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USE OF DEEP-LEARNING TECHNOLOGY FOR AUTOMATED IDENTIFICATION AND MONITORING OF FLYING INSECTS IN INDUSTRIAL FOOD FACILITIES

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Abstract Pest identification and monitoring are essential components in an IPM program. In industrial food manufacturing facilities, pest management professionals monitor insect numbers with glue traps using UV- attraction or sex pheromone. Each trap will be collected and closely examined to identify and count the insects. Identifying and counting the insects is a time-consuming and labor-intensive task, especially when large numbers of glue traps are involved. The identification and counting accuracy could vary between different individuals who must first be trained in insect identification. This study describes two automated insect identification and monitoring devices based on deep-learning technology, named Pest-Vision S (PV-S) and Pest-Vision F (PV-F). Both devices use high-resolution cameras. PV-S scans a glue trap, uploads the image to the cloud for analysis, and the identification and the trapped insect numbers are available in 4 min. On the contrary, PV-F is an on-site device that provides real-time monitoring using IoT. The device takes a glue trap photo every hour and uploads the image to the cloud for analysis. The outcome of the analysis is accessible online, and whenever the insect number exceeds a set threshold, an alert email will be sent. Our study compared the accuracy between manual identification and those by PV-S/PV-F on 25 insect taxa/groups found on glue traps in food facilities. Depending on the prevalence of each taxon/group, the number of verifications ranged from 38–9167. The devices showed highest accuracy (93–95%) when identifying Psychodidae, Phoridae, Drosophilidae, Chironomidae, Dermastidae, Psocodea (winged), and Mycetophilidae, while lowest accuracy was recorded on Scatopsidae (67%) and Ceratopogonidae (69%). Using both devices, the man-hours spent identifying and counting insects on glue traps was reduced by 77.2%. The real-time monitoring could also intercept the infestation at the earliest stage and minimize the number of site visits during the low insect season.

Key words IoT, remote insect monitoring, AI, object detection

INTRODUCTION

Monitoring of traps in factories and stores is the basis of insect control. It is common to consider solutions of insect problems based on the information on how many insects and what species on the traps. To get such information, Pest Control Operators (PCOs) count and identify insects on the traps with microscopes. PCOs usually identify insects as the level of "family", but it is difficult to get such monitoring skills without education and experience because insects on traps are very tiny and unfamiliar species. Moreover, even for experienced operators, it is a time-consuming process to identify a large amount of captured insecticidal paper, and this is an excessive burden on workers, especially during periods of high insect population. It requires a great deal of effort, time, and money to secure and train personnel who possess such skills. Furthermore, no matter how much cost is allocated to this identification work, it cannot be charged to the customer; the PCO needs to be able to perform the identification work in less time and with less manpower. Therefore, the development of an automatic identification system for traps using Artificial Intelligence (AI) has become an urgent issue.

Recently, image identification by using AI technology has increased in agricultural or infectious disease fields. For example, the monitoring system of the traps in the greenhouse (Rustia et al., 2020), identification trial from pictures of mosquitoes (Park et al., 2020) and detection system of tiny herbivorous beetles on crops (Takimoto et al., 2021). There are few experiments on pest control fields. Accordingly, we developed AI to identify some pest insects by using deep-learning techniques; intrusion or outbreak in factories and stores. In this study, we investigate the count accuracy and identify accuracy of this AI, and how fast can AI get results compared to human work.

MATERIAL AND METHODS

Pest-Vision

An overview of the automatic identification system Pest-Vision used in this study is shown in Figure 1. Collect the glue trap attached to the light trap and place it under the camera. “1. Scanning” Take a picture of the entire glue trap with a high resolution camera. At this time, in order to make the shooting environment the same as that of the teacher data, the camera and the glue trap were covered and white LED light was equipped inside the cover. "2. Upload" Upload the image data (Figure 1) to the Web Cloud. "3. Analyze" The AI in the Web Cloud analyzes the images and outputs the number and groups data of insects. The system user can check the results from the website. This AI can classify insects into 25 groups and Other; Psychodidae, Phoridae, Drosophilidae, Chironomidae, Dark-winged fungus gnat (Sciaridae), Winged ant, Small Moth (Indian meal moth and others), Anobiidae, Culicidae, Large fly (Muscidae, Fanniidae, Calliphoridae and Sarcophagidae), Sphaeroceridae, Scatopsidae, Trichoptera, Crane fly(Tipulidae, Limoniidae and Trichoceridae), Staphylinidae, Ceratopogonidae, Cecidomyiidae, Dermestidae(especially *Anthrenus verbasci* and *Attagenus japonicus*), Psocodea (winged), Small Hymenoptera(Parasitoid wasps), Aphididae, Planthopper (especially Delphacidae and Cicadellidae), Heleomyzidae, Mycetophilidae, Thysanoptera. These groups were selected from the list that PCO actually identifies in its monitoring work, and the number of groups is considered to be sufficient for insect control consulting in factories management.

