

Development of a Web-Based Expert System as a Learning Medium for Corn Plant Disease Diagnosis

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Abstract. This study developed and evaluated a web-based expert system as a learning medium for diagnosing corn plant diseases. The research used a research-and-development approach integrating software development, expert validation, practicality testing, and a one-group pretest-posttest effectiveness trial. Two material experts, two media experts, and 20 users participated in product evaluation. Material validity reached 91.43%, media validity 90.00%, and practicality 90.50%. Learning scores increased from 49.15 to 80.55; the paired-samples t-test was significant, $t(19) = 19.73$, $p < .001$, with a mean N-Gain of 0.625. The system was therefore valid, practical, and effective as a diagnostic learning medium.

Keywords: Expert System; Web-Based Learning; Corn Disease; Learning Media; Forward Chaining.

1. Introduction

Digital transformation has expanded the role of technology from administrative support to learning environments that provide information, feedback, simulation, and decision support. Recent studies indicate that technology-enhanced learning spaces, artificial intelligence, and interactive media can improve learning outcomes when technology is aligned with instructional goals and user characteristics (Dong et al., 2025; Hu et al., 2025; Koç & Kanadlı, 2025; Luo et al., 2025). In Indonesia, digital media development increasingly focuses on independent learning, vocational education, and improved learning services (Efendi et al., 2026; Mafarja et al., 2026; Mukhlisin et al., 2025; Sukarjono et al., 2026).

Agriculture is a field that strongly benefits from information technology because production decisions are time-sensitive, contextual, and frequently depend on expert knowledge. The digitalization of agricultural knowledge can broaden access to technical information and advice, but its success depends on usability, user trust, contextual relevance, and the connection between technology and learning processes (Fielke et al., 2020; Ingram & Maye, 2020; Klerkx et al., 2019; Klerkx & Rose, 2020; Lajoie-O'Malley et al., 2020). Agricultural technology should therefore not only produce decisions; it should also help users understand the reasoning behind them.

Disease diagnosis is an important challenge in corn cultivation. Delayed or inaccurate identification can lead to inappropriate control measures and lower productivity. Advances in artificial intelligence, computer vision, and intelligent systems have created substantial opportunities for plant disease diagnosis through symptom mapping, pattern recognition, and knowledge-based inference (Antwi et al., 2024; Ding et al., 2024; Ngugi et al., 2024; Pacal et al., 2024; Sajitha et al., 2024; Upadhyay et al., 2025; Yilmaz et al., 2025). Although recent studies heavily

emphasize deep learning, rule-based expert systems remain relevant when domain knowledge can be expressed explicitly and transparent reasoning is desirable.

A forward-chaining expert system begins with facts or symptoms selected by the user and applies IF-THEN rules until it reaches a diagnostic conclusion. This characteristic has pedagogical value because diagnosis can be represented as a relationship among symptoms, rules, diseases, and solutions. The application can therefore function not only as a consultation tool but also as a learning medium for recognizing symptoms, differentiating diseases, making diagnoses, and selecting control measures. Research on digital and AI-supported media suggests that rapid feedback, interactivity, and structured information presentation support knowledge and skill acquisition (Brummer et al., 2024; Deng et al., 2025; Feigerlova et al., 2025; Han et al., 2025; Pham, 2025).

The expert system underlying this study was previously developed as a web-based corn disease diagnosis application using forward chaining (Pangka & Ali, 2024). Initial testing mainly focused on software functionality. To establish a stronger contribution to educational technology, the product must also be evaluated in terms of content validity, learning-media validity, user practicality, and learning effectiveness. This approach is consistent with current development research that integrates expert validation, user trials, and learning-outcome measurement (Efendi et al., 2026; Rahmawati et al., 2026; Sukarjono et al., 2026).

Accordingly, this study aimed to develop and evaluate a web-based expert system as a learning medium for diagnosing corn plant diseases. Specifically, it examined (1) content feasibility, (2) media feasibility, (3) usability/practicality, and (4) effectiveness in improving diagnostic competence through pretest-posttest comparison. The study contributes by repositioning an expert system from a diagnosis-only tool into a reasoning-based learning medium that can support nonformal education and independent agricultural learning.

2. Method

This study used a Research and Development (R&D) approach that integrated software development and educational-media evaluation. Software development followed a waterfall sequence comprising requirements analysis, design, implementation, verification/testing, and refinement. After the system became operational, we conducted educational evaluation through content-expert validation, media-expert validation, user practicality testing, and an effectiveness trial. This structure allowed assessment from both technical and pedagogical perspectives.

