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SYNDIAG: an expert system for disease syndrome diagnosis of traditional Vietnamese medicine

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ABSTRACT

Vietnam medicine consists of traditional Vietnam medicine and Western medicine. There is a lack of experienced traditional medicine practitioners, therefore, it needs to develop an expert system supporting medical practitioners in diagnosis. In this paper, we present an overview of syndrome diagnosis (SYNDIAG), a rule-based expert system for disease syndrome diagnosis in traditional Vietnamese medicine. The system consists of five components: knowledge base, inference engine, knowledge acquisition, explanation, and user interface. The paper focuses on how the rule base is constructed, managed, and used. At present, this knowledge base contains more than 1,000 rules used for the diagnosis of 50 disease syndromes of traditional Vietnamese medicine. The inference engine of the system applies the knowledge propagation and the algebra structure of MYCIN-like systems. We also present here the first evaluation of SYNDIAG by the practitioners of traditional medicine, who have been playing a very important role by providing the system with their knowledge.

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1. INTRODUCTION

Traditional Vietnamese medicine has a history of thousands of years of experience in disease prevention and treatment. Together with modern medicine, traditional Vietnamese medicine plays an important role in the protection of Vietnamese people's health. Like oriental medicine, traditional Vietnamese medicine is based on the basic regulations of Yin and Yang, five movements, and unified human nature theories. Diagnosis in traditional Vietnamese medicine uses four methods: inspection, auscultation, inquiry, and palpation for the disease symptoms based on position, status, and the common trend of diseases to infer the syndromes of organs, meridians, blood, and vital energy, which called the disease syndromes as mentioned earlier [1]–[6]. Four examination methods of traditional Vietnamese medicine are as:

- Inspection: inspection or "looking" focuses on visual analysis of the face, skin features, and, particularly, the tongue.
- Auscultation: auscultation refers to the analysis of particular sounds, such as shouting, laughing, singing, weeping, and groaning.
- Inquiry: inquiry refers to analysis by asking questions about the person's past health and habits.

– Palpation: palpation refers to analysis by feeling, particularly the wrist pulse, abdomen, and meridian points.

After four methods of examination of the patient, we can get a set of symptoms of the patient, which are considered inputs for the diagnostic system of disease syndromes in traditional Vietnamese medicine. The philosophy of Yin and Yang constitute the basis of traditional Vietnamese medicine. This theory holds that everything in the universe contains two aspects: Yin and Yang, which are in opposition and also in union. They are general terms for two opposite sides of matter and phenomena in nature, which are interrelated and opposed to each other. They represent not only two different matters in opposition but also two opposites in the same entity. Hence, matters are impelled to develop and to change. Generally speaking, matters and phenomena that are dynamic, external, upward, ascending, bright, progressive, hyperactive, or about functional activities belong to the category of Yang. Those which are static, internal, downward, descending, dull, retrogressive, hypoactive, or about the material belong to that of Yin. Disease conditions are first divided into syndromes of Yin and Yang. The etiological factors of disease conditions are divided into internal causative factors, the seven emotional factors (joy, anger, anxiety, worry, grief, apprehension, and fright), external factors, the six pathogenic factors (wind, cold, hot, dampness, dryness, and malignant invasions), factors other than the internal and external (improper diet, fatigue, trauma, sexual indulgence, insect or animal bites). Traditional Vietnamese medicine pays attention to syndrome differentiation (BienChung) and treatment (LuanTri) (drug therapy and non-drug therapy) called “the syndrome differentiation-based treatment” (BienChung-LuanTri). As the pathogenesis is convinced, then the prescription can be given.

In Vietnam, in every hospital, there is one department of traditional medicine where mainly medical doctors examine patients in modern medicine then they examine by traditional medicine manner. Unfortunately, in Vietnam, there is a lack of experienced traditional medicine doctors, especially in remote areas, because young people do not like to study traditional medicine, and the experienced traditional doctors are old and die from year to year. That is the reason why we have been looking for a solution to the problem of traditional medicine doctors shortage. One of the solutions is to develop an expert system that can mimic a traditional medicine.

There are some works concerning the models of diagnosis and treatment of oriental medicine using fuzzy logic and neural networks as mentioned earlier [7]–[10]. In recent years, according to [11], the authors describe an expert system for supporting the traditional Chinese medicine (TCM) consultation process-both in terms of gathering and managing the patients personal and symptomatic data and obtaining accurate diagnoses and treatments under-regulated and reviewed protocols. Nu *et al.* [12] present an approach to including the importance of symptoms in a fuzzy rule-based expert system combining positive and negative knowledge for medical consultations. To combine positive and negative knowledge, an ordered Abelian group operation is applied. Based on this approach, the system can adapt more to real clinical applications of medical consultation. Phuong *et al.* [13] propose a fuzzy model of reasoning for pulse based disease symptoms diagnosis and treatment by acupuncture based on the experience of the famous Vietnamese acupunturist Nguyen Tai Thu. In this study, symptoms are represented as pulse symbols and disease symptoms which are regarded as fuzzy sets. The value of a membership degree in the fuzzy set of a pulse symptom or a disease symptom is given in [0, 1]. The diagnostic and acupuncture treatment process is based on pulse symbols by triple Cun-Quan-Chi of traditional oriental medicine. Based on pulse symbols, the diagnostic and treatment process provides the physician with disease symptoms and acupuncture treatment formula with some types of absolute confirmation, almost confirmation, possible confirmation, and not confirmation.

