Agroai: Leaf-Based Crop Disease Detection for Brgy. Lidong Farmers Using Convolutional Neural Networks, Computer Vision, and Data Analytics

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DOI: https://dx.doi.org/10.51584/IJRIAS.2025.101100007

Received: 27 October 2025; Accepted: 02 November 2025; Published: 28 November 2025

ABSTRACT

The output of the study is an application called AgroAI: Leaf-Based Crop Disease Detection System. This web-based and mobile-enabled system is designed to assist farmers in detecting crop diseases early by providing a platform where users can upload images of crop leaves such as banana, corn, mango, potato, and tomato. The system automatically analyzes the images using a Convolutional Neural Network (CNN) model to identify possible diseases, provide treatment suggestions, and generate confidence scores. Farmers can also access their diagnostic history, view data analytics on crop health, and participate in community forums for agricultural knowledge sharing. For administrators and researchers, the system stores and organizes agricultural data, allowing better monitoring of disease trends and supporting decision-making for improved crop management. Once implemented, the system benefit farmers by giving them fast and reliable diagnoses without requiring expert consultation, while also aiding agricultural experts and researchers through data-driven insights.

The system is built using the following development tools such as: Python with TensorFlow/Keras for building and training the CNN model, PHP and JavaScript for web development, CSS and Tailwind CSS for styling and responsive layout, and MySQL/MariaDB as the database management system. The frontend integrates Chart.js for visualizing disease frequency, confidence scores, and trend data. The mobile interface uses frameworks compatible with Android/iOS to ensure accessibility for rural farmers. To guarantee quality and effectiveness, the system is evaluated using the ISO/IEC 25010 software quality model, which measures functionality, usability, reliability, performance efficiency, and maintainability. This ensures that AgroAI is not only accurate and user-friendly but also reliable, efficient, and practical for addressing the real-world needs of farmers and agricultural communities.

The study followed an applied research approach using the Iterative System Development Life Cycle (SDLC) model. The system is evaluated using the ISO/IEC 25010 Software Quality Model focusing on functionality, usability, reliability, performance efficiency, and maintainability. Fifty (50) respondents participated in the evaluation activities. Results showed that the system performed well across all quality characteristics, with both groups “Strongly Agreeing” that AgroAI is reliable, efficient, and user-friendly.

The findings suggest that AgroAI is a practical, accurate, and effective solution for early crop disease detection. The researchers recommend future enhancements such as offline access, an expanded crop database, and integration of IoT devices for real-time monitoring.

Keywords: AgroAI; Crop Disease Detection; Leaf Image Analysis; Convolutional Neural Network (CNN); Computer Vision; Data Analytics; Mobile Agriculture Application; Web-Based System; Precision Farming; ISO/IEC 25010; Farmers’ Decision Support System.

INTRODUCTION

Accurate and timely detection of plant diseases remain a persistent challenge in global agriculture. Traditional diagnostic approaches, which rely heavily on visual inspection by human experts, are often labor-intensive,

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

subjective, and prone to error (Barbedo, 2019). These limitations frequently result in delayed interventions and increased crop losses that could otherwise be prevented with earlier diagnosis (Ferentinos, 2018). As a result, there is growing demand for automated diagnostic tools that can deliver rapid, consistent, and scalable assessments across diverse agricultural contexts.

Recent developments in computer vision, particularly the application of Convolutional Neural Networks (CNNs), have shown significant promise in addressing this need. CNNs are capable of extracting high-level visual features from leaf images, enabling them to identify a wide range of plant diseases with high accuracy (Mohanty et al., 2016). Studies have demonstrated that, when trained on comprehensive image datasets, CNN-based models can outperform traditional diagnostic methods and even rival human expert performance (Brahimi et al., 2017; Liu et al., 2020). These models offer a scalable approach to disease detection that is well-suited for deployment in field settings.

Accurate crop disease diagnosis is crucial for minimizing crop losses, yet traditional visual inspection methods are often slow, inconsistent, and reliant on expert availability (Barbedo, 2019; Ferentinos, 2018). With advancements in artificial intelligence (AI) and image-based diagnostics, Convolutional Neural Networks (CNNs) have demonstrated superior performance in identifying plant diseases from leaf images—often surpassing human accuracy (Mohanty, Hughes, & Salathé, 2016; Brahimi, Boukhalfa, & Moussaoui, 2017; Liu et al., 2020).

