define the severity of the disease's symptoms. Pattern matching of sentences to determine the similarities is done. The DFS technique is used to traverse DT and to help make crucial decisions about the intensity of the disease. In diagnosing Autism and Achluophobia, Aquabot showcases high efficacy. Even when it comes to assisting

a human psychologist, the proposed model is beneficial for practitioner psychologists. These features ensured that it turned out to be time-efficient and resourceful and even succeeded at achieving an accuracy of 88 percent when measured against the results achieved by a human psychologist.

Uncertainty based models are more efficient than the crisp methods [14]. To make a Chatbot for the Covenant University Doctor (CUDoctor), a telehealth system based on fuzzy inference and logic rules was developed [4]. The system aimed to put its focus over symptoms of Nigeria's tropical diseases. To create the interconnection between the chatbot and the system, Telegram Bot API was used. Twilio was utilized for interconnectivity between the system and an SMS subscriber. Using medical ontologies, the system uses the knowledge base to predict the illness and its severity based on the symptoms received. A fuzzy Support Vector Machine (SVM) is used to predict the disease based on the symptoms received. They are identified by NLP and sent to CUDoctor to gain decision support. User then receives a message which indicates the completion of the process. The system behaves as a mini medical diagnostic center that gives personalized diagnosis based on self-given inputs. The usability was assessed and capitulated a mean SUS score of 80.4, showing positive metric evaluation.

To identify & forecast the presence of a heart disease in an effective and accurate manner, a system was developed by Omoregbe et al. [5]. Based on surveys conducted on algorithms like K-NN, Artificial Neural Network (ANN), SVM, Bayes, Decision Tree (DT) etc., tests were conducted to check for veracity of all. It was seen that the SVM algorithm gives the best possible certainty on a Heart Disease Dataset against others when analyzed from the survey. SVM training algorithm constructs a model that allocates new instances to one or the other category and is a classifier defined by the separation of a hyperplane. We aim to construct a system that can get the reports of the patient, conduct an analysis and thereby infer whether he/she is suffering from any kind of heart disease or not. The process is carried through a one-on-one conversation pattern using Diagflow Platform.

The chatbot developed by Mujeeb et al. [6], can give patients a realistic experience of conversing over text with a Medical Professional. The Chatbot showed its capability to identify and store message patterns as followed by humans using AI Mark-up Language. This language, based on XML, has extended its scope to retrieve and build applications based on AI. It extracts keywords as per the knowledge base from the initial messages to realize the probable medical issues that the patient might have, from the inputs received. Few Medical Chatbots currently exist on similar lines. They connect users with a Medical Question-Answer Platform and under the suggestions tab, show similar previously answered questions by doctors that might have a match with the symptoms the user has entered. The application was compared against HealthTap, Facebook Messenger Chatbot. It was then able to justify its goal of being a medical Chatbot that could prove to be a better and efficient substitute to other existing Chatbots in this sector.

A WhatsApp based service called XraySetu was presented by Bali et al. [7] to provide an instantaneous diagnosis of patients who are susceptible to/ showcased symptoms of COVID-19 by the use of Chest X-Ray imaging technology. A report was generated and consisted of predictions for multiple lung abnormalities including COVID-19 amongst 15 others with clarified semantic markings on chest X-Ray. It was undertaken to help

the doctors to understand the gravity of the ailments and is then put to training using Multi-Task Learning on chest X-Ray datasets provided by sites such RSNA and NIH. A miniscule level pilot was developed and seen over an extensive period of 10 months and could accept a machine generated X-ray Report on sending the concerned authorities chest X-Rays of patients. The obtained Xraysetu showed an efficient mechanism for the usage of occupied doctors since they could plan an early intercession for their patients by just clicking a snapshot of their Xray and sending it to them via WhatsApp.

A chatbot which focuses on cancer patients is proposed by Kudwai et al. [8] which would be equipped with the ability to answer all of their queries pertaining to treatment, survivals or symptoms. There was no limited dataset used since they extracted information from various platforms. Another feature that they aimed to include was sentiment analysis in order to provide a more comforting experience. Hence, this chatbot was an implementation of NLP, Web Scraping, Neo4j. The data preprocessing was done by NLTK. Though experimentally it proved to be a reliable platform, expanding the dataset to help improve the performance along with the inclusion of images in the dataset would be a future scope. Including features like speech recognition and suggesting specialized hospitals were proposed as part of it too.

