PestDSS: An Integrated Decision Support System for Sustainable Pest Management in Agriculture

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***Abstract*—The direct and indirect damage to crops caused by pests is a major factor affecting crop yields. Providing farmers with professional and cost-effective pest management decisions in a timely and accurate manner is a challenge in precision agriculture. Currently, researchers propose agricultural decision support systems using database and data analysis techniques to provide farmers with expert support and economic thresholds for pest management. However, these efforts overlook the challenge of identifying multiple pest species for agricultural workers and human error in the manual monitoring of pest densities. We propose PestDSS, an object detection-based decision support system to address the aforementioned challenges, which integrates agricultural decision support systems and state-of-the-art object detection models to semi-automatically make pest management decisions for farmers. Specifically, PestDSS includes a cloud-based farm information management module that allows users to manage their own farm data, a knowledge base of agriculture module, and a decision-making tool module for pest management. The decision-making tool combines outputs of an object detection model with optimisable thresholds developed through expert knowledge to provide pest management decisions. The proposed pest detection model outperforms current state-of-the-art object detection models on three pest detection datasets. We apply PestDSS to a case study of wheat pest management to demonstrate the usability of the system and illustrate the potential for its use.**

***Index Terms*—Decision Support System, Object Detection, Integrated Pest Management**

I. Introduction

Pests cause significant damage to agricultural products and limit the development of agriculture. According to estimates by the Food and Agriculture Organisation of the United Nations, direct and indirect damage from pests causes a 20% to 40% reduction in agricultural yields each year, where the indirect damage includes fungal infections and disease transmission caused by pests. [1] Although a large number of chemicals are used to counteract the decline in agricultural yields caused by pests, such measures have harmful consequences including chemical contamination of fields and ecological damage. To address the agricultural development challenges posed by pests, computer-aided decision-making systems for agricultural pest management are a feasible solution with the goal of optimising the agricultural return rate while protecting the environment and resources.

Most current state-of-the-art agricultural decision support systems use a large number of expensive sensors to collect data for making decisions [2] or provide decision-making support through data analysis of laboratory data for agricultural workers. [3] The extraordinarily high cost and low robustness of these decision systems hinder their application in real-life scenarios. Meanwhile, most agricultural decision support systems are committed to providing support for irrigation and disease management [4] rather than pest management due to the lack of efficient pest detection methods.

In this paper, we propose an object detection-based decision support system, PestDSS, to provide pest management decisions on whether to use pesticides and explanations of decisions. The system is implemented based on cloud computing architecture, mainly including a farm information management module, an agricultural knowledge base module, and a decision-making tool module. The workflow of PestDSS is shown in Fig. 1. The decision-making tool uses image information from the user to calculate pest densities and species and makes decisions in conjunction with contextual information such as crop growth stages. After a decision-making process, a feedback task is sent to users for optimising the expert system.

The contributions of this work are fourfold. Firstly, we develop an agricultural decision support system based on an object detection model to provide decisions for pest management. Secondly, we construct a pest detection dataset by handheld devices for wheat pest detection in the real environment. Thirdly, a pest detection model is proposed to provide

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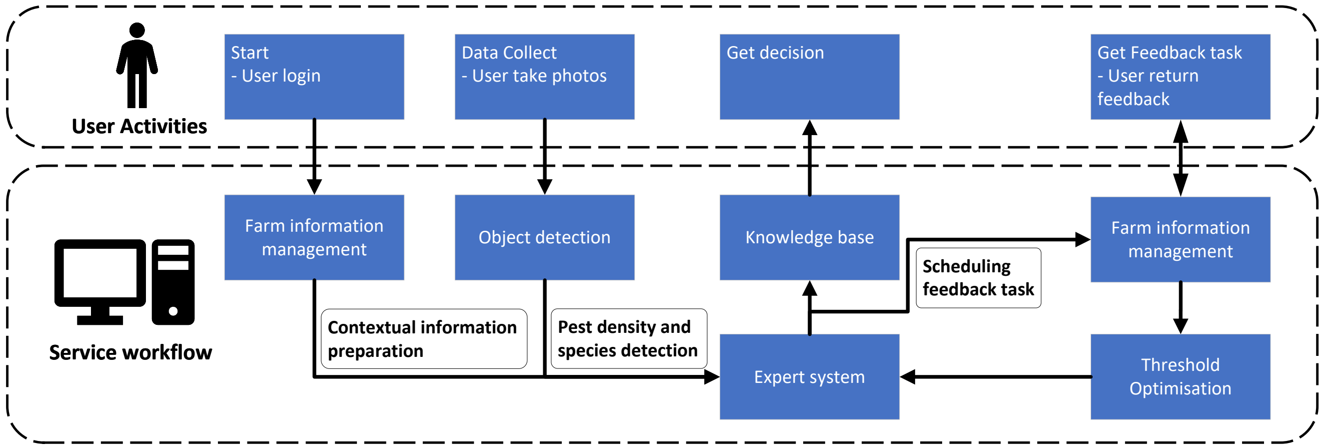

