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Expert System for Diagnosing Autoimmune Diseases Using Dempster–Shafer and Fuzzy Logic: A Case Study of Prof. Dr. Margono Soekarjo Regional Hospital

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Abstract

Autoimmune diseases, particularly lupus, pose a major challenge in healthcare because their symptoms are highly variable and often mimic other medical conditions. Delayed diagnosis can worsen patient outcomes, increase the risk of severe complications, and even lead to death, especially in healthcare facilities with limited autoimmune subspecialists, such as Prof. Dr. Margono Soekarjo Regional Hospital. This study aims to develop a web-based expert system to support early screening for lupus by combining the Fuzzy Tsukamoto method and the Dempster-Shafer theory. The Fuzzy Tsukamoto method is used to represent symptom uncertainty through fuzzification, while the Dempster-Shafer theory is used to combine evidence from individual symptoms to produce confidence levels for possible diagnoses. The research process included a literature review, expert interviews, construction of a symptom–disease knowledge base, design of fuzzy rules, implementation of mass function calculations, and development of a web-based diagnostic application. Testing was conducted using ten patient test cases with confirmed expert diagnoses. The test results showed an accuracy of 100%, with all system diagnoses matching the experts' diagnoses. The strength of this research lies in the integration of two inference methods to improve the accuracy of evidence calculation, and in the use of symptom uniqueness and occurrence parameters that were validated directly by experts. This system has the potential to serve as an effective early screening tool for healthcare providers and patients, particularly in resource-limited settings. From an informatics perspective, this study contributes to the development of intelligent decision support systems by demonstrating the effectiveness of a hybrid reasoning approach in handling uncertainty in medical diagnosis. The integration of Fuzzy Tsukamoto and Dempster–Shafer methods enhances diagnostic consistency and reliability, making the proposed system relevant for research in expert systems and medical informatics.

Keywords : *Autoimmune, Dempster-Shafer, Early Diagnosis, Expert System, Fuzzy Tsukamoto, Lupus.*

1. INTRODUCTION

Health is a fundamental pillar of national development because it directly affects quality of life, productivity, and economic growth. The World Health Organization (WHO) defines health as a state of complete physical, mental, and social well-being. In Indonesia, although access to health services continues to improve, the distribution of services and the management of non-communicable diseases remain major challenges [1]. One of the increasingly concerning health issues is autoimmune diseases, including lupus.

Autoimmune diseases occur when the immune system mistakenly attacks the body's own cells, resulting in a wide range of clinical manifestations that are often non-specific [2]. This condition significantly affects quality of life and can lead to serious complications. Data from the Indonesian Ministry of Health (2021) reported more than 2.5 million individuals with autoimmune disorders and over 35,000 related deaths in the same year. These numbers indicate that delays in identification and treatment may lead to fatal outcomes. For lupus, national estimates indicate a prevalence of

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approximately 0.5%, or more than 1.3 million individuals, based on studies referenced by the SALURI early detection program of the Ministry of Health [3].

There are three common types of lupus in Indonesia, namely Systemic Lupus Erythematosus (SLE), Cutaneous Lupus Erythematosus (CLE), and Drug-Induced Lupus (DIL) [4] [5]. The pediatric SLE registry from 2012 to 2015 reported 210 cases across 12 provinces with a female to male ratio of 9 to 1 and the highest diagnosis occurring at the age of 13 years [6]. Hospital-based studies show that CLE mainly affects women of productive age, with a hospital prevalence of 0.38 percent [7]. For DIL, although national incidence data are still limited, the possibility of drug-induced lupus occurring in long-term medication users highlights the importance of strengthening pharmacovigilance systems [7].

Lupus diagnosis is often challenging because many of its symptoms overlap with other medical conditions such as infections or hormonal disorders [8]. At Prof. Dr. Margono Soekarjo Regional Hospital, the limited availability of autoimmune subspecialists results in early screening that relies mainly on the rheumatology clinic. This situation may cause delays in referral to specialists or delays in receiving appropriate therapy, and both conditions can worsen the patient's health status and may even lead to death[9].

An expert system is a suitable approach for supporting early screening because it is capable of simulating the decision-making process of medical experts through a structured knowledge base. Fuzzy Logic can manage uncertainty and symptoms that tend to be vague, while the Dempster-Shafer theory is effective for combining evidence from multiple symptoms to estimate diagnostic confidence levels [9]. Empirical findings support the use of this combination. Previous research using the Dempster-Shafer method in autoimmune expert systems reported a lupus diagnosis accuracy of up to 94.40 percent [10], and the application of the Fuzzy Tsukamoto method in other medical diagnosis systems produced an accuracy of 90 percent [11]. Several other studies also show that combining Fuzzy Logic and the Dempster-Shafer method increases decision consistency in expert systems [9].

However, most existing expert system studies for autoimmune disease diagnosis focus on the use of a single inference method or rely on subjective certainty values, without explicitly considering symptom severity and uniqueness validated by medical experts. In addition, the implementation of hybrid reasoning methods in web-based expert systems for autoimmune diagnosis remains limited, particularly in real hospital environments. Therefore, this study proposes a web-based expert system that integrates Fuzzy Logic and the Dempster–Shafer method using expert-validated symptom severity and confidence weights to support early autoimmune disease screening. From an informatics perspective, this research contributes to the development of intelligent decision support systems by applying a hybrid reasoning approach to handle uncertainty in medical diagnosis based on real expert knowledge.

