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Mobile-Based AI Platform Integrating Image Analysis and Chatbot Technologies for Rice Variety and Weed Classification in Precision Agriculture

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Abstract

This work presents the development of an intelligent chatbot system capable of identifying rice plants and weeds from aerial photographs captured by smartphones, thereby enhancing precision agriculture. The study involves creating an AI model that utilizes image processing and deep learning techniques. Users can access the model through a LINE chatbot, and the study will also assess users' satisfaction with the model. Researchers gathered 12,000 pictures of rice fields in Phayao Province, Thailand, to train a modified InceptionV3 model using transfer learning. The dataset included images of rice plants and various types of weeds. The model was trained using image data collected under natural lighting and augmented to improve generalization. It achieved training, validation, and testing accuracies of 98.79%, 96.08%, and 97.83%, respectively. When deployed through a LINE Chatbot, it analyzed user-submitted images to estimate rice-to-weed ratios, yielding 73.33% average accuracy with consistent rice detection. Thirty individuals who used the system reported that it functioned well, was user-friendly, and provided significant benefits for farming in real-world applications. These results suggest that the system could leverage easily accessible AI tools to enhance farming efficiency, reduce costs, and positively impact the environment.

Keywords: Aerial Image Analytics, Chatbot System, Plant Classification, Precision Agriculture, Rice Recognition, Weed Recognition

1. Introduction

In the era of the Fourth Industrial Revolution (Agriculture 4.0), integrating information technology, artificial intelligence, and automation into agricultural activities has become a vital approach to enhance production efficiency, management accuracy, and sustainable resource use. One of the core concepts of precision agriculture is the ability to monitor, analyze, and make real-time decisions based on accurate data, particularly in distinguishing between rice plants and weeds, which are crucial factors that directly impact yields and farm management costs.

It results in precision agriculture being crucial in modern times [1], [2], [3]. It is a method of agricultural land management that prioritizes technology and comprehensive data to enhance efficiency and production, reduce costs [4], and sustainably mitigate environmental impacts [5]. The need for sustenance is concurrently escalating in this era, marked by a rapid rise in the global population. As a result, precision agriculture is an essential tool that enables farmers to optimize resource management and adapt more effectively to market demands and climate change.

Furthermore, weed management and plant identification in rice fields are significant challenges for farmers [6], [7]. Weeds greatly affect the growth of essential crops like rice by competing for water, nutrients, and sunlight, ultimately leading to reduced yields. Accurate and timely weed identification and management are, therefore, essential. However, traditional weed detection methods in rice fields are labor-intensive and time-consuming, resulting in errors and delays in management. Consequently, developing technology to assist in identifying plants and weeds based on images has emerged as a more effective alternative. Consequently, the necessity for Artificial Intelligence (AI) technology and image processing to assist agricultural practitioners represents a viable solution to current challenges [8]. Likewise,

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artificial intelligence and image processing are necessary for precise object analysis and classification within images. The deployment of artificial intelligence in agriculture enables fast and accurate picture data analysis from rice fields, resulting in reduced dependency on human inspections and empowering farmers to make more timely and effective decisions [9]. This benefit is especially noteworthy when deep learning technology, capable of identifying intricate visual patterns, is included.

Innovations in smartphone technology and wide-angle photography have profoundly altered image data acquisition in agriculture, particularly in precision agriculture. This process necessitates high-resolution and comprehensive image data for precise analysis and informed decision-making. Researchers can delineate three principal dimensions. The first dimension involves integrating AI-driven image processing with smartphone cameras [8], [10], [11]. AI image processing combines AI technology with smartphone cameras to facilitate faster and more accurate image processing, including auto-lighting, noise reduction, and image sharpening. These enhancements are valuable for analyzing agricultural images to support informed decision-making.

The second dimension emphasizes enhanced convenience and cost efficiency [4], [5]: AI provides farmers with a more convenient and cost-effective method for collecting aerial images using smartphones, which is more affordable than employing drones or other aerial photography equipment. Farmers can use their existing smartphones to take pictures of their fields and run various applications that allow for immediate analysis of the images.

Finally, the last dimension focuses on utilizing chatbots for communication [12], [13]. AI can enhance chatbot communication by developing chatbot platforms that farmers already use, such as LINE, facilitating fast and efficient communication and providing agricultural information. Farmers can request information or receive expert advice via chatbots at any time. With these advancements, smartphones represent a highly effective tool to support precision agriculture, particularly in areas with limited resources or access to advanced technology.

