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Major Course Output 2: ChatBot

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I. Introduction

The Major Course Output 2 aims to develop a medical diagnostic chatbot expert system that can cover at least 10 diseases common in rural or poor areas of the Philippines. This expert system should have a question-and-answer interface and exhibits a backward-chaining approach.

The domain of diseases includes chicken pox, COVID-19 virus, dengue, diarrhea, influenza (A), measles, pneumonia, osteoarthritis, rabies, and tuberculosis. There is no specific reason for choosing this set of diseases except that they are most common in rural and/or poor areas of the Philippines. The overview of the diseases is discussed below.

Chickenpox (formally known as Varicella), is an acute, infectious disease caused by the varicella-zoster virus (Anthony, 2022). It is highly contagious and causes blister-like rashes that appear firstly on the chest, back, and face of the infected person and then spread through the body.

COVID-19, also known as the coronavirus, is a respiratory virus that gave rise to the global pandemic in 2020. This virus easily spreads through the air and enters the mouth, nose, or eyes (WHO, 2023). Mild to moderate respiratory illness will occur when infected, which usually does not need special treatment.

The dengue virus (DENV), which infects mosquitoes that bite people, causes the viral infection known as dengue. Once infected with one of the four dengue viruses, an individual develops lifelong immunity to that specific virus. However, the individual remains susceptible to infection from the other three dengue viruses (Mayo Clinic, 2022).

Diarrhea is recognized by runny, watery feces that deviate from the norm. This ailment can result in severe and ultimately lethal outcomes if disregarded or overlooked. Worldwide each year witnesses a staggering 2 billion occurrences of it, with almost two million young lives lost annually - predominantly concentrated within undeveloped regions (MacGill, 2023).

The dangerous viral infection influenza, usually called the flu, targets your respiratory system. Influenza can be classified into three main groups: A, B, and C (Anthony, 2023). Protecting those who are more vulnerable to developing potentially fatal influenza complications, such as young children, elderly adults, and people with chronic conditions, is especially crucial (Cheng et al., 2020).

According to the CDC, Measles is described as an "*acute viral respiratory illness which is characterized by a prodrome of high fever and malaise, cough, coryza, and conjunctivitis, also called the "3 C's"* (2020). Patients infected by this disease are commonly identified by a rash that appears 14 days after exposure and spreads from the head to the lower extremities. In this period, patients are highly contagious.

According to Health Direct Australia (2021), Pneumonia is a respiratory illness that affects the lungs. Severe cases of COVID-19 could also result in Pneumonia. NHS (2022) describes Pneumonia as the inflammation of tissue in one or both lungs. It can be a mild illness but can be life-threatening, especially in young children and old people. Bacteria, viruses, or fungi can cause this disease.

Osteoarthritis is the most common chronic joint condition. It is also called wear-and-tear arthritis, degenerative joint disease, and degenerative arthritis (Whelan, 2021). According to the World Health Organization, it occurs when the cartilage, the protective tissue covering the ends of the bones, breaks down. The bones within the joint will then rub against each other, causing pain, stiffness, and other symptoms. Joint damage will, in turn, cause osteoarthritis.

Rabies is caused by a virus that affects the brain, particularly the central nervous system (Ben-Joseph, 2019). According to CDC, approximately 59,000 people worldwide die from rabies every year, with around 99 percent being bitten by a rabid dog. As the virus attacks the central nervous system, the diseases it can develop are furious rabies and paralytic rabies. Furthermore, dogs are responsible for most rabies cases around the world.

Tuberculosis (TB) is an airborne disease that usually affects the lungs. However, it can also affect other organs: the brain, the kidneys, or the spine. TB can be fatal if the person infected does not get treatment (Centers for Disease Control and Prevention, 2011). Tuberculosis is the 13th leading cause of death which comes just after COVID-19. Around 10.6 million people were affected by tuberculosis worldwide in 2021 (World Health Organization, 2022).

Developing a medical diagnostic expert system is a complex and challenging task, requiring input and guidance from medical professionals. Accurate diagnoses are crucial to ensure patients receive appropriate treatment, and medical professionals can provide valuable insights into achieving this goal. Although the group, unfortunately, could not find direct access to medical professionals, extensive research from credible sources was conducted to identify diseases and their corresponding symptoms. This approach is noticeably suboptimal compared to having the input and expertise of medical professionals. Nevertheless, the sources researched were ensured to be reputable to increase the likelihood of accurate diagnoses.

This expert system will greatly benefit people in remote areas, such as people living in the mountains and ethnic groups that have limited access to medical facilities. They can utilize this chatbot as a tool to determine what disease they might have. Caregivers may also benefit from this expert system, especially for the home shelter with limited or no access to medical testing facilities. They may use this chatbot to assess the condition of an elder or a patient. Another group that may benefit from this expert system is researchers and public health organizations since they can utilize the data to do further research and improve the expert system.

II. Knowledge Base and Chatbot

According to Zwass (2016), an expert system is a computer program that uses artificial intelligence methods to solve problems within a specialized domain that ordinarily requires human expertise. In other words, an expert system uses AI to simulate the judgment and behavior of a human or an organization with expert knowledge and experience in a particular field. Two essential components are needed to create an expert system: a knowledge base and an inference engine (Zwass, 2016). The knowledge base contains domain-specific knowledge and facts, while the inference engine applies logical rules to the knowledge base to deduce new information and provide solutions to problems. Fortunately, a programming language that has played a significant role in the development of artificial intelligence exists. It is called PROLOG and is commonly used to create expert systems. PROLOG is designed to facilitate the representation and manipulation of knowledge using formal logic.

The chatbot's knowledge base is done in the PROLOG programming language, a language best suited for developing artificial intelligence systems with logic as a base. Prolog allows users to interpret results using user-declared facts and rules about the problem domain (Calapini, 2022). Thus, having conducted extensive research on each disease and ensuring that the knowledge base captures as much medical information as possible, the group has encoded the knowledge base with sets of predefined rules. As a result, the knowledge base does not contain any facts, but rather, it uses rules to process the information and arrive at a diagnosis.

Before expanding upon the rules encoded in the knowledge base, it is important to know the main arguments that all rules contain. For each rule, they contain the following arguments:

- age range,
- symptoms,
- chief complaint,
- duration of experienced symptoms,
- vices,
- typical environment,
- and past medical conditions

The arguments above were determined to be essential by the group from the research of each disease; thus, it was encoded into the database as rule arguments. Age range, vices, typical environment, and past medical conditions are considered general information and are known as “risk factors.” These factors alone do not determine a patient's disease, but they can help narrow down the possibilities when patients report their chief complaint, symptoms, and duration of symptoms. Considering these factors, the system can provide more accurate and specific diagnoses, leading to better treatment outcomes.

With the arguments defined, the group encoded the rules into the knowledge base such that the inference engine will search for every disease in the knowledge base, despite not all the arguments matching the clauses defined by the rule of each disease. By default in PROLOG, if an argument passed to a rule does not match any of the clauses in the rule, the rule will return “false.” However, in real-life diagnosis, it is important to consider all possible diseases and not to rule out any potential disease based on a single non-matching symptom or any other non-matching risk factor. Thus, the rules in the knowledge base are designed to avoid returning “false” when some arguments do not match the clauses defined in each rule. Instead, the rules defined for each disease return a probability value that indicates the likelihood of a disease being the matching disease based on the given arguments. This is achieved through a weighting system, which assigns a probability value to each symptom based on its significance in diagnosing a particular disease. The particulars of the assignment of weights will be discussed in later sections.

The system described is called a rule-based probability system which assigns weights to each matching argument in a defined rule for each disease. To visualize how this works, below is a defined rule pseudocode for the Tuberculosis disease:

```
tuberculosis(Symptoms, Age, TimeLen, Vices, Past_Medical_Conditions,
Environment, Weight) :-
%if argument is a list
findall(SymptomWeight, (member(Symptom, Symptoms), (member(Symptom,
['List of researched symptoms for tuberculosis']) -> SymptomWeight is
x; SymptomWeight is 0)), SymptomWeights), sum_list(SymptomWeights,
SymptomWeightTotal),

%if argument is a single argument
(member(Vices, ['List of vices researched for tuberculosis'] ->
VicesWeight is x; VicesWeight is 0),
%repeat for all arguments

%After getting matching or non matching arguments, get all weight and
return probability value
Weight is %add all total weights%.
```

Figure 1. A defined rule pseudocode for diseases

In this rule, the "*member*" predicate checks if the given element or argument is a member of the given list. If it matches a member in the list, it will assign a particular weight value to a variable (also called an Atom). If no match happened, simply assign a weight value of 0. For the "*findall*" predicate, as its name applies, it simply finds all matching arguments from a list of arguments (in the example above, it is a list of symptoms) and outputs a list of weights. The *"sum_list"* predicate then summarizes the list of weights and outputs the sum value as a single atom.

This process calculates the total weight or probability that a given disease matches the input arguments and stores it in the *Weight* argument. In this way, the inference system of PROLOG will search through all diseases defined in the knowledge base and keep track of the returned probability value for each disease. This allows the system to evaluate all possible diseases based on the given input arguments and identify the most probable disease that matches the symptoms reported by the patient.

For the system to evaluate all the possible diseases in the knowledge base, another rule is defined where its clauses are simply the defined rule for each disease, In this way, the inference system can search through every defined rule easily. The pseudocode of the implementation is defined below:

```
disease_list(%All defined arguments%, Disease, Weight) :-
          disease_name(%All defined argument%, disease_weight),
          Disease = disease_name, Weight = disease_weight;
          %repeat for all rule defined disease
```

Figure 2. A defined rule that contains the list of diseases

This rule simply contains clauses of the list of rules that the inference engine will search through and then get the name and the corresponding weight or probability given the arguments. However, the purpose of the *Disease* and *Weight* arguments in the rule is not only to obtain the name and probability of the matching disease. Rather, they are designed to be treated as a list of disease-weight pairs. This is because another rule is defined, called the diagnosis rule, which is queried by the system once the arguments are gathered from the patient. The diagnosis rule contains clauses that use the "*findall*" predicate to retrieve the list of diseases and their corresponding weights, then order them by weight, starting from the most probable disease (i.e., the largest weight), and finally, return the list to the system for assessment. By treating the diseases and their corresponding weights as pairs, the system can easily evaluate and rank the probability of each disease, making the diagnosis process more efficient and accurate. The diagnosis rule pseudocode is defined below

```
diagnosis(%All defined arguments%, Result) :-
     findall(Weight-Disease, %call disease_list rule%, Pairs),
     %sort the resulting list and then reverse it
     keysort(Pairs, SortedPairs),
     reverse(SortedPairs, Result).
```

Figure 3. The defined rule for diagnosis

The resulting knowledge base implements a rule-based, probabilistic system that can make expert predictions about which disease is most probable. However, in its current state, the inference engine checks every defined rule, which can be inefficient. While this ensures no disease is missed, the system could be improved by implementing more efficient search strategies or pruning irrelevant rules.

To address this issue, diseases are grouped into similar domains. If two or more diseases affect a similar body part (e.g., the respiratory system), they are inserted as clauses into a domain-specific rule. This approach helps streamline the inference process by reducing the number of rules the system needs to evaluate.

