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Research

An Explainable Rule-Based Expert System with Certainty Factor for Early Acne Detection

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Abstract:
Introduction — Early identification of acne-related skin conditions is important to support preventive care and increase user awareness before professional dermatological consultation. Early detection is often challenged by uncertainty in symptom perception and the limited availability of accessible digital decision-support tools. Many digital health systems rely on machine learning models that lack interpretability and transparency. This study proposes an explainable rule-based expert system incorporating a Certainty Factor (CF) approach to support early acne detection in a bio-digital context.
Methods — The objective of this research is to design and implement a digital expert system capable of handling uncertainty in user-reported symptoms while providing transparent diagnostic reasoning. Dermatological knowledge is represented using structured rule-based models enriched with expert-defined certainty values. User inputs are modeled with confidence levels ranging from 0 to 1 and processed using a forward-chaining inference mechanism combined with CF calculations. The system is implemented in Python and deployed through a web-based interface.
Results — Experimental evaluation was conducted using five structured test scenarios representing different symptom combinations. The system generated early acne condition outputs with confidence scores ranging from 35.0% to 72.0%. The highest confidence score (72.0%) was obtained in the Contact Dermatitis scenario, while incomplete symptom inputs produced no diagnostic output. Each valid case included explicit reasoning traces linking symptoms to computed confidence values.
Conclusion — The system demonstrates an interpretable and uncertainty-aware expert system framework for early acne detection. Its novelty lies in integrating CF reasoning within an explainable rule-based architecture for transparent digital decision support.

Keywords: expert system; certainty factor; explainable artificial intelligence; early acne detection; digital health informatics

1. Introduction

Acne is one of the most common skin conditions affecting adolescents and adults, with varying levels of severity and manifestations [1], [2]. Although acne is generally not life-threatening, delayed recognition and improper early handling may lead to inflammation, post-inflammatory hyperpigmentation, scarring, and psychological discomfort [3], [4]. Early identification of acne-related conditions can therefore play an important role in preventive skincare and user awareness prior to professional medical consultation [5].

In practice, early acne detection is often hindered by uncertainty in symptom perception [6], [7]. Individuals may experience similar skin symptoms with different levels of confidence, and non-clinical users typically lack the medical expertise required to interpret these symptoms accurately [8]. While dermatological consultation remains the gold standard, access limitations and cost considerations highlight the need for supportive digital tools that can assist users in preliminary self-assessment without replacing clinical diagnosis [9]. Recent advances in digital health and bio-digital informatics have encouraged the development of intelligent decision support systems to assist early-stage health assessment. Many contemporary approaches rely on machine learning and image-based classification; however, such methods often operate as black-box models and require large labeled datasets [7], [9], [10]. This lack of interpretability and data dependency poses challenges in applications where transparency, explainability, and limited data availability are critical considerations.

Expert systems provide an alternative artificial intelligence paradigm that emphasizes knowledge representation, logical inference, and explainable reasoning [11], [12], [13]. In medical and health-related domains, rule-based expert systems have been widely applied due to their transparency and ease of validation by domain experts [14]. However, classical rule-based systems are often deterministic and unable to represent uncertainty inherent in human symptom reporting [15]. Meanwhile, research on digital support systems for dermatological conditions has grown significantly in recent years, with a strong emphasis on automated diagnosis and image-based classification [5], [6], [7], [8], [9], [10], [16]. Many studies employ machine learning and deep learning techniques to classify acne severity using facial images. While these approaches often achieve high accuracy, they typically require extensive labeled datasets and provide limited explainability, which can reduce user trust and clinical interpretability.

In contrast, rule-based expert systems have long been applied in medical decision support due to their logical transparency and structured reasoning [17]. Several studies have demonstrated the effectiveness of expert systems in health-related early detection tasks, particularly when domain knowledge can be explicitly formalized into rules. These systems allow domain experts to validate the reasoning process and ensure alignment with medical logic [7], [8], [16]. The Certainty Factor method has been widely used to enhance expert systems by incorporating uncertainty into the inference process [18]. Originating from early medical expert systems, Certainty Factor-based reasoning has been applied in various health domains, including disease screening, symptom-based diagnosis, and decision support systems [19]. By combining expert-defined certainty values with user-reported confidence levels, this approach enables systems to produce confidence-weighted conclusions.

