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RESEARCH ARTICLE **Open Access**

Implementation of the Certainty Factor Method in an Expert System for Diagnosing Nervous System Diseases

Aldio Tri Bangkit Sanjaya [1*], Dwi Hartanti [2], Ridwan Dwi Irawan [3]

[1*,2,3] Department of Informatics Engineering, Universitas Duta Bangsa, Surakarta City, Central Java Province, Indonesia.

**Corresponding author*: aldiotri03@gmail.com.

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Abstract: Neurological disorders present diagnostic challenges because of overlapping symptoms and limited access to specialist services in some healthcare settings. This study develops and evaluates a web-based expert system for supporting the preliminary diagnosis of five conditions—Stroke, Vertigo, Migraine, Low Back Pain, and Arthritis—using the Certainty Factor (CF) method. The CF approach incorporates Measure of Belief (MB) and Measure of Disbelief (MD) to represent uncertainty in the relationship between symptoms and diseases. The study adopts a design and development research (DDR) approach, with system development supported by an expert system development life cycle. The diagnostic performance was evaluated using 12 test cases, with the system results compared with assessments from an expert neurologist. The system correctly matched the expert assessment in 11 of 12 cases, resulting in a diagnostic agreement rate of 91.67%. One mismatch occurred in Case 2, in which the system identified Vertigo while the expert assessment indicated early-stage Stroke, reflecting the difficulty of distinguishing conditions with overlapping symptoms using the defined rules. Black-box testing showed that all tested functional scenarios passed, resulting in a 100% functional test pass rate. The developed system can support preliminary neurological disease identification by providing diagnosis results accompanied by Certainty Factor values.

Keywords: Expert System; Certainty Factor; Neurological Disorders; Diagnosis; Web-Based System.

1. Introduction

Technological advances have influenced the healthcare sector, particularly through the development of expert systems that support the reasoning and decision-making processes of human specialists. In healthcare settings, expert systems have been applied to assist medical consultation, support clinical decision-making, and provide structured approaches to disease identification. By organizing expert knowledge into a knowledge base and applying an inference mechanism, these systems can provide users with rapid access to preliminary diagnostic information while still requiring further assessment by healthcare professionals (Hafizah, 2025). The development of artificial intelligence has also expanded clinical decision-support systems, including applications for neurological disease diagnosis and related medical assessment tasks (Surianarayanan *et al.*, 2023; Molnar & Molnar, 2023; Mesraoua, 2024).

Neurological disorders affect the brain, peripheral nerves, and spinal cord, and may interfere with cognitive, sensory, balance, and motor functions. Early identification and appropriate treatment are important for reducing complications and improving patient outcomes (Firdaus *et al.*, 2025). Several neurological and related conditions are frequently encountered in healthcare services, including stroke, vertigo, headache, low back pain, and peripheral neuropathy. Ischemic stroke is among the neurological conditions frequently diagnosed in clinical settings (Dewi & Fitraneti, 2024). Low back pain affects a substantial proportion of the population and is recognized as an important cause of disability (Mastuti & Husain, 2023), while vertigo may interfere with daily activities because of disturbances in balance and spatial orientation (Siagian, 2022). Peripheral neuropathy is also frequently associated with chronic diseases, particularly diabetes mellitus (Labib *et al.*, 2023). These conditions show that disorders involving neurological symptoms may have varied clinical presentations and may require careful preliminary assessment before further medical examination.

Access to neurological healthcare services remains a challenge in some regions because of limited specialist availability and other barriers to timely consultation. Delays in obtaining specialist assessment may make early recognition of neurological and related conditions more difficult, especially when users experience symptoms that are similar across different diseases. A technology-based system may therefore provide initial diagnostic support by organizing symptom information and indicating possible conditions before users seek further assessment from healthcare professionals (Hafizah, 2025). Such a system should not be positioned as a replacement for professional diagnosis, but it can assist users in understanding symptom patterns and deciding whether further clinical consultation is needed.

Several studies have examined expert systems and computational approaches for neurological disease diagnosis. Nasser and Putri (2024) developed a web-based expert system for diagnosing epilepsy in children using the Forward Chaining method and reported that rule-based reasoning could support diagnosis through symptom matching. Sundari *et al.* (2024) applied a Bayesian method to diagnose radiculopathy and reported a maximum diagnostic probability of 72.55%, while Purnamasari *et al.* (2024) used a Decision Tree algorithm to classify stroke cases and identify patterns associated with stroke. These studies indicate that computational approaches can support neurological disease assessment, although their diagnostic scope, reasoning mechanisms, and representation of uncertainty differ.

Despite these developments, limitations remain in representing diagnostic uncertainty and covering multiple conditions within a single inference system. Previous studies have generally focused on specific diseases or diagnostic categories, which may limit their use when users present symptoms associated with more than one condition. Deterministic rule-based approaches such as Forward Chaining can provide clear reasoning paths but do not necessarily represent the degree of confidence associated with diagnostic evidence. Probabilistic approaches, meanwhile, generally require appropriate statistical information to estimate probabilities reliably (Ayuputri *et al.*, 2023). In medical diagnosis, uncertainty is difficult to avoid because similar symptoms may occur across different diseases, and the intensity of symptoms may vary between patients.

