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BAYESIAN NETWORK AND DEMPSTER-SHAFER THEORY FOR EARLY DIAGNOSIS OF EYE DISEASES

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Abstract: An accurate self-diagnosis expert system would prevent the progression of chronic eye disease. However, developing an expert system for medical diagnose requires a robust reasoning capability. In the knowledge acquisition phase, a knowledge engineer faces several issues. For example, an eye disease may contain several similar symptoms to another eye disease. Even worse, a patient may input a set of symptoms that can be attributable to several diseases, and these symptoms may not be readily quantifiable. Dempster-Shafer Theory (DST) and Bayesian Network (BN) are two commonly used techniques for combining uncertain evidence. The literature review showed that there have been no studies, either using BNs or DST, to diagnose eye diseases with a comparative study about both methods, BNs and DST. This paper study the effectiveness and reliability of DST and BN as the reasoning engine of an expert system for early diagnose of eye disease. The primary sources of knowledge on eye diseases are the patient files and human experts. Data were collected from hospitals and ophthalmologists in Riau, Indonesia. BN and DST framework was used to model and estimate the probability of eye diseases in supporting decision making, i.e. diagnosis. Rule-Based Reasoning and the Forward Chaining methods are applied in developing the reasoning structure. The Expert System Development Life Cycle (ESDLC) methodology is used to structure, plan and control the process of developing the expert system. In this study, 20 physical symptoms of illness obtained from the patients' files are used for diagnosing six types of eye diseases. The result of this study is accomplished by comparing the expert system diagnostic results with a human expert diagnostic result. Based on the testing of 10 eye diseases cases, the accuracy of the BN is higher compared to DST.

Keywords: Bayesian Network; Dempster-Shafer; expert system; eye diseases; reasoning

I. INTRODUCTION

Eye diseases are known to affect the quality of life adversely. Geographical location, accessibility to facilities and socio-economic status of an individual play a role in occurrence eye diseases [32]. Expert System (ES) is one of the most important fields of Artificial Intelligence (AI). Since its inception in the 70s, many Expert Systems have been developed, and researches on it have been published containing a wealth of knowledge. The aim of this research is to develop a medical expert system for early diagnosis of eye diseases that can actively improve healthcare advisory service to people. There are many reasons to build such an expert system. First, the expertise of humans, i.e. ophthalmologist is limited and ephemeral. An ophthalmologist is a specialist in ophthalmology. Ophthalmology is a branch of medicine and surgery that deals with the diagnosis and treatment of eye disorders. Human expertise will be lost due to the demise of an expert, illness or migration to another region. Humans are generally influenced by several factors that can affect the quality of decision making. Meanwhile, an expert system provides a more consistent decision because it contains knowledge (i.e. rules and facts) and reasoning model with capabilities that simulates the judgment and behavior of a human expert in a particular field as shown in many earlier works such as in [36]. In [36], the author used the conventional rule-based with forward and backward chaining as the inference engine for managerial decision making.

In this research, the knowledge-based approach is considered for an online expert system for early diagnose of eye disease, which comprises the determination of the disease from cause(s) (i.e. symptoms) of any abnormal eye condition. The expert system is designed to assist the end user to take a decision based upon learned human experts previous choices. However, the proposed ES is not intended to replace human experts (i.e. ophthalmologist) but to assist human in decision making and making them more efficient and their knowledge easily accessed by basically, anyone with Internet access.

However, in developing the necessary system, we believed that the proposed system should be a blend between rule-based (heuristics) and machine learning to handle uncertainty. There are many sources of uncertainty in developing the expert system. The obtained knowledge from experts may be incomplete, error-prone, or approximate while the data may be noisy or unreliable. In the field of the expert system, research methods for handling uncertainty include the Bayesian approach, fuzzy logic, certainty factor approach and the belief theory.

Incomplete information from the user's input is another challenge. Diagnosis may not be completed due to incomplete information given by the user because of uncertainty and uninformed about eye diseases symptoms. Therefore, the expert system requires robust reasoning methods to control the inadequacy of data while making decisions accurately. The underlying rationale for using machine learning is that it will be more adaptive and more accessible to configure than the traditional rules-based expert systems.

Options are between the two most widely used machine learning model for an expert system which is the probability theory in Bayesian Network (BN) and the combination theory owned by Dempster Shafer Theory (DST). Selecting the right model is essential to achieve the best possible diagnostic analysis result.

Therefore, this paper examines the effectiveness of two statistical methods as the inference engines, namely BNs and DST. Moreover, this paper is not about selecting the best model, but about understanding the strengths and weaknesses of each model. To achieve the goal, we will examine and compare BNs and DST in terms of computational time and belief percentage as the effectiveness metric produced by the expert systems.