Recent advancements in data analytics and machine learning have significantly improved the accuracy and scalability of plant disease diagnosis systems. Convolutional Neural Networks, in particular, have been widely adopted due to their strong capability in extracting hierarchical features from leaf images (Ferentinos, 2018). CNN-based architectures such as AlexNet, VGGNet, and ResNet have been successfully used to classify plant diseases with high accuracy across various datasets (Mohanty et al., 2016; Brahimi et al., 2017). In addition to CNNs, techniques such as image augmentation, ensemble learning, and transfer learning have enhanced model performance and reduced overfitting (Liu et al., 2020). Combined with cloud-based analytics, these algorithms not only enable real-time diagnosis but also support ongoing improvement through the retraining of models using updated field data.

Agriculture remains the backbone of rural economies, particularly in developing countries like the Philippines. In areas such as Brgy. Lidong, Polangui, Albay, local farmers rely heavily on crops like banana, corn, mango, potato, and wheat for both livelihood and food security. However, one of the major challenges faced by these farmers is the early detection and accurate diagnosis of crop diseases. The region's tropical climate—characterized by heavy rainfall, flooding during wet seasons, and drought during El Niño events—further complicates plant health management and agricultural productivity.

Traditionally, farmers depend on manual inspection or informal advice for diagnosing plant issues. These methods are often subjective, delayed, or inaccurate, leading to reduced yields, increased use of pesticides, and economic loss. As the agricultural landscape becomes increasingly vulnerable to climate and pest stressors, the need for intelligent, technology-driven solutions becomes more urgent.

This study proposes the development of AgroAI, a web-based application powered by Convolutional Neural Networks (CNNs), designed to detect plant diseases from leaf images. Targeting common crops in the Philippines, AgroAI enables users—primarily farmers and agricultural technicians—to upload photos of affected leaves and receive immediate diagnostic feedback. The system prioritizes usability and precision, ensuring that even users without a technical background can operate the platform effectively. The application's performance is assessed using key evaluation metrics such as accuracy, precision, recall, and F1-score. Unlike advisory platforms, AgroAI focuses specifically on visual disease recognition and classification, positioning itself as a practical tool for early diagnosis and informed decision-making.

This study shows how building a system like AgroAI can help farmers easily detect plant diseases by uploading images of crop leaves. It aims to give accurate results using Artificial Intelligence, specifically Convolutional Neural Networks (CNNs), without needing expert knowledge. This makes the process faster

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

and more reliable, helping farmers take early action to avoid crop damage and reduce losses. Specific objectives are:

- To design and develop AgroAI, a leaf-based crop disease detection system that empowers farmers through accurate diagnosis using Convolutional Neural Networks (CNNs), Computer Vision, and Data Analytics, enhancing crop management and agricultural decision-making.
- To design and develop a user-friendly web and mobile interface that allows farmers to upload leaf images, view diagnoses, and access actionable insights.
- To use and implement a CNN-based computer vision model capable of accurately detecting and classifying various crop diseases from leaf images.
- To develop a data analytics module that provides farmers with disease trends, affected crop statistics, and recommended actions.
- To implement visual diagnostic reporting tools that summarize disease frequency, crop health status, and location-based patterns.

Scope

The proposed AgroAI system covers the following features:

- A smart dashboard that displays relevant insights such as disease detection results, affected crop statistics, and recommendations based on user roles.
- Allow users (e.g., farmers) to upload leaf images for automated disease detection using trained CNN models.
- Store and analyze historical detection data for tracking recurring issues and identifying long-term patterns.
- Provide visual reports highlighting disease frequency, high-risk crop types, and region-specific disease outbreaks.
- Offer AI-powered suggestions for treatment or preventive actions based on detected diseases.
- Provide web-based access across devices with internet connectivity, ensuring platform independence.

Limitation

Despite its potential to enhance agricultural productivity through intelligent disease detection, the AgroAI system is subject to several limitations that may affect its overall performance and applicability. These are:

- The system requires a stable internet connection for image uploads and cloud-based processing; offline use is not supported.
- The accuracy of disease detection depends on the quality of the uploaded images and the diversity of the training dataset.
- AgroAI is currently limited to detecting diseases in a specific set of crops and may not support all plant varieties.
- The system does not include features for pest detection, soil analysis, or weather prediction.
- Recommendations are based on general agricultural guidelines and are not a substitute for professional agronomist advice.
- Geographic disease pattern detection may be limited by the number of active users in a region, especially during initial deployment.