Based on these problems, this study develops a web-based expert system for diagnosing autoimmune diseases by integrating the Dempster-Shafer method and Fuzzy Logic. The system utilizes symptom data and severity weights obtained from consultations with medical experts at Prof. Dr. Margono Soekarjo Regional Hospital. This expert system is designed to generate confidence levels regarding the possible type of lupus experienced by the patient. It is expected to serve as an early screening tool for medical personnel and to reduce the risk of delayed diagnosis that may result in severe clinical consequences.

2. METHOD

This research employed a descriptive and experimental approach to develop and evaluate a web-based expert system for autoimmune disease diagnosis. The research method consists of data collection, data processing using the Fuzzy Tsukamoto method and Dempster–Shafer theory, system design, and system evaluation. This study was conducted at Prof. Dr. Margono Soekarjo Regional Hospital in

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Purwokerto, a referral hospital handling a significant number of autoimmune cases. The system is designed to assist early diagnosis of autoimmune diseases, particularly lupus, based on clinical symptoms reported by patients. In general, the stages of the research are outlined as follows.

1. Data Collection

Data collection in this study was conducted to obtain medical knowledge and system requirements required for expert system development.

1) Literature Study

The literature study was carried out by reviewing books, journals, and clinical guidelines related to autoimmune diseases, particularly lupus, as well as studies on the implementation of expert systems in the medical field. The literature served as a foundation for determining the focus of the disease, identifying relevant symptoms, and understanding the concept and application of the Fuzzy Tsukamoto method and the Dempster-Shafer theory that would be implemented in the system.

2) Interview

Interviews were conducted with an internal medicine specialist who handles autoimmune cases at Prof. Dr. Margono Soekarjo Regional Hospital. Through these interviews, the researcher obtained confirmation regarding the types of diseases used as the diagnostic focus, the symptoms considered important for screening, and an overview of how experts evaluate combinations of symptoms in patients. This information was then translated into the system's knowledge base and is explained in more detail in the results and discussion section.

2. Data Processing

The collected data were processed by constructing a knowledge base consisting of symptom data, disease categories, fuzzy membership functions, and Dempster–Shafer mass functions. The Fuzzy Tsukamoto method was applied to represent symptom severity, while the Dempster–Shafer theory was used to combine evidence from multiple symptoms and calculate diagnostic confidence values.

3. System Design

The system design in this research is illustrated using a diagnostic process flowchart. The diagnostic workflow begins when a user selects the start button. The system then directs the user to log in or register before entering the diagnosis page. The complete diagnostic workflow is illustrated in Figure 1.

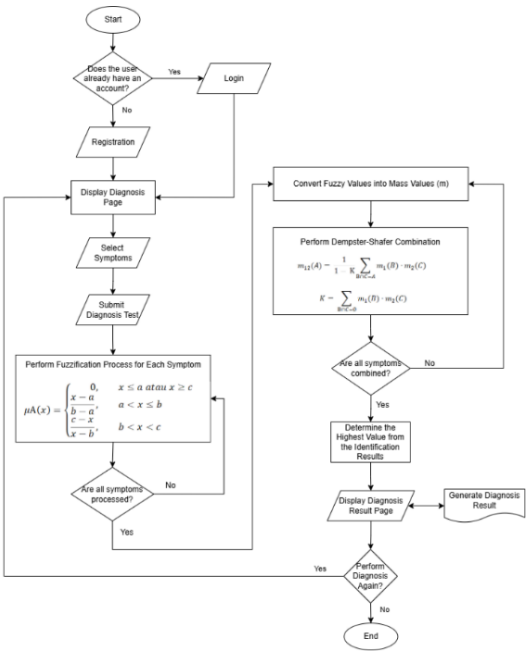

Figure 1. System Flowchart

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Once the user successfully logs in, they proceed to the diagnosis page where they select the symptoms they experience. The user then submits the symptom data to the system. After the symptoms are submitted, the system performs a fuzzification process for each selected symptom. The input values provided by the user are converted into fuzzy membership values using a trapezoidal membership function as represented by the equation μA(x) in the flowchart. The fuzzification process continues until the system identifies that all selected symptoms have been processed. The resulting fuzzy values are then converted into mass values (m), which represent the level of support a symptom provides for each disease hypothesis [12][13].

The mass values derived from each symptom are then combined using the Dempster-Shafer combination rule. In this stage, the system incrementally combines evidence according to the $m_{1,2}$ (A) combination equation and the conflict value K shown in the flowchart. This combination process is repeated until all symptoms selected by the user have been processed. After all mass values are combined, the system calculates the final confidence value for each disease and selects the highest value as the diagnosis result. The diagnosis result is then displayed on the diagnosis result page. Users may choose to perform another diagnosis by returning to the symptom selection page or may end the session if no further consultation is needed [14][15].

To evaluate system performance, accuracy testing was conducted using several patient test cases that already had expert diagnoses. Each test case was entered into the system, and the system's diagnosis was compared with the expert's diagnosis [16]. Accuracy was calculated using the following formula [17].

$$Accuracy = \frac{Number\ of\ correct\ diagnoses}{Total\ number\ of\ test\ cases} \times 100\% \qquad (1)$$

This metric indicates the percentage of agreement between the expert system's diagnoses and the experts' diagnoses used as the reference [18].

2.1. System Design

System design was carried out to describe how users and experts interact with the system, how the diagnostic workflow is executed, and how data are stored and interconnected within the database. The design is represented using a use case diagram, activity diagram, and class diagram, which serve as the blueprint for system implementation [19].