At the same time, the role of deep learning, an AI tool, in plant image classification is meaningful. Deep learning plays a big part in identifying plant and weed images by learning complicated photo patterns and details [14], [15]. This results in better accuracy than older methods like classical image processing or set features. Whereas image processing and deep learning are processes that take raw images and convert and analyze them to extract useful information, deep learning is an AI technique that utilizes multiple layers of neural networks to learn complex image features, enabling high-performance and accurate object classification. Popular deep neural network architectures, such as InceptionV3 [16], ResNet [17], and EfficientNet[18], are utilized to improve image classification performance. InceptionV3 is specifically designed to capture detailed and multidimensional image features, enabling high-accuracy classification of rice and weed images. Ultimately, the model's accuracy and efficiency in classifying rice and weeds led to its ability to classify rice and weed images, demonstrating high precision in differentiating between various plant species. Consequently, it can serve as a decision-making tool for effective rice field management and as a foundation for the future development of smart agricultural technology.

This research proposes an intelligent chatbot system that can collect aerial photography data from users and automatically analyze and identify rice plants and weeds using image processing and deep learning models built on field datasets. Researchers created the chatbot system with a conversational interface to make advanced technologies accessible without technical understanding. The system may also advise on herbicide spraying and field operations, reducing expenses, increasing productivity, and supporting sustainable agriculture. Thus, this research uses artificial intelligence, image processing, human-machine communication, and agricultural science to build tools for the Thai agriculture industry and developing nations in the 21st century.

1.1. Research Objective

This research primarily aims to develop an intelligent chatbot system capable of identifying rice plants and weeds using aerial images captured via mobile devices, thereby enhancing the efficiency of precision agriculture. The study has three main goals: (1) to create an AI model that can identify different types of rice and weeds using image processing and deep learning; (2) to create a platform that farmers can use to get plant analysis data, helping them make better decisions for managing their rice fields; and (3) to assess how satisfied users are with the system that combines image analysis and chatbot features. These objectives support the formulation of both primary and secondary research

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hypotheses. For training and testing, the dataset comprises images of sticky rice, jasmine rice, and various weed species. However, the aim is not to identify specific rice or weed types, but to classify images broadly as either rice or weed.

1.2. Research Hypothesis

The central premise of this research is that an innovative chatbot system, integrating image processing, deep learning, and context-aware communication, can accurately distinguish between rice plants and weeds in aerial photographs while effectively supporting local farmers in their decision-making processes. The researchers propose three sub-hypotheses: (1) A deep learning model trained on real aerial images can correctly identify rice plants and weeds at least 90% of the time while respecting the cultural importance of rural farming; (2) A chatbot that communicates in a way that fits rural users will be easier to understand and more widely used than one that ignores local context; and (3) Users will see the system as a helpful tool that adds to, not replaces, traditional farming knowledge. The research adhered to an ethically sound structure, with all images and data collected with the explicit consent of the landowners. The system was implemented and evaluated with the involvement of users and experts possessing domain knowledge in both artificial intelligence and agriculture.

2. Materials and Methods

This research aims to classify and diagnose weeds in rice fields using wide-angle and aerial images captured exclusively via smartphones, ensuring representation of real-world field conditions. It also focuses on developing and deploying an intelligent Line chatbot that integrates digital image processing with OpenCV and advanced AI techniques to detect common weed species found in northern Thailand, including Echinochloa crus-galli (Ya Khao Nok), Leptochloa chinensis (Ya Hang Ma Jing Jok), Sphenoclea zeylanica (Ya Dok Khao), Fimbristylis miliacea (Kok Khanak), and Cynodon dactylon (Ya Praek). The system is designed not only to classify these weeds but also to estimate field areas and provide actionable guidance for effective weed management, with the overall research framework comprising five core components as shown in figure 1.

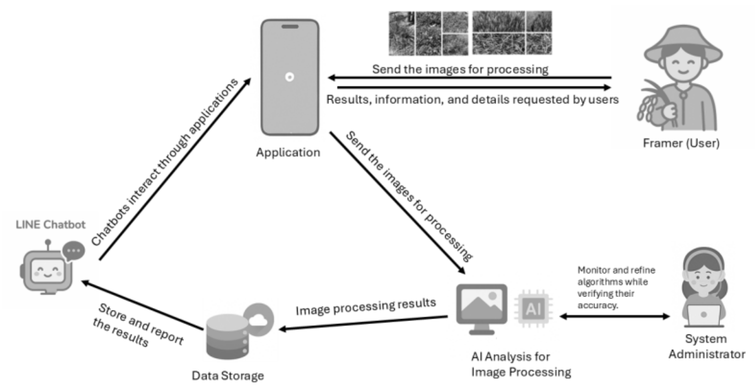

Figure 1. System Architecture Diagram

Figure 1 shows the five main research stages. Researchers create a database of real-world weed and rice samples by taking wide- and high-angle images of rice fields in northern Thailand using high-resolution cellphones. Second, we build an AI model using deep learning to categorize weeds from these photos, continuously modifying it to improve accuracy and efficiency. Third, a Line chatbot analyzes user-submitted pictures and offers diagnostic advice and weed control advice. Fourth, the system is tested in real farms for classification accuracy, processing speed, and user satisfaction. Researchers review the final findings to evaluate the chatbot's effectiveness, pinpoint its shortcomings, suggest improvements, and explore its agricultural potential.

