Title

An effective farmer-centred mobile intelligence solution using lightweight deep learning for integrated wheat pest management

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ABSTRACT

Integrated Pest Management (IPM) techniques have been widely used in agriculture to manage pest damage in the most economical way and to minimise harm to people, property and the environment. However, current research and products on the market cannot consolidate this process. Most existing solutions either require experts to visually identify pests or cannot automatically assess pest levels and make decisions based on detection results. To make the process from pest identification to pest management decision making more automated and intelligent, we propose an end-to-end integrated pest management solution that uses deep learning for semi-automated pest detection and an expert system for pest management decision making. Specifically, a low computational cost sampling point generation algorithm is proposed to enable mobile devices to generate uniformly distributed sampling points in irregularly shaped fields. We build a pest detection model based on YoloX and use Pytorch Mobile to deploy it on mobile phones, allowing users to detect pests offline. We develop a standardised sampling specification and a mobile application to guide users to take photos that allow pest population density to be calculated. A rule-based expert system is established to derive pest management thresholds from prior agricultural knowledge and make decisions based on pest detection results. We also propose a human-in-the-loop algorithm to continuously track and update the validity of the thresholds in the expert system. The achieved accuracy of the pest detection model is 58.17%, 75.29% and 42.6% on three pest datasets, respectively. The usability of the pest management system is assessed by the User Experience Surveys and achieves an SUS score of 76.

1. Introduction

Wheat is an important food crop and is considered one of the world's four major food crops, along with rice, maize and potatoes. Wheat is used as a staple food in more than 100 countries worldwide (Curtis, Rajaram, Gómez Macpherson et al., 2002). About one third of the world's population depends on wheat as a staple food and it accounts for 27% of global cereal production (Shewry, 2009).

The loss in potential yield from pest attack i.e., insect and mollusc, can be substantial, to the point of total loss of crop. Recently investigators have examined the effects of pest attack on wheat yield. The Food and Agriculture Organisation of the United Nations (FAO) estimates that between 20% and 40% of global crop production is lost to pests each year (Department for Environment, Food & Rural Affairs, 2020). Plant diseases cost the global economy an estimated $220 billion annually, while invasive insects cost an estimated $70 billion (Sarkozi, 2019).

In the UK, aphids and the orange wheat blossom midge are two major threats to the wheat, causing 3% yield loss (Garthwaite, Thomas, Parrish, Smith and Barker, 2008). This loss was reduced to 1.5% by using insecticides on 80% of the wheat acres (Clarke, Wynn, Twining, Berry, Cook, Ellis, Gladders et al., 2009). Due to the low cost of insecticides, the economic return from additional production is six times the cost of treating aphids (Oakley, Walters, Ellis and Young, 1998).

Hence growers apply pesticides to mitigate potential yield loss These applications are often done on an insurance basis (i.e., an application is made as a contingency to mitigate potential yield loss) because pest abundance is high. These applications are potentially wasteful (no economic benefit) and damaging to the environment. With sustainable crop protection becoming more important, there is increasing demand for decision support systems that can help farmers grow crops more sustainably with fewer chemical interventions.

To help address these issues, a large and growing body of literature has investigated the pest identification and the economic threshold levels. The Agriculture and Horticulture Development Board (AHDB) have produced an encyclopaedia of pests and natural enemies in field crops. This provides all the information required to make an informed decision on whether pest control is warranted or not (Agriculture and Horticulture Development Board, 2022). Although the reference manual is very comprehensive, it is not specific to wheat and not very user friendly in a field situation either as a hard document or on a mobile phone. A new tolerance-based decision support system to minimise the risk of crop damage by wheat bulb fly (WBF) has been devised under IPM principles by ADAS, a UK-based independent agricultural and environmental consultancy (Leybourne, Storer, Berry and Ellis, 2022). However, the identification of the pest and a risk-based decision still needs to be made by agronomists with specialist knowledge. To automate the detection of pest species, artificial intelligence scientists are using objective detection algorithms for pest identification. Nevertheless, these deep learning-based algorithms can only identify the type of pest, but cannot quantify the severity of the current pest. There are two main scientific problems that contribute to this issue. First, current pest thresholds in the agricultural literature are difficult to use in computer vision, for example, some pest thresholds are measured in terms of the number of pests per plant, yet it is difficult for

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deep learning models to distinguish between different plants. Secondly, because the actual area of a photograph is not known, the density of the pest population in the photograph cannot be calculated, so it is not possible to measure the severity of the infestation directly from the photograph. In addition, the economic thresholds for wheat vary according to climate, water and heat conditions and pest species, and sometimes pests develop resistance, making it difficult to use a constant set of pest thresholds for decision making in all environments.

This study has proposed a solution of integrated pest management decision making for wheat pest aims to the research problems mentioned above. The system combines deep learning models for pest detection and counting with an expert system for pest management decisions, with specific contributions including:

- to design and train a light-weight deep learning model for semi-automatic wheat pest detection on smartphones.
- to propose a sampling standard and a computational graphics-based algorithm for sampling point generation that reflects the challenges of quantifying pest severity from deep learning pest detection results.
- to convert the text-based thresholds for wheat pests in the literature into a rule-based expert system to overcome the difficulties of using textual prior knowledge for computer vision-based integrated pest management.
- to implement a human-in-the-loop threshold optimisation algorithm to semi-automatically adjust inaccurate thresholds due to pesticide resistance or regional differences.