3.1.1. Use Case Diagram

A use case diagram is a modeling tool used to represent the functions provided by a system from the user's perspective, as well as the interactions between actors and the services they can access. This diagram helps summarize all actions that users can perform within the system [20].

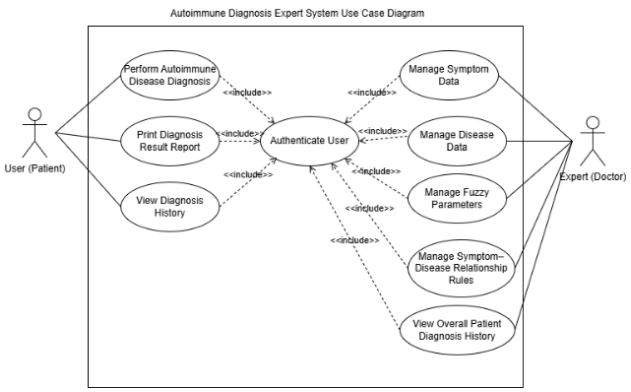

Figure 2. System Use Case Diagram

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Figure 2 shows the use case diagram of the expert system for autoimmune diagnosis. There are two main actors, the user (patient) and the expert (doctor). Patients can perform autoimmune diagnostic tests, view diagnosis reports, and access their test history. Meanwhile, experts manage symptom data, disease data, fuzzy parameters, symptom-disease relationships, and monitor patient diagnosis history. All functions are connected to the login process to ensure that only authenticated users can access the system.

3.1.2. Activity Diagram

An activity diagram models the workflow or sequence of activities within a process in the system, including decisions and transitions between steps. This diagram describes what happens from the beginning to the end of the diagnostic process [20].

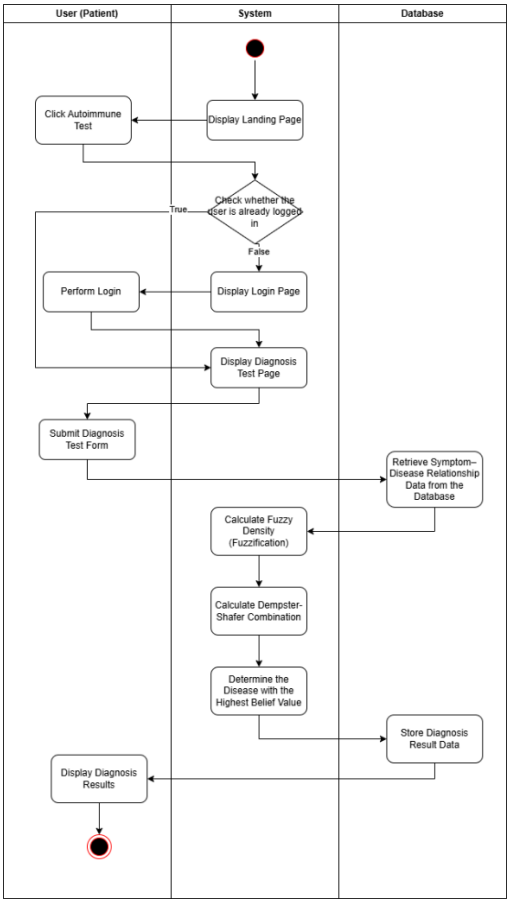

Figure 3. System Activity Diagram

Figure 3 presents the activity diagram of the autoimmune diagnosis system. The process begins when a patient selects the autoimmune test menu. The system displays the initial page and checks the login status before directing the patient to the diagnosis test page. After the patient submits their symptoms, the system retrieves symptom-disease relationships from the database, calculates fuzzy density, combines evidence using the Dempster-Shafer method, determines the disease with the highest belief value, saves the results to the database, and displays the diagnosis output to the patient.

3.1.3. Class Diagram

A class diagram represents the static structure of the system, including the data classes used along with their attributes, operations, and relationships. This diagram serves as the foundation for database and program logic design [20].

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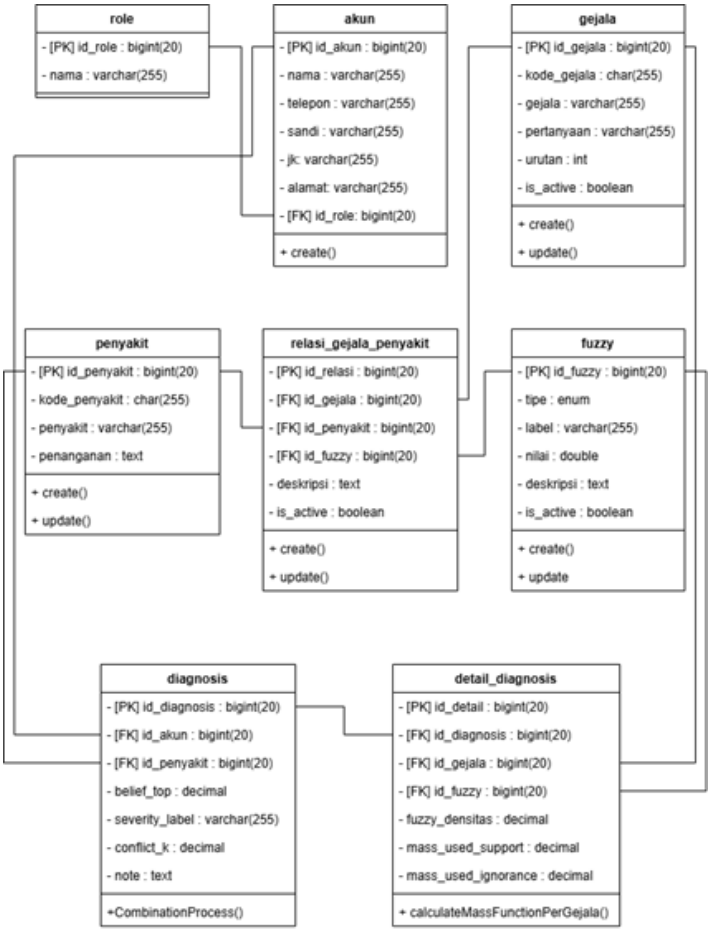

