International Journal of communication and Computer Technologies, 7 (1) (2019)

International Journal of Communication & Computer Technologies

Website: www.ijccts.org
ISSN :2278-9723
Research paper

INTEGRATED PLATFORM AND RESPONSE SYSTEM FOR HEALTHCARE USING ALEXA

Mr. V. Sakthive[1], Mr. P.V.Kesaven[2], Mr. J.Martin William[3], Mr. S.K.Madan Kumar[4]

[1]Assistant Professor (Sr.G)

Department of Computer Science& Engineering
KPR Institute of Engineering and Technology, Arasur, Coimbatore.
[234]B.E Student, Department of Computer Science& Engineering, KPR of Institute of Engineering and Technology, Arasur,Coimbatore

Corresponding Author Email : mackmartin2468@gmail.com
Received: 25-11-2018, **Revised:** 10-02-2019, **Accepted:** 21-02-2019, **Published online:** 23-03-2019

Abstract

This paper presents a Healthcare system by providing a virtual personal assistance using the Amazon Alexa. Amazon Alexa is an application program that understands voice commands and completes that commands for the user. Amazon Echo is not only a smart speaker, but operates as an intelligent personal virtual assistant. Alexa is Hands-free that can allow easier access to the medical information. Alexa has been programmed with the information about the patients, doctors, nurses, pharmacy details, events and general information about the Healthcare. Users can interact with the Alexa to find out the scheduled appointments, availability of the doctor, availability of the rooms, etc.

Keywords: Alexa, Digital Voice Assistants (DVA's), Alexa Voice Service (AVS),Intelligent Personal Assistants (IPA's).

1. Introduction

In modern world, each and every field are deployed with Virtual personal assistant devices. The enormous efforts of the leading Digital Voice Assistant (DVA) device manufacturers (e.g., Amazon and Google) and the third party voice service developers (e.g., Capital One, Dominos, Honeywell), users can do number of things using voice commands helps us to improve the social life. These include so many applications like music, ordering pizzas, shopping online, scheduling an appointment, checking weather, making a payment, controlling smart devices. In order to help the users with usage convenience, many DVA devices like Amazon Echo, Google Home adopts an always-listening mechanism which takes input as voice commands all the time. The best part is that users need not press or hold a physical button on DVA devices before interaction with the devices. The device is programmed in such a way where it accepts voice commands no matter whether any persons are around the device. The sound pressure level (SPL) is considered and works for all the sounds is higher than 60dB. In third party voice services like Alexa-enabled smart device vendors there is no access control deployed at smart devices because they assume all the voice commands from the Alexa service are genuine and harmless. The successful work of Amazon Alexa is that it could work in Omni-direction manner. This helps Amazon Alexa to listen in any direction in order to receive commands. The reasons why we consider Amazon Alexa areas follows. First, they are very popular and the bestselling flagship DVA devices. According to the reports, Alexa devices have been sold for over 5 million within two years since launch. Second, the Alexa provides services to their users with more than 10,000 skills (Alexa voice services) which are large scale than its competitors. DVA devices will help authenticate users by their voice biometrics before taking voice commands. But there are two complications that arise. First, voice of user's may vary with their ages, illness, or tiredness. Second, human voice is vulnerable to replay attacks. Some of the prior works are proposed to deploy wearable devices for user authentication. Solution is to force users to press a physical button for activating the Alexa devices before using it. With the help of the Amazon Alexa were going to retrieve information about a patient, doctor, pharmacy details. We can manage compute operation such as balance of memory, CPU, network, and other resources. The objective is to help the user with various information about the Healthcare system.

