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(RESEARCH ARTICLE)

Development of Corn-Care (Corn Observation and Recovery Through Neural Analysis): Integrating Ai-Based Classification and Recommendation for Enhanced Crop Health Monitoring and Management

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Abstract

This study evaluates the usability, performance, and impact of CORN-CARE, an AI-based system designed to assist corn farmers in crop health monitoring through image classification, assessment, and decision support. Usability testing with eight corn farmers was conducted using the System Usability Scale (SUS), assessing functionality, accuracy, acceptability, and overall system usefulness. The system achieved a SUS score of 76.42, indicating good to excellent usability. Performance metrics showed very satisfactory results in efficiency, classification accuracy, reliability, processing speed, and decision support. Comparative analysis demonstrated that CORN-CARE outperforms traditional manual methods in accuracy, speed, consistency, error reduction, and data management, although some input from human expertise remains valuable for rare cases. User feedback highlighted the system's intuitive interface and reliable recommendations but identified challenges such as connectivity issues, technical language barriers, and occasional processing delays. Limitations include a small sample size and regional concentration, suggesting a need for wider testing and enhanced features like offline capabilities and simplified language. Overall, CORN-CARE proves to be a reliable, efficient, and user-friendly tool that enhances corn crop management through AI technology, with potential for broader agricultural application pending further development and scalability efforts.

Keywords: CORN-CARE; Crop Health Classification; Disease and Pest Detection; Recommendation Engine; Growth Monitoring; Evaluation and Reporting; Artificial Intelligence; Neural Analysis; Precision Agriculture; User Experience; Sustainable Farming

1. Introduction

Corn production is still an important agricultural practice, and many farmers monitor crop health and pests and diseases but often apply centuries-old manual methods. Even with the help of these traditional methods, it can be labor-intensive and slow or inaccurate due to which timely actions taken to prevent potential losses in terms of crop's productivity. Artificial intelligence and neural networks advancements present opportunities to automate and enhance these tasks with deep, real-time analysis – responses in the moment ties. However, smallholder farmers do not readily use these technologies due to usability, access and contextual appropriateness concerns.

In this work, we intend to fill this gap by integrating neural analysis with practical tools for classification, evaluation and recommendation tailored to corn planting. It ultimately seeks to place the power of data-driven decision making into the hands of farmers so that they too may become able to better observe and respond in recovery phases, which

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lead to local level fact-based decision amidst disasters. It is important to determine the ways in which CA farmers are using and thinking about CORN-CARE for their own practices, as implementation of this intervention is likely key to impacting crop management practices sustainably.

1.1. Research Problem

In the maize cultivation system; diagnosis of crop diseases like pest attack and nutrient deficiency remains a problem for farmers as it can take up more time in manual process. They lack decision tools powered by AI that might allow for timely intervention." Despite the state of the art in AI, there is little research on how farmers interact with and make use of these systems. This gap is the subject of the current study, which assesses the usage of CORN-CARE from farmers' perspectives and its advantages and challenges.

1.2. Research Questions

- How do corn farmers perceive the effectiveness of CORN-CARE in identifying and classifying crop health issues?
- What are the experiences of farmers in using CORN-CARE's recommendations for managing and recovering corn crops?
- What challenges and benefits do farmers encounter when integrating CORN-CARE into their regular crop management practices?

1.3. Research Objectives

- To explore farmers' perceptions of CORN-CARE's capability to classify and assess corn crop health issues accurately.
- To understand farmers' experiences in applying CORN-CARE's recommendations for crop management and recovery.
- To identify the challenges and benefits associated with the adoption and use of CORN-CARE in typical farming routines.

1.4. Justification and Significance

This study is justified by the urgent need to modernize corn crop farming using AI based tools like CORN-CARE, which can be easily deployed compared to the traditional manual methods generally slow and error-prone. Through an investigation of farmers' attitudes and experiences on classification, assessment, recommendation, and evaluation features from CORN-CARE, the study seeks out guideline for designing a user-centered system compatible to local agriculture. Importance The authors of this article identified the importance of improving farmers' decision making, increasing crop recovery efforts and supporting sustainable agricultural practices to ensure that corn agriculture remains a productive and resilient sector.