Some recent studies have explored hybrid approaches that integrate rule-based reasoning with uncertainty handling, demonstrating improved flexibility and interpretability compared to deterministic systems [7], [9]. These works highlight that certainty-aware expert systems are particularly suitable for early detection and preliminary assessment scenarios, where incomplete and subjective information is unavoidable. Despite these advances, relatively few studies focus on explainable expert systems for acne-related early detection that explicitly emphasize user confidence, reasoning transparency, and web-based deployment [16]. Most existing acne-related systems either rely heavily on image processing or provide deterministic outputs without confidence measures. This gap motivates the present study, which integrates Certainty Factor-based reasoning within an explainable rule-based architecture to support early acne detection in a digital health environment.

To address this limitation, the Certainty Factor (CF) method has been introduced as a mechanism for handling uncertainty in expert systems. By associating confidence values with both expert knowledge and user input, Certainty Factor-based reasoning enables systems to produce graded conclusions rather than binary decisions. This approach is particularly suitable for early detection scenarios, where incomplete or uncertain information is common. Based on these considerations, this study proposes an explainable rule-based expert system with Certainty Factor reasoning for early acne detection. The system is designed to support users by providing interpretable outputs, confidence scores, and explicit reasoning traces. Rather than replacing medical professionals, the proposed system aims to function as a transparent digital decision support tool within a bio-digital health context.

2. Method

2.1 System Architecture

The proposed system is designed as an explainable rule-based expert system that supports early acne detection by handling uncertainty in user-reported symptoms. The overall architecture follows a modular structure consisting of four main components: user interface, knowledge base, inference engine with Certainty Factor reasoning, and explanation facility.

The system workflow begins with user interaction through a web-based interface, where users select acne-related symptoms and assign confidence levels to each selected symptom. These inputs are then forwarded to the inference engine, which processes the information using a rule-based reasoning mechanism enriched with Certainty Factor calculations. The final output consists of an early acne condition recommendation accompanied by a confidence score and an explicit reasoning explanation. This modular architecture ensures transparency, interpretability, and ease of system validation, making it suitable for bio-digital health applications that prioritize explainable decision support over black-box prediction models. Figure 1 illustrates the overall system architecture and data flow of the proposed expert system.

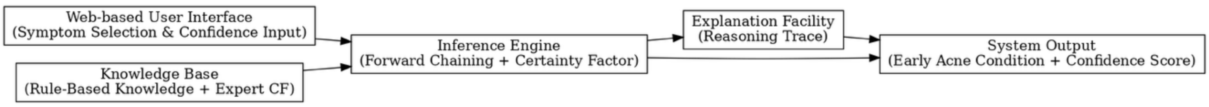

Fig. 1. Architecture of the explainable rule-based expert system with Certainty Factor for early acne detection.

2.2 Knowledge Representation

Dermatological knowledge in the proposed system is represented using a rule-based structure. Each rule consists of a set of symptoms, an associated acne-related condition, and an expert-defined Certainty Factor value. Symptoms are encoded as symbolic identifiers to ensure clarity and consistency during the inference process. Formally, a rule can be expressed as Equation (1).

$$If\ (S_1 \wedge S_2 \wedge \cdots \wedge S_n)\ Then\ D\left(CF_{expert}\right) \quad (1)$$

where S_i represents a symptom, D denotes the acne-related condition, and CF_{expert} indicates the expert's confidence in the rule. This representation allows dermatological knowledge to be explicitly structured, reviewed, and updated without modifying the inference mechanism. By separating knowledge representation from reasoning logic, the system maintains flexibility and scalability, enabling future expansion of symptoms or conditions without altering the system architecture.

2.3 Certainty Factor Inference Mechanism

To handle uncertainty in user-reported symptoms, the proposed system employs the Certainty Factor (CF) method. Users assign confidence values to selected symptoms within a normalized range of 0 to 1, representing their subjective certainty in experiencing each symptom. The inference process applies a forward-chaining strategy. For each rule, the system evaluates whether all required symptoms are present in the user input. If a rule is satisfied, the Certainty Factor of the diagnosis is calculated using the following Equation (2).

$$CF_{diagnosis} = CF_{expert} \times min(CF_{user}) \quad (2)$$

where CF_{user} represents the confidence values provided by the user for the symptoms involved in the rule. The minimum operator is used to reflect the weakest contributing evidence, consistent with classical Certainty Factor reasoning. When multiple rules are activated, the system ranks the resulting diagnoses based on their calculated confidence scores. The diagnosis with the highest confidence value is selected as the primary system output. This approach enables the system to produce graded conclusions rather than binary decisions, which is essential for early detection scenarios characterized by incomplete or uncertain information.

