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Maisip: An AI-Based Offline System for Fungal Disease Detection and Diagnosis in Zea Mays with SMS Integration

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ABSTRACT

Several studies have reported effective image-based methods for detecting fungal diseases in corn. However, development of an AI-based offline system remains to be accomplished, which supports the SDGs no. 9 (Industry, Innovation, and Infrastructure) and 15 (Life on Land). The HuskyLens AI image sensor was incrementally trained on 1,620 maize leaf images which was classified into healthy and three (3) fungal disease categories, with severity level annotation. The HuskyLens AI achieved an overall accuracy of 0.89, precision of 0.90, recall of 0.99, and F1-score of 0.94, which indicates good classification performance. Furthermore, the integrated SIM800L GSM module that allowed offline SMS Alerts showed device responsiveness, with LCD response time achieving 8.13 seconds and SMS delivery time achieving 24.84 seconds, establishing system efficiency. The high-level post-implementation results of the acceptability, adaptability and SMS alert intervention performance of the device indicates that the offline AI-based system provides an effective, accessible, and sustainable solution for early maize disease detection in low-connectivity farming areas, supporting refined crop management and resource efficiency. Future studies for prototype development should expand the dataset to increase accuracy, include additional maize diseases, and refine training, SMS alerts, and power efficiency. The model should be field tested across locations and through multiple crop cycles for further validation. Additionally, the model should be distributed across the region to support smallholder farmers, extension workers, and local governments in low-connectivity areas.

INTRODUCTION

Corn is an essential component in the economic growth of the country, sought after in the food, textile, as well as in the feed and industrial processing sectors, with the crop further accounting for 80% of the total volume traded globally (Cordero, 2015 & Na, 2020). However, fungal diseases have been a growing global concern that will continue to afflict corn crops in the Philippines, posing risks to the country's economic stability. These diseases namely, Downy Mildew (DM) (Peronosclerospora philippinensis), Common Rust (CR) (Puccinia sorghi), and Northern Leaf Blight (NLB) (Exserohilum turcicum), are prevalent within South Cotabato corn crops and can significantly reduce yield (Cruz *et al.*, 2024). These fungal diseases expose the crop to vulnerability in harsh climate conditions, accounting for 23% annual crop loss (Manamgoda *et al.*, 2023) Consequently, the Philippines has experienced a decline in corn production quality, reducing the country's competitiveness in the global market. To address these agricultural crises, there is a rise in traditional disease detection methods, ranging from manual inspections to heavy-powered machines, that are often labor-intensive, inconsistent, inefficient, expensive, and prone to human error (Solorzano-Solorzano *et al.*, 2024 & Tiru *et al.*, 2022).

Leaf diseases in corn require early detection to prevent fungal infections from spreading, which image-based methods now address through models that automatically learn from large datasets (Khirade & Patil, 2015). Studies using inception VE, VGG-16, and similar architectures achieved up to 99.35% accuracy (Ramcharan *et al.*, 2017; Abad *et al.*, 2021; Mohanty *et al.*, 2016). Additionally, recent advances in image-based plant disease detection have explored the use of AI tools such as HuskyLens AI, which performs classification directly on-device, thereby reducing dependence on external computing. For instance, a study developed a Raspberry Pi-based system for Ramie leaves, achieving an F1 score of 93% (Soetedjo & Hendriarianti, 2021). Another paper also applied microcontrollers with image sensors to agricultural object recognition, with low hardware requirements (Singh & Krishnamurthi, 2024). Beyond these approaches, HuskyLens AI has been tested in other fields, where the device exemplified accuracy under real lighting, achieved a strong recall rate of 80% in classification, and a response time of approximately 643 ms in sensor systems (Baloola *et al.*, 2022; Abad, 2021; Pemila *et al.*, 2024) Likewise, HuskyLens AI has achieved 95% accuracy in real-time face recognition (Kennedy *et al.*, 2022). These results confirm HuskyLens AI's reliability, making it a promising candidate for real-time maize crop diagnosis.

Despite the successes of previous image-based detection studies, most relied on large datasets collected under controlled laboratory settings, using general-purpose AI tools (Ramcharan *et al.*, 2017 & Mohanty *et al.*, 2016). These approaches, while accurate, are dependent in high-

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performance computing and stable internet, limiting real-world farming applications, leaving a research gap in developing lightweight, on-device solutions that work effectively in the field. This study developed an image-based classification system using HuskyLens AI to detect DM, CR, NLB, and healthy maize leaves from captured images with diagnostic results transmitted to farmers through SMS even in areas with limited internet access.

This study developed an image-based classification system using HuskyLens AI to automatically identify DM, CR, NLB, and healthy maize leaves from captured images, with diagnostic results transmitted to farmers through SMS. Specifically, this study: (1) developed, labeled, and annotated an image-based classification model for detecting DM, CR, and NLB in Zea mays using captured images of healthy and diseased leaves by integrating the HuskyLens AI module; (2) evaluated the classification performance of the model in terms of accuracy, recall, precision, F1-score, and response times; (3) evaluated the adaptability and acceptability of the prototype; and (4) integrated a GSM-based SMS feature to deliver diagnostic results and a brief description directly to farmers. The researchers focused not only on the system but also on its importance to local farming, especially since corn production in the SOCCSKSARGEN region has suffered from many diseases made worse by the tropical weather and a lack of modern tools. Using the HuskyLens AI, the study allowed farmers to find crop diseases early and use fewer harmful chemicals to manage their resources better while preventing big losses in harvests. This study also supports Sustainable Development Goal (SDG) 9 (Industry, Innovation, and Infrastructure) by bringing affordable smart farming to rural areas and SDG 15 (Life on Land) by using sustainable methods that reduce soil pollution to protect the local environment.

