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Hybrid Decision Support System for Rice Plant Disease Diagnosis and Treatment Recommendation Using Dempster-Shafer, AHP-TOPSIS, and Fuzzy SAW

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Abstract

Rice diseases — blast (Magnaporthe oryzae), bacterial leaf blight (Xanthomonas oryzae pv. oryzae), and sheath blight (Rhizoctonia solani)—cause annual global yield losses of 10–100%, resulting in billions of U.S. dollars in economic damage. Smallholder farmers in remote regions often lack access to agronomy experts and face difficulties using image-based diagnostic systems on low-capacity devices. This study proposes and evaluates a hybrid three-module Decision Support System (DSS) framework based on non-image tabular data to address these challenges. The framework integrates: (1) Dempster–Shafer Theory for probabilistic disease diagnosis using 48 structured clinical symptom parameters from ESforRPD2; (2) a hybrid AHP–TOPSIS module with CRITIC-based objective weight verification for multicriteria treatment ranking; and (3) an adaptive Fuzzy SAW module employing dynamic weights based on crop growth stages derived from Paddy Doctor Metadata. Experimental results show that the Dempster–Shafer module achieved 88.9% accuracy, a macro F1-score of 0.877. and a macro AUC-ROC of 0.939. outperforming Certainty Factor (82.4%), Random Forest (85.7%), and XGBoost (86.1%). The AHP model produced a valid Consistency Ratio (CR = 0.030), while CRITIC analysis revealed substantial differences between expert-assigned and data-driven weights. The adaptive Fuzzy SAW module achieved 100% agreement with agronomy expert recommendations (Spearman's rho = 0.941), surpassing static SAW (25%, rho = 0.487) and standalone TOPSIS (0%, rho = 0.412). The framework operates without image input and provides recommendations in under two seconds, making it suitable for low-capacity devices and remote agricultural environments.

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INTRODUCTION

Rice diseases remain a major threat to global food security, causing substantial yield and economic losses worldwide. Rice blast (*Magnaporthe oryzae*), bacterial leaf blight (*Xanthomonas oryzae* pv. *oryzae*), and sheath blight (*Rhizoctonia solani*) can reduce rice production by 10–100% under severe epidemic conditions, resulting in annual losses exceeding US$10 billion [1]–[3]. Accurate and timely disease identification remains challenging for farmers because many rice diseases exhibit similar early-stage symptoms, often leading to inappropriate treatment decisions and increased environmental impacts [2], [4].

Recent advances in image-based artificial intelligence, including CNNs, DenseNet, and Vision Transformers, have achieved high classification accuracy. However, their deployment is constrained by computational requirements, image-quality sensitivity, and internet dependency, limiting practical use in remote agricultural regions [5], [6], [7]. In contrast, tabular non-image data, such as structured symptom records, crop age, and agronomic attributes, provide a more accessible and resource-efficient alternative [8].

While existing multicriteria Decision Support Systems (DSS) have been applied in agriculture, they typically operate independently of the disease diagnosis process and rely heavily on static, expert-defined weighting schemes. To explicitly address these limitations, this study proposes a unified Hybrid Decision Support System (HDSS) that distinguishes itself from previous hybrid approaches through three unique methodological contributions: (1) integrating Dempster-Shafer uncertainty reasoning for diagnosis seamlessly with multicriteria decision-making (MCDM) within a single tabular data framework; (2) minimizing subjective expert bias by combining AHP-TOPSIS with objective, data-driven CRITIC weight verification; and (3) introducing a dynamic Fuzzy SAW module that adapts treatment criteria weights based on active crop growth stages rather than using static parameters.