2.1. Data Collection

Between August and November 2024, researchers took high-resolution, wide-angle aerial photos of sticky rice and Thai Hom Mali rice fields in Mueang District, Phayao Province, Northern Thailand, using current smartphone cameras. Approximately 12,000 photos were collected at elevations of 2-5 meters, with sizes of 1477 × 1108 and 960 × 1280 pixels. The dataset was evenly split between 6,000 rice plants and 6,000 weed shoots. Weed photos showed green-leaf, flowering, yellow-red, white-flowered, and yellowish-brown grasses. A complete image library of the natural field environment is available at https://shorturl.at/SBXbk. Figure 2 and figure 3 illustrate representative views of sticky rice and Thai Hom Mali rice, along with photographs of each weed species within multidimensional rice fields.

Figure 2. Sticky Rice and Thai Hom Mali Rice Plants in the Rice Field

Figure 3. Weeds in the Rice Field

2.2. Data Preparation

The dataset was prepared by collecting rice and weed photos from various sources. The dataset has 12,000 photos, evenly split between rice plants (6,000) and weeds (6,000). Sticky rice and jasmine rice dominate the images. Each variety has equal representation in three growth stages: green leaves without panicles, green leaves with panicles, and yellow leaves with panicles. The weed category includes green-leaf grasses, flowering grasses, yellow-red leaves, white-flowered grasses, and yellowish-brown vegetation, with photos uniformly dispersed. Agricultural specialists in rice cultivation and weed detection manually annotated and cross-validated all photos to improve labeling accuracy and model reliability. Labeling mistakes were reduced, and rice and weed classification were consistent with this validation approach. Different rice development phases and weed types are included to make the model more robust in real-world agriculture. Table 1 details the dataset.

Table 1. Summary of Dataset Classes and Sample Sizes

Label	Sub-category	Number of Images	Training	Validation	Testing
	Sticky rice, green leaves without panicles	1,000	700	150	150
	Sticky rice, green leaves with panicles	1,000	700	150	150
Rice	Sticky rice, yellow leaves with panicles	1,000	700	150	150
	Jasmine rice, green leaves without panicles	1,000	700	150	150
	Jasmine rice, green leaves with panicles	1,000	700	150	150

Label	Sub-category	Number of Images	Training	Validation	Testing
Weeds	Jasmine rice, yellow leaves with panicles	1,000	700	150	150
	Green-leaf grasses	1,200	840	180	180
	Flowering grasses	1,200	840	180	180
	Leaves with yellow-red pigmentation	1,200	840	180	180
	White-flowered grasses	1,200	840	180	180
	Yellowish-brown vegetation	1,200	840	180	180
	Total	12,000	8,400	1,800	1,800

The images then underwent a comprehensive and meticulous preprocessing phase, which included data cleaning, labeling, and resizing. Subsequently, the dataset was systematically divided into training (70%), validation (15%), and testing sets (15%). This rigorous data preparation ensured the dataset's quality and consistency, ultimately enhancing the model's training efficiency and accuracy. The entire process was structured into five key steps.

2.2.1. Data Cleaning

Data cleaning is a crucial step in creating efficient, highly accurate deep learning models. This step aims to ensure that the collected data is of high quality and suitable for training the model.

2.2.2. Connecting to Data Sources

The dataset used in this study was stored on Google Drive, and a connection was established between Google Drive and Google Colab to enable efficient data access and usage. The dataset was organized into three subsets within the main folder: a training set, a validation set, and a test set. The training set was used to teach the model to distinguish between rice and weed characteristics. The validation set monitored model performance during training and guided the tuning of parameters. The test set, comprising unseen images, was used to evaluate the model's generalization capabilities. This data partitioning approach ensures robust performance evaluation and reduces the risk of overfitting.

2.2.3. Data Volume Monitoring

Before initiating the training process, it is crucial to verify the number of image samples in each classification category. This step ensures that the dataset is both comprehensive and balanced, which is critical for practical model training. Monitoring data volume helps identify and mitigate potential issues such as class imbalance, which can negatively impact model accuracy and generalization performance.

2.2.4. Data Augmentation

Data augmentation is used to enhance a model's performance and prevent overfitting, which occurs when a model focuses excessively on specific details from the training data, resulting in reduced accuracy with new data. In this study, applied data augmentation to the training set using Keras' ImageDataGenerator. Transformations such as random rotations (up to 20 degrees), width and height shifts (up to 10%), shear, zoom, and horizontal flips were used. These augmentations simulate real-world image variations, increasing dataset diversity without requiring additional data collection and helping the model generalize better. The validation and test sets were only rescaled to ensure that performance evaluation reflected realistic, unaltered image conditions.