Theoretical Framework

The AgroAI system's technical design, process optimization, and overall goals are all guided by important theoretical objectives. These are:

- Convolutional Neural Networks (CNNs) form the theoretical foundation for modern image-based plant disease detection systems by automating the identification of visual symptoms through hierarchical feature extraction. Inspired by the structure of the human visual cortex, CNNs learn spatial patterns by

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

passing images through layers of convolution and pooling, progressing from detecting simple features like edges and textures to complex, disease-specific characteristics such as leaf lesions and discoloration (LeCun et al., 2015). This approach removes the need for manual feature engineering, enabling scalable and efficient analysis of agricultural images.

- In plant pathology, CNNs have demonstrated strong capability in associating pixel-level image patterns with disease categories, especially when trained on diverse datasets that include multiple crop species, disease stages, and varying environmental conditions (Mohanty et al., 2016). However, their performance depends on overcoming challenges inherent in field-captured images, such as uneven lighting and soil debris, which require preprocessing techniques like normalization and data augmentation to improve model robustness. Transfer learning—fine-tuning pre-trained CNN architectures like ResNet or VGG16 on specific agricultural datasets—has proven effective in addressing limited data availability while maintaining computational efficiency (Too et al., 2019).

Conceptual Framework

This study is anchored on the Input–Process–Output (IPO) Model, which provides a systematic representation of how the AgroAI system transforms raw data and user inputs into meaningful diagnostic results and decision-support outputs. The model illustrates the logical flow of the system's operations—from user engagement to computational processing—culminating in outputs that assist farmers in managing crop health effectively.

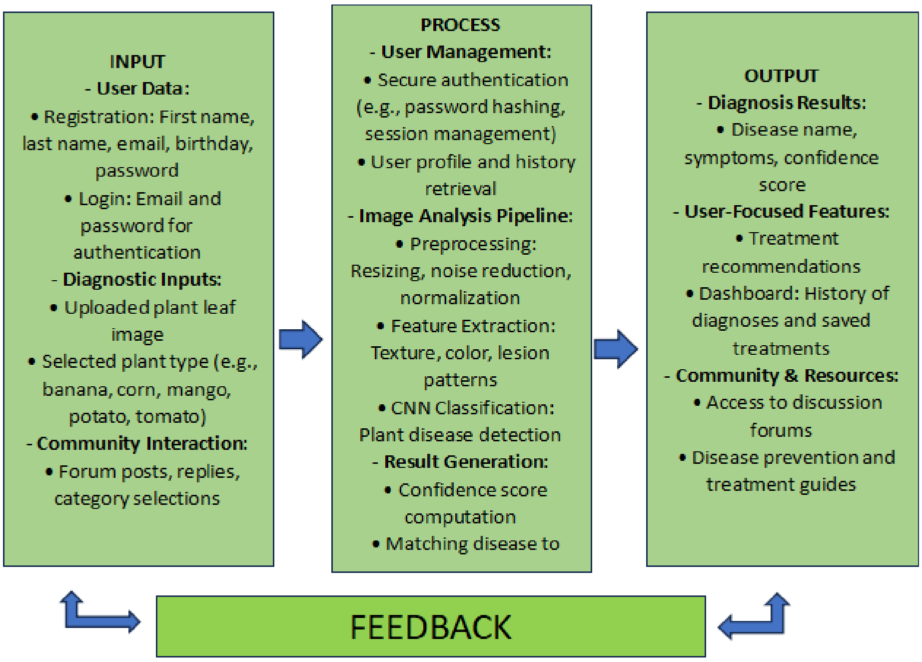

Figure 1: Input-Process-Output Model

The input stage begins with the collection of user data, which includes personal details such as name, email, and password for registration and authentication. Once logged in, users upload a plant leaf image and manually select the plant type—such as banana, corn, mango, potato, or tomato—which is essential for the diagnostic process. In addition, users can interact with the system's community forum by posting questions, replies, or selecting categories for discussion.

The process stage involves multiple system operations. First, secured user authentication is managed through password hashing and session handling. Then, the uploaded image goes through an image analysis pipeline where it is preprocessed by resizing, noise reduction, and normalization. The system extracts important features such as texture, color, and lesion patterns, which are then analyzed by a Convolutional Neural Network (CNN) to identify the disease. The system also generates a confidence score indicating the reliability of the diagnosis and matches the detected disease with the most appropriate treatment recommendations. On the community side, the system categorizes forum content and stores user discussions for future reference.

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The output stage provides the user with a detailed diagnosis, including the disease name, symptoms, and confidence score. Users receive treatment recommendations and can access a personalized dashboard that stores their diagnostic history and saved treatments. Additionally, they can view and contribute to community discussions and access guides for disease prevention and treatment. A feedback loop is also implemented, allowing users to re-upload new images, modify entries, review previous results, and stay updated with new community insights. This continuous feedback mechanism ensures that the AgroAI system remains adaptive and user-centered.