The Certainty Factor method provides an alternative approach for representing uncertainty in expert systems. This method allows expert knowledge and the degree of confidence associated with symptoms to be incorporated into the inference process, producing diagnostic results accompanied by confidence values (Febriyanto *et al.*, 2024). This characteristic makes Certainty Factor suitable for an expert system in which the relationship between symptoms and possible diseases cannot always be represented as a simple deterministic relationship. Based on this consideration, this study proposes a web-based expert system for the preliminary diagnosis of neurological and related conditions using the Certainty Factor method. Unlike studies that focus primarily on a single disease, the proposed system combines multiple conditions within a single knowledge base obtained from a neurologist.

The objectives of this study are to develop a web-based expert system for preliminary disease identification, implement the Certainty Factor method as the inference mechanism, and evaluate the system by comparing its diagnostic results with an expert assessment. The main research gap addressed in this study concerns the application of a Certainty Factor-based expert system to multiple neurological and related conditions within one knowledge base and its evaluation against an expert neurologist's assessment. The proposed system is expected to provide an additional approach for preliminary diagnostic decision support by generating possible disease indications accompanied by confidence values, while maintaining the role of healthcare professionals as the basis for further clinical assessment.

2. Related Work

Research on expert systems for neurological disease diagnosis has employed various artificial intelligence and rule-based approaches, including deterministic inference, probabilistic reasoning, and machine-learning classification. These approaches differ in how they represent diagnostic evidence, handle uncertainty, and obtain the information required to generate diagnostic results. This section reviews relevant previous studies, compares their approaches and findings, identifies the research gap addressed by this study, and discusses the main technologies and methods used in the proposed system.

2.1 State-of-the-Art Research

Several studies have investigated intelligent systems for disease diagnosis using different reasoning approaches. Nasser and Putri (2024) developed a web-based expert system for diagnosing epilepsy in children using Forward Chaining. The system matched user-selected symptoms with diagnostic rules stored in a knowledge base to generate diagnostic conclusions. The study demonstrated the applicability of rule-based reasoning for symptom-based diagnosis, although the approach does not explicitly assign certainty values to the diagnostic results. Sundari *et al.* (2024) applied a Bayesian approach to diagnose pinched nerve disorders. The system calculated disease probabilities from selected symptoms and reported a maximum diagnostic probability of 72.55% for a radiculopathy syndrome case. The Bayesian approach provides probabilistic diagnostic information, but its implementation requires appropriate probability parameters derived from relevant evidence or prior information. Purnamasari *et al.* (2024) applied a Decision Tree algorithm to classify stroke cases. Their study demonstrated the use of health-related variables to identify patterns associated with stroke classification. Unlike rule-based expert systems, this approach relies on data-driven classification and therefore depends on the quality and suitability of the dataset used to develop and evaluate the model. Other studies have applied probabilistic expert-system approaches in different medical domains. Putri *et al.* (2026) developed a web-based expert system for respiratory disease diagnosis using the Naïve Bayes method. The system generated diagnostic support based on combinations of user-selected symptoms and disease probabilities. Khalaf *et al.* (2024) also developed a Naïve Bayes-based expert system for preliminary rhinosinusitis diagnosis using patient symptoms. These studies demonstrate the application of probabilistic reasoning to provide preliminary diagnostic information, although their domains differ from neurological disease diagnosis. Recent reviews also indicate the increasing use of artificial intelligence in neurological disease diagnosis and clinical decision support (Huang *et al.*, 2023; Aljarallah *et al.*, 2024). In contrast to purely deterministic approaches, the Certainty Factor method provides a mechanism for representing the degree of confidence associated with expert knowledge and observed evidence. This characteristic is relevant to medical diagnosis because similar symptoms may be associated with different diseases and may vary in intensity among patients.

2.2 Comparison with Previous Studies

Table 1 summarizes the main characteristics of the previous studies reviewed in this research and compares them with the proposed system.

Table 1. Comparison with Previous Studies

Author (Year)	Title	Method	Main Result	Positioning of This Study
Nasser & Putri (2024)	Website-Based Expert System for Diagnosing Epilepsy in Children Using the Forward Chaining Method	Forward Chaining	Provides symptom-based preliminary diagnosis using rule matching.	Focuses on a single disease, whereas this study applies CF to multiple conditions.
Sundari *et al.* (2024)	Penerapan Metode Bayes untuk Mendiagnosa Penyakit Saraf Kejepit	Bayesian	Reported a maximum diagnostic probability of 72.55%.	Uses CF with expert-assigned certainty values rather than relying on the probability measure reported in the Bayesian system.
Purnamasari *et al.* (2024)	Penerapan Algoritma Decision Tree dalam Klasifikasi Penyakit Stroke Otak	Decision Tree	Applied data-driven classification to stroke cases.	Uses a rule-based CF approach and covers multiple conditions rather than a single stroke classification task.
Putri *et al.* (2026)	Sistem Pakar Diagnosis Penyakit Pernapasan Menggunakan Metode Naive Bayes Berbasis Web	Naïve Bayes	Provides preliminary diagnostic support for respiratory diseases.	Applies CF to neurological disease diagnosis rather than respiratory disease classification.
Khalaf *et al.* (2024)	Sistem Pakar Mendiagnosis Penyakit Rhinosinusitis dengan Menggunakan Metode Naive Bayes	Naïve Bayes	Provides preliminary rhinosinusitis assessment based on symptoms.	Focuses on multiple neurological conditions using a CF-based inference mechanism.