Figure 4. System Class Diagram

Figure 4 presents the class diagram of the autoimmune diagnosis expert system. The diagram includes key classes such as role, account, symptom, disease, symptom-disease relationship, fuzzy parameters, diagnosis, and diagnosis details. These classes store user information, the knowledge base, fuzzy parameters, and diagnosis history to ensure that calculations and data storage are performed in a structured manner.

3. RESULT

This section presents the results of the expert system implementation, including the formation of the knowledge base, fuzzy inference results, and Dempster–Shafer belief calculation based on a sample patient case. The results demonstrate how the proposed system processes symptom inputs to produce diagnostic confidence values.

3.1. Rule Formation and Knowledge Base

This section explains the development of the knowledge base that forms the core of the expert system. It includes the preparation of symptom data and disease data, the formulation of relationships between them, and the determination of fuzzy parameters and rule bases used in the inference process.

3.1.1. Symptom Data

Based on the literature review and interviews with the internal medicine specialist at Prof. Dr. Margono Soekarjo Regional Hospital, a set of symptoms commonly found in patients suspected of having autoimmune lupus was identified. These symptoms were selected and formalized into symptom codes so that they could be processed by the system. Each symptom is equipped with a symptom name

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and a question that will be displayed to the user during diagnosis to ensure consistent interpretation between expert and system. The symptom data used in this expert system are shown in Table 1.

Table 1. Symptom Data

Symptom Code	Symptom Name
G01	Persistent severe fatigue (≥ 2 weeks)
G02	Symmetric small joint pain and swelling, morning stiffness ≥ 30 minutes
G03	Malar rash or photosensitivity (worsens with sunlight)
G04	Recurrent oral or nasal ulcers (often painless)
G05	Generalized non-scarring hair loss
G06	Fever ≥ 38°C for ≥ 2 days without clear signs of infection
G07	Raynaud phenomenon (white to blue to red discoloration during cold or stress)
G08	Pleuritic or pericardial chest pain (serositis)
G09	Leg swelling or foamy urine
G10	Neurological complaints (severe headache, seizures, confusion)
G11	Persistent muscle pain (myalgia)
G12	Unintentional weight loss ≥ 5% within approximately 1 month
G13	Scaly or thick discoid plaques, may leave scars
G14	Persistent itching on rash or plaque areas
G15	Scarring alopecia on the scalp
G16	History of triggering medications (hydralazine, procainamide, isoniazid, and others)
G17	Symptoms appear after starting medication (weeks to months)
G18	Symptoms improve after medication is discontinued

Table 1 summarizes the symptom data used as input parameters in the expert system. These symptoms represent the most common clinical manifestations of lupus variants identified through expert consultation and literature review. This table serves as the primary reference for symptom input within the system interface as well as during manual calculations presented in this study [21][22][23].

3.1.2. Disease Data

The diseases included in the diagnostic focus of this research are three variants of lupus: Systemic Lupus Erythematosus (SLE), Cutaneous Lupus Erythematosus (CLE), and Drug-Induced Lupus (DIL). Table 2 displays the disease data used in the system.

Table 2. Disease Data

Disease Code	Disease Name
P01	Systemic Lupus Erythematosus (SLE)
P02	Cutaneous Lupus Erythematosus (CLE)
P03	Drug-Induced Lupus (DIL)

Table 2 shows the disease categories included in the diagnostic scope of this study, which are limited to three major lupus variants to ensure focused and accurate inference.

3.1.3. Rule Data

The following data serve as the basis for constructing fuzzy rules and calculating the mass function in the Dempster-Shafer method. It reflects expert knowledge regarding the relationships between symptoms and diseases.

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Table 3. Symptom Knowledge Base Data

Symptom Code	P01	P02	P03
G01	Low	Low	Low
G02	High	Low	Moderate
G03	High	High	Moderate
G04	High	Moderate	
G05	Moderate	Moderate	
G06	Low		Moderate
G07	Moderate		
G08	Moderate		Moderate
G09	High		Low
G10	Moderate		Low
G11	Moderate		Moderate
G12	Low		
G13	Moderate	High	
G14		Moderate	
G15		High	
G16			High
G17			High
G18			High

Table 3 represents the knowledge base that encodes expert knowledge regarding the relationship strength between symptoms and each lupus type, which becomes the foundation for fuzzy and Dempster–Shafer inference.

3.1.4. Parameter Fuzzy

To model how frequently symptoms are experienced by patients, fuzzy parameters for symptom occurrence were used. On the system interface, users provide linguistic category inputs, which are then converted to numerical values in the range of 0 to 1 using membership functions.

Table 4. Fuzzy Parameters for Symptom Occurrence

Label	Value
Very Rare	0.2
Occasionally	0.5
Frequent	0.8

In addition to symptom occurrence, the system also considers the uniqueness of a symptom for each disease. Symptom uniqueness describes how characteristic a symptom is for SLE, CLE, or DIL. These values were obtained directly from expert assessment.