2.4 Explanation Facility

Explainability is a core design principle of the proposed system. In addition to providing a diagnosis and confidence score, the system generates an explicit reasoning trace that explains how the conclusion was reached. This explanation includes the list of contributing symptoms, their user-assigned confidence values, and the corresponding expert rule applied during inference.

The explanation facility allows users to understand the logical basis of the system's output, thereby increasing transparency and user trust. From a methodological perspective, this feature also facilitates validation by domain experts, as each conclusion can be traced back to specific rules and certainty values. Figure 2 illustrates the Certainty Factor reasoning process and explanation flow within the inference engine.

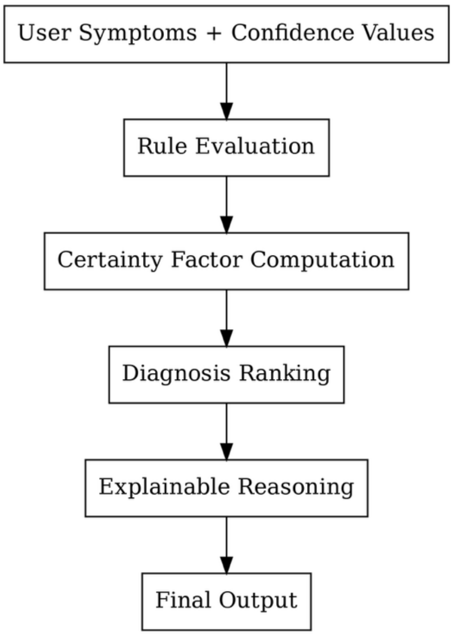

Fig. 2. Certainty Factor-based inference and explanation process.

2.5 Implementation Environment

The inference engine is implemented using the Python programming language due to its flexibility and suitability for rule-based reasoning. The user interface is implemented as a web-based application to enable accessibility and ease of interaction. The separation between inference logic and presentation layer ensures that system reasoning remains independent of interface design, supporting maintainability and reproducibility. Besides, all works is processed using Google Colaboratory [20].

This methodological design aligns with the objectives of digital health informatics by emphasizing transparency, explainability, and responsible use of artificial intelligence for early health-related decision support.

2.6 AI Disclosure

ChatGPT (OpenAI) was utilized solely to assist with language refinement, grammatical correction, and structural organization of the manuscript text. The use of the AI tool was limited to improving clarity, coherence, and academic writing quality, particularly in aligning the manuscript with international journal standards [21]. The AI system did not contribute to the research design, system architecture formulation, knowledge base construction, inference mechanism development, Certainty Factor computation, software implementation, experimental evaluation, or interpretation of results [21], [22]. All methodological decisions, computational procedures, system development processes, and analytical interpretations were independently designed, implemented, and verified by the authors. The authors take full responsibility for the accuracy, integrity, originality, and scientific validity of the work presented in this manuscript [24], [25].

2.7 Ethical Clearance Statement

Ethical Approval — This study did not involve human participants, animal subjects, or clinical interventions. User inputs used in the system evaluation were simulated test scenarios designed solely for system validation purposes and did not contain identifiable personal or medical data. The proposed expert system is intended as an early detection and decision support tool, not as a clinical diagnostic system. As the research exclusively involved computational modeling, rule-based inference, and simulated input data, formal ethical approval was not required for this study. All system outputs are designed to encourage professional medical consultation and do not replace dermatological diagnosis or treatment.

3. Results

3.1 System Evaluation Using Certainty Factor-Based Scenarios

To evaluate the performance and reasoning behavior of the proposed expert system, five structured test scenarios were designed. Each scenario represents a different combination of acne-related symptoms along with user-assigned confidence levels. These scenarios simulate realistic early self-assessment conditions where users report symptoms with varying degrees of certainty. The Certainty Factor inference mechanism was applied to each scenario using the finalized rule base presented in Section 3. The resulting diagnosis and associated confidence scores are summarized in Table 1.

