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USING NATURAL LANGUAGE PROCESSING TECHNIQUES TO PROVIDE PERSONALIZED EDUCATIONAL MATERIALS FOR CHRONIC DISEASE PATIENTS IN INDIA: DEVELOPING AND EVALUATING A KNOWLEDGE-BASED HEALTH RECOMMENDER SYSTEM

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Abstract:
Health education has emerged as a significant strategy for enhancing chronic disease patients' awareness and self-management capacities. Due to the extreme advancement of information technology, the style of patient education resources has shifted from traditional papers to digital. The number of patient education resources found on the website is massive at the present, with varying quality, making it difficult for people without medical expertise to pick the most useful materials. Among the most essential components of healthcare arena in modern times is healthcare. In providing insights as well as assistance in diagnosing disease, a healthcare system needs assess of a large amount of data of patients. A healthcare system must evaluate number patient data in order to develop understanding as well as aid in disease prediction. Such system ought to be smart enough to predict a health of the patient centered on their lifestyle, patient’s history and health records, including social events. The healthcare recommender systems is rapidly establishing itself as significant area for medical services. Therefore this framework, healthcare intelligent systems are becoming an important decision-making instruments throughout the healthcare business. Their main purpose is to make sure that important data is available at the right place by assuring quality of the data, consistency, authenticity, and concerns about privacy. The healthcare recommender systems is essential for deciding consequences since people use social media to gather information regarding their wellbeing for example diagnosis, healthcare coverage, therapeutic methods based on clinical pathways, and substitute drugs regarding healthcare condition of the patient. A recent research highlights the usage of massive amount of healthcare data whereas combining multimodal data from different sources, significantly saves workload as well as expenditures in healthcare services. Whenever it relates to decision-making processes concerning a patient's condition, big data analytics and recommender systems play important part in the healthcare industry.
Patients' availability of medical data is improved when natural language processing (NLP) technologies are used to build interactive devices for diagnosis and medical. Throughout this project, a telehealth system was constructed using a chatbot services which is related to fuzzy inference and principles. The category of patients for which this system is to be used are those having chronic diseases. The chatbot and the system were connected using the Telegram Bot Application Programming Interface (API), the Bitrix API was applied to link service with a short messaging service (SMS) user. The service makes use of a knowledge base derived from medical ontologies that contains known facts about diseases and symptoms. The disease is efficiently predicted using a fuzzy support vector machine (SVM) based on the symptoms supplied. NLP recognizes the users' inputs and forwards them to the doctors for decision-making assistance. Lastly, a message is sent to the user indicating when the diagnostic process is finished. As a result, a medical diagnosis system has been developed that gives a personalized diagnosis based on user input to successfully diagnose disorders.

Keywords: Health Recommender system, Natural Language Processing, Chronic disease patients, Short Message Service

I. INTRODUCTION
Remote diagnosis solutions are getting increasingly popular as well as efficient, as they come with several benefits for example cost-effectiveness, timely and consistent judgment support is essential

for healthcare examinations, and in individuals, illness, disease, accidents, as well as other mental and physical suffering are treated and prevented. The development of remote healthcare services (or telemedicine) given through healthcare organizations corresponded with both the development of supported living systems as well as surroundings, with purpose of facilitating elderly and underserved persons to gain access to adequate healthcare services and therefore improving their clinical and health outcomes [1]. Clinical expert systems which monitor as well as govern diagnostic and therapeutic operations have become more vital as healthcare technology advances [2]. Medical diagnostic procedures which use new signal processing tools for identifying patients' physiological facts [3,4] as well as deep neural networks for decision support [5] have changed doctors' skills and education in making proper disease diagnoses when using computer-related modern technologies which is constantly improving. Due to the growth of artificial intelligence (AI) methods, Chatbots recently considered as a leading path in simplifying interaction among patients and doctors [6]. Such conversations have become increasingly popular as simultaneous text-based conversation platforms [7] are being used to carry out distant treatment strategies. Patients with severe illnesses will gain the most with chatbots which can monitor overall health, provide reliable, current data, as well as prompt them to take their medicine on a regular basis [8]. Regarding effective use of chatbots throughout the medical sector, advanced reasoning abilities centered on the formalization of health information (semantics) as well as the general health of patients, and also English vocabulary and dialog engine, is needed [9].