The remainder of the paper is structured as follows. Section 2 reviews the state of the art research on object detection and integrated pest management. Section 3 presents the datasets and the proposed solution of the semi-automatic integrated pest management decision making system. Section 4 evaluates the performance of the deep learning based pest detection model and the usability of the proposed pest management decision making system. Section 5 briefly concludes the proposed approaches presented in section 3 along with an outline of future work.

2. Literature Review

The scope of this research is deep learning based pest identification and expert system based decision making for pest management. Therefore, the literature review in this section is divided into two parts, the first providing an overview of relevant deep learning techniques in the literature for target detection and the second outlining the application of expert systems in agriculture.

2.1. Object Detection

Object detection is one of the important tasks in computer vision to identify and localise all instances of object in the image data. Early work on object detection was based on hand-crafted feature extractors, such as the histogram of oriented gradients (Dalal and Triggs, 2005) and Harris corner detector (Harris, Stephens et al., 1988). However, for complex multi-classification object detection tasks, these traditional methods lose their effectiveness.

The convolutional neural networks (CNNs) were proposed to solve the problem of low performance of hand-craft features by automatically exploring effective features using large amounts of image data, such as VGG (Simonyan and Zisserman, 2014), ResNet (He, Zhang, Ren and Sun, 2016), and CSPNet (Wang, Liao, Wu, Chen, Hsieh and Yeh, 2020a). Based on the superiority of convolutional neural networks, a series of deep learning-based object detection models have been proposed, which is divided into two-stages detectors and one-stages detectors. The two-stages detector divides the detection process into two steps, the regional proposal stage, and the detection stage. In contrast, the one-stages detector proposed bounding box and classified object in one stage. From the view of model structure, the difference between the two-stage detector and one-stage detector lies in the presence or absence of a separate module for generating bounding box.

Faster Region-based Convolutional Neural Network (Faster RCNN) (Ren, He, Girshick and Sun, 2015) is the latest work following the design of RCNN (Girshick, Donahue, Darrell and Malik, 2014) detection model family, which are all two-stage detection models. As the definition of the two-stage detection model, the models structure of RCNN family can be divided into two steps, the region of interest proposal stage and detection stage. In the early RCNN (Girshick et al., 2014), a traditional algorithm Selective Search (Uijlings, Van De Sande, Gevers and Smeulders, 2013) was used to propose 2000 regions of interest. The proposed regions were then warped and propagated through a CNN backbone. The final detection results were subsequently obtained by Support Vector Machines (SVMs) and Non-maximum suppression (NMS). In order to increase the speed of detection, Faster RCNN use a CNN as a region proposal network (RPN) to propose regions of interest with associated objectness score. The multi-scale bounding boxes obtained by RPN were combined with the feature maps in the backbone network and passed through a classifier and bounding box regressor to obtain the detection results.

In contrast, the Yolo detection model (Ge, Liu, Wang, Li and Sun, 2021) family is representative of the one-stage detectors, which solve the detection problem by directly predicting the likelihood of related pixels being a detection object and the bounding box properties in one stage. This approach used convolutional neural networks to separate the original input images into grids and predict the bounding boxes and object scores for each grid, allowing for a simpler and smaller model to detection. Those models gained faster detection at the cost of detection accuracy in the early works.

In recent work of YoloX (Ge et al., 2021), this cost is offset by a large number training tricks and the adaptation of the model structure. Specifically, various data augmentation methods, batch normalisation, and CLoU loss function were used in the training phase of the detection model. In terms of model structure, Cross-stage partial connections, SPP-Block, PAN path aggregated block neck, Decoupling detection head were used to optimise the model structure to achieve fast and accurate detection. Overall, one-stage detection model solves the problem of fast and accurate object detection in a simpler way.

2.2. Expert Systems

Expert systems use computer models derived from human experts to deal with complex real-world problems that require expert interpretation, and reach the same results as experts (Liao, 2005). The Agricultural Expert System (AES) applies expert system technology to the agricultural sector. It summarises and brings together knowledge and techniques from the field of agriculture and the knowledge of agricultural experts, as well as data obtained through experiments and mathematical models to simulate the decision-making process of agricultural experts.

Since the 1980s, specialist systems technology has been applied to agricultural problems, particularly in the area of integrated pest management, which has been in development for a relatively long time and is particularly well developed (Gerevini, Perini, Ricci, Forti, Ioriatti, Mattedi, Monetti et al., 1992; El-Azhary, Hassan and Rafea, 2000; Harrison, 1991). S. Kaloudis et al. describe an expert system for the identification of forest pests and the provision of related control measures. The system identifies more than 40 species of forest pests based on their growth stage, the damage caused by the pests and the results of their research in the forest. Once a pest has been identified, the system will provide a suitable treatment plan to minimise damage to the forest by the pest (Kaloudis, Anastopoulos, Yialouris, Lorentzos and Sideridis, 2005). CUPTEX is an expert system that has been developed to manage cucumber pests and diseases. The main purpose of the system is to identify the causes of anomalies and to make appropriate treatment recommendations. In this case, the system starts with the identification of the cause before recommendations are given (Rafea, El-Azhari, Ibrahim, Edres, Mahmoud and Street, 1995). The Tomato Expert System developed by Yialouris and Siderdis was used to deal with the problem of identifying tomato pests and diseases. A framework knowledge representation table was used to describe the knowledge base, and notably fuzzy logic was used to deal with uncertainty in the diagnosis (Yialouris and Sideridis, 1996).