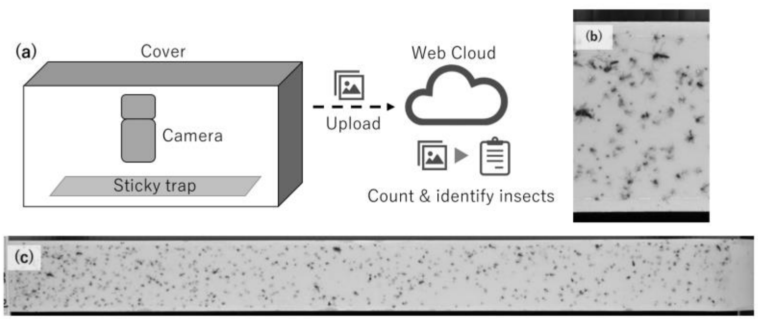

Figure 1. (a) Pest-Vision system overview; (b, c) Image of glue trap (enlarged (b), whole (c).

Identification accuracy survey

62 glue trap images were analyzed using Pest-Vision. If the AI predicts the actual insect as an insect, it will be "True Positive" (correct answer), and if it predicts the actual insect as not an insect, it will be incorrect. It is also incorrect if what the AI expects to be an insect is actually dust or an empty space. The former is called "False Positive" and the latter "False Negative". In order to take these two types of errors into consideration, the percentages Precision and Recall were calculated respectively, and the F-measure was calculated by taking the harmonic mean of these two percentages (Table 1).

Table 1. Confusion matrix for calculating accuracy of counting or identifying.

		Prediction by AI	
		an insect	**not insect**
Correct	**an insect**	TP: True Positive	FN: False Negative
	not insect	FP: False Positive	TN: True Negative

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F= HarmonicMean(Precision, Recall)=2PrecisionRecall / (Precision+Recall)

We prepared the time required by Pest-Vision to the time required for a person to visually identify the glue trap. The sticky area of the glue trap was 5 cm wide and 50 cm long, and both human and Pest-Vision identified the insects captured on this sticky area. For Pest-Vision, we recorded the time from when the insecticidal paper was set inside and ready to be scanned until the results were displayed on the web screen. Since the time required for analysis increases with the number of insects with Pest-Vision, time was measured for each of the three processes: "1. scanning," "2. uploading," and "3. analysis". For the human trial, the time required to write the number of 25 species and Other on a paper was recorded after placing a glue trap under the microscope. Trap identification operators were limited to those who had at least three years of experience in trap identification work.

RESULTS

Identification Accuracy Survey

Table 2 shows the result of the identification accuracy survey. F-measure ranged from 0.69 to 0.95 excluding Other. The number of insect groups with an F-measure of 0.85 or higher was 15, more than half of the total. The groups with the highest accuracy were Psycodidae (F-measure = 0.95), Phoridae (0.95), Chironomidae (0.94), Trichoptera (0.95), Dermestidae (0.94), Psocodea (winged) (0.93) and Mycetophilidae (0.93). On the other hand, groups with low accuracy were Scatopsidae (0.67) and Ceratopogonidae (0.69).

Table 2. Identification accuracy for insect groups.

	Insect Name	Precision	Recall	F
1	Other	0.63	0.74	0.68
2	Psychodidae	0.97	0.93	0.95
3	Phoridae	0.96	0.94	0.95
4	Drosophilidae	0.92	0.92	0.92
5	Chironomidae	0.95	0.94	0.94
6	Sciaridae	0.87	0.90	0.89
7	Winged ant	0.94	0.69	0.79
8	Small Moth	0.83	0.87	0.85
9	Anobiidae	1.00	0.81	0.90
10	Culicidae	0.72	0.86	0.78
11	Large fly	0.83	0.88	0.85
12	Sphaeroceridae	0.74	0.78	0.76
13	Scatopsidae	0.71	0.63	0.67
14	Trichoptera	0.95	0.94	0.95
15	Crane fly	0.7	0.8	0.75
16	Staphylinidae	0.97	0.84	0.90
17	Ceratopogonidae	0.62	0.77	0.69
18	Cecidomyiidae	0.71	0.79	0.75
19	Dermestidae	0.95	0.94	0.94
20	Psocodea (winged)	0.92	0.93	0.93
21	Small Hymenoptera	0.72	0.8	0.76
22	Aphididae	0.94	0.63	0.75
23	Plant hopper	0.89	0.90	0.90
24	Heleomyzidae	0.94	0.84	0.89
25	Mycetophilidae	0.95	0.91	0.93
26	Thysanoptera	0.73	0.97	0.84

The main misidentifications made by the AI are shown in Figure 2. If the arrow points from group A to group B, it indicates that the AI tends to misidentify group A as group B. The thickness of the arrows indicates the percentage of misidentifications to the corresponding group (intra-groups misidentification rate). The arrows only show relationships with intra-groups misidentification rates of 0.3 or higher. Chironomidae and Other have arrows extending from many insect groups, indicating that they are easily mistaken for one another. Small Moth and Trichoptera, Winged ant and Small Hymenoptera are also easily mistaken for each other. From a human point of view, these groups are very similar to each other.