2. MOTIVATION

Digital Voice Assistants (DVAs) are getting popular in recent years. Users can control smart devices and get living assistance through those DVAs (e.g., Amazon Alexa, Google Home) using voice. In this work, we study the application of DVA service by using Amazon Alexaas a case study. DVAs allow for natural-language interactions and offer patients the promise of increased usability, greater engagement, and improved adherence to treatments and/or medications. Despite this interest, there is little ethnographic data on patient's use of DVA or unmet needs. This data is critical to developing DVA applications that interact with medical devices, where regulatory or design control considerations require higher level of complication compared to unregulated consumer applications. In the DVA world, the do-it-yourself culture is encouraged, meaning IoT environments with tiny sensors and programmable brokers can be developed and customize devices and applications by users themselves. However, for people who are unfamiliar with state-of-the-art technologies to build customized IoT environments it is not that easy. Because of this factor most people tend to purchase IoT consumer products such as smart assistants, lights, sensors, switches, hubs, thermostats, and fitness devices. A variety of products are available on the market and we focused on one of the most famous products, Amazon Echo. The Amazon Echo family of smart devices also includes Dot and Tap, connect to the intelligent cloud-based voice service, Alexa Voice Service (AVS). With Alexa as a voice-activated personal assistant, the Echo is capable of doing various things, such as managing to-do lists, playing music, setting alarms, placing orders, searching information, and controlling other smart devices . Additionally, as declared at CES 2017, there's a remarkable convergence of the Alexa with varied devices, like connected cars, good fridges, and robots that indicates that the Amazon Alexa-related environment will become an important source of information retrieval process. For these reasons, the Echo and Alexa were selected as the first targets for developing intuitive response system.

3. BACKGROUND: AMAZON ALEXA

In this section, we introduce Amazon Alexa devices and their common voice service model.

A. Alexa Devices: Alexa devices can be categorized into 9 types as shown below:

Amazon Echo:The first-generation Amazon Echo consists of a 9.25 inch (23.5 cm) tall cylinder speaker with a seven-piece microphone array. The Echo hardware complement includes a Texas Instruments DM3725 ARM Cortex-A8 processor, 256MB of LPDDR1 RAM and 4GB of space for storing.

Echo Dot:In March 2016, Amazon unveiled the original Amazon Echo Dot, which is a hockey puck-sized version of the Echo designed to be connected to external speakers due to the size of the aboard speakers, or to be employed in rooms like the bed chamber as an alternate to the full-sized Echo. Beyond these distinctions, the Amazon Echo Dot possesses an equivalent functions as the original Amazon Echo. External third-party moveable batteries area unit are accessible for the Dot.

Amazon Tap:The Amazon Tap is a smaller moveable version of the Echo. The Tap will do equivalent things as the Echo; but, because it is powered, it is also moveable. The user had to press associate activation button on the front of the Tap to talk commands. However, a 2017 software system update permits the choice of activating the Tap with associate activation word, rather like the Echo and the Dot.

Amazon Echo Look:In April 2017, the Amazon Echo Look was introduced as a camera with Alexa built-in, for US$20 more than the first-generation Echo. The device can provide artificial intelligence outfit recommendations, take photos, and record videos; additionally to the options accessible on the Echo. It offers Amazon Alexa's key feature and a camera to require full-length photos and 360-degree videos with intelligent AI for fashion recommendation. As a client product, it helps catalogue your outfits and rates your look supported by machine learning algorithms with recommendation from fashion specialists. The device was available for purchase by invitation-only within the U.S. But, it became generally available in June 2018.

Echo Show: In May 2017, Amazon introduced the Echo Show, that options a tactile 7-inch liquid-crystal monitor which will be used for enjoying media, making video calls (5 MP front camera), and alternative options. The Echo Show was offered for purchase at a price of $229.99 on June 28, 2017 and was initially only available in the U.S.

Echo Spot: On 27 September 2017, Amazon launched the Echo Spot, a hemispherical device that has the same functions as an Echo Show. The device has a 2.5-inch circular screen, and looks like an alarm clock. The device sells for $129.99.

Echo Plus: On 27 September 2017, Amazon announced the Echo Plus, which was released on 31 October 2017.

It shares style similarities with the first-generation Echo, but also doubles as a smart home hub, connecting to most common wireless protocols to control connected smart devices within a home. It incorporates seven second-generation far field microphones and noise cancellation, while also supporting Dolby Sound.

Echo Input:The Echo Input is Alexa data input device with no on-board speakers. It should be connected to external speakers for audio output.

Echo Link:The Echo Link is a higher-end version of the Echo Input, with additional output ports and a volume knob. The Echo Link Amp has the same controls of the Link, but with an amplifier.