3. Materials and methods

The aim of this work is to automate the process of integrated pest management decision in wheat. To automate pest detection, we introduced deep learning, which relies on a large amount of data. To address this research question, we performed data augmentation of the collected data. Another research problem that hinders the automation of integrated pest management is the interaction between deep learning model detection results and decision making expert system. To address this challenge, we proposed a sample point generation algorithm to aid sampling and a density calculation algorithm to quantify the pest detection results so that they can be used in an expert system. This section also concludes with a description of the human-in-the-loop algorithm for automatic correction of pest level thresholds in expert systems

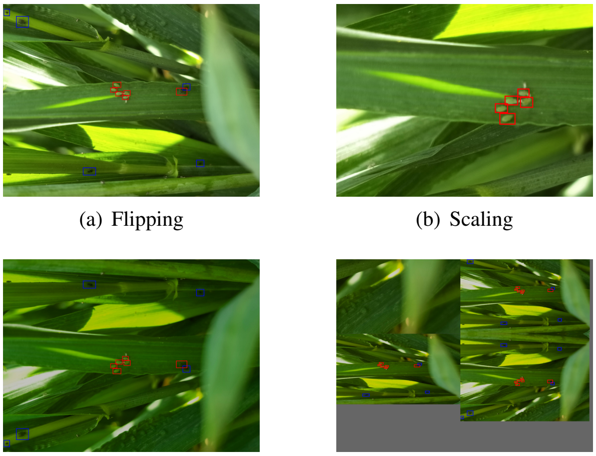
3.1. Pest Datasets

Multiple pest datasets were used for the work on pest detection model, including both public and private datasets. IP102 (Wu, Zhan, Lai, Cheng and Yang, 2019) is a public dataset that includes 19k pest images with annotation belong to 102 classes and 51k pest images without annotation. The images in IP102 is collected through search engine, so the backgrounds are more diverse. Most of the images have a larger percentage of pest than that in images collected in real environments. In comparison, AgriPest dataset (Wang, Liu, Xie, Yang, Li and Zhou, 2021b) includes 49.7k pest images of 14 species collected from natural environment with fixed equipments and mobile equipments. We selected a subset of AgriPest dataset containing two types of aphids by manual screening To verify the ability of the detection model in a realistic sampling scenario. In addition, we collected image data using mobile equipments on three different UK farms according to the proposed sampling specifications.

Table 1
Statistical information of datasets. The columns in the table show the total number of samples, total number of categories, the number of the largest category, the number of the smallest category, and the average percentage of one object pixels in the image.

	IP102	AgriPest	Our Dataset
Num. of samples	19167	1000	661
Num. of objects	22284	6325	822
Num. of categories	97	2	7
Max. Num. of a category	2975	4755	379
Min. Num. of a category	2	1570	14
Avg. object pixels pct.	37.27	0.08	0.34

For improving the accuracy of detection model, multiple data augmentation methods was used during the model training phase. The data augmentation methods includes basic image transformations, such as random flips, random scaling, and random HSV color perturbation. In the work of YoloX, Mosaic (Ge et al., 2021) is proposed for improving the model accuracy, which splice four images randomly after basic image transformations. The augmented image data is shown in Figure 1. This artificially constructed training data contains more invariance and enriches the training sample to improve the accuracy of the model.



(a) Flipping (b) Scaling (c) HSV perturbation (d) Mosaic

Figure 1: Data Augmentation

3.2. Integrated pest management decision making system

Automatic in-field pest detection and recognition using mobile vision technique is a hot topic in modern intelligent agriculture but suffers from serious challenges including complexity of wild environment, detection of tiny size pest and classification of multiple classes of pests. To overcome these obstacles, the popular methods are to design a Convolutional Neural Network (CNN) model that extracts visual features and identifies crop disease images based on these features. These methods work well on laboratory environment under simple background but achieve low accuracy and poor robustness in processing the raw images captured from practical fields that contain inevitable noises. Motivated by the above mentioned inadequacy of existing studies, a light-weight deep learning model for automatic wheat pest detection architecture is established to fuse the features of pest images and the features of contextual information to be deployed on mobile devices towards pest recognition and detection in the wild and make decisions of pest treatments.

The proposed architecture consists of three parts: server, interface and local library. The server refers to a kubernetes cluster that manages a number of RESTful web services for user management, farm management, pest encyclopedia, decision making, thresholds optimisation function. The interface and local library are implemented by Kotlin for Android device.

