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An AI-Enabled Decision Support System for Rice Disease Identification Under Operational Constraints

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Abstract—Timely and consistent identification of crop diseases remains a persistent challenge in agricultural operations due to environmental variability, resource constraints, and the time-sensitive nature of intervention decisions. Although convolutional neural network (CNN)–based image classification systems have demonstrated high diagnostic accuracy in plant disease detection, their contribution to decision quality within decision support systems (DSS) has received comparatively limited analytical attention. This study adopts a secondary analytical research design to evaluate an AI-enabled rice disease identification system using validated performance data reported in prior empirical studies. No new experiments, model training, or data collection were conducted. Instead, reported classification accuracy and category-level performance are re-examined through a DSS lens, drawing on established theories of decision quality and information quality. Results from the source studies indicate high validation accuracy and robust performance under defined operating conditions. Interpreted from a decision support perspective, these findings suggest that reliable and consistent diagnostic outputs can reduce uncertainty and support timely intervention decisions, thereby enhancing decision quality, provided that decision-maker competence and system use conditions are appropriately aligned.

Index Terms—Decision Support Systems; Decision Quality; Artificial Intelligence; Rice Disease Detection; Convolutional Neural Networks

I. INTRODUCTION

Effective disease management in agricultural systems depends on the timely and accurate identification of crop conditions. In rice production, delayed or inconsistent disease diagnosis can result in substantial yield losses and increased production costs. Traditional disease identification practices rely heavily on manual inspection and human judgment, both of which are susceptible to cognitive bias, misinterpretation of information cues, and delayed feedback.

Decision support systems research has long established that human decision making is inherently error-prone and that decision quality can be improved when reliable information cues and feedback mechanisms are made available to decision makers [1]. In parallel, advances in artificial intelligence, particularly in convolutional neural networks, have enabled image-based diagnostic systems capable of identifying plant diseases with high levels of accuracy [2–4]. Empirical studies in agricultural AI demonstrate that deep learning models can effectively classify crop diseases using leaf images and can achieve performance levels suitable for operational deployment, including use in mobile and resource-constrained environments [3,4].

Despite these advances, much of the existing literature emphasizes algorithmic performance metrics, such as classification accuracy, with comparatively limited discussion of how such outputs contribute to decision quality—defined as the extent to which decisions are informed, consistent, and appropriate to the operational context [1,5]. This gap motivates the present study, which reframes

AI-based rice disease identification as a decision support function rather than a standalone analytical task. The contribution of this study lies not in algorithmic development, but in the decision-oriented interpretation of validated AI performance results using established DSS theory.

1. Objective of the Study

1.1. General Objective

To evaluate the decision-support relevance of an AI-enabled rice disease identification system using validated performance data interpreted through decision support systems theory.

1.2. Specific Objectives:

1.2.1. To examine reported classification accuracy and category-level performance of CNN-based rice disease identification systems.

1.2.2. To interpret diagnostic accuracy as an indicator of information quality within a DSS context.

1.2.3. To assess how stable diagnostic outputs may contribute to improved decision quality under operational constraints.

1.3. Significance of the Study

This study is significant for multiple stakeholders. For farmers and agricultural extension officers, reliable AI-generated diagnostic outputs may support more timely and consistent disease management decisions. For system designers and policymakers, the study highlights the importance of aligning AI system performance with decision-maker capabilities and operational contexts. For researchers, the study contributes a decision-oriented analytical perspective that integrates empirical AI performance findings with established DSS theory on decision quality and information quality.

II. METHODOLOGY

1. Research Design

This study employed a secondary analytical research design grounded in decision support systems theory. The analysis is based on validated quantitative performance data reported in peer-reviewed studies on CNN-based rice disease identification and plant disease detection [3,4]. No new experiments, surveys, or empirical data collection were undertaken.

2. Population and Sample of the Study

The analytical basis of the study consists of previously reported datasets used in the source studies, which include thousands of labeled rice leaf images across multiple disease categories [4]. These datasets were used in the original studies to train and validate CNN models and are treated here as the empirical foundation for secondary analysis.

In addition, the performance data analyzed in this study originate from a previously completed and institutionally validated research project that developed and tested an AI-based rice disease identification framework. That prior project established the dataset composition, training–validation split, and baseline classification performance using a total of 6,318 rice leaf images. Of these, 5,055 images (80%) were used for model training, while 1,263 images (20%) were reserved for validation. The present study does not reproduce or extend that empirical work; instead, it re-examines the reported performance outcomes solely for decision-oriented analytical purposes.

3. Research Instruments

The research instrument for this study is the AI-based image classification framework reported in the source literature, specifically CNN architectures applied to rice disease and pest identification [4]. Reported accuracy metrics and category-level results serve as indicators of information quality for decision support analysis.