REVIEW OF RELATED LITERATURE

Cruz & Fernandez (2020) developed a mobile-based system using image processing and CNNs to detect early signs of plant diseases in crops like rice and corn. The system enables farmers to capture images of diseased plants using their smart phones and receive real-time diagnoses. This approach has proven effective in helping farmers take timely action to prevent crop losses, especially in regions where access to agricultural experts is limited.

Reyes & Gonzales (2021) applied machine learning algorithms to detect rice diseases, demonstrating the effectiveness of AI in addressing agricultural challenges in key crops. The study utilized a dataset of rice leaf images to train a model that can identify common diseases such as blast and bacterial leaf blight. This technology has the potential to significantly reduce crop losses and improve food security.

Rivera & Mendoza (2023) focused on using deep learning models to detect diseases in banana plants, achieving high accuracy in identifying diseases like Panama disease and Sigatoka. The study highlights the importance of AI in managing key agricultural products, particularly in regions where bananas are a major export crop. By providing early detection of diseases, the system helps farmers maintain crop quality and reduce economic losses.

Alcantara & Ramos (2022) applied CNNs to detect diseases in mango orchards, using a dataset of mango leaf images to identify disease such as anthracnose and powdery mildew. The study underscores the potential of AI in addressing challenges faced by mango farmers, particularly in regions where the fruit is a significant source of income. The system's ability to provide accurate and timely diagnoses has been well-received by farmers.

Tan & Lim (2022) reviewed the current state of smart farming technologies, including AI and IoT, highlighting their growing adoption for crop monitoring and disease detection. The study emphasizes the potential of these technologies to improve agricultural productivity and sustainability, particularly in regions facing challenges such as climate change and limited resources.

Cruz & Fernandez (2023) explored the use of AI-driven systems for pest and disease management in vegetable farms, using machine learning models to analyze data from sensors and drones. The study highlights the potential of AI in addressing challenges faced by smallholder farmers, particularly in regions where vegetables are a key source of income. By providing early detection of pests and diseases, the system helps farmers reduce crop losses and improve yields.

According to Lizada & Dela Cruz (2021), the integration of artificial intelligence (AI) in agriculture is becoming increasingly significant. Their study focused on the use of computer vision for the early detection of pests and diseases in crops, highlighting the potential of deep learning algorithms, particularly Convolutional Neural Networks (CNNs), in enhancing crop health monitoring. The research found that these technologies could improve the accuracy and efficiency of disease detection, ultimately reducing crop losses and increasing overall productivity.

According to Villanueva & Mendoza (2022), the use of drones equipped with AI-powered image recognition for monitoring crop health is gaining momentum. The study explored how drones, paired with computer vision technologies, could identify early signs of plant diseases in large-scale farms. The research emphasized that implementing AI-based crop disease detection systems could support farmers in making timely decisions, leading to more sustainable farming practices and higher yields.

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According to Garcia & Reyes (2020), CNNs have shown promise in detecting diseases in fruit crops such as mangoes and bananas. The study explored the development of an automated system for disease identification using CNN-based models, which were trained on image datasets collected from local farms. The findings suggest that CNNs could enhance the ability to detect diseases early, which is crucial for preventing widespread damage and ensuring the sustainability of fruit farming.

According to De Guzman & Fernandez (2023), agricultural innovation has seen an increased focus on AI and machine learning tools for disease diagnosis and prevention. Their study introduced a computer vision system designed to identify common diseases in rice crops using CNNs. The study highlighted the positive impact of AI-powered solutions on improving crop management practices and suggested that such systems could be scaled to other agricultural sectors, benefiting both smallholder and large-scale farmers.

According to Santos & Hernandez (2021), the use of machine learning models in crop disease detection is not only improving early detection but also providing farmers with valuable insights for crop management. Their research showed how CNNs could be utilized to predict and classify disease symptoms in crops like tomatoes and peppers. The study emphasized the role of computer vision in automating the disease detection process and improving the overall efficiency of agricultural practices.

Synthesis

The reviewed literature collectively underscores the transformative role of Artificial Intelligence (AI), computer vision, and deep learning in revolutionizing modern agriculture. International studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in automating plant disease detection, significantly improving the accuracy, efficiency, and reliability of image-based diagnosis. Research by Zhang and Kovacs (2012) and Mulla (2013) emphasized the contribution of computer vision and remote sensing technologies to real-time crop monitoring and early disease identification. These technologies have enabled data-driven farming decisions and reduced the dependency on manual inspection. Such findings reveal that AI-based systems not only streamline agricultural processes but also enhance productivity and sustainability on a global scale.