Fig. 2 also displays an overall process of users to use the system. Prior to using the system, users login the logs in on the mobile application and the server grants access to the successfully logged-in user. After logging in, the application requests the server to obtain the field information associated with the current user. Then the user selects the field for pest management and selects the growth stage of the current crop. At the same time, the sampling point generation algorithm in the local library generates sampling points for the selected field. Then the application interface jumps to the map interface of the selected field, which shows the generated sampling points and the user's location, and the user goes to each sampling point in turn to take pictures. Each sampled picture calls the pest detection model in the local library for classification and counting, and calls the density calculation model to calculate the population density of the pests detected in the photo. When all sampling points are sampled, the pest detection results and population density calculation results are uploaded to the decision-making expert system in the server to request pest management suggestions. In the pest management suggestion interface, the application also requests the description of detected pests from the Pest encyclopedia server.Every time a pest management decision is completed, the system will send a questionnaire to the user two to four weeks later to evaluate the effect of the last pest detection, and the user's feedback will be returned to the threshold optimisation algorithm in the server to optimise decision-making expert system.

3.2.1. Pest Detection Model

In this study, we proposed using YoloX as a detection model framework to address the problem of counting pest populations.(Yuan, Li, Yang and Li, 2022) As described in related work, the detection model provides the ability to draw a bounding box and classification for each instance of object. We redesigned the detection model based on YoloX in order to obtain high pest detection accuracy. The architecture of proposed detection model is shown in Figure 3, including a CNN backbone for features extraction, a detection neck for fusion of multi-scale features, multiple decoupled detection heads for obtaining the potential bounding box and corresponding classification information in the input image, and a Non-extreme suppression for obtaining the final detection result.

In our detection model, we use CSPDarknet (Bochkovskiy, Wang and Liao, 2020) as the backbone. In the CSPDarknet, each CSP module has a residual block to learn more and different features, which facilitates the accuracy of small object detection. In addition, Spatial Pyramid Pooling is used before the last CSP module to improve the perceptual field of the network by pooling with different size of maximum pooling kernels. An improved version of the ReLU activation function, SiLU (Elfwing, Uchibe and Doya, 2018), is used throughout the detection model, which has a smoother gradient change compared to the original ReLU activation function. For detection neck, we use Path Aggregate Network (Liu, Qi, Qin, Shi and Jia, 2018) which is more accurate in tiny object detection. The decoupled detection heads used separate convolutional neural networks for classification, bounding box, and object score prediction, improving detection accuracy at the cost of an acceptable number of parameters.

3.2.2. Generating Evenly Distributed Sampling Points

Generating evenly distributed sampling points is the first step in pest management. There are many mature sampling point selection methods in the agricultural field. Such as five-point sampling method, equidistant sampling method,

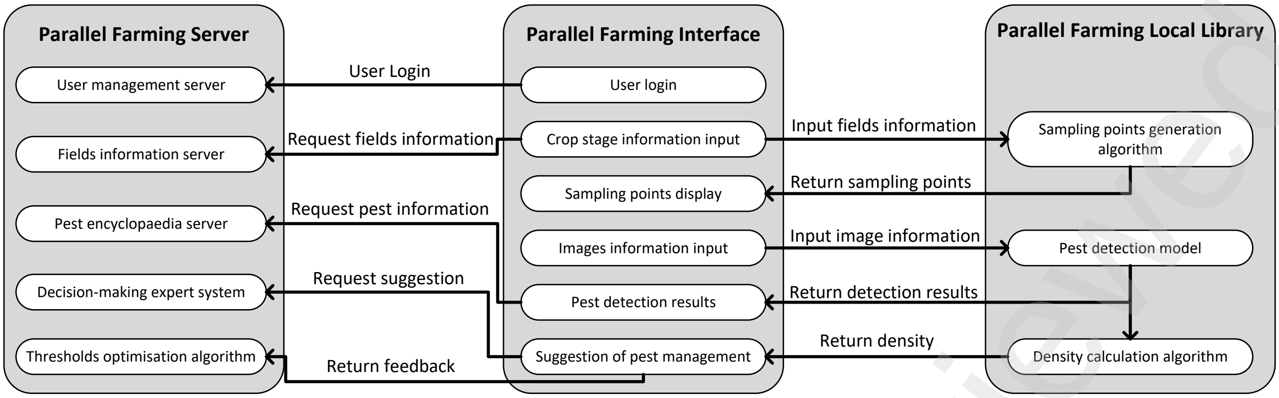


Figure 2: Interaction between server, interface and local library

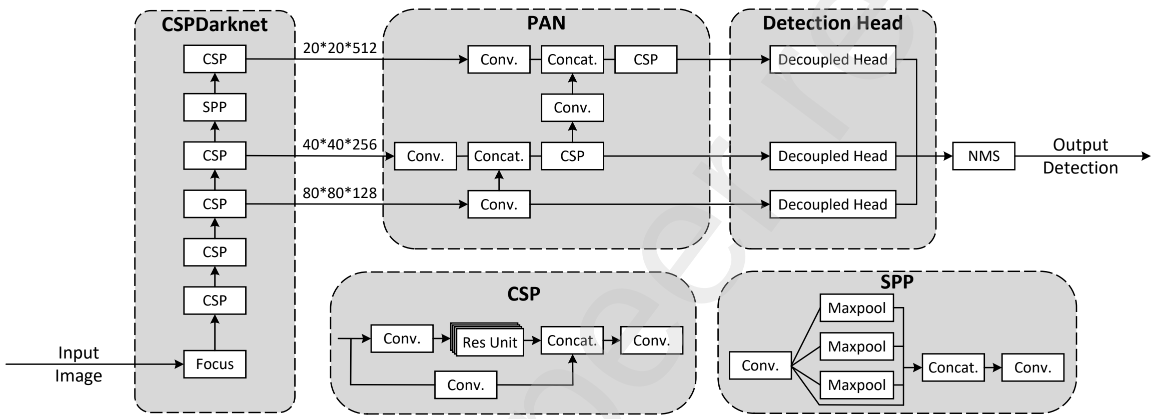


Figure 3: The detection model structure.