Table 5. Fuzzy Parameters for Symptom Uniqueness

Label	Value
Low	0.3
Moderate	0.5
High	0.8

3.1.5. Fuzzy Rule Base

Based on symptom occurrence and uniqueness, a set of fuzzy rules was constructed for the Tsukamoto method. The rules follow the general structure. If symptom occurrence is within a certain category and uniqueness is within a certain category, then the symptom density output follows a corresponding fuzzy category.

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Table 6. Fuzzy Rule Base

Minimum Occurrence	Maximum Occurrence	Minimum Uniqueness	Maximum Uniqueness	Output
0.7	1	0.7	1	0.9
0.7	1	0.4	0.6	0.8
0.7	1	0	0.3	0.6
0.4	0.6	0.7	1	0.7
0.4	0.6	0.4	0.6	0.5
0.4	0.6	0	0.3	0.3
0	0.3	0.7	1	0.4
0	0.3	0.4	0.6	0.2
0	0.3	0	0.3	0.1

The fuzzy rule base shown in Table 6 enables the system to translate symptom occurrence and uniqueness into quantitative density values, which serve as intermediate evidence before belief combination using the Dempster–Shafer method.

3.2. Calculation Process

This section demonstrates the expert system's calculation process for a sample patient case. The user first selects the experienced symptoms and indicates their occurrence level. The system then matches each symptom with its uniqueness value for each disease. Table 7 summarizes the patient's inputs and their corresponding uniqueness values.

Table 7. Patient Symptom Input

Code	Occurrence	Uniqueness SLE	Uniqueness CLE	Uniqueness DIL	Mean Uniqueness
G13	0.8	0.5	0.8	-	0.65
G14	0.5	-	0.5	-	0.5
G15	0.8	-	0.8	-	0.8

The next stage is the activation of the Tsukamoto fuzzy rules. The membership degrees for symptom occurrence μ_{occ} and uniqueness μ_{uniq} are determined based on their respective linguistic labels.

To calculate μ_{occ}, the following formula is used with the range [a, b] (where a is the minimum occurrence value and b is the maximum occurrence value), and a transition width of 0.3 for each value of x (x = occurrence) [24].

$$\mu_{occ}(x,[a,b]) = \begin{cases} 1, & a \le x \le b \\ \max\{0; 1 - \frac{a-x}{0.3}\}, & x < a \\ \max\left\{0; 1 - \frac{x-b}{0.3}\right\}, & x > b \end{cases} \quad (1)$$

Meanwhile, to calculate μ_{uniq}, the following formula is used with the range [a, b] (where a is the minimum uniqueness value and b is the maximum uniqueness value), and a transition width of 0.3 for each value of y (y = average uniqueness) [24].

$$\mu_{uniq}(y,[a,b]) = \begin{cases} 1, & a \le y \le b \\ \max\{0; 1 - \frac{a-y}{0.3}\}, & y < a \\ \max\left\{0; 1 - \frac{y-b}{0.3}\right\}, & y > b \end{cases} \quad (2)$$

Therefore, to calculate μ_{occ} and μ_{uniq} for symptom G13, the computation is performed using the fuzzy rule base with an occurrence value of x = 0.8 and an average uniqueness value of y = 0.65. The resulting values are shown as follows.

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Table 8. Result of μ_{occ} and μ_{uniq} for Symptom G13

Minimum Occurrence	Maximum Occurrence	Minimum Uniqueness	Maximum Uniqueness	Output	μ_{occ} G13	μ_{uniq} G13
0.7	1	0.7	1	0.9	1.00	0.83
0.7	1	0.4	0.6	0.8	1.00	0.83
0.7	1	0	0.3	0.6	1.00	0.00
0.4	0.6	0.7	1	0.7	0.33	0.83
0.4	0.6	0.4	0.6	0.5	0.33	0.83
0.4	0.6	0	0.3	0.3	0.33	0.00
0	0.3	0.7	1	0.4	0.00	0.83
0	0.3	0.4	0.6	0.2	0.00	0.83
0	0.3	0	0.3	0.1	0.00	0.00

Next, to calculate μ_{occ} and μ_{uniq} for symptom G14, the computation is performed using the fuzzy rule base with an occurrence value of x = 0.5 and an average uniqueness value of y = 0.5. The resulting values are shown as follows.

Table 9. Result of μ_{occ} and μ_{uniq} for Symptom G14

Minimum Occurrence	Maximum Occurrence	Minimum Uniqueness	Maximum Uniqueness	Output	μ_{occ} G14	μ_{uniq} G14
0.7	1	0.7	1	0.9	0.33	0.33
0.7	1	0.4	0.6	0.8	0.33	1.00
0.7	1	0	0.3	0.6	0.33	0.33
0.4	0.6	0.7	1	0.7	1.00	0.33
0.4	0.6	0.4	0.6	0.5	1.00	1.00
0.4	0.6	0	0.3	0.3	1.00	0.33
0	0.3	0.7	1	0.4	0.33	0.33
0	0.3	0.4	0.6	0.2	0.33	1.00
0	0.3	0	0.3	0.1	0.33	0.33

Finally, for the last symptom, G15, the calculation of μ_{occ} and μ_{uniq} is performed using the fuzzy rule base with an occurrence value of x = 0.8 and an average uniqueness value of y = 0.8. The resulting values are shown as follows.