Fig. 1. The workflow of PestDSS.

population density and species of pests for the decision-making tool. The proposed pest detection model achieved higher mean average precision on three pest detection datasets compared to Faster RCNN [5] and YoloX [6]. Last, a case study on wheat pest management is conducted to validate the effectiveness of the system conceptually and to demonstrate the usability and limitations of our system based on user surveys.

II. Related Works

A. Decision support systems for agriculture

With the rapid development of computer technologies in the context of precision agriculture, such as Cloud Computing, Big Data, the Internet of Things, and Artificial Intelligence, researchers are committed to building a system to provide agricultural workers with precise and sustainable agricultural decisions to balance agricultural inputs and outputs. The systems are called the decision support system. The agricultural decision support system is more formally defined as a smart system which is capable of providing decisions based on data or supporting the agricultural decision-making process in different situations. [7]

Some work demonstrated the effectiveness of agricultural decision support systems. For example, a decision support system was proposed for irrigation management. [8] Meanwhile, the best irrigation solution in terms of water use efficiency was identified in a case study of maize through the proposed system. [8] In disease management, a decision support system combined with drones to reduce environmental pollution by using ultrasonic sensors and images to detect plant diseases and apply herbicides precisely. [2] Moreover, a Bayesian model was utilised in the decision support system [9] to predict the risk of wireworm infestation for providing pest management strategies.

Overall, a large number of successful agricultural support systems have been proposed and some of the work have recorded the use of pesticides. However, there is still a lack of general decision support systems to support pest management, due to the lack of effective and cost-effective pest detection methods.

B. Object detection for pest management

Object detection is a classical computer vision task that focuses on acquiring bounding boxes and classifying all instances of interest in an input image. In the early work on computer vision methods applied to pest management, manually designed image feature extraction methods were used in object detection tasks, such as the local binary pattern operator [10] and entropy-based histogram thresholding algorithm [11]. These efforts have some obvious limitations such as the inefficiency of the methods in complex image backgrounds.

With the success of deep neural networks for computer vision tasks, convolutional neural network-based object detection models are applied to pest detection tasks. Current advanced convolutional neural network-based object detection models are divided into two categories based on model structure, two-stage detection models and one-stage detection models. The difference between two-stage detection models and one-stage detection models is whether there is a structure for proposing bounding boxes. Faster RCNN [5] as a state-of-the-art two-stage detection model was used in pest detection through a fixed detection device and optimised by integrating a local attention module and a global attention module. [12] Yolo is a series of one-stage object detection models that demonstrate higher performance with a lightweight model structure than Faster RCNNs. [6] Due to the advantages of the Yolo object detection model, a large number of pest detection efforts were proposed based on the Yolo object detection model. [13] These efforts were able to obtain pest numbers. However, due to the lack of sampling methods and standards, it is not possible to obtain population densities of pests that are more effective in making decisions.

