Image Detection of GT Pesticide Test Kit Results in Organic Agricultural Products Using the CiRACORE Deep Learning Model

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Abstract:

This research aims to develop a modern and efficient tool for analyzing pesticide test results in organic agricultural products. This research uses 3,432 test tube images, divided into 3,120 training images and 312 testing images. The research steps are as follows: 1) Data collection: Test tube images were collected from testing of pesticides on organic agricultural produce. Each image has 3 or more test tubes. Each image has accompanying information, 2) AI system development: Use Deep Learning methods to develop an AI model for test tube image analysis, 3) AI system training: Train the AI model with a dataset of 2,746 test tube images, 4) Performance evaluation: Evaluate the performance. of the AI model with a test dataset of 686 images, 5) Results Analysis: Analyze the performance evaluation results of the AI model. From the analysis of the results, it was found that the AI model was effective in analyzing test tube images as follows: The average test tube accuracy was 92.48%. The average image accuracy was 92.62%. The AI system was able to correctly classify the test tubes. The AI system was able to quickly read the test results. This research demonstrates the potential of AI technology to be utilized in developing tools for analyzing pesticide test results, which will benefit farmers, consumers, and agencies responsible for detecting pesticide residues in agricultural products.

Keywords: Pesticide testing, Organic produce, Artificial intelligence technology, Deep Learning, CiRA CORE

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Introduction:

Organic production in Thailand is rapidly developing due to factors such as government initiatives, increasing consumer demand, and a focus on sustainability. Market growth and the potential of this kind of product show that Thailand's organic food exports have experienced remarkable growth, with an average increase of 44.46% per year from 2017 to 2023 (Lima Santos, 2024). The demand for organic products is also rising at a rate of 7% annually, particularly among health-conscious consumers. A survey conducted in September 2023 indicated that a significant portion of Thai consumers prioritize organic food, with many willing to pay a premium for certified organic products (Bangkok Post, 2023). However, only about 0.30% of Thailand's agricultural land is certified organic, which is lower than the global average of 1.00%. As a result, Thailand's government has implemented an action plan on organic agriculture for 2023–2027, focusing on technology, supply chain management, and raising organic standards (IFOAM - Organics International, 2024). The Thai Agricultural Standard for Organic Agriculture (TAS 9000-2021) outlines the production, processing, labeling, and marketing of organic products. These standards aim to harmonize with international requirements and improve recognition at both national and international levels. Meanwhile, a participatory guarantee system (PGS) has been applied to promote organic agriculture in Thailand since 2016, due to its ease of use for beginners in organic production. As of 2022, there are over 50,000 PGS organic producers in Thailand, with 7,524 certified and 6,972 hectares of PGS-certified land. These PGS groups follow the National Organic Agriculture Standard of Thailand, which aligns with international guidelines (IFOAM - Organics International, 2024).

However, organic products from PGS-certified land have faced consumer skepticism regarding pesticide residue content. To address this, a quality test of organic products using a GT-test kit is conducted as a screening tool for detecting certain pesticide residues. This implementation has been occurring in Lampang province, located in the North of Thailand, since 2017, with support from Lampang Rajabhat University funding. The quality confirmation with the GT-test kit helps increase the income of organic farmers and consumer confidence (Oliveri et al., 2024). The GT-test kit, which received the third award on "Inventor's Day 1997" from the National Research Board of Thailand (Patent No. 8446), is designed to detect pesticide residues in food, specifically targeting substances that inhibit the enzyme cholinesterase. If the sample contains these pesticides, it will inhibit the enzyme, which is detected by a color change in the test kit. However, the kit is limited to a specific group of pesticides and provides qualitative results, which can lead to false positives from other substances. Interpreting the results requires comparing the color intensity in the sample tube with control tubes. Experience with more than 2,000 samples for the GT-test kit demonstrated that accurate results depend on the correct type of sample, maintaining the control temperature within a range of 32–34°C, and using the correct amount of GT solution (GT Trading, 2024a). Proper interpretation of results requires expertise. The integration of Artificial Intelligence (AI) into organic farming practices is becoming increasingly vital as the industry expands in Thailand. AI models designed to interpret pesticide residue test results, such as those from the GT-test kit, represent a significant advancement in ensuring the quality and safety of organic products. This application of AI is crucial in maintaining the integrity of produce, which is essential for consumer trust and market growth.

Moreover, AI can streamline the testing process by reducing the time and cost associated with manual interpretation. Developing an AI-powered mobile application could enable instant analysis of test results, making the process more accessible even for those with limited technical expertise. This would enhance testing efficiency and broaden the use of the GT-test kit across various regions and types of produce (Lima Santos, 2024; Thai Organics Farm, 2024). AI also offers benefits beyond improved test accuracy. By aggregating results from multiple tests over time, AI can identify trends and patterns in pesticide residue levels across different regions and farming practices. This data can inform policy decisions, guide organic certification processes, and assist farmers in adjusting their practices to meet organic standards more effectively (Suwonnakan, Sayasoonthorn, & Chueasamat, 2023; Zhang et al., 2023). This research aims to develop an artificial intelligence (AI) model for interpreting results from the GT-test kit. The development of this AI model will help reduce human error, lower testing costs, and provide convenience for users. It will benefit farmers, consumers, and regulatory agencies involved in monitoring pesticide residues in agricultural products in the future.