Chronic (or non-communicable) diseases are the most common and expensive diseases in the world. To increase the rate of survival as well as standard of living of patients with chronic diseases, self-management over a long period of time, guidance, plus clinical intervention all are recommended. However, due to a lack of requisite information, skills, and confidence, some patients may not undertake efficient self-management regimes in practice, resulting in reduced treatment effectiveness or even treatment failure. In the treatment of chronic illnesses, education programs provided by health care professionals has been seen as an important intervention for increasing patient knowledge as well as self-management abilities. The growth of eHealth-improved chronic disease management has been supported by advances in IT (information technology) that has led to a change from outdated manual to digital patient instructional materials. Patients can choose between getting specialist data from their clinicians and educating according to their own through website. There are currently a massive proportion of patient teaching materials available on the web; nevertheless, the quality of the health information in these materials varies greatly. Patients without a medical background may struggle to find the most useful and relevant items for themselves. A device capable of simultaneously recognizing as well as presenting adequate support to individual patients on actual requirements or choices could be effective in addressing the listed difficulties. Such sort of information is referred to as a health recommender system (HRS).

A. Health Recommender System

1. Preliminaries and Recommender System Basic Concepts

Two main entities, patients and products, play critical roles in recommender systems. Patients report personal choices regarding particular products, as well as the information collected should be used to find their choices. The information is organized into a utility matrix, with values within each patient-item connection representing the person's ability of desire for certain items.

In this respect, there are 2 sorts of recommender engines: based on patient and based on item. In a recommender system based on patient, patients submit actual preferences including evaluations of items [52]. We can propose a certain things to a patient who still hasn't evaluated it using a recommender engine based on patient, centered mostly on patients' commonalities. Recommender system based on item, we use the similarities among things (not patients) for generate recommendations from patients. The initial step in prediction is to collect data for recommender systems [53].

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The areas of expertise of recommender systems are HRS, which tries to suggest appropriate health information to patients or healthcare professionals or [22]. There's been a number of researchers on HRS formulation and construction, with recommendations in domains like diets [23], insurance services for health care [24], instructional methods [25], and decision-making advice for doctors [26]. Pincay et al [27] divided HRSs in 4 groups: wellness, diagnostic and medicines, medical services, as well as health resources. The area of healthcare resources includes patient instructional items. The objectives of this research has been to create an HRS to offer patients with severe disorders using specialized instructional materials, considering that just 3% of studies [27] concentrated here on subject.

The recommender system that forecasts as well as suggests suitable things to patients, is built on predictive modeling. This method can be used in a variety of situations. Health informatics is a subset of big data analytics that can be used to improve HRS. The recommender system based on health seems to be a decision-making platform which enables both medical experts as well as end-users with relevant medical records. Patients can benefit from extraction of useful data for diagnostic criteria and the distribution of increased health treatments for sick people, as well as healthcare providers advantage from collection of useful data for treatment guidelines or the distribution of lots of health therapies besides sick people to use this framework. The HRS must be reliable and trustworthy for the patients to get benefit from all this.

2. Recommender System Stages

(1) Information Gathering Stage: Important data of patients is acquired throughout that phase, and a patient record is based primarily mostly on patient's characteristics, behaviors, as well as resources accessed. A recommender engine cannot function correctly without creating a well-defined patient profile.

A system of recommender is built on data gathered in a variety of ways, such as explicit, implicit, and hybrid evaluation. Explicit response gathers information from patients based on their interest in a particular item, whereas implicit feedback gathers information from patients indirectly by observing their behavior [50].

(2) Learning Stage: This stage comprises the prior stage information as input and generates a learning algorithm that utilize that patient's traits for outputs [50, 51, 54].