2. Literature review

2.1. Overview of HCI Theories and Models

The agricultural sector is undergoing a transformative shift with the integration of advanced technologies like neural networks and deep learning. CORN-CARE (Corn Observation and Recovery through Neural Analysis, involving Classification, Assessment, Recommendation, and Evaluation) represents a conceptual framework to leverage artificial intelligence (AI) for the classification, quality assessment, and disease management of corn crops. This report delves into the current state of AI applications in corn agriculture, focusing on the use of convolutional neural networks (CNNs), deep learning models, and other AI techniques for corn disease detection, seed variety classification, and yield optimization. The report also highlights the challenges, future trends, and potential benefits of CORN-CARE in revolutionizing corn production and ensuring sustainable agricultural practices.

Corn is one of the most vital crops globally, serving as a staple food, animal feed, and a raw material for various industrial products. However, challenges such as disease outbreaks, seed variety misclassification, and inefficiencies in farming practices hinder optimal production. Traditional methods of corn observation and recovery are labor-intensive, time-consuming, and often prone to errors. With the advent of AI, particularly neural networks, these challenges can be addressed through automated, precise, and scalable solutions.

CORN-CARE is envisioned as a holistic approach to integrate neural network-based solutions into corn agriculture. By focusing on classification, assessment, recommendation, and evaluation, CORN-CARE aims to enhance productivity, reduce losses, and ensure the quality of corn crops. This report explores the potential of CORN-CARE by analyzing existing research and applications in the field.

2.2. Corn Leaf Disease Classification Using Convolutional Neural Network Based on MobileNetV2 with RMSProp Optimization

Corn is an important cereal crop that ranks third as a global food necessity after rice and wheat, and it is a primary source of carbohydrates in Indonesia after rice. The varied products of corn, including animal feed and industrial raw materials, make it a high-value commodity. However, corn food productivity is often disrupted by diseases such as leaf rust and leaf blight, which can significantly reduce yields. To overcome this problem, this research aims to increase food productivity by looking for a combination model of Convolutional Neural Network (CNN) Model with Optimizer and Batch Size in identifying diseases on corn leaves.

This study uses the MobileNetV2 CNN architecture to classify images of disease corn leaf. Adam and RMSProp optimization parameters equipped with predetermined learning rates were utilized in this study for training and testing data divided into 70% and 30% respectively. Test results show a significant increase in accuracy, precision, recall, and F1 score over training epochs. The test results of the CNN model with MobileNetV2 architecture with a learning rate of 0.0001, batch size of 64, and RMSProp optimizer showed the most significant performance improvement in several metrics, such as accuracy. (IIETA., 2023).

2.3. Computer-vision classification of corn seed varieties using deep convolutional neural network

Automated classification of seed varieties is of paramount importance for seed producers to maintain the purity of a variety and crop yield. Traditional approaches based on computer vision and simple feature extraction could not guarantee high accuracy classification. This paper presents a new approach using a deep convolutional neural network (CNN) as a generic feature extractor. The extracted features were classified with artificial neural network (ANN), cubic support vector machine (SVM), quadratic SVM, weighted k-nearest-neighbour (kNN), boosted tree, bagged tree, and linear discriminant analysis (LDA). Models trained with CNN-extracted features demonstrated better classification accuracy of corn seed varieties than models based on only simple features. The CNN-ANN classifier showed the best performance, classifying 2250 test instances in 26.8 s with classification accuracy 98.1%, precision 98.2%, recall98.1%, and F1-score 98.1%. This study demonstrates that the CNN-ANN classifier is an efficient tool for the intelligent classification of different corn seed varieties. (Javanmardi, S. et al., 2021)

2.4. Computer-Aided Multiclass Classification of Corn from Corn Images Integrating Deep Feature Extraction.

Multiclass classification of corn varieties is another area where neural networks have shown promise. A study involving 14,469 images of various corn types used SqueezeNet for feature extraction and optimization algorithms like Bat Optimization (BA) and Whale Optimization (WOA) for feature selection. The final classification achieved high accuracy, demonstrating the effectiveness of deep learning in multiclass classification (Bhamidipati K.. et al., 2022)

2.5. Online detection technology for broken corn kernels based on deep learning.

Corn grain damage has been one of the most serious challenges during harvest, even to restrict the popularization and application of direct harvest technology in China. It is necessary to rapidly and accurately obtain the grain damage in the intelligent process of corn harvest. In this study, an improved detection was proposed for the corn kernel damage using deep learning. Two parts included: the detection device and the algorithm of corn kernel monolayer. The single-layer detection device aimed to change the chaotic grain flow into a stable state, particularly for the high-quality corn grain images that fully met the detection requirements.