B. Alexa Voice Service Model

The Alexa voice service supports the identification of voice commands to Alexa devices. Figure one illustrates the working of voice service with Alexa devices to regulate smart home devices (e.g., smart bulb, thermostat, etc.). To control a smart device, a user will speak a voice command to an Alexa device, assuming that the Alexa device is already awaken using the command “Alexa”. The Alexa then sends the sounds of that voice command to a remote voice process cloud via its connected Wi-Fi network. Once the cloud acknowledges the sounds as a convincing command, it's forwarded to a server, referred to as skill-sets, that is maintained by Amazon to allow the cooperation with third-party service providers. Afterwards, that command is transferred to a different cloud which manages the corresponding smart home device remotely. Note that additionally to the management of smart home devices, some functions (e.g., checking the weather, inserting orders on Amazon.com, etc.) provided by Alexa devices may also be accessed by voice commands.

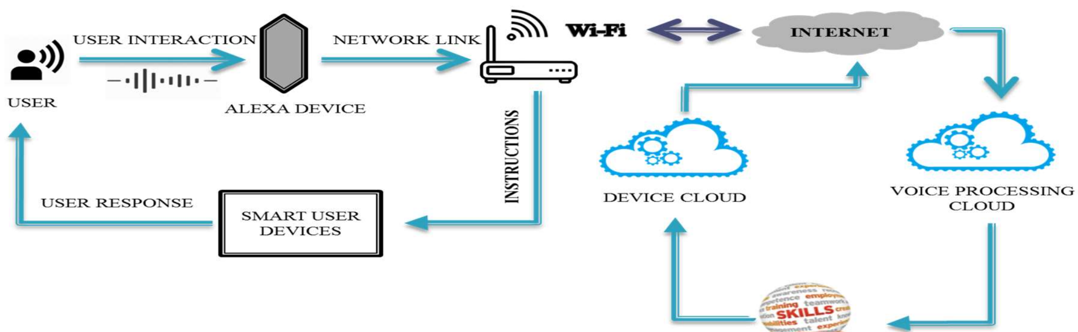

Fig.1:Alexa voice Service model

UNDERSTANDING BASIC CONCEPT AND USED SERVICES:

Alexa voice service: Alexa Voice Service (AVS) is Amazon's suite of services built around its voice-controlled An assistant for the home and other environments. Alexa is available for an ever-increasing number of other devices, including smart phones, tablets and remote controls. AVS is tightly integrated with Amazon's e-commerce environment, which means that it makes purchases fast and simple.

The system can operate a home automation hub, allowing the user to control heating and lighting systems and also customized query. Alex also connects to streaming media services online, and supports If This Then That (IFTTT), an online service that automates Web-based tasks so that when user-specified events occur, follow-up tasks are triggered and handled. In the AVS environment, services are known as skills. Alexa Skills Kit, a software development kit (SDK), is made freely available to developers and skills are available for instant download from Amazon.com.

A. **Alexa skill kit:** The Alexa Skills Kit is a software development kit (SDK) that enables a developer to build skills, also called conversational applications, on the Amazon Alexa artificial intelligence assistant. The Alexa Skills Kit is comprised of tools, application program interfaces (APIs), code samples and documentation that enables a developer to add skills to the 10,000-plus voice recognition capabilities available on Alexa. Amazon Alexa is based in the Amazon Web Services (AWS) public cloud. A developer can upload Alexa skill code to AWS Lambda functions to execute code that is triggered by voice interactions. AWS automatically manages the compute resources for Lambda. A developer can certify, publish and update skills, which are made available through the Alexa Skills Store. An organization can build an Alexa skill to connect to end users via the conversational Amazon Echo platform. A developer programs the voice user interface to return a variety of voices, accents and responses based on the code for the skill. Custom skills allow the developer to define requests that the skill can handle, define the vocabulary required from the end user

Alexa to recognize the task. Custom skills are flexible and can handle several requests, but they require the most code to generate. A developer does not need to build a custom voice interaction model with smart home skills, but must create code to respond to a request. Flash briefing skills enable businesses to share pre-recorded audio content from feeds on Alexa with end users, such as news and weather updates. The Flash Briefing Skill API uses Amazon's language model and removes the need for a developer to build a custom voice interaction model.