There are some other works concerning the development of fuzzy systems for diagnosis in medicine as mentioned earlier [14]–[17]. Adlassnig and Kolarz [18] developed a model of a computer-assisted medical diagnostic system using fuzzy subsets (CADIAG-2). The knowledge base of the system consists of IF-THEN rules and the diagnostic process provides confirmed and excluded diagnoses as well as diagnostic hypotheses based on the fuzzy max-min inference. According to Nguyen [19], a fuzzy rule-based expert system shell combining positive and negative knowledge for consultation of Vietnamese traditional medicine is implemented. We found that fuzzy systems can’t have very similar rules whose contributions sum up to high weight. For example, in the case, if the contributions of two rules having the same conclusion get the value of 0.7 then applying the fuzzy max-min inference, we get max (0.7, 0.7)=0.7. In recent years, there have been some other works designing knowledge-based systems for Chinese medicine as demonstrated in [20], [21]. Several recent studies [22]–[37] have suggested that artificial intelligence methods are useful for developing intelligent systems in the detection and classification of diseases and especially, for COVID-19 detection.

In our study, SYNDIAG is a computer program that inputs the patient’s symptoms and uses its inference applied forward chaining strategy and the knowledge base provided by traditional medicine doctors to infer whether the patient has a disease syndrome. In developing this system, we observe that almost all symptoms in traditional medicine are not precisely defined as severe aversion to cold, slight fever, absence of sweat, and headache, while a computer requires the input data to be exact and digitized. Therefore, we must model the uncertainty so that the computer will be able to handle the input data of traditional medicine.

For such modeling, SYNDIAG uses approximate reasoning theory of MYCIN system system (which is an expert system for identification of bacteria and recommendation of antibiotics – the name derived from the antibiotics themselves, as many antibiotics have the suffix "-mycin") as shown by Shortliffe [38] and MYCIN like systems reasoning according to [39], [40] which can process uncertainty in traditional medicine. Applying the inference engine of MYCIN like systems, we can overcome the weakness of fuzzy max-min inference above. To summarize, the main contributions of this paper are:

- Applying a novel model of diagnosis of traditional Vietnamese medicine based on MYCIN-like systems approach to develop SYNDIAG which can improve the limitation of fuzzy max-min inferences.
- Building a rule base for diagnosis of disease syndromes of traditional Vietnamese medicine
- Implementing the expert system SYNDIAG, which consists of a rule base and inference engine applying Abelian group operations to combine the contributions of confirmed conclusions and excluded conclusions of the rules having the same conclusions.
- The expert system SYNDIAG can help to improve the shortage of experienced traditional medicine practitioners in Vietnam.
- With the explanation module, which can show how SYNDIAG infers the disease syndrome, students and inexperienced traditional medicine doctors can use SYNDIAG as a good teacher available anywhere at any time.

The organization of the paper is as folows: section 2 presents the structure of the system. Section 3 gives an example of the performance of the system. Section 4 shows the evaluation of the system's accuracy by traditional medicine experts. Conclusions and future works are discussed in section 5.

2. STRUCTURE OF THE SYSTEM

The system was developed using C++ programming language based on NET framework 4.5.2. The implementation framework of the system is Visual Studio 2015. In this section, we describe the structure of the expert system which consists of most components of the system as knowledge base, inference engine, knowledge acquisition, and explanation. The system contains the main elements as:

2.1. Knowledge base

In this subsection, we develop the knowledge base of the expert system of diagnosis of disease syndromes of traditional Vietnamese medicine. The knowledge base of SYNDIAG contains IF-THEN rules provided by traditional medicine doctors of the Vietnam Hospital of Traditional Medicine. A weighted rule in the knowledge base consists of a rule and its weight. Let us recall some definitions:

- Let $S = \{S_1, S_2, \ldots S_m\}$ denotes the set of symptoms. Symptom $S_i (i = 1, .., m)$ takes values $\mu_{R_{PS}}(P_q, S_i)$ in [-1,1]. The value $\mu_{R_{PS}}(P_q, S_i)$ indicates the degree to which a patient exhibits symptoms S_i where $\mu_{R_{PS}}(P_q, S_i) = 1$ means symptom S_i surely present for a patient P_q, $\mu_{R_{PS}}(P_q, S_i) = -1$ means symptom S_i surely absent for the patient P_q, $0 < \mu_{R_{PS}}(P_q, S_i) > 1$ means symptom S_i present for a patient P_q to some degree, $0 < \mu_{R_{PS}}(P_q, S_i) < -1$ means symptom S_i absent for patient P_q with some degree and the value $\mu_{R_{PS}}(P_q, S_i) = 0$ meaning "no preference" that symptom S_i is "unknown" about presence or absence for a patient P_q.
- Let $E = \{E_1, E_2, \ldots E_n\}$ denotes the set of all elementary conjunctions of some symptoms, i.e., conjunction of some symptoms and some other negated symptoms (e.g., S_1, $\neg S_2$, and S_3 mean symptom S_1 is present and S_2 absent and S_3 present), which take values $\mu_{R_{P\_E}}(P_q, E_h)$ where the value $\mu_{R_{P\_E}}(P_q, E_h)$ is a value of the conjunction E_h $(h = 1, .., n)$. The values$\mu_{R_{P_E}}(P_q, E_h)$ take values in [-1,1].
- Let $SYND = SYND_1, SYND_2, \ldots, SYND_g\}$ denotes the set of disease syndromes $SYND_k$ $(k = 1, .., g)$ which take values $\mu^c_{R_{P\_SYND}}(P_q, SYND_k)$, where the value $\mu^c_{R_{P\_SYND}}(P_q, SYND_k)$ confirms about belief degree of $SYND_k$ the patient $P_q$from observed symptoms defined by questionnaire q.

1) For diagnosis of disease syndromes, we have the following relations:
   The form of rules: $E_h \rightarrow SYND_k(\mu^c_{R_{E_{SYND}}}(E_h, SYND_k))$, where $\mu^c_{R_{E_{SYND}}}(E_h, SYND_k)$ take values in [-1,1].
   - $\mu^c_{R_{E_{SYND}}}(E_h, SYND_k) = 1$ means that $SYND_k$ is confirmed
   - $0 < \mu^c_{R_{E_{SYND}}}(E_h, SYND_k) < 1$ means there is a certain possibility of $SYND_k$;
   - $\mu^c_{R_{E_{SYND}}}(E_h, SYND_k) = 0$ means that $SYND_k$is not confirmed and not excluded;
   - $-1 < \mu^c_{R_{E_{SYND}}}(E_h, SYND_k) < 1$ means being a certain possibility of excluding $SYND_k$;

– $\mu^c_{R_{E_{SYND}}}(E_h, SYND_k) = -1$ means that $SYND_k$ excluded.

E_h-a symptom or elementary conjunction of symptoms S_i in the form of $E_h = S_1, \ldots, \neg S_m$, for each $i, i = 1, \ldots, m$. $SYND_k$ is a disease syndrome.

The values $\mu^c_{R_{S_{SYND}}}(E_h, SYND_k)$ indicate degrees in which the present symptoms or the elementary conjunction of symptoms E_h confirm the pathogenesis labeled with disease syndrome $SYND_k$.

2) For diagnosis of intermediate syndromes, we have the following relations:
The form of rules: $E_h \rightarrow IS_l(\mu^c_{R_{E\_S}}(E_h, IS_l))$ where IS_l is an intermediate symptom. $\mu^c_{R_{E\_S}}(E_h, IS_l)$ indicate degrees in which the present symptoms or the elementary conjunction of symptoms E_h confirm the intermediate symptom IS_l. Where $\mu^c_{R_{E\_S}}(E_h, IS_l)$ take values in [-1,1].

Rules of this type formalize the way traditional medicine doctors reason: "if a patient is suffering from these symptoms, so he should be suffering from this other symptom because this symptom is usually observed together with the first group of symptoms". To simplify, we don't include the negated symptoms in elementary conjunctions of some symptoms. Currently, the knowledge base contains more than 1,000 rules used to diagnose 50 disease syndromes of traditional Vietnamese medicine. Examples of rules of some disease syndromes in knowledge base:

– Rule 1: IF severe aversion to cold, slight fever, absence of sweat, headache, aching pain of extremities, stuffy nose with nasal discharge, cough with thin sputum, thin and whitish coating of tongue, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 1.
– Rule 2: IF slight fever, absence of sweat, headache, aching pain of extremities, stuffy nose with nasal discharge, cough with thin sputum, thin and whitish coating of tongue, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.9.
– Rule 3: IF severe aversion to cold, slight fever, absence of sweat, headache, aching pain of extremities, stuffy nose with nasal discharge, cough with thin sputum, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.85.
– Rule 4: IF absence of sweat, headache, aching pain of extremities, stuffy nose with nasal discharge, cough with thin sputum, thin and whitish coating of tongue, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.8.
– Rule 5: IF severe aversion to cold, slight fever, absence of sweat, Headache, stuffy nose with nasal discharge, cough with thin sputum, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.75.
– Rule 6: IF aching pain of extremities, stuffy nose with nasal discharge, cough with thin sputum, thin and whitish coating of tongue, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.7.
– Rule 7: IF stuffy nose with nasal discharge, cough with thin sputum, thin and whitish coating of tongue, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.6.
– Rule 6: IF cough with thin sputum, thin and whitish coating of tongue, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.5.
– Rule 8: IF stuffy nose with nasal discharge, cough with thin sputum, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.45.
– Rule 9: IF thin and whitish coating of tongue, floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.4.
– Rule 10: IF floating and tight pulse THEN confirms influenza caused by wind-cold syndrome with degree 0.15.
– Rule 11: IF severe aversion to cold THEN confirms influenza caused by wind-cold syndrome with degree 0.15.
– Rule 12: IF slight fever and absence of sweat THEN confirms influenza caused by wind-cold syndrome with a degree 0.25.
– Rule 13: IF absence of sweat, headache THEN confirms influenza caused by wind-cold syndrome with degree 0.35.
– Rule 14: IF aching pain of extremities THEN confirms influenza caused by wind-cold syndrome with degree 01.
– Rule 15: IF stuffy nose with nasal discharge THEN confirms influenza caused by wind-cold syndrome with degree 0.2.
– Rule 16: IF slight fever THEN confirms influenza caused by wind-cold syndrome with a degree 0.1.
– Rule 17: IF absence of sweat THEN confirms influenza caused by wind-cold syndrome with a degree 0.1.
– Rule 18: IF headache THEN confirms influenza caused by wind-cold syndrome with degree 0.1.
– Rule 19: IF aching pain of extremities THEN confirms influenza caused by wind-cold syndrome with degree 0.15.

- Rule 20: IF cough with thin sputum THEN confirms influenza caused by wind-cold syndrome with degree 0.3.
- Rule 21: IF thin and whitish coating of tongue THEN confirms influenza caused by wind-cold syndrome with degree 0.2.
- Rule 22: IF sore throat with congestion THEN confirms influenza caused by wind-heat syndrome with degree -0.1.
- Rule 23: IF expectoration of yellowish sputum THEN confirms influenza caused by wind-heat syndrome with degree -0.1

2.2. Inference engine

In our system, we follow the doctor's way of making a disease syndrome diagnosis. The global weight of a diagnosis of a disease syndrome $SYND_k$ is given by a questionnaire q, and the contribution of a rule R given q is defined as:
Step 1: a user assigns weights $\mu_{R_{P\_S}}(P_q, S_i) = q(S_i)$ to symptoms if S_i is a question.
Step 2: calculating the conjunction in the rule's premise E_h by:
- $\mu_{R_{P\_E}}(P_q, A\&B) = CONJ(\mu_{R_{P\_E}}(A), \mu_{R_{P\_E}}(B))$ where $CONJ(x,y) = min(x,y)$
- $\mu_{R_{P\_E}}(P_q, \neg A) = NEG(\mu_{R_{P\_E}}(P_q, A))$ where $NEG(x) = -x$.

Step 3: calculation of the contribution of a rule R given q by:
- $\mu^c_{R_{P\_SYND}}(P_q, E_h \rightarrow SYND_k) = CTR(\mu_{R_{P\_E}}(P_q, E_h), \mu^c_{R_{S\_SYND}}(E_h, SYND_k))$

(The contribution of a rule R is computed from the weight of the rule and the global weight of its antecedent E using CTR which is a formula for computing a contribution of the rule), where:
- $CTR\left(\mu_{R_{P_E}}(P_q, E_h), \mu^c_{R_{S_{SYND}}}(E_h, SYND_k)\right) = 0, if \mu_{R_{P\_E}}(P_q, E_h) \leq 0$
- $CTR\left(\mu_{R_{P_E}}(P_q, E_h), \mu^c_{R_{S_{SYND}}}(E_h, SYND_k)\right) = min(\mu_{R_{P\_E}}(P_q, E_h), \mu^c_{R_{S\_SYND}}(E_h, SYND_k))\ if$ $\mu_{R_{P\_E}}(P_q, E_h), \mu^c_{R_{S\_SYND}}(E_h, SYND_k) \geq 0$
- $CTR\left(\mu_{R_{P_E}}(P_q, E_h), \mu^c_{R_{S_{SYND}}}(E_h, SYND_k)\right) = -min(\mu_{R_{P\_E}}(P_q, E_h), -\mu^c_{R_{S\_SYND}}(E_h, SYND_k))\ if$ $\mu_{R_{P\_E}}(P_q, E_h) > 0, \mu^c_{R_{S\_SYND}}(E_h, SYND_k) < 0$