Literature Review:

1. Pesticide residue analysis

Pesticide residues are usually analyzed by methods such as Gas Chromatography-Mass Spectrometry Coupled (GC-MS), particularly for volatile compounds in complex samples, and Liquid Chromatography-Mass Spectrometry Coupled (LC-MS), suitable for non-volatile compounds (thermally unstable molecules) (GT Trading, 2024b). However, these methods require advanced technology, highly qualified operators, are time-consuming, and necessitate special sample preparation. Recently, spontaneous Raman spectroscopy has been applied for in situ pesticide detection on fruits (Oliveri et al., 2024). Agricultural products like vegetables are often affected by pests, such as worms, aphids, and fungi, which prompt farmers to use pesticides and antifungal chemicals to protect their produce. The chemical substances commonly found in pesticides are divided into four groups: organophosphate, carbamate, pyrethroid, and organochlorine. The first three groups are commonly used in agriculture and general products, while the fourth group, organochlorine, is prohibited in many countries due to its persistence in the environment and bioaccumulation in the human body, leading to health problems. The most common chemical residues are organophosphate and carbamate, which affect the central and peripheral nervous systems. When used in large quantities, these chemicals cannot be completely removed by cleaning because the residue can be absorbed into the produce's tissue, leading to pesticide residues in humans and potential health risks (Thai Organics Farm, 2024). Therefore, the GT-test kit, which is based on the cholinesterase inhibitor principle, provides a simplified method for pesticide residue analysis with minimal equipment, such as a small water bath controlled by light bulbs (GT Trading, 2024b).

In the context of organic farming, detecting pesticide residues is crucial. The use of AI models for analyzing pesticide test results is a growing area of research. The GT-Test Kit offers a practical solution for this purpose, providing detailed information on pesticide levels in agricultural products (GT Trading, 2024b; Oliveri et al., 2024). The integration of YOLO-based deep learning models enhances the accuracy and efficiency of pesticide detection, supporting the efforts of organic farmers in maintaining product purity and safety (Suwonnakan et al., 2023; Sirisha et al., 2023).

2. Principle of GT-Test Kit

The principle of the GT-Test Kit is based on measuring the inhibition of the enzyme cholinesterase. Some pesticides, such as organophosphorus and carbamates, inhibit this enzyme. The GT-Test Kit can detect whether substances in the sample inhibit the enzyme. The GT-Test Kit is very easy to use and can be carried out anywhere, such as in markets. The results are produced very rapidly compared to other pesticide residue analysis methods and at a very low price with inexpensive instruments. Pesticides and insecticides are poisonous agents limited to agricultural use only. The target samples include fresh vegetables and fruits, as well as salted fish. The color of a sample is evaluated by comparing it to the color of a control tube and a color of a cut point tube, as shown in Fig. 1 and Table I (GT Trading, 2024a, 2024b).

3. CiRA CORE

CiRA CORE is a Thai-developed AI platform aimed at supporting various industries, including manufacturing, healthcare, and education. It was created through collaboration between multiple universities and research institutions in Thailand, with the goal of providing a locally-developed AI solution that can compete globally. The platform allows for the development of applications without needing to train new models from scratch, simplifying the AI development process for users (Boonrod et al., 2022; Pongsakonpruttikul et

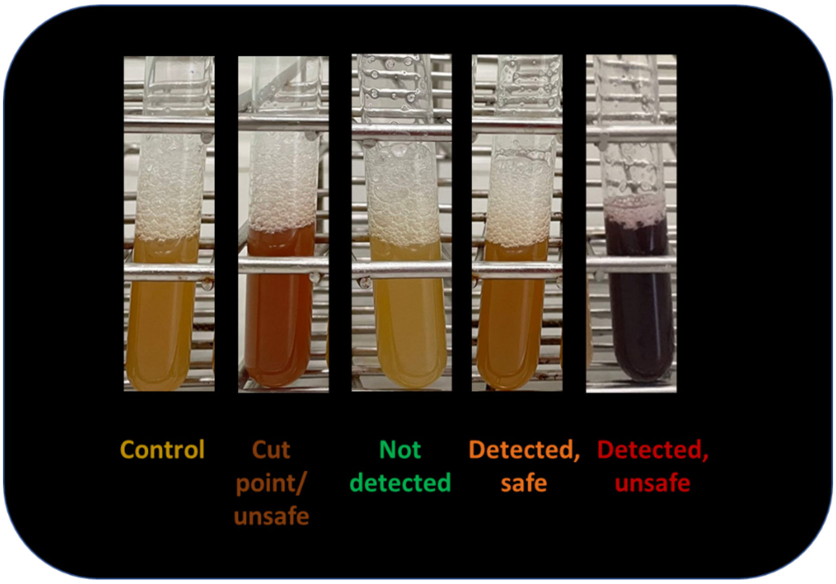


Figure 1. Result Evaluation : compare color in the tubes

Table 1. The meaning of color in the tube

Color in the tube	The result
Sample tube ≤ tube 1 (control/not detected)	Not detected
Sample tube > tube 1 but < tube 2 (cut point / unsafe)	There are some toxic residues expected safe* for consumption
Sample tube > tube 2 and ≥ tube 1 (cut point /unsafe)	There are some toxic residues expected unsafe** for consumption