4. LITERATURE REVIEW:

Digital Voice Assistant (DVAs) increased the interaction between the human and the machine. DVAs often observed as Virtual Personal Assistants (VPA), Intelligent Personal Assistants (IPA), digital personal assistants, voice-controlled or informal agents. Microsoft Cortana, Apple Siri, Google Assistant, and Amazon Alex are some of the popular DVAs and are embedded in smart phones or dedicated home speakers. Earlier hand-held computers that were developed and designed to store information (e.g. contacts, calendars) and wont to perform easy tasks (calculations, messaging). The DVAs designed to simply accept user inputs through speech, text, image, video and answer user queries in a natural language and perform different tasks, like play music, weather forecasts, set calendar reminders and place online shopping orders (Canbek and Mutlu, 2016). Natural language processing avoids the inconvenience of the earlier voice recognition system, which required phrases and patterns in order to work properly. It performs voice-operated functions by communicating through a local Wi-Fi or Internet connection with Amazon’s AWS cloud servers, or other networked devices, to carry out these voice- operated functions. In addition to obtaining data from Amazon’s servers, the software can be used to control smart home devices, such as lighting and security systems. The Amazon provides the advanced deep learning functionalities of automatic speech recognition (ASR) for converting speech to text, and natural language understanding (NLU) to recognize the intent of the text, to enable developer to build applications with highly engaging user experiences and lifelike conversational interactions. Alexa can be activated when its speech recognition software receives a word or phrase “Alexa” from a user which helps to activate the device, but this trigger word can also be customized by the user. Alexa users can train Amazon's voice assistant to learn how to recognize different voices and personalize its services for multiple users. When recognizing a registered user's voice, Alexa can deliver personalized results for messages, Alexa-to-Alexa calling, music playback, shopping, and news briefings.

to make the skill request, and define the invocation name for

Alexa in Healthcare can be useful for appointment scheduling, patient details, doctor details and pharmacy information. Anyone can use Alexa to check the availability of the doctor and we can schedule our appointment, availability of rooms. The patients or the attender of the patient can use the Alexa to get the patients details like drugs used, diet, doctor attended them. Alexa can also be used in ICU. It provides nurses with basic intelligence on medication dosing, specific protocols, staff contact info. Alexa is very helpful with basic questions but it cannot use wide in the complex medical world. Complex medial terms and intense use of Alexa in the Healthcare field cannot be made. Because medical symptoms can be common for two or more disease. In this case Alexa cannot retrieve the correct detail. But now-a-days Alexa becoming a part of the family working in day-to-day activities like controlling homeland other activities. Custom skills can be developed to Alexa for remainders of their tablet intake, diet intake, physiology works. Basic activities, basic questions can be posted to Alexa and we can get back the details needed and we can also perform the simple task.

5. COMPARISION: ALGORITHMS FOR SPEECH RECOGNITION AND RESPONSE IN HEALTHCARE

A. Hidden Markov Model:

There are several methods for capturing speech and converting it into text. One of the more effective methods is the Hidden Markov Model (HMM) with an end point detection algorithm for pre-processing to remove unwanted noise. The HMM requires the addition of other tools to correctly interpret speech. Before the HMM method is applied to detect the speech, “the speech samples are extracted to features or coefficients by the use of Mel Frequency Cepstral Coefficient (MFCC)”. This process separates the audio clip into small segments that the HMM can use as an input. The HMM uses a dictionary of word pronunciations to determine the word W by choosing the maximum probability $P\ (W|Y)$ where$Y$ is the audio clip recorded. This maximum probability is computed using the probability $P\ (W)$ which is calculated using a language model. There is an HMM for each basic pronunciation in the dictionary. $P\ (Y|W)$ is the expected acoustic data when W is constructed from the stored HMMs in the dictionary. This data is used to determine the maximum probability by comparing it to the$P\ (W)$ s that were calculated using the pronunciation dictionary. By using this technique, the HMM is able to produce the text from the given speech.

