Expert judgment, limitation inference, and threshold values to optimize diagnosis in eye diseases expert system

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Article Info

Article history:

Received Jan 19, 2024
Revised Aug 10, 2024
Accepted Aug 25, 2024

Keywords:

Expert judgment
Eye diseases
Limitation inference
Optimize expert system
Threshold value

ABSTRACT

This research aimed to develop an optimal expert system by adopting a simplified approach. The methodology integrates an expert judgment approach, limitation inference, and establishing a threshold value. Expert judgment is pivotal in assigning a percentage weight to each rule, facilitating a nuanced evaluation of diagnostic criteria to augment the system's precision. Moreover, incorporating limitation inference strategically constrains the number of user inquiries, streamlining the diagnostic process and enhancing overall efficiency. Additionally, the imposition of a threshold value ensures a more precise early diagnosis by delineating specific criteria for condition identification. This comprehensive approach underscores the paramount importance of user experience and aims to alleviate the burden on individuals seeking a diagnosis. Ultimately, the anticipated outcome of this study is the development of an expert system poised to deliver early diagnoses with heightened efficiency and accuracy. By integrating expert judgment, limitation inference, and threshold values, this research embodies a refined and user-centric paradigm for eye disease diagnosis, promising significant advancements in global eye health.

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1. INTRODUCTION

Eye diseases are a significant global health issue, impacting billions of people and leading to varying degrees of disability [1]. This issue directly affects the impacted individuals and influences the global healthcare system [2], [3]. Proper and early diagnosis is essential in eye care to prevent further damage [4]–[6]. A comprehensive approach to eye health is needed, including prevention, early diagnosis, and treatment of eye diseases [7]. A comprehensive approach of this nature is paramount for alleviating the burden on individuals affected and optimizing the effectiveness and sustainability of the global healthcare system, which confronts various challenges arising from eye health.

Expert systems have been extensively developed to provide early diagnosis of eye diseases [8]–[10]. Expert systems use a combination of rules and algorithms to analyze symptoms and provide a diagnosis [11]–[14]. The knowledge base of this system includes information about eye diseases and their symptoms, while the inference engine applies rules to symptoms to make a diagnosis [8], [15]. Expert systems are generally made with a consultation model that must be answered by users as if they were communicating with human experts [16], [17].

However, expert systems frequently encounter delays in delivering diagnoses as they are compelled to address a multitude of rules, leading to prolonged diagnostic durations [18]. Furthermore, the resulting diagnosis also does not indicate the percentage level of possible diseases suffered [19]. This, of course, makes it difficult for decision-making to take further handling actions. Research to optimize the consultation process in expert systems is needed to obtain an efficient and more accurate initial diagnosis [20]–[23]. Such endeavors are essential to enhance the overall effectiveness of expert systems, ensuring timely and accurate diagnoses that can facilitate more informed and prompt decision-making in subsequent medical procedures.

The purpose of this study is to create a more optimal expert system for producing early diagnoses for eye diseases with a consultation model. This study employs expert weighting in the form of percentages applied to each rule base. A threshold value is subsequently implemented to identify diagnoses that exceed this specified weight. To streamline the consultation process and enhance user experience, symptoms associated with a "No" response are not further investigated, thus eliminating the need for patients to answer all rules within the database. This innovative approach aims to optimize both the efficiency and accuracy of the expert system. By presenting a refined methodology for early diagnosis, the study concurrently prioritizes user convenience by minimizing unnecessary rule interactions, thereby enhancing the overall diagnostic process.

2. METHOD

This research develops a rule-based expert system for eye diseases. This system model optimizes the diagnostic process by integrating expert judgment, threshold values, and limited inference to produce a more efficient and specific early diagnosis. The designed approach model is illustrated in Figure 1.