The reviewed studies demonstrate that expert systems and classification methods can support preliminary disease identification through symptom-based reasoning or data-driven prediction. However, the reviewed neurological applications differ in diagnostic scope and in their treatment of uncertainty. Forward Chaining provides deterministic rule-based reasoning, whereas Bayesian and Naïve Bayes methods represent diagnostic information through probabilities. Decision Tree methods use data-driven classification and depend on the characteristics of the dataset used. This study addresses these differences by applying the Certainty Factor method to a multi-condition neurological diagnostic system. CF allows expert-assigned certainty values to be incorporated into the inference process and provides a confidence value with the resulting diagnosis. The knowledge base is constructed from information obtained from a neurologist at Klinik Utama dr. Tunjung.

2.3 Positioning of This Research

Based on the reviewed literature, several previous expert systems have focused on individual diseases or specific diagnostic domains, including epilepsy, stroke, and radiculopathy. Other studies have applied probabilistic or machine-learning approaches to generate diagnostic results. This study differs by combining multiple diagnostic conditions within a single web-based expert system and using Certainty Factor to represent uncertainty in the inference process. The knowledge base is developed from neurologist knowledge and is used to construct the diagnostic rules and certainty values. The system provides a diagnosis accompanied by a CF value, allowing the diagnostic output to be interpreted in relation to the certainty associated with the available symptom evidence. The main contribution of this study is the implementation of a multi-condition expert system that combines neurologist-derived knowledge with Certainty Factor reasoning and evaluates the resulting diagnoses against an expert assessment.

2.4 Review of Technologies, Frameworks, and Algorithms

The proposed system is based on several related concepts and technologies. 1) An expert system is an artificial intelligence application designed to represent knowledge and reasoning within a specific domain. A typical expert system consists of a knowledge base, an inference mechanism, and a user interface that enables users to provide information and obtain conclusions. In medical applications, these components can be used to represent expert knowledge and provide preliminary diagnostic support (Markkandan *et al.*, 2024). 2) Neurological and related conditions involve disorders or complaints associated with the nervous system and its clinical manifestations, including disturbances in motor function, balance, sensory perception, and pain. In this study, the diagnostic scope is limited to five conditions: Stroke, Vertigo, Migraine, Low Back Pain, and Arthritis. The symptoms and diagnostic relationships used by the system are defined in the knowledge base based on information obtained from a neurologist. 3) The knowledge base stores structured information required by the expert system, including disease information, symptoms, relationships between symptoms and diseases, and expert-defined certainty values. In this study, the knowledge base was developed through interviews with a neurologist and used as the basis for constructing diagnostic rules. The inference process in this study uses the Certainty Factor method to represent the degree of certainty associated with a disease hypothesis based on available symptom evidence. The method was introduced in the MYCIN expert system to address uncertainty in medical diagnosis. In this study, CF combines expert-defined certainty information with user-provided symptom evidence to determine the degree of certainty associated with each disease hypothesis. The resulting CF value is then used to support the diagnostic conclusion (Priyambadha & Eviyanti, 2024; Mardiana & Ninosari, 2024; Febriani & Wijaya, 2024). The Certainty Factor approach uses two components, namely Measure of Belief (MB) and Measure of Disbelief (MD). MB represents the degree of belief that available evidence supports a hypothesis, whereas MD represents the degree of disbelief associated with the same hypothesis. These values are combined according to the CF formulation to obtain the certainty value used in the diagnostic inference.

3. Methodology

3.1 Study Characterization and Technology Stack

This study employed a design and development research (DDR) approach to develop and evaluate a web-based expert system for preliminary disease identification. The system was developed using PHP version 8.2.12, MySQL version 8.0.35, and Apache HTTP Server version 2.4.58 through the XAMPP v3.3.0 development environment.

3.2 System Architecture and Data Flow

The system architecture consists of three main components: the User Interface (UI), the Inference Engine, and the Knowledge Base. The diagnostic process begins when the user selects symptoms and provides a confidence level for each selected symptom using a scale from 0 (Not Sure) to 1 (Very Sure). The selected symptom data and user confidence values are then processed by the Inference Engine. The engine retrieves the corresponding diagnostic rules and expert Certainty Factor (CF) values from the Knowledge Base. The user and expert CF values are subsequently processed using the CF calculation and combination procedures. The resulting CF value for each disease is used to determine the disease with the highest confidence value, which is then displayed through the user interface.

3.3 Knowledge Validation and Scope

The knowledge base covers five conditions: Stroke, Vertigo, Migraine, Low Back Pain, and Arthritis. These conditions were selected based on the knowledge obtained from the neurologist and their relevance to the symptoms included in the diagnostic system. The production rules and expert CF values were reviewed with the neurologist before implementation to ensure that the symptom-disease relationships represented in the knowledge base were consistent with the expert's clinical knowledge. The proposed system uses the Certainty Factor (CF) method to represent the degree of confidence associated with symptom-disease relationships. The method combines expert confidence values with user confidence values to produce a confidence value for each diagnostic hypothesis. The research process consisted of system architecture design, knowledge acquisition, CF algorithm design, knowledge base preparation, system development, technology implementation, functional testing, and diagnostic validation.

3.4 Black-Box Testing Methodology

Functional testing was conducted using the Black Box Testing approach to evaluate whether the system operated according to the specified functional requirements. The testing scenarios included normal user interactions and boundary conditions involving invalid or incomplete inputs.
The functional testing covered the following components:
1) Login functionality
2) Disease management
3) Symptom management
4) Consultation process
5) Certainty Factor calculation
6) Diagnostic result display

In addition to functional testing, diagnostic validation was conducted by comparing the system-generated diagnosis with the diagnosis provided by the neurologist. This comparison was used to assess the agreement between the system output and the expert diagnosis.