The reimplementation involves using the argument for the chief complaint as the identifier for the domain rule the inference engine should search for. The change will involve modifying the disease_list rule by replacing all the disease-specific rules with domain-specific rules, each associated with a chief complaint. Consequently, the inference engine will only search for the domain rule corresponding to the chief complaint, and the process of obtaining the disease-weight pairs will be repeated. The rule defined pseudocode below visualizes this change:

```
sample_domain(%All defined arguments%, Disease, Weight) :-

      disease(%All defined arguments%),
      Disease = disease_name, Weight = disease_weight;
      %Repeat for every disease of this type domain

disease_list(%All defined arguments%, ChiefComplaint, Disease, 
Weight) :-

      ChiefComplaint = this_domain, sample_domain(%All defined 
arguments%, Disease, Weight),
      %Repeat for every rule defined domain in the knowledge base.
```

Figure 4. Reimplementation using specific domain rule

With this in mind, the system follows a specific process when querying the diagnosis rule and obtaining the result. The flowchart below illustrates this process.

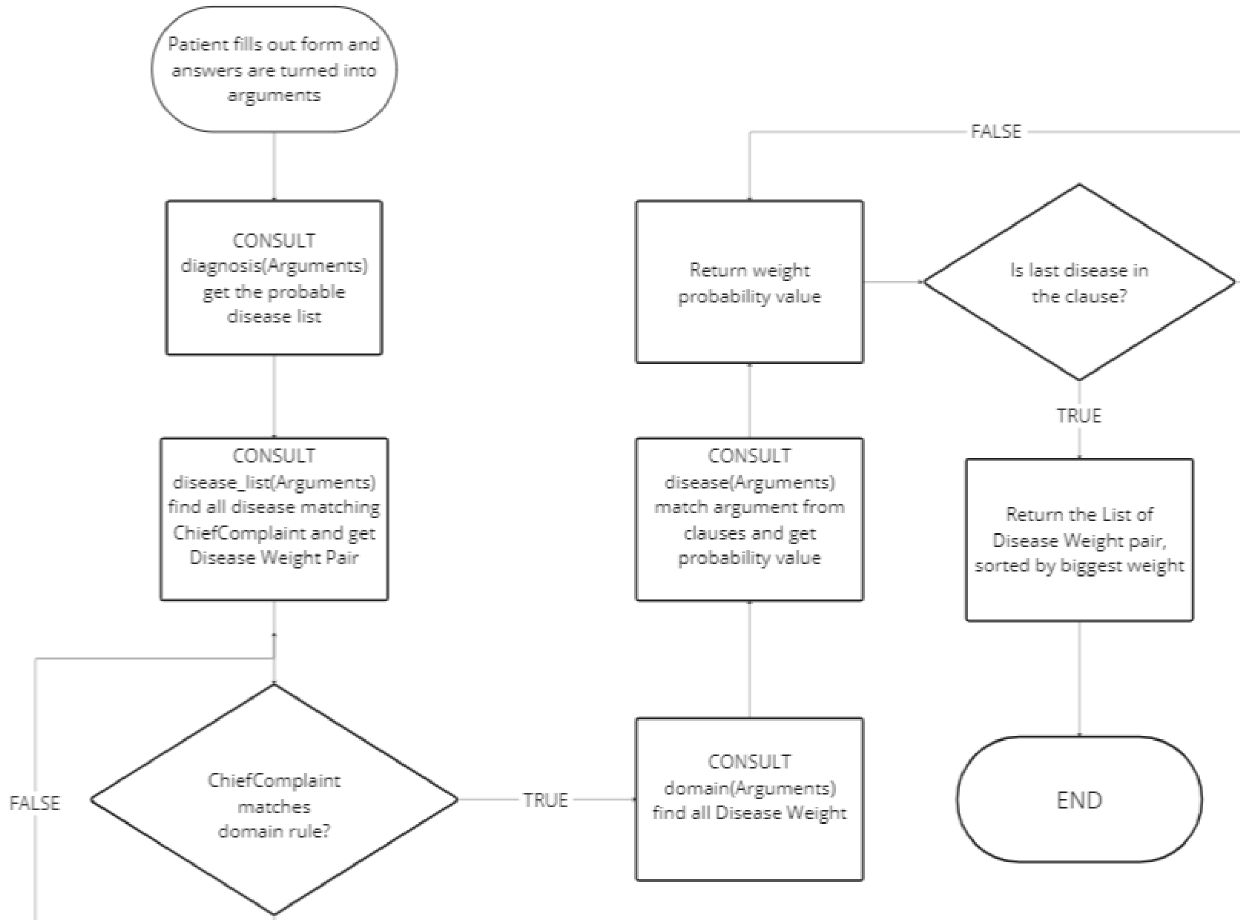


Figure 5. Expert System Knowledge Base Consult Flowchart

Once the knowledge base is encoded with verified rules, the development of a medical diagnosis chatbot expert system is done. According to Kalinin (2022), a chatbot is a software developed to provide real-time assistance to patients. More powerful and industry-used chatbots are developed using machine learning algorithms; however, chatbots developed using logic-based algorithms are still useful provided that it has a clear set of rules and a well-defined structure.

Thus, it is essential to have a well-defined flow of how the medical diagnosis chatbot will work when used by patients. Developing the medical chatbot begins with understanding how diagnosis works and what steps should be taken during the diagnosis process. This process will be further expounded upon in the next section.

The figure below demonstrates how a patient is typically diagnosed by a medical professional.

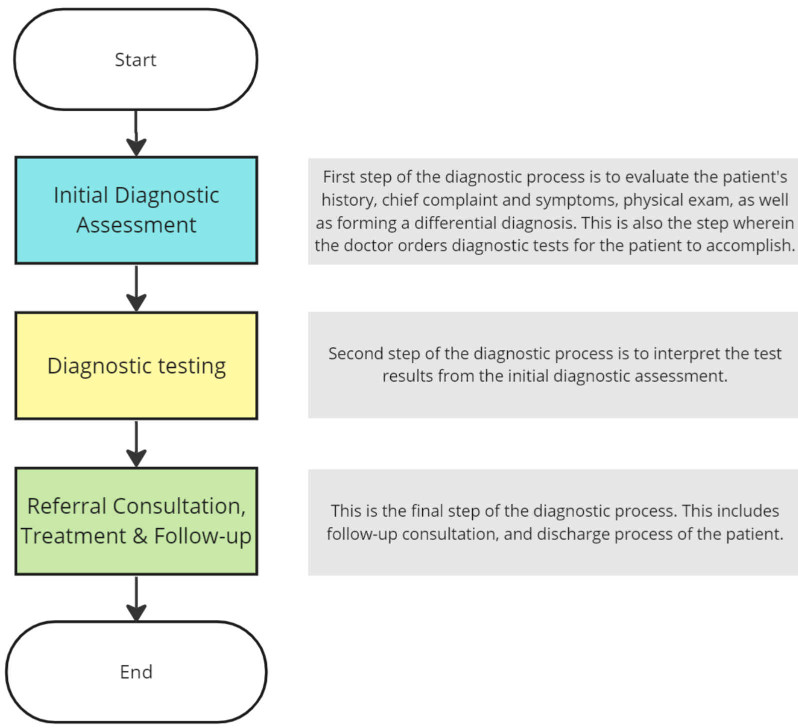


Figure 6. The Diagnostic Process: Rediscovering the Basic Steps (Syzek, n.d.)

According to Syznek (n.d.), there are three main categories when diagnosing: Initial Diagnostic Assessment, Diagnostic Testing, and referral, consultation, treatment & follow-up.

The initial Diagnostic assessment is the stage where misdiagnosis often starts (Syzek, n.d.). Many factors can contribute to this, such as limitations of current medical knowledge or diagnostic technology, or it may be due to human error, such as failure to consider all possible diagnoses or to order the appropriate test. Thus, to help reduce the likelihood of misdiagnosis, the medical chatbot expert system is implemented with a rule that weighs all matching diseases in its current knowledge base and outputs the most probable disease the patient might have. This system is further expanded upon in the next section.

The figure below shows the diagnosing process of the medical diagnostic expert system.

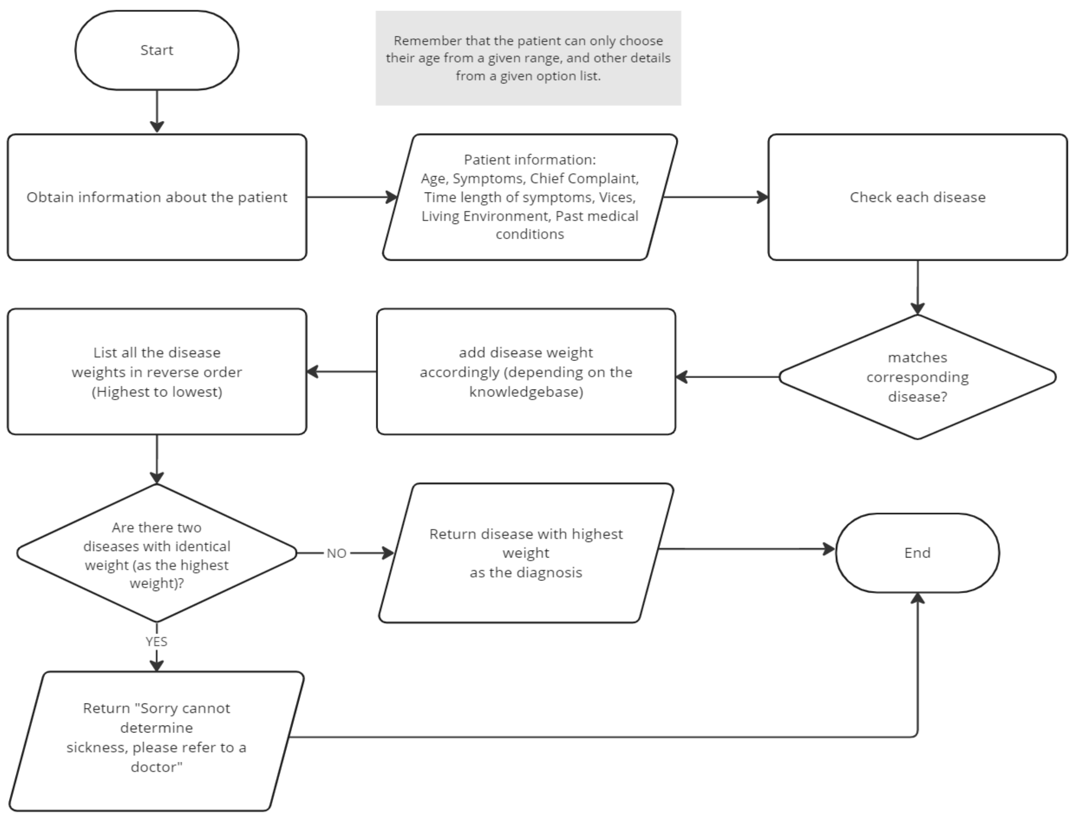


Figure 7. Diagnosing Process of the Expert System

The system takes advantage of giving the patient choices instead of a free-form question-and-answer format. This enables the system to be more specific and quickly identify the different weights for each disease. Data is first collected from the patient in the diagnosing process of the expert system visualized in Figure 7.

Symptoms, associated vices, typical environment, and associated past medical conditions of the diseases are indicated as is. While the age range is divided into three categories: ‘A’, which means 18 years old and below, ‘B’, which means above 18 years old but below 65 years old; and ‘C’, which means above 65 years old. The chief complaint of a disease is one of the five covered in this expert system: respiratory infections, viral infections with rash, vector-borne infections, degenerative joint disease, and gastrointestinal infections. The time length or duration of the disease is also divided into three categories: ‘A’ - 1 - 2 days, ‘B’ - 3 - 6 days, and ‘C’ - more than 7 days.