A chatbot to reduce the time and efforts required in getting a reliable diagnosis by implementing a chatbot. The framework to be used was RASA. The chatbot would diagnose and provide treatment recommendations [9]. It would be able to provide a health analysis and track the nutrients. The chatbot would be able to provide the information regarding their macronutrients by asking the users to enter the food that they had throughout the day. The use of conversational AI to interact with the users in an efficient/operating system and architecture supported future integrations of features and ease of updating.

A health assistant that can handle quick seeking treatments using the PRISMA method is proposed by Tjiptomongsoguno et al. [10]. They used NLP, ML, Braun and Clarke's algorithm, compared keyword and data mining and inferred that NLP and ML make the best combination for a medical diagnostic chatbot. Based on the needs, several technologies bridge to serve accurate results. However, the question still remains of when and how a machine can predict fully correct output.

In [11, 12], a chatbot named AgentG is proposed for the lovers of e-commerce who can chat through it in a friendly manner. Similarly, another system which is based upon the clustering and auto-tagging techniques is proposed and studied in the name of TagIT [13].

Tripathy et al. [14] proposed a measure using fuzzy logic, neurocomputing and probabilistic reasoning to explore methodologies to exploit the tolerance of imprecision and uncertainty to achieve robustness and low solution cost.

3 Experimental Setup

The experimental setup for DiagZone is shown hereby:

3.1 Software

Using the knowledge base of diseases and symptoms acquired from medical ontologies and by using pattern detection methodologies, we set a goal to devise an integrated application and wish to derive our results in the form of an identifying tool that provides a diagnosis by identifying inputs inserted by the users. Using AWS Lex Chatbot service and Channel Twilio, this is then integrated to WhatsApp using a business account providing dataset through AWS Lambda function and constantly refining it. We used Twilio due to its encryption-based support system that facilitates communications and secure mechanisms.

3.2 Hardware

We just require a smartphone and good internet connectivity to use this chatbot efficiently. Our chatbot, when launched by the user, processes the query entered by the user. On successful processing of the same, the chatbot retrieves solutions apt for the condition. These solutions are then presented to the user and the workflow arrives at the end. In case the query is not processed successfully, error feedback is provided to the user.

3.3 Security Checks

The base necessity for any chatbot is the assurance of a good security check so as to ensure that no vulnerabilities can penetrate it henceforth.

- It ensures that confidential data such as customer's information is accessible to Twilio-owned devices only.
- It consists of data loss prevention system scans for sensitive data that might be susceptible to being exposed publicly or improperly stored. It additionally has alerting and quarantine capabilities for our primary collaboration systems.
- Data parsing and classification is followed by Twilio through a sequence of four priority steps- Secret, Restricted, Confidential and Public. The data segregation here is implemented as logical separation and its access mechanism follows the principle of least privilege.
- The credibility is ensured using AWS certifications. Through this, Twilio can maintain the confidentiality, availability, and integrity of our data which is extremely necessary while handling patient details owing to their highly personal nature along with the services while maintaining compliance with necessary requirements of the legislative, contractual and regulatory forms.
- Amazon Lex, it is observed that security is implemented through technical and physical controls, that involves encryption at rest and in transit, designed to prevent unauthorized access to, or disclosure of our content.

3.4 Modules Description

Our chatbot consists of certain chunks of functionalities that have been mentioned below:

1. Decoding the natural language messages
2. Detection of diseases from symptoms
3. Suggest remedial measures for the same
4. Locate doctors/helpline for the user
5. Book appointments for the user and provide confirmations

The blended dialogue at the heart of its framework consists of Natural Language Processing, a part of Artificial Intelligence and ML. An AI-enabled chatbot determines and processes language that is understandable to the target person. It understands the minimum number of personal conversations and recognizes that instructions or questions made by users do not require much specificity.