In recent years, transformer-based neural networks have shown advantages in encoding global features. The transformer-based object detection model, DETR, was used

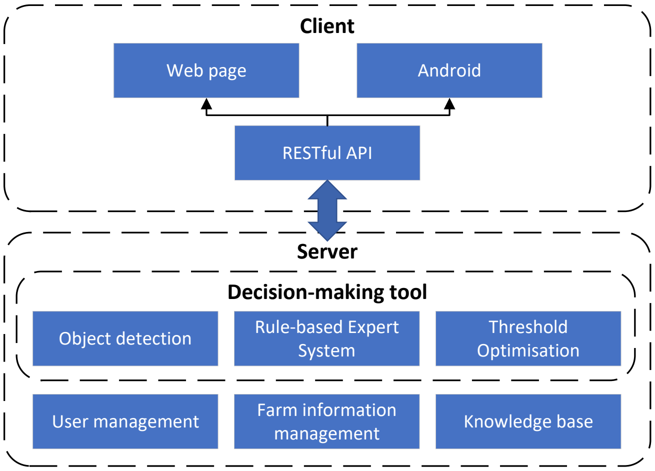

Fig. 2. System architecture of PestDSS.

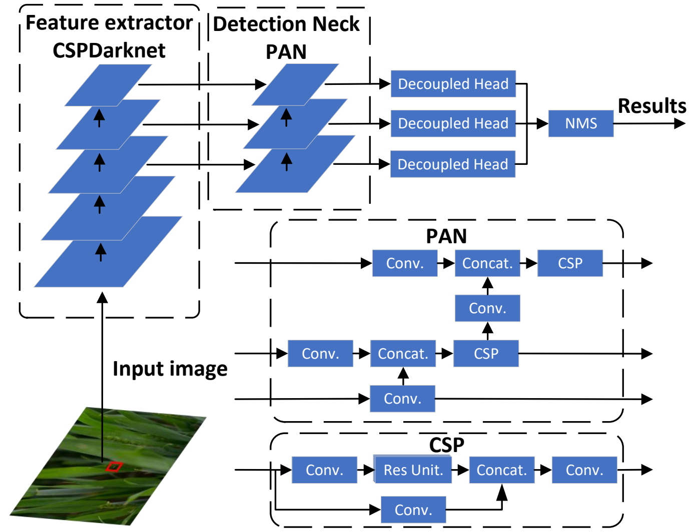

Fig. 3. Pest detection model for pest management.

to detect the pests in the traps through images. [14] However, the training of such models requires a larger number of datasets due to the lack of inductive biases in the transformer structure, such as rotation invariance and scale invariance in the convolutional structure. In general, the object detection model solves the pest detection problems in pest management tasks. However, there is still a gap between pest detection and pest management decision-making.

III. Proposed Methods

Decision support systems are computer-assisted tools that improve the quality of decision-making by extracting and implementing rules or systematic knowledge from collected data. [15] In this work, we propose an agricultural decision support system, called PestDSS, which extends a farm information management module to an agricultural decision support system by integrating a pest management decision tool and an agricultural knowledge base. The farm information management module in PestDSS provides contextual information for the pest management decision tool by capturing and recording farm and crop-related information from users to reduce production costs, maintain high crop quality, and comply with agricultural and environmental standards. The pest management decision tool is built based on an object detection model and a rule-based expert system. The object detection model is used to detect the densities and species of multiple pests through manually acquired images of farmland. The detection results are processed by the rule-based expert system, which integrates the farm and crop information to provide a decision recommendation on whether pests need to be repelled.

A. System architecture

The system architecture of PestDSS is based on cloud computing and is therefore highly reliable and scalable. The various modules of the system consist of separate services and provide interfaces in the form of RESTful APIs as Fig. 2 shown. These separate services are implemented through Springboot and are deployed on Kubernetes clusters. The object detection service in PestDSS is a trained pest detection model implemented by Pytorch. PestDSS offers three different clients focusing on different concerns, such as the web page client focusing on farm information management, the android client focusing on decision-making tools for pest management, and the RESRFul API focusing on providing access and the ability to extend functionality for technicians.