Symptoms and past medical conditions were implemented in a way that the patient could input as many as they could. Furthermore, these diseases were grouped based on their chief complaint as this will help narrow down which possible diseases the patient might have.

This chatbot medical diagnostic expert system is implemented based on rule-based, probabilistic reasoning. The group assigned weights to each factor to determine the probability that a patient may have a particular disease. These weights are estimations made by the group, and symptoms were given higher weights since they are often the most direct and reliable indicators of a patient's condition. Symptoms are also commonly accessible, and objective data points available for consideration. In contrast, the other factors, such as the patient’s age and medical history, were given weights ranging from 0 to 0.2. The chatbot will then consider the disease if it is weighted greater than or equal to 1; this would be possible if several symptoms and other factors matched the disease. To review the comprehensive list of weights, please check this file: CSINTSY_Chatbot.

It is important to note that the weights assigned to each disease factor are not definite and can be changed from further research. In theory, the implemented system could help reduce the likelihood of misdiagnosis by considering all possible matching diseases and outputting the one with the highest probability. However, the system is imperfect and cannot completely eliminate the probability of misdiagnosis. The field of medicine is complex, and various other factors play a big part in diagnosis that cannot simply be captured by a logic-based algorithm. Nevertheless, the system is made to be updated. Thus, further research from credible sources, along with expertise from qualified healthcare providers and professionals, will help improve the accuracy of the diagnosis.

The figure below shows the general overview of the actual medical chatbot expert system implementation, which covers the order of input taken from the patient.

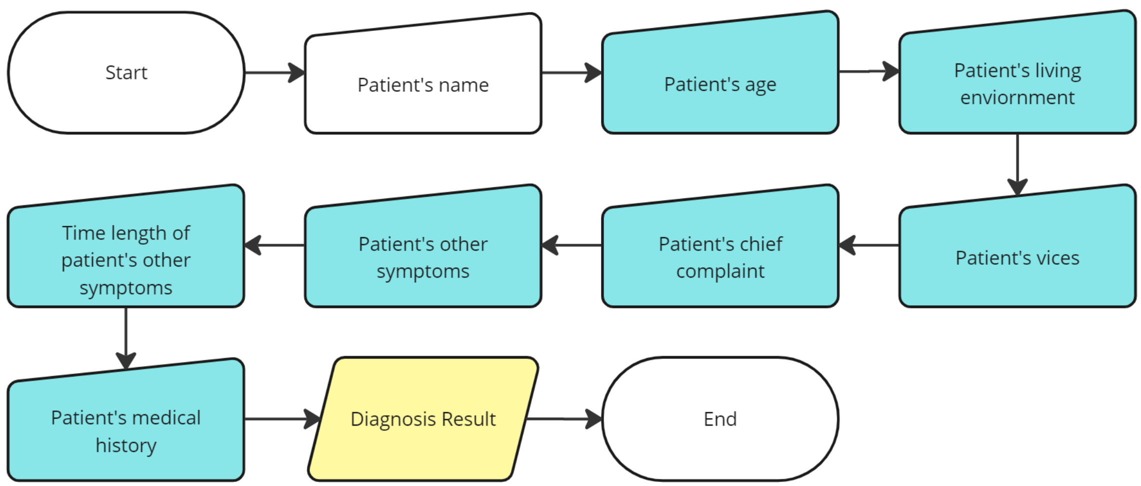


Figure 8. Expert System Flowchart General Overview

The group wanted to mirror the diagnostic assessment mentioned by Syznek (n.d.). Figure 6 is a visual representation of the 3 main categorical diagnostic processes. However, due to some limitations, the programmers can only implement the first step, the initial diagnostic assessment. Referring to Figure 7, the color-coded inputs are based on the previous figure. This means, asking for the patient's age, living environment, vices, chief complaint, other symptoms, time length of symptoms persisting, and medical history from Figure 8 are all part of the initial diagnostic assessment in Figure 7.

Creating a medical chatbot expert system is a complex and challenging task. The responsibility of developing such a system does not solely rely on the software development side but also heavily depends on extensive research in the field of medicine. A medical chatbot cannot easily capture many intricacies and nuances in medicine. Nevertheless, through a rigorous process of ensuring the accuracy and reliability of the chatbot's knowledge base, the group developed an expert system capable of diagnosing patients. The group will detail their experience in developing this medical chatbot expert system in the following section.

The easiest to finalize in the knowledge base are the components of each disease, such as their symptoms, chief complaints, the age that the disease is common, the time length of the disease, vices that cause more risk to the disease, typical environment, and associated past medical conditions. Finalizing those caused the least problems since the internet is there to find credible sources to verify if the information the group collected is true. Furthermore, translating this information into the knowledge base is also not the hardest part, and it also causes the least problems. The group made a predicate for each disease and added members who were the components mentioned above.

Developing the medical chatbot system's Graphical User Interface or GUI was also easy to finalize. This is because the diagnosis flowchart was defined extensively, which gave way to how the flow of the program will be.

The hardest to finalize would be determining the weight of each parameter/component of the disease, which is also the rule set of this program. The program follows probabilistic rule-based reasoning, and the group sets a weight on each parameter to find which disease matches the highest based on the patient's input. With this method, all diseases in the chief complaint group that the patient selected would be given weights that depends on which parameters matched from the input. Nevertheless, finding the right weight amount depending on the inferred information from credible sources was difficult. There were many instances where the group had to readjust weights for every disease due to the assessment not being what was expected. Only through rigorous testing did the group find the right balance of an acceptable chatbot that would give an adequate diagnosis of the patient.

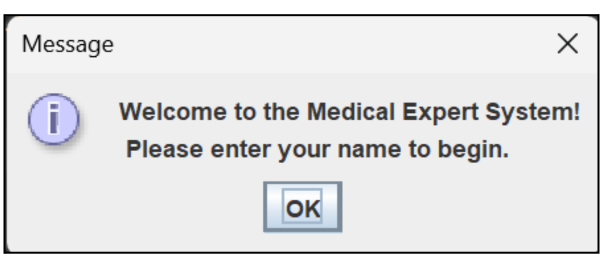
III. Results and Analysis

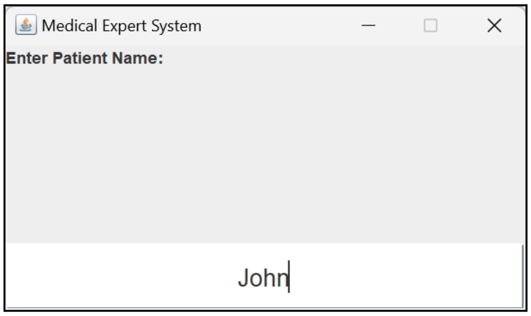
All conversations with the medical expert system, will always begin with a greeting, followed by the chatbot asking for the patient's name. As for the flow of the program, the chatbot will first prompt a welcome screen, bespoke to the patient's name, and ask the patient to select their age group. Afterward, the bot will ask what type of environment he lives in only if it is describable; else, the patient can input none or 'well'. The bot then asks if the patient has vices and also has the option to select 'none'. After the general information, the bot asks specific questions about the patient's condition.

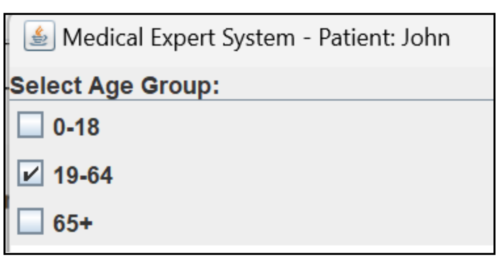
First, the bot asks what the chief complaint of the patient is; choices include what part of their body he feels pain in or if he is exposed to animals or insects with viruses. The bot will then display symptoms relevant to the patient's chief complaint and accept multiple selections. Then, the bot will now ask for the timeline or how long the patient has been feeling these symptoms. Lastly, the bot will ask the user to select their past medical conditions, if any. After the series of prompts, the chatbot will display the diagnosis. Moreover, the patient has the option to check which other diseases match and what are their weight depending on the input. Additionally, the patient's records are visible to them to verify correct input.

The following tables detail impressive conversations with the medical chatbot.

Table 1. First Impressive Sample Conversation

1	

2	Medical Expert System Enter Patient Name: John
3	Message Happy to serve you, John! OK
4	Message Please select your age group. OK