Table 1. System output across five evaluation scenarios

Test Case	Diagnosis	Confidence (%)
Case 1 – Acne Vulgaris Dominant	Acne Vulgaris	59.5
Case 2 – Comedonal Acne	Comedonal Acne	60.0
Case 3 – Mild Acne	Mild Acne (Bruntusan)	35.0
Case 4 – Contact Dermatitis	Contact Dermatitis	72.0
Case 5 – Incomplete Symptoms	No condition identified	0

The results show that the system generated confidence scores ranging from 35.0% to 72.0%, depending on symptom completeness and certainty levels. The highest confidence score (72.0%) was produced in Case 4 (Contact Dermatitis), where both required symptoms were reported with high user certainty values (0.9). This demonstrates that the system appropriately amplifies diagnostic confidence when both expert certainty and user certainty are strong.

In contrast, Case 3 (Mild Acne) produced the lowest non-zero confidence score (35.0%). This occurred due to moderate user certainty inputs (0.6 and 0.5) combined with an expert certainty factor of 0.70. The use of the minimum operator in the Certainty Factor calculation appropriately reduced the overall confidence to reflect weaker supporting evidence.

Case 5 illustrates the system's handling of incomplete evidence. Since only one symptom (G4) was provided and no rule was fully satisfied, the inference engine correctly produced no diagnosis output. This behavior confirms that the system does not force conclusions in the absence of sufficient rule activation.

3.2 Interpretation of Certainty Factor Behavior

The observed results validate the mathematical consistency of the Certainty Factor model implemented in the inference engine. As described in Equation (2), the diagnostic confidence is calculated. The proportional relationship between user certainty values and final confidence scores confirms that the system behaves predictably under varying uncertainty levels. Higher user confidence inputs directly increase diagnostic certainty, while weaker inputs proportionally reduce the final output value.

Meanwhile, based on Fig. 2 illustrates the inference flow underlying this process, highlighting the sequential stages of rule evaluation, Certainty Factor computation, and diagnosis ranking. The ranking mechanism ensures that when multiple rules are activated, the system selects the diagnosis with the highest computed confidence score.

3.3 Explainability and Reasoning Trace Output

Beyond numerical outputs, the system generates explicit reasoning traces for each valid diagnosis, thereby enhancing interpretability and transparency. For instance, in Case 1 (Acne Vulgaris), the system identifies "Inflamed red pimples" with a user confidence value of 0.8 and "Pus-filled pimples" with a user confidence value of 0.7 as the contributing symptoms that activate the corresponding rule. These contributing factors are explicitly displayed in the output, allowing users to trace how their reported symptoms influence the final confidence score. This explanation mechanism directly reflects the architectural design illustrated in Fig. 1 and the Certainty Factor reasoning flow presented in Fig. 2. By clearly linking symptom inputs, rule activation, and computed confidence values, the system ensures logical transparency. The integration of structured rule representation, Certainty Factor-based uncertainty modeling, ranked diagnostic outputs, and explicit reasoning traces confirms that the proposed system functions as a transparent and interpretable digital decision support tool rather than a black-box classification model. Last, the system's interface shows in Fig. 3.

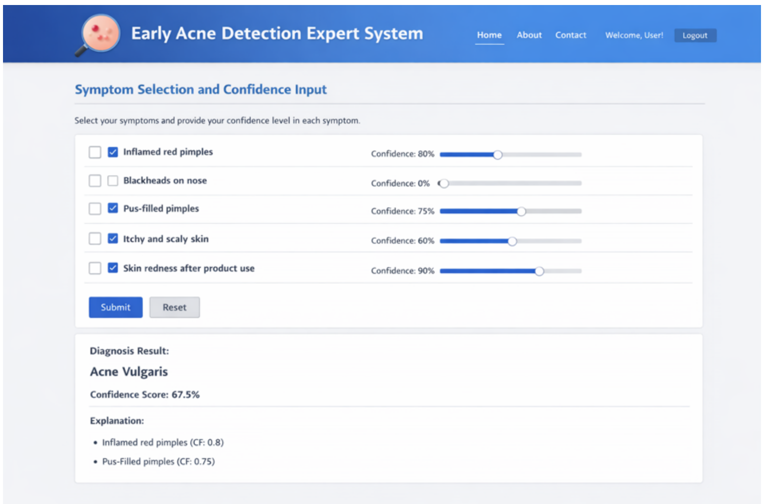

Fig. 3. Certainty Factor-based inference and explanation process.