Wagner [35] in his longitudinal analysis of expert systems applications by industry shows that in the last ten years, most of the expert systems were developed for the medical industry. One of the leading public health problems in the world is eye disease. Estimated annual economic burden of vision loss and eye diseases and vision disorders in the United States alone is USD139 billion [11]. Eye diseases were categorized according to internationally recognized statistical classification of diseases such as diseases of eyelids, conjunctiva, episclera and sclera, cornea, glaucoma, retina, strabismus, trauma to the eye, and refractive errors [32].

Researchers have strived to develop theories to model diagnostic procedures regarding eye diseases. The earliest work found in the literature published in 1984 about an expert consultation system [13]. The expert system was developed for frontline health workers in primary eye care. An expert system also is used to support eye muscle surgery [6]. Ibrahim et al. [10] developed an expert system for early diagnosis of eye diseases to detect five types of the most frequent eye diseases experienced by the Malaysian population. The various eye diseases that can be identified by this system are cataract, glaucoma, conjunctivitis, dry eyes syndrome and keratitis. This system uses a symptom-based approach to diagnose eye diseases.

Engaging the services of an ophthalmologist for diagnosis is expensive for most people. Thus, many patients do not seek treatment from a specialist until it becomes severe. Therefore, Asghar et al. [1] developed an online expert system for diagnosis of red-eye disease, i.e. disease in which red-eye is the common symptom. The expert rules were established on the symptoms of each type of Red-eye disease, and they were presented using tree-graph and inferred using forward-chaining with depth-first search method. The web-based expert system can detect and give an early diagnosis of twenty Red-eye diseases.

An expert system for self-diagnosis can be a learning tool that provides practitioners and medical students with the advantages of improving their ability, minimizing the error and cost in their learning to diagnose accurately. For the same reasons, Asghar et al. [1] developed a rule-based web-supported expert system to assist ophthalmologists, medical students doing specialization in ophthalmology, researchers as well as eye patients having computer know-how. An expert system uses the Case-Based Reasoning and Naïve Bayes method for classifying eye diseases [16].

Syiam[31] developed an expert system using an artificial neural network to assist general practitioners to make better decisions. A general practitioner, also called a GP or generalist, is a physician who does not specialise in one particular area of medicine. The expert system is used in early medical diagnosis of eye diseases in patients. A multilayer feedforward artificial neural network with a single hidden layer is used to diagnose a patient based on symptoms. The backpropagation algorithm is employed for training the network in a supervised mode. To evaluate the performance of the developed system, Syiam gave several cases as a test to both GPs and specialists. The result indicates that the performance of the designed system exceeds that of the GPs, and it reaches the level of performance of the eye specialists.

Therefore, it is the goal of this study to provide cheap but effective online 'consultation' when patients are not able to find or afford an ophthalmologist. The aim is to provide useful information related to eye diseases and provide health warnings as early as possible to society, so that they may seek professional advice as soon as possible. An accurate and early self-diagnosis system would prevent the progression of chronic eye disease. However, an eye disease may contain several similar symptoms to another eye disease, which could confuse the knowledge engineer and even the most experienced ophthalmologist. Even worse, a patient may input a set of symptoms that can be attributable to several diseases, and these symptoms may not be readily quantifiable. When observing these symptoms, an ophthalmologist with varying professional levels and clinical experience may differ in their diagnosis, resulting in misdiagnosis. Besides, patients may be unsure of their symptoms, which hinder diagnostic accuracy. The challenge for knowledge engineer in medical diagnosis and prognosis is to model and develop robust reasoning framework in dealing with noise and uncertainty to provide consistent diagnostic results. The performance of two reasoning framework in handling noise and uncertainty for eye disease diagnosis will be compared.

A. Bayesian Network

The background information on BN reasoning is based on Verbert et al. [34] and Soni[12]. Bayesian networks are a type of probabilistic graphical model that uses Bayesian inference for probability computations. The graphical model is in the form of a directed acyclic graph in which each edge corresponds to a conditional dependency; therefore causation and each node corresponding to a unique random variable. In other words, edges in a directed graph representing conditional dependence. Through these relationships, one can efficiently conduct inference on the random variables in the graph through the use of factors.

Formally, if an edge (A, B) exists in the graph connecting random variables A and B, it means that P(B|A) is a factor in the joint probability distribution. The P(B|A) for all values of B and A must be known to conduct inference. Verbert et al. [34] explains that for each reasoning step, a probability between zero and one inclusive is assigned to each element in the frame of discernment ΘY of variable Y such that

$$\sum_{a \epsilon \Theta Y} \Pr(a) = 1 \qquad (1)$$

When a new evidence $b \epsilon \Theta_Y$ regarding a variable X that is related to variable Y becomes available, the probability distribution of Y is updated using Bayes' rule.

$$\Pr(a|b) = \frac{\Pr(b|a)\Pr(a)}{\sum_{a' \epsilon \Theta Y} \Pr(b|a')\Pr(a')} \qquad (2)$$

with Pr(a) the prior probability of a, Pr(a|b) the posterior probability of a, i.e. the probability of a after observing b, and Pr(b|a) the likelihood function, i.e. the probability of observing b given a. The principle of insufficient reasoning is also important in using BN. This principle states that in the absence of knowledge, all possible outcomes should be assigned equal probabilities. Another commonly used rule is the additivity axiom [34], which directly follows from (1) and states that:

$$\Pr(a) + \Pr(\sim a) = 1 \quad (3)$$

Using the relationships specified by a Bayesian network, a representation of the joint probability distribution can be obtained. Inference over a Bayesian network is by evaluating the joint probability of a particular assignment of values for each variable in the BN.