2.2.5. Loading Data in Batches

Loading all images at once can degrade system performance due to the large dataset size. Batch processing addresses such an issue by loading data in predefined batches during training. This technique reduces memory consumption, improves efficiency, and enables parallel processing. When using GPUs or TPUs, selecting the optimal batch size is crucial for achieving both speed and stability during training.

2.3. AI Model Development and Training

This study developed a model to classify images of rice and weeds using five techniques: DenseNet121, InceptionV3, MobileNetV3, ResNet-50, and VGG16. These techniques are types of deep Convolutional Neural Network (CNN) architecture designed to improve the analysis and sorting of complex images. Researchers constructed and trained the model using those deep learning methods, as demonstrated by its performance in table 2. Moreover, the training approach relies on systematically prepared data to optimize model parameters for accurate and reliable results, whereas researchers have divided this process into four main steps.

2.3.1. Importing Libraries and Defining Initial Parameters

Before creating a model, import essential libraries for machine learning, such as TensorFlow, Keras, and OpenCV for image processing and neural network building. Next, define the basic model training parameters for efficient and stable training. Key parameters include (1) the size of the input images, which should be set to a standard resolution that works well with the InceptionV3 architecture for accurate image analysis; (2) the number of classes, as this study is looking at two categories: rice and weeds; and (3) training settings, such as batch size, number of training cycles (epochs), and learning rate. Proper configuration of these parameters is crucial to achieving optimal model performance and preventing issues such as unstable training or poor convergence. The detailed training parameter settings used in this study are presented in table 2.

Table 2. Model Training Parameter Settings

Parameter	**Value**	**Parameter**	**Value**
Model	InceptionV3	Learning Rate	0.0001
Epochs	80	Loss Function	Categorical Cross-Entropy
Batch Size	32	Activation Function	SoftMax
Image Size	299 x 299	Data Augmentation	Rotation, Flip, Zoom, Shear
Optimizer	Adam		

This study's parameter configurations are in table 2. The model design uses InceptionV3, a pre-trained convolutional neural network learned on ImageNet that can classify difficult pictures. The 80 epochs allow enough learning iterations without overfitting. Training with 32 photos in reasonable batches improves memory efficiency and computational performance. The input image is rescaled to a normalized range of [0, 1] by dividing pixel values by 255, where the size is 299×299 pixels. The Adam optimizer's variable learning rate improves training stability and efficiency. The learning rate is 0.0001 for gradual and stable model updates.

2.3.2. Transfer Learning Using InceptionV3

This study employs transfer learning using the InceptionV3 model pre-trained on ImageNet, with its original top layer removed (include_top=False) to preserve learned low- and mid-level features. A custom classification head was added, consisting of global average pooling, a dense ReLU layer, dropout for regularization, and a final layer with softmax activation to predict the two classes: rice and weeds. The base model's weights were initially frozen to maintain learned features while training the new layers. This strategy reduces training time, improves accuracy with limited labeled data, and facilitates faster convergence, making it suitable for deployment on resource-constrained devices.

2.3.3. Defining the Loss Function and the Optimizer

In the process of training a model, it is necessary to define the loss function and the optimizer, which are the key components that enable the model to learn efficiently. Loss Function: Uses categorical cross-entropy since it is a classification problem with multiple classes. Optimizer: Uses the Adam Optimizer, which can automatically adjust the learning rate, making the learning process stable and rapid. Evaluation Metrics: Uses accuracy as a measure of model performance.

2.3.4. Training the Model

Once the model structure is defined, training is performed using previously prepared datasets, and batch processing techniques are employed to reduce memory load and increase training efficiency. During training, the model learns from rice and weed image data, adjusting the parameters within the neural network accordingly. Accuracy and loss are checked in each training epoch.

2.3.5. Real-World Area Estimation Using Camera Parameters

To estimate the physical dimensions of objects or areas captured in an image, the pinhole camera model is often employed. This model describes the geometric relationship between the real-world scene and its image projection on the camera sensor. By applying the principle of similar triangles, a proportional relationship can be established between the object in the real world and its corresponding image on the sensor [19], as shown in the following equation:

$$\frac{s_j}{d_i} = \frac{s_0}{d_0} \tag{1}$$

S_i represents the dimension of the object as it appears on the camera sensor (measured in millimeters), d_i denotes the focal length of the camera lens (in millimeters), S_o refers to the actual size of the object in the physical world (in millimeters or meters), d_o indicates the distance between the camera and the object in the scene (in millimeters or meters). The ground width and height can be computed using the following equations:

$$Width = \frac{D \times w_s}{f}, Height = \frac{D \times h_s}{f} \tag{2}$$

D represents the vertical distance between the camera and the ground (e.g., in mm), w_s and h_s denote the physical width and height of the camera sensor, f is the focal length of the camera lens. refers to the focal length of the camera lens

By multiplying the resulting width and height, researchers obtain an approximation of the total area in the real world that is covered by the image. This method is particularly effective in field applications where cameras are mounted at known heights, such as in agricultural monitoring using smartphones or drones.