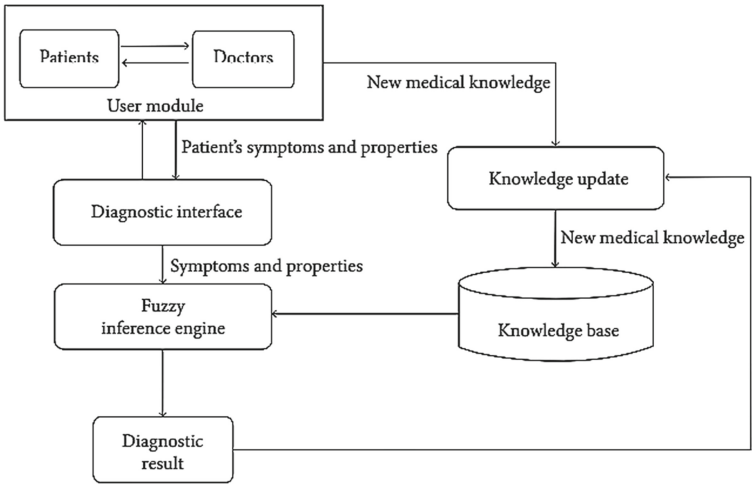

Fig. 1. System architecture

In our proposed system as shown in Fig. 1, we proceed with a functionality of identification of text-based keywords and meaningful extraction to create sympto-mapping or matching the symptoms with the knowledge base. The relevant queries presented by the users will be tallied from the database and suggestions for possible major or minor disease along with referrals to a doctor will be presented. This will be done as follows:

a. Decoding Intent: NLP will break down users' inputs and comprehend the positioning, conjugation, etc. that a human conversation may be like.
b. Recognizing Utterance: The chatbot is capable of recognizing instances from the words given, the user is referring to.
c. Dealing with Entity: Chatbot will trace to the database to retrieve the most similar possible result.
d. Contextual Understanding: NLP also provides conversation, tone and sentimental analysis for more human-like language processing.

To train our dataset for pattern-based matching and identifying diseases, we use decision tree classifiers and algorithms that give us a predictive approach. The supervised learning algorithm as such will work on N training examples such that a feature vector with a label will contain an input and an output space for learning and predicting respectively. Further text processing operations will include noise removal: erasure of irrelevant characters in the string and related subjects, tokenization: fragmentation of string into lexical elements using NLTK, tagging of document: useful knowledge source, parser: in-case of speech-to-text, term-matching: extracting matching keywords and tallying to knowledge base, feature selection and extraction: the feature vector will come into play where we will look towards giving the output.

3.5 Algorithm

The expected inputs and outputs are shown here with the help of a devised pseudocode:

Step 1: Start
Step 2: Parse query in text box eg: (I am having stomachache and headache, best relieving medicine quickly)
Step 3: Pre-process, words like stomachache, headache, medicine, quickly are highlighted
Step 4: The information is stored in logs.
Step 5: Matching the keywords are fetched from the Knowledge base, the AWS Lex performs its functions and response is generated.
Step 6: The output is thus presented to the user eg: (In case of mild, take a crocin or paracetamol).
Step 7: Exit

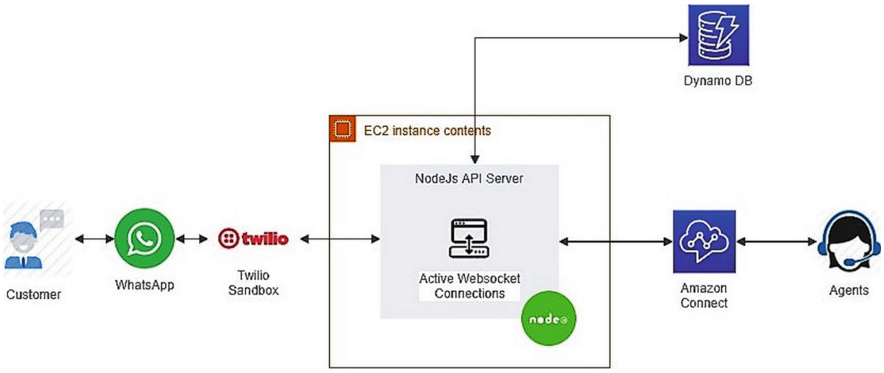

Fig. 2. Whatsapp integrated with AWS Lex via Twilio

Process of setting up the chatbot as shown in Fig. 2 can be summarized as:

- User interacts with the Chatbot via Whatsapp.
- Amazon Lex (AI powered chatbot) integration with WhatsApp via channel Twilio.
- Create the Lambda function to initiate the outbound API call to Amazon Connect.
- Lambda Function runs the business logic deriving parameters from DynamoDB to perform knowledge base matching for response.
- User when parsing the query receives a response on Whatsapp itself. Followed by this, relay takes place.

4 Dataset Description

We provide the necessary solutions based on inputs received from the user's side, thereby saving up their time as well as consultation fee expenses. This is done with the help of a dedicated team that constantly updates any new symptoms/diseases which need to be taken into account for the portal. It provides the users with a platform that is neither outdated nor time-consuming or inefficient. The dataset Disease Symptom Prediction with 9.7 usability score is obtained from Kaggle.