5	Medical Expert System - Patient: John Select Age Group: 0-18 19-64 65+

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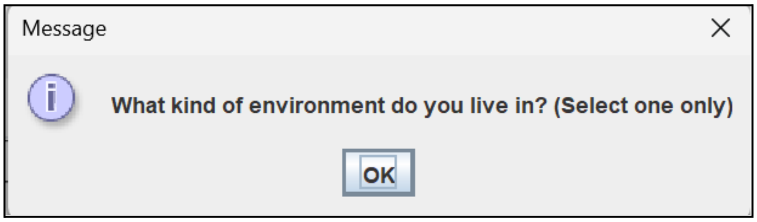
<tr><td>6</td><td>
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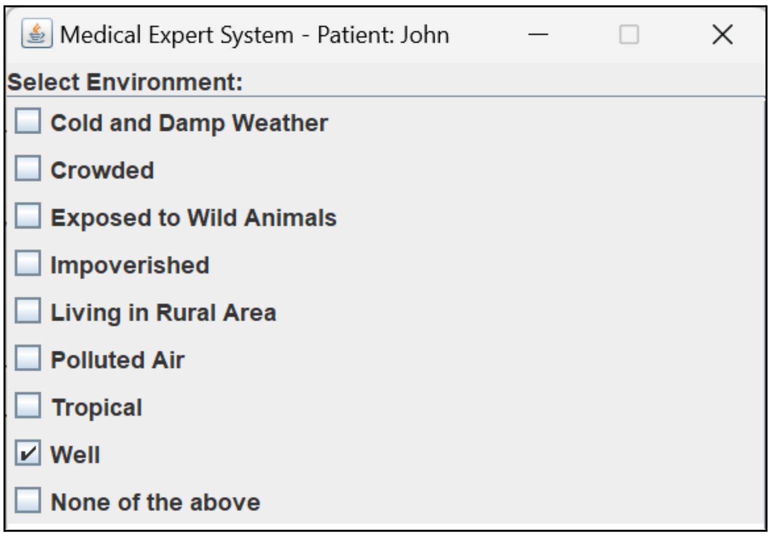
<tr><td>7</td><td>
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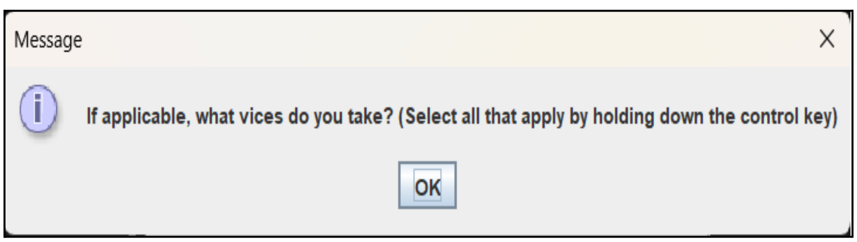
<tr><td>8</td><td>
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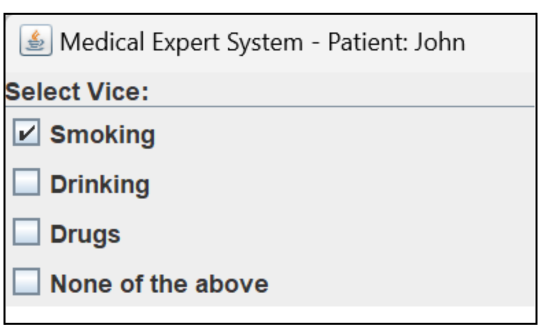
<tr><td>9</td><td>
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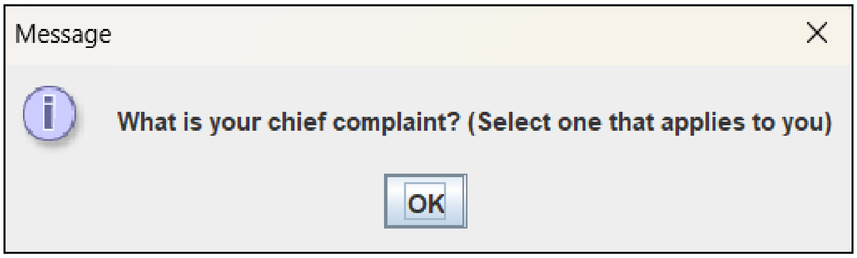
<tr><td>10</td><td>
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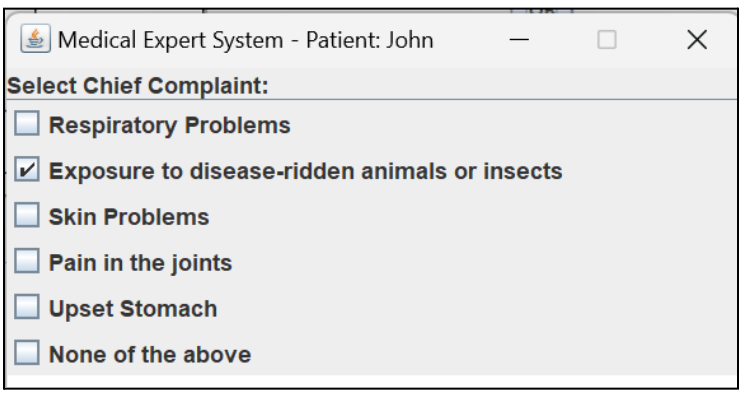
<tr><td>11</td><td>
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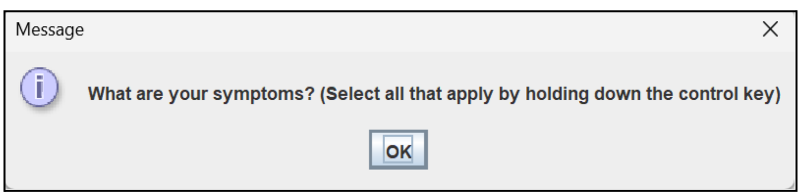
<tr><td>12</td><td>
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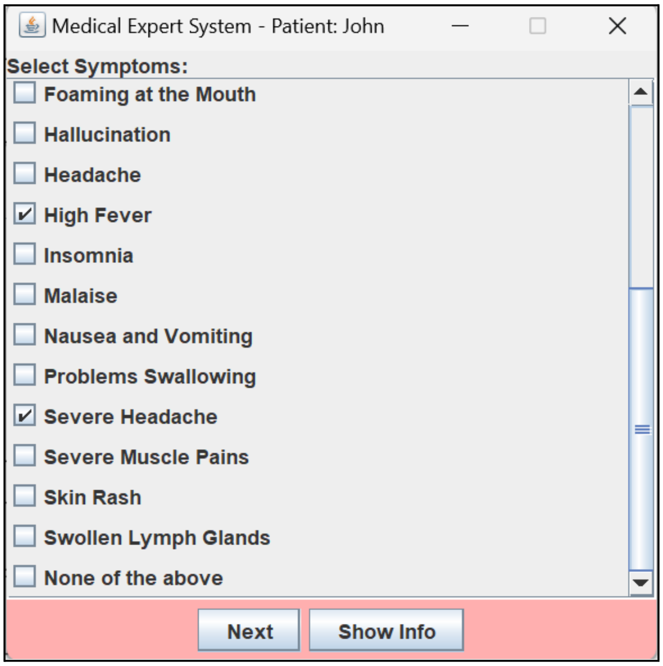
<tr><td>13</td><td>
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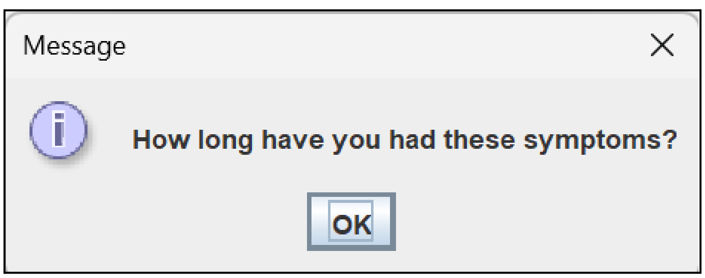
<tr><td>14</td><td>
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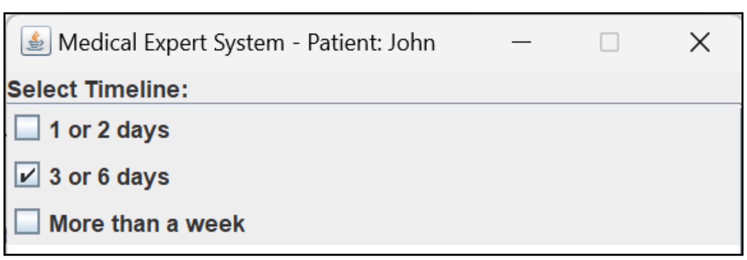
<tr><td>15</td><td>
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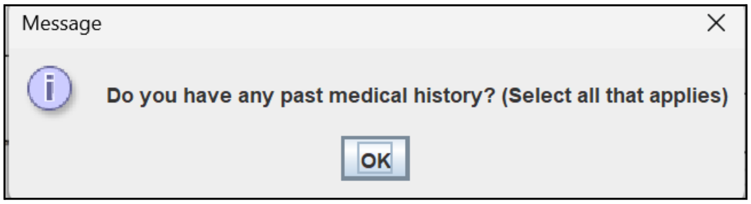
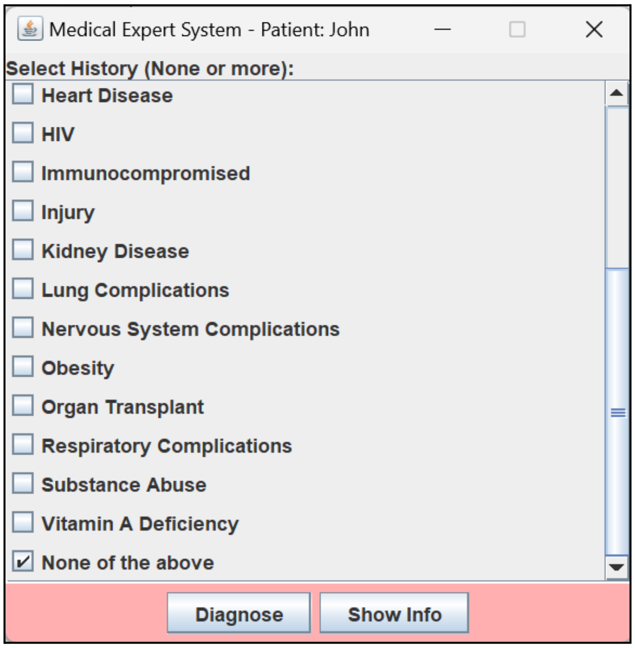
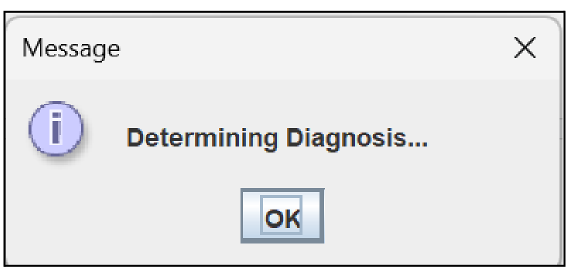
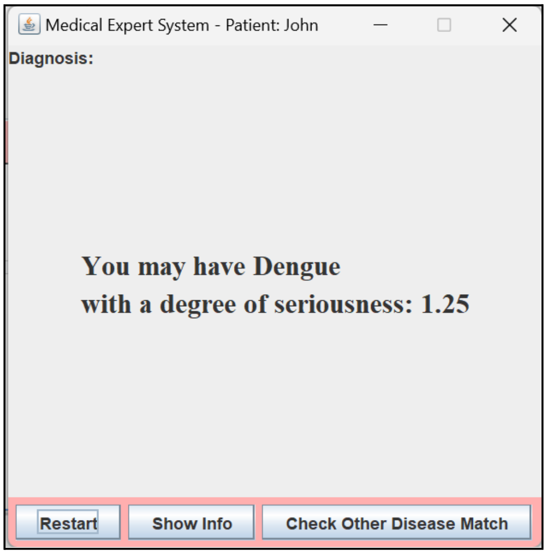
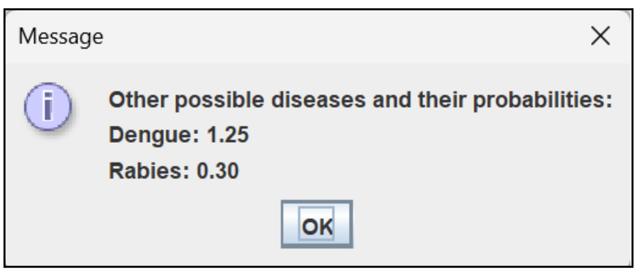
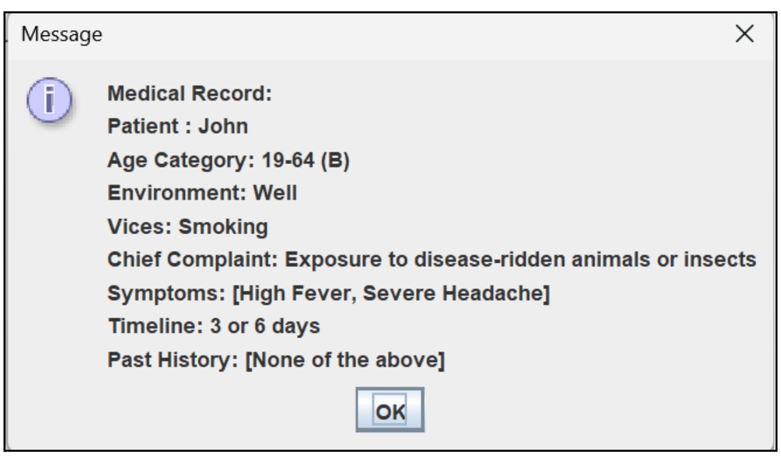
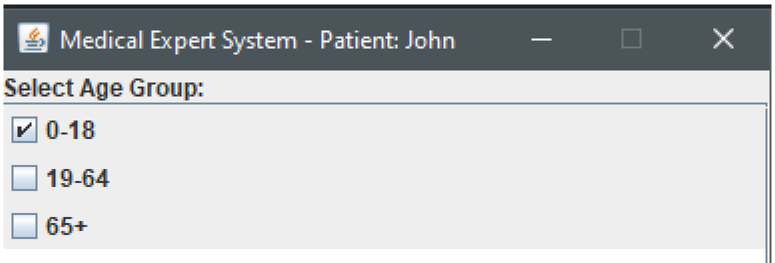
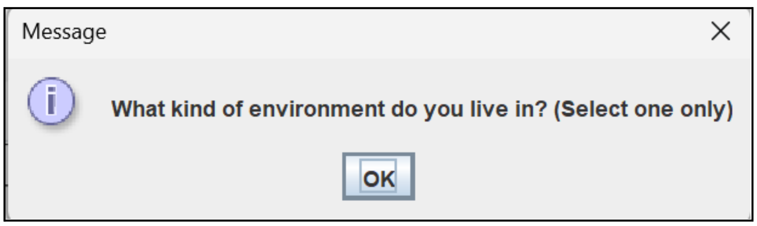
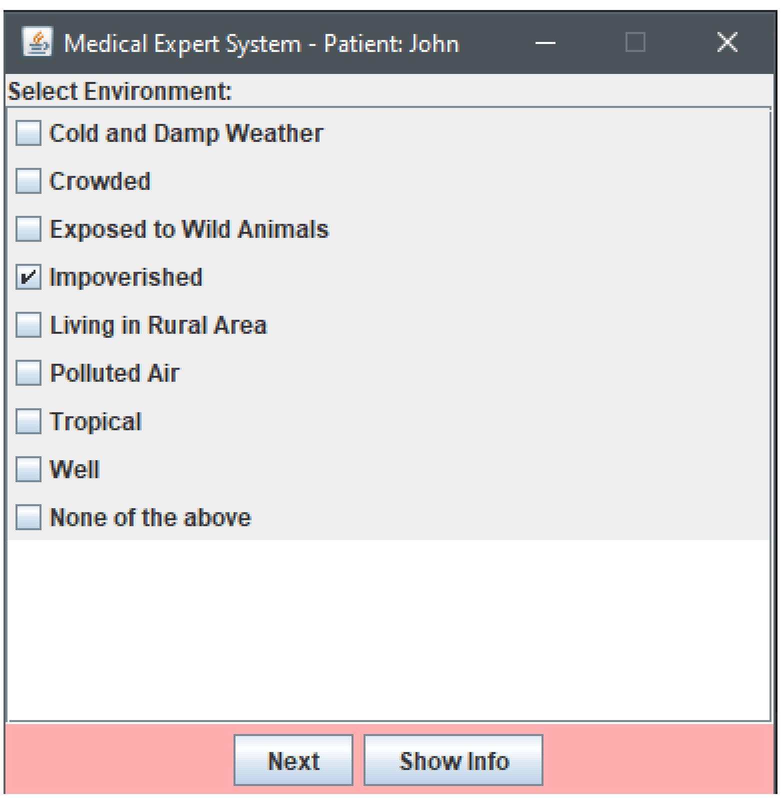
16	Message Do you have any past medical history? (Select all that applies) OK
17	Medical Expert System - Patient: John Select History (None or more): Heart Disease HIV Immunocompromised Injury Kidney Disease Lung Complications Nervous System Complications Obesity Organ Transplant Respiratory Complications Substance Abuse Vitamin A Deficiency None of the above Diagnose Show Info
18	Message Determining Diagnosis... OK