(3) Prediction/Recommender Stage: Patients in this phase are given recommendations for preferred goods. This process comprises the prior phase's information as input and generates a learning algorithm that utilize the patient's traits for outputs.

In the graphic below, the stages of recommender system are depicted:

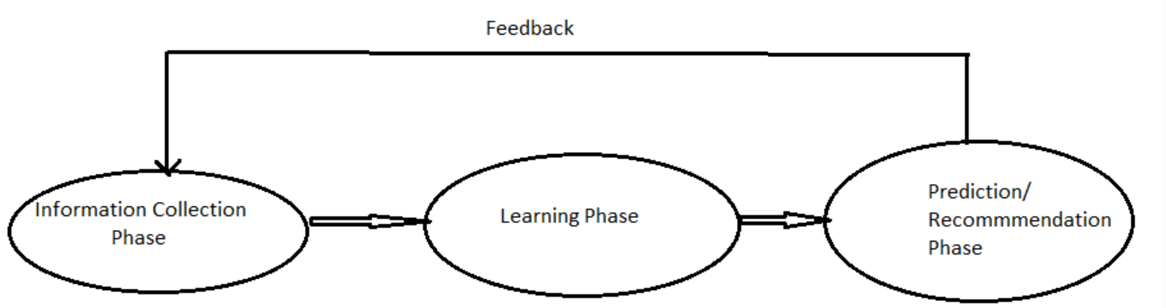

Figure 1: Recommender System Stages

3. Natural Language Processing (NLP)

NLP technology can help computers and humans connect by extracting knowledge from unstructured free text by means of analysis of linguistic and approaches of deep learning [10]. Mostly in aspects of information collection, NLP systems have proved its significance as well as creativity, especially notably throughout the extraction and analysis of large volumes of unorganized patient information and also the delivery of data structure through user-defined requests. The system of NLP aims to reflect explicitly the knowledge provided in natural language text. Given the massive amount available text-based data which may be gathered through self-narration of patients, NLP techniques in diagnosis of diseases are still underutilized [11]. The primary challenges handled by NLP for patient history are adaptable design, peculiar parts of speech (POS), structure without sentences, words as well as punctuation that should be there but aren't, medical jargon, and spelling mistake [12]. Medical writings are difficult to comprehend due to linguistic elements such as co-references [13]. Furthermore, distinctive language features like medical abbreviations which is a more difficult to derive knowledge using medical books [14].

This study describes how the NLP model was used to increase self-assessment of health as well as decision assistance in electronic healthcare organizations using an SMS and a chatbot system. The adoption of electronic medical records (EMRs) in hospitals as well as on the internet [15] also led in a vast number of data to be investigated, and the retrieval of data from EMR is a growing area of importance in healthcare. An EMR is a computerized database information related to health which healthcare experts develop, gather, and maintain [16]. The problems of accumulating existing and relevant medical information include mixing NLP into several EMRs, confirming the security as well as privacy of patients' information [17], as well as medical evaluation of a device. Most of these problems would conduct healthcare efforts to investigate patient care challenging. Moreover, by analyzing text book of complaints stated by patients, adopting NLP techniques for reviewing data as well as assist medical professionals in their assessment will be a major step forward towards effectively upgrading medical care.