We briefly discuss the statistical framework here. Current speech recognition systems are based on the principles of statistical pattern recognition. An input speech waveform is converted by a front-end signal processor into a sequence of acoustic vectors, Y=$y1$, $y2$, ⋯, yT.

Each of these vectors is a compact representation of the short time speech spectrum covering a time period. The dictionary database consists of a sequence of words,

$$W=w1, w2, \cdots, wn.$$

The speech recognition system is used to select the best word sequence$W$ for given the observed acoustic signal Y. Bayes" rule is used to implement this idea,

$$W = \text{argmaxW} PWPWPYWPY$$
$$= \text{argmaxW } PWPYW.$$

This is an optimization problem. In order to find the best word sequence$W$ to match the observation Y, this equation indicates that W needs to be selected to maximize the product of $PW$and P (Y|W). HerePY is fixed. In Bayes philosophy, PW is a priori probability of observing W which is independent of the observed signal Y. This probability is determined by a language model. P (Y|W) is the probability of observing the vector sequence$Y$ given some specified word sequence$W$. This probability is determined by an acoustic model.

B. Gaussian Mixture Model

The Gaussian Mixture Model (GMM) is one of the more commonly used functions for the HMM and is a "parametric probability density function represented as a weighted sum of Gaussian component densities". The HMM uses the Gaussian component parameters as the base classifier and acquires the temporal variations while the GMM captures the special variations. This allows it to efficiently and effectively handle time-sequences. Basically, a sequence of GMMs are used to analyse the input data for the HMM which gives it the sensitivity to temporal changes. The Gaussian Mixture model does fall short in the sense that it "prevents an HMM from taking the full advantage of the correlation that exists among the frames of a phonetic segment" because it assumes a conditional independence. Another drawback is that because it uses probability to determine the input, it can incorrectly choose the more common choice. GMMs are widely used as probability distribution features, such as vocal-tract related spectral features in a speaker recognition or emotion recognition systems. GMMs having advantage that are more appropriate and efficient for speech emotion recognition using spectral feature of speech. GMM is a powerful method to estimate the density of the acoustic vector Y. Recently in the cluster analysis, the mixture model-based approach has been widely adopted. This model is more flexible, accurate, and easy to fit into the given multivariate data set. In computation, it is very easy to handle. The conditional probability P (Y|W) requires the estimated density of Y for its computation. Therefore the HMM can be implemented to find the best word sequence$W$ to match the given the observed acoustic signal Y. Recall that,

$$Y=y1, y2, \cdots, yT.$$

For every vector yi= $yi1$⋮yid is a vector of length d. Based on Y, the acoustic signal models are fitted as the follows:

The multivariate Gaussian density function is given by

$$fy; \mu, \Sigma = 1\ 2\pi(\Sigma)\ e{-12}\ y-\mu T\Sigma{-1}\ (y-\mu),$$

whereμ is the mean vector and Σ is the covariance matrix. A Gaussian mixture density is a weighted sum of k Gaussian densities fy;μi,Σi , fy,$\mu1$,⋯,μk,Σ1,⋯,Σk = $pify$;μi,Σi ,ki=1

where the weights pi≥0 and

$$piki=1=1.$$

The GMM modelling parameters are specified by

$$\lambda= pi, \mu i, \Sigma ii=1, \cdots, k.$$

k is the number of mixture components. The GMM parameters can be iteratively estimated using the expectation maximization (EM) algorithm. A practical issue here is the covariance matrix estimators. In theory, covariance matrix is positive definite and invertible. For the given data set, some statistical methods may provide a noninvertible matrix estimator. There are many discussions regarding this issue in statistics community.

C. K-Means Clustering Algorithm:

In the Gaussian Mixture Model, the number of mixture components k has to be estimated through optimization method. Then we use K-means clustering algorithm to partition all data points into k clusters. Each data point belongs to one and only one cluster with the nearest mean in Euclidean distance. Here is the logic of the algorithm:

1) For each data point, the nearest cluster centre in is identified;

2) Each cluster centre is replaced by the average of all data points that are closed to it.