19	Medical Expert System - Patient: John Diagnosis: You may have Dengue with a degree of seriousness: 1.25 Restart Show Info Check Other Disease Match
20	Message Other possible diseases and their probabilities: Dengue: 1.25 Rabies: 0.30 OK
21	Message Medical Record: Patient : John Age Category: 19-64 (B) Environment: Well Vices: Smoking Chief Complaint: Exposure to disease-ridden animals or insects Symptoms: [High Fever, Severe Headache] Timeline: 3 or 6 days Past History: [None of the above] OK

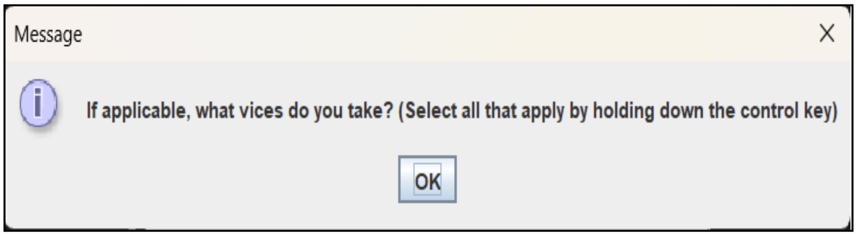
For the first impressive sample conversation, patient John belongs to the age group B, 19 to 64 years old. He lives in a tropical environment, and his vice is smoking. In this conversation, the patient stated that he is exposed to insects with viruses. John stated that his symptoms were a high fever and a severe headache he had already had for the past 3-6 days. John has no past medical conditions, so he stated ‘none’ for this prompt.

In this conversation, the chatbot determines that John has true dengue. The bot determined that John has dengue even if other factors were not related to dengue, such as smoking, since there are no vices related to dengue. Another factor is John’s age group. The age group most affected by dengue is age group A, below 19 years old. Which means John is less likely to have dengue. Furthermore, a person has a higher chance of being diagnosed with dengue if they have already contracted the virus before, but for this example, John did not. The bot determined John had dengue with the symptoms he had, which were ‘Severe Headache’ and ‘High Fever.’ These symptoms are directly associated with dengue since dengue is sometimes or mostly known as dengue fever. This was also possible since the chatbot immediately distinguished the possible diseases associated with the patient’s chief complaint.

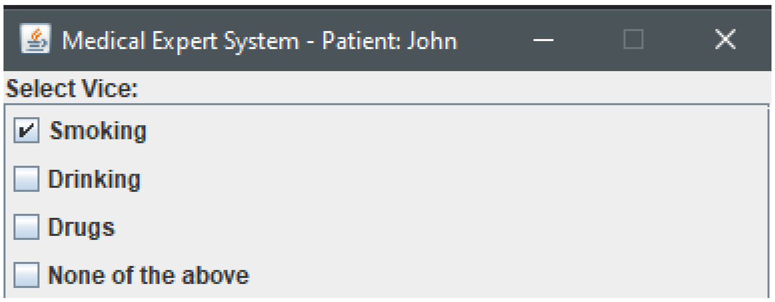
Table 2. Second Impressive Sample Conversation

5	
6	
7	

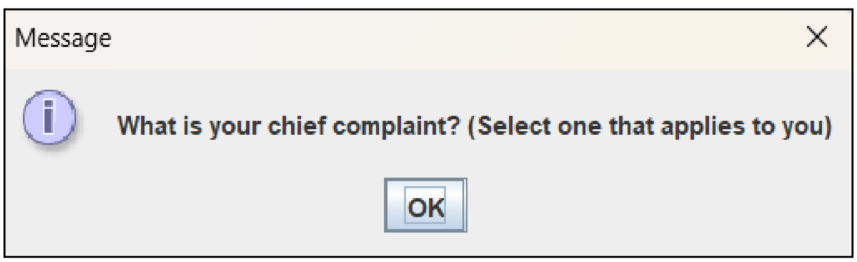
8


Message
If applicable, what vices do you take? (Select all that apply by holding down the control key)
OK

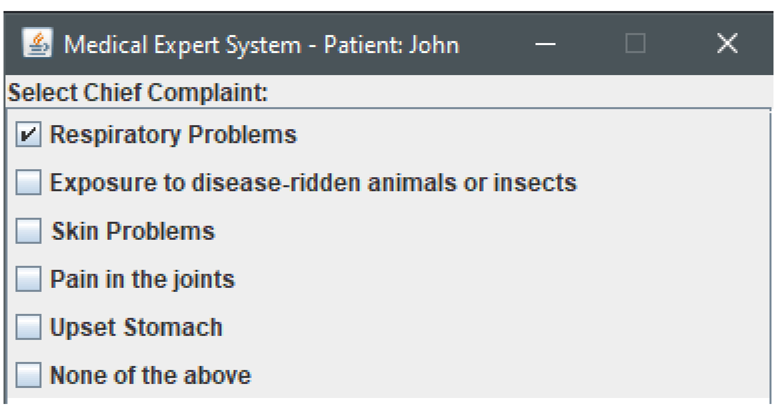
9


Medical Expert System - Patient: John
Select Vice:
Smoking
Drinking
Drugs
None of the above

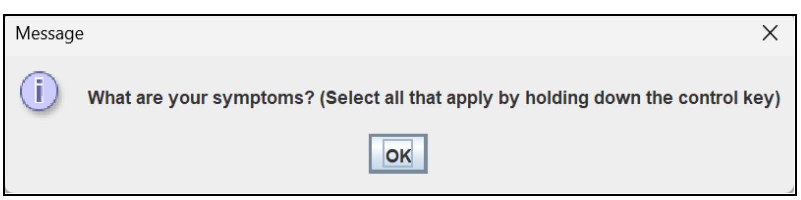
10

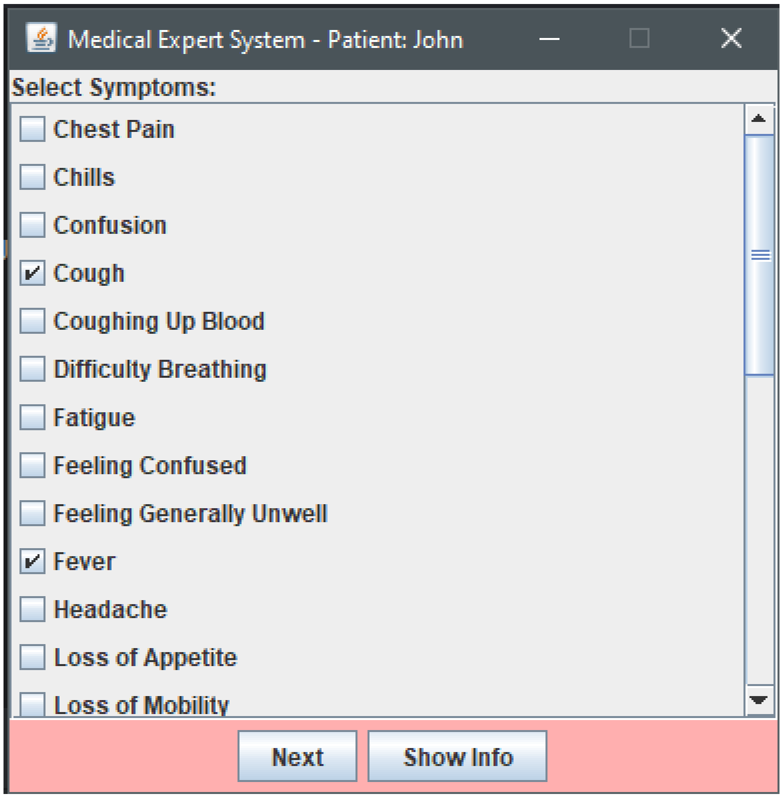
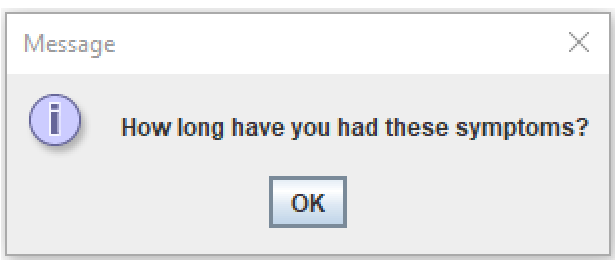
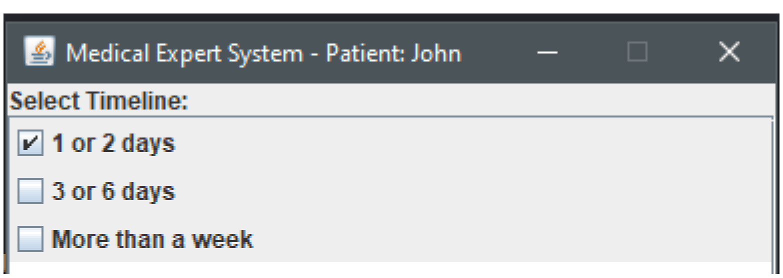