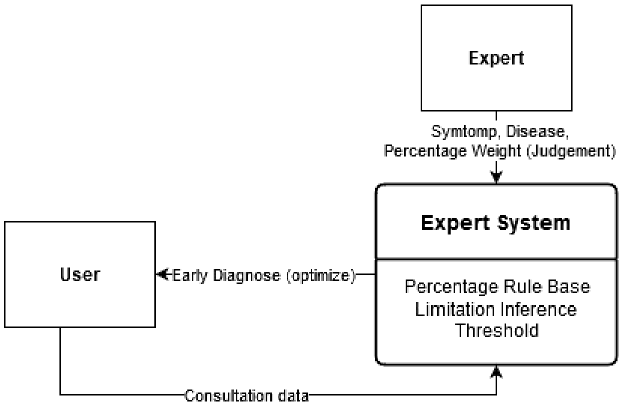

Figure 1. Expert system optimization with expert judgment, threshold value, and limitation inference

2.1. Expert judgment

Expert systems are designed to handle real-world problems requiring the involvement of experts, using rule-based expert knowledge [24]–[26]. In a rule-based expert system, the knowledge is represented by production rules, which consist of an IF part (a condition or premise) and a THEN part (an action or conclusion) [27], [28]. Most rule-based expert systems in healthcare focus on symptom and disease data, as these are the primary factors used in medical diagnosis [29]. This study will conduct a survey among eye disease specialists to obtain their expert judgments, which will be translated into weightings for each rule-based system. The formula for calculating expert weighting is as (1):

$$\mathrm{D} = \mathrm{WS1} + \mathrm{WS2} + \cdots \mathrm{WSn} = 100\% \quad (1)$$

where D is disease and WS is weigth of symptom.

The total weight for each disease is assigned a value of 100%, with each influential symptom contributing incrementally to the diagnostic weight. Consequently, the percentage of the diagnosis is contingent upon the symptoms that receive affirmative responses. The resultant diagnostic percentage is subsequently refined based on a predetermined threshold value.

2.2. Inference limitation

The restriction of consultation questions is implemented by excluding symptoms associated with diseases for which symptoms have been answered "No". This approach prevents the system from presenting the complete range of symptoms for user input. Restrictions on tracing symptom questions are applied under the following conditions: i) the symptom with the highest weight for a given disease, ii) the next highest weight symptom of the disease, provided that a symptom has been answered "Yes", iii) exclusion of symptoms associated with diseases for which symptoms have been answered "No", and iv) exclusion of symptoms that have already been answered.

2.3. Threshold value

The threshold value can be calibrated according to user expectations. This value, expressed as a percentage, serves to constrain the diagnostic outcomes generated by the expert system:

$$Result = \mathrm{D} \geq \mathrm{T} \tag{2}$$

where D is disease and T is threshold value.

By applying limit values, the results provided by the expert system become more specific. The application of this limit value aims to narrow the scope of diagnosis so that the decision to take appropriate medical action can be made more optimally. Success in implementing this limit value can also help reduce ambiguity in providing an early diagnosis of eye diseases suffered by users.

Following the optimization process, the subsequent step involves evaluating the expert system. The evaluation entails comparing the system's performance before and after the optimization process. This comparison aims to identify changes and enhancements in the expert system's functionality as a result of implementing various performance improvement strategies. By analyzing the results from both pre-and post-optimization phases, the extent of improvements can be systematically assessed.

3. RESULTS AND DISCUSSION

Preliminary data on eye symptoms and diseases were collected in prior studies. The survey results from ophthalmologists were subsequently used to implement weightings for each rule base. The weighting rules are illustrated in Table 1.

The establishment of a robust rule base holds significant importance in the development of an expert system intended for conducting searches to facilitate diagnostic processes [30]–[33]. The rule-base listed in Table 1 will be used as the basis for consultation questions that must be answered by users. The system will employ a consultative framework, prompting users with a series of symptom-related inquiries. Users will respond with "Yes," "No," or "Unknown" options, with their answers guiding the subsequent line of questioning. This consultative model facilitates dynamic interaction between the expert system and users, allowing users to provide responses based on their experience or knowledge. These user inputs inform the direction and progression of subsequent questions, thereby enhancing the adaptability of the consultation process to the user's specific conditions or symptoms.

3.1. Expert system before being given a weight from an expert

The research entails the development of a preliminary general expert system, which serves as a baseline for comparison with an optimized expert system. This investigation aims to elucidate disparities and potential enhancements resulting from the optimization process in expert system development. The illustration of the expert system in its pre-optimized state is depicted in Figure 2.