4. Data Collection Procedure and Statistical Treatment

Data for this study were obtained exclusively from published empirical results in peer-reviewed journals. No direct interaction with respondents or field deployment was conducted. The analysis is limited to the interpretive evaluation of reported results, consistent with accepted practices in DSS research [1,5]. Reported descriptive performance metrics—such as overall accuracy and category-level classification accuracy—were analyzed qualitatively from a decision support perspective. No additional statistical computation or inference was performed.

III. RESULTS AND DISCUSSION

This section presents the analysis and interpretation of secondary quantitative performance data obtained from previously published studies. Results are discussed in terms of their implications for decision quality and decision support rather than algorithmic novelty.

1. Validation and Field Performance

Empirical studies on CNN-based rice disease identification report high classification accuracy under controlled validation conditions, as well as strong performance under defined field conditions [4]. These results indicate that deep learning models can generate accurate diagnostic information when image acquisition conditions are appropriate.

2. Category-Level Performance

This subsection summarizes classification accuracy across individual rice disease categories based on secondary performance data.

Table 1 summarizes classification accuracy across individual rice disease categories based on secondary performance data.

Table 1. Classification of Accuracy per Disease Category (Secondary Data)

Disease Category	Classification Accuracy (%)
Healthy	100.00
Bacterial Leaf Blight	96.67
Brown Spot	93.33
Rice Blast	90.00
Disease Not Covered	90.00
Overall Accuracy	94.00

Beyond overall accuracy, this study introduces Diagnostic Output Stability (DOS) as a conceptual decision support metric. DOS refers to the consistency of diagnostic classifications across similar input conditions and disease categories, as reflected by uniformly high category-level accuracy. In DSS theory, stable information cues reduce cognitive load, minimize ambiguity, and support more standardized decision responses, particularly under time and resource constraints. Although DOS is not computed numerically in this study, the reported consistency of classification accuracy exceeding 90% across all disease categories suggests a high level of output stability.

From a decision quality perspective, high DOS enhances the reliability of AI-generated diagnostic outputs as decision inputs, provided that users are trained to interpret outputs appropriately and understand system limitations. DSS research further emphasizes that stable system outputs must be complemented by appropriate user training and feedback mechanisms to avoid misinterpretation or overreliance on automated recommendations [1].

3. Discussion

The reported performance of CNN-based rice disease identification systems aligns with broader findings in the agricultural AI literature, which consistently show that deep learning approaches outperform traditional image processing methods [2,3]. However, interpreting these results through a DSS framework highlights important caveats. As demonstrated by theoretical and simulation-based DSS research, higher information accuracy can improve or degrade decision quality depending on the decision-maker's knowledge, experience, and capability [5].

Accordingly, AI-based disease detection systems should be deployed as decision aids rather than decision replacements. Their effectiveness depends not only on technical accuracy but also on integration into decision processes, user competence, and contextual constraints. Participatory approaches to DSS development, as demonstrated in agricultural DSS case studies, can enhance system acceptance and alignment with user needs [6].

IV. LIMITATIONS

This study is subject to several limitations inherent to its secondary analytical design. First, the analysis relies exclusively on previously published and institutionally validated performance data and does not include new empirical validation, field deployment, or user-centered experimentation. Consequently, the study does not capture real-time decision behavior, user interpretation variability, or organizational adoption dynamics that may influence decision quality in operational settings. Second, the evaluation focuses primarily on reported classification accuracy and category-level performance as indicators of information quality; other potentially relevant DSS attributes—such as timeliness, explainability, and system usability—are discussed conceptually but not empirically assessed. Finally, while the decision-oriented interpretation is grounded in established DSS theory, the findings should be interpreted as analytical insights rather than causal evidence of improved decision outcomes.

V. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

A. Summary of Findings

This study re-examined validated performance results of CNN-based rice disease identification systems through a decision support systems perspective. Reported high classification accuracy and consistent category-level performance indicate strong information quality, which constitutes a necessary condition for effective decision support.

B. Conclusions

The study concludes that AI-enabled rice disease identification systems have the potential to support agricultural decision making when framed and evaluated as decision support tools. In addition to diagnostic accuracy, the consistency of outputs across disease categories, conceptualized as Diagnostic Output Stability, further supports the system's potential contribution to decision support when appropriately integrated into decision processes. While high diagnostic accuracy is essential, decision quality ultimately depends on the interaction between information quality, decision-maker capability, and the conditions under which the system is integrated into operational decision processes. The primary contribution of this study lies in its decision-oriented interpretation of existing empirical results, clarifying how validated AI performance can inform and enhance decision quality within decision support systems.

C. Recommendations

Future research should examine how AI-based disease detection systems influence actual decision outcomes in field settings, including user interpretation and response behavior. Participatory design approaches and training interventions are recommended to ensure that improvements in information quality translate into improved decision quality. Additional empirical studies may also explore the integration of AI diagnostics into broader agricultural decision support systems.

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