Message
What is your chief complaint? (Select one that applies to you)
OK

11

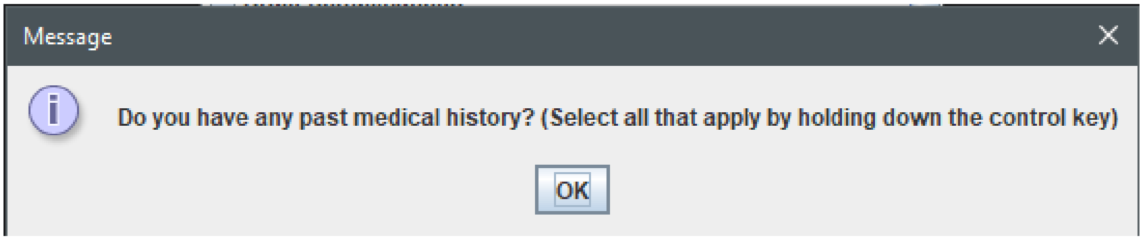

Medical Expert System - Patient: John
Select Chief Complaint:
Respiratory Problems
Exposure to disease-ridden animals or insects
Skin Problems
Pain in the joints
Upset Stomach
None of the above

12

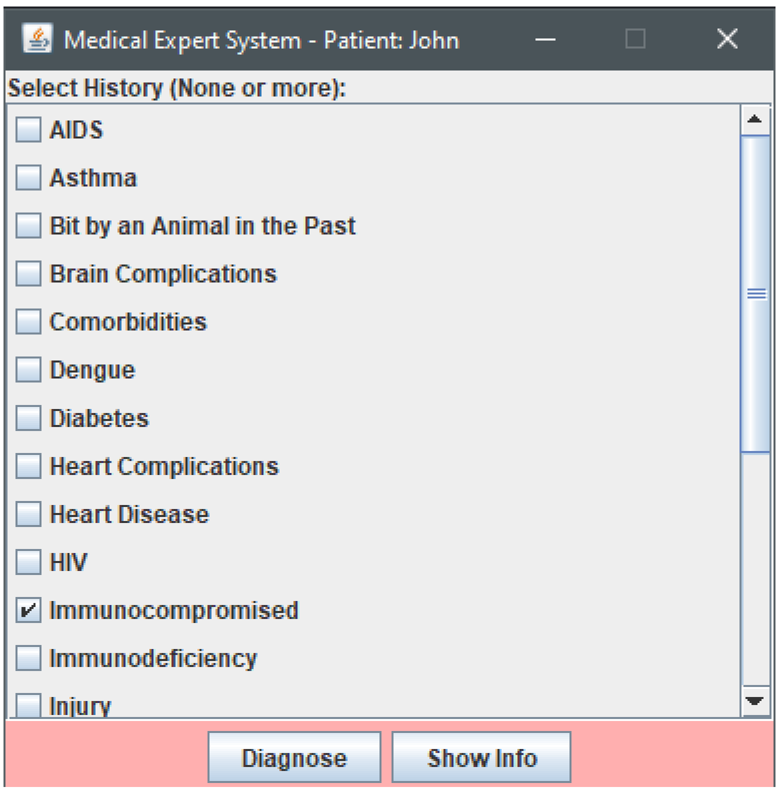

Message
What are your symptoms? (Select all that apply by holding down the control key)
OK

13	Medical Expert System - Patient: John Select Symptoms: Chest Pain Chills Confusion Cough Coughing Up Blood Difficulty Breathing Fatigue Feeling Confused Feeling Generally Unwell Fever Headache Loss of Appetite Loss of Mobility Next Show Info
14	Message How long have you had these symptoms? OK
15	Medical Expert System - Patient: John Select Timeline: 1 or 2 days 3 or 6 days More than a week

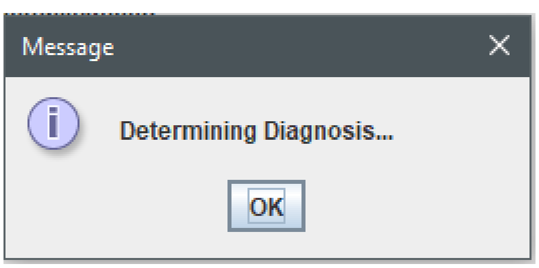
16

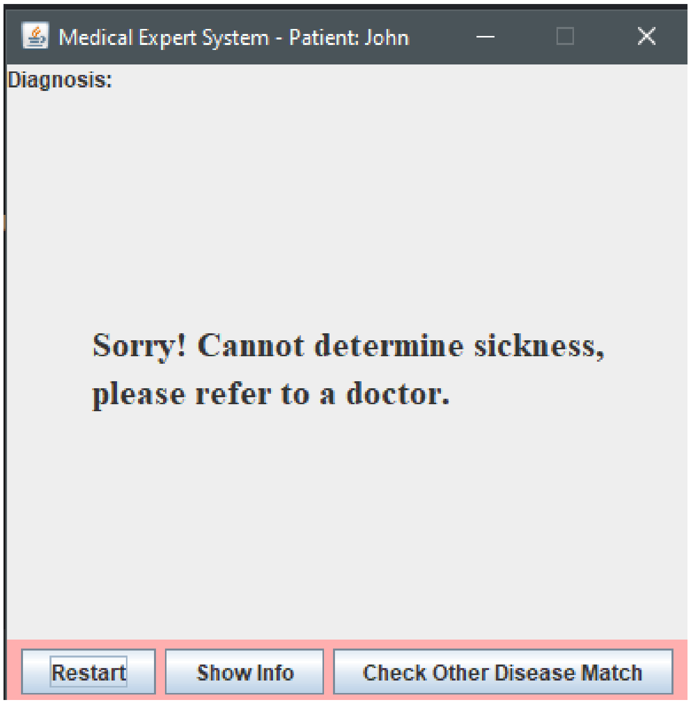
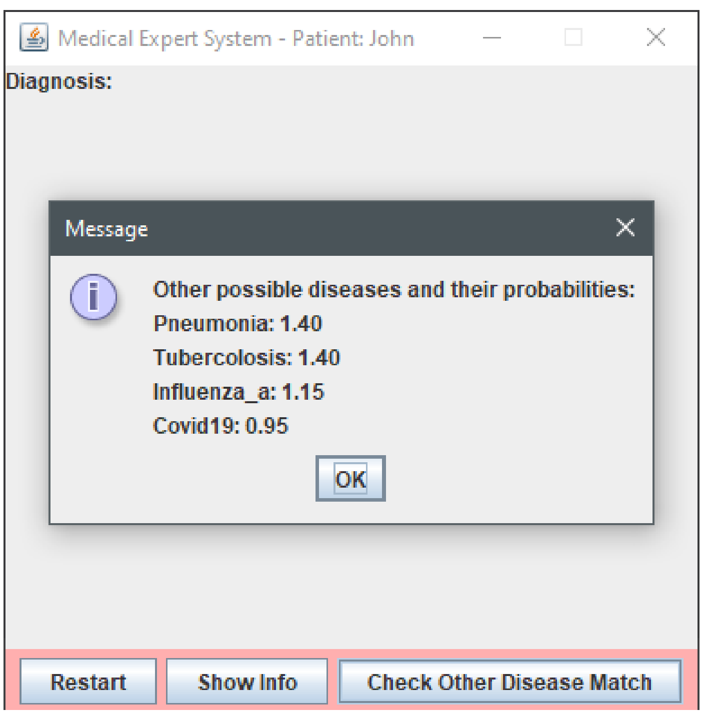

Message
Do you have any past medical history? (Select all that apply by holding down the control key)
OK

17


Medical Expert System - Patient: John
Select History (None or more):
AIDS
Asthma
Bit by an Animal in the Past
Brain Complications
Comorbidities
Dengue
Diabetes
Heart Complications
Heart Disease
HIV
Immunocompromised
Immunodeficiency
Injury
Diagnose
Show Info

18

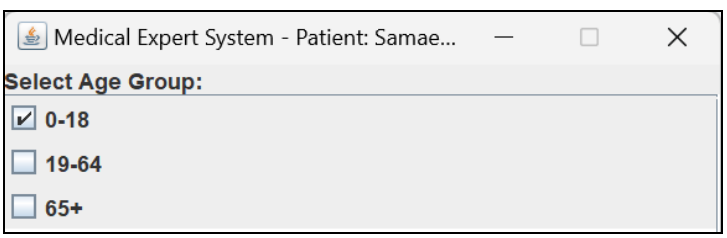
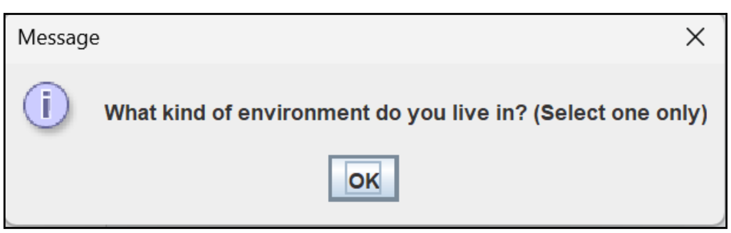

Message
Determining Diagnosis...
OK

<table>
<tr><td>19</td><td>
</td></tr>
<tr><td>20</td><td>
</td></tr>
</table>

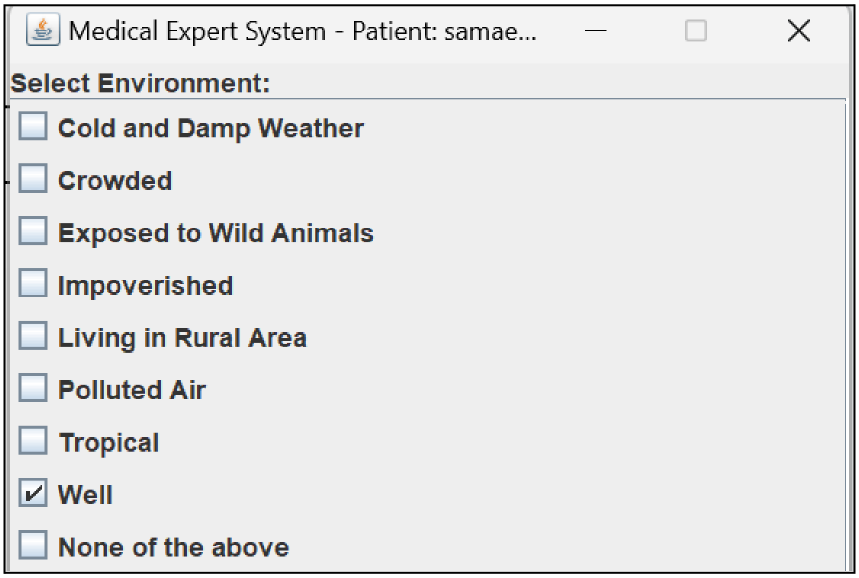
For the second impressive sample conversation, patient John belongs to the age group A, 0 to 18 years old. He lives in an impoverished environment. John's vice is smoking. His chief complaint is that he is experiencing respiratory problems, accompanied by cough and fever symptoms he had already had for the past 1-2 days. Additionally, John has a past medical condition of being immunocompromised.

