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A Framework for Chatbots in Medical Pre-Diagnosis

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ABSTRACT

Conversational AI systems or bots are a software framework designed to simulate human conversations. They interact with users, understand their needs and preferences, and recommend the next-best action with minimal human intervention. The core function of chatbots is to give the best response to any query that it receives. It shall answer sender's questions, providing the most relevant information, asking follow-up questions, and making the conversation as realistic as possible.

For accomplishing the "realism" goal, these bots need to understand the intentions, sentiment, or underlying emotion of the sender's message, and determine the most appropriate response. The bots may use metadata, such as speaker identity, preferences, or emotional state to provide relevant, grammatically correct response. Sometimes, sentiment analysis allows the Chatbot to 'understand' the user's mood by analyzing verbal and sentence structuring clues.

Bots are common in HR, IT help desk, hospitality, and self-service applications with various levels of sophistication. Currently, these chatbots are a little rigid and underperform in-person counselling which are required in medical pre-diagnosis. However, one of the areas ripe with opportunities is in Healthcare Dialog systems. They have significant impact in democratizing the latest medical interventions globally with scale.

In this paper, we will identify key functional requirements for a practical bot, particularly for pre-diagnosis based on the symptom extraction, extract the most appropriate and suggest a framework for achieving some of the functionality with algorithms.

Keywords : Conversational AI, NLP, Chatbot, Medical Diagnosis, Triage, healthcare.

I. INTRODUCTION

The use cases for chatbots in medicine are wide and varied, ranging from disease self- management, disease monitoring, screening, and diagnosis.

In locations where the healthcare infrastruc- ture is scarce, pre-diagnosis and triage appli- cations, chatbots can assist in managing emer- gencies, access ambulatory care, handle sen- sitive diseases (psychiatric) or chronic disease self-management. Bots should determine if the patient has a life-threatening emergency as quickly as possible and direct/alert for appro- priate medical attention. These applications could reach significant portion of the popula- tion, resulting in a substantial impact.

2 Diagnosis of Medical conditions

Due to the scarce resources and paucity of time, clinicians ask specific, closed-ended questions to elicit biomedical data from their patients. This might result in an incomplete and/or inaccurate diagnosis due to a limited ability to form a differential diagnosis and order subsequent diagnostic tests.

The techniques that focus on the personal and emotional context encourage patients to describe their symptoms spontaneously. Interactions that use these methods have also resulted in better blood pressure and diabetic control, better perinatal outcomes, shortened lengths of stay, improved mortality in critically ill patients, and improved cancer outcomes. It

is essential to conduct an effective symptom extraction method to probe and yet build relationships with the patient simultaneously. This strategy can yield rich medical data and improve patient satisfaction, compliance, knowledge, and recall.

Although this method provides important psycho- social information, it is rarely suffi- cient to diagnose a given symptom. Hence, two different interviewing strategies must be adopted – one for profiling and gathering information for pre-diagnosis and one specific to the present illness. Clinicians consider symptom characteristics, family history, and social history are needed to augment their decision process. Here clinicians inquire about symptom information not yet mentioned by the patient to complete the history of the current condition. The patient's life and history are explored to consider diseases apart from the present illness and assess disease risk.

The best practice in the clinical diagnosis is to lead the patient through a series of open-ended followed by closed-ended questions, moving from general information to specific details.

Currently, the pre-diagnosis bots use explicit declarations that are menu-driven and rule- based navigation and keyword search. These bots carry considerable limitations because they overwhelm and frustrate users with lengthy, rigid, and weak interactions. Since the medi- cal conditions tend to explode combinatorically, these solutions often will be ineffective. Elicit- ing symptoms and diagnosis are often mixed up in the initial stages of interaction, thus not cap- turing the relevant information. This makes the eventual diagnosis process long and painful.

3 Requirements for the Chatbot

An agent that could incorporate the following mechanisms and the capabilities would be adopted in the Healthcare delivery and could yield tremendous value to the patients.