Literature studies indicate that BNs and DST have been used as inference engines in many applications [9]. BN is seen as more popular because it is more consistent when faced with uncertain problems. Researchers have proven the advantages of BNs in many applications because the method can produce good predictions. Shafer and Pearl [29] have discussed rigorously on subjective, and frequentist approaches and they note several defining attribute of the Bayesian approach. The first notable feature of Bayesian approach is the reliance on a complete probabilistic model of the domain or ``frame of discernment".

Moreover, BNs can facilitate learning about the causal relationship between the variables [33]. It is easy to update beliefs with new knowledge because it uses Bayes theorem (conditionally) as the primary mechanism and therefore it is suitable to be used for reasoning purposes in expert system or decision support systems [18]. One of the many reasons for easy adaption of BN is the graphical nature of the method that can clearly show the relationship between different components of the system. Therefore, it can provide facilities for researchers in various fields to understand BN concepts [24].

However, the Bayesian technique is not without its critics as Beynon et al. [3] have compiled many findings from previous researchers and discussed the difficulty arising when conventional Bayesian analysis is presented only with weak information sources. Beynon et al. [3] state one of the critical criticism is the "Bayesian dogma of precision", whereby the information concerning uncertain statistical parameters, no matter how vague, must be represented by standard, correctly specified, probability distributions.

In developing an expert system for early diagnose of eye disease, one of the difficulties is to reach an agreement with the experts to build a BN structure. A similar experience has been reported in [23, 33]. This problem occurs when there are not enough data or evidence to form the posterior evidence and thus require the expert to express their knowledge into probability distributions based on their experience or subjective evaluation and estimation. The absence of enough evidence causing difficulties for experts to determine the conditional probability [15]. In some cases, BN may have limited ability with continuous data representation [20, 21], spatial and temporal dynamics [2].

The limitations of the Bayesian approach reside in the assumptions that the pieces of evidence are independent, prior probabilities are known, and the sets of hypotheses are both inclusive and exhaustive.

B. *Dempster-Shafer Theory (DST)*

DST is an improvement of Bayesian inference and an effective method for handling imprecise and uncertain information. The background information on DST reasoning in this section is based on Verbert et al.[15], Cobb and Shenoy [4, 5].
The theory of belief functions was developed to handle incomplete information. This is realized by allowing the assignment of belief to sets of elements of Θ_Y instead of assigning belief only to individual elements, like in the Bayesian framework. A belief function $m^{\Theta Y}: 2^{\Theta Y} \rightarrow [0,1]$ is a function that assigns a "mass of belief" to each subset A of Θ_Y. Such that:

$$\sum_{a \epsilon 2^{\Theta Y}} m^{\Theta Y}(a) = 1 \quad (4)$$

When a piece of new evidence about Y, in the form of a mass function $m_e^{\Theta Y}$ becomes available, the mass function is updated using Dempster's combination rule:

$$m_e^{\Theta Y}(\mathrm{A}) = \begin{cases} 0 & \mathit{if}\ A=\emptyset \\ K \sum_{\substack{A' \cap A''=A \\ A' . A'' \subseteq \Theta Y}} m^{\Theta Y}(A') m_0^{\Theta Y}(A'') & \mathit{otherwise} \end{cases} \quad (5)$$

with $m^{\Theta Y}$, $m_e^{\Theta Y}$ and $m_u^{\Theta Y}$ mass functions on the same space Θ_Y, K a normalisation constant, and $m_u^{\Theta Y}$ the updated mass function [34]. The DST method also has several advantages and disadvantages. The main benefit of DST is that it can ignore the difficulty of determining prior probability values. Therefore, it is easy to decide on the evidence for different cases with uncertainty. The combination theory can be used to combine the evidence to get better decisions. However, DST is not accessible and seldom used to make decisions because it has a very complicated calculation.

Cobb and Shenoy [4] have compared generally the similarities and differences between Bayesian and DST. The main conclusion is that although there are apparent differences in semantics, representations, the rules for combining and marginalizing representations, there are many similarities. They obtain that the two statistical methods have roughly the same expressive power. Both of these methods are effective to use when suitable in the domain and not that every algorithm can be featured in any area.