MATERIALS AND METHODS

Materials

The system was made up of several hardware components. The HuskyLens AI 2.0 image sensor from DFRobot was used to mainly detect maize leaves. The ESP32 microcontroller served as the main controller of the system. A GSM SIM800L module was included for sending messages via SMS, powered by a 7.4 V two-cell lithium-ion (Li-Ion) battery. An I²C LCD displayed the results. To keep the connections stable, a PCB with header pins, jumper wires, and soldered parts was used. The system also had tactile switches and buttons for user input, along with an RGB light to indicate the system's status. A SIM card, battery holder, and protective casing were also part of the setup.

Research Design

The study followed a quantitative Design and Development (D&D) research design, a step-by-step method used to plan, build, and test a product to make sure it really works and can be improved using its results (Richey & Klein, 2005). To keep the quality and performance solid, the work involved different tasks like getting expert reviews, checking usability, and running field tests. Following this process, the researchers were able to develop a prototype to see how well the HuskyLens AI could find and diagnose diseases in Zea mays as it focused on testing the system's ability to identify the severity of DM, CR, and NLB on the leaves.

Procedure

Block Diagram of the Prototype Zea mays Disease Detection Device

The HuskyLens AI sensor scanned and classified maize leaves into 4 categories, which were Healthy, DM, CR,

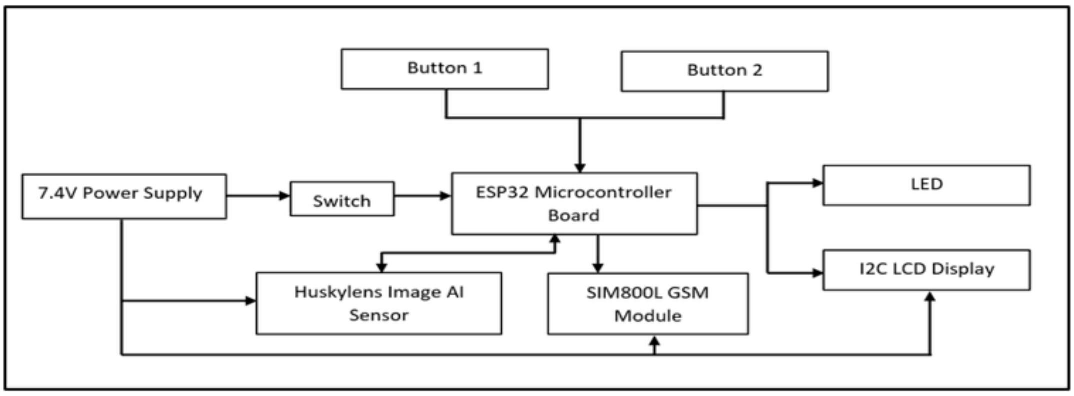

Figure 1: Block Diagram

and NLB. It then sent the classification ID to the ESP32 microcontroller via UART (Universal Asynchronous Receiver/Transmitter). The ESP32 processed this ID and relayed the result to the I²C LCD display for viewing while simultaneously transmitting it to the GSM SIM800L module, which sent an SMS containing the diagnosis to the farmer's registered mobile number. Power was supplied by a 7.4 V lithium-ion battery, while RGB LEDs provided visual indicators, and buttons were used where users could scan and transmit, as shown on Figure 1.

Prototype Design of Zea mays Disease Detection Device

Figure 2 illustrates the visual appearance (from left to

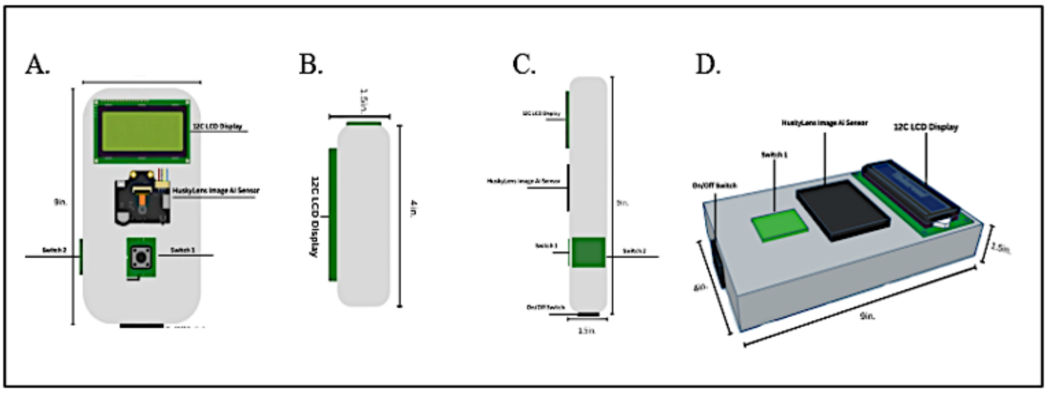

Figure 2: Prototype Design

right) of the prototype from A) front view, B) top view, C) side view, and D) isometric view. The prototype uses the HuskyLens AI image sensor with an ESP32 microcontroller, GSM SIM800L module, and I²C LCD. Including RGB LEDs as indicators and is housed in a protective casing for durability and ease of use in field conditions. The device measures two 2 inches in height, 8 inches in length, and 4.5 inches in width.