- Dataset for symptoms:

  Columns: 18
  Rows: 4981
  Column Labels: Disease, Symptom_1, Symptom_2, Symptom_3, Symptom_4, Symptom_5, Symptom_6, Symptom_7, Symptom_8, Symptom_9, Symptom_10, Symptom_11, Symptom_12, Symptom_13, Symptom_14, Symptom_15, Symptom_16, Symptom_17
  File Size: 632.2 kB
  Used for predicting symptoms related to a particular disease further classified on the basis of severity.

- Dataset for severity:

  Columns: 2
  Rows: 134
  Column Labels: Symptom, weight
  File Size: 2.33 kB
  For overlapping symptoms, high severity to least shown during user output request.

- Dataset for Description:

  Columns: 2
  Rows: 42
  Column Labels: Disease, Description
  File Size: 11.03 kB
  To provide users with the detailed definition of the disease predicted.

- Dataset for precaution:

  Columns: 5
  Rows: 42
  Column Labels: Disease, Precaution_1, Precaution_2, Precaution_3, Precaution_4
  File Size: 3.49 kB

As soon as all the Datasets shown as samples are loaded the csv files are loaded to DynamoDB using object creation through a bucket and Lambda Function Programming to import the csv file. Data is loaded to DynamoDB and using lambda function is integrated with lex bot.

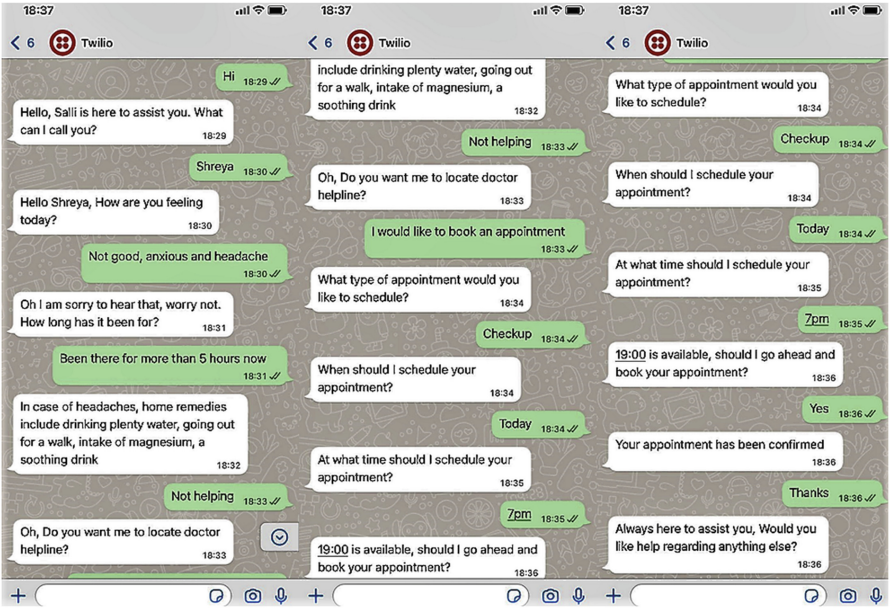

Fig. 3. Sample chat between User and Bot Salli

5 Result Analysis

Considering a high amount of population nowadays, everyone has adapted themselves to the virtual world and are comfortable in using Whatsapp as an immediate mode of communication. As our chatbot gives the desired comfortable environment with the help of end-to-end encryption, it lets the users maintain their privacy while discussing their symptoms with the virtual bot. We successfully implemented the bot predicting disease or disease like entities to the given set of symptoms user inputs and also provide precautionary measures. We also trained a set of nearest available doctors according to geolocation. The bot identifies and books the nearest possible doctor available at the earliest (sample conversation presented in Fig. 3). However, the appointment module is just for testing purposes since integration with clinics and hospitals still remains under review for accuracy and approval.

6 Comparative Analysis

The following Table 1 illustrates a comparative analysis of some of the related Chatbots that we came across. These were then tabulated and performed accordingly.