Simon and Weber [30] have successfully computed system reliability and manage epistemic uncertainty using BN and DST to overcome data incompleteness and incoherency. Simon and Weber [30] show how the epistemic uncertainty is propagated through the BN. The paper has shown that both of the methods have been used to manage the type of uncertainty and extract most of the information from available data. Hoffman and Murphy [9] show that BNs and DST produce similar results while Koks (2005) states that DST is better than Bayes theorem [14]. The scientific community has been continuously discussing the advantages and disadvantages of BN and DST, but no discussion compares the two methods in real case studies. For instance, Hoffman and Murphy [30] used a simulation called "The Fantasy Airport" as a comparison media. The literature review also shows that there have been no studies, either using BNs or DST, to diagnose eye diseases with a comparative study about both methods, BNs and DST.

No Free Lunch Theorem states that any method or algorithm will have different advantages depending on the problem [17, 27]. This theorem stresses two essential things. First, this theory states that if a method has good results in solving a problem in a particular domain, then this method may not have the same good results in another domain. A method may not answer all of the issues with consistent quality (super algorithm). Second, the effectiveness of methods is not the same as efficiency. For example, a method may have excellent efficiency to solve a problem but perhaps require more extended calculation. It also includes Bayesian theorem as evidenced in the paper entitled "No Free Lunches for Anyone, Bayesian Included" [8].

This paper is organized as follows: In Section 2, the research material and method used in this research is presented. In Section 3, the two reasoning methods are compared, and additional performance criteria and trade-offs are discussed.

II. Materials and Methods

An This research method section describes in more detail the steps that are used for conducting the research. The Expert System Development Life Cycle (ESDLC) framework is used in developing the expert system, ESDLC is a systematic process for building an expert systems [7]. Figure 1 shows the general phases in developing and testing the developed expert systems for diagnosing eye diseases. The following are the research methodology of this study. The stages are as follows:

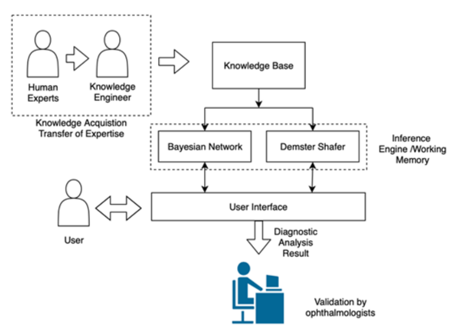

Figure 1. Research methodology for early of eye diagnosis system

A. *Feasibility Study*

A feasibility study purposes to objectively and reasonably discover the strengths and weaknesses of an existing system, opportunities and risks present in the system, the resources required to build an expert system, and eventually identify the accomplishments. This phase is where the problems are defined, the objectives are stated, and the resources, methods, experts, costs and the time frame are identified. This step is the requirement analysis usually carried out in the system development life cycle.

Eye checkup must be taken to ensure health and to avoid infection by eye diseases. The examination is carried out by an ophthalmologist to get an accurate diagnosis. A Feasibility study is done to identify the problem. We are required to determine the objectives and scope of this study and verify the problem for expert systems development. Amongst the reasons that people do not perform a comprehensive eye exam are lack of medical knowledge, financial issues and transport difficulties in reaching an ophthalmologist. Therefore, the public is not getting the attention and appropriate action to solve this problem. Some constraints causing the patient did not get the optimal treatment are discovered. Therefore, people need an application to facilitate the procedure, especially for eye diseases diagnosis, to produce a consistent decision and show the probability based on Bayesian probability and DST.

B. Knowledge Acquisition

Knowledge acquisition is the step in this study for extracting, organizing and structuring knowledge from human experts to the computer. This step is often the major obstacle in building an expert system. In this research, the knowledge acquisition is obtained from an interview with an ophthalmologist, which includes the analysis of data requirements, identifying the software requirements to analyze both methods BNs and DST, such as creating a flow chart. Knowledge engineers will transfer ophthalmologist's knowledge into the knowledge based on the Expert System to solve complex problems just like a human expert would.

We need the symptom and probability of each symptom, the type of disease, the cause of the disease, solution and early treatment through interviews with an ophthalmologist. The probability value obtained from estimation of ophthalmologists based on the relationship between the symptoms and disease. We have gathered data from the Bangkinang General Hospital, in Riau, Indonesia. Knowledge elicitation is also conducted, and test cases were prepared at this time. The type of knowledge gathered in this stage is factual knowledge.

C. Development

In this step, we select the appropriate method to address the problem. BN and DST are used for the inference engine. Subsequently, the data collection and the knowledge acquisition process are done by a knowledge base system. We determine the structure of the menu system, user interface and database, and therefore the system will be made following the detailed design. An analysis is carried out to make the system work according to expectations. First, we build a small system containing few of the features and it will evolve into a better system after a few cycles. The expert system to diagnose eye diseases is a web-based system, coded using the PHP programming language, and will allow users to perform self-diagnosis.