Note: * safe for consumption = there are some toxic residues inhibited the cholinesterase enzyme at less than 50 %, these toxic residue amounts can be washed out by the consumer

** unsafe for consumption = there are some toxic residues inhibiting the cholinesterase enzyme at 50 % or more than, these toxic residue amounts cannot be washed out by the consumer, they are only decreased by washing.

al., 2022). CiRA CORE is designed to be a flexible and accessible platform, enabling users to build applications that can leverage deep learning and other AI technologies. It has been used in various fields, such as the study that utilized CiRA CORE deep learning technology to enhance the identification and classification of mosquito species in field applications (Eiamsamang et al., 2024). Although artificial intelligence has been used in entomological identification, optimizing its accuracy and practical application in the field presents ongoing challenges. The research focuses on improving the accuracy and efficiency of AI models for mosquito vector identification, with the ultimate aim of deploying the trained model in real-world field scenarios (Jomtarak et al., 2021). The study developed a CiRA CORE deep learning platform designed to identify major mosquito vectors and process annotated color images at three different resolutions. The platform's performance was evaluated using wild-caught mosquitoes. The model was trained and tested with processed images from a digital microscope, with verification by entomologists (Veerayuth et al., 2024). This deep learning prototype not only aids in identifying mosquito vectors but also holds potential for identifying other medical vectors. Furthermore, it supports local vector surveillance and control programs, especially in remote areas with limited entomological expertise (Eiamsamang et al., 2024). Deep learning technologies, including YOLO (You Only Look Once) models, have become crucial tools for image-based analysis in agriculture (Nitmai et al., 2023). Recent studies demonstrate the effectiveness of YOLO models in various applications, such as detecting impurities in frozen vegetables (Suwonnakan et al., 2023), recognizing vehicle license plates (Nitmai et al., 2023), and sorting labels in packaging processes (Moolpho, 2022). These models are also employed in the development of sorting systems for agricultural products, such as sweet tamarind (Hadkhuntod et al., 2023) and marigold leaves (Jomsri et al., 2021). The application of these technologies extends to the identification and classification of mosquito species and other agricultural pests (Pongsakonpruttikul et al., 2022; Suksangvoravong et al., 2024; Zhang et al., 2023).

4. Image Processing

Image analysis encompasses a variety of techniques used to extract meaningful information from images. This process is crucial across multiple fields, including medicine, security, and industrial applications (Akkaralaertsest et al., 2023). However, image analysis requires an image processor to interpret results from captured pictures. To date, many researchers have been applying image analysis in agricultural fields (Yammen et al., 2016; Rityen et al., 2019; Jantapit et al., 2019). For example, image processing technology has been used to detect visual characteristics of rice, such as shape and color, which help in distinguishing between marigolds and other objects that may be contaminated under storage conditions (Jomsri et al., 2021). Another study took 100 images of kale seeds and weed seeds, such as spinach, and processed the images using a computer program developed in Python to analyze the dimensions, including width, length, and area of the seeds, as well as color factors like red, green, and blue. Results showed that the mean width, length, and seed area of kale seeds were significantly higher than those of spinach seeds (Dathamart et al., 2019). Furthermore, the color value of kale seeds was found to be significantly different from that of spinach seeds, while the color value of amaranth and spinach seeds showed no difference. Thus, factors such as width, length, area, and color can be used to separate weed seeds mixed with kale seeds (Jantapit et al., 2019).

A sweet tamarind sorting system was developed using image processing techniques, classifying tamarind based on defects and size categories (Hadkhuntod et al., 2023). This system was tested on 3,000 images of tamarind, with the YOLOv8 algorithm used to evaluate three models (n, s, m). The model with the highest speed (7.28 fps) and highest precision (1.0) was selected. This technology aids farmers in sorting sweet tamarind efficiently and helps consumers gain confidence in the products (Hadkhuntod et al., 2023).

5. Deep Learning

Deep learning, a subset of machine learning, uses multilayered neural networks, known as deep neural networks, to simulate the complex decision-making processes of the human brain (Rana & Bhushan, 2023). Although machine learning has limitations when dealing with large amounts of data, deep learning works efficiently regardless of data size. Deep learning techniques have been widely used in various fields, including species and gender identification of mosquitoes with 95% accuracy (Veerayuth et al., 2024), lemon classification (Rityen et al., 2019), and spine injury detection (Boonrod et al., 2022). A recent study used the YOLO network to detect impurities in frozen food products, achieving an overall accuracy of 76% (Suwonnakan et al., 2023).

