DocBot: A Novel Clinical Decision Support Algorithm

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Abstract— **DocBot is a web-based clinical decision support system (CDSS) that uses patient interaction and electronic health record analytics to assist medical practitioners with decision making. It consists of two distinct HTML interfaces: a preclinical form wherein a patient inputs symptomatic and demographic information, and an interface wherein a medical practitioner views patient information and analysis. DocBot comprises an improved software architecture that uses patient information, electronic health records, and etiologically relevant binary decision questions (stored in a knowledgebase) to provide medical practitioners with information including, but not limited to medical assessments, treatment plans, and specialist referrals.**

I. Introduction

A clinical decision support system (CDSS) is an application that provides clinicians, patients, or other particular entity with patient-centric knowledge to help medical practitioners in their decision making [1]. Historically, CDSSs have been used to help with diagnosis – beginning with the Pathfinder project by Heckerman which was designed to help pathologists diagnose lymph-node diseases [2].

In an age of big data analytics and a rise of health informatics, each hospital is sitting upon a gold mine of information that can be mined and anonymously used (to comply with regulations set by HIPAA, the Health Insurance Portability and Accountability Act) to improve clinical diagnoses and prevent misdiagnoses. With the permanent adoption of electronic health records (EHRs) in the U.S., this ever-growing treasure trove of medical information is extremely powerful.

Throughout the years, CDSSs such as the Pathfinder have developed, both in its algorithms [3-5] but also in its complex features from administrative tools [6] to applications in evidence-based medicine [7]. In particular, Heckerman and Nathwani found that all diseases should be represented mutually exclusive and exhaustive, and that the diagnostic abilities of CDSSs are essentially only as accurate as the expert [5], or data that is used. With the development of natural language processing algorithms (NLP), CDSSs can more easily model a human physician's mental thinking procedure and naturalize the CDSS [8].

It is crucial that this information be readily available as it is intended to not narrow down the process in which a physician determines a diagnosis (current technology isn't capable of full diagnosis and should be used to assist a physician), but rather act as a computer-aided tool that can look at angles a physician may have missed and will point a physician to the right direction – a blanket diagnosis. A too-narrow interpretation might hinder a physician's perspective. DocBot also builds on prior art by displaying two crucial elements to a diagnosis: optimal treatment options and specialist referrals [9].

II. Materials and Methods

DocBot closely simulates medical algorithms and a physician's decision-making process and is capable of the following features:

- A medical assessment of the patient's condition (blanket diagnosis) using EHR data analytics that the physician can use to guide his/her diagnosis.
- Treatment options and medical tests/procedures based on EHR data of past patients, of which the patient and/or medical professional can decide on the most optimal decisions.
- Medical specialist referral based on a patient's desired, physician suggested, or related treatment option.

A. User Input

The program utilizes a simple interface that requires the user to enter standard demographic information (age, sex, height, weight, ethnic background) and presenting problems (reasons for visit, symptoms, region of body affected). The patient will select demographic information, such as off a checklist, but is allowed to freely type in their symptoms in the present problems input. There is an autocomplete option with recognized symptoms to help guide the patient.

Presenting problems and symptoms are required fields, because they narrow down the EHRs the program has to search through. Demographic information is of secondary importance to the program as it can help narrow down diagnostic interpretation (for genetic or demographically dependent illnesses) and also helps determine optimal treatment options based on EHR profiles of previous patients.

This is the first DocBot interface and can only be viewed by the patient who accesses it through a unique URL. On this particular interface, the patient will be able to access a form on which he/she will enter his/her primary input as well as answer an etiologically-relevant questionnaire.

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B. Natural and Medical Language Processing

The presenting problem (chief complaint) input is partitioned into an array of key words and their auxiliary descriptions and each element is divided using a simplified Viterbi algorithm. This array of medical terminology is converted into a standard lexicon which is then parsed through a disease knowledgebase (of symptoms and correlating illnesses) to score each potential illness based on patient input.

DocBot parses the patient's symptom array through the hospital's or clinic's anonymized EHR database to find previous profiles with similar presenting problems and demographic information to arrive at a blanket medical assessment, treatment options, and medical specialist referrals.

C. Etiologic Questionnaire Knowledgebase

DocBot extends the capabilities prior art by interacting with the patient, as a doctor would, by asking etiologically-related questions from a questionnaire knowledgebase. These questions are binary decision trees although DocBot does ask other standard questions that healthcare professionals must ask (i.e. "On a scale of 1 to 10 how bad is your pain?"). Back and forth patient interaction is an extremely powerful tool that can immensely improve the precision of a blanket diagnosis. For example, it would be extremely difficult for a symptom checker or current CDSS to determine whether chest pain is due to a musculoskeletal, cardio, or pulmonary condition. Clinically, doctors would ask distinct questions (such as "Do you experience difficulty breathing") that would easily determine a blanket diagnosis. Following an established blanket diagnosis, retrieving treatment plans, tests necessary, and specialist referrals becomes a much quicker task. Furthermore, asking particular questions can help determine whether or not a patient's condition is due to familial origins or acquired during a patient's lifestyle.