The following Functional Requirements put a human face to a conversational agent and are much more complicated; in some cases, they may be beyond the current technological capability:

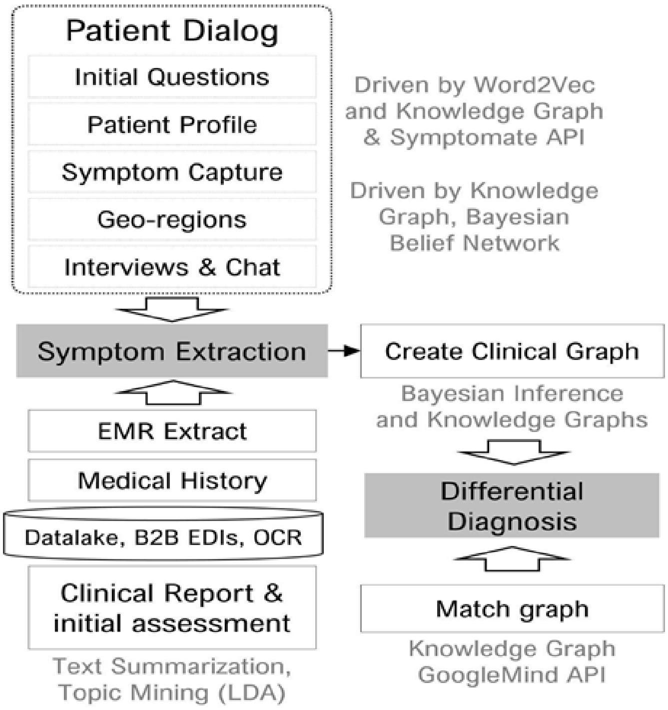

Figure 1 : Symptom extraction Process

Ability to field and understand open-ended questioning: This strategy helps generate the patient's agenda and elicit personal descriptions of symptoms and concerns. They encourage the patient to express their minds (questions, feelings, fears) rather than responding to the bot's goals.

Simulate the relationship-building: This en- courages the patient to express their emotions and nurture them. Once the patient shows or verbalizes an emotion, the bot can respond emphatically using the following empathy skills: naming, understanding, respecting, and supporting.

Inquire Symptoms: After obtaining all relevant cardinal features, ask about related symptoms within the same body system. In essence, perform a "focused review of systems" for that system, ascertaining which other symptoms are present and which ones are absent. For example, the absence of dyspnoea in a patient with chest pain weighs against a diagnosis of pulmonary embolism.

Probing relevant Symptoms: It is also impor- tant to find out the symptoms that may appear pertinent to a diagnosis. For example, when

evaluating a patient with rheumatoid arthritis and fatigue, one asks about gastrointestinal bleeding symptoms ("Any black stools?"). Even though such symptoms are outside the musculoskeletal system, it is still pertinent because nonsteroidal anti-inflammatory agents may cause bleeding. In patients with more than one problem, inquiry into multiple systems will be required.

Inquiring about non-Symptoms: Explore the relevant secondary data not yet introduced by the patient, including medications, diagnoses, treatments, doctors, and hospital stays. Clarify possible etiologic explanations for diagnoses being entertained to narrow the differential diagnosis. For example, if pulmonary embolism concerns, asking about recent long car rides or air travel is warranted.

EMR should be used for the patients: They should have the ability to ingest the Medical History. The Ability of the Bot framework to glean as much information from the history to avoid repetitive questions or seek answers to the information already known.

Some technical requirements for the bots are:

Graceful termination, maintaining the flow of dialog; These interactions are not isolated, stateless sessions. The information may need to be summarized, important details of entities and relationships maintained, and the continu- ity between and across the entire chat history. This also entails tailoring the subsequent dialog based on all the earlier dialogs. It also involves handling interruptions and turn-taking or digressions.