Step 4: calculating all contributions of the rule $R_1, \ldots.. R_n$ with the same conclusion $SYND_k$ given q by:
$\mu^c_{R_{P_{SYND}}}(P_q, SYND_k) = \mu^c_{R_{P\_SYND}}(P_q, R_1) \oplus \ldots. \oplus \mu^c_{R_{P\_SYND}}(P_q, R_n)$, where $SYND_k$ is a propositional variable and $R_1 \ldots. R_n$ are all rules in the rule base θ whose succedent is $SYND_k$. The group operation $\oplus$ is computed by:

$$X \oplus Y = X + Y - X \times Y\ if\ X, Y \geq 0$$
$$X \oplus Y = X + Y + X \times Y\ if\ X, Y \leq 0$$
$$X \oplus Y = \frac{(X+Y)}{(1-(|X|,|Y|))}\ if\ X \times Y \leq 0 \quad (1)$$

We assume that the ordered set weights $\mu^c_{R_{P\_SYND}}(P_q, SYND_k)$ are in [- 1, l].

More precisely, for diagnosis of disease syndromes:
- Degree $\mu^c_{R_{P_{SYND}}}(P_q, SYND_k) = 1$ means absolutely confirmation of the conclusion $SYND_k$.
- Degree $\mu^c_{R_{P\_SYND}}(P_q, SYND_k)$ such that $0.6 \leq \mu^c_{R_{P_{SYND}}}(P_q, SYND_k) > 1$ means almost confirmation of the conclusion $SYND_k$.
- Degree $\mu^c_{R_{P\_SYND}}(P_q, SYND_k)$ such that $\varepsilon \leq \mu^c_{R_{P_{SYND}}}(P_q, SYND_k) < 0.6$ means possible confirmation of the conclusion $SYND_k$.
- Degree $\mu^c_{R_{P\_SYND}}(P_q, SYND_k)$ such that $-\varepsilon < \mu^c_{R_{P\_SYND}}(P_q, SYND_k) < \varepsilon$ means "unknown" about Confirmation of conclusion of $SYND_k$.
- Degree $\mu^c_{R_{P\_SYND}}(P_q, SYND_k)$ such that $-0.6 < \mu^c_{R_{P\_SYND}}(P_q, SYND_k) \leq -\varepsilon$ means possible exclusion of conclusion of $SYND_k$.
- Degree $\mu^c_{R_{P\_SYND}}(P_q, SYND_k)$ such that $-1 < \mu^c_{R_{P_{SYND}}}(P_q, SYND_k) \leq -0.6$ means almost exclusion of conclusion $SYND_k$.
- Degree of $\mu^c_{R_{P\_SYND}}(P_q, SYND_k) =$ -1 means absolute exclusion of conclusion $SYND_k$.

here ε is a heuristic value and, in our case $\varepsilon = 0.01$.

The system will list all conclusions of syndromes $SYND_k$ with their degrees of belief. The final diagnosis result is a maximum of all degrees of all conclusions of syndromes $SYND_k$.

2.3. Knowledge acquisition

In our system, we selected the rules by approaches:

- Rules from experts. Most rules are formed by traditional medicine physicians and doctors from the Thai Nguyen University of Medicine and Pharmacy and the national hospital of traditional medicine, Vietnam. To form these rules, we listed all symptoms seen in patients of disease syndromes (there are about 40 such symptoms) and stored these symptoms by the frequency of their occurrence and by the importance of symptoms for each disease syndrome. Then, we formed all possible combinations of the most frequent symptoms and some combinations involving less frequent symptoms and symptoms with less importance and asked the traditional medicine practitioners to estimate the degree to which this combination of symptoms confirms or excludes the disease syndrome.
- Rules from a statistical approach. In this approach, for each combination of symptoms, instead of asking a traditional medicine practitioner, we look into the database of already diagnosed patients, find all the patients who had these symptoms, and estimate the possibility degree as, e.g., the proportion of those who had such symptoms. This approach is efficient and fast, but to get statistically justified estimates, we must have a large database of patients' records with correct diagnoses, and the existing database is sometimes not large enough.

Verifying the rule base. Rules may come from multi-experts and traditional medicine practitioners, or maybe doctors are not perfect, and as a result, their rules may not be exactly correct. Similarly, statistical rules are gathered from limited data, and some of them may therefore be wrong. It is desirable to maintain the correctness of the knowledge base and to avoid conflicts between the rules. The accuracy of expert rules depends on traditional medicine practitioner's skills. At present, we simply combine all traditional medicine practitioners rules together; in the future, we are planning to test the doctors diagnostic abilities and to "weigh" the rules proposed by different traditional medicine practitioners based on their different diagnostic abilities.

At present, the knowledge base is maintained by a committee consisting of leading traditional medicine practitioners. These doctors evaluate all the rules, including the statistical rules, and eliminate rules that they believe to be false. After that, the system is applied to different patients, and the results are shown to the doctors committee. If the committee sees a wrong diagnosis, it proposes a way to correct the rules. To avoid conflict between the rules, every time a new rule is added to the rule base, the system checks whether this new rule is in conflict with any existing rules; if there is a conflict, the doctors committee decides which of the two conflicting rules to keep.