The etiologically-related questions are stored in a questionnaire knowledgebase in a JSON-like format (Figure 1). Each question stored in the knowledgebase has a binary response and each response is weighted. Non-binary questions are procedural and are required. These questions are designed to be identical to those a physician or mid-level practitioner must ask and they are also designed to help the DocBot algorithm.

```
{"Disease1": {
  "id": "disease_ID",
  "Question": "Example question",
  "Answers": {
    "weight": [ {
      "Yes": "0.8",
      "No": "0.2"
    }]
  }
}}
```

Figure 1. A sample question in JSON format.

The less information the user provides the program, the more questions the program would have to ask in order to reach a definitive blanket diagnosis.

All combinations of questions and answers the program capable of asking and understanding are manually created and are stored in a separate database.

D. Medical Specialist Referral

Another problem many primary care physicians, nurses, physician's assistants, and patients face is that they simply do not know the right medical specialist – this will be increasingly difficult as the program offers an array of treatment options the patient may choose from.

Because the program relies on the clinic's EHR database, it is able to, depending on results, decide and refer the physician and patient to the appropriate medical specialist (presumably of that hospital) depending on the chosen treatment option.

E. Scoring System

Unlike most CDSS's scoring systems, which often match entered symptoms to generic textbook symptoms of illnesses and divide them by total generic symptoms (so 6 symptoms matched out of 7 would provide a confidence of 85%), DocBot uses a more natural, physician-like approach. It uses symptoms to agilely parse through an EHR database and demographics to potentially narrow down results. With an ordered array of potential illnesses, the program parses through a question database which it uses to finalize a medical interpretation. Once blanket assessment is decided, it aligns previous treatments in EHRs to determine all available treatments. Ultimately, this is to broaden the physician's perspective and patient's choices.

DocBot relies on symptoms the patient initially provides the program to create a general understanding of the patient's presenting problem. Instead, the blanket diagnosis relies heavily the patient's response to the questionnaire knowledgebase to discover more information and a patient's demographics is heavily used to extract data from similar EHRs.

F. Results and Display

After narrowing down the list of prospective illnesses to a blanket diagnosis several or less potential conditions, the program then ranks them in order of probability and displays them to the medical practitioner. Like the patient interface, this display can only be accessed by the appropriate medical practitioner(s) who are notified either by email or a patient portal (if applicable).

Based on which past EHR profiles the program is able to align a patient's symptoms with, the program is also able to find similarities among treatment procedures and patient outcomes, and would be able to inform both the doctor and patient. For example, if a certain medical procedure has produced a lower chance of remission, this information will be noted. This helps inform patients as well as even eliminating blind spots novice doctors may have.

Information displayed consists of the patient's demographic information, medical information, questions DocBot asked and the patient's response, and an interactive GUI that shows a branch of potential illnesses, treatment options, and specialists involved.

Due to current limitations of the program, such as being unable to analyze complex x-ray images or interpreting a patient's dermatological conditions the program is unable to determine specificity or severity of a condition and currently would serve to provide blanket diagnoses.

G. Administrative Tasks

Additionally, many CDSSs have evolved to perform administrative tasks including entering information into an EHR system or aiding with hospital-patient communication.

DocBot in particular receives the aforementioned patient input and stores that in a hospital's EHR system. DocBot helps eliminate the need for a patient to fill out a lengthy preclinical test in the waiting room.

Furthermore, having patient details prepared preclinically will aid physicians during an actual appointment by not forcing the medical practitioner(s) to ask the same questions repeatedly. This allows for a more efficient transition of care between the patient and multiple physicians or mid-level practitioners,

TABLE I
COMPARISON OF DOCBOT WITH OTHER CLINICAL DECISION SUPPORT SYSTEMS

Disease	Correct Assessment Clinical Decision Support System				
	DocBot	Isabel	WebMD	Esagil	SymCAT
Addison's Disease	1.0	1.0	0.0	0.0	0.0
Cushing's Syndrome	0.5	0.0	0.0	0.0	0.0
Graves' Disease	1.0	0.5	0.5	0.0	0.0
Hashimoto's Thyroiditis	0.5	0.0	0.0	0.0	0.0
Klinefelter Syndrome	1.0	0.5	0.0	0.0	0.0
Menopause	1.0	1.0	0.0	0.0	0.0
Pituitary Tumor	1.0	0.5	0.5	0.0	0.0
Prolactinoma	1.0	0.5	0.0	0.0	0.0
Sheehan's Syndrome	0.5	0.0	0.0	0.0	0.0
Turner Syndrome	1.0	1.0	0.0	0.0	0.0
Average	0.85	0.50	0.10	0.00	0.00