Table 10. Result of μ_{occ} and μ_{uniq} for Symptom G15

Minimum Occurrence	Maximum Occurrence	Minimum Uniqueness	Maximum Uniqueness	Output	μ_{occ} G15	μ_{uniq} G15
0.7	1	0.7	1	0.9	1.00	1.00
0.7	1	0.4	0.6	0.8	1.00	0.33
0.7	1	0	0.3	0.6	1.00	0.00
0.4	0.6	0.7	1	0.7	0.33	1.00
0.4	0.6	0.4	0.6	0.5	0.33	0.33
0.4	0.6	0	0.3	0.3	0.33	0.00
0	0.3	0.7	1	0.4	0.00	1.00
0	0.3	0.4	0.6	0.2	0.00	0.33
0	0.3	0	0.3	0.1	0.00	0.00

For each active rule, the activation weight is calculated using the minimum operator, defined as [25].

$$\text{weight} = \min(\mu_{\text{occ}}, \mu_{\text{uniq}}) \quad (4)$$

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Since the Tsukamoto consequents are monotonic, each rule produces an output value. The contribution of each rule to the final output is calculated as follows [25].

$$\text{contribution} = \text{weight} \times \text{output} \quad (5)$$

Based on the μ_{occ} and μ_{uniq} values obtained, the weights and contributions for each symptom are determined as follows.

Table 11. Weight and Contribution Results for G13

Output	μ_{occ} G13	μ_{uniq} G13	Weight G13	Contribution G13
0.9	1.00	0.83	0.83	0.75
0.8	1.00	0.83	0.83	0.67
0.6	1.00	0.00	0.00	0.00
0.7	0.33	0.83	0.33	0.23
0.5	0.33	0.83	0.33	0.17
0.3	0.33	0.00	0.00	0.00
0.4	0.00	0.83	0.00	0.00
0.2	0.00	0.83	0.00	0.00
0.1	0.00	0.00	0.00	0.00

Table 12. Weight and Contribution Results for G14

Output	μ_{occ} G14	μ_{uniq} G14	Weight G14	Contribution G14
0.9	0.33	0.33	0.33	0.30
0.8	0.33	1.00	0.33	0.27
0.6	0.33	0.33	0.33	0.20
0.7	1.00	0.33	0.33	0.23
0.5	1.00	1.00	1.00	0.50
0.3	1.00	0.33	0.33	0.10
0.4	0.33	0.33	0.33	0.13
0.2	0.33	1.00	0.33	0.07
0.1	0.33	0.33	0.33	0.03

Table 13. Weight and Contribution Results for G15

Output	μ_{occ} G15	μ_{uniq} G15	Weight G15	Contribution G15
0.9	1.00	1.00	1.00	0.90
0.8	1.00	0.33	0.33	0.27
0.6	1.00	0.00	0.00	0.00
0.7	0.33	1.00	0.33	0.23
0.5	0.33	0.33	0.33	0.17
0.3	0.33	0.00	0.00	0.00
0.4	0.00	1.00	0.00	0.00
0.2	0.00	0.33	0.00	0.00
0.1	0.00	0.00	0.00	0.00

After all values are calculated, the final value for each symptom (density) is determined using the weighted average, which is computed as follows [26].

$$\text{density} = \frac{\sum \text{contribution}}{\sum \text{weight}} \quad (6)$$

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Table 14. Fuzzy Density Results

Symptom Code	Fuzzy Density
G13	0.779
G14	0.500
G15	0.783

As shown in Table 14, symptoms G13, G14, and G15 yield relatively high fuzzy density values, indicating strong support for cutaneous-related lupus manifestations. These density values are subsequently used as evidence strengths in the Dempster–Shafer belief calculation. After the fuzzy stage produces a density value for each symptom, the system then treats these values as evidence strengths that must be mapped into the hypothesis framework through the mass function m. For symptoms that are associated with more than one disease, such as G13 which is relevant to both SLE and CLE, the density is distributed proportionally based on the uniqueness value of each disease. The remaining portion, represented by $1 - \mathrm{d}$ is assigned to θ to represent uncertainty. Mathematically, for a symptom g with density $\mathrm{d_g}$ and uniqueness value $\mathrm{u_{g,i}}$ for disease $\mathrm{P_i}$, the following formulation is used [9].

$$\mathrm{m_g}(\{\mathrm{P_i}\}) = \mathrm{d_g} \times \frac{\mathrm{u_{g,i}}}{\sum_j \mathrm{u_{g,j}}} \quad (7)$$

$$\mathrm{m_g}(\theta) = 1 - \mathrm{d_g} \quad (8)$$

The calculation process for mapping the density values to the mass function is as follows.

1. Mass for Symptom G13

   With a density value of 0.779, symptom G13 is associated with the diseases SLE and CLE.

   a. Calculate the total uniqueness:

   $$\text{Total uniqueness of G13} = \mathrm{u_{G13\ (SLE)}} + \mathrm{u_{G13\ (CLE)}}$$
   $$= 0.50 + 0.80$$
   $$= 1.30$$

   b. Calculate the mass of G13 toward SLE:

   $$\mathrm{m_{G13}}(\{\mathrm{SLE}\}) = \mathrm{d} \times \frac{\mathrm{u_{G13\ (SLE)}}}{\mathrm{Total}}$$
   $$= 0.779 \times \frac{0.50}{1.30}$$
   $$= 0.299$$

   c. Calculate the mass of G13 toward CLE:

   $$\mathrm{m_{G13}}(\{\mathrm{CLE}\}) = \mathrm{d} \times \frac{\mathrm{u_{G13\ (CLE)}}}{\mathrm{Total}}$$
   $$= 0.779 \times \frac{0.80}{1.30}$$
   $$= 0.479$$

   d. Calculate the mass of G13 toward θ (uncertainty):

   $$\mathrm{m_{G13}}(\theta) = 1 - \mathrm{d}$$
   $$= 1 - 0.779$$
   $$= 0.221$$

2. Mass for Symptom G14

   With a density value of 0.500, symptom G14 is associated with the diseases CLE.