In this conversation, the chatbot does not give a diagnosis. This is because 'Pneumonia' and 'Tuberculosis' have the same weight. Both diseases share the same weight of factors: age group, vices, symptoms, and past medical condition. The weights they only differ from are from the time length of the symptoms and the environment they live in. Since both 'Pneumonia' and 'Tuberculosis' are possible diagnoses, the chatbot avoids the potential harm and risk that comes with an incorrect diagnosis by not selecting either of them. Instead, the bot refers the patient to a medical professional for a correct diagnosis.

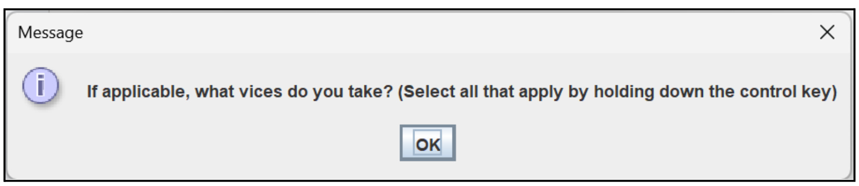
Table 3. A Not-so-Good Conversation

5	
6	

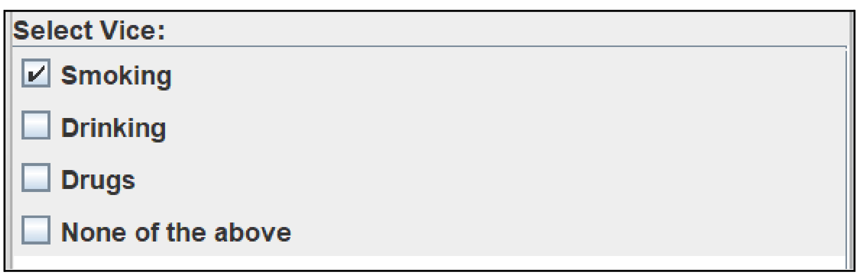
7


Medical Expert System - Patient: samae...
Select Environment:
Cold and Damp Weather
Crowded
Exposed to Wild Animals
Impoverished
Living in Rural Area
Polluted Air
Tropical
Well
None of the above

8

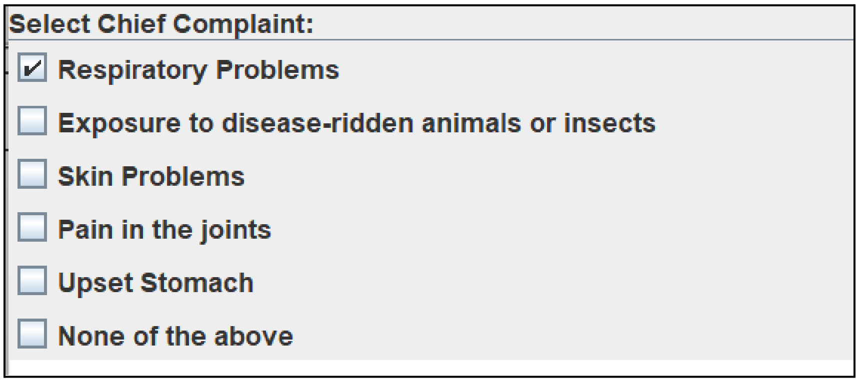
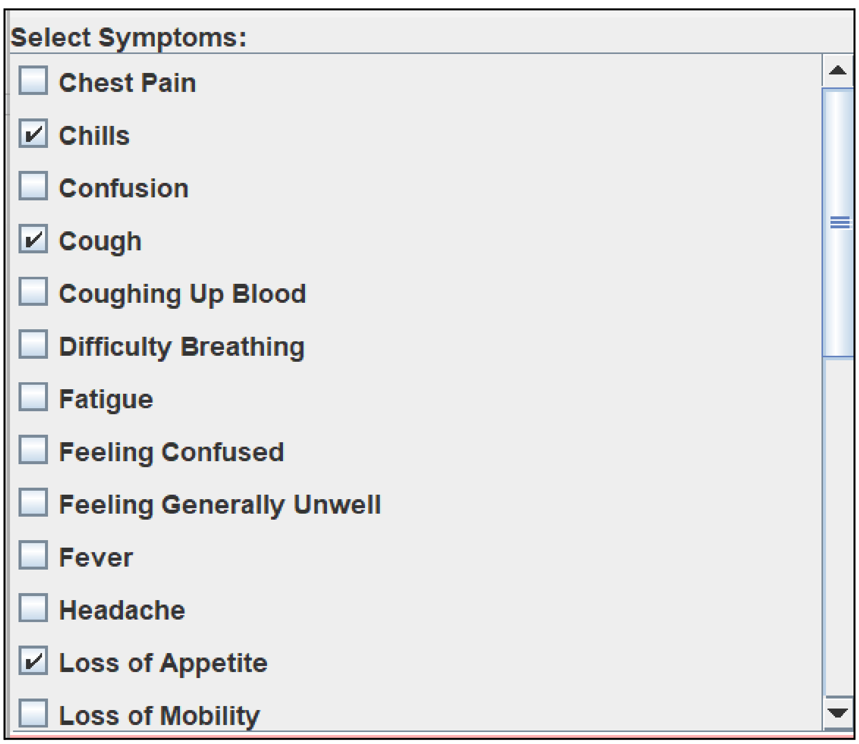

Message
If applicable, what vices do you take? (Select all that apply by holding down the control key)
OK

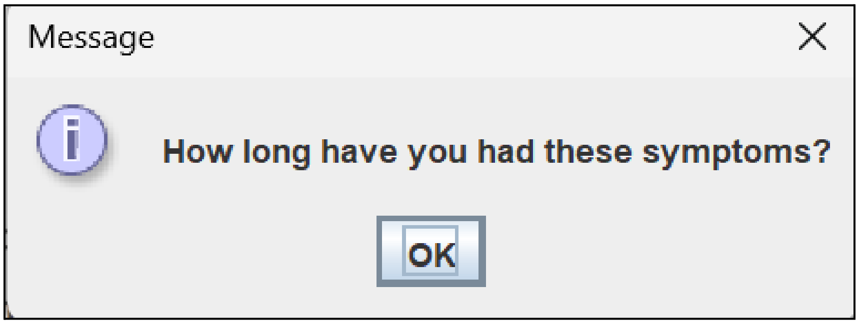
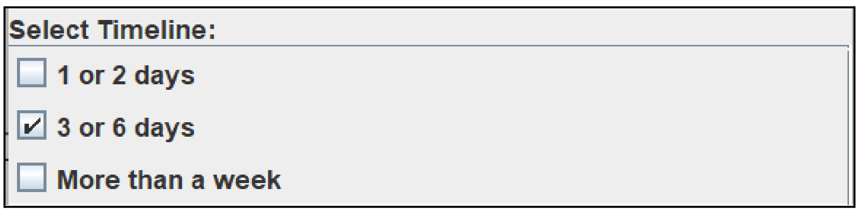
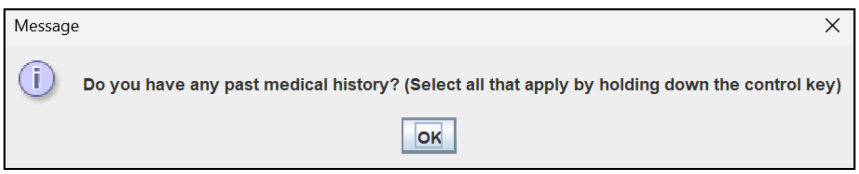
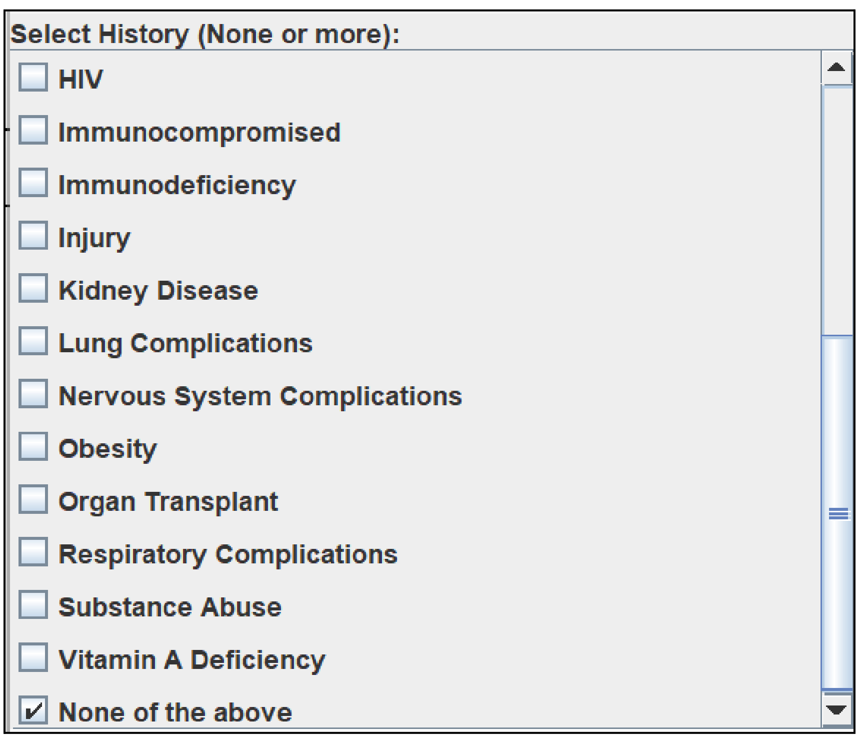
9