Table 1. Comparative analysis of a range of chatbots

Chatbot	Functionality	Advantages	Disadvantages
Diagzone	An NLP-based chatbot that gives end-to-end diagnoses by accepting symptoms directly from the user via Whatsapp with Twilio as the channel. It parses the message to extract symptoms from the input. These symptoms are matched as keywords against the knowledgebase using business logic run by Lambda functions. AWS Lex then returns the generated response	The overhead computation time is low – providing a fast remote accessible service, owing to the cloud services being availed. Twilio and Whatsapp inherently add security, preventing third parties from accessing personal information	Due to the lack of real-world data from regional hospitals, not all the variables pertaining to geographic changes and their corresponding effects on individual's health have been considered

(*continued*)

Table 1. (*continued*)

Chatbot	Functionality	Advantages	Disadvantages
Diabot	An NLU-based chatbot that combines an ensemble of five classifiers – Decision Tree, Bernoulli Naïve Bayes, Multinomial Naïve Bayes, RF, and SVM in the case of general disease prediction using the dataset – General health. Followed by that, the bot then narrows down to Diabetes prediction, an ensemble of six classifiers – NB, K-Nearest Neighbors (KNN), DT, RF, LR and GB are used on the dataset – Pima Indian diabetes	The generic framework implemented is used for various disease predictions and can be extended to develop more complex and integral disease-specific chatbots	Due to real-time implementation, accuracy becomes a major issue More supervised training required for specialized disease prediction beyond just the generic prediction
Aquabot	Proposed to strike a conversation with the user and find out the psychological problem. It deals with Autism and Achluophobia. The system processes entered text, then the decoded message is split into sentences then into phrases. Synonyms of phrases are taken from the knowledge base to generate new sentences. If found in the brain, it is served on the screen, else the user has to ask Aquabot on their own	Aquabot uses decision trees (DFS traversal) for its performance improvement. Usage of Dtrees improves the response time and regularity in responses. Exhibited a high accuracy of almost 88% when compared to a human physiologist's diagnosis for Autism	Cannot save case history of physical disease currently No facial recognition, thereby hindering the identification of facial expressions of the user to identify the issues

(*continued*)

Table 1. (*continued*)

Chatbot	Functionality	Advantages	Disadvantages
Florence Chatbot	The chatbot finds the most likely disease by analyzing the symptoms given by the user and forecasts the disease using the extracted signs. The use of the RASA system has been achieved to incorporate this chatbot. Now, it can accurately diagnose patients with the analysis of the basic symptoms and a conversational approach	From symptoms, provides the most suitable disease to them along with the nutritional breakdown of the food that they have consumed. Gives near perfect results of almost 92% when compared to humans	Lack of image recognition facilities, thereby hindering any image that a user could send for diagnostics purposes and providing patient care
Graphican-Cancer Care Chatbot	User's messages are forwarded to the bot and sent to a parser. Sentences are resolved into components and keywords are identified from it. The parser runs its natural language engine to perform searches. Intent and entities fetch data from the cancer database. Converted to a graph model using a graph database- Neo4j to process highly connected data and identify the relationship between different data. The engine shortlists cancer from input and gives remedies	Can impersonate the human conversation either through text or audio. Uses supervised learning concepts to learn from previous experience	No sentiment analysis being performed Lack of image recognition, thereby hindering any image that user could send for diagnostics purposes Limited data accessibility, cannot access data directly from the web

7 Conclusion

This project elucidates the natural language processing development in the healthcare industry using chatbots and how they are built. Current chatbots are high in performance and reliability when it comes to providing users responses as compared to the traditional systems. Taking into account the revolutionary demand of smartphones and ease of use as a handy device, users in time of need can contact the assistance tool for medical diagnosis. A telehealth platform requires response efficiency and cost-optimization for detection and prediction. Reliability plays a major role here since effective communication between patients (users) and a diagnosis system (doctor at proxy) holds on to the bridge of trust. This system provides an end-to-end diagnosis via self-input response from users, we conclude that it is a remote tool for SOS patients in less risk zones to get a diagnostic approach, and if doubtful, connect to a doctor. The proposed system combines NLP and cloud services with embedded machine learning algorithms and provides a connecting medium from AWS Lex and Twilio to create DiagZone.

8 Future Scope

The chatbots are hoped to assist doctors in arriving at the right diagnosis and to provide these diagnoses as a single source of information by increasing the efficiency, accuracy and understanding of the human language. The futuristic blueprint of the remaining module implementation of our chatbot involves its ability to give out doctor details, ask the user (patient) about his/her convenient timings along with the location and cross check in the database whether it can schedule an appointment in that particular duration. It will ultimately give a confirmation of whether the appointment is scheduled or not. Through text-to-speech/speech-to-text or speech-to-speech method, the audio interaction will introduce more ease. This takes up only the usage of cloud services, hence reducing costs and the workload on medical doctors in rural areas as well as urban areas. Chatbots can be used to draw conclusions beyond one thought process by removing human biases.

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