The product was a web-based expert system implementing forward chaining. Users selected symptoms observed in corn plants, after which the system matched the facts against its rule base until it generated a diagnosis and recommended solution. For learning purposes, the symptom menu, diagnosis output, disease information, and solutions were organized into a learning sequence: recognizing symptoms, understanding symptom-disease relationships, determining a diagnosis, and learning control recommendations.

Product evaluation involved two content experts and two media experts. Content validation addressed seven aspects: accuracy of disease information, symptom accuracy, accuracy of symptom-diagnosis relationships, accuracy of control recommendations, content completeness, language clarity, and alignment with learning objectives. Media validation addressed eight aspects: visual quality, text readability, navigation consistency, ease of use, interactivity, feedback clarity, suitability for the learning process, and website functionality. Each item used a 1–5 scale. We calculated the feasibility percentage using the following formula.

$$\text{Feasibility (\%)} = (\text{Obtained score} / \text{Maximum score}) \times 100\%$$

The practicality test involved 20 users and eight assessment aspects. We examined effectiveness using a one-group pretest-posttest design. We measured diagnostic competence before and after use of the medium on a 0–100 scale. Data analysis included descriptive statistics, the Shapiro–Wilk test on difference scores, a paired-samples t-test, normalized gain (N-Gain), and Cohen’s d_z . The significance level was $\alpha=.05$. N-Gain was calculated as follows.

$$g = (Posttest - Pretest) / (100 - Pretest)$$

We interpreted N-Gain as low ($g < 0.30$), medium ($0.30 \leq g < 0.70$), and high ($g \geq 0.70$). We calculated the paired t-test and within-group effect size as follows.

$$t = D / (S_D / \sqrt{n})$$

$$d_z = D / S_D$$

Where D is the mean difference, S_D is the standard deviation of the difference scores, and n is the number of participants. We recalculated validation, practicality, and participant-level scores to ensure arithmetic consistency before reporting.

3. Result

The final product is a web-based expert system providing diagnosis, diagnostic results, disease information, control solutions, and knowledge-base management. On the diagnosis page, users select observed corn-plant symptoms. The system executes forward chaining and returns the disease, causal information, supporting images, and recommended control measures. This interface structure allows users to use diagnosis as a case-based learning activity.



Figure 1. Symptom-selection page of the expert system



Figure 2. Diagnostic-result page as learning feedback

Expert validation indicated that the product met very high feasibility criteria. Content validation reached 91.43%. The highest scores were obtained for disease-information accuracy and alignment with learning objectives, while the control-solution component received a relatively lower score but remained in the good category. Media validation reached 90.00%; website functionality obtained the maximum score, whereas feedback clarity was the aspect most in need of refinement.

Table 1. Content-expert validation results

No.	Assessment aspect	Expert 1	Expert 2	Mean	Category
1	Accuracy of corn disease information	5	5	5.00	Very good
2	Accuracy of disease symptoms	5	4	4.50	Very good
3	Accuracy of the relationship between symptoms and diagnosis	4	5	4.50	Very good
4	Accuracy of solutions/control measures	4	4	4.00	Good
5	Completeness of materials	5	4	4.50	Very good
6	Clarity of language	4	5	4.50	Very good
7	Alignment of materials with learning objectives	5	5	5.00	Very good
Feasibility percentage				91.43%	Very feasible

Table 2. Learning media expert validation results

No.	Assessment aspect	Expert 1	Expert 2	Mean	Category
1	Display quality	4	5	4.50	Very good
2	Text readability	5	4	4.50	Very good
3	Navigation consistency	4	5	4.50	Very good
4	Ease of use	5	4	4.50	Very good
5	Media interactivity	4	5	4.50	Very good
6	Clarity of feedback	4	4	4.00	Good
7	Media compatibility with the learning process	5	4	4.50	Very good
8	Website function quality	5	5	5.00	Very good
Feasibility percentage				90.00%	Very feasible

The practicality test involving 20 users produced an average of 90.50%, categorized as very practical. The highest rating was obtained for the usefulness of the medium for independent learning (93%), followed by clarity of diagnostic results (92%). Language clarity was the lowest-rated aspect at 88%, but it still fell within the very practical category. These findings indicate that users could access and understand the system flow and perceived it as useful for independent learning.