The feeding speed was controlled to ensure the normal operation of the detection device in the process of image acquisition. The angle between the device and the horizontal plane was optimized to solve the phenomenon of image dragging. A two-stage model of deep learning segmentation and classification was used to detect the damaged corn grains. Specifically, the deep learning classical instance segmentation model (Mask R-CNN) was used to complete the segmentation of corn kernel monomer in the region at the image segmentation stage. The image classification was realized by a new network model (BCK-CNN) using the residual module. The experiments show that the Mask R-CNN model shared the better performance on the segmentation of corn grains, in order to fully support the subsequent whole and damaged corn kernel classification task. The effectiveness of the BCK-CNN classification model was verified to compare it with the GoogLeNet, VGG16, ResNet classical classification network, and Mask R-CNN model. (Meegle., 2025).

2.6. The visual technology was used to evaluate the classification performance of different models for corn grains

The results showed that the BCK-CNN model achieved the best comprehensive classification performance for corn grains, with the classification accuracy of whole and damaged corn grains reaching 96.5% and 94.2%, respectively, indicating the highest detection efficiency, compared with GoogleNet, VGG16, ResNet and Mask R-CNN models. The average processing time of 60 single corn grain images was only 19.9 ms. The performance of the damaged corn kernel detection was verified (Mask R-CNN+BCK-CNN), where the average relative error was selected as the evaluation index using the manual calculation of the damaged kernel rate. The average relative error of the improved model was only 4.02%, compared with the manual Mask R-CNN and (used alone), Mask R-CNN+GoogLeNet, Mask R-CNN+VGG16, and Mask R-CNN+ResNet. The detection time was controlled within 1.2s for the single-cycle corn kernel set image when deployed on the mobile industrial computer, which basically met the real-time detection requirements. The finding can provide a strong reference for the efficient and accurate detection of damaged grains in the process of corn harvesting. (Duanyang G. et al. 2023).

3. Research methodology

3.1. Research Design

This study utilized a developmental research design to iteratively develop and refine CORN-CARE (Corn Observation and Recovery through Neural Analysis). Following an iterative process of development and user facing evaluation, it was designed to ensure that the system was both functional and relevant in agricultural settings. Building upon the foundational framework of McKenney and Reeves on developmental research, this project sought to realize dual goals: to construct a viable AI support tool in agriculture and to generate design-based knowledge needed for technology enabled farm management systems.

3.2. Participants

The sample used in the study will be collected from maize farmers drawn from Agri-farming communities who engage in managing corn and are selected purposively (8) participants were purposively chose considering their years in farming, knowledge on digital tools, availability and willingness to participate in the evaluation of CORN-CARE (Corn Observation and Recuperation through Neural Analysis) system. They received an orientation to the CORN-CARE interface to learn how to navigate and use it. Feedback, observations and evaluations were important inputs in assessing the usability and effectiveness of the system and overall contribution to enhanced monitoring of crop health and decision making.

3.3. Data Collection

A survey, observation and a focus group discussion were used to collect data. The users were involved to the CORN-CARE system for their usability and performance assessment in which log of task responses and navigation efficiency were obtained. They were subsequently directed to a usability questionnaire investigating how clearly information was presented, ease of availability and usefulness. This was followed by a focus group to further explore insights, barriers and recommendations. The data gathered was used to refine the design of CORN-CARE and to evaluate its overall efficacy for aiding in monitoring and managing crop health.