Deep learning models are trained using various techniques, with Convolutional Neural Networks (CNN) being one of the most widely used methods for image classification tasks. For instance, CNNs have been successfully applied to classify the species and gender of mosquitoes with 95% accuracy (Veerayuth et al., 2024; Jomsri et al., 2021). Moreover, deep learning techniques have been employed to recognize and accurately classify lemons by size (Rityen et al., 2019). A particular focus has been on creating models that can accurately determine lemon size from images, utilizing popular deep learning libraries such as YOLO (You Only Look Once). For example, YOLO networks have been used in studies like the one that employed the CiRA CORE platform for training and testing deep learning models on CT images to detect cervical spine subluxations. The study compared YOLO versions 2, 3, and 4, finding that the YOLO V4 model outperformed the others with an AUC of 0.743, sensitivity of 80%, specificity of 72%, and overall accuracy of 75% (Boonrod et al., 2022). Additionally, another study implemented a deep learning system using YOLO V4 to detect impurities in frozen food products and assess their quality and safety. The results indicated that the model achieved an overall accuracy (mAP) of 76%, with a loss value of 5.55. In detecting contaminants in spinach images, the model was most effective in identifying plastic, followed by rope, glass, stone, and wood. The model's accuracy, precision, recall, and F-1 score for detecting plastic were 52.22%, 52.94%, 55.38%, and 54.14%, respectively (Suwonnakan et al., 2023). Looking ahead, the advancement of AI technologies in agriculture holds the promise of more precise and efficient farming practices. The use of deep learning for species identification, pest management, and quality control in agricultural products is expected to become increasingly sophisticated. The continuous improvement of AI models will play a crucial role in advancing sustainable farming practices and ensuring the safety and quality of organic produce (Lima Santos, 2024; He et al., 2024).

Materials and Method

1. Materials

Dataset

Pictures of a testing tube from GT test kits analysis from images were input to a reading system. Collect data on 3432 photographs of the results of pesticide residue analysis by naming the photographs. According to the category and source of test tube images which consists of CORRECT is an accurate GT, AOSNA is an examination with a GT test kit that uses an inappropriate amount of substance, TB32D is an examination with a GT test kit at a temperature lower than 32 degrees and TA36D is an examination with a GT test kit at temperatures higher than 36 degrees, as show in Fig. 2(a)- (d) and example of ground truth from Safe4Sure Laboratory as show in Fig.3

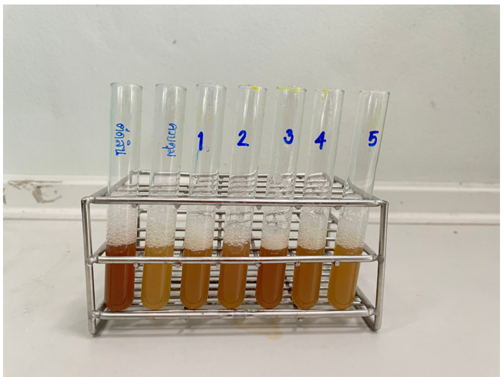


Fig. 2(a) sample image in CORRECT category

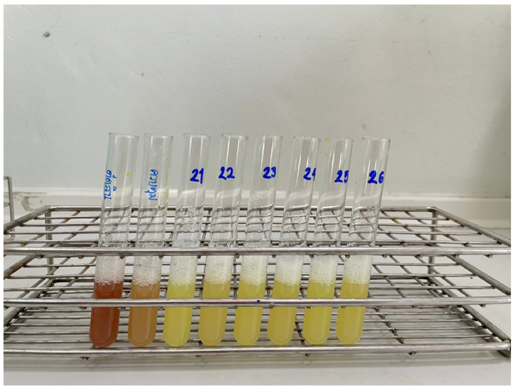


Fig.2(b) sample image in AOSNA category

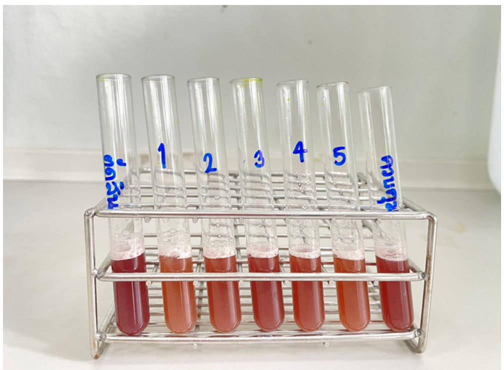


Fig.2(c) sample image in TB32D category

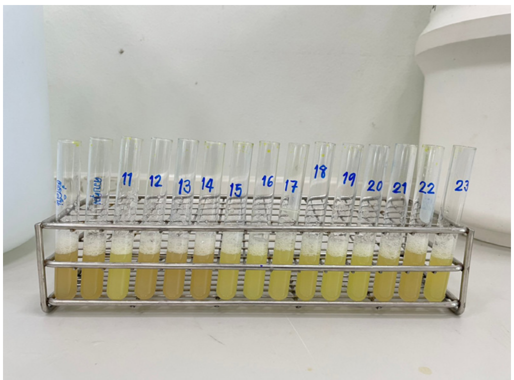
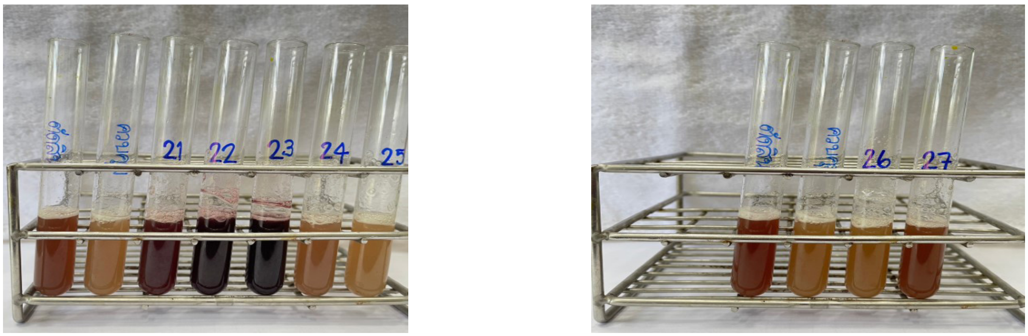