Circuit Diagram of the Prototype Zea mays Disease Detection Device

As shown in Figure 3, a 7.4 V lithium-ion battery was

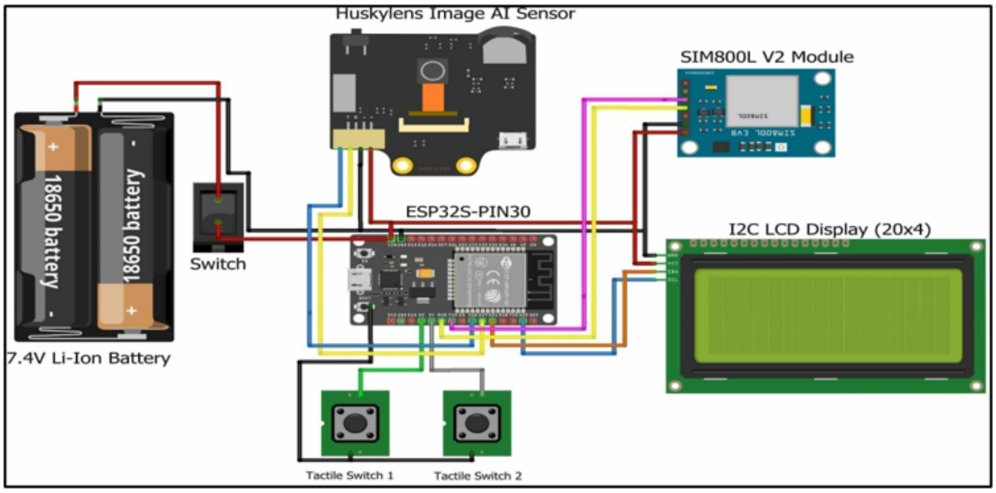

Figure 3: Circuit Diagram

connected through a switch that provided power to the system. At the center was the ESP32 microcontroller board, which served as the main processing unit that received data and executed the functions of all modules. The HuskyLens AI image sensor was directly linked to the ESP32 microcontroller to capture and identify maize leaf images. An I²C 20×4 LCD was included to show results for output display, while the SIM800L V2 GSM module enabled the device to send notifications through SMS. A tactile switch was connected to allow users control for functions such as scanning leaves and sending SMS.

Device Development

System Programming Setup

The Arduino IDE software was used to program the ESP32 microcontroller, enabling it to control the HuskyLens AI camera and the GSM SIM800L module. The GSM module was set up to send SMS results directly to farmers for offline accessibility. The HuskyLens AI was programmed to capture, identify, and classify maize leaves into four groups which are Healthy, Downy Mildew, Common Rust and Northern Leaf Blight.

Integration of SMS Feature

Using Arduino IDE, the researchers designed in programming the SMS feature allowing the user to register multiple mobile numbers to receive data from the device. The ESP32 microcontroller was used to encode the result and send it to the GSM SIM800L module which sent an SMS to the farmer's mobile phone. Each message relayed the detected maize leaf condition, a description of the symptoms, and a brief recommendation for management.

System Flow of the Prototype

Figure 4 illustrates the system flow, which begins when the power switch is turned on. The first button activates the

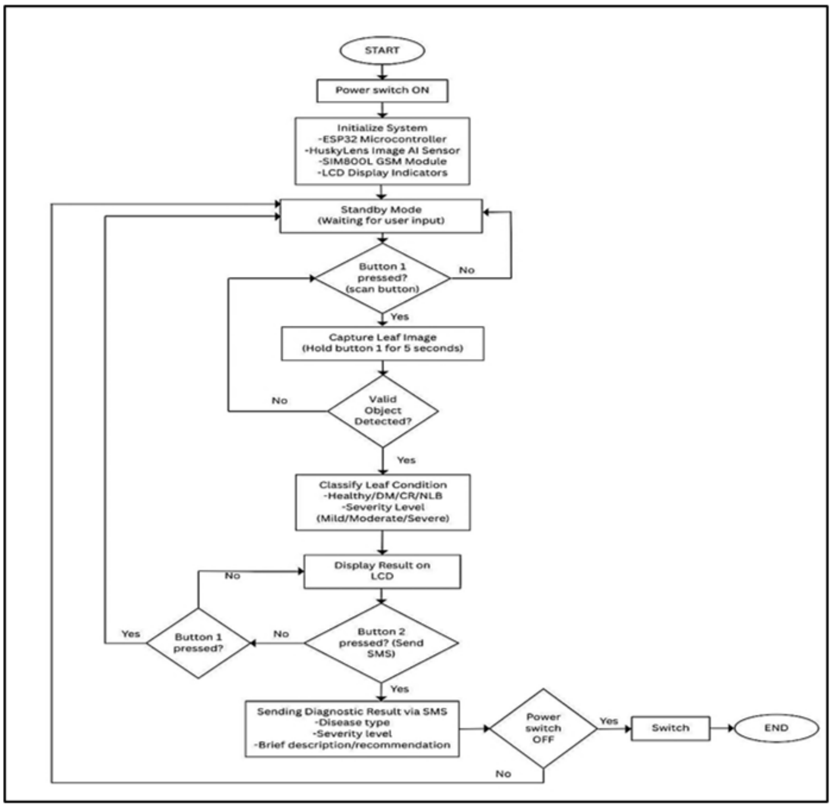

Figure 4: System Flow

scanning process and the detection result is displayed on the I²C LCD. The second button allows the transmission of the detection and diagnosis through SMS using the GSM SIM800L module. Once the power is turned off, the system will shut down.