II Literature Review

Langer et al. [18], for example, employed a combination of NLP tools and classification approaches to deal with drug-related issues. They came up with a language-based component that allows users to ask inquiries as well as obtain an exact response in around 81 percent of questions related to drugs. Pendyala et al. [19] developed a program that enables machines to conduct life-sustaining tasks. The research focused on health diagnosis, as well as a study was performed to establish the link among information extraction and text analytics along with the difficulty in medical diagnosis. The suggested technique, as per the results, will help accomplish the objective of providing a comprehensive diagnostic testing. Fernandez-Millan et al. [20] proposed an expert system based on rules for diagnosing laboratory test results based on a list of potential disorders. The authors concluded that the proposed method improved clinical accuracy and speed, resulting in increased efficiency and service quality. Having F-scores of 0.963, 0.838, and 0.952 for Hungarian, French, and Italian, however, Atutxa et al. [21] used deep learning models for retrieving codes of ICD using death records presented inside a normal linguistic form. Having 91.8 percent accuracy as well as 86.9% memory, Combi et al. [22] proposed a NLP technique to convert linguistic form statements of drug reactions to MedDRA common term. Evans et al. [23] used 0.891 as well as 0.708 precision to categorize occurrence type and degree of consequence in unrestricted patient care witness statements Kloehn et al. [24] generate interpretations for complicated healthcare words in English and Spanish using WordNet substitutes and summarization, and the term embed vectors like a form of information. For an aggregate F1-measure of 0.89, Sarker et al. [25] used fuzzy logic as well as set theory-based techniques to recognize proper thoughts in medical checks from a limited percentage of annotation instances of unorganized responses. Zhou et al. [26] applied deep learning models which had been pre-trained using text documents research to create competence for extracting data from published publications. Lauraitis et al. [27] used input text using a mobile application to measure motor and cognitive impairments in individuals with indications of central nervous system (CNS) illnesses as portion of self-administered cognition assessment evaluations.

The creation of healthcare domain-oriented interactive chatbots has been studied by a number of academics. These AI-powered conversational agents may assist patients' with mild health problems yet freeing up clinicians to handle very severe patients [28] or discover suitable donors [29]. Patients having chronic diseases such as obesity, hypertension, or diabetes must use a chatbot-powered healthcare system to react promptly to everyday difficulties and also improvements in overall state of health [30]. For example, Ahmad et al. [31] developed a chatbot which can suggest various medicines to consume depending on the information of the user. Avila et al. [32] developed a chatbot which seeks again for lowest drug prices then recommends the best alternatives. Bao et al. [33] suggested adopting a hybrid method that incorporates a graph database as well as a text similarities analysis to create a system of responding medical questions through HBAM (Hierarchical BiLSTM Attention Model). Chaix et al. [34] developed a chatbot for women with breast cancer aimed at providing assistance and responses to any inquiries regarding their condition, and to encourage patients to consume respective medicines as recommended. Denecke et al. [35] developed a mobile application with chatbot that apply cognitive behavior treatment characteristics to help people with mental illness cope with difficult situations. Harilal et al. [36] developed a chatbot system to promote empathetic conversations, identify related emotions, as well as deliver health advice to depressed individuals. Huang et al. [37] developed another AI-powered chatbot to encourage a healthier life to help in losing weight. Furthermore enhance the chatbot's understanding for guiding people with diabetes about diabetes treatment, Hussain and Athula [38] constructed a chatbot which collects information from Wikipedia by using the Media Wiki API. Kökciyan et al. [39] merged information through healthcare insurance devices, electronic medical records, as well as clinical recommendations with a conversation chatbot which provides extra medical information depending on an argumentation-based discussion. A experience and understanding primary healthcare chatbot method is presented by Ni et al. [40], which features an analytic NLP-based engine for deciphering patient symptom reports, a rationalist for matching signs to possible explanations, and a query maker for producing further conversation queries. Zini et al. [41] developed a digital patient which can be used to educate health professionals regarding patient inspection using a conversational agent related to a deep learning architecture.

Techniques of machine learning (ML), especially SVM, results showed potential in categorizing free text in health information, including Georgian language [42]. SVM using a polykernel has been used to classify the information and intensity of primary healthcare patient care occurrence records [23]. Furthermore, the researchers state that simplifying definitions as well as expanding training dataset of different categories will help the system improve and develop. Deep learning algorithms were proposed by Zhou et al. [26].

III Methodology

A. Architecture Outlay

The research examines the medical documents demands as well as necessities for patients that have chronic diseases. With this inquiry, there is a corpus of patient instructional content obtained from a variety of resources, and also a patient information dataset obtained through a tele-health network. The purpose of this study was to implement and evaluate an automated recommender system which might predict a patient's needs in the future related to nutritional information and afterwards suggest a most relevant learning information to patients. We also wanted to sort out how to evaluate the network efficiency.