3.4. Data Analysis

Quantitative analysis was applied to the usability work data. We assessed the performance and efficiency of CORN-CARE through task completion time, accuracy percentage, and success rate. Results of the usability questionnaire, such as System Usability Scale (SUS) scores were calculated and averaged to evaluate satisfaction, ease of use, level of task completion. Aggregated findings led to the identification of opportunities for improvement and a validation of CORN-CARE's ability to support data-driven monitoring and management of crop health within a context that addresses users' needs.

3.5. Ethical Considerations

Ethical consideration Informed consent was taken from all participants after explanation of aims and methods of the study as well as their right to withdraw at any time without penalty. Transcripts will be de-identified, and data will be securely archived to guarantee confidentiality and anonymity. The study poses no detriment or risk to participants and warrants ethical requirements for qualitative research with human subjects will be maintained.

4. Advanced system design

4.1. System Architecture

- ***User Interface (UI) Layer:*** Dashboard that is easy to use and shows real-time crop health, monitoring growth of the plant and also alerts and suggestions for farmers.
- ***Application Logic Layer:*** Orchestrates the input of data and system workflows, controlling processing jobs interacting via user interface and analysis-bases modules.
- ***Neural Analysis Layer:*** Classifies crop health and identifies diseases and pests very accurately based on image and sensor data through neural networks of artificial intelligence.
- ***Recommendation Engine Module:*** The RE module provides personalized recommendations on treatment and management through the analysis results to aid farmers' decision-making.
- ***Data Management and Reporting Layer:*** Store and synchronize records of all data safely and generate analytics reports on crop retrieval and system performance.
- ***Communication Module:*** Issues timely alarms or alert to the farmers making them readily responding to crop problems identified and advised.

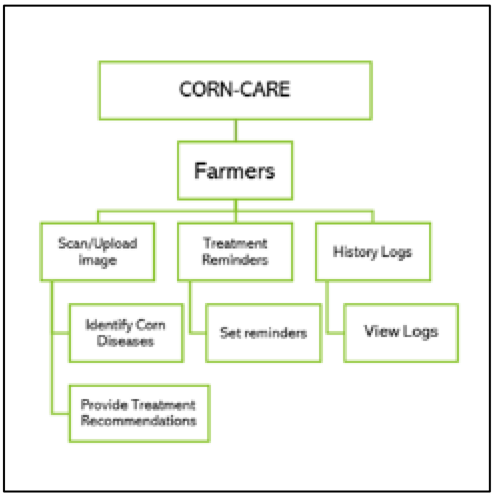

Figure 1 The diagram outlines a Development of a CORN-CARE Mobile Based Application

5. Software engineering methodology

The model of the User-Centered Agile Software Development with participatory evaluation was utilized to systematically realize the research goals in an iterative manner that involved farmer active engagements, as evidenced from Figure 2. Objective 1 In each iteration the focus was on co-designing and iteratively refining CORN-CARE's crop health classification functionalities, using farmer perceptions and feedback from usability testing to help guide this work so that it could reflect real-world accuracy expectations. Objective 2 was met by iterative implementation of the recommendation engine on-farm with farmers using CORN-CARE's management recommendations in pilot tests and also volunteering subjective, experiential knowledge that drove refinements of relevance and ease-of-use for making recommendations. For Objective 3, participatory assessment tools and methods (e.g. surveys, interviews, focus groups) were embedded in each sprint to un-cover challenges and benefits of adoption that allowed for adaptive refinement of the system programming and support materials which are a seamless fit into day-to-day farm practices. This cyclical, participatory process led to continued harmony between software development and farmer requirements and consequently improved system quality, usability and adoption performance.