2.4. Model Evaluation

Model evaluation is essential for assessing classification performance and reliability. In this study, key metrics such as the confusion matrix, accuracy, precision, recall, and F1 score were used [20], [21], [22]. The confusion matrix summarizes correct and incorrect predictions, offering insight into how well the model distinguishes between classes. From this, accuracy reflects overall correctness, precision indicates the reliability of positive predictions, recall measures the model's ability to detect actual positives, and the F1 score balances both precision and recall, especially useful for imbalanced data. In summary, these evaluation metrics collectively provide deep insights into the model’s strengths and weaknesses, guiding further refinement to enhance classification accuracy, minimize prediction errors, and support more effective decision-making.

2.5. Chat Bot Development

2.5.1. Webhook and LINE Developers Console Settings

Developing a chatbot capable of receiving and analyzing images of paddy fields involves a coordinated system built using the LINE Messaging API for user interaction, a Flask web server for backend logic, and NGROK for secure, temporary public access during development. Central to this system is the integration of a machine learning model to provide efficient and accurate image classification. The LINE Messaging API supports bi-directional communication, enabling users to send both text and images, with development starting by registering a channel on the LINE Developers Console to obtain credentials such as the access token, channel ID, and channel secret. After configuring the Webhook URL, the Flask server can receive real-time events, including image uploads and messages. Using Python and the LINE Messaging API SDK, researchers implement logic to manage incoming data, classify images, and generate real-time feedback. The system’s responsiveness and communication reliability depend on seamless orchestration between event handling, image processing, and dynamic response delivery, as illustrated in figure 4.

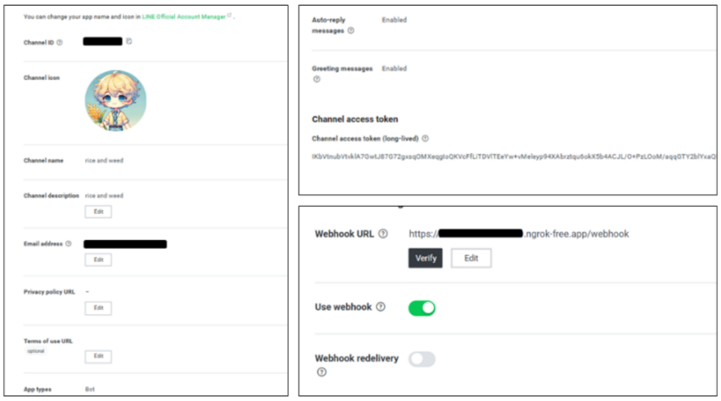

Figure 4. Webhook and LINE Developers Console Settings

2.5.2. Connection between Server and Generated Model

A critical step in building a fully functional system involves developing a web server to process images and interface with the LINE Chatbot, for which researchers used Flask as the web framework and NGROK to expose the local server to the internet. The core application logic is housed in an `app.py` file, which handles incoming requests from the LINE Messaging API, processes uploaded images, and returns classification results to the chatbot. Setting up the Flask server requires installing Flask via pip and coding the application's structure, including API endpoints that handle HTTP POST requests containing user messages or images. These endpoints route data through image processing algorithms and the integrated classification model to generate appropriate responses. To enable real-time communication during development, NGROK is configured to generate a temporary public URL that tunnels requests to the local Flask server, allowing seamless interaction between the chatbot and backend services. This setup is essential for debugging and iterative testing prior to deployment in a production environment.

2.5.3. Integrating Models with Chat Bots

The interaction between the chatbot and the machine learning model is a critical component in ensuring the system accurately distinguishes rice from weeds in user-submitted photos. This process begins with the development of a Python script, which is responsible for loading the trained model and performing image classification tasks. The script loads the pre-trained model, processes input images received from users, performs any necessary preprocessing steps, and executes inference to determine whether each image depicts rice or weeds. The chatbot then organizes and returns the resulting classification for user interpretation.

To facilitate communication between the chatbot and the model, a Flask-based API is implemented. This API handles the incoming image data sent by the chatbot, passes it through the machine learning model for prediction, and returns the classification results. The API functions as a bridge, enabling seamless integration between the LINE Messaging API and the core deep learning model. The final stage involves testing and system optimization. This step includes verifying the reliability of image transmission, model inference, and response generation. Results from this phase are used to troubleshoot potential issues and fine-tune system performance, ensuring the model operates accurately and efficiently in real-world conditions.