2.4. Explanation

To understand the reasoning process and the diagnosis and treatment result, the system applies the forward chaining strategy to be able to explain how it comes to a certain conclusion about the possibility of being infected by a patient. During the diagnosis, the reasoning engine browses the rule base and marks all the matched rules. When the diagnosis is completed, the explanation is formed by collecting all the matched rules and every step of reasoning using each matched rule. In this explanation, SYNDIAG shows its conclusion, all sets of patients symptoms, and the rules that match each set. As a result, the users can see the intermediate diagnostic conclusion from all four steps of the diagnosing process and the way the rules affect the final conclusion.

3. EXAMPLES OF THE PERFORMANCE OF THE SYSTEM

Figure 1 presents the interface of the system. When the system runs, the functions of the system are activated. There are four main functions: knowledge acquisition, the syndrome diagnosis, the explanation facility, and the exit function. Figure 2 illustrates the function of knowledge acquisition, which consists of two parts: the left part manages the information of symptoms, and the right part manages the information of rules. In the right part, the rules of the system are listed, and the below parts are the functions "add", "update", and "delete" used for editing the rules in the system. Similarly, the left part shows the functions "add", "update", and "delete" used for editing the symptoms in the system.

In Figure 2, our system consists of four examination methods: inspection containing 22 symptoms, inspection containing four symptoms, auscultation and olfaction containing four symptoms, interrogation containing 20 symptoms, and pulse and palpation containing seven symptoms.

In order to use the function of editing symptoms, we use the functions "edit or delete symptoms" in the left part of the interface. Firstly, we choose the symptom that needs to be edited by choosing the symptom in the "inspection" of the combo box "add symptoms", then we can use the combo box "edit or delete symptoms" to choose the symptom, for example, "sweet" of "inspection" of the examination method. Finally, we use the combo box "updated value" for updating a new symptom.