Image Data Collection

Images of maize leaves were captured using the HuskyLens AI sensor to detect the target diseases: DM, CR, and NLB. The whole maize leaf roughly centering in the frame was scanned to create the data set. The captured images were stored in the HuskyLens AI microSD card and then transferred to a computer for manual labeling and dataset annotation. The images were stored and labeled for incremental training with the microSD card preserving the trained models for recognition.

Construction and Annotation of Image Dataset Data Classification

Figure 5 displays the sampled conditions images of maize leaf. Leaf images were sorted into four categories: “Healthy” (no visible disease), “DM” (chlorotic streaks

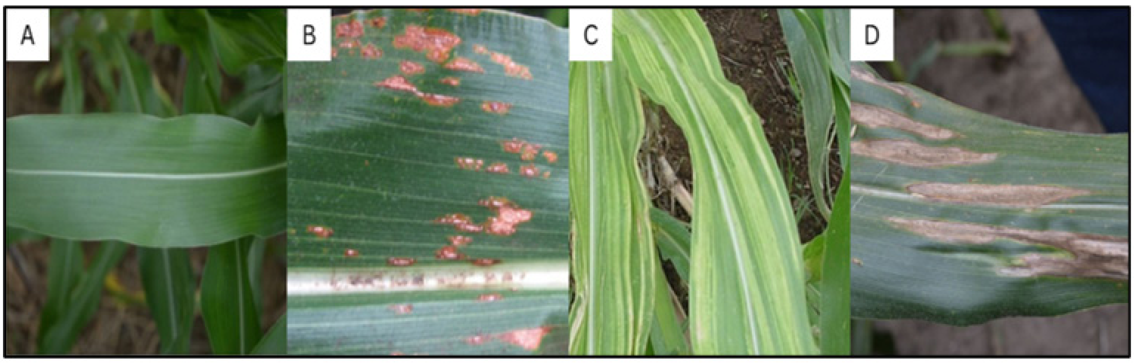

Figure 5: Leaf Sample Classification

with downy growth), “CR” (reddish-brown pustules), and “NLB” (elongated lesions with gray-green discolouration). There were a total of 2,316 images acquired for the study. An agricultural specialist confirmed these classifications to ensure the accuracy of disease identification and mitigating errors in trials.

Data Labeling and Dataset Splitting

The researchers manually labeled the pre-processed images into four different classes and placed them into separate folders. The whole dataset was then split into three parts: 70% for training, 15% for validation, and 15% for testing. After that, specific samples from these folders were uploaded to the HuskyLens AI for more training and testing. This process was repeated until the model was able to recognize the diseases accurately.

Data Pre-processing

After the experts finished checking the study images, the researchers preprocessed them by resizing each one to 320 × 240 pixels. This step was done to make sure every image was uniform for the system. The team also took out any blurry or low-quality photos so the HuskyLens AI could do a better job spotting the diseases in the Zea mays samples.

Table 1: Distribution of Maize Leaf Images Used for Model Development

Class	Training	Validation	Test	Total
Healthy	405	87	87	579
Common Rust	405	87	87	579
Downy Mildew	405	87	87	579
Northern Leaf Blight	405	87	87	579
Total	1620	348	348	2316

Severity Level Annotation

To get the data ready, the researchers went through an annotation process by labeling every leaf image based on the amount of disease on the surface. They used this method to sort the pictures into three groups: Mild, Moderate, and Severe. After that part was finished, agricultural experts double-checked the images to make sure the labels were actually right and that the categories stayed consistent across the whole set.

Model Training

Pre-training Module

In the pre-training phase, the HuskyLens AI was trained using actual maize leaf samples on field, where all the information was held using a microSD card. After that, through programming, it was registered into the HuskyLens AI and every disease category, along with the healthy class, had a unique ID label that was assigned for proper identification.

Incremental Training

Samples were added after the 5 baselines pre-training images until the healthy and per severity class reached approximately 135 images, adding up to 405 per disease. The training process in improving robustness involved capturing the samples from different lighting conditions, angles, and stability of scanning. Additional samples were gradually added until the sensor was able to consistently distinguish between four classes and their three (3) different severity levels.

Post-training Module

After initial training, the model was then tested with independent maize samples that were excluded in the training set. Misclassifications were identified when the HuskyLensAI assigned an incorrect class ID compared to the ground truth analysis conducted by expert assessments. These were then corrected by adding more training samples to the underperforming class. All categories underwent more than 10 exposure attempts to demonstrate differences in symptom types and the reliability of the AI for classifying the different symptoms. The AI classified the images directly during training. Any images that had been misclassified were re-exposed to the AI until it maintained reliability for classifying that specific image based upon training. Independent leaf images, not included in training, were then tested to compute the final accuracy as the percentage of correctly classified samples over the total tested samples. Misclassifications were again recorded, and additional exposures were introduced to improve weak categories.

Device Evaluation

Functionality Test

A checklist was used to confirm whether each component of the device was functional. The functionality test was necessary to ensure that each part of the device worked properly and was ready to proceed to system validation.

System Validation

The device underwent system validation which made sure that the device could detect maize leaf diseases and send SMS results directly to farmers, which was the main purpose of the design of the prototype. The system's answers were compared with the judgment of experts to check if the classifications were correct, and field trials were done to see if the device worked consistently under real farm conditions.