Rice (*Oryza sativa* L.) is vulnerable to a wide range of fungal, bacterial, and viral pathogens throughout its growth cycle, each exhibiting distinct infection mechanisms and management requirements [2]. Among these, rice blast caused by *Magnaporthe oryzae* is considered the most destructive disease globally, capable of causing severe yield losses under favorable environmental conditions [1]. Other major diseases include bacterial leaf blight (BLB) caused by *Xanthomonas oryzae* pv. *oryzae*, brown spot caused by *Bipolaris oryzae*, sheath blight caused by *Rhizoctonia solani*, and tungro disease associated with Rice Tungro Bacilliform Virus (RTBV) and Rice Tungro Spherical Virus (RTSV) [2], [9], [10]. These diseases often exhibit overlapping symptoms during early infection stages, complicating field diagnosis and increasing the risk of inappropriate management decisions.

Decision Support Systems (DSS) are computer-based systems designed to support semi-structured and unstructured decision-making by integrating human judgment with computational analysis [11]. A typical DSS comprises three core components: data management, model management, and user interface subsystems [12]. In agricultural applications, a knowledge base is often incorporated to capture domain-specific expertise and decision rules [13]. Unlike conventional expert systems, DSS enhance rather than replace human decision-making by providing ranked alternatives supported by transparent analytical justifications.

Dempster–Shafer (DS) Theory, introduced by Dempster (1967) and formalized by Shafer (1976), provides a mathematical framework for reasoning under uncertainty. Unlike Bayesian probability, DS theory explicitly represents ignorance, making it well suited for disease diagnosis based on incomplete or ambiguous symptom information. The framework is built upon a frame of discernment (Θ), representing all possible disease hypotheses, while each observed symptom contributes a mass function that quantifies the degree of support for a given hypothesis.

Evidence from multiple symptoms is iteratively combined using Dempster’s rule of combination, enabling the aggregation of uncertain and potentially conflicting information. The resulting belief and plausibility measures provide confidence estimates for each disease hypothesis.

This capability makes DS particularly suitable for plant disease diagnosis, where symptom overlap and uncertainty are common in real-world field conditions [14].

The Analytical Hierarchy Process (AHP) was introduced as a multicriteria decision-making (MCDM) technique that decomposes complex problems into hierarchical structures. Judgment consistency is evaluated using the Consistency Ratio (CR):

$$CR = \frac{CI}{IR} \leq 0.1$$

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) evaluates alternatives according to their distances from the positive ideal solution (A^+) and negative ideal solution (A^-), producing a relative closeness score:

$$RC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

A fundamental limitation of AHP is its reliance on expert judgment, which may introduce subjective bias. The CRITIC method addresses this limitation by deriving objective criterion weights based on data variability and inter-criterion correlation:

$$C_j = \sigma_j \times \sum\nolimits_k (1 - r_{jk})$$

Higher variability and lower correlation result in larger criterion weights. This study introduces an AHP–CRITIC integration mechanism using harmonic averaging to balance subjective and objective perspectives:

$$w_j^{final} = \frac{2w_j^{AHP} w_j^{CRITIC}}{w_j^{AHP} + w_j^{CRITIC}}$$

Simple Additive Weighting (SAW) is a widely used MCDM method that calculates preference scores through weighted aggregation of criteria [15], [16]. Fuzzy SAW extends this approach by representing linguistic assessments using Triangular Fuzzy Numbers (TFNs) [17], [18]. In this study, the conventional framework is enhanced with a dynamic fuzzy weight vector (w^f) that automatically adapts to the active rice growth stage (F1–F4), enabling biological-temporal context to directly influence the decision-making process.

Three publicly available tabular datasets were utilized in this study. The ESforRPD2 Knowledge Base provides 48 binary clinical symptom features and expert-validated symptom–disease relationships for eight rice disease classes [14]. The Paddy Doctor Metadata dataset contains 10.407 records with variety and age information, where plant age serves as the key variable for dynamic weighting adaptation in the proposed Fuzzy SAW model [19]. The UCI Paddy Dataset includes 2.790 instances with 45 agronomic attributes, such as soil type, variety, and fertilization practices, providing additional agronomic context for decision-making [20].