The diagram depicted in Figure 2 provides a visual representation of the expert system in its initial state before undergoing the optimization process. Within this configuration, the consultation protocol mandates responses to all posed questions, contingent upon the volume of symptom data stored in the database. Notably, the symptom inquiry persists until all database symptoms receive attention, resulting in a less efficient process characterized by a prolonged timeframe for obtaining an initial diagnosis. This extended duration proves time-consuming and can potentially overwhelm patients with the sheer volume of inquiries. Additionally, the initial diagnostic outcomes exhibit excessive variability, further complicating the determination of appropriate subsequent medical actions.

Recognizing this approach's limitations, the subsequent optimization process becomes imperative. This optimization aims to streamline the consultation procedure, alleviate patients' time burden, and refine the precision of initial diagnostic outcomes. The optimized expert system seeks to provide a more efficient and user-friendly experience through targeted enhancements, ultimately contributing to a more effective and reliable diagnostic framework for eye diseases.

Table 1. Rule-based with expert judgment

No	Diseases	Symptoms	Weight
1	Glaucoma	Hardened sensation in the eyes	20
		Cloudiness in the eye lens	10
		Blurred vision	20
		Redness in the eye	5
		Excessive tearing	5
		Eyeball pain	20
		Headache	20
2	Conjunctivitis bacteria	Redness in the eye	30
		Eye irritation	10
		The sensation of closed eyelids	20
		Swelling of eyelids	10
		Excessive eye discharge	30
3	Conjunctivitis virus	Redness in the eye	30
		Eye irritation	5
		The sensation of heat in the eyes	5
		Soreness in the eyes	10
		Swelling of eyelids	20
		Excessive tearing	30
4	Conjunctivitis allergen	Redness in the eye	20
		Eye irritation	10
		Itchiness in the eyes	20
		Mucous-like eye discharge	10
		Swelling of eyelids	10
		Excessive tearing	30
5	Gonoblenore	Redness in the eye	40
		Pus-like eye discharge	40
		Venereal disease factors	5
		Swelling of eyelids	15
6	Trachoma	Redness in the eye	20
		Itchiness in the eyes	10
		Excessive tearing	10
		Excessive eye discharge	20
		Swelling of eyelids	20
		Cloudiness in the cornea	10
		Light sensitivity	10
7	Cataract	Blurred vision	40
		Double vision in one eye	5
		Cloudy eye lens	30
		Diabetes-related symptoms	5
		Light sensitivity	10
		White spots on the pupils	10
8	Hypermetropia	Difficulty in near vision	50
		Headache	15
		Excessive tearing	15
		Eyeball pain	15
		Get sleepy quickly while reading	5
9	Myopia	Difficulty in far vision	50
		Headache	15
		Excessive tearing	15
		Eyeball pain	15
		Get sleepy quickly while reading	5
10	Astigmatism	Difficulty in far vision	20
		Uneven perception of objects	10
		Perceived movement of objects (visual instability)	10
		Headache	20
		Get sleepy quickly while reading	10
		Excessive tearing	15
		Eyeball pain	15
11	Pterigium	Redness in the eye	30
		Eye irritation	15
		Blurred vision	5
		Triangular-shaped lump in the eye area	50

Source: researchers' preparations

3.2. Expert system after inference limitation is applied

The first optimization is conducted by restricting the inquiry of symptoms that must be addressed. The limitation of inquiries in this research is referred to as inference limitation. Inference limitation only seeks symptoms that are related to those previously answered. This restriction in inquiry enables not all symptoms in the database to be addressed, thereby rendering the search process more effective and efficient. The implementation outcomes of inference limitation are depicted in Figure 3.