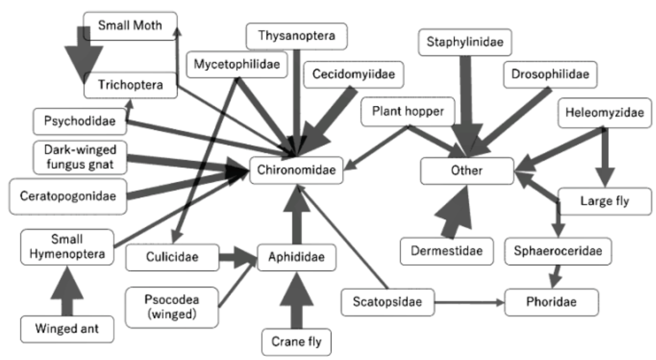

Figure 2. Trend diagram of misidentification by the AI.

Analysis Time Survey

Figure 3 shows the result of the time required for analysis (counting and identifying). As the number of insects captured on the glue trap increased, the analysis time for both humans and AI increased. The increase in analysis time for the AI was small enough to be ignored compared to that of the human. The analysis time for humans increased exponentially with the number of insects, and in particular, it took more than an hour to identify the 900 or so captured insects on a glue trap.

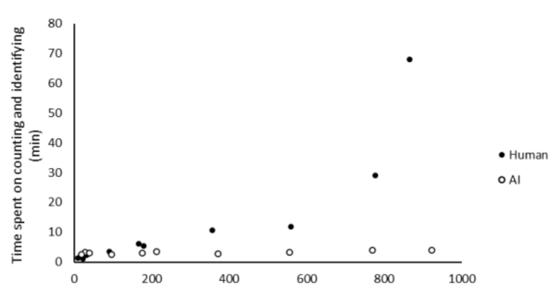

Figure 3. Time spent counting and identifying by Human (●) and AI (Pest-Vision) (○). Horizontal: number of insects on trap, Vertical: Time to finish counting and identifying glue trap.

DISCUSSION

AI Makes Same Mistakes as Humans

Anobiidae and Dermestidae both became highly accurate (Table 2). Most of the groups in the list which the AI can identify are Diptera or insects which have prominent wings, and they are not similar to Coleoptera, resulting in high accuracy for Coleoptera. Chironomidae is a taxon that is easy to make a mistake in the AI. Because of the diversity of morphology in Chironomidae, it tends to be difficult to distinguish from other Diptera, especially for beginners in identification. It turns out that the AI is easy to make the same mistakes as humans. AI and humans tend to be similar in their abilities and disabilities. AI that makes mistakes that humans can readily identify will not gain trust of users.

AI Will Reduce Time Required For Trap Identification.

When the analysis time of the same glue traps was compared between the AI and humans, the AI exceeded the speed of humans over 200 insects. There is a significant difference from the AI in glue trap with more than 200 insects. The total analysis time for the 10 glue traps was 31.7 min for AI / 139.1 min for human, resulting in 22.8% of the work time for AI compared to human. The use of the AI can reduce 77.2% of the conventional manual work. In the conventional way, it was impossible to identify glue traps without knowledge of insects, but with this machine, anyone can easily perform the identification work. In actual identification work, factors such as deadlines for reporting, fatigue due to long work hours, and differences in individual experience can cause identification accuracy to be unstable. The identification accuracy of AI is stable and is not affected by long-term operation. This can be a great advantage in that it can standardize identification done by individuals. PCO may spend a lot of time on identification, but with Pest-Vision, the time saved can be used for investigating the source of insects and spraying insecticides more carefully. This will reduce the invasion and outbreak of pest insects compared to the past and bring benefits to factories and stores.

Application of AI Identification

If the light traps are equipped with the same scanning equipment and upload system as the Pest-Vision, it will be possible to monitor the insect trapping situation in real time (for example, once an hour) without the PCO collecting glue traps. This system is called Pest-Vision Fly (PV-F) (the device that takes glue trap back to the office and identifies it is called Pest-Vision Station (PV-S)). The following advantages can be expected from this PV-F.

Real-time monitoring. The images taken by the glue trap installed at the site are uploaded regularly, it is possible to monitor the situation at the site in near real time. Alerts can be set with a threshold value for each sensor, it is possible to take immediate action when the insect capture exceeds the threshold value. In addition, since the groups of insects can be grasped remotely, the source of the outbreak and countermeasures can be estimated without visiting the site. This means that in some cases it is possible to consult remotely, or to prepare countermeasures in advance and then visit the site, making operation more efficient and labor-saving than before.

Monitoring the number of insects captured every hour. Since images of traps are uploaded at regular intervals, it is possible to compile data on changes in the number of trapped insects by hour, which could not be grasped with conventional monitoring. By comparing the actual activities at the site with the time when a large number of insects were captured, it is possible to detect the cause and take countermeasures.

Minimize the number of people entering and leaving the clean area. Until now, PCO have been making regular visits to their customers even when there is no insect infestation. Unnecessary regular visits to the factory can increase the possibility of introducing insects and debris into the factory and contaminating products, and also increased the risk of infection control, as seen in the recent COVID-19. PV-F allows the PCO to know the status of the site in real time, so that the PCO can choose not to visit the site if no insects are captured, thus avoiding the mentioned risks associated with visiting the cite as much as possible.

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