Automatic Identification of Diseases and Pests for Thai Rice Leaf from IoT Camera Using ResNet50

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ABSTRACT
This paper presents the combination of IoT cameras and the ResNet50 classification technique to remotely detect and identify rice diseases and pests. The training image data was collected from the locals of Ron Thong, Satuek District, Buriram Province, Thailand. The focused rice anomalies for detection are five common diseases and three types of pests in Thailand, including rice blast disease, bacterial leaf blight disease, rice tungro disease, sheath blight disease, brown spot disease, brown planthopper, green rice leafhopper, and rice gall midge. The annotated local images are trained for the best compatibility with the local environment. For detecting anomalies, installed IoT cameras are set to capture images of rice leaves within the field three times a day and upload the image as an input to the cloud API, which contains the classification model to detect the symptoms of disease and pest. If a disease or pest is detected, the system automatically alerts with the identified anomaly to responsible field workers. The experiment results show that the performance of the model from the ResNet50 technique achieves a satisfied result of 0.956 F1 score.

Keywords: Rice Diseases Identification, Thai Rice Leaf, ResNet50, IoT

1. INTRODUCTION

Thailand is one of the world's leading rice exporters, with rice exports bringing in significant foreign exchange revenue [1]. Rice is Thailand's most significant agricultural product, and it contributes substantially to the GDP. Furthermore, rice is the staple food for the Thai population; thus, stable rice supply is critical for food security and nutritional stability in Thailand. Rice crops are susceptible to diseases and pests which can significantly reduce yields and affect quality. Effective pest and disease detection in rice farming hence is essential for maintaining crop health and ensuring high yields by acting accordingly. Traditional method of detecting rice pest and disease is for farmers to inspect rice crops for symptoms of pests and diseases such as spots, discoloration, wilting, or unusual growth patterns [2]. The methods generally demand minimal financial investment but require farmers' knowledge and experience including understanding of local conditions, and common pests and diseases for effective monitoring and management. However, such methods require significant manual labor, particularly in large fields, making them time-consuming and physically demanding as regular and thorough inspections are needed to catch early signs of pests and diseases, which can be challenging to maintain consistently. Furthermore, visual inspections rely on human judgment which can be subjective and prone to errors. Different individuals may interpret symptoms differently and lead to inconsistent results or a miss in detecting early signs.With advances in technology, technologies such as computer vision and remote sensing have been applied to assist agricultural management, and they have significantly improved the accuracy and efficiency of pest and disease detection. For the computer vision technology, machine learning is used to generate classification models to analyze images of crops to identify and classify objectively such as rice varieties [3], rice sickness [4], and rice grade [5]. The remote sensing technology provides large-scale monitoring of crops using high-resolution cameras and sensors to help in monitor an agriculture field [6]. There are research projects developing AI-based systems [7] that use smartphone cameras to diagnose rice diseases. The systems allow farmers to upload images of rice leaf and automatically identify the disease if infected and suggest management practices. Automated systems reduce the need for extensive manual labor involved in scouting and inspecting fields. Unlike human inspectors, automated systems based on machine learning approaches provide consistent and objective assessments which reduce the variability and subjectivity inherent in manual inspections and return high accuracy in detection of diseases and pests even in early stages.

This work combines the use of IoT camera with deep learning-based classification model, called ResNet50 [8][9], to detect Thai rice diseases and pests towards the concept of smart farming. The model is specifically trained with data from local to perfectly fit the rice diseases and pests frequently found in the local. The developed system thus will assist and lessen burden of field workers to identify unwanted diseases and pests in early stage and tackle the issue effectively.

2. LITERATURE REVIEWS

2.1 Background Knowledge of Rice Diseases and Pests in Thailand

Rice diseases and pest invasion in Thailand pose significant challenges to rice production impacting product yield and quality. In Thailand, there are several common diseases and pests affecting rice crops. Details of common rice diseases and pests in Thailand are given in Table 1and Table 2 respectively.