The overview of the implementation of a BN and DS in the expert system is shown in Figure 2 and Figure 3.

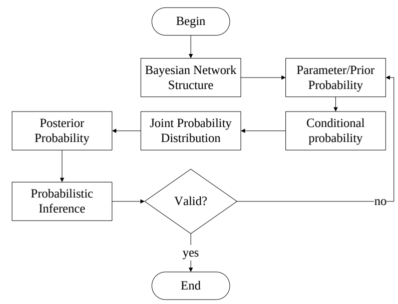

Figure 2. A flowchart of the Bayesian Network

The BN and DS used to determine the probability of the kind of eye disease experienced by the user based on symptoms or characteristics. There are several steps to implement the BN and DS that is shown in Figure 2 and Figure 3.

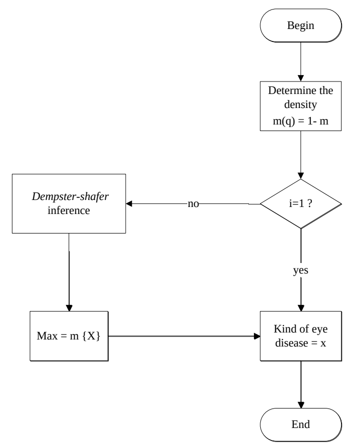

Figure 3. A flowchart of Dempster-Shafer

We examine the effectiveness of techniques for a relatively small data set with the 6 types of eye disease and 20 physical symptoms.

III. Results and Discussions

The system testing and validation are based on the black box method and User Acceptance Test (UAT). UAT is conducted by using several cases of eye diseases. A domain expert will assess the results of the expert system. Based on the analysis and advice, the development step will go back to the Knowledge Acquisition step to correct and expand the factual knowledge from the domain expert's comments. The purpose of this cyclic development is to improve the quality of knowledge (i.e. rules) in the knowledge-based systems.

The primary purpose of the experiment testing is to find out the effectiveness of incorporating BNs and DST in the developed expert system for eye diseases. The system is assessed by considering the accuracy as the indicator. For this experiment, a 10-case sample extraction was made. Each case was then presented to the system to obtain the corresponding diagnosis. This diagnosis was later compared to the one provided by the expert to determine whether the system's diagnosis is correct or not.

A BN that provides the diagnostic results employs rule bases as the learning tool. The process was performed using the BN method that calculates the probability of each symptom from users. Subsequently, the final diagnosis is based on the probability of the final process.

A. *The structure of the Bayesian Network*

The structure of the BN is formed using graph theory that connects the symptoms or characteristics with the kind of eye diseases. The following figure is an example of the BN structure.

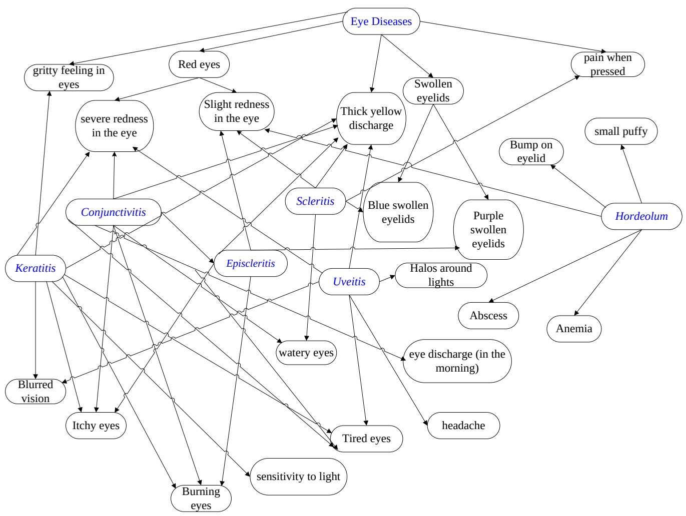

Figure 4. An example of the BN structure

B. *Prior Probability*

In statistical model explains that given data and parameter, a simple Bayesian analysis beginning with a prior probability and likelihood to compute a posterior probability. In this study, the prior is given by example if there are 100 patients suffered eye diseases and 70 of them have red eyes, so the prior probability is 0.7. Prior probabilities are the original probabilities of an outcome, which will be updated with new information to create conditional, joint and posterior probabilities.