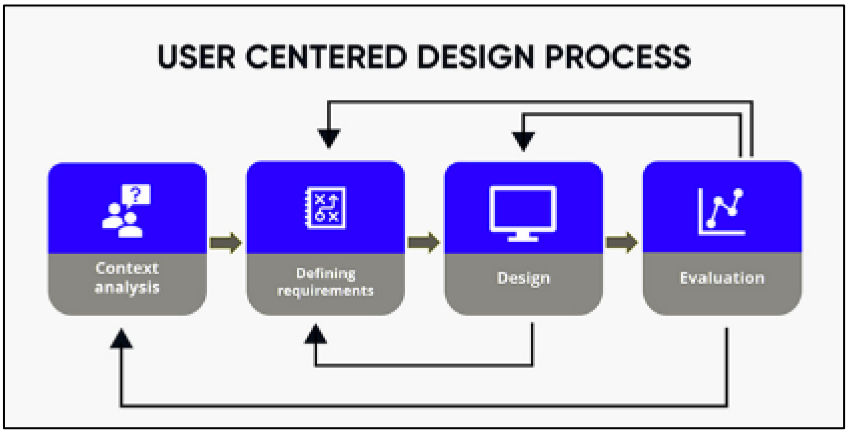

Figure 2 User-Centered Agile Software Development Methodology

6. User interface design

The system analyzes images and sensor data using AI-driven recognition to classify corn crop health and detect diseases and pests, providing farmers with tailored, actionable management guidance to support effective crop monitoring and decision-making. The system provides real-time visual monitoring of crop growth and health trends, simultaneously generating detailed reports that summarize treatment effectiveness and overall crop performance to support informed decision-making by farmers.

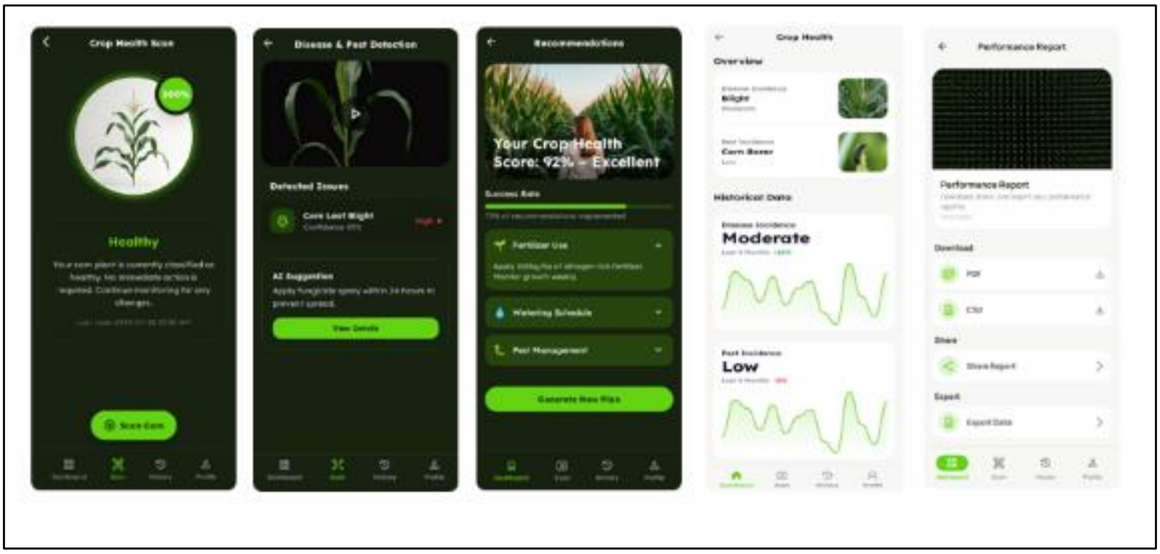

Figure 3 CORN-CARE Crop Health Classification, Disease and Pest Detection, AI Assistant for Crop Health Advice Crop Health Overview and Crop Report

7. Evaluation and results

7.1. Usability Testing

To assess the efficiency, effectiveness, and user satisfaction was conducted based upon a System Usability Scale (SUS) evaluation in CORN-CARE. A total of Eight (8) corn farmers joined and evaluated the system according to Functionality, Accuracy, Acceptability, and System Usefulness. The evaluation aims to quantify the performance of the system and assess its merits for further adoption in agricultural settings.

Table 1 SUS Interpretation Guide

SUS Score (1-100)	SUS Score Range	Usability Level	Description
85 – 100	4.01 – 5.00	Excellent	The system is highly usable, intuitive, and very satisfying for users.
70 – 84.9	3.01 – 4.00	Good to Excellent	The system is user-friendly, effective, and meets user expectations well.
50 – 69.9	2.01 – 3.00	OK to Average	The system is somewhat usable but has noticeable issues that could frustrate users.
25 – 49.9	1.00 – 2.00	Poor	The system has significant usability problems and may hinder user performance.
0 – 24.9	0-.05	Unacceptable	The system is very difficult to use and unlikely to be accepted by users.