H. Testing Procedure

DocBot's demos are run on a sample electronic health record database consisting of fake patients with randomly generated endocrinological diseases (10 patients for 10 common endocrinological diseases; total of 100 data points) and randomly generated symptoms, correlating to each disease. The ten endocrinological diseases are: Addison's Disease, Cushing's Syndrome, Graves' Disease, Hashimoto's Thyroiditis, Klinefelter Syndrome, Menopause, Pituitary Tumor, Prolactinoma, Sheehan's Syndrome, and Turner Syndrome. Ten patients, each corresponding with the above conditions, were generated to test DocBot's algorithms against those of other clinical decision systems.

Since most of these symptom checkers and CDSSs produce more than one medical assessment along with one confident assessment (usually with a percentage), we gave each CDSS a score of 1.0 if the confident assessment was correct, a score of 0.5 if the confident assessment was incorrect but one of the other potential conditions was correct, and a score of 0.0 if none of the assessments were correct.

III. RESULTS

We scored and averaged the results of DocBot and CDSS (Table 1) based on the ability to generate an accurate blanket diagnosis. DocBot received an average score of 0.85: 7 correct confident assessments, 3 correct likely assessments (the confident diagnosis was incorrect), and 0 missed assessments. Isabel, a clinical CDSS, received an average score of 0.50: 3 correct confident assessments, 4 correct blanket assessments, and 3 missed assessments. WebMD received a score of 0.10: 2 correct blanket diagnoses, and 8 missed diagnoses. Esagil and SymCAT received scores of 0.00: all 10 diagnoses were missed.

Additionally, it was noticed that of the aforementioned CDSS/symptom checkers, the majority provided some arbitrary percentage of confidence. Only SymCAT used real user data albeit the data being from previous users rather than real EHR patient data. Isabel was the only CDSS that provided the user (patient) with useful links. Isabel and SymCAT allowed for natural patient input rather than a checklist. Esagil was the only CDSS to provide medical tests and suggested course of treatment in addition to potential diagnoses.

IV. DISCUSSION

According to Table 1, DocBot was able to correctly interpret the symptoms to the correct illness, in addition to providing treatment options, and specialist recommendations.

Among the aforementioned symptom checkers, WebMD follows a linear process in which the user chooses options and answers questions until the algorithm is able to narrow down symptoms. Esagil requires the user to choose 1 to 15 symptoms in a dropdown button, which gives the user a choice of 258 symptoms to choose from. Isabel and SymCAT are different in that they are differential – the user is able to type in symptoms without having to choose from a list or checkbox.

Through the comparison, we noticed that the scoring algorithms and human-like understanding of these symptoms are sorely lacking. For example, WebMD, SymCAT, and Esagil all provide arbitrary percentages of confidence. However, WebMD's and Esagil's scoring matrices are not exclusionary, meaning if there is a high match between several conditions, the artificial intelligence isn't able to distinguish them. SymCAT's scoring matrix is hard to decipher as the program follows machine learning (depending on previous profiles of past users), but returns highly unconfident results.

Another crucial shortfall of these symptom checkers is a lack of personalization in treatment and outcomes due to use of textbook information rather than real medical data. SymCAT is a slight exception since it uses previous engine entries to guide its decision making.

V. Conclusion

A growing trend has people searching the internet for health diagnosis and guidance. However, this may prove to be a difficult process because ordinary people are not trained in medical terminology, and online sources are either unreliable or impersonalized.

To combat this, an online non-linear medical assessment platform was developed and that takes demographic information and presenting problems as patient input and interacts with user by prompting more questions to reach an accurate diagnostic interpretation.

DocBot is able to parse through EHRs of individuals with similar conditions to determine available treatments, corresponding outcomes, and even medical specialist referrals. This gives the patient and medical practitioner more (guided) power in deciding their best treatment and provides them the available resources and medical specialists.

Through comparison with other similar symptom checkers available, including one that is supposedly used by doctors (Isabel), it was found that current symptom checking programs and clinical decision support systems can be inaccurate, mostly because they are not built to model a physician's mental diagnostic process.

More backend algorithms will be implemented to undergo user-uploaded image processing and feature detection, and real-time webcam analysis. In future research, the program is continually being tested for accuracy and impeccability with professionals in specific medical areas.

In future development, this can potentially make DocBot a very powerful triaging device while at the same time providing medical practitioners with information during critical situations.

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