Table 3. User practicality test results

No.	Practicality aspect	Percentage	Category
1	Ease of accessing the website	91%	Very practical
2	Ease of selecting symptoms	90%	Very practical
3	Clarity of diagnosis results	92%	Very practical
4	Ease of understanding diseases	89%	Very practical
5	Ease of understanding solutions	90%	Very practical
6	Clarity of language	88%	Very practical
7	Attractiveness of display	91%	Very practical
8	Usefulness of the media for independent learning	93%	Very practical
Average		90.50%	Very practical

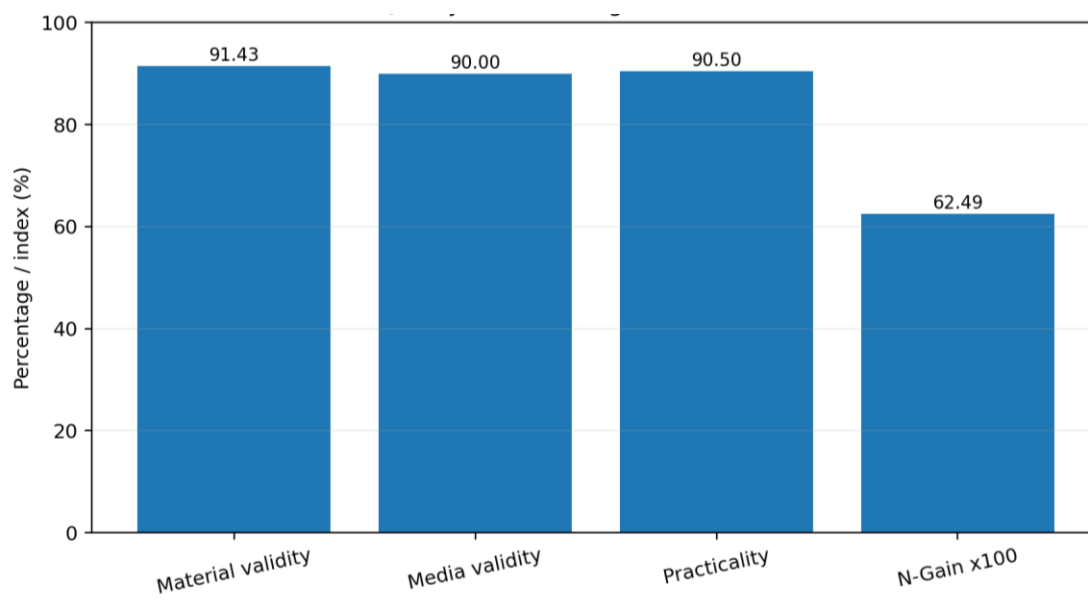


Figure 3. Summary of product quality and effectiveness indicators

In the effectiveness trial, recalculation from the participant-level data yielded a mean pretest score of 49.15 (SD=8.63) and a mean posttest score of 80.55 (SD=8.29). The mean gain was 31.40 points. All participants improved, with individual N-Gain scores ranging from 0.410 to 0.825 and a mean N-Gain of 0.625, indicating medium-to-high learning improvement.

Table 4. Pretest, posttest, gain, and N-Gain scores

Participant	Pretest	Posttest	Gain	N-Gain
P1	35	72	37	0.569
P2	42	76	34	0.586
P3	45	79	34	0.618
P4	51	86	35	0.714
P5	47	69	22	0.415
P6	63	88	25	0.676
P7	54	91	37	0.804
P8	39	66	27	0.443
P9	60	93	33	0.825
P10	49	80	31	0.608
P11	47	72	25	0.472
P12	44	84	40	0.714
P13	37	82	45	0.714
P14	61	77	16	0.410
P15	52	89	37	0.771
P16	46	71	25	0.463
P17	64	92	28	0.778
P18	50	75	25	0.500
P19	57	90	33	0.767
P20	40	79	39	0.650
Mean	49.15	80.55	31.40	0.625