Previous studies on rice disease management can be grouped into three categories: rule-based diagnostic systems, image-based disease classification, and multicriteria decision support systems (DSS). Rule-based approaches provide interpretable diagnoses but lack treatment recommendation capabilities, whereas deep learning models achieve high classification accuracy at the cost of substantial computational requirements and dependence on image data. Meanwhile, multicriteria methods such as AHP, TOPSIS, and Fuzzy SAW have been applied to agricultural decision-making but generally operate independently of disease diagnosis and rely on static expert-defined weights [6], [14], [19], [21], [22].

Despite these advances, three research gaps remain. First, no study has integrated Dempster–Shafer evidence reasoning with multicriteria decision-making in a unified tabular-data framework. Second, existing agricultural DSS models employ static weighting schemes without incorporating crop growth stages as dynamic decision variables. Third, the combined use of multiple public tabular rice disease datasets within a reproducible comparative framework remains largely unexplored [8], [14], [19].

METHOD

Datasets

The ESforRPD2 dataset [14] is publicly accessible through the PMC/NIH repository. It consists of 48 structured clinical symptom parameters covering disease manifestations on leaves, stems, sheaths, and panicles for eight target rice disease classes. Features are represented in binary format (1 = symptom present, 0 = symptom absent) and are accompanied by a symptom–disease relationship weight table validated by three agronomy experts with more than 15 years of professional experience.

The Paddy Doctor Metadata dataset [19], derived from the Kaggle Paddy Disease Classification competition, contains 10.407 records. Its primary attributes include *variety* (e.g., ADT45. IR20. and Karnataka Ponni) and *age* (crop age in Days After Transplanting [DAT], ranging from 10 to 130 DAT) across ten disease classes, including the Normal class. The class distribution is imbalanced, with Blast representing the dominant class (21.3%) and Grassy Stunt the minority class (4.2%). The *age* attribute serves as the key variable for the dynamic weight adaptation mechanism implemented in the Fuzzy SAW module.

The UCI Paddy Dataset [20] comprises 2.790 instances with 45 multivariate agronomic features, including soil type, rice variety, nursery management practices (*LP_nurseryarea*), and early fertilization attributes (*DAP_20days*). This dataset is utilized to analyze varietal susceptibility to endemic rice diseases under specific soil and fertilization conditions, thereby providing additional contextual information for Module III.

To integrate the three independent datasets (ESforRPD2, Paddy Doctor Metadata, and UCI Paddy Dataset) into a unified framework, a sequential module-level integration strategy was implemented rather than a direct row-level concatenation. Compatibility validation was established by standardizing the 'disease class' as the primary relational key across the heterogeneous sources. Specifically, the eight target disease classes from the ESforRPD2 dataset were mapped and intersected with the overlapping classes in the Paddy Doctor dataset (which originally contained ten classes) to ensure consistent class boundaries and prevent diagnostic misalignment. Operationally, the datasets are integrated architecturally: Module I exclusively utilizes the standardized ESforRPD2 symptom data for disease diagnosis. The resulting diagnostic output then acts as a bridge, triggering Module III to extract matching contextual variables—specifically crop age (DAT) from the Paddy Doctor metadata and varietal susceptibility from the UCI dataset —to dynamically adapt the Fuzzy SAW weighting scheme. This strategy ensures functional compatibility and systematic data flow across the modules without requiring direct feature-level merging.

Data Preprocessing

The preprocessing stage consisted of four sequential procedures:

1. Missing Value Handling – Binary features were imputed with 0. categorical features with the class-wise mode, and numerical features with the class-wise median. Features with more than 40% missing values were removed.
2. Categorical Variable Encoding – Label Encoding was applied to ordinal variables, while One-Hot Encoding was used for nominal variables.
3. Numerical Feature Normalization – Min–Max normalization was performed as follows:
$$x'_{ij} = \frac{x_{ij} - x_{j,min}}{x_{j,max} - x_{j,min}}$$
4. Feature Selection – A combination of Variance Threshold filtering, elimination of feature pairs with Pearson correlation coefficients |r| > 0.90. and Random Forest-based Recursive Feature Elimination (RFE) was employed. This process reduced the feature set from 48 to 32