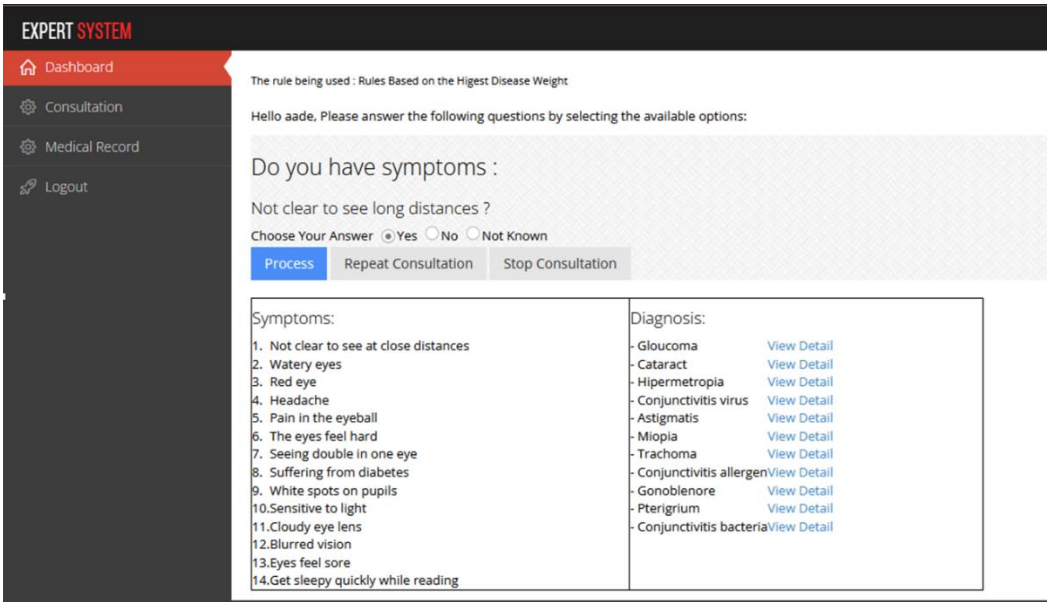

Figure 2. Expert system process without optimization approach

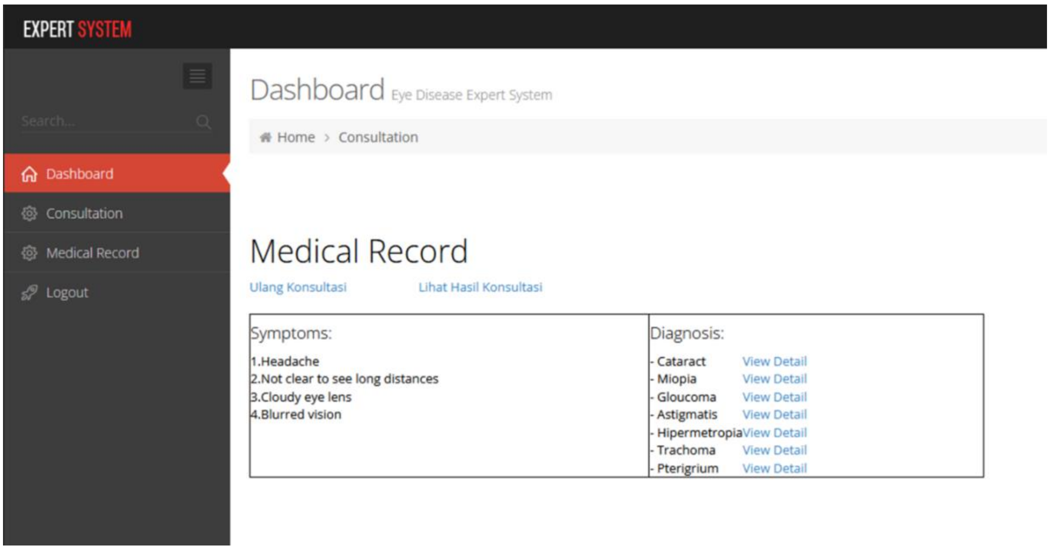

Figure 3. Expert system optimization with inference limitation

The utilization of inference limitations dictates that symptoms answered in the negative will not be scrutinized by the inference engine. Consequently, diseases associated with negative responses to symptoms are eliminated, along with all related symptoms, from subsequent symptom-tracing endeavors. Leveraging this inference limitation facilitates the possibility of rendering an initial diagnosis by simply responding to a few questions, as illustrated in Figure 3. However, notwithstanding these advancements, there remain shortcomings, notably in the diversity and specificity of the initial diagnoses generated. The dominant disease stemming from the symptoms experienced by patients remains indeterminate at this stage.

3.3. Expert system after being given a percentage expert judgment

Further optimization is carried out by assigning weights to each rule in the rule base. The assignment of weights to each rule has been accomplished by acquiring expert knowledge regarding the weight of each symptom for every disease. This weighting process has been presented in Table 1, rule base. The results of implementing these rule weights are presented in Figure 4.