Table 1. Common Rice Diseases in Thailand

Rice Disease	Type/Description	Image examples
Rice Blast	Caused by fungi "Pyricularia oryzae". Symptoms are lesions on leaves, nodes, and panicles. Lesions start as white to gray-green spots, which then enlarge and become spindle-shaped with brown borders.	
Bacterial Leaf Blight	Caused by fungi "Xanthomonas oryzae pv. oryzae". Symptoms are yellowing and drying of leaves starting from the leaf tips. In severe cases, leaves turn brown and die.	
Rice Tungro Disease	Caused by Rice Tungro Spherical Virus (RTSV) and Rice Tungro Bacilliform Virus (RTBV). Symptoms are Stunted growth, yellow-orange discoloration of leaves, reduced tillering, and poorly filled grains.	
Sheath Blight	Caused by fungi "Rhizoctonia solani". Symptoms are lesions on leaf sheaths that start as greenish-gray and become brown with a cottony mycelium. Infected plants may lodge.	
Brown Spot	Caused by fungi "Bipolaris oryzae". Symptoms are small circular to oval brown spots on leaves and seeds. In severe cases, leaves can become blighted.	

Table 2. Common Rice Pests in Thailand

Rice Disease	Symptoms	Examples
Brown Planthopper (Nilaparvata lugens)	Feeding on the phloem of rice plants, causing hopperburn where plants turn yellow and dry up. Also transmits Rice Ragged Stunt Virus (RRSV) and Rice Grassy Stunt Virus (RGSV).	

Green Rice Leafhopper (Nephotettix spp.)	Feeding on the phloem of rice plants, causing yellowing and stippling of leaves. Severe infestations can lead to stunted plant growth and reduced tillering. Transmits the rice tungro virus.	
Rice Gall Midge (Orseolia oryzae)	Larvae induce the formation of galls (silver shoots) in place of normal tillers, reducing tiller number and overall plant vigor	

Diseases manifest symptoms on the rice leaves, whereas pests are physically visible. Thus, detecting them early offers numerous benefits, including healthier crops, improved yields, and sustainable farming practices. Traditionally, rice field workers need to be educated in identifying signs of common pests and diseases; they implement a routine scouting schedule to monitor crops for early signs. With the advancement of technology, tools such as remote sensing and identifying applications can help to protect their rice crop more effectively, reduce monitoring burdens, and contribute to sustainable agricultural practices.

2.2 Information Technologies Supporting of Thai Rice Agriculture and Production Management

Rice is one of the most food products in Thailand in terms of domestic consumption and exporting goods. Thus, there are several studies applying information technology (IT) aiming to improve rice production and management. In this section, we review related works in the fields of image classification and smart farming towards supporting Thai rice production and management in the past decade.

For image classification, images of rice leaves and milled rice products were collected locally and trained to identify different objectives using image processing techniques. Kongsilp and Sangsai[10] proposed to use deep learning-based image processing for automatic rice grain physical quality inspection to classify the quality of rice grain. To train the classification model, they adopted Mask-RCNN, which is an instance segmentation variant framework of the convolutional neural network (CNN) technique, to perform tasks of detection, segmentation, and classification. Their experimental evaluation pointed out that their proposed system received acceptable results of 0.96 mean average precision. In 2023, Thammastitkul and Petsuwan[11] presented their work for classifying Thai jasmine rice by its category and grade based on the given image using a deep learning approach. They applied the multi-class support vector machine (SVM) and CNN techniques for the categorization and grading tasks. Their experimental results showed that their method obtained a satisfying classification result of an average accuracy of 94.52% across six categories for the rice grading task.Onmankhong et al. [12] presents their work on the classification of rice varieties among three rice varieties, including genuine Thai jasmine rice (Khao Dawk Mali 105) from Pathum Thani1 (PTT1) and Phitsanulok2 (PSL2) from images of both milled rice and unprocessed brown rice products. As their physical appearances are similar, they used long-wave near-infrared hyperspectral imaging to obtain images for training data for CNN and SVM learning techniques. Their CCN classification method could classify milled rice with the highest accuracy of 95.2%.Temniranrat, et al.[7] presents the LINE Bot system to interact with users and diagnose rice diseases from images of rice leaves in a paddy field. In their classification model, they used a deep learning neural network technique to detect rice diseases with 95.6% accuracy in the study. The input image from users is to be submitted in LINE chat, and the bot then shortly retunes the disease status of the rice leaves.