Model Evaluation

After building the prototype, the performance of the prototype was evaluated using evaluation metrics, specifically the confusion matrix–based metrics for

machine learning models.
TP = true positive is the number of diseased leaves correctly identified as diseased
TN = true negative, is the number of diseased leaves correctly classified as diseased
FP = false positive, is the number of diseased leaves incorrectly predicted as diseased
FN = false negative, is the number of diseased leaves incorrectly classified as healthy

Eq. 1. Accuracy
$$\frac{TP + TN}{TP + TN + FP + FN}$$

Eq. 2. Precision
$$\frac{TP}{TP + FP}$$

Eq. 3. Recall
$$\frac{TP}{TP + FN}$$

Eq. 4. F1-Score
$$\frac{2\ x\ Precision\ x\ Recall}{Precision + Recall}$$

Eq. 5. Device Response Times
$$\frac{1}{n}\sum(Ti - Tf)$$

Testing and Performance Evaluation

In addition to these quantitative measures, the expert evaluation was conducted by a panel of five (5) agricultural and information technology (IT) specialists selected based on the following criteria: a) at least five (5) years of professional or research experience in plant pathology, agronomy, crop science, or information technology related to agricultural systems; b) direct knowledge or field experience in maize production and disease management, or the development and implementation of agricultural information systems; c) current affiliation with a recognized academic institution, agricultural agency, or government office; and d) preferably holding a valid license or professional certification in agricultural, information technology, or a related field. To assess the prototype, the experts used a 5-point Likert Scale to evaluate two (2) main aspects: 1) Acceptability, how well the system meets the needs of farmers and stakeholders and 2) Adaptability, how suitable the system is for real-time agricultural use. Moreover, the Likert scale used in the study was interpreted as follows: mean scores ranging from 4.50 to 5.00 indicate Strongly Agree, 3.50 to 4.49 indicate Agree, 2.50 to 3.49 indicate Neutral, 1.50 to 2.49 indicate Disagree, and 0 to 1.49 indicate Strongly Disagree.

Data Analysis

This study used a confusion matrix–based metrics and descriptive statistical methods to analyze and interpret the collected data. The performance of the system was evaluated in terms of accuracy of classification, recall, F1 score, precision, device response time, and SMS response time. Accuracy, recall, F1 score and precision was calculated using the confusion matrix–based metrics to ensure consistency and reliability across all trials. On the other hand, response time and SMS response time were taken from the classification results and descriptive statistics (mean). This was measured by a timer, in terms of the duration between when the button is pressed, presented on the LCD and when the SMS is successfully received by a device. In addition, expert evaluations were analyzed using descriptive statistics to assess the prototype's acceptability, or how well it meets the needs of farmers and stakeholders and adaptability, or its suitability for real-world agricultural applications.

Ethical Consideration

This research was carried out with a firm commitment to ethical standards to ensure the protection of the participants and the validity of the research. The researchers wrote a formal request letter to the school principal to seek approval, and coordination was made with the Department of Agriculture-Region XII and the Bayer Crop Science Breeding Nursery, which is located in the City of Koronadal to comply with the local policies and to seek technical support. Individuals involved in data gathering and system testing were given informed consent before the study was conducted. The information collected from the participants was used for research purposes only. Written works as well as system-generated documents were checked for plagiarism to ensure academic integrity, and AI-assisted documents were also reviewed and checked for originality.

RESULTS AND DISCUSSION

Following the functionality testing and evaluation of the prototype, the collected data underwent analysis and interpretation. Therefore, this segment unveils the graphical, tabular, and narrative representations of the study's findings alongside their associated implications. Furthermore, this section offers discussions of the results substantiated by various research studies.

Table 2: Functionality Test for the Prototype

No.	Components	Functional
1	HuskyLens AI	/
2	ESP32 Microcontroller	/
3	LCD Display	/
4	GSM SIM-800L Module	/
5	User Interface Components (e.g., buttons & switches)	/

Table 2 shows the checklist for the components and their functionality. It can be shown in the table that the following components are functional and can work together to create a functional system.

Image-based Classification Model using HuskyLens AI

Figure 7 illustrates the LCD screen outputs of the system for four detection categories: a) healthy, b) common rust, c) Downy Mildew, and d) Northern Leaf Blight,

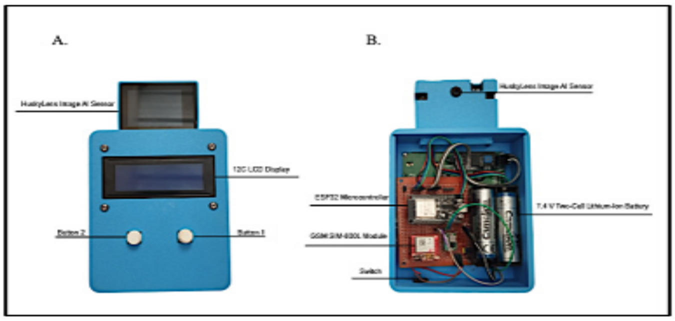

Figure 6: Developed Prototype

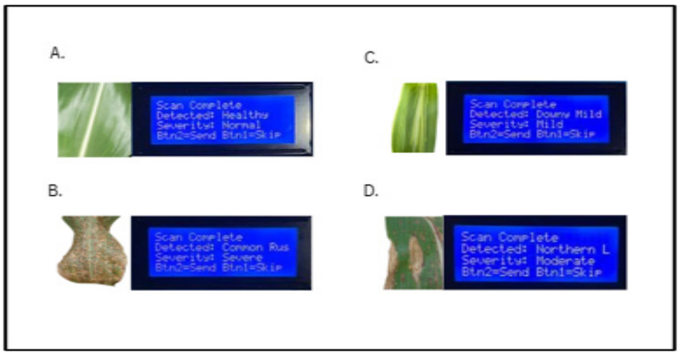

Figure 7: LCD Screen Outputs

each classified according to severity levels, including normal, mild, moderate, and severe. The system was able to accurately identify maize leaf health conditions and distinguish severity degrees. This performance may be attributed to the dataset development process, which involved systematic image capture, proper labeling, and detailed annotation. These are well-established image-based plant disease detection practices for heightened model accuracy and reliability (Khirade & Patil, 2015). Consistency of previous studies that have adopted this method highlights the reliability of image processing and deep learning approaches in plant disease diagnosis (Mohanty *et al.*, 2016).