highly discriminative attributes. The reduction of clinical symptoms from 48 to 32 features was deliberately conducted to eliminate redundant data, retaining only the most highly discriminative attributes. Empirical evidence confirms that removing these 16 features did not negatively impact the model's performance. Instead, using this optimized and leaner feature set, the proposed Dempster-Shafer module achieved an outstanding diagnostic accuracy of 88.9% and a macro AUC-ROC of 0.939. Furthermore, this dimensionality reduction proved highly effective; it allowed the proposed framework to statistically outperform six complex machine learning algorithms—including XGBoost and Random Forest—while maintaining an extremely efficient computation time of less than 0.003 seconds per diagnosis, making it highly suitable for low-resource devices.

Class imbalance was addressed using the Synthetic Minority Over-sampling Technique (SMOTE). SMOTE was applied exclusively to the training data within each cross-validation fold to prevent data leakage, ensuring that the test data preserved the original imbalanced class distribution.

Module I: Dempster–Shafer Disease Diagnosis

The frame of discernment was defined as:

$$\Theta = \{P_1, P_2, \dots, P_8\}$$

representing the eight disease classes.

Each observed symptom $G_k$generates a mass function $m_k(A)$extracted from the ESforRPD2 weight table. Disease diagnosis is performed through iterative evidence accumulation using Dempster's rule of combination:

$$m_1 \oplus m_2(A) = \frac{\sum_{B\cap C=A} m_1(B) m_2(C)}{1-K}, K = \sum_{B\cap C=\emptyset} m_1(B) m_2(C)$$

The final diagnosis is determined by the disease hypothesis with the highest belief value:

$$P^* = \arg\ \max_{A\subseteq\Theta} m_{final}(A)$$

Cases with $K > 0.8$(high conflict) are labeled as *ambiguous* and recommended for further examination. Model performance was evaluated using stratified 10-fold cross-validation to ensure representative assessment across all disease classes.

Module II: AHP–TOPSIS with CRITIC Verification

Four evaluation criteria were established based on expert consensus: C1: Purchase Cost (Cost), C2: Treatment Effectiveness (Benefit), C3: Ecological Impact (Cost), C4: Accessibility and Availability (Benefit). Four treatment alternatives were evaluated: A1: Systemic Chemical Fungicide, A2: Chemical Bactericide, A3: Biological Control Agent, A4: Cultural Management Practices. The processing workflow of Module II consists of: Construction of the AHP pairwise comparison matrix; Computation of the AHP weight vector (w^{AHP}) and consistency verification ($CR \leq 0.1$); Objective weighting using the CRITIC method (w^{CRITIC}); Harmonic integration of subjective and objective weights (w^{final}); TOPSIS vector normalization; Weighted distance calculation to positive and negative ideal solutions (D^+ and D^-); Computation of the relative closeness coefficient (RC_i) for alternative ranking. Weight integration is performed using harmonic averaging:

$$w_j^{final} = \frac{2w_j^{AHP} w_j^{CRITIC}}{w_j^{AHP} + w_j^{CRITIC}}$$

The harmonic mean was selected because it is more sensitive to disparities between values than the arithmetic mean, thereby providing a more conservative balancing mechanism between subjective and objective weighting schemes.

Module III: Adaptive Fuzzy SAW Based on Crop Growth Stages

The active growth stage is automatically determined from the *age* variable (DAT) in the Paddy Doctor dataset: F1: Early Vegetative Stage (15–30 DAT), F2: Active Tillering Stage (31–45 DAT), F3: Reproductive/Booting Stage (46–75 DAT), F4: Grain Maturation Stage (76–100 DAT), Linguistic health conditions are transformed into Triangular Fuzzy Numbers (TFNs):

$$TFN = (l, m, u)$$

using triangular membership functions. The fuzzy weight vector w_j^F is automatically updated according to the active growth stage (Table 1). The fuzzy preference value is calculated as:

$$\tilde{V}_i = \sum_j w_j^F \tilde{r}_{ij}$$

Subsequently, defuzzification is performed using the centroid method:

$$V_i^{crisp} = \frac{l_i + m_i + u_i}{3}$$

The alternative with the highest crisp preference score is selected as the final recommendation:

$$R^* = \arg\ \max\ (V_i^{crisp})$$

Table 1. Adaptive Weight Vector Based on Rice Growth Stages

Evaluation Criterion	**F1: Early Vegetative Stage (15–30 DAT)**	**F2: Active Tillering Stage (31–45 DAT)**	**F3: Reproductive Stage (46–75 DAT)**	**F4: Grain Maturation Stage (76–100 DAT)**
C1: Purchase Cost (Cost)	0.20	0.30	0.20	0.15
C2: Treatment Effectiveness (Benefit)	0.25	0.30	0.40	0.20
C3: Ecological Impact (Cost)	0.35	0.20	0.20	0.45
C4: Accessibility and Availability (Benefit)	0.20	0.20	0.20	0.20
Total	1.00	1.00	1.00	1.00

Evaluation and Validation Procedures

Module I was evaluated using stratified 10-fold cross-validation with accuracy, precision, recall, macro F1-score, macro AUC-ROC, and confusion matrix analysis. Module II was validated through AHP consistency testing (CR), CRITIC-based objective weight verification, and sensitivity analysis under ±10% weight variations. Module III was compared with static SAW, non-adaptive Fuzzy SAW, and standalone TOPSIS using Spearman's rank correlation coefficient (ρ) against expert reference rankings.

Statistical significance was assessed using McNemar's test for classification performance comparison ($\alpha = 0.05$) and the Wilcoxon signed-rank test to evaluate differences between TOPSIS rankings generated from conventional AHP weights and the proposed AHP–CRITIC integrated weighting scheme.

RESULTS AND DISCUSSION

Preprocessing and Feature Selection Results

The Recursive Feature Elimination (RFE) procedure successfully reduced the dimensionality of the dataset from 48 to 32 highly discriminative features. The three most influential features according to the RFE ranking were: (1) diamond_spot_leaf (Gini importance = 0.187), a primary diagnostic indicator of rice blast; (2) lesion_neck_brown (0.163), a critical indicator of neck blast infection; and (3) leaf_edge_yellowing (0.141), a characteristic symptom of bacterial leaf blight (BLB). Class distribution analysis revealed moderate imbalance, with Tungro (P8) representing only 5.9% of total observations. The application of SMOTE successfully balanced the class distribution, reducing inter-class discrepancies to less than 5%.

Results of Module I: Dempster–Shafer Disease Diagnosis

The Dempster–Shafer (DS) module achieved an overall classification accuracy of 88.9% under stratified 10-fold cross-validation. As shown in Table 2. the proposed method demonstrated consistently strong performance across all disease classes, yielding a macro F1-score of 0.877 and a macro AUC–ROC of 0.939. indicating excellent discriminative capability.

Table 2. Classification Performance of the Dempster–Shafer Diagnostic Module Across Rice Disease Classes

Disease Class	Precision	Recall	F1-Score	AUC-ROC	Support
P1: Blast (Magnaporthe oryzae)	0.913	0.944	0.928	0.967	142
P2: Brown Spot (Bipolaris oryzae)	0.891	0.875	0.883	0.941	128
P3: Narrow Brown Spot (Cercospora janseana)	0.862	0.839	0.850	0.923	87
P4: Sheath Blight (Rhizoctonia solani)	0.884	0.903	0.893	0.948	103
P5: False Smut (Ustilaginoidea virens)	0.833	0.812	0.822	0.908	64
P6: Grassy Stunt (RGSV)	0.901	0.887	0.894	0.951	71
P7: Bacterial Leaf Blight (Xanthomonas oryzae)	0.907	0.924	0.915	0.963	118
P8: Tungro (RTBV+RTSV)	0.844	0.822	0.833	0.912	45
Macro Average	0.880	0.876	0.877	0.939	758
Weighted Average	0.888	0.889	0.888	0.942	758

Confusion matrix analysis revealed that the most frequent misclassifications occurred between Brown Spot (P2) and Narrow Brown Spot (P3), with eight mutually misclassified cases. This finding is biologically plausible, as both diseases are caused by phylogenetically related fungal pathogens and exhibit highly similar morphological symptoms during early infection stages. Tungro (P8) produced the lowest F1-score (0.833), primarily due to its limited sample size despite class-balancing through SMOTE.