Another IT approach supporting rice farming is IoT-based smart farming or precision farming, which includes managing irrigation [13] and monitoring a rice field. Boonying [14] proposed to combine the Internet of Things (IoT) and machine learning technology towards water management in a rice paddy field. The water level in a field is detected in real-time with the installed water level sensors, while the classification model is trained from the local environmental features to decide if the water should be released or filled automatically using a solar-powered water pump based on the farming method called the Alternative Wetting and Drying method. Regarding the usefulness of the proposed system, the evaluation showed very satisfying results for the ease of usage and its ability to reduce resource waste compared to the traditional method. In 2022, Somsuphaprungyos [15] developed a data center to collect real-time data on agriculture-related features using IoT remote sensing from rice fields in Ayutthaya province, Thailand. The widely used environmental parameters necessary for smart farm applications were collected from the deployed sensors and opened for use in smart farm applications such as weather monitoring and light management. In the study, the author also reported on the possible issues from

practical IoT sensor usage in a private and public area to be aware of, such as sensor malfunction from environmental harshness, internet connectivity issues, and sensors being stolen by outsiders.
From the reviews, we learn that CNN-based image classification is one of the best techniques in terms of accuracy performance, and its models can be used to identify classes effectively. Furthermore, IoT technology is widely used to detect real-time data or to remotely monitor environmental parameters. Combining the two technologies thus can cover automated decision-making tasks and remote sensing/monitoring.
Unlike other studies, Temniranrat, et al. [7] has a similar scope to our work's objective; however, it requires users to provide images of paddy fields manually to identify rice diseases. Thus, it leans towards clarifying diseases for already-found symptoms and providing solutions to solve the issues. Our work aims to detect anomalies, including common local rice diseases and pests, via IoT cameras for remote monitoring, using the renowned CNN approach called ResNet50 for its high accuracy performance [9],[16],[17] in image classification.

3. Framework of Automatic Identification of Diseases and Pests from IoT Camera using ResNet50

This work presents a framework to detect and identify Thai rice diseases and pests using IoT camera for notifying field workers. The overall architecture is illustrated in Figure 1 The framework consists of IoT cameras installed in a rice field, a classification model trained from an annotated dataset, cloud API to receive captured inputs and to execute a detection and identification task, and application in a smartphone to receive a notification once disease/pest is detected.
The IoT camera captures the images of rice leaf in the field and send them to Cloud API as an input. For generating a model to identify Thai rice diseases and pests, annotated image dataset is trained using CNN, and the model is uploaded to Cloud API. The model in Cloud then classifies the input and notify field workers if the classification results are positive to rice disease or pests.

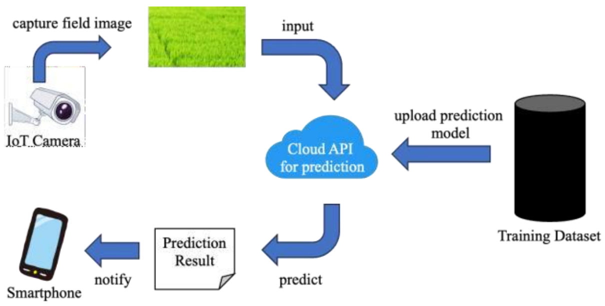

Figure 1. An overview architecture of detection and identification of Thai rice diseases and pests using IoT and image classification