Moreover, the system demonstrates its capabilities to process images while generating diagnostic results which are displayed directly on an LCD screen thus proving that AI models can function within embedded systems without needing external computer power. Also, the device functions better in agricultural environments because it operates independently of internet access which makes it suitable for use in areas where internet service is irregular or nonexistent. This aligns with related works emphasizing the successful application of compact, edge-computing vision systems for real-time agricultural monitoring (Soetedjo & Hendriarianti, 2021; Singh & Krishnamurthi, 2024).

HuskyLens AI System Evaluation

Table 3 highlights the summary of the performance of the maize disease classification model with the HuskyLens AI model demonstrating the reliable and well-balanced performance in all the classes of the disease. The model

Table 3: Performance Matrices and Interpretation of the Classification Model

Performance Matrix	Pre-training (Means±SD)	Post-training (Means±SD)
Accuracy	0.86±0.04	0.89±0.06
Precision	0.88±0.09	0.90±0.09
Recall	0.96±0.07	0.99±0.02
F1-Score	0.92±0.03	0.94±0.04

Note: Values nearest to 1.00 represent optimal performance (100%). Results are expressed as mean ± SD from 87 validation trials per disease class, where lower SD indicates greater consistency) showed consistent post-training improvement in all the evaluation metrics, accuracy of 0.89, precision of 0.90, a significant improvement of recall between 0.96 and 0.99 and a F1-score of 0.94, demonstrating better learning effectiveness post-training. It demonstrates that the HuskyLens AI system was capable of processing more discriminative visual characteristics of maize leaf diseases that led to more consistent prediction and better classification of healthy and diseased phenotypes. In addition, the smaller variability of the performance measures post-training indicates higher levels of confidence and strength of the model when making the inference.

Furthermore, the high and constant recall value of 0.99 indicates that it is highly sensitive to the occurrence of the disease and thus the occurrence of false negatives is reduced. This is necessary in the agricultural sector where infected plants are not ignored much and therefore early detection and containment of the disease is achieved. As a result, the system will lead to better decision-making in the discipline and lessening possible losses of crops especially in the smallholder farming settings.

Although the overall accuracy of the 0.90 remains lower than cloud-based deep learning models, its emphasis on offline operation, with real-time processing and low power consumption makes it more suitable for deployment in low-connectivity regions such as South Cotabato, where accessibility, immediacy, and practical field usability are prioritized.

System Performance and Model Evaluation

Table 4 shows the mean response time of the device, in terms of the duration between when the button was pressed, presented on the LCD and when the SMS is successfully received by a device, during the pre-training and post-training of the device. The mean of the device's response time in the pre-training was 11.08 seconds. While in the post-training after 348 trials, the device achieved a short response-time of 8.13 seconds. The device demonstrated a 26.6% improvement rate. The SMS response time of the prototype was measured from button press to message receipt. In 30 pre-training trials, the average response time was 30.2 seconds, ranging from 25 to 35 seconds. After 370 post-training trials, the prototype improved, with an average response time of 24.8 seconds (20–28 seconds), showing a 17.9% improvement. This demonstrates that the system became faster and more consistent in delivering messages, although it remains slower than typical SMS delivery of 5–10 seconds reported in previous studies (Mary, 2023).

Table 4: Device and SMS Response Times

Device Response Times	Pre-training (Mean±SD)	Interpretation	Post-training (Mean±SD)	Interpretation
Device Response Time (Scan to LCD)	11.08±1.10	Good	8.13±0.48	Excellent
Device Response Time (Scan to SMS receipt)	30.2±1.16	Good	24.84±1.78	Good

Source: BulkSMSNigeria, 2025 (2-10 seconds= Excellent, 10-60 seconds= Good, 1-5 minutes= Slow, 5+ minutes= Concerning)

The acceptability evaluation results in Table 5 show that users highly accepted the prototype, with an overall mean of 4.52, indicating a very high level of satisfaction. The most notable indicators include overall satisfaction, likelihood to recommend the prototype, and ease of use and intuitiveness, which suggest that the system is user-friendly and reliable. As shown, users also evaluated the prototype as easy to understand and that its features matched its purpose, indicating that it is practical for agricultural field use. This supports recent studies which emphasize that systems perceived as easy to use and useful are more likely to be accepted, especially in AI-based and agricultural technologies (Mary, 2023 & Rijswijk, 2021). These findings imply that the AI-based offline