   a. Calculate the total uniqueness:

   $$\text{Total uniqueness of G14} = \mathrm{u_{G14\ (CLE)}}$$
   $$= 0.50$$

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b. Calculate the mass of G14 toward CLE

$$m_{G14}(\{CLE\}) = d \times \frac{u_{G14\,(CLE)}}{Total}$$
$$= 0.500 \times \frac{0.50}{0.50}$$
$$= 0.500$$

c. Calculate the mass of G14 toward θ (uncertainty)

$$m_{G15}(\theta) = 1 - d$$
$$= 1 - 0.500$$
$$= 0.500$$

3. Mass for Symptom G15

With a density value of 0.783, symptom G15 is associated with the diseases CLE.

a. Calculate the total uniqueness:

$$\text{Total uniqueness of } G15 = u_{G15\,(CLE)}$$
$$= 0.80$$

b. Calculate the mass of G15 toward CLE:

$$m_{G15}(\{CLE\}) = d \times \frac{u_{G15\,(CLE)}}{Total}$$
$$= 0.783 \times \frac{0.80}{0.80}$$
$$= 0.783$$

c. Calculate the mass of G15 toward θ (uncertainty)

$$m_{G15}(\theta) = 1 - d$$
$$= 1 - 0.783$$
$$= 0.217$$

Thus, the initial mass values for each symptom are obtained as follows.

Table 15. Initial Mass Results per Symptom

Symptom Code	m ({SLE})	m ({CLE})	m (θ)
G13	0.299	0.479	0.221
G14	-	0.500	0.500
G15	-	0.783	0.216

Table 15 presents the initial mass assignments derived from fuzzy density values. A portion of mass is assigned to θ to represent uncertainty due to overlapping symptom characteristics, which is a common condition in autoimmune disease diagnosis. The values above serve as the input for the Dempster-Shafer combination process. The core of combining two mass functions, m_1 and m_2, is to calculate the conflict and then normalize the intersecting parts using the following formula [9].

$$K = \sum_{X \cap Y = \emptyset} m_1(X) m_2(Y) \quad (9)$$

$$m_{12}(A) = \frac{\sum_{X \cap Y = A} m_1(X) m_2(Y)}{1 - K} \quad (10)$$

1. Combination Step 1

Calculating $m_1 = G13$ combined with $m_2 = G14$ produces m_{12}. Conflict arises only from the pairing between SLE and CLE.

$$K = m_{G13}(\{SLE\}) \times m_{G14}(\{CLE\})$$
$$= 0.299 \text{ X } 0.500$$
$$= 0.150$$

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The normalization factor is (1 - K) = 0.850

Next, the combined mass is calculated from the intersecting sets.

a. For SLE (P01) the mass comes only from {P01} ∩ θ

$$m_{12}(\{P01\}) = \frac{0.299 \times 0.500}{0.850}$$
$$= 0.176$$

b. For CLE (P02) the mass comes from {P02} ∩ θ, θ ∩ {P02}, and {P02} ∩ {P02}

$$m_{12}(\{P02\}) = \frac{(0.479 \times 0.500)+(0.221 \times 0.500)+(0.479 \times 0.500)}{0.850}$$
$$= 0.694$$

c. For θ

$$m_{12}(\theta) = \frac{0.221 \times 0.500}{0.850}$$
$$= 0.130$$

Thus, the combined mass m_{12} is obtained as shown in the following iteration table.

Table 16. Combined Mass Results m_{12}

Disease Code	$m_1 = G13$	$m_2 = G14$	m_{12}
P01	0.299	0	0.176
P02	0.479	0.500	0.694
θ	0.221	0.500	0.130
	Conflict		0.150
	Normalization (1 – K)		0.850

2. Combination Step 2

Calculating $m_3 = m_{12}$ combined with $m_4 = G15$ produces m_{34}. Conflict arises from the pairing between {P01} in m_{12} and {P02} in G15.

$$K = m_{12}(\{P01\}) \times m_{G15}(\{P02\})$$
$$= 0.176 \text{ X } 0.783$$
$$= 0.138$$

The normalization factor is (1 - K) = 0.862

Next, the combined mass is calculated from the intersecting sets.

a. *For P01*

$$m_{34}(\{P01\}) = \frac{0.176 \times 0.217}{0.862}$$
$$= 0.044$$

b. *For P02*

$$m_{34}(\{P02\}) = \frac{(0.694 \times 0.217)+(0.130 \times 0.783)+(0.694 \times 0.783)}{0.862}$$
$$= 0.923$$

c. For θ

$$m_{12}(\theta) = \frac{0.130 \times 0.217}{0.862}$$
$$= 0.033$$

This second combination step integrates the previous belief result (m_{12}) with additional evidence from symptom G15. The inclusion of G15 significantly strengthens the belief toward CLE, as this symptom provides strong and more specific support for cutaneous lupus manifestations. Thus, the combined mass m_{34} is obtained as shown in the following iteration table.