3.1 IoT Devices

To detect diseases and pests in a rice field, solar-powered IoT cameras are deployed to capture images of rice leaves. Solar-powered cameras are recommended as a rice field is not often connected to electricity to prevent accidental electrocution. In terms of durability, the camera should be weatherproof and durable enough to withstand harsh outdoor conditions including rain, swing humidity, and extreme temperatures. The internet connectivity is cellular, as the field may be too far from a Wi-Fi spot. High resolution is mandatory for the cameras, but night vision is optional since this work focuses on capturing images of rice leaves affected by disease or pests. For details, IoT cameras used in this framework have the following specs:

- Image Quality: 4K (Ultra HD) 3840 x 2160 pixels with low-light performance
- Zoom Option: 4x Zoom option available
- Connectivity: Cellular connectivity
- Durability: Weatherproof for outdoor use
- Power Options: Solar-powered with battery storage
- Setting Angle: 45 degrees towards the rice leaves

The cameras are set to capture a still image 3 times daily at 8:00, 12:00, and 17:00. The captured images are sent to Cloud for storage with timestamp and as inputs to prediction model. The image of 3840 x 2160 pixels is processed to scale down to 1280 x 720 pixels to reduce computational complexity. The 1280 x 720 pixels then are cropped into 15 chunks (5 vertical and 3 horizontal chunks with some area overlapping). Each chunk is to process as input for detecting diseases and pests separately.

3.2 Classification Model Generation

3.2.1 Data Collection and Processing

In this work, our area of study is Ron Thong, Satuek District, Buri Ram Province, Thailand. The collection of images in this work is images of rice with both infected and uninfected in a span of 3 years, from January 2020 to December 2022. These images were taken using mobile phones and IoT cameras with a resolution of more than 1 megapixel. The images are annotated for the infection by experienced rice farmers and verified by rice disease experts. The infected images include 5 diseases (mentioned in Table 1) and 3 pests (given in Table 2). These images are in JPEG format and need to be scaled down to 224x224 pixels. Training data, however, has a lot of noise, missing values, and is inconsistent. Thus, we need data preprocessing to remove the noise, discard images with missing values, and organize data in a proper format to uphold the training input quality. The preprocess includes data cleaning to remove noise and data compression to reduce data dimensions for less computation. For the background subtraction method, the Gaussian Mixture-based Background/Foreground Segmentation Algorithm (MOG2) is applied. The division of the dataset ratio is approximately 70:15:15 for training, testing, and validation, respectively. Details of the data division for each class are given in Table 3.

Table 3. Details of Data Division of the Dataset

Class		**Training**	**Testing**	**Validation**
Healthy		210	45	45
Disease	Rice Blast	210	45	45
	Bacterial Leaf Blight	140	30	30
	Rice Tungro Disease	140	30	30
	Sheath Blight	210	45	45
	Brown Spot	140	30	30
Pest	Brown Planthopper	140	30	30
	Green Rice Leafhopper	140	30	30
	Rice Gall Midge	140	30	30

3.2.2 Classification Model Using ResNet50

In this work, we apply ResNet50 [8][9], a deep convolutional neural network architecture with 50 layers that belongs to the family of residual networks. The architecture of this work ResNet50 is given inFigure 2.