Algorithm 1. Webhook-based Integration Algorithm for LINE Messaging API

1. *START PROGRAM*

2. *IMPORT necessary libraries: Image processing, I/O, DateTime, Web Framework (Flask), Model loading, etc.*

3. *SET LINE API credentials:*
4. *CHANNEL_ACCESS_TOKEN*
5. *WEBHOOK_ENDPOINT*

6. *LOAD pretrained model:*
7. *MODEL_PATH = "inceptionv3_model.h5"*

```
model = load_model(MODEL_PATH)
CLASS_NAMES = ["Rice", "Weed"]

INITIALIZE Flask app

DEFINE route for GET "/":
FUNCTION home():
RETURN "Webhook is running"

DEFINE route for POST "/webhook":
FUNCTION webhook():
GET JSON data from incoming request
PRINT data as JSON (formatted)
RETURN "OK"

DEFINE function start_ngrok():
START subprocess to run ngrok on port 5000
LOOP indefinitely:
TRY to fetch public URL from ngrok API (localhost:4040)
EXTRACT public URL
PRINT the public URL
RETURN the URL
IF error: continue loop

DEFINE function update_line_webhook(url):
SET HTTP headers with Authorization and Content-Type
PREPARE payload to update LINE webhook endpoint with new URL
SEND PUT request to LINE endpoint
PRINT response

IF __main__:
public_url = start_ngrok() + "/webhook"
CALL update_line_webhook(public_url)
RUN Flask app on port 5000

END PROGRAM
```

3. Results

3.1. Model Analysis and Performance Assessment

In table 3, researchers compared the accuracy and processing time of five models—DenseNet121, InceptionV3, MobileNetV3, ResNet-50, and VGG16—using different methods. Table 4 and table 5 show the selected top-performing models. Google Colab used a Pascal-based NVIDIA Tesla P100 GPU for the trials. This GPU has 16 GB of HBM2 memory.

Table 3. Evaluation Results of Model Performance

Models	Accuracy	Time (Sec.)	Models	Accuracy	Time (Sec.)
DenseNet121	0.9161	442.5388	ResNet-50	0.7946	15.6503
InceptionV3	0.9783	918.2502	VGG16	0.8532	1675.6260
MobileNetV3	0.7191	450.6975			

Table 3 presents a performance comparison of five deep learning models based on classification accuracy and inference time. InceptionV3 achieved the highest accuracy (0.9783) but required the longest processing time (918.25 seconds), while DenseNet121 offered a strong trade-off with 0.9158 accuracy and faster inference at 442.54 seconds. ResNet-50 struck an effective balance between speed and performance, delivering 0.7946 accuracy in just 15.65 seconds, making it suitable for time-sensitive applications. VGG16, despite its reasonable accuracy (0.8532), was the slowest at 1675.63

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seconds. MobileNetV3, despite being lightweight, demonstrated limited classification capability, achieving only 0.7191 accuracy. These results suggest that while InceptionV3 leads in accuracy, DenseNet121 and ResNet-50 offer viable alternatives depending on specific application requirements. The effectiveness of the binary classification model was confirmed using a test set of 1,800 samples (evenly split between two classes), as shown in the confusion matrix in table 4.

Table 4. Confusion Matrix of InceptionV3 Model

	Predicted: Rice	Predicted: Weeds
Actual: Rice	883	17
Actual: Weeds	22	878

Table 4, the model performs well in distinguishing between the two classes, with a low number of misclassifications in both False Positive (FP) and False Negative (FN) categories. The slight imbalance in FN compared to FP suggests that the model is marginally more likely to misclassify class weeds instances as class rice than vice versa. Table 5 the model achieved high classification performance for both classes. For rice, precision was 0.9899 and recall 0.9768, indicating highly accurate and consistent identification. For weeds, the precision and recall were similarly strong at 0.9766 and 0.9899, respectively. The F1 scores for both classes were balanced at approximately 0.983, demonstrating the model's robustness in distinguishing between rice and weeds.

Table 5. Confusion Matrix of InceptionV3 Model

Class	Precision	Recall	F1 Score
Rice	0.9899	0.9768	0.9833
Weeds	0.9766	0.9899	0.9832

Table 6 illustrates the performance of the most effective model, InceptionV3, across selected training epochs. The model demonstrated consistent improvements in both training and validation accuracy, with validation accuracy peaking at 0.9608 by epoch 79. Simultaneously, training and validation loss decreased over time, indicating enhanced generalization and reduced overfitting. These results confirm the model’s progressive learning and optimal performance near the final training stage.

Table 6. The Most Effective Models (InceptionV3)

Epoch	Train Accuracy	Validation Accuracy
1	0.9279	0.9263
3	0.9647	0.9479
5	0.9682	0.9229
77	0.9879	0.9496
79	0.9879	0.9608

3.2. Classification of Rice and Weeds using LINE Chatbot

Researchers developed a system to assist mobile-using smallholder farmers by integrating a LINE chatbot with a Flask backend server via ngrok, enabling users to upload images and receive real-time predictions from a server-hosted InceptionV3 model. Chosen for its high classification accuracy, InceptionV3 operates entirely on the server, avoiding computation on user devices and maintaining low latency even for users with limited hardware. In testing with 60 wide-angle smartphone images, 30 of rice and 30 of weeds, the model achieved perfect classification in both categories, demonstrating real-world applicability. The test set, which was different from the training data, included a variety of examples: rice images showed sticky and jasmine rice at three different growth stages, while weed images included

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five different types with different colors and shapes, making sure the model was thoroughly tested in different visual situations.