3.5 System Architecture and Design

The proposed system uses a web-based client-server architecture consisting of users, the expert system application, and a database. Users access the system through a web browser and conduct consultations by selecting symptoms that correspond to their conditions. The selected symptoms are processed by the inference engine using the Certainty Factor method to determine the disease with the highest confidence value. Web-based expert systems can provide flexible access because users can conduct consultations through a web interface without being restricted by geographical location (Hafizah, 2025). The system supports two types of users: administrators and general users. Administrators manage disease data, symptom data, diagnostic rules, Certainty Factor values, and consultation records. General users can conduct consultations and view diagnostic results, confidence values, and recommendations. The database stores disease information, symptom information, diagnostic rules, Certainty Factor values, and consultation records. After the inference process is completed, the system displays the resulting disease diagnosis together with its confidence value and the available recommendations.

3.6 Algorithm and Framework Design

Knowledge acquisition is an important stage in expert system development because the quality of the resulting diagnosis depends on the quality of the knowledge represented in the system. Medical expert systems commonly obtain domain knowledge through consultation with experts and supporting literature (Febriyanto *et al.*, 2024). The acquired knowledge is then organized into a structured knowledge base that can be processed by the inference engine. In this study, knowledge was obtained through direct interviews with dr. Retno Tunjungsari, Sp.S., M.Kes., a neurologist at Klinik Utama dr. Tunjung. Additional information was obtained through observation and literature review. The collected information included disease types, symptoms, symptom-disease relationships, and expert confidence values. Based on the knowledge acquisition process, five conditions were selected as diagnostic targets: Stroke, Vertigo, Migraine, Low Back Pain, and Arthritis.

Table 2. Disease Data

Disease Code	Disease Name
P01	Stroke
P02	Vertigo
P03	Migraine
P04	Low Back Pain
P05	Arthritis

These conditions were selected based on the clinical knowledge obtained during the knowledge acquisition process and their relevance to the symptom data used in the system. Each disease is represented by a set of symptoms that serve as evidence in the diagnostic process.

Table 3. Symptom Data

Symptom Code	Symptom Name
G01	Weakness on one side of the body
G02	Slurred speech or difficulty speaking
G03	Balance disorders
G04	Spinning dizziness
G05	Nausea and vomiting
G06	Blurred vision
G07	Recurrent headaches
G08	Sensitivity to light
G09	Difficulty concentrating
G10	Lower back pain
G11	Back stiffness
G12	Difficulty bending or moving
G13	Joint pain
G14	Joint swelling
G15	Joint stiffness

The symptom list was reviewed by the neurologist and used as the primary evidence in the diagnostic process. The relationships between symptoms and diseases are represented using IF–THEN rules. Rule-based representation can be used to organize expert knowledge in medical expert systems (Nasser & Putri, 2024).

Table 4. Diagnostic Rules

Rule Code	Rule
R1	IF G01 AND G02 AND G03 AND G06 THEN P01
R2	IF G03 AND G04 AND G05 AND G06 THEN P02
R3	IF G07 AND G08 AND G09 THEN P03
R4	IF G10 AND G11 AND G12 THEN P04
R5	IF G13 AND G14 AND G15 THEN P05

The rules are processed by the inference engine to determine the disease with the highest Certainty Factor value based on the symptoms selected by the user. To represent the user's confidence in experiencing a particular symptom, the system provides five confidence options.

Table 5. User Certainty Factor Values

Option	Description	CF Value
1	Not Sure	0.0
2	Slightly Sure	0.4
3	Moderately Sure	0.6
4	Sure	0.8
5	Very Sure	1.0

These values allow the system to represent uncertainty in the user's assessment of the selected symptoms. The Certainty Factor method was introduced to represent uncertainty in medical expert systems. In this study, the method combines expert confidence values with user confidence values to calculate the confidence associated with each disease hypothesis. The Certainty Factor is calculated based on the Measure of Belief (MB) and Measure of Disbelief (MD):

$$CF(H,E) = MB(H,E) - MD(H,E) \quad (1)$$

Where CF represents the Certainty Factor, MB represents the Measure of Belief, MD represents the Measure of Disbelief, H represents the disease hypothesis, and E represents the symptom evidence. Because the expert confidence values are predefined in the knowledge base, the CF for each symptom is calculated by combining the user confidence value with the corresponding expert CF value:

$$CCF_{combine} = CF_{old} + CF_{new}(1 - CF_{old} \quad (2)$$

When multiple symptoms contribute to the same disease hypothesis, their CF values are combined using the following combination formula:

$$Percentage = CF_{combine} \times 100\% \quad (3)$$

The resulting CF value for each disease is then compared, and the disease with the highest Certainty Factor value is selected as the system-generated diagnosis. The resulting CF may be expressed as a percentage to communicate the confidence value to the user.

3.7 Development Process

The system was developed using the Expert System Development Life Cycle (ESDLC), which provides a structured process for developing knowledge-based systems. According to Sutedi *et al.* (2025), ESDLC can be used to organize the development of expert systems from problem identification through maintenance.