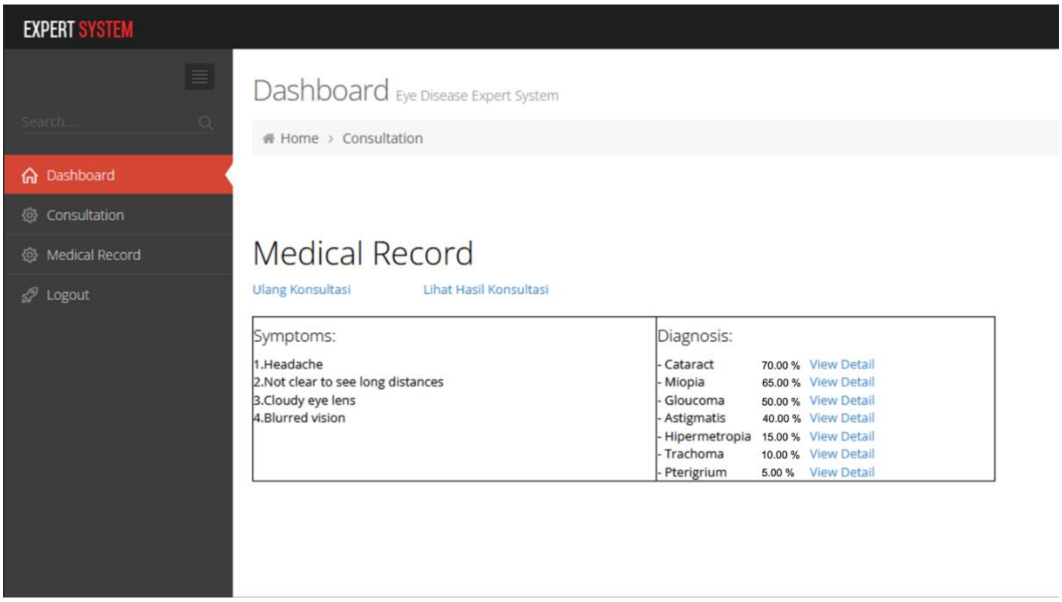

Figure 4. Expert system optimization with inference limitation and expert judgment

In Figure 4, the graphical representation highlights the integral role of expert judgment in assigning weights to the resulting diagnosis within the system. Specifically, the expert system accords additional weight to each symptom answered in the affirmative, with the weight attributed to the associated disease. Subsequently, the cumulative weight for the resulting diagnosis is computed based on the total number of symptoms answered positively. This approach aims to enhance diagnostic accuracy by providing a comprehensive evaluation that considers the relative importance of symptoms in contributing to the overall diagnosis. The weighted calculation allows for a more nuanced and precise determination, presenting the total percentage of the disease derived from the symptoms that have received affirmative responses.

3.4. Expert system after threshold implementation

The final optimization phase of this study involves enforcing threshold values. These threshold values are utilized to select the initial diagnoses to be established by the expert system based on the cumulative weights obtained from previous optimizations. The outcomes of enforcing the threshold values can be observed in Figure 5.

In optimization algorithms, threshold values are often used to determine when a certain condition is met or surpassed, influencing the behavior of the optimization process. Threshold values, as shown in Figure 5, then increase the perfection of the optimization process. The source code snippet from the display, which shows the threshold value, is follows:

```
Source Code
$qry = mysql_query("SELECT id_diseases,name_diseases,total_weight FROM tb_diagnose WHERE
id_user='".$_SESSION[id_user]."' AND active='1' AND
 total_weight>='$threshold[0]' ORDER BY total_weight DESC
```

In the context of diagnostic procedures, the establishment of a threshold value at the 70% limit holds significant implications. When this threshold is imposed, diagnoses exhibiting a cumulative value falling below this predetermined benchmark undergo trimming. Consequently, this procedural adjustment instigates a refinement in the initial diagnostic outcomes generated by the expert system, fostering enhanced specificity. Through this calibrated approach, the diagnostic precision of the system is augmented, facilitating more accurate and tailored assessments of the respective conditions under consideration. This methodological refinement underscores the imperative of fine-tuning diagnostic algorithms to optimize their efficacy in clinical or analytical settings. Based on the research that has been done, it was found that the development of expert systems with a consulting model can be optimized through the application of the expert judgment approach, threshold values, and inference limits. The approach adopted in the development of this expert system results in a more effective and specific initial diagnosis.