Local studies likewise affirm the potential of AI in improving agricultural productivity within the Philippine context. Research by Lizada and Dela Cruz (2021) and Garcia and Reyes (2020) showed that CNN-based systems effectively identify diseases in crops such as rice, banana, and mango, empowering farmers to mitigate crop losses and increase yield. Both local and international literature highlight the importance of integrating AI and computer vision into agricultural practices to promote efficiency and sustainability. However, challenges persist in terms of scalability, dataset diversity, and adaptation to local farming conditions. Addressing these gaps, the present study introduces AgroAI, a localized and user-friendly system designed to leverage CNNs, computer vision, and data analytics to provide Filipino farmers with accurate, real-time crop disease detection and data-informed agricultural management.

METHODOLOGY OF THE STUDY

The study utilized an applied research design aimed at developing a practical technological solution to address real-world agricultural problems. Rather than focusing on theoretical expansion, the research applied existing technologies—specifically Convolutional Neural Networks (CNNs), computer vision, and data analytics—to create a functional system that assists Brgy. Lidong farmers in detecting and managing crop diseases effectively.

Data are gathered through a Likert scale-based survey questionnaire designed to evaluate the system's quality and effectiveness. The assessment is anchored on the ISO/IEC 25010 software product quality model. Responses collected via Google Forms are analyzed using the weighted mean method, allowing the researchers to determine user satisfaction and the system's compliance with recognized software quality standards.

The Iterative Model is employed as the software development methodology, emphasizing incremental design, coding, and testing across multiple cycles. This approach allowed for continuous refinement of system features, early error detection, and incorporation of user feedback. The model is particularly suitable for

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AgroAI, as it involves complex components such as image recognition, data analytics, and user interface design ensuring that the system remains accurate, efficient, and responsive to the evolving needs of farmers.

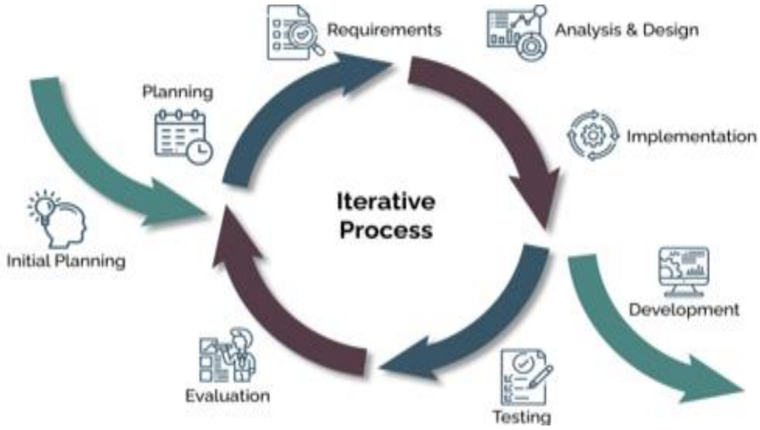

Figure 2: System Development

During the planning phase, a common challenge faced by farmers in rural agricultural communities—the lack of timely and accurate diagnosis of crop diseases is identified. This issue often leads to delayed interventions, reduced yields, and increased production costs. In response, AgroAI's intelligent, image-based solution aimed at providing farmers with fast, accessible, and reliable disease detection through leaf analysis is conceptualized. To ensure the feasibility of the project, team roles and responsibilities are clearly defined, and a development timeline is established to ensure systematic progress. This initial phase allowed researchers to clarify the project's goals, allocate resources effectively, and assess its potential impact on improving agricultural productivity in Brgy. Lidong and similar farming communities.

A data management system is created, implemented, and maintained with the aid of database design. Creating logical and physical representations of the proposed database system is the main goal of database design.

The Context Diagram provides an overview of the AgroAI system and illustrates how external entities interact with the application. It visually represents the flow of data between the system and its users, showing how inputs are transformed into outputs through automated processes. At the center of the diagram is the AgroAI Web Application, which serves as the main processing unit that connects users, external modules, and databases.