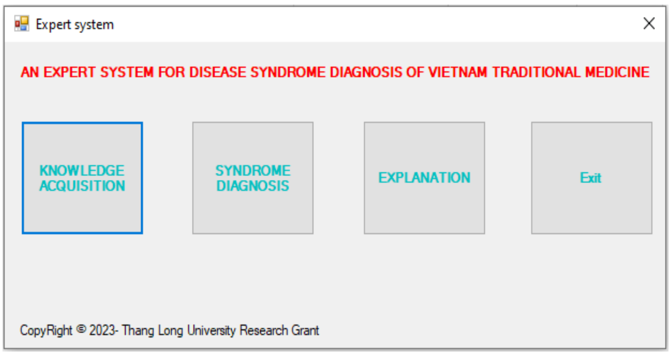

Figure 1. The interface of the system

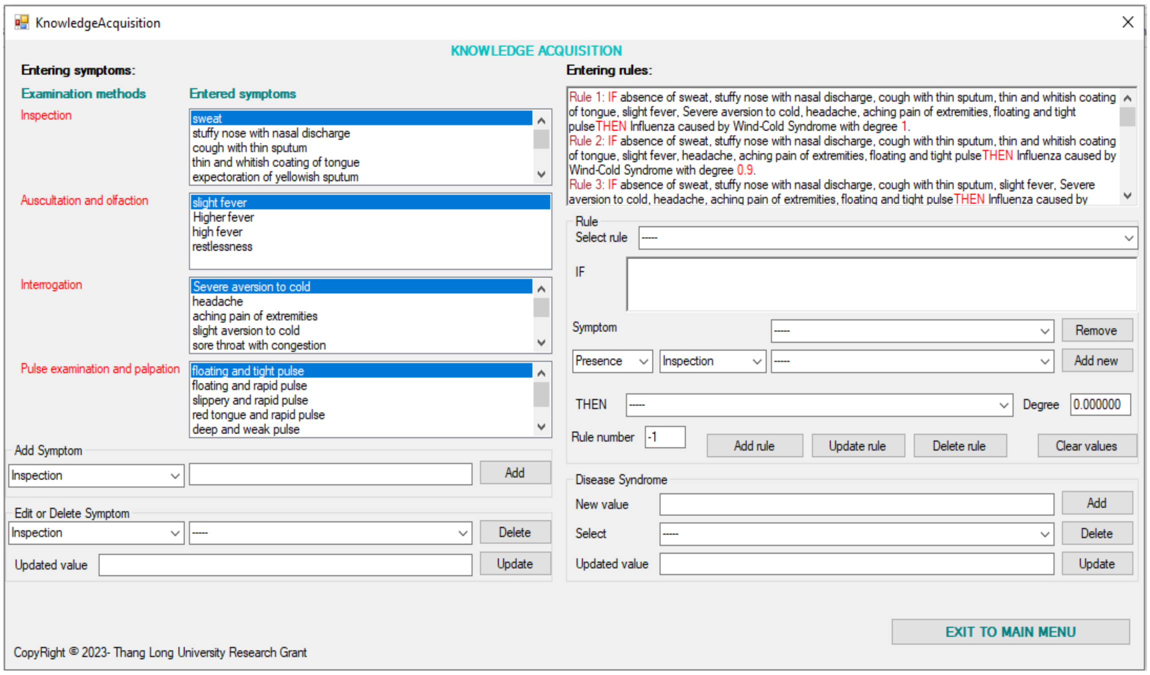

Figure 2. Knowledge acquisition

For syndrome diagnosis, the system SYNDIAG communicates with traditional medicine doctors via a menu mode by selecting the appropriate answers. These answers are used as input for the syndrome diagnosis process. In the diagnosis process, first, SYNDIAG lists all possible symptoms of disease syndromes with possible degrees of presence of each symptom, which is represented by the patient.

The interface syndrome diagnosis allows a user to choose symptoms that are present in a given patient, together with their degrees of presence. This information forms an input for the diagnosis process. After the input is completed, the inference engine of the system processes this input by matching it with the premises of all symptoms in the knowledge base. If the premise of the rule is matched with the input data, the conclusion of the rule is inferred. The inference engine of the system will combine all contributions of all "fired" rules with the same syndrome diagnosis conclusion in order to return the diagnosis conclusion with its degree of belief. An example of the result of the syndrome diagnosis is given in Figure 3. In the combo box "diagnosis" the diagnosis is "influenza caused by wind-heat syndrome with degree 0.9964728, which means almost confirmation of the disease syndrome".

Figure 4 illustrates an example of how to explain the syndrome diagnosis "influenza caused by wind-heat syndrome" by listing all the "fired" rules with the same diagnosis and combining the contributions of these rules to get the combined degree of diagnosis. Users can look at this explanation by using the combo box "explanation".