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Table 17. Combined Mass Results m_{34}

Disease Code	$m_3 = m_{12}$	$m_4 = G15$	m_{34}
P01	0.176	0	0.044
P02	0.694	0.783	0.923
θ	0.130	0.217	0.033
	Conflict		0.138
	Normalization (1 – K)		0.862

The final belief combination results in a dominant belief value for Cutaneous Lupus Erythematosus (CLE), indicating that the accumulated evidence consistently supports this diagnosis despite the presence of minor conflict values. Based on the final mass combination, the highest belief value is obtained for P02, which corresponds to Cutaneous Lupus Erythematosus (CLE), with a value of 0.923 or 92.3%. The final conflict value recorded is K = 0.138, which reflects the level of disagreement between pieces of evidence during the combination process and has been normalized at each stage of aggregation. The system's decision is determined by selecting the disease with the highest belief value in the final output. The presence of mass assigned to θ indicates residual uncertainty due to limited symptom information or overlapping characteristics between diseases. However, its proportion is relatively small and does not affect the main decision. The moderate conflict value shows that some evidence is contradictory, but the Dempster-Shafer process successfully consolidates this conflict so that consistent evidence remains dominant. The final diagnosis result generated by the system is visualized through the diagnosis result interface, which presents the disease with the highest belief value along with its corresponding confidence level based on the Dempster–Shafer calculation.

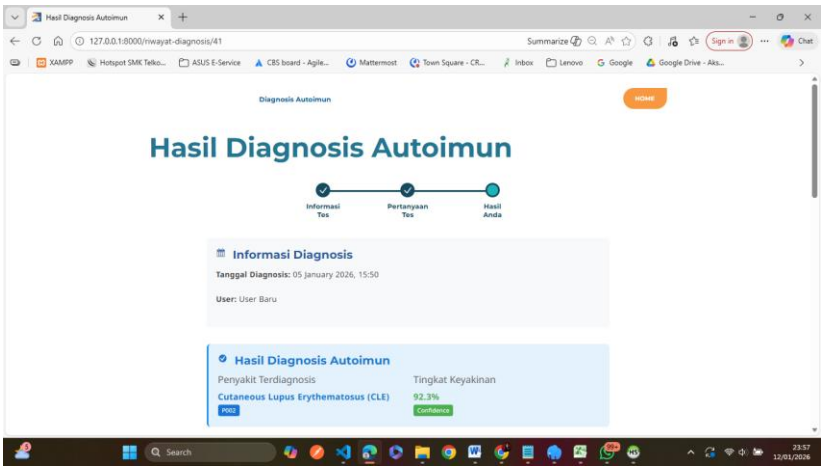

Figure 5. Screenshot of the Autoimmune Diagnosis Result Page

As shown in Figure 5, the system displays Cutaneous Lupus Erythematosus (CLE) as the diagnosis result with the highest belief value, consistent with the final mass combination obtained in the calculation stage. This output confirms that the system is able to translate the inference results into a clear and interpretable diagnosis for the user.

4. DISCUSSIONS

The diagnosis result indicating Cutaneous Lupus Erythematosus (CLE) demonstrates that the proposed expert system is able to capture clinically relevant symptom patterns in accordance with established medical knowledge. The final output aligns with the classification of Cutaneous Lupus Erythematosus described by Warastridewi et al., who characterize CLE as a chronic cutaneous

manifestation of lupus marked by erythematous or discoid scaly plaques that may result in scarring, often accompanied by pruritus and scarring alopecia when the scalp is involved [22].

In this case, the symptom combination selected by the patient G13 (discoid scaly or thick plaques that may leave scars), G14 (persistent itching on rash or plaque areas), and G15 (scarring alopecia on the scalp) corresponds closely with these clinical characteristics. This consistency indicates that the system's inference mechanism, which integrates fuzzy-based symptom severity and Dempster–Shafer evidence combination, is capable of reflecting expert clinical reasoning rather than relying solely on rigid rule matching.

Furthermore, the results suggest that incorporating symptom occurrence and uniqueness as expert-validated parameters improves the system's ability to distinguish between different lupus variants with overlapping manifestations. By translating these expert assessments into quantitative belief values, the system provides a more interpretable and structured decision support output for early screening purposes in a clinical setting.

5. CONCLUSION

This study developed a web-based expert system for diagnosing autoimmune lupus at Prof. Dr. Margono Soekarjo Regional Hospital, focusing on three disease types, namely Systemic Lupus Erythematosus (SLE), Cutaneous Lupus Erythematosus (CLE), and Drug-Induced Lupus (DIL), based on eighteen clinical symptoms. The diagnostic process integrates the Fuzzy Tsukamoto method to handle symptom severity and uncertainty, along with the Dempster-Shafer theory to combine multiple pieces of evidence in a structured belief framework. Evaluation using 10 test cases showed that the system's diagnostic results were fully consistent with expert diagnoses, achieving an accuracy rate of 100%. These results indicate that the proposed approach is effective in modeling expert reasoning and managing uncertainty in medical decision-making, particularly in conditions such as lupus that exhibit overlapping and ambiguous symptom patterns. From the perspective of informatics and computer science, this research contributes to the development of intelligent decision-support systems in the healthcare domain by demonstrating how fuzzy logic and evidence-based reasoning can be combined to enhance diagnostic consistency and interpretability. The proposed system can function as an early screening and decision-support tool to assist medical professionals and patients, especially in environments with limited access to autoimmune disease specialists. Nevertheless, this system is not intended to replace direct clinical diagnosis by physicians, as it does not yet incorporate additional supporting factors such as laboratory test results or comprehensive patient medical histories. Future work may include expanding the range of autoimmune diseases, integrating additional clinical and laboratory parameters, connecting the system with electronic medical record data, and conducting evaluations using larger and more diverse datasets to improve system reliability, scalability, and generalizability.

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