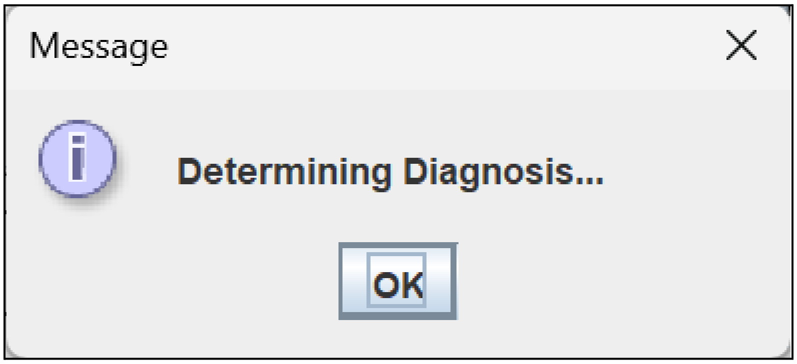
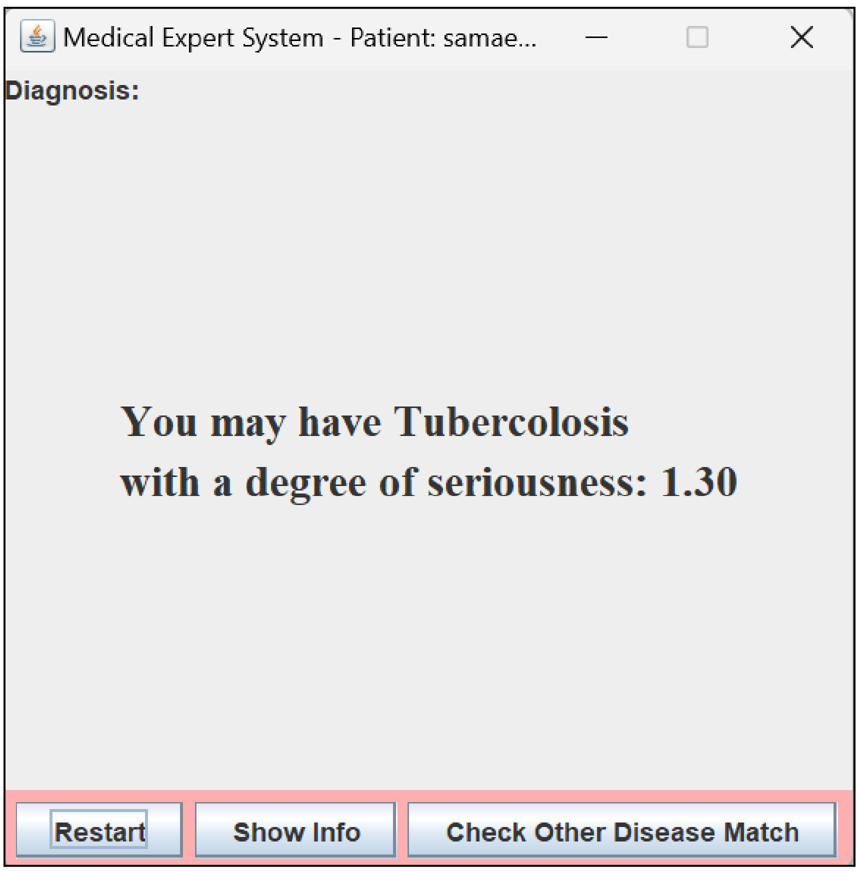

Select Vice:
Smoking
Drinking
Drugs
None of the above

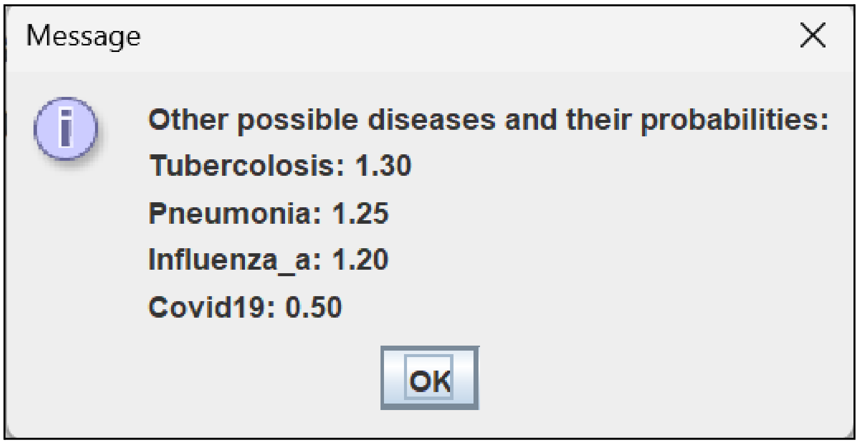
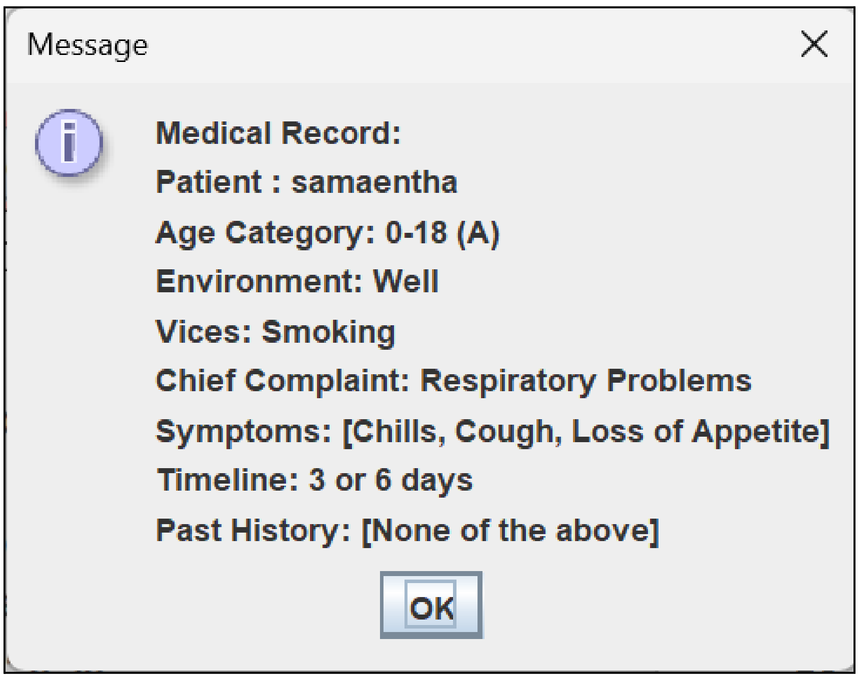
10


Message
What is your chief complaint? (Select one that applies to you)
OK

11	Select Chief Complaint: Respiratory Problems Exposure to disease-ridden animals or insects Skin Problems Pain in the joints Upset Stomach None of the above
12	Message What are your symptoms? (Select all that apply by holding down the control key) OK
13	Select Symptoms: Chest Pain Chills Confusion Cough Coughing Up Blood Difficulty Breathing Fatigue Feeling Confused Feeling Generally Unwell Fever Headache Loss of Appetite Loss of Mobility

14	Message How long have you had these symptoms? OK
15	Select Timeline: 1 or 2 days 3 or 6 days More than a week
16	Message Do you have any past medical history? (Select all that apply by holding down the control key) OK
17	Select History (None or more): HIV Immunocompromised Immunodeficiency Injury Kidney Disease Lung Complications Nervous System Complications Obesity Organ Transplant Respiratory Complications Substance Abuse Vitamin A Deficiency None of the above

18	Message Determining Diagnosis... OK
19	Medical Expert System - Patient: samae... Diagnosis: You may have Tubercolosis with a degree of seriousness: 1.30 Restart Show Info Check Other Disease Match

20	
21	

Shown above, Table 3 is a sample of a not-so-good conversation between a patient and the medical expert system. In this conversation, the selected factors were common among the three diseases: tuberculosis, pneumonia, and Influenza A. The result of the diagnosis is the patient has tuberculosis with a weight or degree of seriousness of 1.30, and the other diseases considered pneumonia with a weight of 1.25 and influenza A with a degree of 1.20. It might seem reasonable since the bot determined the patient's most likely disease because of the highest weight. However, since the patient has common symptoms between these three diseases and the only thing differentiating them are the time length of the disease and the vices associated, the bot may or may need to be more accurate. It is because the weights of these three diseases are so close, with a difference of only 0.5. As a result of this, there is a need for further testing to verify or prove what disease the patient may have. For example, utilizing this chatbot in a remote area where medical facilities are limited, and a situation like this happens, people would tend to believe that the patient has tuberculosis and ignore the possibility that pneumonia and influenza A are the diseases of the patient. It is because they have no access to other testing equipment and facilities that may prove that Tuberculosis is the patient's disease.

To summarize the strengths and weaknesses of the medical expert system, the chatbot is designed to prompt users for symptoms based on their selected chief complaint. It enables the chatbot to identify relevant diagnoses for the user accurately.
The chatbot also can correctly diagnose a patient based on the specific symptoms of a disease, despite other factors being unrelated to the disease. The chatbot was able to distinguish possible diseases associated with a patient's chief complaint and provide information on other diseases that match the symptoms. Furthermore, the patient has the option to check and verify their record to ensure accuracy.

However, the chatbot also has weaknesses, including failure to perform other tests that would further assess a patient's disease. Other tests such as blood tests, imaging tests, and urine tests may help the diagnosis of having close or similar weights of different diseases.

Furthermore, the weights of the factors are set by the group from limited research. In other words, they only produced the values through inference from sources. This means that the effectiveness of the program in determining the disease is dependent on the group's understanding of the factors and their relative importance to the disease. The ability of the chatbot to give accurate diagnoses is affected entirely if the weights are inaccurate and inconsistent.

IV. Recommendations

One weakness of the chatbot is that it heavily relies on the patient's input and performs diagnosis based on it. When multiple diseases closely match the patient, the chatbot will only provide which disease has the highest degree. This instead can be addressed by having the bot perform other procedures or ask for further input to distinguish which disease the patient has. At the current state of the bot, it does not determine what disease the patient has but rather it only suggests the possible diseases they may have since the information provided is not enough. Inputs from various probes, such as visual inspection of the affected area, using a stethoscope, and other procedures, will be helpful to assess the patient's disease further.

Another weakness of the chatbot is that the weights of the diseases are based on estimations of the group that came from research on medical articles and websites. This method might be inaccurate as this is not how a diagnosis is performed in real life. The group recommends seeking advice from a medical professional to provide the weights or to seek different methods diagnosing a patient. The reliability of the chatbot will be higher if a medical professional is involved because of their expertise and experience.

Another recommendation would be to incorporate machine learning techniques to greatly improve the system. Through learning techniques, like supervised ones, the system will be able to learn from a dataset of past diagnoses and this knowledge can be incorporated into the system's decision-making process aiding its accuracy. The specific machine learning technique to implement could be in the form of NLP or natural language processing. In this way, the chatbot will be able to ask more intricate questions and understand the patient more, leading to a better diagnosis. There could also be a system of a virtual or electronic health record that can confidentially store past medical history, diagnosis, and other important information about the patient, which will help in future diagnoses.

Overall, applying advanced techniques and updating the knowledge base with better facts from experts in the medical field will immensely improve the diagnosis capability of the bot. Finally, the current weight-based system can be improved upon or reimplemented by further research regarding how certain factors can affect the probability of a disease matching a patient.

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VI. Contributions of Each Member

Contribution Table

Names	Contributions
Balderosa, Ernest	• Researched 3 diseases (Tuberculosis, Diarrhea, Pneumonia) • Helped with the initial implementation of the DB (Identifying points to use for the chatbot–Chief complaint, Other symptoms, Age groups, and etc.) • Created flowcharts for visualization purposes
Caasi, Samantha Nicole	• Researched 2 (Ostheoarthritis and Rabies) diseases and encoded them into the knowledge base • Contributed to Knowledge Base and Chatbot, Results and Analysis, and Recommendations parts of the paper • Helped identify the easiest and most difficult parts to finalize in the knowledge base

Marcellana, John Patrick	● Contributed to most parts of the report ● Researched 2 diseases and encoded them into the knowledge base ● Helped to finalize the code for the knowledge base in adding weights and modifying for multiple inputs of a factor ● Helped debugged the knowledge base code for weight inaccuracies
Noche, Zach Matthew	● Researched 3 diseases (Measles, COVID-19, and Dengue) and encoded them into the knowledge database ● Contributed to the creation of the GUI for the medical chatbot expert system ● Contributed to Part II of paper, about knowledge base and the chatbot system ● Helped finalized the overall paper