These tasks guided the study's design. The overall study design is depicted in Figure 2. The dotted box depicts the entire recommendation process. The Patient Education Ontology for chronic diseases is a bespoke ontology that describes patient attributes for suggestion creation, lies at the heart of the recommendation process. The steps in the suggested text-based clinical diagnosis process are as follows: (1) knowledge base description; (2) text-based document preprocessing; (3) document tagging; (4) answer extraction; and (5) rating of candidate answers

The Python language was used to build the diagnosis system framework because of its cross-platform capabilities as well as wide availability of modules to third-party for ML and processing applications of natural language. To use the ML, the system uses Python library modules and natural

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language processing functions required for categorization. The system will be evaluated using a test collection of educational resources that will be manually assembled by domain experts.

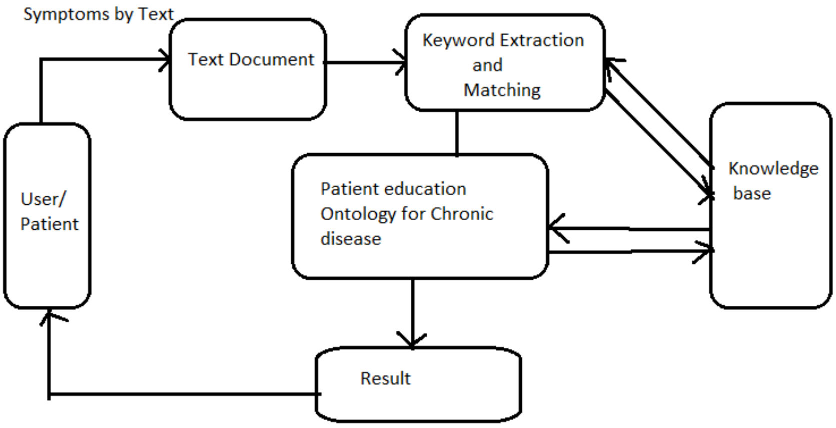

Figure 2: Architecture Proposed

A framework is required for collaborating with healthcare professionals, surgeons, doctors, and patients to create a health system. The framework's architecture is broken into following sections - collection of data collection, transformation of data, analysis of data, and lastly visualization. The very first step is to gather information. The medical system's sources of data are categorized into two types:

(i) Structured data (organized data with an established structure, format, and type of data) and unstructured data (unstructured data without a preset format, data type, or structure). Sensor-generated data, data on different illnesses, details on specific symptoms as well as treatments, results from the lab, medical status of the patient, prescription medication, X-ray, and lastly CT Scan are examples of such data.

(ii) Semi-Structured Data: Information which does not fit into a database schema and yet is structured enough to facilitate for effective patient behavior monitoring.

(iii) Unstructured data: Information with no clear organization, such as medications given in human languages, notes on research, summary of discharge, and so on.

Healthcare is a perfect example of how well the 3 Vs of information, velocity, variety, and volume, are deeply embedded inside the information providers produce. A vast amount of documents is shared among multiple medical systems, healthcare companies, hospitals, academicians, government organizations, as well as other groups. Prescriptions, medical information, medical records, information of patient, X-rays, vital symbols, CT scans, fingerprints that are biometric, prescriptions from doctors, and various other sources of data are used. Healthcare automation systems in the form of computer intelligence which provides guidance in almost the same manner that experienced professionals do, using reasoning techniques with domain-specific information. We must first understand the various sorts of suggestions, just as we must with any other recommender domain. The following are the many categories:

(iv) Nutritional Data: Creating suggestions to improve nutrition. Here, the doctor may alter a patient's eating habits to ensure that he or she receives adequate nourishment in order to make a full recovery from a medical condition. Well-balanced diet, replacements for foods, eat less spicy food, and additions to your diet are all possible recommendations.

(v) Physical Exercise: Depending on the needs of the patients, producing suggestions with what type of meditation and regular exercise patients must perform to improve their recovery. Location, disease-related, weather, and other factors may be important to the patient.