4. Discussion

The experimental results demonstrate that the proposed rule-based expert system with Certainty Factor reasoning behaves consistently with its mathematical foundation and knowledge representation design. The confidence scores obtained across the five evaluation scenarios ranged from 35.0% to 72.0%, reflecting the proportional relationship between expert-defined certainty values and user-reported confidence levels. The highest confidence score (72.0%) observed in the Contact Dermatitis scenario confirms that when both the expert certainty factor and user confidence inputs are high, the resulting diagnostic confidence increases accordingly. This behavior validates the correctness of the Certainty Factor implementation and confirms that the inference mechanism operates as theoretically intended [16].

The intermediate confidence values obtained in cases such as Acne Vulgaris (59.5%) and Comedonal Acne (60.0%) further illustrate the system's sensitivity to partial certainty. In Case 1, although the expert rule for Acne Vulgaris carries a relatively high certainty factor (0.85), the final output was moderated by the minimum user confidence value of 0.7. This demonstrates that the system does not exaggerate conclusions based solely on expert certainty; instead, it proportionally integrates user uncertainty into the final computation. Such moderation is essential in early detection systems, where user-reported symptoms are often subjective and incomplete [12].

The lowest non-zero confidence value (35.0%) observed in the Mild Acne scenario highlights the conservative nature of the Certainty Factor model. Because the rule's expert certainty (0.70) was combined with relatively moderate user confidence values (0.6 and 0.5), the resulting diagnostic certainty was significantly reduced. This outcome confirms that the system appropriately reflects weaker evidence by lowering diagnostic confidence, thereby avoiding overconfident outputs. In practical terms, this conservative behavior supports responsible decision support, encouraging users to seek professional consultation when confidence levels are low [12], [14], [16], [18].

The system's response to incomplete evidence, as demonstrated in Case 5, further strengthens its reliability. When only one symptom was provided and no rule was fully satisfied, the inference engine correctly produced no diagnosis output. This behavior prevents forced classification and aligns with safe design principles in digital health systems. Rather than attempting to guess or approximate a condition without sufficient evidence, the system preserves logical integrity by returning a null result. Such a design choice enhances trustworthiness and reduces the risk of misleading recommendations [11].

From an explainability perspective, the reasoning trace output significantly differentiates this system from black-box machine learning models. Each diagnosis is accompanied by explicit identification of contributing symptoms and their associated user confidence values. This transparency allows users to understand how their inputs influence the final decision and enables domain experts to audit the reasoning process [26]. The integration of structured rule representation, Certainty Factor uncertainty modeling, ranked diagnostic outputs, and explanation generation confirms that the system operates as an interpretable artificial intelligence framework rather than an opaque classifier [27], [28], [29].

Despite these strengths, several limitations must be acknowledged. The current system relies on a predefined rule base and does not incorporate adaptive learning or data-driven optimization [30]. As a result, its performance is dependent on the completeness and accuracy of expert-defined rules. Additionally, the evaluation was conducted using structured test scenarios rather than real patient data, limiting generalizability. Future work may involve expanding the knowledge base, incorporating hybrid reasoning strategies, or validating the system using anonymized clinical datasets. Nonetheless, within the scope of early acne detection and transparent digital decision support, the proposed approach demonstrates methodological consistency, interpretability, and responsible uncertainty handling.

Conclusion

This study presented an explainable rule-based expert system with Certainty Factor reasoning for early acne detection within a digital health informatics context. The proposed system was designed to address uncertainty in user-reported symptoms by integrating expert-defined certainty values with user-assigned confidence levels through a forward-chaining inference mechanism. Experimental evaluation using five structured test scenarios demonstrated that the system produced graded confidence scores ranging from 35.0% to 72.0%, reflecting proportional uncertainty handling and logical consistency in diagnostic computation. The highest confidence output was obtained in cases with strong supporting evidence, while incomplete symptom inputs appropriately resulted in no diagnosis, confirming the system's conservative and responsible decision-support behavior. In addition to numerical outputs, the system provided explicit reasoning traces that transparently linked symptom inputs to diagnostic conclusions, thereby reinforcing explainability and interpretability. The integration of structured rule representation, Certainty Factor-based uncertainty modeling, ranked diagnostic outputs, and explanation generation distinguishes the proposed approach from black-box models and supports its role as a transparent early detection support tool rather than a clinical diagnostic system. Overall, the study contributes an interpretable, uncertainty-aware, and web-oriented expert system framework that aligns with bio-digital health principles and emphasizes responsible artificial intelligence for preliminary dermatological assessment.

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