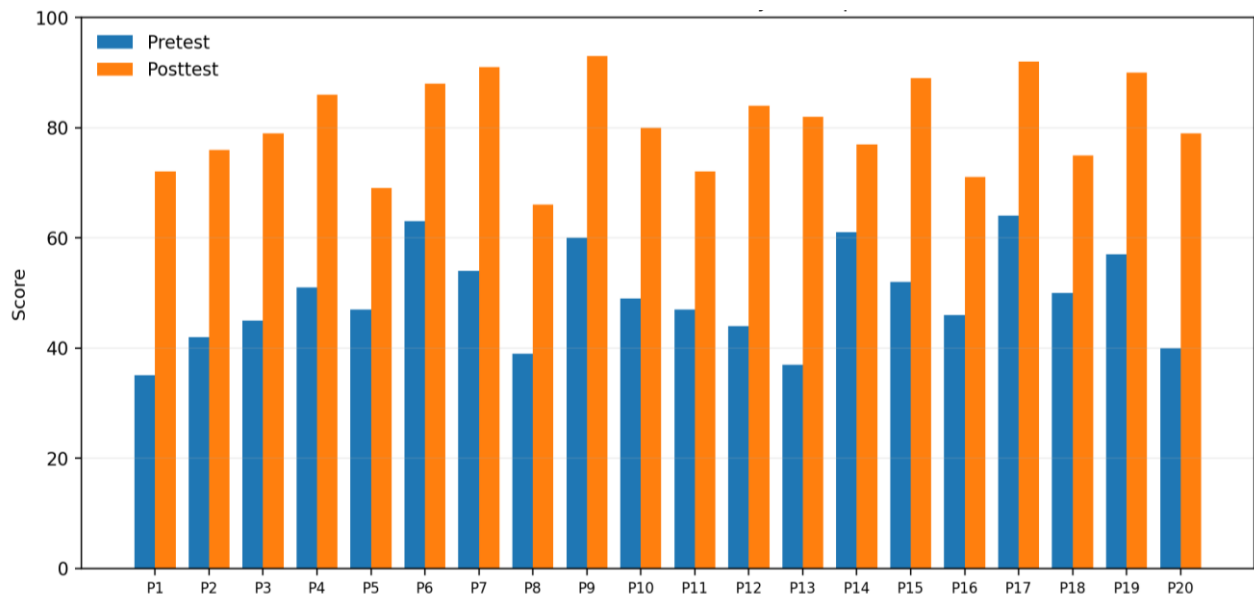


Figure 4. Participant pretest and posttest scores

The Shapiro–Wilk test on difference scores yielded $W = 0.972$, $p = .796$, satisfying the normality assumption. The paired-samples t-test showed a significant pretest-posttest difference, $t(19)=19.73$, $p<.001$, with a 95% confidence interval for the mean gain of 28.07–34.73. Cohen’s $d_z=4.41$ indicates a very large within-group effect.

Table 5. Media effectiveness test results

Analysis	Value	Interpretation
Mean pretest	49.15	Initial competence
SD pretest	8.63	Initial score variability
Mean posttest	80.55	Post-learning competence
SD posttest	8.29	Final score variability
Mean gain	31.40	Substantial improvement
Shapiro–Wilk	$W=0.972$; $p=0.796$	Normal
Paired-samples t-test	$t(19)=19.73$; $p<.001$	Significant
95% CI mean gain	28.07–34.73	Consistent improvement
Mean N-Gain	0.625	Medium to high
Cohen's d_z	4.41	Very large effect

Competence-by-indicator analysis showed the largest improvement in symptom identification (33.50 points), followed by differentiating disease types (30.50), determining diagnoses (30.00), and determining solutions/control measures (27.20). This pattern suggests that the medium was particularly effective for symptom recognition and initial classification, while solution-related competence requires richer content and more complex practice.

Table 6. Competence by indicator

Competence indicator	Pretest	Posttest	Gain
Identifying disease symptoms	49.00	82.50	33.50
Differentiating disease types	47.50	78.00	30.50
Determining diagnosis	51.00	81.00	30.00
Determining solutions/control measures	53.50	80.70	27.20

4. Discussion

The content-validity score of 91.43% indicates that the expert-system knowledge base can serve as a relevant learning resource. In an expert-system learning medium, content validity is essential because errors in symptom–disease relationships affect both diagnostic output and user understanding. This finding aligns with educational R&D studies emphasizing expert validation before large-scale implementation (Efendi et al., 2026; Rahmawati et al., 2026; Sukarjono et al., 2026). High content feasibility strengthens the system’s role as a domain-learning resource rather than merely an operational application.

The media-validity score of 90.00% indicates that the interface, navigation, readability, interactivity, and website functions were appropriate for learning. Effective digital media must do more than function technically; it should help users understand information structures, make decisions, and receive meaningful feedback. Similar results have been reported for Google Sites media, augmented-reality instruction, and IT-based learning applications, where usability and interactivity were closely related to acceptance and learning outcomes (Efendi et al., 2026; Mukhlisin et al., 2025; Sukarjono et al., 2026). Meta-analytic evidence also shows that technology-enhanced learning environments tend to improve outcomes when technological affordances are integrated with pedagogy (Hu et al., 2025; Koç & Kanadlı, 2025).