Speech intonation (used to convey a range of context information), and Discourse markers (words or phrases like ”anyway” that signal changes in discourse context), and discourse ellipsis (omission of a syntactically required phrase)

Continuity over multiple interactions: Conver- sation initiation from where the previous con- versation ended. Patient-Clinician interactions depend on the medical conditions - Emergency or a Specific consultancy, chronic illness, or be- havioral change. Some exchanges require mul- tiple interactions over extended periods. Inter-

action frequencies differ between the types of medical conditions. They can range from mul- tiple times a day (e.g., in wearable monitoring applications) to daily, more times per week, to once every few months.

4 Components of Chatbot

The three principal components of Conversa- tional AI are: the following are some approaches to building chatbots. Each implementation will have a different capability and applicability.

Natural Language Understanding (NLU): The NLU transforms the user statement into a predefined semantic frame understood by the system. Its function includes the task of slot-filling and intent detection. The intents and the slots indicate the closed-domain nature intrinsic to the conversations. The slot-filling and intent detection are often modeled as a sequence tagging problem. Hence, the NLU component is implemented as a Long-Short- term Memory based Recurrent Neural network with a Conditional Random Field layer.

Natural Language Generation (NLG): NLG plays a critical role in machine translation, text summarization, and conversational AI. NLG generates text from a meaning representation. In NLG, the system response is a semantic frame; it maps back to a natural language sentence, understandable for the end-user. The NLG can be rule, model-based, or hybrid. The rule-based NLG outputs some predefined template sentences for a given semantic frame; thus, they are very limited without the power of generalization. At present, Machine learning- based NLG systems are common. These NLG systems use several inputs such as content plan, meaning representation (what to communicate with the user), a knowledge base, a structured database to return domain-specific entities, a user model, a model to impose constraints on output, dialog history, the information from previous turns to avoid repetitions, referring expressions, etc.,

Dialogue Management (DM): The DM could be driven by a Knowledge Base (KB) or a knowl- edge graph to produce meaningful responses. The Dialogue Manager consists of one, a Dia- logue State Tracker (DST) should infer the be- lief correctly about dialogue’s state, given all

the history and precedence, and two, a Policy Learning component that is responsible for re- sponding with the most appropriate response to the user dialog. It can be implemented as a Reinforcement Learning agent.

5 Types of Chatbots

The following are some approaches to building chatbots. Each implementation will have a different capability and applicability.

Rule-Based: A bot answers questions based on some rules on which it is trained. The com- plexity of rules can range from being simple to very complex. Creating these bots is straight- forward, using some rule-based approach, but the bot is inefficient in answering questions whose pattern does not match the rules the bot is trained. However, these systems cannot respond to input patterns or keywords that do not match existing rules.

Information Retrieval (IR) Based: The system uses heuristics to locate the best response from a set of predetermined answers for a given user input. Heuristics could be simple algorithms like keyword matching, or they may be based on deep learning. These systems only regurgitate predefined responses and do not generate new output. Here, dialogue selection becomes a prediction problem.

It is intuitive to build a retrieval-based con- versational system with large corpora. The IR techniques consider user input as a query, and search for the best candidate response guided by matching metrics. The modeling effort of these systems is to find the mapping from the original inputs to the feature vectors, known as representation learning.

The retrieval process consists of a ranking by TF-IDF measurement and the re-ranking process using conversation-oriented features designed with human domain expertise.

Generative Based: A generative model chatbot does not use any predefined repository. It is suc- cessfully used to solve text summarization and question answering problems. Generative mod- els use Machine Translation techniques, but in- stead of translating from one language to an- other, they ”translate” from input to output.

6 Data and algorithms

The medical texts are derived from over 3700 EMRs, among which 207,480 sentences were determined to be valid for the experiments. We first conduct entity recognition on EMRs with the help of the existing knowledge bases. The adopted knowledge bases and ICD-103 diagno- sis codes (International Classification of Dis- eases). We extracted positive mentions of dis- eases, symptoms and other factors from EMRs by string matching with the knowledge bases.