3.3. Results from Rice-to-Weed Ratio Image Analysis

The evaluation of the rice-to-weed ratio derived from image processing was conducted to objectively measure the percentage of rice plants to weeds in each image. This research gave an understanding of the density and distribution of rice and weed coverage in the field, facilitating subsequent decision-making for weed management. Moreover, researchers have created a function capable of calculating the traversable area by processing wide-angle photographs from cellphones, facilitating quick image analysis and providing a clear perspective of the rice fields. The proposed rice and weed classification system was evaluated using 60 wide-angle images captured by a smartphone in real rice field conditions through the LINE Chatbot interface. The results had been analyzed and interpreted, as presented in table 7.

Table 7. Performance Results of Rice and Weed Classification via LINE Chatbot

Class	Classification Accuracy (%)	Area Detection Accuracy (%)
Rice	73.33	63.33
Weeds	70.00	56.66

Table 7 shows that the model detected rice in all 30 photos of rice plants, with an average classification accuracy of 73.33% and an area detection accuracy of 63.33%. Part 2 used 30 weed-containing photos, and the model had 70.00% classification accuracy and 56.66% area detection accuracy. These results demonstrate that chatbot interaction can be used for realistic in-field classification.

3.4. User Satisfaction and Acceptance

The researcher conducted a study on user satisfaction and acceptance through a questionnaire survey that targeted 30 computer science students from the School of Information and Communication Technology at the University of Phayao in Thailand. The participants have personal or family backgrounds in farming, which provides them with relevant experience related to the application context of the system. The study utilized specified criteria and a designed questionnaire, presented in table 8 and table 9. Data collection occurred during the second semester of the 2024 academic year.

Table 8. The Five-Level Evaluation Criteria

Level	Description	Score Range
5 = Excellent	The system can accurately classify rice and weeds (accuracy ≥ 80%) and calculate the rice-to-weed ratio with high precision. Users express very high satisfaction with the LINE Chatbot's usability and clarity of results.	80 – 100
4 = Good	The system classifies rice and weeds with reasonable accuracy (70 – 79%). The ratio calculation is reliable, and users are generally satisfied with the system.	70 – 79
3 = Fair	Moderate classification accuracy (60 – 69%) with some minor errors in ratio calculation. Users can use the system but may provide suggestions for improvement.	60 – 69
2 = Needs Improvement	Classification accuracy falls below standard (50 – 59%), and errors in ratio calculation are apparent. Users encounter difficulties using the system or interpreting the results.	50 – 59
1 = Poor	The system functions poorly (accuracy < 50%); the ratio calculation is incorrect, and users are unable to utilize the system effectively.	0 – 50

Table 8 illustrates the five-level evaluation criteria. This evaluation framework aims to assess the performance and usability of a system that classifies rice and weeds using the LINE Chatbot and calculates the rice-to-weed ratio through image processing. Researchers analyzed the quantitative data from the questionnaire by computing the average score for each item. These average scores were then interpreted according to a five-level scale: very low or strongly disagree

(1.00–1.50), low or disagree (1.51–2.50), moderate or neutral (2.51–3.50), high or agree (3.51–4.50), and very high or strongly agree (4.51–5.00). The collected data had been analyzed and interpreted, as presented in table 9.

Table 9. Satisfaction Assessment Results

Evaluation Item	Average	S.D.	Interpretation Results
1. Ease of use of the LINE Chatbot	3.97	0.72	Agree
2. Accuracy in classifying rice from images	4.06	0.72	Agree
3. Accuracy in classifying weeds from images	4.03	0.72	Agree
4. Reliability of the rice-to-weed ratio calculation	4.04	0.69	Agree
5. Speed of data processing	4.10	0.75	Agree
6. Clarity of the results displayed	3.94	0.70	Agree
7. Applicability in real agricultural settings	4.37	0.66	Agree
8. Overall satisfaction with the system	4.17	0.64	Agree

Table 9 displays the user satisfaction survey and system evaluation. The scoring criteria included five levels (5 = excellent, 4 = good, 3 = fair, 2 = needs improvement, 1 = poor), as outlined in the scope and definitions in table 4.

All eight evaluation items received average scores above 3.9, indicating overall agreement among users regarding the system's effectiveness. The highest-rated item was applicability in real agricultural settings (mean = 4.37, S.D. = 0.66), followed by overall satisfaction (mean = 4.17, S.D. = 0.64) and data processing speed (mean = 4.10, S.D. = 0.75). Other aspects, including classification accuracy, reliability, and result clarity, also received favorable responses. These findings reflect strong user approval and suggest the system is practical and well-received in real-world agricultural contexts.