grid sampling method, etc. However, these methods need to be used manually by a person. When we use computers to generate sample points using these methods, it is not guaranteed that all the points generated will be in the field because the computer cannot tell if a point is inside or outside the field (see figure 4(a)(b)(c)(d)(e)(f). This is not usually a problem in areas with large plains. However, it can limit the use of our software in areas with complex field shapes.

To overcome the dependency of the agricultural experts on sample point selection, computer science researchers started to develop computer-aided sample point selection methods. A representative method for selecting uniform sampling points is developed by ArcGIS and is based on computational graphics. The mathematical basis of the method is triangulation. This method can generate very uniform sampling points, but its computational cost is extremely high, and it needs to generate a large number of sampling points to make sure these points are uniformly distributed which will significantly increase the workload at our user end.

In response to the disadvantages of both traditional methods, modern methods, and computer-aid methods, we proposed our own methods which can generate relatively uniform sampling points with exceptionally low computational cost and the number of sampling points is significantly reduce to relief our users from heavy workload. In principle, our approach is based on two theories: equidistant sampling method and ray casting algorithm. Equidistant sampling is also known as equal-distance sampling which is been widely used by the agronomists. Equidistant sampling first divides the sampled field into several equal parts, the distance or interval is determined by the sampling ratio, and then the sample squares are drawn according to this equal distance or interval in order to get uniformly distributed sampling points. To addressing the challenge of determining whether the generated sampling points are within the polygonal fields, Wo introduced ray casting algorithm. This algorithm is sometimes also known as the crossing number algorithm or the even–odd rule algorithm, and was known as early as 1962 (Wo et al,. 2020). The algorithm is based on a simple observation that if a point moves along a ray from infinity to the probe point and if it crosses the boundary of a polygon, possibly several times, then it alternately goes from the outside to inside, then from the inside to the outside, etc.