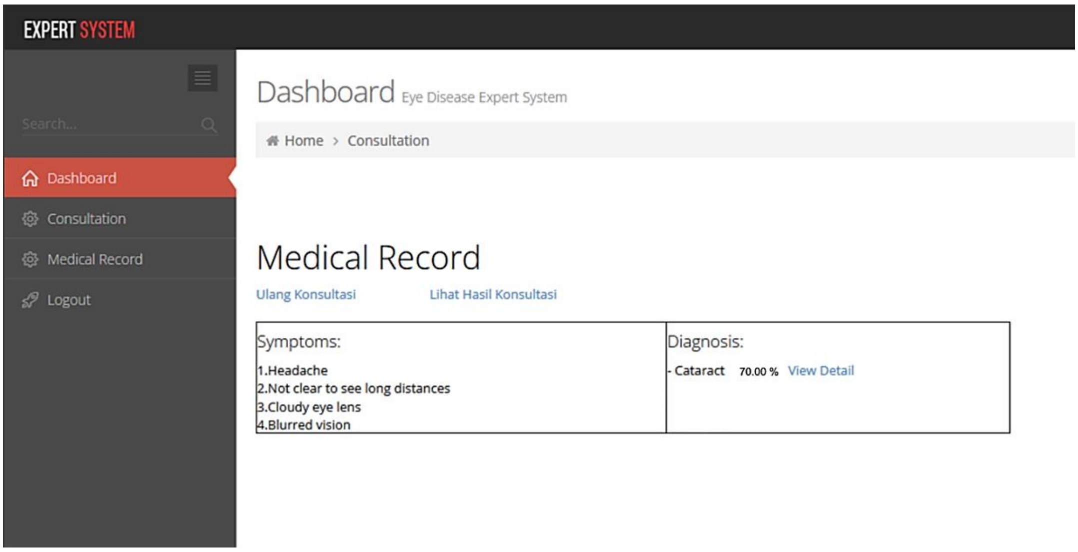

Figure 5. Expert system optimization with inference limitation, expert judgment, and threshold values

The expert judgment method allows expert assessments to assign weights or percentage values to each rule, thereby increasing the accuracy of diagnostic criteria evaluation. Furthermore, threshold values play a role in setting a specific limit value, for example, 70%, so that diagnoses with total values below that limit can be filtered. The application of inference limits also makes an essential contribution by limiting the number of questions that must be answered by users. Thus, the consultation process becomes more efficient and does not burden users with excessive questions.

The combination of these three approaches results in the development of an expert system capable of producing a more effective and specific initial diagnosis. This result signifies the solution for optimizing the expert system, substantiated by prior research [34]–[36]. The incorporation of expert judgment, threshold values, and inference limits stands as a pivotal step toward enhancing both the efficacy and precision of expert systems, particularly in the context of disease diagnosis, with a specific focus on eye diseases within the scope of this investigation.

4. CONCLUSION

This research has successfully advanced the development of a more refined expert system model by integrating expert judgment, inference limitations, and threshold values. Incorporating these elements has alleviated the need for users to respond to the entire set of formulated rules, thereby enhancing the system's overall efficiency. The expert-driven weighting process, coupled with the application of threshold values, contributes to more precise diagnostic outcomes. While the findings of this research are promising, there remains an avenue for further refinement, particularly in addressing the normalization of values when multiple experts contribute weights, ensuring the validity of the results. This research makes a notable contribution by presenting a model that can serve as a reference for the development of optimized expert systems. Furthermore, the optimization methodologies employed in this study have broader applicability, extending beyond the realm of eye diseases, thereby offering global utility in the advancement of expert systems in diverse healthcare domains.

ACKNOWLEDGEMENTS

The authors express their gratitude to Universitas Pendidikan Nasional in Bali, Indonesia, for its invaluable support in facilitating the completion of this research. In addition, the authors would also like to thank Universitas Pendidikan Ganesha and Universitas Bali International for providing the opportunity to conduct research together with their researchers.

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