Table 3. Performance Comparison of Dempster–Shafer and Alternative Classification Methods

Method	Accuracy (%)	Macro F1-Score	Computation Time (s)	Key Characteristics
Dempster–Shafer (Proposed)	88.9	0.877	0.003	Rule-based; training-free; interpretable
Certainty Factor	82.4	0.819	0.002	Rule-based; limited conflict handling
Naïve Bayes	79.8	0.784	0.015	Assumes feature independence; requires training data
Decision Tree (C4.5)	81.3	0.806	0.021	Susceptible to overfitting; requires training data
Random Forest (100 Trees)	85.7	0.851	0.487	Ensemble model; less interpretable; requires training data

SVM (RBF Kernel)	84.2	0.835	0.312	Limited interpretability; requires training data
XGBoost	86.1	0.854	0.241	High predictive performance; black-box model

Table 3 Comparative evaluation against six benchmark methods demonstrated the superiority of the proposed DS framework. McNemar's test confirmed that the accuracy difference between DS (88.9%) and the strongest competing model, XGBoost (86.1%), was statistically significant ($\chi^2 = 5.18$. $p = 0.023$). Beyond numerical performance, the DS approach offers a distinct methodological advantage: as a rule-based reasoning framework requiring no training phase, it provides fully interpretable diagnostic outcomes through explicit belief values, thereby enhancing transparency and trustworthiness in agricultural decision-making environments.

Results of Module II: AHP–TOPSIS with CRITIC-Based Verification

The AHP pairwise comparison matrix generated the criterion weight vector wAHP = [0.447, 0.227, 0.087, 0.239], with a Consistency Ratio (CR) of 0.030. well below the accepted threshold of 0.10. indicating a high degree of judgment consistency among experts.

Objective verification using the CRITIC method revealed substantial divergence for the cost criterion, where the expert-derived weight (0.447) differed markedly from the data-driven weight (0.970). This discrepancy suggests that the actual variability in treatment costs was considerably greater than perceived by experts, largely due to the substantial price difference between systemic chemical fungicides and cultural management practices.

After harmonic integration and normalization, the final weight vector was obtained as: wfinal = [0.931, 0.011, 0.044, 0.014]. The Wilcoxon signed-rank test indicated that TOPSIS rankings generated using integrated AHP–CRITIC weights differed significantly from those produced using AHP weights alone ($Z = -2.197$, $p = 0.028$), demonstrating that the CRITIC component introduced meaningful adjustments rather than marginal refinements.

Table 4. TOPSIS Ranking Results Using Integrated AHP–CRITIC Weights

Treatment Alternative	D^+ (Distance to Positive Ideal Solution)	D^- (Distance to Negative Ideal Solution)	Relative Closeness (RCi)	Rank	Interpretation
A1: Systemic Chemical Fungicide	0.654	0.024	0.035	4	Lowest preference score
A2: Chemical Bactericide	0.533	0.122	0.186	3	Moderate preference
A3: Biological Control Agent	0.309	0.348	0.529	2	Favorable alternative
A4: Cultural Control Practices	0.024	0.654	0.965	1	Highest preference score

TOPSIS ranking results identified Cultural Management Practices (A4) as the most preferred alternative (RC = 0.965), followed by Biological Control Agents (A3). The dominance of A4 was primarily attributed to its minimal implementation cost and negligible ecological impact. This outcome is consistent with Integrated Pest Management (IPM) principles, which prioritize preventive and cultural interventions before chemical control measures.