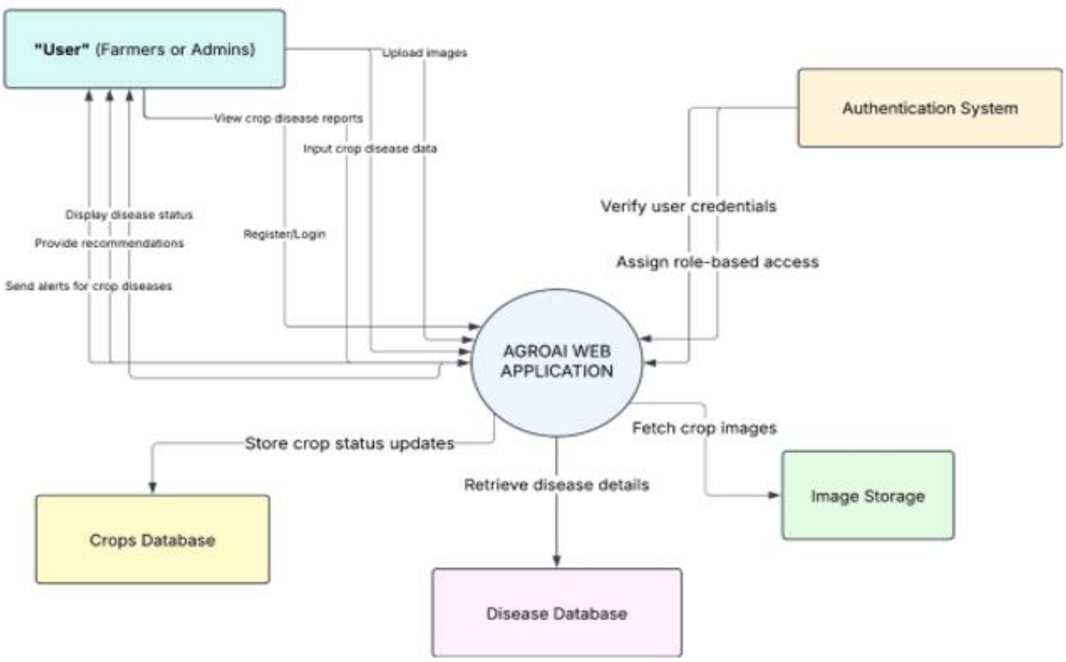

Figure 3: Context Diagram

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The context diagram illustrates the overall structure and interactions within the AgroAI Web Application, highlighting how users, external systems, and databases communicate with the platform. It provides a clear view of the major components involved and how data flows through the system.

Respondents Of The Study

The respondents of the study consisted of two primary groups: (a) user respondents and (b) technical experts.

The user respondents are composed of local farmers and agricultural workers from Barangay Lidong, who represent the target end-users of the AgroAI system. They are selected because they possess firsthand experience in crop cultivation and are directly affected by issues related to crop diseases and farm productivity. Their participation provided valuable insights regarding the system's usability, accessibility, and relevance to real-world agricultural conditions.

The technical experts, on the other hand, included information technology (IT) professionals, software developers, and agricultural experts. This group evaluated the system from a technical and functional perspective, focusing on its accuracy, reliability, and performance efficiency. By involving both groups, the study ensured a balanced evaluation that covered both user experience and system performance.

A total of fifty (50) respondents participated in the evaluation—thirty (30) user respondents and twenty (20) technical experts—selected through purposive sampling. This sampling method is deemed appropriate since the study required participants who are knowledgeable and experienced in either agriculture or technology, ensuring that their feedback would be credible and relevant.

Development And Evaluation Procedure

The development of AgroAI focused on creating a web-based interface supported by a secure backend and robust CNN architecture. Tools such as Python, TensorFlow, and Keras were employed for AI model training and testing, while PHP, MySQL, and JavaScript facilitated system logic, database management, and user interaction. Each prototype underwent testing at the end of every iteration to detect bugs and incorporate user feedback, ensuring the system met the functional and usability needs of farmers.

In this study, two approaches of evaluation are used to assess the AgroAI system. The first type of approach focused on the system's practical impact—specifically, how well it assists farmers in identifying crop diseases through image analysis. The second type centered on the system's technical quality. The system is evaluated to satisfy the ISO 25010 criteria such as:

- Functional Suitability – The degree to which the system provides functions that meet the stated needs of users, such as accurate disease detection and actionable insights.
- Reliability – The system's stability, consistency of operation, and ability to perform under various conditions without failure.
- Performance Efficiency – Accuracy, speed, and responsiveness of disease detection.
- *Usability* – Ease of use, interface design, and learnability of the platform.
- Maintainability – Ease of updating, fixing bugs, and making enhancements to the system with minimal disruption.