(vi) Diagnosis: A doctor's recommendation for a patient's diagnosis related to symptoms observed in same circumstances.

(vii) Medication/Therapy: Making suggestions for different kinds of medications for certain ailment or specific treatment of patient.

B. Knowledge Base

In a question and answer system, the fundamental data source is the level of expertise that can be both structured and unstructured. To develop the knowledge and understanding, which would be known as illness contextual understanding, data from a healthcare database was collected as well as organized into classifications.

As shown in Figure 3, a three-layer model that is DSP (disease-symptom-property) has been adopted and was first proposed in [55] for knowledge representation. The information is kept as triples that is symptom, disease, and property throughout the database system, as well as the computing system is based mostly on illness compasses [56], that enables for disease causal network research. The knowledge base contains information, common problems faced by patients having chronic illness and common remedies for them. Different data are stored as to support patients having chronic diseases. All the information included in this has been based on doctor advises, case studies conducted and so on.

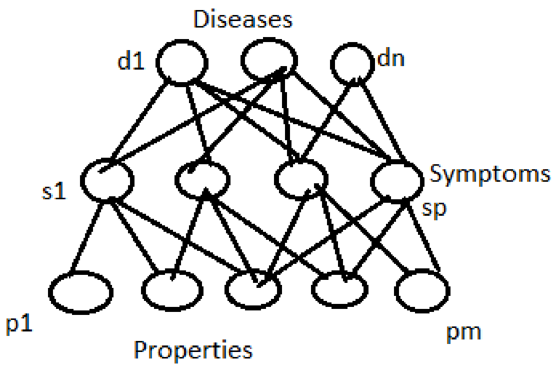

Figure 3: Data Analysis Process Framework

The data analysis process is the framework second component. Health-specific recommendations can be generated during the data analysis process. Let's start with the patients who will be using this domain. Medical researchers, clinicians, and patients are the system end-users.

C. Communication

The communication system was built on a knowledge base to allow consumers to communicate with the medical practitioner via implementing a criteria of question and answer in SMS or telegram. Every diagnosis inquiry has a unique set of features and attributes that provide more context for the request. The following are the many attributes of a request/question:

(1) Question related to Diagnosis: The exact question of diagnosis which perhaps the client will ask.

(2) Response: The client may see a series of statements which indicate the responses which they might give to system through SMS or Telegram GUI.

(3) Serial id: The question should be asked in this order.

(4) Question Types:

(i) Information collection questions:

Basic user questions include age, gender, weight, height etc. Algorithm model is shown below:

```
def question _data ()
return {
'patient_age':{
'diagnosis_query': "what is your age?"
'diagnosis_response: ['below 18', '18 – 25', '25-40', '40 – 55', '>55']
'serial_number:1'
```

(ii) Symptom related queries:

Yes or no questions were presented relating to common symptoms along with a line for description of the symptom. There are two types of questions in this category:

(i) Questions to elicit a diagnosis: These are questions being used to see how symptoms develop.

(ii) Diagnosis Questions that are linked: When the answers by users is 'yes' to the targeted symptoms questions, those queries are being used to collect more information about ailment.

D. Content Extraction

The content package is in charge of extracting content information from SMS messages. The package includes various distinct extractors of content that specialize in taking out various data types through SMS for your convenience. The NLP package is used by the content extractors to do text processing. Whenever a patient transmits an SMS explaining their problems, the system SMS receiver obtains this and delivers the message (SMS body) to a NLP modules that evaluates it, adjusts it as needed, as well as collects important keywords.

Three primary processes are included in the text processing operations: noise removal, tokenization of document sentences, and sentence splitting. Keyword matching is done against the database or knowledge base.

E. Fuzzy Module

Its primary function is to use algorithms based fuzzy logic [68] to evaluate and understand the answers of users, track and manage most of the signs/symptoms to which the user already has responded, ultimately ask them the most important queries depending mostly on illness datasets. A bucket represents all ailment, with every bucket representing a sign/symptom. To deal with multiple symptomatic disorders, appropriate fuzzy rules are developed. The following is how the procedure is carried out (Figure 4):

(1) Fuzzification: The sharp inputs get converted to fuzzy values.The degree of membership function is determined by expert judgement. Throughout fuzzification, a fuzzy rule/variable receiver takes data input as well as assesses it by using membership function parameters.