3) Steps 1 and 2 are alternated until convergence. Algorithm convergence to a local minimum.

Two practical issues need to be addressed here. First, how to select the right number k of clusters to use is often not obvious. Hamerly and Elkan present an algorithm for learning k while clustering. One simple rule of thumb is to use the square root of half data size as the number k. There are some discussions for the optimal clustering, including merging clusters and dividing a cluster into two or more clusters. In practice, around 10 mixture components will provide good performance in speech recognition system. The second issue is the k initial cluster centres. Typically, k data points are randomly selected as the staring guesses in practice.

D. EM Algorithm:

The expectation-maximization (EM) algorithm is an iterated method for finding maximum likelihood estimates of parameters in statistical models. The convergence analysis has been done by Dempster-Laird-

Rubin. Multivariate data is used fit the Gaussian mixture models via this EM algorithm. This algorithm is powerful and robust. However it does require the specification of an initial estimate of these unknown parameters with respect to the components of the mixture model. We proposes the following algorithm to derive an initial estimate of unknown parameters:

1) Using the K-means algorithm to classify all data point into k clusters;

2) Within each cluster, estimating its density mean and covariance matrix from its own cluster data points via the sample mean and sample covariance methods.

3) Using the cluster data size proportions to estimate the mixing proportions of the normal mixture model.

Here is the description of the EM algorithm. Given the observed data Y, a set of unobserved latent data or missing values Z, and an unknown parameter $\theta= \mu, \Sigma$ with a likelihood function $L\theta; Y, Z = pY, Z, \theta$. The maximum likelihood estimate (MLE) of the unknown parameters is determined by maximizing the marginal likelihood of the observed data,

$$L\theta;Y = pY\theta = \int pY,Z\theta dZ.$$

The EM algorithm seeks to find the MLE of the marginal likelihood by iteratively applying these two steps:

1) Expectation step (E step): Define$Q\theta\theta t$as the expected value of the log likelihood function of θ, with respect to the current conditional distribution of Z given Y and the current estimates of the parameters $\theta\ (t)$:

$$Q\theta\theta t = EZ|Y, \theta\ (t)\ [\log L\theta; Y, Z].$$

2) Maximization step (M step): Find the parameters that maximize this quantity:

$$\theta t{+}1 = \mathrm{argmax}\theta Q\theta\theta t.$$

With the maximum likelihood approach to the estimation of θ, an estimate is provided by an appropriate root of the likelihood equation,

$$\partial \log L\theta; Y, Z\partial\theta{=}0.$$

Under mild conditions, EM converges to a maximum of $L\theta; Y$. The key to the efficient implementation of this algorithm is the choice of an observed/missing data structure, such that the E and M steps have simple closed-form expressions.

The main difficulties in using EM for mixture model fitting are: its critical dependence on initialization; the possibility of convergence to a point on the boundary of the parameter space with unbounded likelihood (i.e., one of the m parameters approaching zero with the corresponding covariance becoming arbitrarily close to singular). If the covariance is close to singular, a non-singular robust covariance matrix estimate is proposed by to solve this popular serious problem.

6. THE VARIOUS ALEXA HEALTHCARE SYSTEMS THAT HAS BEEN DEVELOPED BY OTHER AUTHORS ARE STUDIED BELOW

System	Author	Concept	Results
Monitoring Elderly Patients With Cardiac Procedures	Irina-Mihaela Cracana, Et al	To assess the correlations between different cardiac procedures on groups of age. A group of patients with history of cardiac procedure was divided in three Age Groups. Demographic data, medical history, type of intervention and geriatric assessment were analysed in accordance with each Age Group.	The correlation between our data provide useful information about the most common type of cardiac procedure in elderly, show the most frequent causes and provides feedback regarding the quality of life after intervention.