Data Analysis Plan

Data analysis in this study aimed to determine the effectiveness and user acceptance of the AgroAI system based on quantitative feedback collected through a structured Likert-Scale evaluation questionnaire. The data are analyzed using descriptive statistical methods, specifically the weighted mean and frequency and percentage distribution. The weighted mean is used to assess the degree of agreement among respondents regarding the system's performance, while the frequency and percentage distribution summarized the demographic profile of the participants.

The analysis is anchored on the ISO/IEC 25010 quality model, which guided the evaluation across five key dimensions: functionality, usability, reliability, maintainability, and performance efficiency. Each criterion is

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rated on a four-point Likert Scale ranging from strongly agree to strongly disagree. The resulting weighted mean scores are interpreted according to predefined ranges of weights to determine the overall user satisfaction and software quality level. The findings from this analysis provided empirical evidence on how well AgroAI met its design objectives and its potential applicability as a sustainable solution for crop disease detection in rural agricultural communities.

The System

The output of the study is an application called AgroAI: Leaf-Based Crop Disease Detection System. This web-based and mobile-enabled system is designed to assist farmers in detecting crop diseases early and automatically analyzes the images using a Convolutional Neural Network (CNN) model to identify possible diseases, provide treatment suggestions, and generate confidence scores. Farmers access their diagnostic history, view data analytics on crop health, and participate in community forums for agricultural knowledge sharing. The system stores and organizes agricultural data, allowing better monitoring of disease trends and supporting decision-making for improved crop management. The system is built using the following development tools such as: Python with TensorFlow/Keras for building and training the CNN model, PHP and JavaScript for web development, CSS and Tailwind CSS for styling and responsive layout, and MySQL/MariaDB as the database management system. The frontend integrates Chart.js for visualizing disease frequency, confidence scores, and trend data. The mobile interface uses frameworks compatible with Android/iOS to ensure accessibility for rural farmers. To guarantee quality and effectiveness, the system is evaluated using the ISO/IEC 25010 software quality model. This ensures that AgroAI is practical for addressing the real-world needs of farmers and agricultural communities. These are some of the user interfaces of the system:

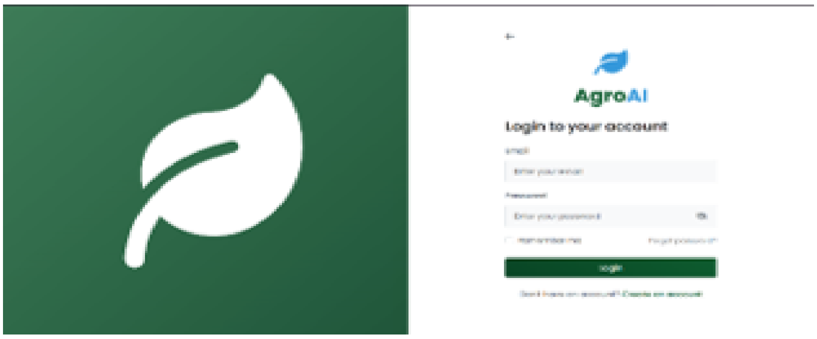

Figure 4: Login Page

The Login Page Interface of the AgroAI system serves as the secure entry point for users accessing the platform. This interface allows both farmers and administrators to log in using their registered email and password, and ensures data privacy and system security by authenticating users before granting access to the dashboard and other core features. It also provides a link for new users to create an account, promoting accessibility and inclusivity for first-time users.