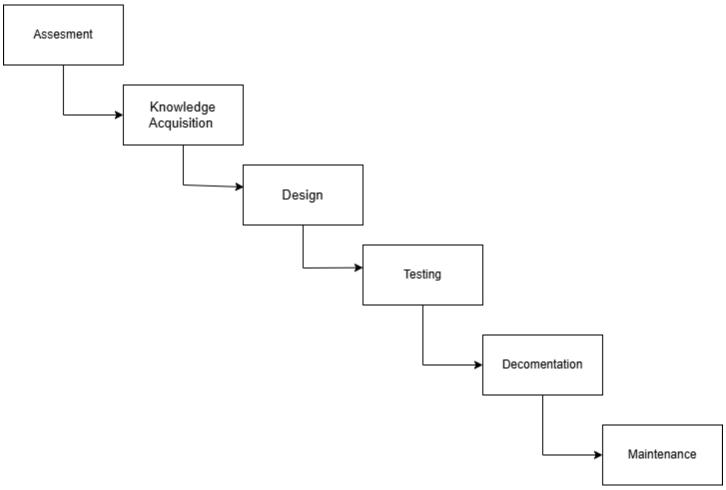

Figure 1. Expert System Development Life Cycle (ESDLC).

The ESDLC stages applied in this study were assessment, identifying the problems and system requirements; knowledge acquisition, obtaining knowledge from the neurologist and supporting literature; design, designing the database, user interface, and knowledge base; testing, evaluating system functionality and diagnostic outputs; documentation, documenting the system development process; and maintenance, updating the knowledge base and correcting system errors when required. The study used primary and secondary data sources. Primary data were obtained through interviews with the neurologist and observations at Klinik Utama dr. Tunjung. The data included disease categories, symptom information, symptom-disease relationships, and expert Certainty Factor values. Secondary data were obtained from scientific journals, conference proceedings, books, and previous studies related to neurological disorders, expert systems, and the Certainty Factor method (Nasser & Putri, 2024; Purnamasari *et al.*, 2024; Sundari *et al.*, 2024). The resulting knowledge base consisted of five target conditions, fifteen symptoms, diagnostic rules, and Certainty Factor values. The expert system was developed using the following technologies.

Table 6. Tools and Technologies

Component	Technology
Backend	PHP 8.2.12
Frontend	HTML, CSS, Bootstrap, JavaScript
Database	MySQL 8.0.35
Web Server	Apache 2.4.58 through XAMPP 3.3.0

Code Editor	Visual Studio Code
Operating System	Windows

System testing was conducted to determine whether the implemented functions operated according to the specified requirements. Black Box Testing was used to evaluate system functionality from the user's perspective. The tested functions included login, disease management, symptom management, consultation, Certainty Factor calculation, and diagnostic result display. In addition to functional testing, diagnostic validation was performed by comparing the diagnoses generated by the system with the diagnoses provided by the neurologist. The comparison was used to measure the agreement between the system results and the expert benchmark across the test cases. The diagnostic process is illustrated in Figure 2. The flowchart describes how user-selected symptoms and confidence values are processed using the knowledge stored in the system.

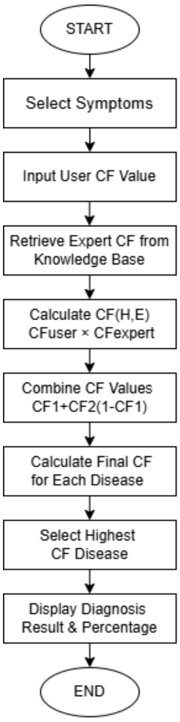

Figure 2. Certainty Factor Diagnosis Process Flowchart

The process begins when the user selects symptoms corresponding to their condition and provides a confidence value for each selected symptom. The system then retrieves the corresponding expert Certainty Factor values from the knowledge base. The system combines the user confidence value and expert CF value to obtain the CF associated with each selected symptom. When multiple symptoms contribute to the same disease hypothesis, their CF values are combined using the specified Certainty Factor combination formula. The resulting CF values for the disease hypotheses are then compared. The disease with the highest CF value is selected as the system-generated diagnosis. Finally, the system displays the diagnosis and its corresponding confidence value as a percentage. The process ends after the diagnostic result is displayed.

4. Result and Discussion

4.1 Results

4.1.1 Implementation Results

The proposed expert system for the preliminary diagnosis of neurological and related conditions was implemented as a web-based application using PHP, MySQL, HTML, CSS, Bootstrap, and JavaScript. The system was developed to assist users in identifying potential conditions based on symptoms selected during the consultation process. The implemented system consists of two user roles: administrator and user. The administrator is responsible for managing disease data, symptom data, diagnostic rules, Certainty Factor values, and consultation records. Users can conduct consultations by selecting symptoms and specifying confidence levels according to their conditions. The system processes the selected symptoms using the Certainty Factor method and generates diagnostic results accompanied by confidence values expressed as percentages.

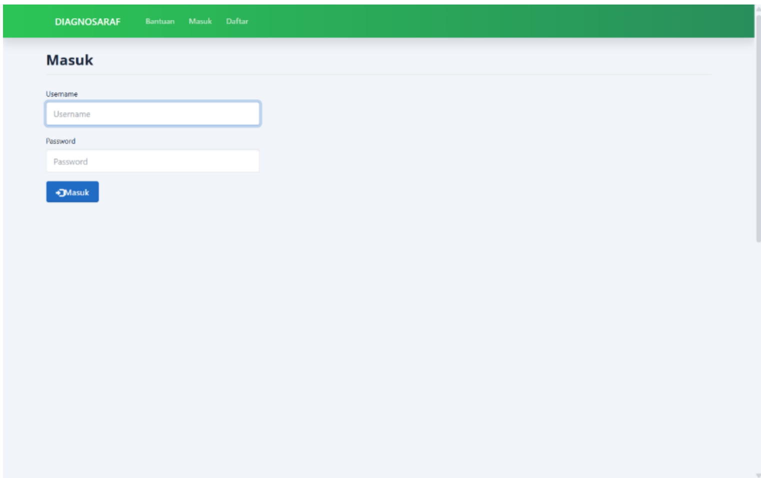

Figure 3. Login Page.