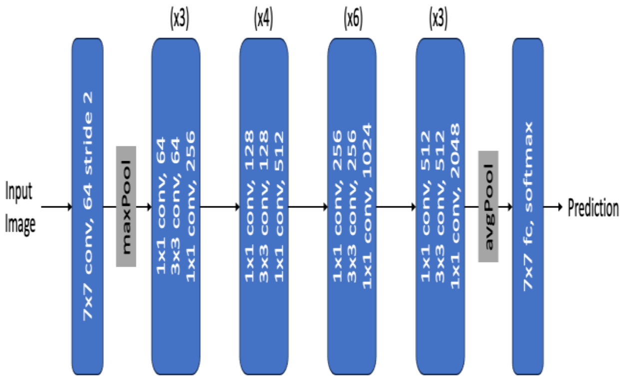

Figure 2. ResNet50 architecture

The input image for ResNet50 is an RGB image with dimensions of 224x224 pixels. In an initial convolutional layer, the input image passes through 64 filters of size 7x7, followed by batch normalization and ReLU activation functions. After the initial convolutional layer, a max pooling layer (maxPool) with a pool size of 3x3 and a stride of 2x2 reduces the spatial dimensions of the feature maps. This ResNet50 is composed of 48 stacked residual blocks, and each containing different convolutional layers and skip connections. Each residual block consists of three convolutional layers as follows.

• 1x1 convolutional layer with assigned filters (64 filters in the first block and 128 filters in second block for example)

• 3x3 convolutional layer with assigned filters (64 filters in the first block and 128 filters in second block for example)

• Bottleneck layer of 1x1 convolutional layer with 256 filters (for first block) and 512 filters (for second block for example)

The output of the bottleneck layer is added to the input of the block through the shortcut connection, while each residual block uses batch normalization and ReLU activation functions after each convolutional layer. After passing through the stack of residual blocks, a global average pooling (avgPool) layer aggregates spatial information across the feature maps to reduce the spatial dimensions to a 1x1x256 tensor by taking the average of each feature map. The output of the avgPool is flattened to a vector and passed through one fully connected layer. Last, a softmax activation function is used to produce the probability distribution over the given classes. In this work, Adam optimizer [18] with a learning rate of 0.0001 with 32 batch sizes is applied to adjust the weights of the network layers based on the gradients of the loss function with respect to those weights. The applied loss function in this work is categorical cross-entropy to measure the difference between predicted and true class labels.

4. Experiments

In this section, two evaluations are conducted. Firstly, classification performance is evaluated using confusion matrix and calculate the count in the confusion matrix for precision, recall, and F1 score. A confusion matrix is a table that describes the performance of a classification model on a set of test data for which the true values are known. Precision is the ratio of correctly predicted positive observations to the total predicted positives. Recall is the ratio of correctly predicted positive observations to all observations in the actual class. The F1 score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. Secondly, we observe and calculate accuracy of disease/pest notification from practical usage. To evaluate performance of practical usage, we compare the notifications of disease/pest during an experimental period if they match to the observation of field workers or not.

4.1 Results of Classification Performance

The training dataset involves 9 classes for a healthy rice leaf, 5 infected rice diseases (Table 1), and 3 invaded rice pests (Table 2) The ratio of training data, validation data, and testing data is 70:15:15. The results of classification in confusion matrix are given in Figure 3. The calculation results of precision, recall, and F1 score of each class is given inTable 3.

From Figure 3. Results of classification in confusion matrix, the matrix represents the confusion matrix for the classification model. The vertical axis represents the actual classes (ground truth labels), while the horizontal axis represents the predicted classes. Each cell (i, j) in the matrix represents the number of instances where the true class is i and the predicted class is j. The diagonal cells (i, i) represent the number of correctly classified instances for each class, whilst off-diagonal cells represent misclassified instances. For an example of diagonal cells, the cell (1,1) has a value of 43, which means the model correctly classified 43 instances as "Rice Blast". It misclassified 1 instance of "Rice Blast" as "Bacterial Leaf Blight" and 1 instance as "Rice Tungro Disease". For off-diagonal elements, the cell (0, 4) has a value of 1, meaning 1 instance of "Healthy" was incorrectly classified as "Sheath Blight". The result of the model demonstrates strong performance across most classes, with perfect or near-perfect accuracy in many cases. There are some minor misclassifications particularly between similar classes, but the classification accuracy overall is high.

