



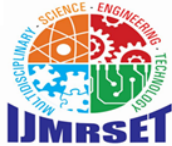
# International Journal of Multidisciplinary Research in Science, Engineering and Technology

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## International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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# AgriAid: An AI-based Crop Disease Identification and Advisory System for Farmers

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**ABSTRACT:** Diseases in crops continue to be a common problem among agricultural communities, especially in areas where farmers depend on manual methods and experience to diagnose diseases. This study introduces AgriAid, an artificial intelligence-based application intended to detect diseases in rice and corn crops through image processing and generate automated advisories on how to address such diseases. AgriAid applies a CNN with the MobileNetV2 algorithm to classify the crops into two classes, healthy and sick crops. Additionally, it has a decision support feature that provides advice on treating diseases found within the crops. According to ISO/IEC 25010, the application was tested for its quality features, receiving an average rating of 4.06. Experiments revealed that AgriAid could classify crops with 99.7% accuracy and detect diseases in rice and corn crops with 91.6% and 93.2% accuracy, respectively.

**KEYWORDS:** Artificial Intelligence, Crop Disease Detection, Deep Learning, MobileNetV2, Decision Support System, Rice and Corn Diseases

## I. INTRODUCTION

Agriculture continues to be one of the principal occupations for many people living in rural areas; however, the diseases affecting their crops pose a serious threat to productivity and farmers' revenues. The techniques used by humans to detect such diseases traditionally involve the examination of visual features that usually takes much time and produces rather imprecise results.

The current research seeks to develop AgriAid, an AI-enabled solution for diagnosing plant diseases on rice and corn crops and offering advice on handling the problem. Different from other solutions dealing solely with the task of disease detection, AgriAid incorporates decision support capabilities.

## II. LITERATURE SURVEY

Crop diseases and pest infestations remain major challenges in agriculture, contributing to reduced crop yield, economic losses, and food insecurity worldwide. Traditional disease detection methods primarily rely on manual inspection and expert knowledge, which are often time-consuming, costly, and prone to human error. Recent advancements in artificial intelligence (AI), particularly in machine learning and deep learning, have enabled more efficient and accurate approaches to plant disease detection through image analysis.

Several studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in identifying crop diseases. For instance, CNN-based architectures have achieved high classification accuracy in detecting diseases in various crops, including rice, cassava, and tomato. Models such as VGG16, ResNet, and YOLO have shown strong performance, with reported accuracy rates often exceeding 90%. These approaches significantly reduce reliance on manual diagnosis and enable faster decision-making for farmers, especially in remote areas where access to agricultural experts is limited.

Based on the reviewed literature, it is evident that AI and deep learning technologies have significant potential to transform crop disease management. However, there remains a gap in developing systems that integrate accurate disease



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detection with context-aware advisory support, particularly for staple crops such as rice and corn in local settings. This study addresses these gaps by developing an AI-based system that not only identifies crop diseases through image analysis but also provides actionable recommendations tailored to the needs of farmers.

### III. METHODOLOGY / APPROACH

#### Research Design

The study used a descriptive-developmental research design in developing AgriAid, an AI-powered crop disease detection and advisory system for rice and corn plants. The study focused on designing, developing, training, and evaluating machine learning models integrated into a web-based/mobile application. This research design is appropriate because it helps describe the whole development process while also allowing improvements step by step. It is important for this study because it supports continuous testing and refinement of the system, ensuring that the final output works well, is reliable, and can be used in real farming situations.

#### Data Collection

The dataset was collected from multiple reliable sources, including Kaggle and the PlantVillage dataset, and supplemented with locally captured crop images using smartphones. The study developed three (3) deep learning models: a crop classification model, a rice disease detection model, and a corn disease detection model.

The crop classification model consisted of four classes: corn, rice, non-leaf, and other leaf images to ensure accurate crop identification before disease analysis. The rice disease detection dataset included Leaf Blast, Bacterial Leaf Blight (BLB), Brown Spot, Tungro, and Healthy leaves, while the corn disease detection dataset included Common Rust, Gray Leaf Spot (GLS), Northern Corn Leaf Blight (NCLB), and Healthy leaves. There were a total of 13,676 images for crop classification, 4,037 images for rice disease detection, and 3,806 images for corn disease detection.