(2) A fuzzy definition database and a fuzzy IF-THEN rule base make up the knowledge base. The information structure is composed of a fuzzy definitions databases as well as a fuzzy IF-THEN rule base.

(3) Inference Engine: Uses the supplied data to apply the necessary fuzzy rules.

(4) Defuzzification: Creates crisp output values as a result of fuzzy values.

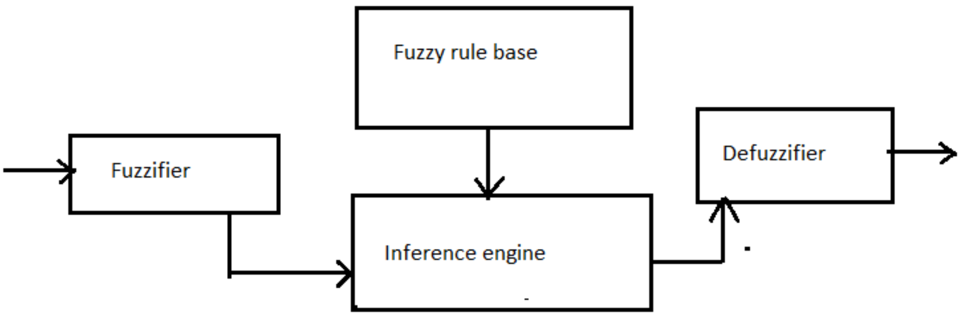

Figure 4: Procedure of Fuzzy Module

F. Graphic User Interface/ Application Program Interface

The system initiates a conversation with user/patient in order to know something about their primary private information, for example weight, height, gender, and age. After you've gathered the preliminary information, you can move on to the next step, the second stage, which involves querying the patient for symptoms using the algorithms described above is executed. The Telegram API was used for the GUI design, along with a bespoke keyboard that the Telegram API also provides.

Text messages, request, as well as response are included for communications since the application doesn't really need a Connection to the internet and is suitable among all smart phones. The python-telegram-API service includes a Python framework for communicating only with Telegram API. It makes it simple to create method hooks that are activated anytime the Telegram chatbot executes a function. Furthermore, the program makes a query to Bitrix24 communications API for SMS text message format servers for incoming queries that further sends response to logical layer for dealing out and performance to users/client. The Python wrapper that executes message with the Bitrix24 API was the python-Bitrix24-communication-SMS-API module.

IV. RESULTS

The results obtained are discussed under the following subsections:

A. Data Collection: The data with this investigation was obtained from a healthcare facility, and an interview was done to extract written content from experts and others who knew a lot about chronic illness. The collected text material was subsequently saved to the system's local file.

B. Participants: Sampling was used to select responders. According to the selection criteria, participants must have recently been diagnosed with some chronic disease and have the interest in the research being done. To be eligible for the survey, Individuals who did not meet any of these inclusion requirements were not allowed to participate. In addition, full disclosure was given to the participants regarding the use of data and the ethical consent was obtained for this. The data used to create the system was chosen as a result of some people's personal experiences with the disease.

C. Results Evaluation: The Bilingual Evaluation Understudy (BLEU) score [57] to assess the performance of the generated service, this has been a common criterion for assessing chatbot services. The BLEU-2 algorithm, that compares generated and source texts using unigram as well as bigram similarity. The BLEU-2 algorithm, which relies on unigram and bigram matching between the created and reference texts. The ROUGE-L (Recall-Oriented Understudy for Gisting Evaluation) measure has also been used, that is centered mostly on LCS (longest common subsequence). BLEU-2 has a score of 24.56, while ROUGE-L has a score of 32.23.