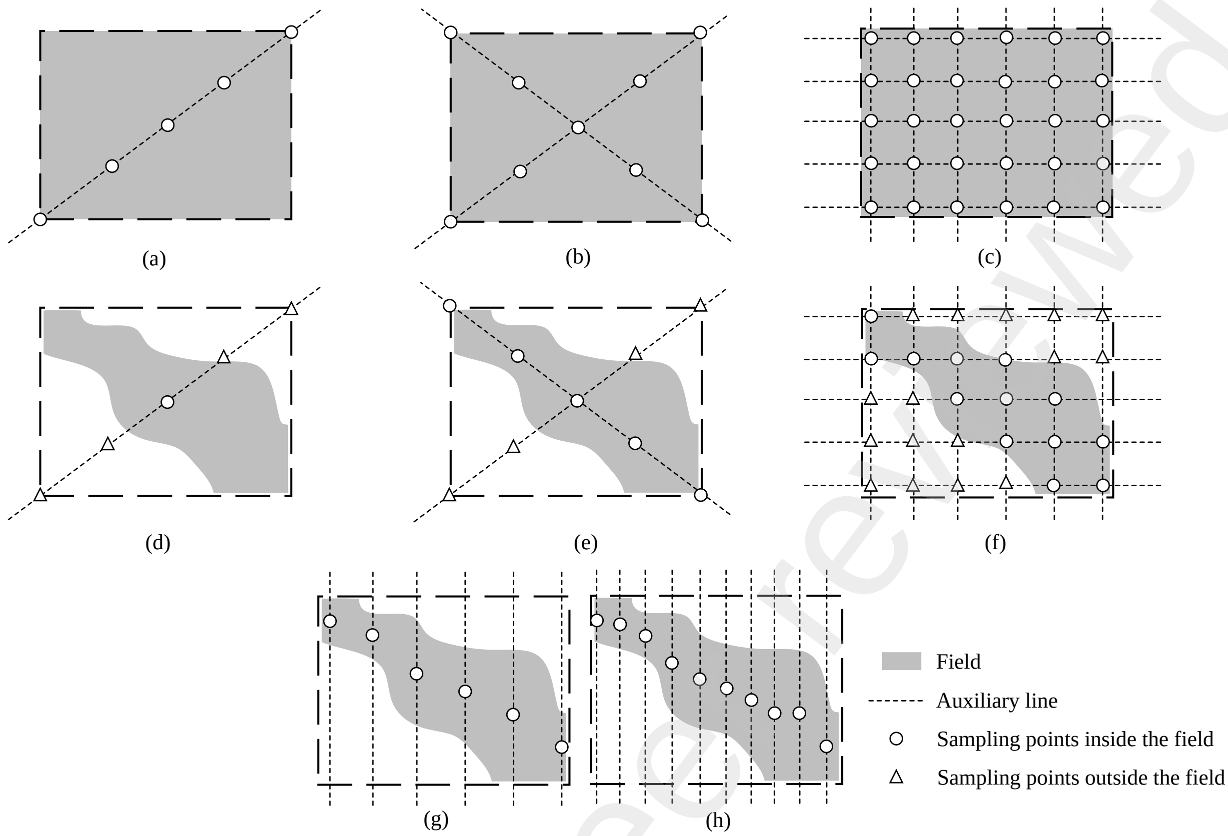


Figure 4: Equidistant Ray Casting Sampling (ERCS)

As a result, after every two "border crossings" the moving point goes outside. This observation may be mathematically proved using the Jordan curve theorem.

By fusing these two method and algorithm, we proposed our sampling methods: Equidistant Ray Casting Sampling (ERCS). ERCS firstly first place the field in a rectangle, the size of which depends on the coordinates of the point at the very edge of the field. Rays then vertically and equally divide the rectangle. According to the ray casting algorithm, the computer will be able to know which part of the ray is inside the polygons by counting the number of intersections between the ray and the field's boundaries. Hence, the midpoints of the line segment inside the polygon will be selected as the sampling points. In addition, as shown in figure 4(g)(h) by adjusting the distances between the rays, our users can adjust the number of sampling points, making it easy to optimise their workloads.

3.2.3. *Calculating population densities of pests using single photographs*

At present, most of the products on the market only do the previous step, that is, pest detection. However, in order to realise semi-automatic IPM in the whole process, we not only need to realise pest detection, but also need to conduct quantitative analysis on the detection results. In order to achieve this goal, we need to relate the number and species of pests detected by the deep learning model with our prior knowledge of agriculture (Economic thresholds for integrated pest management). However, the current existing thresholds are usually the population density per unit area or the number of pests per crop, whereas deep learning models can only detect the species and quantity of pests in a photo and cannot calculate the population density of each type of pest, as the actual area of the photo is unknown. It is also difficult for deep learning models to detect the type and number of pests on a single plant, because when taking pictures of most densely planted crops, one photo usually contains multiple plants.

To achieve a link between thresholds in a prior agricultural knowledge and pest detection results from deep learning models, we have designed a set of sampling methods and population density calculation algorithms to solve the above-mentioned problems. First of all, we standardised the user's photo-taking process, that is, taking pictures at a distance of 30 cm from the target vertically. In order to achieve this, in the camera interface of our software, we use gyroscope to help users judge whether their shooting angle is vertical, and minimise the artificial error of the shooting distance through multi-point sampling. Then, we calculate the actual area of the photo by extracting the Exchangeable Image File (EXIF) information of the photo:

$$S_{actual} = \frac{D_{target}}{F_{35mm}} \cdot 24 \times 36(mm^2) \tag{1}$$

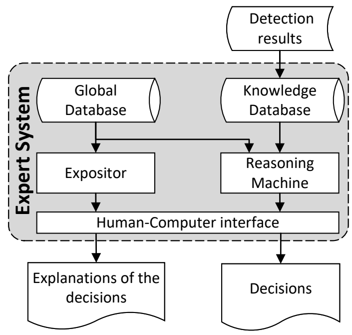


Figure 5: The proposed Integrated Pest Management decision making expert system

Where S_{actual} is the actual area of the single photos, D_{target} is the distance between the camera and the target which has been stipulated by us as 30cm. $24 \times 36(mm^2)$ is the actual sensor area of a full frame camera. F_{35mm} is the 35mm equivalent focal length, which is the actual focal length of the current camera when converted to a full-frame camera. Because the sensor size of a full frame camera is fixed, and our sampling criteria fixes the distance between the object and the lens at 30cm, we only need the equivalent focal length of the current camera to calculate the actual area of the photo. Hence, we can calculate the population density of each species of pest in a single photo and in the entire field:

$$\rho = \frac{n_{pest}}{S_{actual}} \tag{2}$$

$$\rho_{field} = \frac{1}{n_{photo}} \sum_{n_{photo}}^{i=1} \rho_i \tag{3}$$

where ρ is the population density of a certain pest in a single photo, n_{pest} is the quantity of the pest and S_{actual} is the actual area of the photo. ρ_{field} is the population density of a certain pest in the entire field, n_{photo} is the total number of samples taken in that field.

With the photos taken by the above photography standards, supplemented by the population density calculation algorithm we proposed, the system can link the data obtained from the sampling of mobile phone photography with the threshold value in agricultural prior knowledge for subsequent pest management decision making.