Table 5: Acceptability Test Results of the Prototype

No.	Indicator	(Mean±SD)	Interpretation
1	Understanding the functionality of the prototype was easy.	4. 6 ± 0.70	Very High Level
2	It is easy to add new features or functions to the prototype. The user is satisfied with the performance of the prototype	4.5 ± 0.85	Very High Level
3	I am likely to recommend this prototype to others.	4.7 ± 0.48	Very High Level
4	The prototype was intuitive and easy to use.	4.6 ± 0.70	Very High Level
5	The prototype design/layout is intricate and well–thought out.	4.2 ± 0.63	High Level
6	The wire management of the prototype is satisfactory.	4.5 ± 0.53	Very High Level
7	The features of the prototype are relevant to its purpose.	4.6 ± 0.52	Very High Level
8	The different parts of the prototype are easy to navigate.	4.5 ± 0.53	Very High Level
9	Overall, the user is satisfied with the prototype.	4.8 ± 0.42	Very High Level
Overall Post-implementation Mean		4.52	Very High Level

fungal disease detection system with SMS integration is user-friendly and suitable for practical agricultural use, particularly in areas with limited internet access.

The adaptability test results in Table 6 show that users rated the prototype with a very high level of adaptability, with an overall post-training mean of 4.52. Strong ratings were observed in indicators including the ability to add new features, adjust the system to different user needs, keep up with technological changes, and the quality of the materials which shows that the prototype is flexible and durable. Users also reported that they could change settings easily, assemble and disassemble the device, use it in different places and conditions indicating that the system is useful for field use. This supports studies emphasizing that AI- and IoT-based agricultural systems must be adaptable and robust to perform effectively in real farm environments[22-23]. These findings suggested that the prototype is suitable for practical agricultural use and can be applied in real farm conditions with only minor setup adjustments.

Table 6: Adaptability Test Results of the Prototype

No.	Indicator	(Mean±SD)	Interpretation
1	The prototype can easily be adjusted to fit different user needs.	4.5 ± 0.71	Very High Level
2	It is easy to add new features or functions to the prototype.	4.8 ± 0.42	Very High Level
3	Users can change settings or how the prototype works without trouble.	4.3 ± 0.67	High Level
4	The prototype can keep up with new trends or technological changes.	4.5 ± 0.71	Very High Level
5	Users can make the prototype fit different places or conditions.	4.4 ± 0.52	High Level
6	Putting together or taking apart the prototype is simple and doesn't need special tools.	4.3 ± 0.67	High Level
7	The prototype's materials are strong and can handle different kinds of weather.	4.5 ± 0.53	Very High Level
8	Storing, moving, and using the prototype in different places is easy.	4.3 ± 0.82	High Level
Overall Post-training Mean		4.52	Very High Level

GSM-based SMS Integration

Figure 8 presents the GSM-based SMS user interface that uses said technology to send alert messages which include information about detected diseases, severity, and the corresponding diagnosis or recommended course of action. The message format was intentionally kept concise and direct to enhance readability and practicality in field conditions which is consistent with studies that show brief SMS alerts improve comprehension and response efficiency in agricultural settings (Aker, 201; Mittal & Mehar, 2016). To ensure accessibility for local users, the SMS notifications were programmed in Filipino. The use of the local language improves understanding, usability, and technology adoption among farmers, as supported by previous research on digital agricultural systems (Qiang *et al.*, 2012 & FAO, 2019). This allows farmers to easily interpret critical crop health information without the need for technical expertise. Survey results from the researchers further indicate that the direct message format effectively provides clear results and actionable instructions without requiring extended reading time. The concise structure also enables users to read messages directly from their mobile phone lock screens, reducing interaction complexity and cognitive load. This design is particularly beneficial for farmers operating in time-

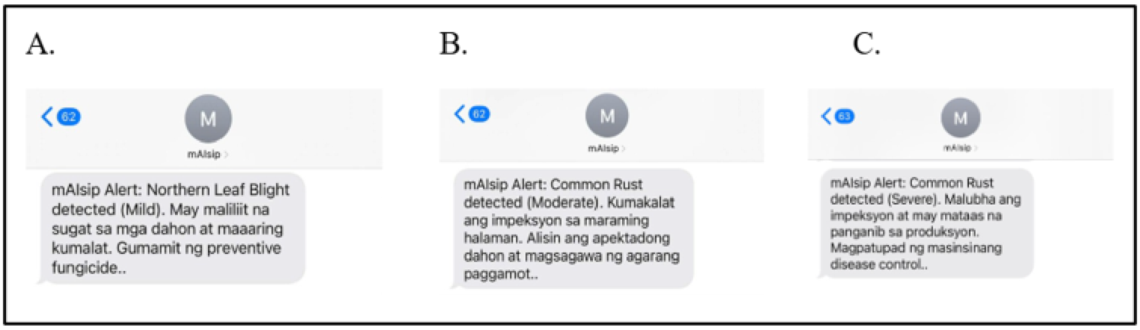

Figure 8: Offline GSM-based SMS Feature

constrained field environments (Nakasone, Torero, & Minten, 2014).

CONCLUSION

The study 1) developed, labeled, and annotated an image-based classification model for detecting Healthy leaves, Downy Mildew, Common Rust, and Northern Leaf Blight in Zea mays using the HuskyLens AI and an ESP32 to build a standalone device that diagnoses diseases right in the field. This tool provides a clear look at Zea mays health by identifying severity levels from Normal to Severe and replaces simple guessing with a system that works offline without any need for the internet. 2) The classification performance of the model shows 99% recall, 89% accuracy, and a 94% F1 score, with quick results taking only 8.13 seconds on the LCD and 24.84 seconds for an SMS alert. 3) Along with the technical testing, adaptability and acceptability of the prototype, users find it very easy to use with an average score of 4.52, which confirms the portable design is reliable and strong enough for the weather on local farms. 4) The project also integrates a GSM based SMS feature to send diagnostic results and brief instructions in Tagalog directly to mobile phones, which helps farmers in the SOCCSKSARGEN region manage their crops and stop diseases from spreading in the tropical climate.