Table 4. shows the precision, recall, and F1 score of the classification results. For the class “Healthy”, precision of 1.00 is obtained as the model's predictions for "Healthy" are all correct, while recall of 0.96 shows that the model correctly identifies 96% of actual "Healthy" instances. The class “Rice Tungro Disease” receives the perfect 1.0 recall score indicating that the model correctly identifies all "Rice Tungro Disease" instances, and its 0.97 precision shows that 3% of "Rice Tungro Disease" predictions are incorrect. Among all classes, “Rice Gall Midge” yields the perfect precision and recall as both metrics are 1.0.

To calculate the overall F1 score, we use the micro averaging methods. Micro-averaging aggregates the contributions of all classes to compute the average metric as it gives equal weight to each instance in the dataset, regardless of its class. The obtained overall F1 score is 0.956. Considering all instances together, the score indicates that the classifier from ResNet50 technique performs well overall for the task of detecting rice diseases and pests.

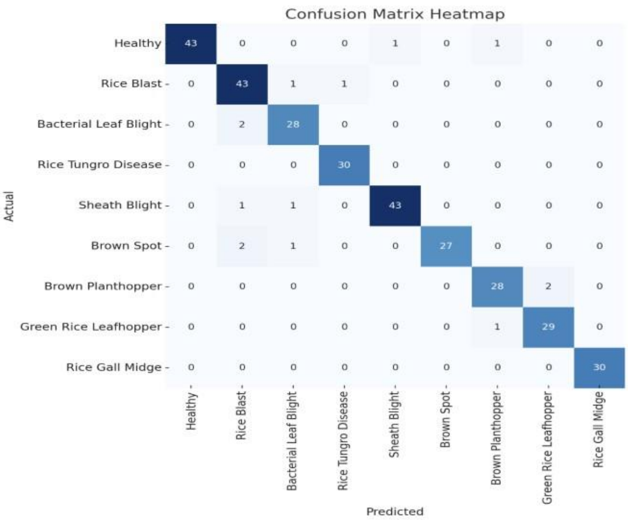

Figure 3. Results of classification in confusion matrix

Table 4. Results of precision, recall, and F1 score

Class	Precision	Recall	F1 Score
Healthy	1.00	0.96	0.98
Rice Blast	0.90	0.96	0.92
Bacterial Leaf Blight	0.90	0.93	0.92
Rice Tungro Disease	0.97	1.00	0.98
Sheath Blight	0.98	0.96	0.97
Brown Spot	1.00	0.90	0.95
Brown Planthopper	0.93	0.93	0.93
Green Rice Leafhopper	0.94	0.97	0.95
Rice Gall Midge	1.00	1.00	1.00

4.2 Results in Practical Use

To evaluate performance of the classification in practical use, we deployed the system in a rice field for 6 months between 11th March to 15th September 2023 and reviewed the notification of disease/pest comparing to the observation of field workers. We asked the field workers to check the rice leaves once the notification was alerted, and also kept note of finding the disease/pest that they found without the alert. There were 7 notifications from different date and not of the same ongoing incident within the experimental period, and the comparison results are given inTable 5.

There were 7 notifications sent based on the system detection, but field workers found 9 incidents from manual observation. All 7 notified alerts were matched to the found incidents correctly. Unfortunately, two cases of brown planthoppers were not notified by the system. When asking the field workers, they mentioned that the missing incidents happened far from the deployed cameras and were not in camera line of sight. Moreover, the brown planthoppers found were very few, with at most 3 and 5 specimens per case.

4.3 Discussion

In terms of limitation, the practical result signifies that the line of sight of the camera can be limited to the assigned location of the camera. Since the cameras are installed in a specific location despite their ability to rotate and change ankles, there are blind spots that cannot be seen with immobile cameras. Although the issues can be solved by simply adding more cameras to cover the blind spots, the cost of additional cameras and their setup may become too expensive for the expected results and impractical as the many cameras may obstruct the work on the field, such as the use of tractors for plowing. Thus, it is crucial to balance the number of deployed cameras with their expected coverage in practical usage. From the test and consulting with field workers, the suggested camera-installed location is around the four corners of the fields (for a common rectangle shape of a rice field), as they will not much obstruct farmers' work and have a good ankle for capturing the incidents, but it may have a blind spot in the middle of the field. Aside from the capability to detect targeted diseases and pests, there were four cases of unexpected occurrences during the practical experiments, as follows:

- 2 cases of missing data from bad network connection
- 1 case of missing data from losing power
- 1 case of disfunction of the installed camera

Table 5. Matching notification and observation from field workers

Notification	Worker Observation	Comparison Result
Bacterial Leaf Blight disease	Bacterial Leaf Blight disease	Matched
Brown Planthopper	Brown Planthopper	Matched
Rice Blast disease	Rice Blast disease	Matched
Brown Spot	Brown Spot	Matched
Brown Planthopper	Brown Planthopper	Matched
Brown Planthopper	Brown Planthopper	Matched
-	Brown Planthopper	Unmatched
Rice Blast disease	Rice Blast disease	Matched
-	Brown Planthopper	Unmatched

The missing data cases were due to the instability of the infrastructure in the field. The 2 cases were from bad network connections, as we used cellular connections since the location of the field is far from a Wi-Fi facility and directly affected by weather, similar to the issue reported by Remote Sensing. Extreme weather can significantly impact cellular network connections. Heavy rainfall may absorb and scatter radio signals, especially at higher frequencies used in 4G and 5G networks. This phenomenon, known as rain fade, reduces the strength and quality of the signal, leading to potential drops in connectivity. Moreover, electrical activity from thunderstorms and lightning is able to cause electromagnetic interference, disrupting signal transmission and reception, leading to temporary connectivity issues and reduced data speeds. For the case of missing data from losing power, the installed cameras are solar-powered, and the obstruction of sunlight towards the solar panel affects the ability to produce the necessary power to operate the camera. Despite requiring a low amount of power, the occurrence was caused by accumulated leaves from nearby trees covering parts of the solar panel and completely blocking sunlight. The leaf blocking led to a significant drop in energy production and the shutdown of the camera due to insufficient power. Last, the case of camera malfunction was reported as one of the four installed cameras was malfunctioned by a damaged electronic circuit and could not capture the image due to an unknown reason. The camera was thus replaced to resume the experiment. From the unexpected occurrences, we found that weather and other environmental factors play a crucial role in applying IT technology to practical usage in an actual environment, especially smart farming technology. Unexpected accidents may occur to the deployed devices since the agricultural fields are typically outdoors, against many possible incontrollable factors. It is recommended that field workers should at least be educated on how to maintain the devices and receive a guideline for troubleshooting for the system to keep running smoothly. In addition, spared devices should be prepared in advance, as some electronic smart devices may not be on the shelves of a local store in rural areas.

5. CONCLUSION

This work applies ResNet50 to develop a classification model to detect and identify rice diseases and pests, tailored specifically for local Thai issues. The classification model is used with captured images and automatic gathering from IoT cameras to assist rice farmers in lessening the burden of monitoring early symptoms of diseases and pests to prevent spreading and reduce production yields. The training image data involving 5 common diseases and 3 types of pests, including rice blast disease, bacterial leaf blight disease, rice tungro disease, sheath blight disease, brown spot disease, brown planthopper, green rice leafhopper, and rice gall midge, were collected from locals in Ron Thong, Satuek District, Buri Ram Province, Thailand, for the best compatibility of detection and identification. The IoT cameras capture images of rice leaves within the field and send them to the cloud API with the model to detect anomalies. The model then classifies the image and notifies field workers via smartphone if the disease or pest is found. The experiment results show that the performance of the model using the ResNet50 technique achieves a reliable result of 0.956 F1 score. In practical usage, all seven notification alerts from the system are accurately matched to human observation of finding diseases and pests, but there are two missing cases due to the incidents occurring in the blind spot of the cameras.