Algorithm 1: Topology learning

```
Input: order = {V1,V2,...,Vn}, ordered node
       sequence; D, dataset;
       pmax, the maximum dimension
       limit of the parent node.
Output: G, optimal Bayesian network
[H] G ←− ∅
for i ←− 1 to n do
    P_i ←− ∅
    Score_old ←− Score(V_i, P_i)
    for j ←− 1 to i ←− 1 do
        G ←− G ∪ (V_i)
        if |P_i| < pmax then
            Score_new ←−
              Score(V_i, (P_i ∪ V_j))
            if Score_new > Score_old then
                P_i ←− P_i ∪ V_j
                G ←− G ∪ {V_j −→ V_i}
            end if
        end if
    end
end
```

The extracted information covers including gender, age, occupation, chief complaint, patient’s condition, personal history, personal medical history, family medical history, physical examination, auxiliary examination, admis- sion diagnosis, discharge diagnosis, admission information, medical treatment process, dis- charge information, discharge instructions, and progress note.

We used Word embeddings as the first layer of the network is the word-embedding layer, which transforms words into representations that capture syntactic and semantic information about the words.

In the Topology learning, Order, D, and G represents a set of different nodes that were extracted, The data set, and the optimal Bayesian network, respectively. While iterating through each node, the maximum weighted score with the other corresponding nodes will be computed. It will be updated to the graph’s edges, G, along with the nodes to construct an optimal bayesian model.

Inquiring relevant Non-symptom Data: Ask about the relevant secondary data not yet introduced by the patient including medications, diagnoses, treatments, doctors, and hospital stays. Clarify possible etiologic explanations for diagnoses being entertained to narrow the differential diagnosis. For example, if pulmonary embolism is a concern, asking about recent long car rides or air travel is warranted.

Clinician-centered interviewing helps uncover diagnostically important information and devel- ops a routine database about the patient. In- formation from the patient centered interview, the clinician develops the patient's bio-psycho- social story, encompassing not only the patient's disease problems but also the personal and emo- tional context in which they occur.

Algorithm 2: Algorithm for diagnosis

```
Input: S
Output: D
[H] Function Diagnosis(S):
    D ←− (d1, d2, .., dk)
    S ←− (s1 : n1, s2 : n2, ..., sm : nm)
    while len(D) > 1 do
        si = argmin(len(D/2) − ni)
        prompt user to ask if he/she is
          observing si
        mark si based on user response
        remove corresponding diseases
        from D
    end
    return D
End Function
```

In the proposed algorithm, S denotes the set of Symptoms and D denotes the set of possi- ble Diseases. In every iteration the argmin for the probability of a symptom is computed and prompts user if he/she is observing that partic- ular symptom and eliminates the corresponding disease from set, D based on the user response. The final result will be a list of all possible dis- eases based on information given by the patient.

II. CONCLUSION

We just laid out overall framework; however, chatbots will need inclusion and harmonizing between various models to arrive at the best response for a dialog. Each of the responses needs to be critically evaluated, lot more data needs to be analyzed from the real conversa- tions to model the dialogues better.

No single approach can solve deep empathy- based chatbots in medical diagnosis. Creating conversational agents close to human Ability of empathy, context, and diagnosis is years away. However, currently, each of the challenges of building "intelligence" is being frenetically re- searched and developed in this exciting area of Conversational AI for Health. Achieving the so- phistication for Human-level interaction would prove to be a real boon for millions of consumers around the globe.

III.CONCLUSION

The Hummers modified method was used to make graphene. A dip-coating method was used to coat the graphene on the glass. Five, ten, fifteen, and twenty coating cycles were used. Various characterization techniques were used to evaluate the structural, morphological, and optical features of the produced samples. When compared to pure glass, coated glass has a large bandgap value. As the number of coating cycles rises, the contact angle value for coated glass increases.

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