Fig.2(d) sample image in TA36D category

Figure 2. (a)-(d) Sample test tube image ground truth and labeling



Test tube no. 21 means having pesticide residue with unsafety level

Test tube no. 22 means having pesticide residue with unsafety level

Test tube no. 23 means having pesticide residue with unsafety level

Test tube no. 24 means not found pesticide residue

Test tube no. 25 means not found pesticide residue

Test tube no. 26 means having pesticide residue with safety level

Test tube no. 27 means having pesticide residue with unsafety level

Figure 3. Ground truth from Safe4Sure Laboratory by Lampang Rajaphat University Result

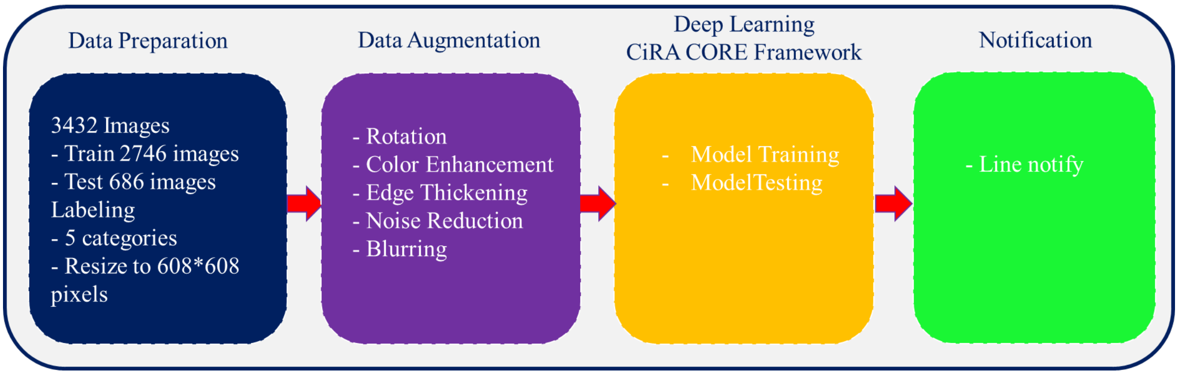


Figure 4. The sequence method Framework

2. Methods

This section presents details of our proposed framework including Data Preparation, Data Augmentation, Deep Learning CiRA CORE Framework, and Notification. An abstract representation is provided in Fig.4

Data Preparation

- Prepare Image Data: A total of 3,432 images will be used for training and testing. The data will be split into 80% for training (2,746 images) and 20% for testing (686 images).

- Labeling and Resizing Images: The images will be labeled and categorized into five groups: 1. Control Group, 2. Decision Group, 3. No Chemicals Detected, 4. Safe Group, and 5. Unsafe Group. Each image will be resized to 608 pixels by 608 pixels.

Data Augmentation: The images will undergo augmentation to increase the dataset size. This includes rotating the images by 90-degree increments, enhancing color sharpness, thickening the image borders, reducing noise, and applying blurring effects. This process will generate a total of 12,791 images for training the model.

Deep Learning CiRA CORE Framework

- AI Model Training: Train an AI model using YoloV8 with a batch size of 32 and a subdivision of 16.

- Model Testing: Test the model on the Deep Learning Framework CiRA CORE.

Notification

- Notification Setup: Implement a notification system using Line Notify.