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REFERENCES

[1] W. Petchseechoung, "Rice industry", Thailand Industry Outlook 2017-19, pp. 1-7, 2017.

[2] Sethy, P. K., Barpanda, N. K., Rath, A. K., & Behera, S. K. (2020). Deep feature based rice leaf disease identification using support vector machine. Computers and Electronics in Agriculture, 175, 105527.

[3] Koklu, M., Cinar, I., & Taspinar, Y. S. (2021). Classification of rice varieties with deep learning methods. Computers and electronics in agriculture, 187, 106285. https://doi.org/10.1016/J.COMPAG.2021.106285.

[4] Asfarian, A., Herdiyeni, Y., Rauf, A., & Mutaqin, K. H. (2014). A computer vision for rice disease identification to support Integrated Pest Management. Crop Protection, 61, 103–104. https://doi.org/10.1016/j.cropro.2013.12.044

[5] Bejerano, K. M. A., Hortinela IV, C. C., & Balbin, J. J. R. (2022, September). Rice (Oryza Sativa) Grading classification using Hybrid Model Deep Convolutional Neural Networks-Support Vector Machine Classifier. In 2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET) (pp. 1-6). IEEE.

[6] Alfred, R., Obit, J. H., Chin, C. P. Y., Haviluddin, H., & Lim, Y. (2021). Towards paddy rice smart farming: a review on big data, machine learning, and rice production tasks. Ieee Access, 9, 50358-50380.

[7] Temniranrat, P., Kiratiratanapruk, K., Kitvimonrat, A., Sinthupinyo, W., & Patarapuwadol, S. (2021). A system for automatic rice disease detection from rice paddy images serviced via a Chatbot. Computers and Electronics in Agriculture, 185, 106156.

[8] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[9] Sharma, N., Jain, V., & Mishra, A. (2018). An Analysis Of Convolutional Neural Networks For Image Classification. Procedia Computer Science, 132, 377–384.

[10] Kongsilp, P., & Sangsai, N. (2022, March). Thai Milled Rice Quality Classification Based on Deep Learning Approach. In 2022 International Electrical Engineering Congress (iEECON) (pp. 1-4). IEEE.

[11] Thammastitkul, A., & Petsuwan, J. (2023). Thai Hom Mali rice grading using machine learning and deep learning approaches. IAES International Journal of Artificial Intelligence, 12(2), 815.

[12] Onmankhong, J., Ma, T., Inagaki, T., Sirisomboon, P., & Tsuchikawa, S. (2022). Cognitive spectroscopy for the classification of rice varieties: A comparison of machine learning and deep learning approaches in analysing long-wave near-infrared hyperspectral images of brown and milled samples. Infrared Physics & Technology, 123, 104100.

[13] Laphatphakkhanut, R., Puttrawutichai, S., Dechkrong, P., Preuksakarn, C., Wichaidist, B., Vongphet, J., & Suksaroj, C. (2021). IoT-based smart crop-field monitoring of rice cultivation system for irrigation control and its effect on water footprint mitigation. Paddy and Water Environment, 19(4), 699–707.

[14] Boonying, S. (2021). A Smart Water Management in a Paddy Field Using IOT Technology and Machine Learning. Information Technology Journal, 17(2), 1-10.

[15] Somsuphaprungyos, S. (2022). Centralizing Real-time Data Using Remote-Sensing towards Smart Farming Applications in A Public Area: A Case Study of Ayutthaya. Information Technology Journal, 18(2), 1-12.

[16] Reddy, A. S. B., & Juliet, D. S. (2019, April). Transfer learning with ResNet-50 for malaria cell-image classification. In 2019 International conference on communication and signal processing (ICCSP) (pp. 0945-0949). IEEE.

[17] Behar, N., & Shrivastava, M. (2022). ResNet50-Based Effective Model for Breast Cancer Classification Using Histopathology Images. CMES-Computer Modeling in Engineering & Sciences, 130(2).

[18] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.