Table 1. The example of prior probability

S. No.	Symptoms	Values
1	Red Eyes	0.7
2	Tired Eyes	0.25
3	Itchy Eyes	0.7
4	Burning Eyes	0.6
5	Watery Eyes	0.75
6	Thick Yellow Discharge	0.8

C. *Conditional Probability*

The conditional probability of an event B is the probability that the event will occur given the knowledge that an event A has already occurred. In the statistical model, the Bayes Formula [18]:

$$P(A|B) = \frac{P(A)\ P(B|A)}{P(B)} \qquad (6)$$

Where:
A = a particular state, conditional on the evidence provided.
P(A|B) = posterior
P(A) = prior probability of the hypothesis
P(B|A) = likelihood

Table 2. The example of Conditional Probability Table (CPT)

Red eyes	Eye disease	
	present	***absent***
present	0.7	0.25
absent	0.3	0.75

D. *Joint Probability Distribution*

We have used the formula (7) Joint distribution formula to obtain the Joint Distribution Table. Based on the formula (7), the calculation of joint probability distribution is multiplying the prior probability A to the conditional probability. Joint probability distribution table (JPT) formula:

$$P(A\,|B) = P(A)\ P(B|A) \qquad (7)$$

This probability is written in this formula where event A does not affect the probability of event B, the conditional probability of event B given event A is simply the probability of event B, that is P(B). Suppose the joint probability distribution will be calculated in the red eyes. The red eyes present probability is 0.7, while absent is 0.3. The Joint Distribution Table is shown in Table 3.

Table 3. Joint Distribution Table

Red eyes	*Eye Disease*	
	present	***absent***
present	0.7 x 0.7 = 0.49	0.3 x 0.25 = 0.075
absent	0.7 x 0.3 = 0.21	0.3 x 0.75 = 0.225

E. *Posterior Probability*

In statistical terms, the posterior probability is the probability of event A occurring given that event B has occurred. The Posterior probability is shown in Table 4. Based on The Joint Distribution Table (JPT) in red eyes, the posterior probability is: $\frac{0.49}{0.49+0.075} = 0.87$.

Table 4. Example of Posterior probability for eye diseases

S. No.	Symptoms	Values
1	Red Eyes	0.87
2	Tired Eyes	0.27
3	Itchy Eyes	0.38
4	Burning Eyes	0.67
5	Watery Eyes	0.7
6	Thick Yellow Discharge	0.95

F. Probabilistic Inference

The Probabilistic inference is made by tracing the relationship of each symptom and kind of eye diseases based on the BN structure. Sometimes, BN combined with Rule-Based Reasoning (IF-THEN) will assist the probabilistic inference [19]. Example:

$$\mathrm{P\ (Conjunctivitis|\ Red\ eyes, tired\ eyes\ and\ itchy\ eyes)} = \frac{0.87 + 0.27 + 0.38}{3} = 0.51$$

Thus, it can be concluded that a patient suffered Conjunctivitis with a belief percentage is 0.51 * 100% = 51%.

G. Belief, Plausibility of Dempster-Shafer

Generally, Dempster-Shafer is written in an interval:
[Belief, Plausibility]
Pl(s) = 1 – Bel (~s)
Bel(s) = 1 and Pl(~s) = 0.

Belief (Bel) is a measurement of the power of evidence in supporting a proposition assemblage. If it is worth 0 (zero), it indicates that there is no evidence; if it is worth 1, it shows that there is certainty [28]. The density of each symptom was obtained from an ophthalmologist. To determine the theta probability (m(q)) we use the formula:

m(q) = 1- m
For example:
Symptoms of Redeye, (m) = 0.7
So m(q) = 1 - 0.7 = 0.3

Evidence in DST is shown by a rule known as Dempster's Rule of Combination.

$$m1 \oplus m2(Z) = \frac{\sum_{x \cap y = z} m1(X)m2(Y)}{1 - \sum_{x \cap y = \theta} m1(X)m2(Y)} \qquad (8)$$

Where:
m1m2(Z) = mass function of evidence (Z)
m1(X) = mass function of evidence (X)
m2(Y) = mass function of evidence (Y)

A patient experienced the symptoms namely: red eyes, tired eyes and itchy eyes. Based on expert knowledge, some diseases may be suffered: Episcleritis (EPS), Conjunctivitis (KJV), Keratitis (KRS), Scleritis, and Uveitis (UVT).

Table 5. Example of density values of each symptom

No.	*Symptoms*	*Eye Diseases*				*m*	*m(q) =1– m*
		EPS	*KJV*	*KRS*	*UVT*		
1	Red eyes		√	√	√	0.7	0.3
2	Tired eyes	√	√		√	0.25	0.75
3	Itchy eyes	√	√			0.7	0.3

Symptom 1: *red eyes* ➔Diseases: *Conjunctivitis (KJV), Keratitis (KRS) and Uveitis (UVT):*
$m_1\{KJV, KRS, UVT\} = 0.7$
$m_1\{\theta\} = 1 – 0.7 = 0.3$

Symptom 2: *tired eyes* ➔Diseases: *Episcleritis(EPS), Konjunctivitis (KJV), and Uveitis (UVT):*
$m_2\{EPS, KJV, UVT\} = 0.25$
$m_2\{\theta\} = 1 – 0.25 = 0.75$