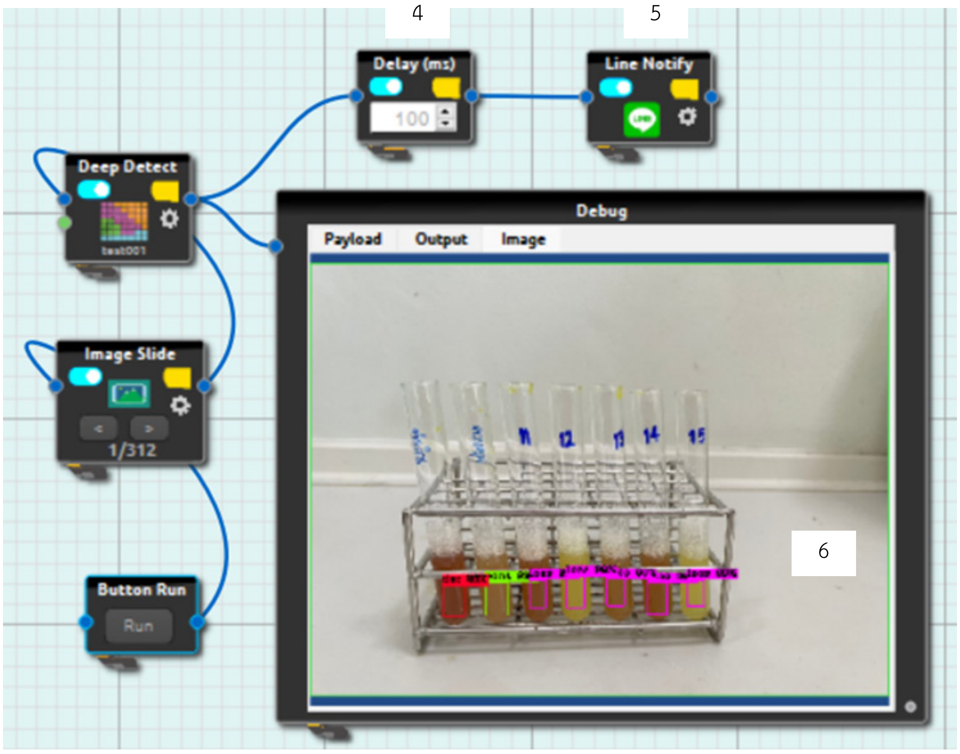


Figure 5. Diagram of CiRA CORE Deep Detection

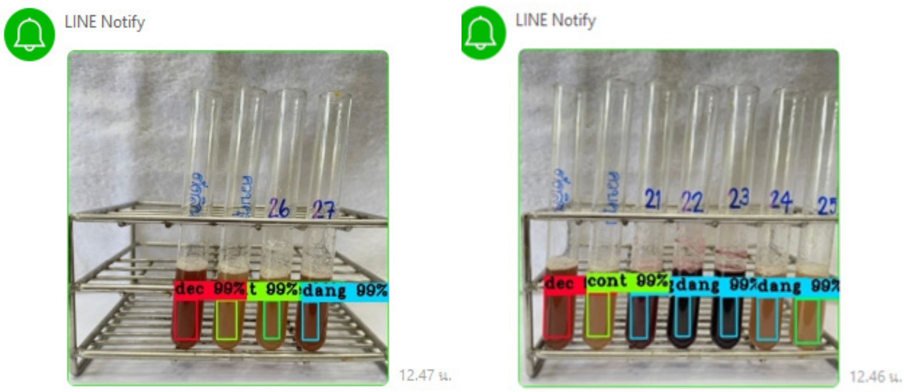


Figure 6. The result image Deep Detection show on Line Notify application.

The Diagram of CiRA CORE Deep Detection in this Experiment has 6 stations as shown in Fig. 5 In each station has a different commander and functions as follows

Station no. 1 Button Run: Use for start image Deep Detection

Station no. 2 Image Slide : Use for ship to a next picture Use for collecting and inserting picture to Deep Detect Mode

Station no. 3 Deep Detect :Use for analyzing picture according to AI model

Station no. 4 Delay: Use for putting of reporting time to Line notify

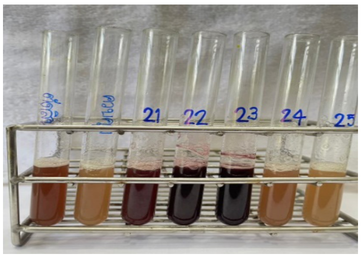
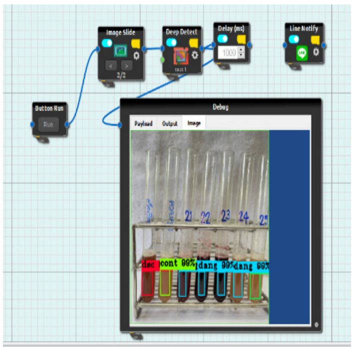
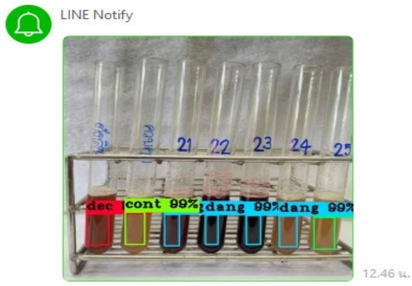
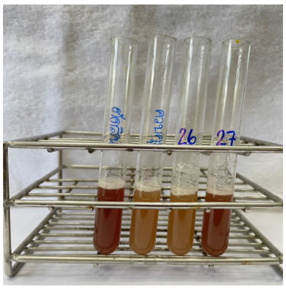
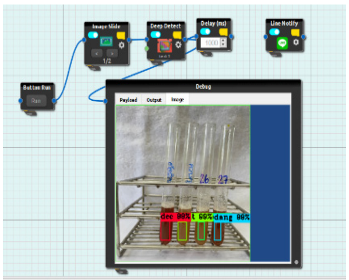
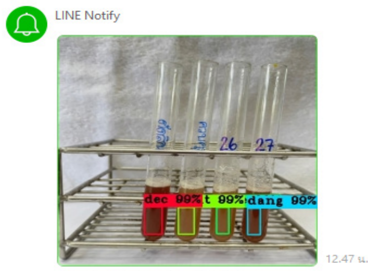
Station no. 5 Line Notify: Use for sending result image Deep Detection as show in Fig.6