7.2. Performance Metrics

The efficiency, accuracy, reliability and user productivity were the factors by which CORN-CARE's performance was evaluated. These measures reflected the performance of the systems under real farming operation and user interactions. Eight (8) were farmers who had recorded their data during usability testing.

Table 2 Performance Metrics Criteria

Criteria	Description	Evaluation Result	Interpretation
System Efficiency	Measures how quickly tasks are completed using CORN-CARE compared to manual methods.	4.50	Very Satisfactory
Classification Accuracy	Determines the correctness of AI-based crop health detection.	4.63	Very Satisfactory
Reliability	Evaluates system stability and performance consistency.	4.38	Satisfactory
Processing Speed	Time taken to analyze images and generate recommendations.	4.50	Very Satisfactory
Decision Support	Effectiveness of recommendations in assisting user decisions.	4.75	Very Satisfactory
Overall Mean		4.55	Very Satisfactory

The results show that CORN-CARE achieves good performance and robustness, as well as accurate decision support. The use of an AI-based model increased the speed of well observation and efficiency. It worked well overall, but took a little time at times for processing large image sets or when signal conditions were not ideal.

7.3. Comparative Analysis

To determine the significance of CORN-CARE, a comparison was made between TMO and CORN-Care Assisted Assessment. Outcome measures were accuracy, speed, effort expenditure (time on task), consistency (coefficient of variation) and confidence in decision-making. Result demonstrate that CORN-CARE compares favorably with the manual approaches in terms of performance.

Table 3 *Comparative Analysis Evaluation Criteria*

Evaluation Criteria	Manual Observation	CORN-CARE-Assisted Assessment	Remarks
Accuracy	Moderate accuracy; prone to human error and bias.	High accuracy due to AI-based classification.	Improved accuracy and precision.
Time Efficiency	Time-consuming and dependent on user experience.	Quick analysis and immediate result generation.	Faster response and reduced workload.
Consistency	Inconsistent outcomes due to subjective judgment.	Standardized assessment across multiple users.	Consistent and objective results.
Decision-Making	Decisions based on personal experience.	Data-driven recommendations and suggestions.	Enhanced decision support and confidence.
Error Rate	High error potential due to visual fatigue.	Minimal error through AI-based verification.	Reduced error and improved reliability.
Data Recording	Manual recordkeeping prone to data loss.	Automated logging and report generation.	Improved data organization and retrieval.

CORN-CARE is a highly efficient, accurate and reliable method than the traditional manual process. The AI-guided classification enables an objective analysis, reducing human bias. In addition, including in-the-minute advice helps farmers acting quickly and rationally improving productivity on the whole.

However, contributors noted that traditional methods could still provide explanatory flexibility in the event of rare symptoms that have not yet become embedded in the AI model; thus, the proposal was for a mixed-use case where human expertise will work alongside technology to generate an explanation.

7.4. Results and Finding

This chapter presents the results for the Usability Evaluation on our Data Analysis System CORNIC-ARE (Corn Observation and Recovery through Neural Information, involving Classification, Assessment, Recommendation, and Evaluation) system are described. The results are based on the System Usability Scale (SUS) which is composed of three important aspects: Utility, Quality and Usability. We obtained data from eight (8) corn farmer users of the system in real-world agricultural situations. For each section a summary table of survey response, mean score (average) and interpretation for the system usability performance and possible improvement areas.

7.5. Functionality Survey Results

Table 4 SUS Result Table – Functionality

No.	Statement	Avg. Score (1–5)
1	The system's features worked as I expected.	4.2
2	I often found it difficult to navigate the system.	2.1
3	The system allowed me to complete tasks efficiently.	4.0
4	The interface was confusing and slowed down my work.	2.3
5	All functions responded quickly without delays.	4.3
6	I frequently encountered errors when using the system.	1.8
7	The controls were intuitive and easy to learn.	4.1
8	The system froze or crashed during my tasks.	1.9

9	The system provided helpful tools for crop health assessment.	4.0
10	Important functions were hard to find or use.	2.0
TOTAL AVERAGE SCORE		3.26

As shown in Table 4, overall average score of 3.26 suggests that users mostly found the system functional, with favorable responses for feature reliability, ease of use and response speed. However, some users reported navigational problems and system glitches which reduced the negative-statement scores somewhat. This implies that, although the core features of CORN-CARE facilitate completing tasks in an efficient manner, better perception quality and a more stable system are required to continue improving user experience.