Improving quality of life of elderly people aged 85 and older by improving treatment adherence	Ioana Dana Alexa, Et al	Therapeutic adherence represents the extent to which the patient's behaviour follows medical Recommendations. It is a complex process that strongly Influences the quality of life of the each and every one.	There were no statistically significant differences between groups A and B regarding gender (42,3% males and 57,7% females in the compliant group vs. 35,4% males and 64,6% females in the non-compliant group) and age (mean age in group A = 83,9 ± 2,9 years, whereas in group B it was 83,5 ± 2, 8 years). There was an important difference between the groups regarding income, but it did not reach statistical significance (1058, 1±902, 1 RON in group A vs. 680, 4±318, 3 RON in group 2), with p = 0, 1.
The Role of Voice Service Technologies in Creating the Next Generation Outpatient Data Driven Electronic Health Record (EHR)	Jaya Shankar Vuppalapati, Et al	Interweaving voice services generated data with outpatient Electronic Health Records (EHR) could breed new clinical pathways that are not only beneficial to the individual outpatients but can also improve overall population heath outcomes. To propose voice services integration with the EHR and aim to solve one of the most important issues in outpatient healthcare - "remote monitoring".	This paper presented a novel approach to integrate voice services with Electronic Health Records. The conversational user interfaces services such as voice services will play an important role in generating valuable outpatient data and integrating the data with EHR.
Personalized Prediction of Asthma Severity and Asthma Attack for a Personalized Treatment Regimen	Quan T. Do Et al	Control of asthma is critical for disease management and quality of life. Asthma treatment depends on the patient demographic information (e.g., age), and disease severity, which is determined by: (1) how symptoms affect a patient's daily life, (2) measured lung function, and (3) estimated risk of having an asthma attack. The proposed idea is the Tensor flow Text Classification (TC) method to classify a patient's asthma severity level. Also propose a learning method to train an agent through trials and errors to improve the prediction accuracy and create personalized treatment regimen for asthma patients.	This approach makes the system Scalable. It allows users to pose high level queries and relieves the user from the burden of deciding which resources to access, how to access them, and how to process the data.

Document Storage and Retrieval in a Neural Database	P. Parodi, Et al	It is mainly a document database, collecting papers on the leech nervous system, which is maintained in a largely automatic fashion.	This method is accurateand fast. It deals successfully with documents. with an arbitrary layout, documents where graphical features are added.
Home Blood Pressure Monitoring	Adina Carmen Ilie, Et al	Hypertension is one of the major risk factors for developing cardiovascular diseases such as heart failure, stroke, coronary heart disease, and renal failure, and one of the most frequent reasons for access to medical care. Use of blood pressure tele monitoring technique might help in improving blood pressure control and adherence, helping the quantification and definition of the psychological trait of the hypertensive patient and preventing defensive medicine expressed by un-necessary hospitalization and Interdisciplinary consults.	This method helps to monitor the blood pressure of especially elderly citizens and prevent cardiac arrests and high BP problem.
Onto Wrap-Extracting Data Records from Search Engine Results Pages Using Ontological Technique	Jer Lang Hong, Et al	Ontological technique using existing lexical database for English (Word Net) for the extraction of data records. We find that wrappers designed based on ontological technique are able to reduce the number of potential data regions to be extracted, thus they are able to improve the data extraction accuracy.	Ontological technique could extract data records effectively. It is robust in its performance. This is an advantage as the list of potential data regions for extraction of relevant data region is significantly reduced .enhances the extraction accuracy.

7. CONCLUSION AND FUTURE WORKS

DVAs enable users to control smart devices and get living assistance using voice commands. In this work, we have viewed different information retrieval algorithms that might help to develop an Alexa response system that can be used for Healthcare system. Also that we have compared different papers about the information retrieval systems and the advantages are listed. We hope Neural Network Information retrieval system will be best suited for our response system. We believe that our idea help user to get information about the Healthcare in a very quick manner. In future work we can enable Alexa skill to work on other Healthcare project that responds for other information such as behavioural activity and character of a patient.

References

[1]. Cracana, R. Stefaniu, A. Ilie, A. Paslaru and I. Alexa, "Particularities of monitoring elderly patients with cardiac procedures," 2015 E-Health and Bioengineering Conference (EHB), Iasi, 2015, pp. 1-4. Doi: 10.1109/EHB.2015.7391548

[2]. Jacek Gwizdkaand Irene Lopatovska "The Role of Subjective Factors in the Information Search Process", 2009.