Table 6. Combination Rules m3

	{EPS, KJV, UVT} (0.25)	**θ (0.75)**
{KJV, KRS, UVT} (0.7)	{KJV, UVT} (0.175)	{KJV, KRS, UVT} (0.525)
θ (0.3)	{EPS, KJV,UVT} (0.075)	θ (0.225)

Because the θ of m1(X).m2(Y) is not available, so the value is 0

$$m_3\{KJV,UVT\} = \frac{0.175}{1-0} = 0.175$$
$$m_3\{KJV,KRS,UVT\} = \frac{0.525}{1-0} = 0.525$$
$$m_3\{EPS,KJV,UVT\} = \frac{0.075}{1-0} = 0.075$$
$$m_3\{\theta\} = \frac{0.275}{1-0} = 0.225$$

Symptom 3: *itchy eyes* ➔Diseases: *Episcleritis (EPS) and Conjunctivitis (KJV)*
$m_4\{EPS, KJV\} = 0.7$
$m_4\{\theta\} = 1 – 0.7 = 0.3$

Table 7. Combination rules m5

	{EPS, KJV} (0.7)	**θ (0.3)**
{KJV,UVT} (0.175)	{KJV} (0.1225)	{KJV,UVT} (0.0525)
{KJV,KRS, UVT} (0.525)	{KJV} (0.3675)	{KJV,KRS,UVT} (0.1575)
{EPS, KJV, UVT} (0.075)	{EPS,KJV} (0.0525)	{EPS,KJV,UVT} (0.0225)
θ (0.225)	{EPS, KJV} (0.1575)	θ (0.0675)

$$m_5\{KJV\} = \frac{0.1225 + 0.3675}{1-0} = 0.49$$
$$m_5\{KJV,UVT\} = \frac{0.0525}{1-0} = 0.0525$$
$$m_5\{EPS,KJV\} = \frac{0.0525 + 0.1575}{1-0} = 0.21$$
$$m_5\{EPS,KJV,UVT\} = \frac{0.0225}{1-0} = 0.0225$$
$$m_5\{\theta\} = \frac{0.0675}{1-0} = 0.0675$$

Based on the result of the calculation of probability value, obtained the biggest density is KJV that is 0.49. Thus, it can be concluded that a patient suffered Conjunctivitis with a belief percentage of 0.49 * 100 % = 49 %.

The decision-making ability of the developed expert system for early diagnose of eye disease was compared with the diagnoses of a human expert. The human expert is an ophthalmologist at the Bangkinang General Hospital, Indonesia. Ten real cases are randomly selected from patients referred to the hospital. The expert system and the ophthalmologist had identical information on symptoms without the patient's history. The human expert was allowed to use the full medical records to ensure accurate and effective decision making because their diagnoses are the benchmark gold standard. The evaluation tabulated in the following table is presented using belief percentage as effectiveness metric achieved by expert systems using BN and DST, and the diagnoses result by the human expert.

Table 8. Expert system results

No.	*Diagnosis Result*		
	Bayesian Network (BN)	*Dempster-Shafer (DST)*	*Human Expert*
1	Keratitis (69%)	Keratitis (37%)	Keratitis
2.	Uveitis (46%)	Uveitis (80%)	Uveitis
3.	Conjunctivitis (73%)	Conjunctivitis (98%)	Conjunctivitis
4.	Conjunctivitis (51%)	Conjunctivitis (49%)	Conjunctivitis
5.	Hordeolum (38%)	Hordeolum (70%)	Hordeolum
6.	Scleritis (67%)	Scleritis (49%)	Scleritis
7.	Episcleritis (46%)	Episcleritis (79%)	Episcleritis
8.	Keratitis (63%)	Keratitis (37%)	Keratitis
9.	Conjunctivitis (82%)	Conjunctivitis (49%)	Conjunctivitis
10.	Conjunctivitis (83%)	Conjunctivitis (72%)	Conjunctivitis
Win	60%	40%	

Further evaluations are made by comparing the belief percentage generated by BN and DST. The results show that both BN and DST were able to diagnose all ten cases accurately when compared to the system's conclusion to the human expert's decision-making. However, the expert system with BN did better in the decision in term of higher belief percentage compared to DST when both had identical information on a patient. BN has a higher belief percentage on six cases compared to four cases by DST.

The result shows a distinct pattern that BN is more effective in diagnosing Keratitis, Conjunctivitis and Scleritis while DST is better on diagnosing Uveitis and Episcleritis. BN has been criticised that this traditional probability theory is capable of capturing epistemic uncertainty. Sentz[26] define epistemic uncertainty as a type of uncertainty which results from the lack of knowledge about a system and is a property of the analysts performing the analysis. BN is a probabilistic analysis that requires that the BN based reasoning engine have information on the probability of all events. Sentz[26] states that when information is not available, the uniform distribution function is often used, justified by Laplace's Principle of Insufficient Reason [25]. This can be interpreted that all simple events for which a probability distribution is not known in a given sample space are equally likely.