B. Pest detection model

We propose an object detection model and a density calculation method to detect pest densities and species by image information. The object detection model structure is modified from one stage detection model, YoloX [6], which includes a convolutional neural network for feature extraction, a path aggregation network (PAN) as detection neck structure for incorporating lower-level features into higher-level features, and multiple decoupled detection heads for higher detection accuracy, as shown in Fig. 3. The main structural change lies in the optimisation of the detection neck structure, where the direction of data fusion has an impact on the accuracy of tiny object detection. We used a PAN to replace the structure in the original work of YoloX to obtain higher performance on pest datasets.

In addition to model structure, there are some training tricks used in this work including data augmentation and label assignment strategy. We use image flipping, splitting, HSV perturbation, and object copy and paste during the model training stage. The difference with YoloX is that we turn off the mix-up function and mosaic function due to its unfavourable performance of smaller detection models [6] [16]. The task-aligned assigner [17] is used as the label assignment strategy, rather than SimOTA in YoloX. The task-aligned assigner uses

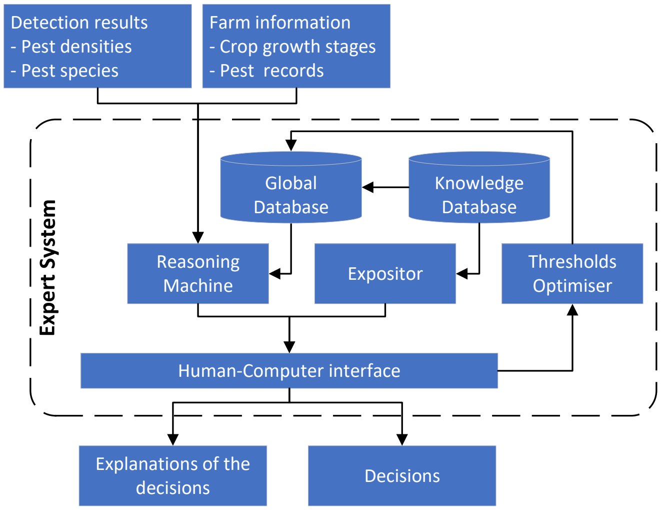

Fig. 4. The workflow of the rule-based expert system for pest management.

an anchor alignment metric to combine the assignment of the bounding box with the classification task to select the positive sample of the generated anchor. The loss function is shown as

$$Loss = \lambda Loss_{CIoU} + Loss_{Obj} + Loss_{Cls}, \qquad (1)$$

where λ is a balance coefficient for Complete-IoU loss used for location, $Loss_{Obj}$ and $Loss_{Cls}$ are binary cross entropy loss for object and classification.

To calculate the population density of pests in the field, we propose an algorithm to calculate the actual area of an image through the equivalent focal length. Equation (2) is a basic method for calculating the actual area of images, where $F_{equivalent}$ and S_{sensor} are the focal length of a camera lens and film frame size, respectively. The file frame size is also known as the size of the camera sensor. However, it is a challenge to obtain the camera setting from image data, especially for the film frame size. Meanwhile, it is unreliable to maintain a dynamic table of all camera models and sensor information. Therefore, we use the equivalent focal length as $F_{equivalent}$ in (2). The equivalent focal length is the focal length applied to another lens used on $35mm$ film frame size that would give the same field of view on this camera. The 35mm film frame size is also known as the size of full-frame sensors. We obtain the equivalent focal length $F_{equivalent}$ from the Exchangeable Image File (EXIF) information. The size of full-frame sensors is a fixed $24 \times 36 (mm^2)$. By this method, we are able to obtain the density of pests.