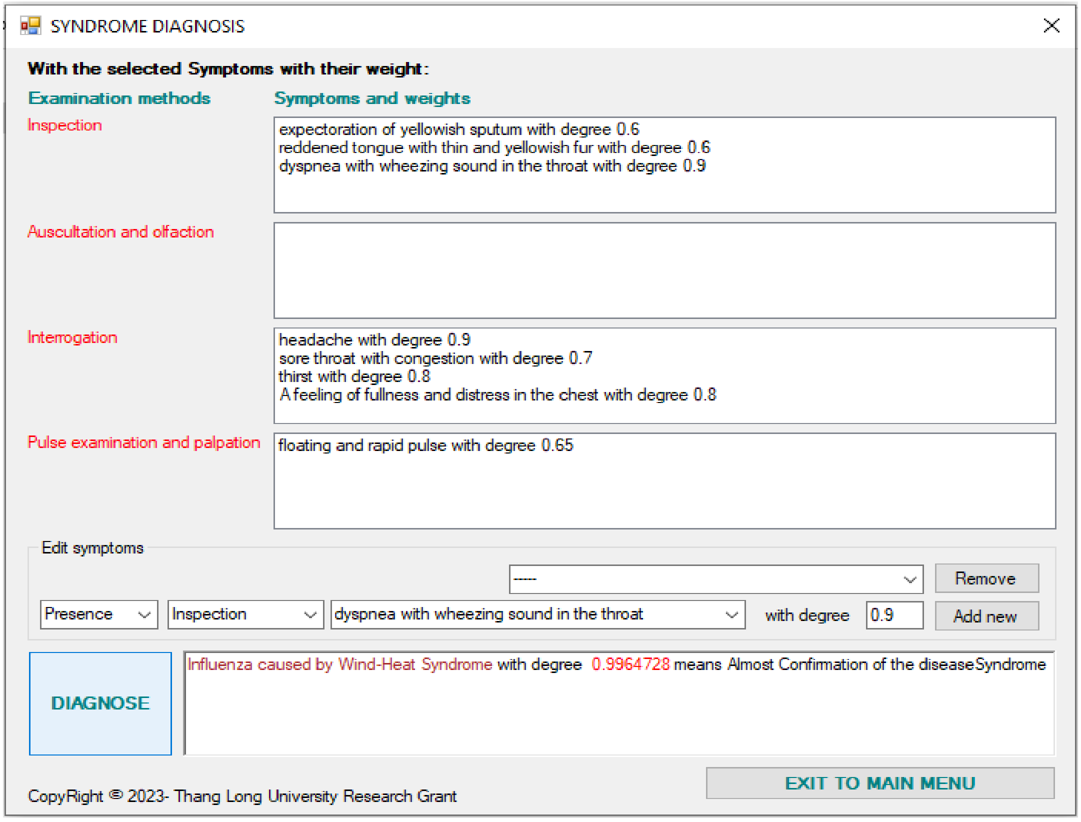

Figure 3. Results of syndrome diagnosis

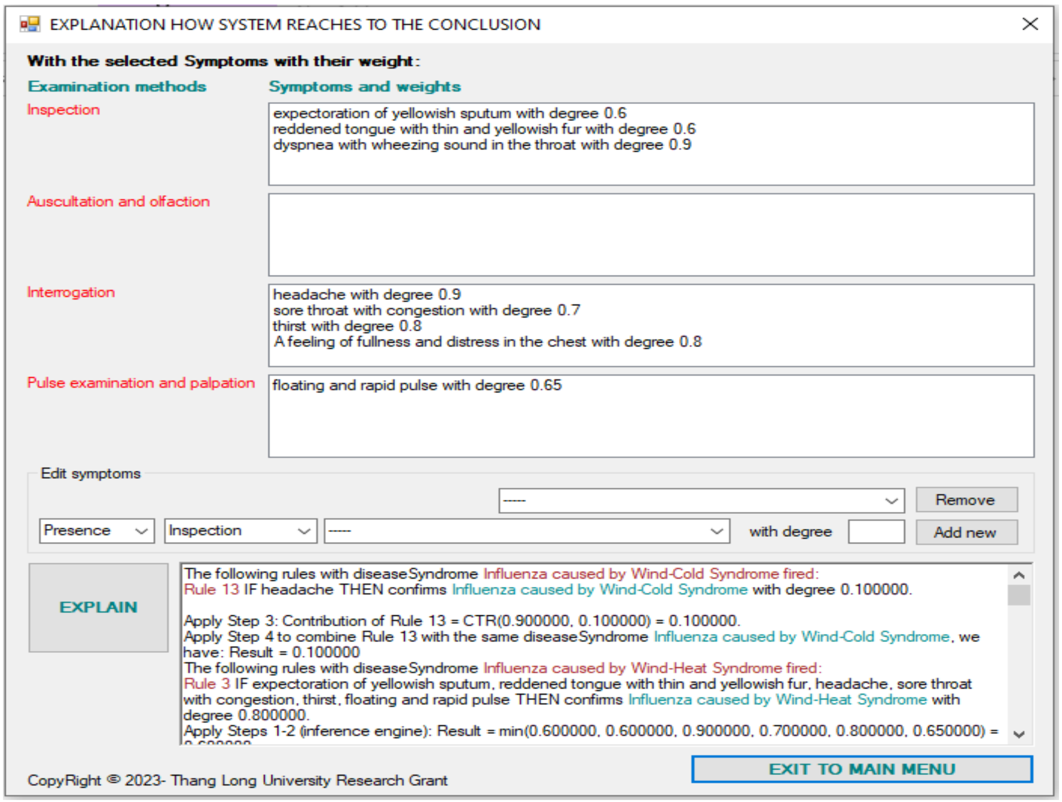

Figure 4. An example of an explanation of the system

4. EVALUATION

To test SYNDIAG, we applied it to several patients and compared the system's diagnoses with the diagnoses of experienced traditional medicine physicians from traditional medicine hospitals. The information about these patients was added to our database. We also used hundreds of archived patients records from some traditional medicine hospitals in Hanoi and Thai Nguyen as the medical input data for SYNDIAG and then compared the system's conclusion with the recorded diagnoses. In the majority of cases, SYNDIAG's diagnosis was the same as recorded by the doctors. There were differences in diagnosis only in a few cases in which patients had rare symptoms, which we originally did not take into consideration in our design of the system. This drawback of our system was corrected by updating the list of symptoms and the list of combinations of symptoms by adding new rules and slightly adjusting the possibility values in several existing rules. After this correction, the system worked well on all recorded patient data.

5. CONCLUSION

This paper presents an overview of the SYNDIAG project-a rule-based expert system for disease syndrome diagnosis in traditional Vietnamese medicine. In this paper, we describe some notions of traditional Vietnamese (oriental) medicine and the lack of traditional medicine practitioners. An expert system for disease syndrome diagnosis in traditional Vietnamese medicine would be a good solution as a second traditional Vietnamese medicine practitioner, which can improve doctors performance in diagnosing disease syndromes. We described the general structure of the system, such as the system's knowledge base, inference engine knowledge acquisition, and explanation modules. The evaluation shows that the system can help traditional medicine practitioners in diagnosis, and we can use the system to teach medical students and inexperienced doctors about the diagnosis process of traditional Vietnamese medicine anywhere at any time.

In order to improve SYNDIAG, we keep maintaining and updating the system's rule base; in particular, we try to select more rules and make the rule base more accurate and robust. On the other side, we improve the inference engine of the system by including the importance of symptoms in the system so that it can diagnose with higher accuracy and the degrees of similar disease syndrome diagnoses can be more separable. In order to make the system's diagnosis more explainable by including explanation functions by showing the backward chaining of the system, the system can answer the question of why such a diagnosis is correct.

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