3.2.4. *Rule-based reasoning expert system for pest management decision making*

The calculation of the pest population density in the sampled photos provides a data basis for semi-automated IPM decision making. However, we still need to use relevant prior agricultural knowledge to conduct qualitative analysis on these data to make pest management decisions. There have been many studies (Dewar, Ferguson, Pell, Nicholls and Watts, 2016; Ellis, Berry, Walters et al., 2009; Wang, Bai, Zhao, Su, Liu, Han and Chen, 2020b; Wang, Zhao, Bai, Shang, Zhang, Hou, Chen and Han, 2021a; Gong, Li, Gao, Wang, Li, Zhang, Li, Liu and Zhu, 2021; Honek, Martinkova, Saska and Dixon, 2018) on the main invertebrate pests affecting wheat crops. However, the representation of such prior knowledge from the literature is usually text, which cannot be understood by computers. To address this problem, we developed an expert system that allows a prior knowledge of pests from the literature to be used to quantify the pest detection results obtained from the deep learning model.

Expert Systems are programme systems with expertise and experience that use the knowledge and experience provided by one or more experts in a particular field to reason and make judgements, simulate the decision making process of human experts, and use computers to automate the solution of complex problems that need to be handled by human experts. The rule-based expert system is currently the most commonly used method, mainly due to a large number of successful examples, as well as simple and flexible development tools. It directly imitates the human mental process and utilises a set of rules to represent expert knowledge.

In response to the above problems, we propose a rule-based expert system whose structure is shown in the figure 5. It consists of five parts: Knowledge Database, Global Database, Reasoning Machine, expositor and Human-Computer Interface. The Knowledge Database stores the knowledge of domain experts in a certain storage structure, including facts and feasible operations and rules. The Knowledge Database contains domain knowledge related to decision making. We summarised the thresholds about wheat pest management decision making in the previous literature (Dewar et al., 2016; Ellis et al., 2009; Wang et al., 2020b, 2021a; Gong et al., 2021; Honek et al., 2018) and normalised them into a computer-understandable Knowledge Database. It has an IF (condition) THEN (behaviour) structure. When the condition of the rule is met, the rule is triggered, and then make a decision. The Global Database is used to store initial data and intermediate data obtained during the decision making process. The Reasoning Machine selects matching rules from the Knowledge Database according to the input, and makes pest management decisions by executing the rules. The Expositor is used to explain the behaviour of the expert system to the user. The Human-Computer interface is used to display the decision results and their explanations.

3.2.5. *Human-in-the-loop threshold optimisation algorithm*

Although we have obtained some thresholds from the literature, the above work is still not sufficient for a pest management decision making system. There are a number of reasons for this: First of all, not all crops have known thresholds for each pest in each growth stage. For example, there is no known threshold for gout fly in spring cereals, despite the high risk of yield reduction (Ellis et al., 2009; Dewar et al., 2016). Second, because some studies were conducted a long time ago (more than ten years ago), their pest thresholds may not still be applicable today. last but not least, pests will lead to increased resistance to pesticides after natural selection, so we cannot use a constant threshold for pest management in the future.

To keep the thresholds up-to-date in our pest management expert system, we designed a human-in-the-loop threshold optimisation algorithm. Human-in-the-loop (HITL) is a branch of artificial intelligence in which people participate in a virtuous circle in which they train, adapt and test specific algorithms to improve the accuracy of the model.

Specifically, each time a user makes a pest management decision using the mobile software, in addition to recording that decision, the server sends a questionnaire to the user at regular intervals, asking the user to observe the situation on the farm to determine the effectiveness of the previous decision. The system then automatically adjusts specific thresholds in the database based on this user's observations.

4. Results and discussions

4.1. Evaluation Metrics

Multiple metrics were used to evaluate the object detection model, including mean average precision (mAP), the number of frames deal within a second (FPS), and the number of parameters (Parameters) in the detection model. The mean average precision is a general evaluation metric for object detection model, which is defined as the mean value of the area under the Precision-Recall (PR) curve:

$$mAP = \frac{1}{N} \sum_{n \in N} \int_0^1 Pr(n) d\, Re(n) \tag{4}$$

$$Pr(n) = \frac{TP_n}{TP_n + FP_n} = \frac{TP_n}{AllObservations_n} \tag{5}$$

$$Re(n) = \frac{TP_n}{TP_n + FN_n} = \frac{TP_n}{AllGroundTruth_n} \tag{6}$$

where N is the number of object categories, TP_n, FP_n, and FN_n refer to the number of true positive samples, false positive samples, and false negative samples for class n, respectively. The true positive samples in object detection tasks is defined by intersection over union (IoU), which is a ratio of the overlap area in the union area between the predicted bounding box and the annotated bounding box. FLOPs and Parameters metrics measure the size of the object detection model. The larger object detection model requires more computational resources.

4.2. Performance Evaluation of the Detection Model

We evaluated the performance of the detection model using three pest datasets, including IP102, AgriPest, and Our Dataset. Each dataset were divided into training dataset, validation dataset, and test dataset in a ratio of 8:1:1. The mAP for each trained model on the test dataset is calculated and presented in Table 2. The compared models were pre-trained on the COCO dataset (Lin, Maire, Belongie, Hays, Perona, Ramanan, Dollár and Zitnick, 2014). As mentioned before, multiple data augmentation methods were used in training dataset. The dropout method was used in order to avoid overfitting.