D. Usability Survey: The participants of the research, at the end were provided with a questionnaire for obtaining their feedback. A Likert scale was used to determine the convenience use of a network in the system usability scale examination (The scale ranges from strongly agree to strongly disagree on a five-point scale). The usability test had 30 participants, 11 females and 19 males, with 2 below 18', 9 being '18 – 25', 14 in the ages '25-40', 3 being '40 – 55', 5 being '>55 age group. Each session of the usability study lasted less than 45 minutes. The participants were given information booklets about the study and asked to use their smart phones to access with chatbot. The answers have all been kept anonymous.

The responses obtained are expressed in a pie chart as shown below. The numbers 1, 2, 3, 4, 5 show the percentage of participants ranking in the Likert scale.

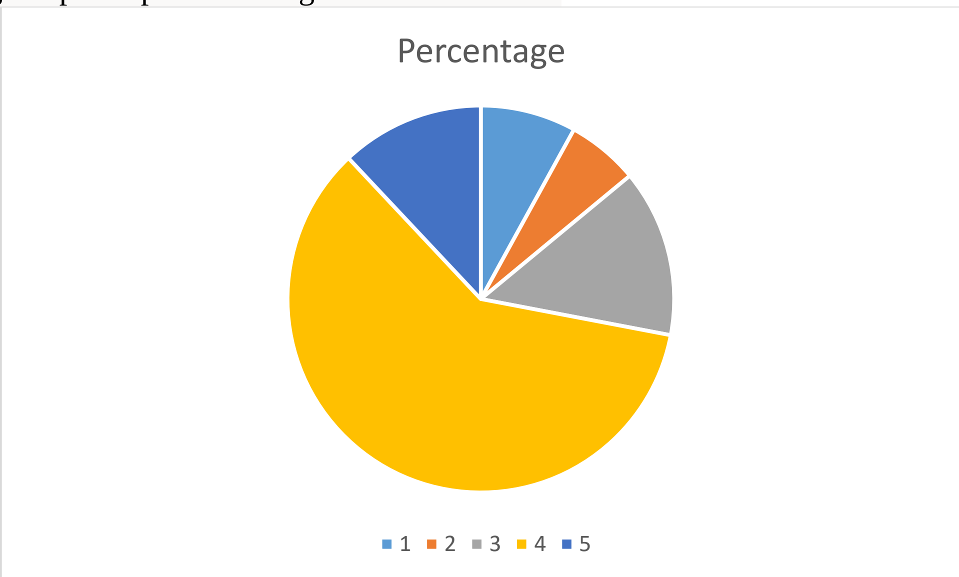

Figure 5: Pie Chart

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The survey showed that majority of the users found the system developed to be useful.

V. CONCLUSION AND FUTURE SCOPE

A knowledge-based recommender systems can effectively suggest healthcare educational materials to patients with chronic diseases, according to this study. Through the ontology, patient attributes can be linked to document themes. For processing instructional content, NLP approaches such as extraction of keywords and the usage of pre-trained word embedding was found to be beneficial. However, given the growing development of users of mobile as well as the demand for a real-time disease detection assistance instrument, it's vital to look at the requirement for a low-cost telehealth platform that enables for early detection of diseases and patients (users) communicate with a diagnosing system (remote doctor at proxy). This study was able to construct a text-based clinical diagnosis structure which provides a personalized diagnostic through using user self-input to offer a diagnosis of the disease stated in the research criteria. The suggested solution of SMS as well as Telegram bots has been able to combine machine learning techniques and NLP. This system helps in suggesting a treatment by taking a particular approach to the issue and response method.

This system can be used in basic treatments and commonly faced issues by chronic disease patients. However, this system cannot replace the necessity of a doctor's consult when more complexities arise which can said as a limitation of this research.

Future recommendations include automating this medical diagnosis system to make it easier to diagnose ailments, prescribe treatments, and track medication adherence. To make the system more interactive, audio interaction will be added. These enhancements will help to reduce costs and death rates, as well as the workload of medical doctors in disadvantaged areas. Further research might look into the usage of other cutting-edge NLP approaches in HRS to improve precision, or look into the impact of such systems on patients in a real-world setting.

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