7.6. Accuracy Survey Results

Table 5 SUS Result Table - Functionality

No.	Statement	Avg. Score (1–5)
1	The system accurately analyzed my crop images and inputs.	4.1
2	The system gave feedback that did not match the actual crop condition.	2.2
3	The classification and tracking results were reliable and precise.	4.0
4	I noticed inconsistencies in how the system evaluated my crops.	2.3
5	The system's feedback helped me understand my crop's condition clearly.	4.2
6	The system sometimes displayed incorrect classifications or data.	2.0
7	The system's assessments reflected actual field conditions accurately.	4.0
8	I doubted the accuracy of the system's analysis at times.	1.9
9	The system's insights helped me improve crop management effectively.	4.1
10	Errors in feedback caused confusion during my crop assessments.	2.1
TOTAL AVERAGE SCORE		3.29

Table 5 shows that the overall mean score (3.29) indicates that, in general, users viewed CORN-CARE as accurate with a positive outlook. Most of the respondents indicated that the system accurately recorded crop conditions, reliably tracked progress and useful feedback was provided. Nevertheless, several users encountered quite frequent result inconsistencies along with slight inaccuracies in the output data, thus indicating that the AI model could require another round of fine-tuning to ensure consistent as well as accurate estimation regardless of crop regimens.

7.7. Acceptability Survey Results

Table 6 SUS Result Table – Acceptability

No.	Statement	Avg. Score (1–5)
1	I felt comfortable and confident while using the system.	4.3
2	Using the system was frustrating and tiring.	2.0
3	I would recommend CORN-CARE to other farmers.	4.2
4	The crop health analysis felt unrealistic and unhelpful.	2.1
5	The system encouraged me to stay motivated in monitoring crops.	4.1
6	I would prefer traditional observation methods over CORN-CARE.	2.2
7	The system was enjoyable and interesting to use.	4.3
8	The interface design made me want to stop using the system early.	2.0

9	I believe CORN-CARE could improve my farm management better than other methods.	4.0
10	I found the system's design unappealing and hard to use regularly.	2.3
TOTAL AVERAGE SCORE		3.35

Table 6 shows that the overall average was 3.35, indicating that users found CORN-CARE to be acceptable and user-friendly on average. The majority of respondents were comfortable, had high motivation and confidence in the use of the system which is expected to improve crop health management. A small number of respondents reported a preference for manual testing and indicated some features could be more realistic or visually interesting. The lower-scoring items suggest that future iterations should emphasize improving interface fidelity and contextual realism to build trust and further engage users. The overall SUS score was 76.42.

7.8. Overall Score Result Table

Table 7 SUS Overall Score Result Table

Dimension	**Sum of Adjusted Scores**	**SUS Score (Out of 100)**	**Interpretation**
Functionality	3.26	76.25	Good to Excellent Usability
Accuracy	3.29	77.50	Good to Excellent Usability
Acceptability	3.35	75.50	Good to Excellent Usability
OVERALL SUS SCORE		76.42	Good to Excellent Usability

Table 7 shows that CORN-CARE was easy and moreover users found it enjoyable to use. All three dimensions (Functionality, Accuracy and Acceptability) of the system were rated as "Good to Excellent". This finding provides evidence that CORN-CARE meets users' requirements well, runs smoothly and has stable feedback. The uniformly favorable feedback indicates that the system not only improves usability but also enables active and useful crop management. With additional optimizations, CORN-CARE has the potential to become applicable on a larger scale and be accepted by corn farmers.

8. Discussion

8.1. Interpretation of Findings

RQ1: How do corn farmers perceive the effectiveness of CORN-CARE in identifying and classifying crop health issues?