Results of Module III: Adaptive Fuzzy SAW Based on Growth Stages

Simulation experiments conducted across four crop growth stages under an identical disease scenario (Blast, belief = 0.830) produced substantially different treatment recommendations, demonstrating the contextual adaptability of the proposed framework.

Table 5. Defuzzified Preference Scores and Rankings Across Rice Growth Stages

Treatment Alternative	**F1: Early Vegetative**	**F2: Active Tillering**	**F3: Reproductive**	**F4: Grain Matu’ration**	**Expert Recommendation**
A1: Chemical Fungicide	0.512	0.538	0.621 (Rank 1)	0.334	F3: A1
A2: Chemical Bactericide	0.498	0.521	0.589	0.318	—
A3: Biological Control Agent	0.631 (Rank 1)	0.584	0.543	0.712 (Rank 1)	F1 & F4: A3
A4: Cultural Control Practices	0.578	0.612 (Rank 1)	0.478	0.689	F2: A4

The adaptive Fuzzy SAW model achieved perfect agreement with expert recommendations across all four growth stages (4/4 cases, 100% consistency), whereas static SAW and standalone TOPSIS achieved agreement rates of only 25% and 0%, respectively.

Table 6. Comparison of Recommendation Consistency Against Expert Reference

Growth Stage	**Expert Recommendation**	**Adaptive Fuzzy SAW**	**Static SAW**	**Standalone TOPSIS**
F1: Early Vegetative Stage	A3 (Biological Control Agent)	A3 ✓ Correct	A4 ✗	A4 ✗
F2: Active Tillering Stage	A4 (Cultural Control Practices)	A4 ✓ Correct	A4 ✓	A4 ✗
F3: Reproductive Stage	A1 (Chemical Fungicide)	A1 ✓ Correct	A4 ✗	A4 ✗
F4: Grain Maturation Stage	A3 (Biological Control Agent)	A3 ✓ Correct	A4 ✗	A4 ✗
Overall Consistency with Expert Reference	Reference	4/4 = 100% (ρ = 0.941)	1/4 = 25%	0/4 = 0%

The observed recommendation shifts closely reflected agronomic best practices. During the early vegetative stage (F1), ecological impact received the highest priority, resulting in the selection of biological control agents. During active tillering (F2), cultural management emerged as the preferred option due to a balanced trade-off between effectiveness and cost. During the reproductive stage (F3), treatment effectiveness became the dominant criterion, leading to the recommendation of chemical fungicides to protect vulnerable panicles. Finally, during grain maturation (F4), ecological considerations and residue avoidance again favored biological control measures.

The adaptive Fuzzy SAW model achieved a Spearman correlation coefficient of 0.941 with expert rankings, substantially outperforming non-adaptive Fuzzy SAW ($\rho = 0.623$), static SAW ($\rho = 0.487$), and standalone TOPSIS ($\rho = 0.412$). The improvement of $\Delta\rho = 0.318$ over the non-adaptive variant highlights the significance of incorporating biological growth stages as dynamic weighting factors within agricultural decision-support systems.

Table 7. Spearman Rank Correlation Between Model Recommendations and Expert Rankings

Evaluation Scenario	Spearman's ρ	Interpretation
Standalone TOPSIS (all growth stages)	0.412	Moderate correlation
Static SAW	0.487	Moderate correlation
Non-Adaptive Fuzzy SAW	0.623	Strong correlation
Adaptive Fuzzy SAW (Proposed)	0.941	Very strong correlation

Overall Framework Performance

The proposed three-module Hybrid Decision Support System demonstrated consistently strong performance across all evaluation dimensions. The DS module achieved the highest diagnostic accuracy among tabular symptom-based approaches while maintaining computational efficiency (<0.003 s per diagnosis). The AHP module produced a valid consistency ratio, and CRITIC verification successfully identified substantial discrepancies between subjective and objective criterion importance. The adaptive Fuzzy SAW module achieved perfect agreement with expert recommendations and exhibited a very strong rank correlation ($\rho = 0.941$), confirming its effectiveness in generating context-sensitive treatment recommendations.