Station no. 6 Image: Show image Deep Detection result on image stage

Results and Discussion:

Sampling pictures of test tubes from GT test kit were rename and resize and then compare with the correct testing results. A percentage of accuracy reading report from AI model was evaluated. The correct data without any missing point or damage point were except for a prototype of AI model. The interpreted results from AI model have been compared to the reading results from expertise shown in Table II. Additionally, the experimental results from Fig. 6(a)-(d) also demonstrate the detection accuracy across different image categories. In this research, experimental results were also presented using Bar Charts as shown in Fig.7 comparing the analysis reading results from laboratory answers, which were verified by experts (shown in blue bars as Ground Truth), with the results from the AI model detection (shown in orange bars). The test involved 686 images, and the results revealed that the AI model was able to detect and report the results correctly, with an average test tube accuracy of 92.48% and an average image accuracy of 92.62%.

Table 2. The results that AI model Detection compare with results from expertise.

Results from expertise	Results from AI model	Reporting on Line Notify
		
		

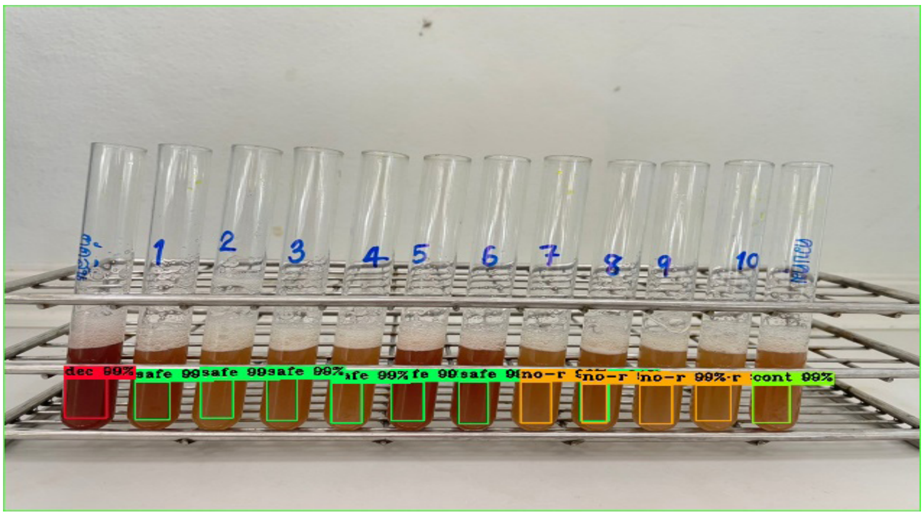


Figure 6(a). The results that AI model image Detection in CORRECT category

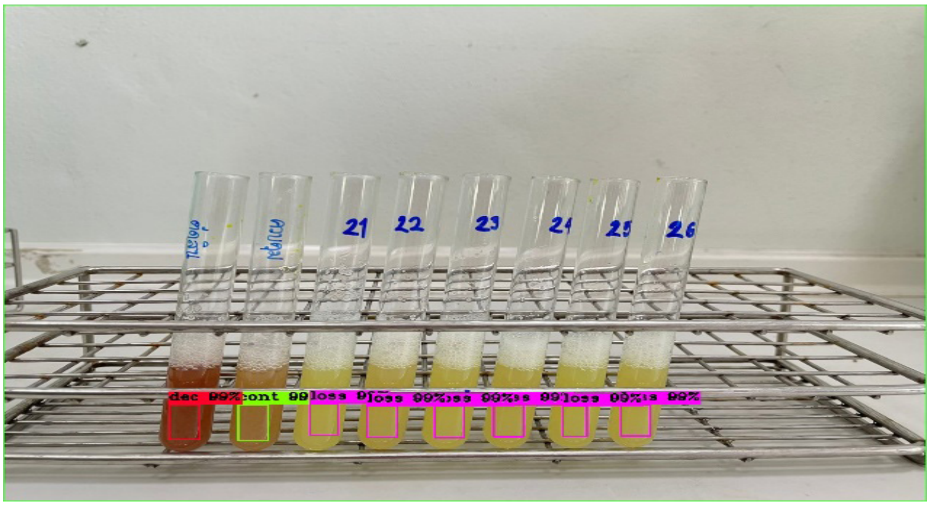


Figure 6(b). The results that AI model image Detection in AOSNA category

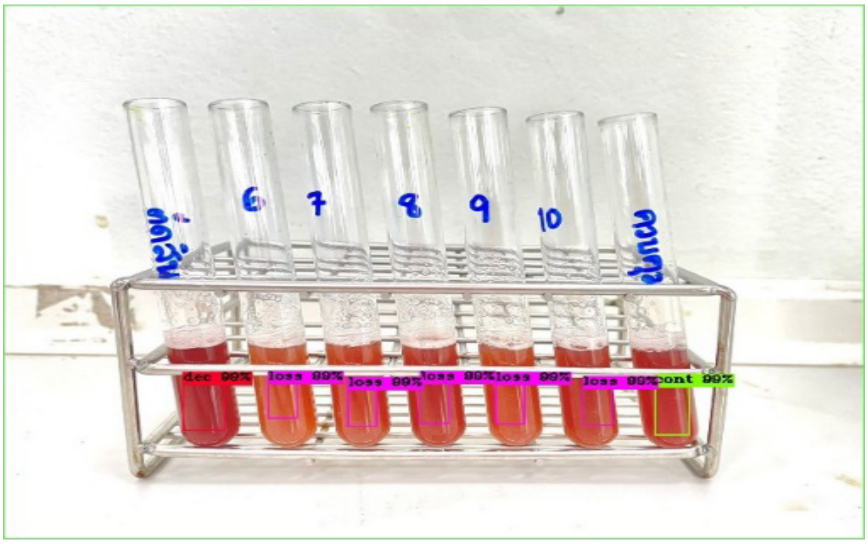


Figure 6(c). The results that AI model image Detection in TB32D category

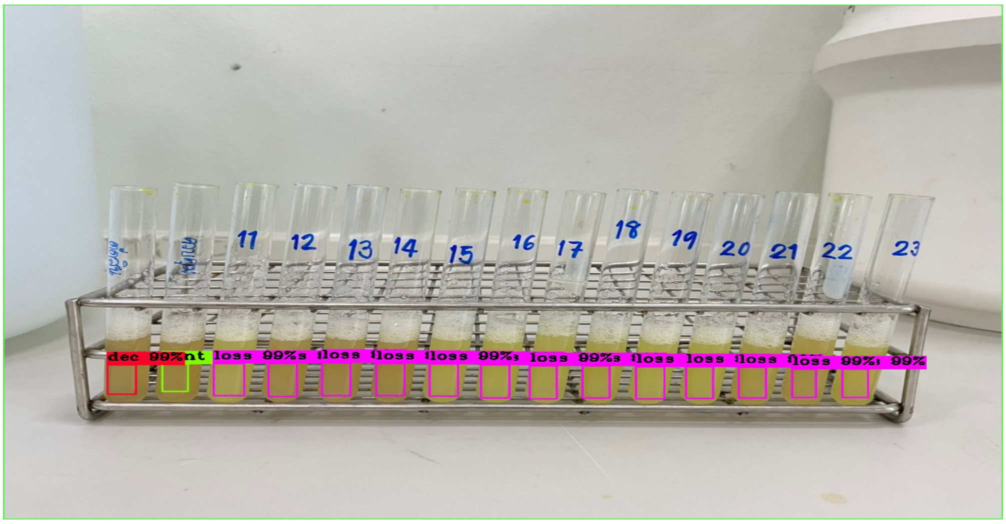


Figure 6(d. The results that AI model image Detection in TA36D category

Figure 6(a)-(d) Examples of reading results from AI model image Detection

Figure 7. Bar Chart of experimental results on test image data.

Discussion

The developed application is accurately read imaging results of pesticide testing in soil, water, and organic produce. The average of accuracy was 92.48% and the image accuracy average was 92.62%. The performance of this application revealed that 1) highly accuracy level was able to demonstrate a reliable on the results, 2) quickly reporting result and can analyze many test tube images in a short time, 3) more convenience and users do not need any special knowledge or skills to analyze test results. Furthermore, advantages of this application were 1) Increase efficiency of pesticide analysis using GT test kit in terms of speed, accuracy and convenience. 