Table 2
The results for different detection model

	Faster RCNN	YoloX	Our Model
FPS	11.45	12.97	13.21
Parameters	28275k	8976k	6759k
mAP (IP102)	55.25%	56.87%	58.17%
mAP (AgriPest)	7.18%	66.24%	75.29%
mAP (Our dataset)	7.76%	11.01%	42.6%

As Table 2 shown, we compare our model with Faster RCNN and YoloX on the multiple pest dataset. Our model outperforms Faster RCNN and YoloX due to it adopts the Path Aggregation Network to fuse multi-scale features. In particular, our models obtained mAP of 75.29% and 42.6% on the AgriPest and our datasets, respectively. Meanwhile, YoloX and our model achieves faster detection speed with fewer training parameters than Faster RCNN. The main difference between our model and YoloX is the more efficient necks of detector and data augmentation methods for pest detection. In summary, our model achieves state-of-the-art results in pest detection task.

4.3. Usability Evaluation of the proposed solution

The usability of the proposed solution rely on the friendliness of user interface and function design, in addition to the stability of system. The mobile application provides end users with the ability to browse farm information, add farm records, respond to tasks, detect pests, view weather forecast, modify app settings and more. Meanwhile, a manually collected encyclopaedia of knowledge about pests and crops is integrated as a knowledge base for providing the basic knowledge and advice for model decisions in the integrated pest management function. The above functional design is based on a user requirements analysis of the system in early stage. The usability evaluation process invites end users to make subjective evaluations of the functionality of the mobile application, the efficiency and accuracy of the functions, and the user-friendliness of the interface. Specifically, evaluation participants were asked to follow an instructional document after logging into the app to complete their experience of the functions in the mobile application and to rate the usability of key functions. The results are shown in Table 3

In addition to the evaluation of functional usability, an open access experiment which invite participants to use the application without restrictions was processed. The results of this experiment was collected by the System Usability Scale (SUS) questionnaire, which consists of ten questions with a scale from strongly agree (5 points) to strongly disagree (1 point) for each question.(Lewis, 2018) The questions in the SUS questionnaire focus on the system usability,

Table 3
Questionnaire results for User Experience Tasks (Including login, fields information, record, task, detection, and IPM)

Task	1 (Hard)	2	3	4	5 (Easy)
Task 1	0%	0%	18%	36%	46%
Task 2	0%	0%	18%	18%	64%
Task 3	0%	0%	18%	36%	46%
Task 4	9%	0%	9%	9%	73%
Task 5	18%	9%	36%	9%	27%
Task 6	27%	9%	27%	27%	9%

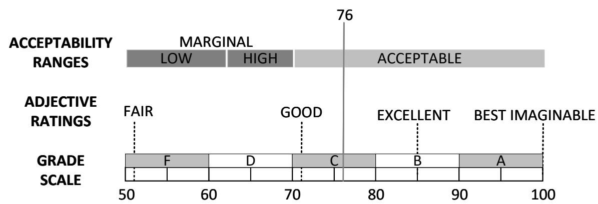


Figure 6: SUS Score of the our mobile application

such as, I think that I would like to use this system frequently, and I needed to learn a lot of things before I could get going with this system. The final evaluation results are calculated according to Equation 7, where $S1$ to $S10$ indicate the scoring of each of the 10 questions.

$$SUS = 2.5 \times (20 + SUM(S1, S3, S5, S7, S9) - SUM(S2, S4, S6, S8, S10)) \quad (7)$$

Figure 6 presents the results for the open access experiment. According to the grading based on SUS scores(Lewis, 2018), the mobile application with an average score of 76 is considered as a good product.

5. Conclusion and Future Work

In this work, we develop a practical application of an end-to-end decision making system for integrated pest management that allows users to take just a few photos to get pest management advice, enabling growers with no agricultural knowledge to apply sustainable crop protection. The present study has offered a framework which integrated deep learning objective detection and expert system for the exploration of environmentally friendly pest management thresholds for wheat. In this study, we proposed a low computational cost sampling point generation algorithm that enables mobile devices to generate evenly distributed sampling points in arbitrary-shaped farmlands. We used PyTorch Mobile to generate a lightweight pest detection model that can be deployed on mobile devices, so that our application can get rid of the constraints of communication infrastructure. We have developed a standardised sampling protocol and used our software to assist users with sampling, enabling the calculation of pest population densities from a single photograph. A rule-based expert system has been established for deriving pest management thresholds from prior agriculture knowledge and making decisions based on pest detection results. We proposed a human-in-the-loop algorithm to continuously track the validity of thresholds in the expert system and keep them up-to-date.

The experimental results show that our detection model outperformed Faster RCNN and YoloX in term of FPS and mAP. In the user evaluation of system usability, the proposed system received 76 in SUS score.

A number of limitations need to be noted regarding the present study. Firstly, our decision making expert system and the human-in-the-loop threshold optimisation algorithm have not been validated for the time being as this would take many years of experimentation over multiple crop cycles to complete. In terms of this direction for future research, further work of validation of the decision making expert system and the threshold optimisation algorithm in practice is required to confirm the effectiveness of our proposed solution. Secondly, our current sampling specification still requires the user to manually control the distance between the camera and the target, which inevitably affects the accuracy of the pest population density calculation results. Therefore, considerably more work will need to be done to develop a distance measurement algorithm to enable more accurate pest population density calculations.

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