$$S_{actual} = \frac{D_{target}}{F_{equivalent}} \cdot S_{sensor} \qquad (2)$$

C. Rule-based expert system

For providing advice on pest management decisions, we are required to integrate prior agricultural knowledge in the text form and automated decision-making processes. We propose a rule-based expert system that extracts quantified rules for pest management from literature review through regular expressions and data cleaning to address the aforementioned challenges. The effectiveness of expert systems has been proven in a wide range of works that use computers to automatically simulate the decision-making process of human experts solving complex problems by extracting rules from the knowledge and experience provided by one or more experts in a particular field [18] [19]. The proposed rule-based expert system in this work includes five main components, reasoning machine, expositor, knowledge database, global database, and thresholds optimiser, as Fig. 4 shows. The reasoning machine is a set of continuous IF (CONDITION) (BEHAVIOUR) ELSE (BEHAVIOUR) structures used to make decisions based on pest densities and species from detection models, crop growth stages, and pest management records from farm information management module. The expositor generates explanations of the decision for end users based on the decision and decision path. Meanwhile, relevant expert knowledge from the knowledge database is provided to end users. The knowledge database stores a large amount of agricultural knowledge in text and image form, which is used to initialise the thresholds required by the reasoning machine. The initialised rule thresholds are stored in Global Database. When user feedback is obtained, the threshold optimiser is able to optimise the thresholds.

D. Threshold Optimisation

The initial thresholds extracted from the knowledge database are insufficient to construct an effective automated pest management decision tool. There are several reasons for this problem. Firstly, we identify the problem of missing data for quantitative agricultural pest management thresholds. For example, some works identified spring outbreaks of gout fly that can severely affect crop yields [20], but there are no defined population density thresholds for which eradication is required. Secondly, we identify some lower thresholds, close to the point where pests are required to be removed as soon as they are identified. These thresholds are obviously dependent on the particular data sampling method. Due to differences in sampling methods, thresholds for pest management should also be adjusted. Last but not least, the early research of pest management thresholds may not be suitable for the current agricultural environment due to the extensive use of pesticides and the introduction of biological control in recent years. The pests may develop resistance to pesticides or have natural enemies.

As shown in Fig. 2 and Fig. 4, a feedback task is scheduled by the farm information management module after the expert system has completed a decision. Moreover, the decision recorder is stored by the farm information management module. The feedback task is sent to users at regular intervals, including a questionnaire and pest detection. Users are required to provide feedback on the validity and impairment of the decision and the optimiser adjusts the threshold globally with a small learning rate.

TABLE I
STATISTICAL INFORMATION OF THREE DATASETS.

Indicators	***IP102***	***Aphids***	***WheatPest***
Num. of images [a]	19,167	1,000	661
Num. of objects [b]	22,284	6,325	822
Num. of categories [c]	97	2	7
Avg. object pixels pct. [d]	37.27%	0.08%	0.34%

[a] The number of images in a dataset.
[b] The number of objects in a dataset.
[c] The number of category in a dataset.
[d] The average percentage of object pixels in one image.

TABLE II
THE MEAN AVERAGE PRECISION OF OBJECT DETECTION MODEL ON THREE DATASETS.

	Faster RCNN	***YoloX***	***Our Model***
mAP (IP102)	55.25%	56.87%	**58.17%**
mAP (Aphids)	7.18%	66.24%	**75.29%**
mAP (WheatPest)	7.76%	11.01%	**42.6%**

IV. EXPERIMENTATION AND RESULTS

For evaluating the usability of PestDSS, two parts of work are performed including evaluating the performance of the pest detection model and evaluating the decision support system in a case study of wheat pest management during this project.

A. Image dataset

During the development of PestDSS, a wheat pest dataset is constructed, named the WheatPest dataset. Current common agricultural pest datasets are constructed through the use of search engines or in a laboratory environment. Unlike those datasets, images in the WheatPest dataset are collected from a real environment and conform to specific sampling criteria to ensure the sample distribution of objects in real-use scenarios, especially for the images used to calculate pest densities. Compared to the datasets constructed by taking photos of pests caught in traps, our dataset is more challenging due to the complex natural environment.

In addition to the WheatPest dataset, two public datasets are used in the evaluation of the pest detection model including the IP102 dataset [21] and an Aphids dataset from AgriPest dataset [22]. IP102 is a large public pest image dataset including 19,167 annotated images for 97 classes. However, this dataset is collected by search engines and has larger objects for detection. The Aphids dataset [23] is built for two kinds of aphids through data cleaning from the AgriPest dataset [22]. This dataset is a typical tiny object detection dataset for pests. The statistical information of those datasets is shown in Table. I.

B. Experimentation setting

For evaluating the performance of the proposed pest detection model, we compare the proposed pest detection model with two state-of-the-art object detection models including Faster RCNN [5] and YoloX [6] in terms of mean average precision (mAP). The mAP is defined as the mean value of the area under a Precision-Recall curve.