2) Reduce costs of mankind and expertise for doing the test, 3) Value-added in organic products in terms of providing scientific evident of pesticide residues testing quickly and accurately.

Conclusion

This research has developed a prototype system for image-based detection of pesticide test results in organic agricultural products, using a deep learning model developed on the CiRA CORE platform. The system demonstrates high efficiency and accuracy in analyzing test results, achieving an average accuracy of 92.48% in reading test results and 92.62% in image accuracy. This indicates the system's effectiveness in classifying test tubes accurately.

The analysis of the AI-generated results shows that the model can quickly and accurately detect and report results, reducing errors compared to manual reading by experts. Additionally, the system enhances testing efficiency by allowing for the analysis of a large number of test tubes in a short period. The implementation of this AI system makes the pesticide testing process more convenient and less reliant on specialized knowledge for interpreting results.

The development of this system also helps in reducing testing costs, as it eliminates the need for highly skilled personnel to conduct the tests. This cost-saving is significant for farmers and relevant agencies. The system's ability to provide scientific evidence for pesticide testing rapidly and accurately adds value to organic agricultural products and builds consumer trust.

However, there are some limitations to this research, such as the size of the dataset used for model training, the identification of pesticide types, and environmental differences that may impact model accuracy in real-world scenarios. These limitations should be considered and addressed in future research to improve the system's performance and expand its applicability.
In summary, the research demonstrates that AI technology has significant potential for developing tools that aid in the analysis of pesticide test results, benefiting farmers, consumers, and regulatory agencies involved in monitoring pesticide residues in agricultural products.

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