The login page provides a form that allows users and administrators to enter valid usernames and passwords to access the system's home page.

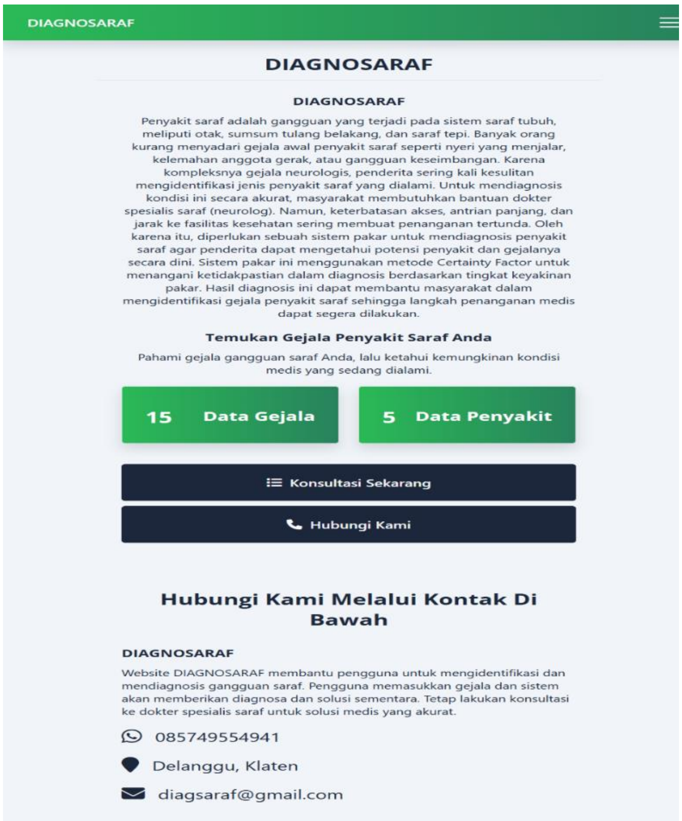

Figure 4. Dashboard Page.

The dashboard page displays the main website information, including contact details, email address, clinic location, and an interactive map to help users find the clinic's location.

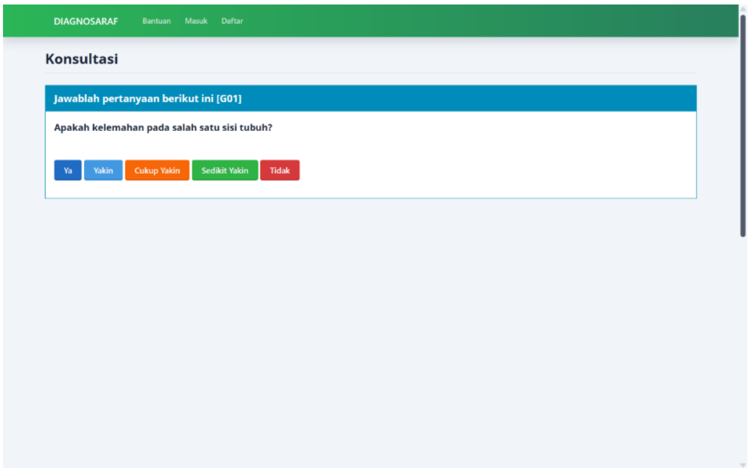

Figure 5. Consultation Page.

The consultation page contains a series of symptom-related questions that can be selected by users and administrators before obtaining the diagnostic results. This page is also equipped with a Cancel button that allows users to clear their selected symptoms and restart the consultation process from the beginning.

Figure 6. Consultation Results Page.

The consultation results page displays the history of answered symptom-related questions provided by users and administrators, the selected symptoms, the disease analysis results based on the selected symptoms, and the recommended solutions or treatments. The page is also equipped with a Consult Again button that redirects users to the symptom selection page to repeat the consultation process, as well as a Print button to print the consultation results. During implementation, several technical challenges were encountered, including database relationship management, rule processing, and Certainty Factor calculations involving multiple symptoms. These issues were addressed through database normalization, optimization of the rule evaluation process, and manual verification of the Certainty Factor calculations.

4.1.2 Testing Results

System testing was conducted using the Black Box Testing method to evaluate whether the implemented functionalities operated according to the specified requirements.

Table 7. Black Box Testing Results

Module id	Test Scenario Description	Expected System Behavior	Actual System Output	Type	Status
MOD-01	User authentication using valid institutional credentials.	User successfully enters the system	Authenticated successfully and redirected to the dashboard.	Positive	Pass
MOD-02	Form submission with completely empty or missing symptom selections.	Successful login; system grants access and redirects to the clinical dashboard.	Execution halted; displayed "Symptom input required" validation banner.	Negative	Pass
MOD-03	Core diagnostic processing using standard, linear symptom combinations (Case 1).	Halt execution; block database queries; trigger dynamic validation warning banner.	Executed CF logic perfectly; correctly rendered Stroke (CF: 0.8872).	Positive	Pass
MOD-04	Administrative data operations for managing disease master records (Add/Edit/Delete).	Correct execution of Certainty Factor combination logic; render final disease outcome.	Data records successfully stored, updated, and purged in the database.	Positive	Pass
MOD-05	Administrative data operations for managing clinical symptom lists (Add/Edit/Delete).	Successfully write, update, and remove disease data parameters within the database.	Symptom records successfully stored and updated in the database.	Positive	Pass
MOD-06	Malicious injection of extreme, out-of-bounds boundary values via raw HTTP POST requests.	Sanitize input parameters; reject non-array payload data; display structured error page.	Input vectors blocked; data sanitation executed; system structural integrity maintained.	Negative	Pass

The testing results in Table 7 show that all tested scenarios were successfully completed. The negative testing scenarios in MOD-02 and MOD-06 also showed that the system was able to reject incomplete or invalid inputs under the tested conditions. These results indicate that the tested functional and validation scenarios operated according to the expected system behavior. However, the expected behavior recorded for several modules should be checked against the original testing records to ensure consistency between the test scenarios and their expected outcomes.