The practicality score of 90.50% indicates that the system was easy to use in the trial context. The high rating for independent-learning usefulness suggests that the system can reduce users’ dependence on direct consultation for initial understanding of corn diseases. This is relevant to the digitalization of agricultural knowledge, which emphasizes rapid access to advice while still recognizing the ongoing importance of experts and extension services (Fielke et al., 2020; Ingram & Maye, 2020). Agricultural technologies must nevertheless account for differences in digital skills, device access, and social context so that digital tools do not widen existing inequalities (Klerkx et al., 2019; Rotz et al., 2019).

Learning effectiveness is demonstrated by the increase from 49.15 to 80.55, the mean N-Gain of 0.625, and the significant paired t-test. These results indicate that interaction with the system did more than provide diagnostic answers; it strengthened the knowledge structure needed to recognize symptoms and relate them to diseases. The result is consistent with recent evidence that intelligent and interactive technologies can enhance cognitive outcomes through feedback, visualization, and structured interaction (Dong et al., 2025; Luo et al., 2025; Pham, 2025). Meta-analyses of educational technology likewise report positive effects on learning outcomes (Deng et al., 2025; Han et al., 2025; Hu et al., 2025).

Forward chaining has particular pedagogical value because its inference process is explicit. Users begin with facts or symptoms and move through rules toward a diagnosis. This sequence can function as cognitive scaffolding by decomposing diagnostic reasoning into structured steps. Compared with black-box approaches used in some deep-learning applications, rule-based systems can be easier to explain because the relationship between facts and decisions is directly representable. Although computer vision and deep learning are rapidly advancing for plant-disease diagnosis (Antwi et al., 2024; Ding et al., 2024; Ngugi et al., 2024; Pacal et al., 2024; Upadhyay et al., 2025; Yilmaz et al., 2025), rule-based expert systems retain educational value through transparent reasoning.

The largest gain in symptom identification suggests that the system is particularly effective as a medium for learning diagnostic patterns. By contrast, the smaller gain in solution/control competence shows that diagnosing a disease and managing it are not the same competency. Selecting a solution requires additional contextual knowledge regarding field conditions, crop stage,

disease severity, and feasible control options. Future versions should therefore incorporate remediation materials, case examples, adaptive quizzes, and explanations of why particular solutions are recommended.

In agricultural education, digital media may be more meaningful when combined with participatory learning, demonstration, and mentoring. Extension studies indicate that knowledge, attitudes, and skills are strengthened when learners are actively involved and have opportunities to apply knowledge in authentic settings (Davis et al., 2012; Kiptot & Franzel, 2019; Mariyono et al., 2021; Nakano et al., 2018; Purwanti et al., 2026; Waddington et al., 2014). The expert system should therefore be positioned as a support medium for extension, field practice, or independent learning rather than a complete replacement for human experts.

The novelty of this study lies in repositioning a corn-disease expert system as a learning medium and evaluating it across four dimensions: content validity, media validity, practicality, and effectiveness. This approach bridges software engineering, rule-based intelligence, educational technology, and agricultural learning. This contribution aligns with the broader digital transformation of TVET and competence-oriented learning (Mafarja et al., 2026; Salsabilla et al., 2026).

The study has limitations. The effectiveness trial involved only 20 users and included no control group. The posttest was administered after the learning intervention; therefore, long-term retention is unknown. The very large effect size should be interpreted in light of the small sample and one-group design. Future research should employ larger samples, quasi-experimental comparison groups, delayed posttests, and assessments of competence transfer to authentic field cases. Future research could also explore integration with computer vision or explainable AI while preserving transparency of reasoning (Sajitha et al., 2024; Upadhyay et al., 2025).

5. Conclusion

The developed web-based expert system met the criteria for use as a learning medium for corn plant disease diagnosis. Content validation reached 91.43% and media validation 90.00%, both in the very feasible category. The practicality score was 90.50%, indicating that the system was very practical to use. In the effectiveness trial, the mean score increased from 49.15 to 80.55; the paired-samples t-test confirmed a significant difference, $t(19)=19.73$, $p<.001$. The mean N-Gain of 0.625 indicates medium-to-high improvement, while Cohen's $d_z=4.41$ indicates a very large within-group effect. Thus, the expert system functions not only as a diagnostic tool but also as a digital learning medium that supports understanding of symptoms, diseases, diagnostic reasoning, and control solutions. Future studies should use control groups, larger samples, and delayed assessments of retention and field application.

6. References

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