[3]. D. Alexa, G. I. Prada, V. I. Donca, L. M. Mos and O. Alexa, "Improving quality of life of elderly peopleaged 85 and older by improving treatment adherence," 2013

E-Health and Bioengineering Conference (EHB), Iasi, 2013, pp. 1-4. Doi: 10.1109/EHB.2013.6707380

[4]. A. C. Ilie, A. I. Pîslaru, I. Crăcană, R. Ştefăniu and I. Dana Alexa, "Home blood pressure monitoring — One step towards reducing defensive medicine," 2015 E-Health and Bioengineering Conference (EHB), Iasi, 2015, pp. 1-4.doi: 10.1109/EHB.2015.7391466

[5]. Q. T. Do, A. K. Doig, T. C. Son and J. M. Chaudri, "Personalized Prediction of Asthma Severity and Asthma Attack for a Personalized Treatment Regimen," 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, 2018, pp. 1-5.doi: 10.1109/EMBC.2018.8513281

[6]. Irene Lopatovska, Irene Lopatovska, Ian Knight, Kieran Raines, Kevin Cosenza, Harriet Williams, Perachya Sorsche.

[7]. Ben Krause, Marco Damonte, Mihai Dobre, Daniel Duma, Joachim Fainberg, Federico Fancellu, Emmanuel Kahembwe, Jianpeng Cheng and Bonnie Webber "Edina: Building an Open Domain Socialbot with Self-dialogues", 2017.

[8]. Iulian V. Serban, Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim, Michael Pieper, Sarath Chandar, Nan Rosemary Ke, Sai Rajeshwar, Alexandre de Brebisson, Jose M. R. Sotel, Dendi Suhubdy, Vincent Michalski, Alexandre Nguyen, Joelle Pineau and Yoshua Bengio "A Deep Reinforcement. Learning Chatbot", 2017.

[9]. J. S. Vuppalapati, S. Kedari, A. Ilapakurti, S. Kedari, M. Gudivadaand C. Vuppalapati, "The role of Voice Service technologies in creating the next generation outpatient data driven Electronic Health Record (EHR)," 2017 Intelligent Systems Conference (IntelliSys), London, 2017, pp. 184-193.Doi: 10.1109/IntelliSys.2017.8324289

[10]. Colby Thomas, Ashley Collimore, Chris Franzese, Charles Hwang. Originally published in Iproceedings (http://www.iproc.org), 22.09.2017 [11] Djoerd Hiemstra "A Tutorial on Information Retrieval Modelling".

[11]. Amazon.com Help: Set Up Your Amazon Echo". Amazon.com. Retrieved 2015-03-04.

[12]. Greenwald, Will (21 September 2018). "Hands On With Amazon's New Echo Dot, Plus, Input, and More". PC Magazine. Retrieved 21 September 2018.

[13]. Veton Këpuska, Gamal Bohouta, "Next-Generation of Virtual Personal Assistants (Microsoft Cortana, Apple Siri, Amazon Alexa and Google Home)".

[14]. Poonam Patil, Rudrappa B Gujanatti, "AlexaPi on Amazon Ecosystem for Home Assistant Environment and IFTTT recipes", Aug-2017.

[15]. Matthew B. Hoy, "Alexa, Siri, Cortana, and More: An Introduction to Voice Assistants", Jan-2018.

[16]. Supriya Tambe, Trupti Waghmare, "Smart Use of Alexa with Lambda Function in Hospital", Jun-2018.

[17]. Alaaal Deen, Mustafanofaland suliemanbani-Ahmed, "Classification Based Onassociation-Rule Mining Techniques: A General Survey and Empirical Comparative Evaluation" Ubiquitous Computing and Communication. Journal, vol.5, No.3, pp.9-17.

[18]. C.Pabitha, G.Sangeetha "Refining SERP – Search Engine Result Pagefor Enhanced Information Retrieval "– IIR- IJDMTA Jan 2013

[19]. G.Sangeetha, B.Saranya "An Effective Approach for Increasing the Efficiency of Web searching with Feedback Session". IJIRSET March 2014.