4.1.3 Performance Evaluation

Performance evaluation was conducted by comparing the diagnoses generated by the expert system with the diagnoses provided by the expert neurologist. Twelve consultation scenarios representing different symptom configurations were used to evaluate the agreement between the system output and the expert benchmark.

Table 8. Performance Evaluation

Test Case	Dominant Symptoms Present	System Predicted Diagnosis	System CF Value	Expert Benchmarked Diagnosis	Expert Confidence	Status
Case 1	Hemiparesis, Facial Palsy, Dysarthria	Stroke	0.8872	Stroke	High Confidence	Match
Case 2	Sudden Vertigo, Nausea, Nystagmus, Mild Numbness	Vertigo	0.8120	Stroke(early stage)	High Confidence	Missmatch
Case 3	Rotational Dizziness, Vomiting	Vertigo	0.9240	Vertigo	High Confidence	Match
Case 4	Chronic Knee Inflammation, Stiffness	Arthritis	0.8560	Arthritis	Confirmed	Match
Case 5	Unilateral Throbbing Headache, Photophobia, Nausea	Migraine	0.8415	Migraine	Confirmed	Match
Case 6	Finger Joint Swelling, Morning Stiffness >30 Minutes	Arthritis	0.8920	Arthritis	High Confidence	Match
Case 7	Sudden Ataxia, Confusion, Slurred Speech	Stroke	0.9115	Stroke	High Confidence	Match
Case 8	Positional Dizziness, Spinning	Vertigo	0.8640	Vertigo	Confirmed	Match
Case 9	Asymmetric Muscle Weakness, Sudden Numbness	Stroke	0.8432	Stroke	High Confidence	Match
Case 10	Sharp Lumbar Pain Radiating to Buttocks, Spasms	Low Back Pain	0.8790	Low Back Pain	Confirmed	Match
Case 11	Recurrent Headache Preceded by Visual Aura	Migraine	0.8350	Migraine	High Confidence	Match
Case 12	Hemiplegia, Sudden Vision Loss, Aphasia	Stroke	0.9412	Stroke	High Confidence	Match

The evaluation results show that the proposed expert system produced diagnoses that agreed with the expert benchmark in 11 of the 12 test cases. One mismatch occurred in Case 2, where the system generated Vertigo with a CF value of 0.8120, while the expert neurologist classified the case as early-stage Stroke. This result indicates that the system was able to produce an expert-aligned diagnosis in most of the tested scenarios, while Case 2 represents a symptom-overlap condition that requires further examination of the knowledge base and rule structure. The Certainty Factor method provides a mechanism for representing the degree of confidence associated with symptom-disease relationships. Unlike a purely deterministic rule output, the system produces a CF value for each diagnostic hypothesis, allowing the resulting diagnosis to be accompanied by a numerical confidence value. However, the present study does not directly compare the CF system with a separate Forward Chaining system; therefore, claims of superiority over Forward Chaining should be interpreted cautiously.

4.1.4 Metrics

To evaluate the diagnostic performance of the proposed system, the results in Table 8 were classified into matching and non-matching outcomes. Of the 12 clinical test cases, 11 matched the expert benchmark, while 1 case produced a different diagnosis. The diagnostic accuracy was calculated using the following formula:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Test Cases}} X\ 100\% \qquad (4)$$

The resulting accuracy was:

$$\text{Accuracy} = \frac{11}{12} X\ 100\% = 91.66\%$$

The error rate was calculated as:

$$\text{Error Rate} = 100\% - 91.66\% = 8.34\%$$

The results indicate that the system matched the expert benchmark in 11 of the 12 evaluated cases. The single mismatch occurred in Case 2, indicating that symptom overlap remains a limitation of the current rule and knowledge structure. Therefore, the obtained accuracy demonstrates the performance of the system on the tested cases but should not be interpreted as evidence of general clinical accuracy across a larger patient population.

4.2 Discussion

The implementation results show that the proposed expert system was successfully developed as a web-based application that combines clinical knowledge with Certainty Factor-based reasoning. The system supports user authentication, administrative data management, consultation, Certainty Factor calculation, and diagnostic result presentation. The black-box testing results indicate that all tested functional scenarios were completed successfully, suggesting that the main system functions operated according to the specified requirements. In addition to functional testing, diagnostic evaluation showed an agreement rate of 91.67%, with 11 of the 12 test cases matching the expert benchmark. This result indicates a high level of agreement between the system output and the expert diagnosis within the tested cases. However, because the evaluation involved only 12 test cases, the result should be interpreted as evidence of system performance under the specified evaluation conditions rather than as a general measure of clinical diagnostic accuracy.