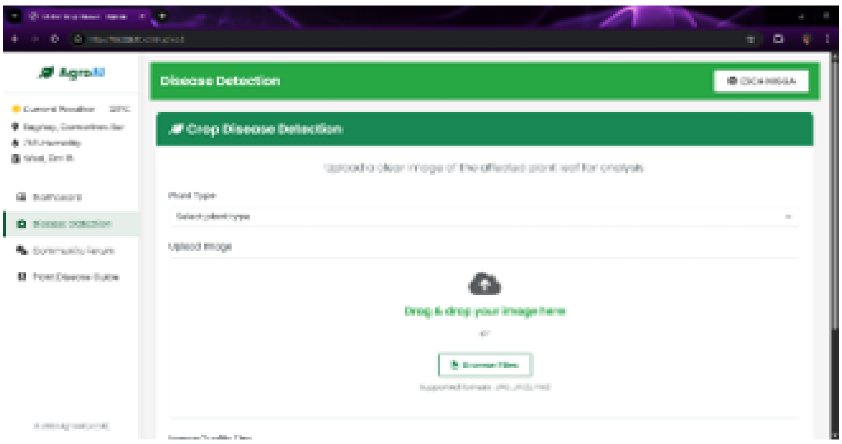

Figure 5: Analytics Dashboard Interface

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The Analytics Dashboard Interface serves as the central hub for monitoring, analyzing, and visualizing agricultural data. The dashboard provides users and administrators with an organized overview of system activities, such as uploaded crop images, disease detection results, and overall diagnostic trends. Through this interface, users can view summarized reports of detected diseases, including frequency charts, percentage distributions, and recent analyses. The Analytics Dashboard enhances decision-making by allowing farmers to observe real-time updates on crop health conditions and identify recurring disease patterns. Administrators utilize the dashboard to track system performance, manage user activity, and generate analytical reports for further evaluation.

Assessment: Summary Of Respondents On The System

The table shows the distribution of respondents:

Respondents (groupings)	Size (n)	Percentage
Users	30	60%
Technical	20	40%
Total (n)	**50**	**100.0%**

Table 1: Distribution of Respondents

Table 1 shows the number and percentage of people who participated in the evaluation of the AgroAI system. Out of 50 respondents, 30 or 60% are users (farmers and agricultural workers), while 20 or 40% are technical experts (IT professionals and agricultural researchers). This means that most feedback came from users, while the technical group provided analytical insights to check the system's performance.

	Users (30)		Technical (20)	
	WM	VI	WM	VI
Functionality	3.57	SA	3.93	SA
Reliability	3.65	SA	3.90	SA
Efficiency	3.54	SA	3.68	SA
Usability	3.65	SA	3.88	SA
Maintainability	3.67	SA	3.85	SA
Overall Average Mean	3.62	SA	3.85	SA

Table 2: Summary of Evaluation of Respondents

Table 2 presents the summary of user and technical evaluations based on the ISO/IEC 25010 criteria. Users gave an overall mean of 3.62 (Strongly Agree), while technical experts gave 3.85 (Strongly Agree). Users rated the criteria from 3.54 to 3.67 average means while the technical experts rated the same criteria from 3.68 to 3.93 average means. Both groups strongly agreed that AgroAI meets the ISO/IEC 25010 standards, demonstrating accuracy, usability, and reliability in detecting and managing crop diseases.

Ethical Considerations

The researchers ensured that all ethical standards are observed throughout the study. Participation is voluntary, and informed consent is obtained from all respondents after explaining the study's purpose and procedures. Personal information is kept strictly confidential, and all data collected are used solely for academic purposes. The study posed no physical or psychological risks to participants, as it only involved system assessment through evaluation. All electronic data are securely stored and accessible only to the research team. Proper acknowledgment of all sources, tools, and references is maintained to uphold academic integrity and avoid plagiarism.

Summary

The AgroAI System is a web-based and mobile-enabled application designed to assist farmers in detecting crop diseases early through image analysis using a Convolutional Neural Network (CNN) model. Its primary goal is to help farmers identify crop diseases such as those in banana, corn, mango, potato, and tomato by uploading leaf images, which are then analyzed. The system provides accurate disease identification, treatment recommendations, and confidence scores, helping users take immediate action to protect their crops. Evaluated using the ISO/IEC 25010 software quality model, the system performed effectively across all quality characteristics.

Overall, AgroAI is found to be accurate, reliable, secure, and easy to use, providing farmers and agricultural researchers with a practical and efficient tool for early crop disease detection and data-driven agricultural management.

CONCLUSION

The study successfully developed AgroAI system that enables efficient and accurate identification of crop diseases through image recognition. Evaluation results based on the ISO/IEC 25010 standards showed that both user and technical respondents agreed the system performs effectively. The findings confirm that AgroAI provides a secure, dependable, and user-friendly platform for farmers, with only minor areas for improvement in system efficiency. Overall, the system meets the standards of quality software and serves as a valuable tool for enhancing crop disease management, supporting informed decision-making, and improving agricultural productivity.

RECOMMENDATION

Future researchers and developers are encouraged to enhance AgroAI by improving its functionality, scalability, and accessibility for broader agricultural use. It is recommended to develop a mobile version with offline capabilities to support farmers in areas with limited internet access and to expand the system’s crop and disease database for greater accuracy. Optimizing the CNN model and image processing performance can further improve detection speed and efficiency, while strengthening data security will ensure the protection of user information. Integrating Internet of Things (IoT) technologies such as smart sensors for real-time monitoring is also advised. Continuous maintenance, system updates, and user training programs are essential to sustain the system’s effectiveness and promote its long-term adoption in supporting sustainable and data-driven farming practices.

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