The input of detection models is 640*640 images. The convolutional neural network, CSPDarknet [6], is used as the feature extractor in this work. Input sizes of the detection neck in YoloX and our proposed model are 20*20*512, 40*40*256, and 80*80*128, respectively. The anchor setting of Faster RCNN is 64, 128, and 256 with the ratio of 1:1, 1:2 and 2:1. All three models are trained with early stopping and data augmentation which is turned off 20 epochs earlier. All three datasets are split into a training dataset, a validation dataset, and a test dataset in the ratio of 8:1:1.

C. Pest detection model

Table. II presents the performance of object detection models on three datasets. Our model outperformed in three datasets compared with Faster RCNN and YoloX due to the optimised model structure and suitable data augmentation methods. The reason for the similar mAP of three detection models in the IP102 dataset is that the dataset has a large amount of data and is built for large objects. Therefore, the data augmentation methods and detection neck for fusing multi-layer features do not show a significant improvement in mAP. In contrast, the benefit of detection neck for small object detection is presented in the Aphids dataset and WheatPest dataset. As described in the method section, the orientation of the data fusion in the detection neck affects the final performance of the detection model, which demonstrates the advantages of the PAN structure. In addition, the mAP of YoloX model which uses mixup and mosiac data augmentation methods lagged behind our model, especially on the WheatPest dataset.

D. Case study: Wheat Pest Management in fields

After the development of PestDSS, we conduct a user-based case study, Wheat Pest Management in farmlands, to evaluate the usability of PestDSS. The aims of the case study are to demonstrate the functionality of PestDSS, obtain decision results as proof-of-concept, and obtain user feedback for system optimisation. Eleven participants are invited to use the PestDSS system via an Android client and to evaluate the pest management decision-making process in the form of Likert scales. Participants are asked to use the pest management decision-making tool by following the PestDSS guidelines. All participants complete the decision designation process and receive a decision with explanations. Table. III shows how users rated the ease of use of the decision-making tool where the detection process as the main interaction process is rated separately. According to the feedback from participants, PestDSS provides a semi-automatic pest management decision tool and effective access to relevant agricultural knowledge. However, the semi-automatic detection process is a serious limiting factor for the usability of the system.

V. CONCLUSIONS

Rapid advances in computer technology have made it possible to provide farmers with accurate advice on sustainable pest management decisions. We develop a decision support system,

TABLE III
THE MEAN AVERAGE PRECISION OF OBJECT DETECTION MODEL ON THREE DATASETS.

	1 (Hard)	*2*	*3*	*4*	*5 (Easy)*
Decision-making	27%	9%	27%	27%	9%
Detection	18%	9%	36%	9%	27%

PestDSS, that provides a cloud-based farm management information solution, an agricultural knowledge base, and an object detection-based decision-making tool for pest management. Through PestDSS, users are able to manage farm data, gain agricultural expertise, and use the pest management decision tool. In the experiment, the pest detection model used in the decision-making tool achieves higher mAP compared to Faster RCNN and YoloX on the three pest detection datasets through data augmentation methods and optimised model structure. In the case study of wheat pest management, we demonstrate the functionality of PestDSS via the Android client and outline the potential benefits of the decision-making tool that is able to save costs and provide sustainable pest management advice based on optimisable economic thresholds without human error. With the benefit of cloud-based architecture, PestDSS shows great reliability and scalability. The limitation of this case study is that we do not compare the decision from PestDSS with the decisions from agricultural experts, due to the fact that the positive decisions do not occur in our case study.

In our further work, we will add more decision-making tools to PestDSS than just pest management decisions. The further features will include disease detection and management, fertilizer management, and weed management. Although the current implementation of PestDSS provides a semi-automatic pest management decision-making tool, experimental results show that the accuracy of the decision is limited by that of the object detection model. In addition, the scalable PestDSS has the potential to build fully automated farm management solutions for a large range of farms in combination with drones or robots. Furthermore, the acceptance of decision support systems is an important research question.

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