Recommendations

Future studies should look at increasing the overall number of images, as well as the diversity of images used in the classification process to improve the accuracy of the classification process and should include additional maize diseases such as viral infections (i.e. Maize Mosaic Virus) in order to account for the changing conditions of the crops. Since the AI model can be retrained with new datasets it can be adapted for other crops allowing for scalability and applicability in a variety of agricultural systems. Method refinement should include optimizing the training process to maximize the management of the device's memory, and under adverse lighting conditions it may increase the accuracy by using standard data collection protocol where lux levels are specified. Incorporating an exhaust fan for the device is recommended to reduce heat buildup, and moving the ON button from the bottom of the device to the side will improve usability. Improving the power efficiency is also recommended which will allow for a more efficient field operation while reducing interruptions. The user experience could be further improved by refining the SMS alert feature to minimize repetitive messages that are clearer. The use of innovative technology; providing more affordable technology to detect diseases as early as possible while providing technology-based solutions for monitoring crops in under-resourced areas is how this system supports smarter farming practices. From an implemented perspective, smallholder farmers located in low-connectivity areas can use this system, along with agro-technology extension agents, and local government agencies, to implement a practical solution for the early detection of diseases and effective crop management. Prior to its widespread implementation, this system should be field tested in different geographical regions on numerous crops and for more than one growing cycle for evaluation.

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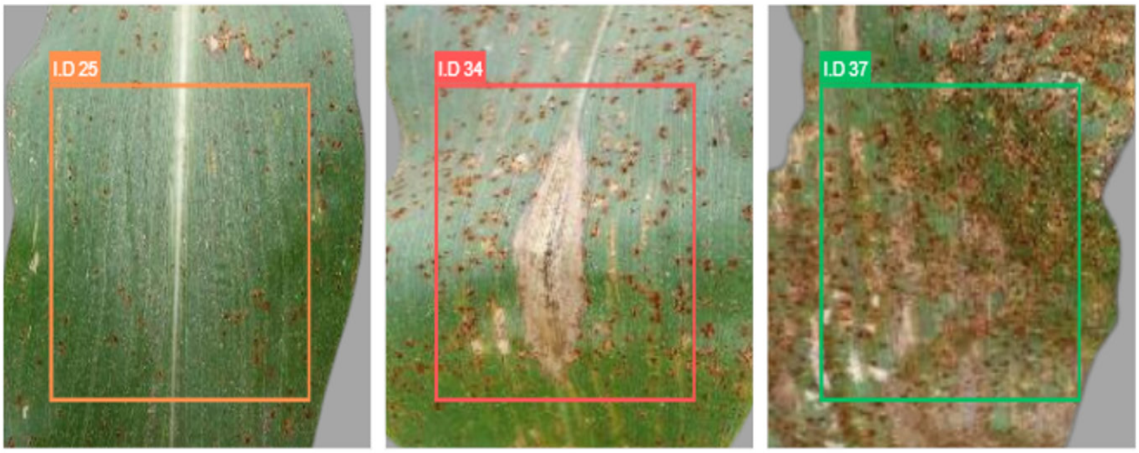
APPENDICES

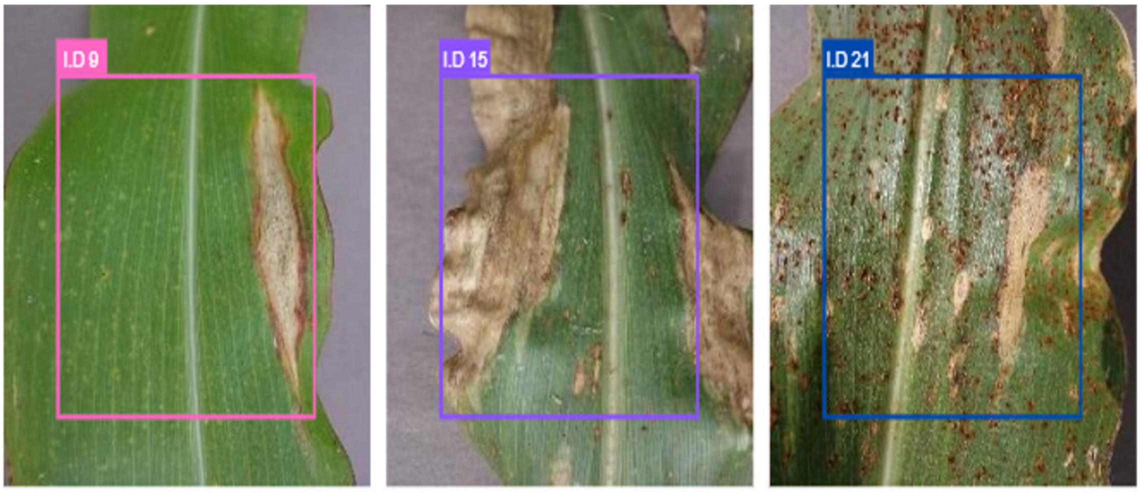
Appendix A. Annotation of Maize Leaf Images

Appendix A.1: Healthy

Appendix A.2: Common Rust



Appendix A.3: Northern Leaf Blight



Appendix A.4: Downey Mildew