Table 8. Overall Performance Summary of the Proposed Hybrid DSS Framework

Module	Component	Evaluation Metric	Value	Interpretation
I	Dempster–Shafer	Accuracy (10-fold CV)	88.9%	Highest performance among tabular symptom-based diagnostic methods
I	Dempster–Shafer	Macro F1-Score	0.877	Robust performance across eight imbalanced disease classes
I	Dempster–Shafer	Macro AUC-ROC	0.939	Excellent class discrimination capability
I	Dempster–Shafer	Computation Time	0.003	Highly efficient; suitable for low-resource and IoT devices
II	AHP	Consistency Ratio (CR)	0.030	Valid and consistent expert judgments (CR < 0.1)
II	CRITIC	Weight Divergence (C1: Cost)	AHP = 0.447; CRITIC = 0.970	Indicates substantial cost variability across treatment alternatives
II	TOPSIS	Best Relative Closeness Coefficient (A4)	0.965	Strong differentiation among treatment alternatives
III	Adaptive Fuzzy SAW	Agreement with Expert Recommendations	4/4 (100%)	Complete agreement across all growth-stage scenarios

III	Adaptive Fuzzy SAW	Spearman's Rank Correlation (ρ)	0.941	Very strong correlation with expert rankings

The results demonstrate that integrating Dempster–Shafer reasoning, AHP–TOPSIS–CRITIC evaluation, and adaptive Fuzzy SAW yields more effective decision support than applying each method independently. This finding supports the view that agricultural DSS performance can be enhanced through the coherent integration of knowledge, data, and analytical models.

A major contribution of this study is the incorporation of growth-stage-based dynamic weighting. Unlike conventional DSS approaches that rely on static weights, the proposed framework adapts treatment priorities according to biological crop growth stages, resulting in recommendations that closely align with expert agronomic judgments.

From a practical perspective, the framework operates without image input and requires less than two seconds of processing time, making it suitable for deployment on low-capacity devices in remote agricultural settings. In addition, the belief values generated by the Dempster–Shafer module provide transparent and interpretable diagnostic outputs, which can improve user trust and system adoption [23].

The observed differences between AHP and CRITIC weights, particularly for the cost criterion, further demonstrate the importance of combining subjective expert assessments with objective data-driven weighting. This integration improves the robustness and objectivity of treatment recommendation outcomes.

CONCLUSION

This study proposed and evaluated a three-module hybrid Decision Support System (DSS) for rice disease diagnosis and treatment recommendation using publicly available tabular, non-image datasets. The Dempster–Shafer module achieved 88.9% accuracy, a macro F1-score of 0.877. and a macro AUC-ROC of 0.939. outperforming benchmark methods while providing transparent and computationally efficient inference. The AHP module produced a valid consistency ratio (CR = 0.030), whereas CRITIC analysis revealed notable discrepancies between expert judgments and data-driven criterion importance. The proposed adaptive Fuzzy SAW model, incorporating crop growth stage–based dynamic weighting, achieved perfect agreement with expert recommendations (100% consistency; Spearman's $\rho = 0.941$), substantially surpassing Static SAW and standalone TOPSIS.

Several limitations remain, including the absence of field validation under diverse agroecological conditions, reliance on a limited expert panel for weight elicitation, and restricted disease coverage. Future work should focus on mobile application development, IoT-based environmental sensing integration, broader expert-driven weight calibration, hybridization with machine learning models, and large-scale field validation across multiple rice-growing regions.

Additional limitations include the absence of real-time environmental variables such as humidity, temperature, and rainfall, which significantly influence disease progression. Furthermore, the current framework evaluates only eight disease classes and does not consider simultaneous co-infections. Future studies should integrate IoT-based environmental sensing, temporal forecasting models, and larger multi-regional datasets to improve system generalizability.

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