4. Discussion

4.1. Model Performance

A comparison of five deep learning models—InceptionV3, DenseNet121, MobileNetV3, ResNet-50, and VGG16—revealed that while InceptionV3 achieved the highest accuracy (0.9783), it required more processing time, whereas ResNet-50 was the fastest (15.65 seconds), making it ideal for time-sensitive applications. DenseNet121 offered a strong balance of accuracy and speed, making it suitable for scenarios demanding both. However, all models struggled with misclassifying visually similar vegetation types in remote sensing imagery, such as mistaking green/yellow leaves with panicles for yellowish-brown vegetation or grasses for early-stage rice. These mistakes probably happen because the colors and shapes of the plants look similar in certain images, showing that the models have trouble telling apart small visual differences. This suggests a need for more diverse and representative datasets, the inclusion of discriminative features like texture and morphology, and potentially more advanced architectures—such as hierarchical or attention-based models—that can better handle subtle class differences.

4.2. Deployment of the Model in the LINE Chatbot

The chosen InceptionV3 model was used in a LINE chatbot and tested with 60 wide-angle smartphone pictures, successfully identifying all 30 images with rice and 30 images with weeds, showing it works well in real-life situations. While the current integration using Flask and NGROK is sufficient for prototyping, it lacks production-grade features such as scalability, reliability, and security. To overcome these limitations, the system will be migrated to a cloud-based, containerized infrastructure (e.g., Docker on AWS or GCP) with support for autoscaling, load balancing, and continuous deployment. NGROK will be replaced by a stable API gateway like NGINX or AWS API Gateway to ensure secure and consistent access, making the system more reliable and scalable for real-world agricultural applications.

4.3. Rice-to-Weed Ratio Analysis

The system had a function that analyzed the ratio of rice to weeds using wide-angle images, allowing for a detailed look at how crops and weeds are spread out, which helps in better weed management. This analysis also included field area estimation, providing users with visual and spatial insights that extend the system's utility beyond basic classification. Training data were collected between 10:00 AM and 4:00 PM under strong sunlight and consistent lighting in Thailand to ensure high-quality input. In contrast, the LINE Chatbot testing images were captured under uncontrolled conditions, introducing lighting variability that may have impacted performance, highlighting the practical challenges of deploying AI systems in real-world agricultural environments.

4.4. User Satisfaction and Acceptance

A user evaluation was conducted among 30 computer science students from the University of Phayao. The results indicated that all evaluation items received average scores above 3.90, indicating a high level of user satisfaction. The highest-rated item was applicability in real agricultural settings (mean = 4.37), followed by overall system satisfaction (mean = 4.17) and processing speed (mean = 4.10). These findings confirm that the system is perceived as effective, user-friendly, and suitable for real-world agricultural use.

5. Conclusion

This paper reveals how an intelligent chatbot system employed deep learning and image processing to recognize weeds and rice in aerial photographs, satisfying all three research aims. Researchers trained a deep learning model using the InceptionV3 architecture on 12,000 aerial photographs of northern Thai rice fields to achieve Objective 1. InceptionV3 could distinguish rice plants from weeds in real life with 98.79% training, 96.08% validation, and 97.83% testing accuracy. Second, to achieve Objective 2, researchers implemented the system on the LINE chatbot, enabling users to upload field photos and receive immediate feedback. In wide-angle field photos, the platform's ratio analysis function measured rice to weeds, aiding precision agriculture decision-making. Third, 30 participants were systematically evaluated for user satisfaction after Objective 3. Most users agreed on key usability factors, such as how easy it is to use, how quickly it works, how clear the information is, and how relevant it is to farming, confirming that the system aids decision-making.

The findings show that smallholder agriculture can benefit from incorporating AI, image analytics, and chatbot technology. This method improves decision-making and provides swift, data-driven crop management insights. For scalability and reliability, future work should focus on production-ready deployment, including cloud infrastructure and secure API integration, rather than experimentation with Flask and NGROK. Researchers should look into supporting multiple languages, including more types of crops, combining GIS and weather data, and conducting large field tests to see how well these methods work in different farming situations. Although not mobile-optimized, InceptionV3 was utilized for its dependable categorization performance. For mobile and edge real-time performance, EfficientNet-Lite and other lightweight architectures will be studied.

6. Declarations

6.1. Author Contributions

Conceptualization: S.W., N.S., K.S., K.R., and N.P.; Methodology: N.P.; Software: S.W.; Validation: S.W., N.P., and K.R.; Formal Analysis: S.W., N.P., and K.R.; Investigation: S.W.; Resources: N.P.; Data Curation: N.P.; Writing Original Draft Preparation: S.W., N.P., and K.R.; Writing Review and Editing: N.P., S.W., and K.R.; Visualization: S.W.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The author received financial support for the research from the Thailand Science Research and Innovation Fund (the Fundamental Fund) and the University of Phayao.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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