#### Data Preprocessing

All images underwent preprocessing before training to improve consistency and model performance. Images were resized to  $224 \times 224$  pixels and normalized to scale pixel values between 0 and 1. Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment were also applied to reduce overfitting and simulate real-world environmental conditions.

#### Model Training, Validation, and Testing

The datasets were divided into training, validation, and testing sets using a 70:15:15 ratio. The study used MobileNetV2 as the primary deep learning architecture due to its efficiency in image classification tasks. Transfer learning was applied using a pre-trained MobileNetV2 model with customized classification layers for crop and disease prediction. The model was trained using the categorical cross-entropy loss function and the Adam optimizer, while early stopping and fine-tuning techniques were implemented to improve performance and prevent overfitting. Model evaluation was conducted using accuracy, precision, recall, F1-score, and confusion matrix metrics.

#### Model Deployment

The trained models were then integrated into the AgriAid web/mobile application to enable real-time crop disease detection. Uploaded crop images underwent preprocessing before prediction, and the system displayed the detected disease along with descriptions and recommended treatment or prevention measures.

#### System Design

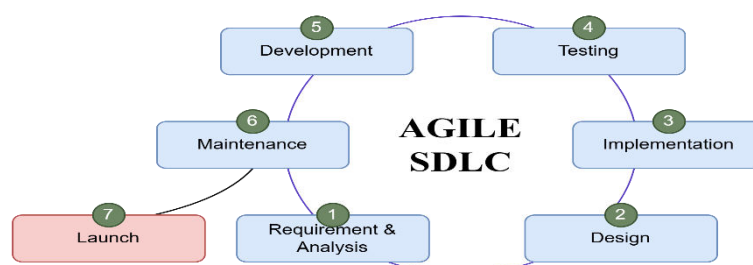


Figure 1. Agile Software Development Life Cycle



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Figure 1 illustrates the Agile Software Development Life Cycle (SDLC) used in the development of AgriAId. The methodology follows an iterative and flexible development approach consisting of requirement and analysis, design, implementation, testing, development, maintenance, and launch phases. This approach enabled continuous system improvement, regular testing, and integration of user feedback throughout the development process. Agile SDLC was selected to ensure effective enhancement of the crop disease detection system and to improve the accuracy, usability, and reliability of the application.

### AgriAId System Architecture

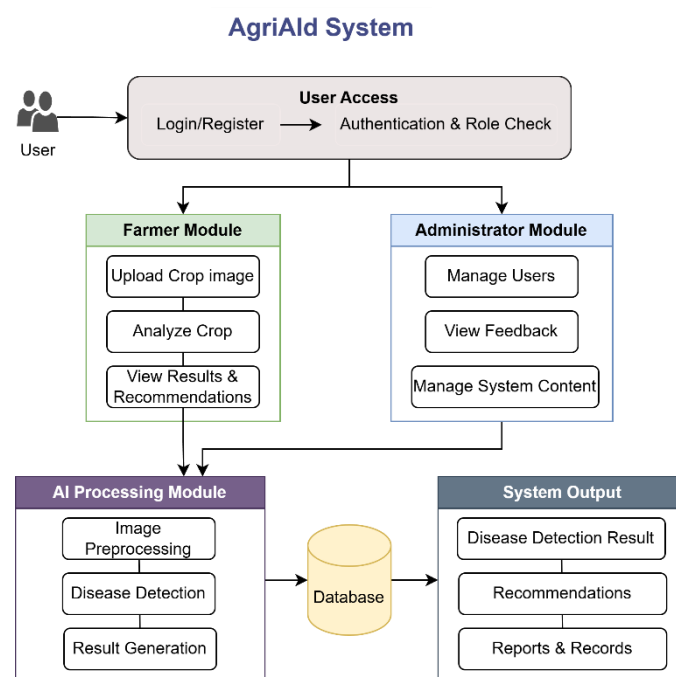


Figure 2. AgriAId System Architecture

Figure 2 illustrates the overall architecture of the AgriAId system. Users access the application through login or registration, followed by authentication and role verification. Farmers can upload or capture crop images for analysis, while administrators manage users, feedback, and other system content. The uploaded images are processed through the AI module for preprocessing, disease detection, and result generation. The system stores all relevant data in the database and provides disease detection results, recommendations, and reports to users.