For example, if there is no information available between the symptom and disease (e.g., Uveitis) is through the logical constraint (i.e., their compatibility relation), the BN has difficulty providing for a meaningful inference regarding symptoms and disease. However, DST is designed to handle such problem and would be able to represent the relationship, between symptom and disease by a subset of the joint frame 'Symptom Disease'. This experiment shows that DST will complement BN when it is not possible to obtain a piece of complete information or precise symptom from a patient or even from experts. We have demonstrated that there are potential gains available through the use of different types of reasoning either the BN or the DST approach. BN requires an estimation of probabilities from the available records and data, but they use subjective prior probabilities to improve the estimates if the information between an element (e.g. symptom) and type of disease is missing or incomplete. The DST does not require an assumption regarding the probability of the individual constituents of the set [26].

H. Computational Time

The second performance evaluation in this study is computational time. The tests were conducted using the same computer specification. Table 9 tabulates the computational time for each method. Based on the collected data, the DST method requires a longer time to produce output for all ten cases compared to BN. The collected computation time from this study has advanced the understanding of these methods. Pearl [22] has promoted BN for reasoning for its ability to efficiently handle complex types of reasoning, like explaining away and bi-directional (both predictive and diagnostic) reasoning.

The DST requires a longer computation time. DST involves the combination of existing evidence for a decision and this phase. Table 9 shows the comparison of computational time by both algorithms, BNs and DST.

Table 9. Computational time of Bayesian networks and DST

Exp	***Time Taken***	
	Bayesian Net	***Dempster-Shafer***
1	**0.0001 second**	0.00022 second
2	**0.0003 second**	0.00078 second
3	**0.00071 second**	0.0009 second
4	**0.0003 second**	0.00077 second
5	**0.0003 second**	0.00071 second
6	**0.00041 second**	0.00072 second
7	**0.0001 second**	0.00027 second
8	**0.00024 second**	0.00063 second
9	**0.00052 second**	0.00064 second
10	**0.00025 second**	0.00067 second
Win	**10**	0

I. User Acceptance Test

The user acceptance test results were also obtained based on the questionnaire previously distributed to 30 respondents. Some of the aspects used in the assessment are detailed in Figure 5. It may be concluded that the expert system can be used efficiently to obtain information regarding eye disease by the users.

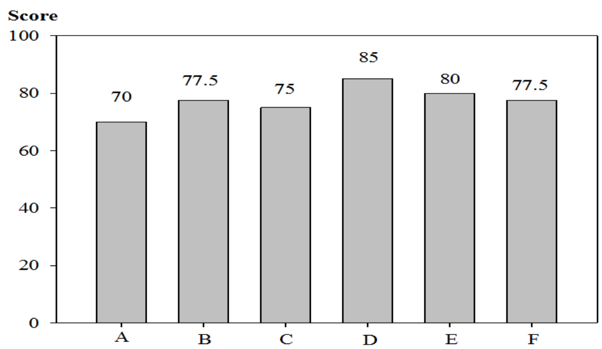

Figure 5. User acceptance test result

Where:
A= Graphical user interface
B= Easiness of the use application
C= Completeness of expert system features
D= Easiness in obtaining information regarding eye
E= Usability
F= Overall expert system assessment

IV. CONCLUSIONS

This study proposes a method based on BNs (BN) and DST (DS) as an inference engine in an expert system for early diagnosis of eye diseases. BNs (BN) and DST (DS) methods can reveal the percentage of disease probability for a user. Based on computational complexity aspect, DST is more complicated than BNs. DST combines all the existing evidence to get results, and this process dampers the computation effort and thus takes a longer time to complete the processing. Expert systems based on BN methods are difficult to combine with the DST method because it has an inference engine and a different way of diagnosing. BN uses graph theory for tracking BN structure, while DST uses a combination of evidence to make a decision. Construction of a BN structure is complicated due to the need to reach an agreement with the experts, while the DST method does not require either the structure or the prior probability. BNs allows users to choose the symptoms because of the BN structure, while in the DST method, it is difficult for the user to select the symptoms if there are many symptoms and options. A user of BN faces difficulty to make a diagnosis when the symptoms are outside the scope of BN structure, while DST gives self-determination to the user to select any symptoms. In this case, the BN is more appropriate in generating the probability of a disease based on symptoms experienced. Bayesian produces six higher probability value than DST in 10 correct diagnoses. BNs are appropriate for use in small data as long as the BN structure is assisting the inference, while DST requires more knowledge acquisition and combines the evidence to make a decision. However, the DST is impressive for uncertainty. DST can conclude the likelihoods of every symptom. Medical expert system development required a dynamic relationship between symptoms and diseases. In this case, the BN is more effective in generating the probability of a disease based on the given symptoms.

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