When viewed alongside previous studies, the result suggests that the proposed system can provide competitive preliminary diagnostic support within its evaluation setting. Sundari *et al.* (2024), for example, reported a maximum diagnostic probability of 72.55% for a Bayesian-based approach. The difference between that value and the 91.67% agreement obtained in this study should not be interpreted as direct evidence that the Certainty Factor method is generally superior to the Bayesian approach, because the two studies used different methods, datasets, test cases, and evaluation procedures. The comparison is more appropriately understood as contextual evidence that the proposed system produced a relatively high agreement value within its own test-case-based evaluation.

The only mismatch occurred in Case 2, where the system generated Vertigo with a CF value of 0.8120, while the expert neurologist classified the case as early-stage Stroke. The case involved sudden rotational vertigo, nausea, nystagmus, and mild numbness. The system selected Vertigo because the symptoms associated with the Vertigo rule produced a higher CF value than the competing diagnostic rule. This difference indicates a limitation in handling symptom overlap, particularly when neurological warning signs occur together with symptoms commonly associated with Vertigo. In such cases, the current rule structure may not sufficiently represent clinical patterns that an expert would consider as possible early-stage Stroke. Therefore, additional symptom relationships and rules may be required to improve the system's ability to represent overlapping presentations between Stroke and Vertigo.

This finding also shows that rule-based diagnostic systems depend strongly on the completeness and clinical representativeness of their knowledge base. When a symptom pattern is not sufficiently represented by the available rules, the system may select the disease whose existing rule receives the highest CF value even when an expert considers another diagnosis more appropriate. Compared with previous studies, the proposed system combines five target conditions within a single web-based expert system: Stroke, Vertigo, Migraine, Low Back Pain, and Arthritis. Nasser and Putri (2024) developed a rule-based approach using Forward Chaining, while Purnamasari *et al.* (2024) investigated a Decision Tree-based approach for stroke classification. The present system differs by incorporating Certainty Factor values to represent uncertainty in the relationship between user-reported symptoms and disease hypotheses, allowing the diagnostic output to include both a disease indication and a numerical confidence value.

The use of Certainty Factor values is useful when several symptoms contribute differently to a disease hypothesis. Nevertheless, the effectiveness of this approach remains dependent on the quality and completeness of the expert-defined rules and CF values. The system was developed using knowledge obtained from dr. Retno Tunjungsari, Sp.S., M.Kes., a neurologist at Klinik Utama dr. Tunjung, which provided the basis for constructing symptom-disease relationships and CF values in the inference engine. However, because the knowledge base was derived from a single expert and the diagnostic evaluation was limited to 12 test cases, the reported agreement rate should not be generalized to broader clinical settings. Further development should involve multiple independent neurologists in the knowledge acquisition and validation process, expand the number and variety of test cases, and refine the rule base for clinically important overlapping symptoms, especially those involving Stroke and Vertigo.

5. Conclusion and Recommendations

This study developed a web-based expert system for the preliminary identification of neurological and related conditions using the Certainty Factor method. The system integrates expert knowledge into a structured knowledge base consisting of disease data, symptom data, diagnostic rules, and Certainty Factor values. The implemented application supports user authentication, disease and symptom management, consultation, Certainty Factor calculation, and presentation of diagnostic results with corresponding confidence values. The system covers five target conditions, namely Stroke, Vertigo, Migraine, Low Back Pain, and Arthritis, and provides users with disease indications accompanied by numerical confidence values.

The diagnostic evaluation showed an agreement rate of 91.67%, with 11 of 12 test cases matching the diagnosis provided by the expert neurologist. One mismatch occurred in Case 2, where the system classified the case as Vertigo with a CF value of 0.8120, while the expert classified it as early-stage Stroke. This finding indicates that the system generally produced diagnostic results consistent with the expert benchmark within the tested cases, while also showing limitations in cases involving overlapping symptoms between different conditions, particularly Stroke and Vertigo.

The main contribution of this study is the development of a single web-based expert system that accommodates five target conditions within one knowledge base and applies Certainty Factor reasoning to represent uncertainty in symptom-disease relationships. The resulting platform can serve as a preliminary diagnostic decision-support tool based on expert-defined knowledge obtained from a neurologist at Klinik Utama dr. Tunjung. However, the findings should be interpreted within the limitations of the study. The system does not cover the full range of neurological disorders encountered in clinical practice, the knowledge base was developed and validated using knowledge from a single neurologist, and the diagnostic evaluation involved only 12 test cases. Therefore, the reported agreement rate reflects the system's performance under the tested conditions and should not be interpreted as a measure of general clinical diagnostic accuracy.

The system also depends on the symptoms and confidence levels entered by users, so incorrect or incomplete symptom selection may affect the resulting diagnosis. In addition, this study did not use a larger clinical dataset or electronic medical records for broader validation. Future research should expand the knowledge base by including additional conditions, involve multiple independent medical experts in knowledge acquisition and validation, and include more diverse test cases from different patient conditions and clinical settings. The rule base should also be refined by adding clinically relevant symptom combinations, especially for cases involving overlapping symptoms between Stroke and Vertigo.

Further studies may compare the Certainty Factor approach with other diagnostic methods, such as Bayesian Networks, Fuzzy Logic, Decision Trees, Random Forests, or Deep Learning, using comparable datasets and evaluation procedures. From a technological perspective, future development may include mobile application support, integration with electronic health record systems, and cloud-based deployment to extend system accessibility and support its use in different healthcare environments. Broader validation with multiple experts and larger clinical datasets is required before the system can be considered for wider clinical application.

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