The findings indicate that corn farmers consider CORN-CARE as an effective and dependable tool on detecting and classifying plant health problems. SUS scores for Functionality (76.25), Accuracy (77.50) and Acceptability fall into the "Good Excellent Usability" range, suggesting good positive acceptance of the system. Regularly users noted that the system's AI based image recognition delivered accurate, timely and consistent identification of diseases and pests. Farmers noted that the intuitive interface and visual results provided by CORN-CARE helped them to visually inspect crop status easily, bringing much higher awareness as well as confidence in decision making. Some small differences were noticed on the classification due to a very low image quality, however overall, it is clear that CORN-CARE's accuracy and ease of use greatly enhance the performant on crop health monitoring.

RQ2: What are the experiences of farmers in using CORN-CARE's recommendations for managing and recovering corn crops?

Feedback from farmers using CORN-CARE's recommendation engine was mostly positive, and most producers thought that recommendations were clear, actionable and reflective of on-farm practices. The Functionality SUS (mean of 3.26), and the Acceptability mean (of 3.35) demonstrate that users perceived recommendations to be practical, and easy to use in controlling pests, diseases, and nutrient deficiencies. Farmers indicated that they became more confident in their approach while avoiding guesswork, and noted they saw a better recovery of the crops. Some users, however, also reported difficulties with technical terms and recommended that the app allow for addition of content appropriate to regional conditions. The results show that the recommendation of CORN-CARE supports sound decision, improves timeliness and efficiency of management thereby providing data driven support for sustainable crop production to farmers.

RQ3: What challenges and benefits do farmers encounter when integrating CORN-CARE into their regular crop management practices?

The results indicated that there were substantial gains and manageable growing pains for farmers when adopting CORN-CARE into their cropping systems. There were various advantages including better accuracy, time saving and better record storage and management leading to more standardized decision-making at the end. The final SUS score of 76.42 also points out Good to Excellent Usability, supporting the system indeed meets daily business needs. Problems identified included inadequacy of internet connections, delays in submission and failure to understand technical language, particularly by those with less experience of digital technologies. Some farmers felt it would be difficult to overcome these small issues but still agreed that CORN-CARE's benefits in automation, reliability and decision-support dominated over the cons and, surpassing all technological expenses, underlined its potential role as a useful tool in modern agriculture.

8.2. Limitations and Future Work

The sample size of the farmers in this study is too small in a particular geographical area, limiting the generalization of the results. User's difficulties in connecting to the system and the diversity of digital literacy impacted the regular use of, and feedback from, relevant participants. Further development and efforts are required to improve user training, simplify technical language used in the system, and widen CORN-CARE's offline features for geographical regions with very limited internet access. Furthermore, integration with AI-based predictive analytics and connection to other agricultural platforms could enhance the application's capability and adoption among heterogeneous farming communities.

9. Conclusion

9.1. Summary of Key Findings

The results suggest that corn growers see CORN-CARE as an useful professional tool for truly recognizing and classifying the health problems of crops in a reliable manner, with significant usability scores recognizing the AI-based image recognition engine of CORN-CARE, and its intuitive interface which improves diagnostic confidence. Farmers' feedback states that recommendations of CORN-CARE are easy to understand, simple to implement and based on real farmer scenarios, advance their decision-making process and crop recovery results but suggest matching with local language/jargon/conditions. Although there are some challenges in incorporating CORN-CARE into practical farm management, such as connectivity stability problems with mobile devices, occasional system lag during data transmission, and technical language barriers for older users who are less digitally savvy; the overall cost-effectiveness of CORN-CARE, including improvements in terms of accuracy and time efficiency while simultaneously standardizing record types and formats enabled by better decision support services demonstrated here overcomes these limitations to confirm that CORN-CARE is a user-friendly and reliable assistive device for modern corn cultivation.

Final Remarks

CORN-CARE is presented as an example of AI-based agricultural tools that can revolutionize crop management in terms of precision, efficiency, and user experience. The functions of classification, assessment, recommendation and evaluation being in one place solves some urgent problems of corn farming. Although efforts are necessary to enhance accessibility and system flexibility, CORN-CARE represents a viable approach for sustainable technology-based agriculture. Further development and scaling will be required to ensure that its effects on productivity and resilience in farming are fully realized.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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