### Sampling Method

The study used purposive sampling to select respondents with relevant knowledge and experience related to crop disease management and system usage. Purposive sampling enables researchers to gather information from information-rich participants (Purwandari, Fryonanda, & Ibrahim, 2022). This approach allowed the researchers to evaluate the AgriAId system in terms of usability, functionality, and contextual relevance. Consequently, the collected information helped identify the strengths and weaknesses of the system.

### Research Instrument

The survey questionnaire used in this study was developed based on the selected quality characteristics of ISO/IEC 25010 to assess user evaluation of the AgriAId application, which includes usability, functional suitability, performance efficiency and reliability. The instrument used was a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).



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### Statistical Treatment

The AgriAId system was evaluated using accuracy, precision, recall, F1-score, and confusion matrix metrics to measure model performance (Sood & Singh, 2020; Ngugi, Akinyelu, & Ezugwu, 2024). Usability and acceptability were assessed using a five-point Likert scale, and the responses were analyzed through Weighted Mean and Verbal Interpretation (Siebert et al., 2022).

## IV. RESULTS AND DISCUSSION

### Performance Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-score
Crop Classification Model	99.7%	99.7%	99.7%	100.00%
Rice Model	91.6%	91.8%	91.8%	91.6%
Corn Model	93.2%	91.75%	92.5%	92%

Table 1. Performance Evaluation Metrics

The results indicate that the Crop Classification Model achieved near-perfect performance, demonstrating strong capability in classifying crop types. The Rice Model obtained an accuracy of 91.6%, with slightly lower performance likely due to visual similarities among disease classes such as blast and blight. The Corn Model achieved 93.2% accuracy, showing reliable performance with minor misclassifications, particularly in visually similar disease categories. Overall, all models demonstrate good generalization ability and are suitable for practical crop and disease classification tasks.

### ISO/IEC 25010 system evaluation

Criteria	Mean	Verbal Interpretation
Usability	4.24	Strongly Agree (SA)
Functional Suitability	3.99	Agree (A)
Performance Efficiency	3.98	Agree (A)
Reliability	4.02	Agree (A)
<b>Overall Mean</b>	<b>4.06</b>	<b>Agree (A)</b>

Table 2. ISO/IEC 25010 evaluation results including the overall average

This presents the evaluation results of the AgriAId system based on the ISO/IEC 25010 software quality model. The system obtained an overall mean of 4.06, interpreted as *Agree*, indicating that it is effective and acceptable to users. Among the evaluated criteria, usability achieved the highest mean score of 4.24, suggesting that the system is user-friendly and easy to operate. Functional suitability (3.99) and reliability (4.02) also received positive ratings, showing that the system performs its intended functions accurately and consistently. However, performance efficiency recorded the lowest mean score of 3.98, indicating that improvements are still needed in processing speed and system



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responsiveness. Overall, the results demonstrate that the AgriAid system is functional, reliable, and usable, with minor areas for optimization in performance efficiency.

### V. CONCLUSION

This study successfully developed AgriAid, an artificial intelligence-based crop disease detection and advisory system designed to identify diseases in rice and corn crops using image processing and deep learning techniques. The system employed MobileNetV2 for classification and demonstrated strong performance, achieving high accuracy in crop classification and reliable results in disease detection for both rice and corn. Based on the evaluation, AgriAid obtained an overall ISO/IEC 25010 mean score of 4.06, interpreted as *Agree*, indicating that the system is acceptable, usable, and effective for end users.

The results show that integrating AI with decision-support capabilities can enhance early disease detection and provide farmers with timely recommendations, thereby reducing crop losses and improving agricultural decision-making. Although the system performed well, minor misclassifications were observed in visually similar disease classes, suggesting the need for further model optimization. Overall, AgriAid demonstrates strong potential as a practical tool for supporting precision agriculture and promoting more effective and sustainable farming practices.

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