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# Methods of insect image capture and classification: A Systematic literature review

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ABSTRACT

Insects are the largest, most diverse organism class. Their key role in many ecosystems means that it is important they are identified correctly for effective management. However, insect species identification is challenging and labour-intensive. This has prompted increasing interest in image-based systems for rapid, reliable identification supported by advances in deep learning, computer vision, and sensing technologies. We conducted a systematic literature review (SLR) to analyse and compare primary studies of image-based insect detection and species classification methods. We initially identified 980 studies published between 2010–2020 and selected from these 69 relevant studies using explicitly defined inclusion/exclusion criteria. In this SLR, we conducted a detailed analysis of the primary studies' dataset properties (i.e. insect species targeted, crops, geographical locations, image capture methods) and insect classification techniques. We provide recommendations for future research based on the gaps our survey identified. We found many studies were conducted in China, the USA, and Brazil, but none in the African continent. The majority of the studies (78.3%) aimed to identify crop pests, mainly of rice and wheat. Only three studies specifically targeted beneficial insects, bee species and predatory species. Insect species targeted by the studies were centred around 10 insect orders out of 28. The analysis of classification methods shows a recent trend toward applying deep learning techniques compared to shallow learning techniques for insect identification. The SLR provides insight into the current state of the art and indicates promising future directions for image-based insect identification and species classification relevant to Computer Science, Agriculture and Ecology research.

## 1. Introduction

Insects are the largest and most diverse class of living organisms and account for nearly 60% of the 1.82 million described species of plants and animals [51]. Since the early stages of life on earth, insects have adapted to nearly all environmental conditions to become a significant part of our planet's biodiversity. The important role of insect species in ecosystems make their biodiversity important to conserve. For example, some insects are loosely termed "beneficial" in that they act as pollinators, biological controls (i.e., predators and parasitoids) of agricultural pests, or as food sources to humans and other animals. By contrast, some insect species' interactions with humans mean that we term them "pests". These insects may damage crops, ornamental plants or stored-grains, resulting in quantitative and qualitative losses to our food or the aesthetics of our environment. Some insects may sting or bite, or they may act as disease vectors. Not all interactions between humans, ecosystems and insects are so simplistically labelled as beneficial or pest-like. Quite simply, insects are a key part of earth's ecosystems regardless of how humans perceive their value. Together, this great diversity of roles makes insects a common subject of research. Their accurate identification to species level is therefore often of key importance.

Various techniques have been used for accurate and effective insect identification. Conventionally in laboratories, insects are manually classified using observation of different morphological traits. This process is time-consuming and labour-intensive. And, it requires domain knowledge related to insect taxonomy and their minute morphological structure. These techniques rely on skills of entomologists and trained technicians that are considered in global shortage [20]. Even skilled entomologists find this to be a difficult task due to the vast number of insect species.

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In response to these challenges, much research has been carried out focusing on automating the insect detection and classification task, especially concerning monitoring crop/stored-grain insect pests [4,8], invasive insect species [44], etc. For example, successful insect identification systems have included image-based systems [43], audio sensor-based systems based on the unique sounds of insects [9,47,50], and E-noses/olfactory devices [12] based on volatiles released from their bodies (e.g., brown planthoppers and stink bugs). Among these techniques, image-based systems are widely used to differentiate insect species as visual evidence is the primary key to identify insect species by entomologists. Also, distinct insect species generally exhibit morphological differences which can be captured using image sensors. Hence, images can be used to classify a wide range of insect species while other systems such as acoustic and olfactory devices are limited to set of insect species. Moreover, images can be easily processed, compared to other techniques, and also collected insect images can be stored for future reference.

Computer vision is a rapidly advancing area in computer science with many downstream applications in insect identification, including pest management and biosecurity. However, when it comes to applying general image classification techniques to differentiate insect species, it is crucial to select the most suitable classification technique, which depends on various factors such as experimental settings (e.g., online or offline, on-site or off-site), targeted insects groups, expected performance (e.g., time complexity, memory complexity, precision and recall), and image acquisition techniques. Hence, it is worthwhile to investigate the existing image-based insect detection and classification methods and their suitability for accurate identification of insects.

A few survey papers have compared and analysed a subset of existing image-based insect identification methods [32,43]. To the best of our knowledge, a systematic literature review in this research domain has not yet been conducted. Hence, this study aims to analyse and synthesise the relevant studies on image-based insect detection and classification methods published during 2010–2020 in a systematic way. The main contributions of this study are:

1. we identified which insects species targeted and data acquisition methods have been used in the previous studies;
2. we identified and evaluated which image-based insect detection and classification methods have been trialled to date and their relative performance; and
3. we identified key limitations and gaps in current research and promising directions for future work.

The rest of this paper is organised as follows. Section 2 shows an overview of related work. The methodology used in this Systematic Literature Review (SLR) is elaborated in Section 3. Section 4 presents and discusses the review results on dataset properties and insect classification methods and Section 5 provides a set of recommendations for future research in this domain. Section 6 discusses threats to validity, and finally, a summary of this SLR is provided under Section 7.

## 2. Related work

A few literature surveys have previously compared and analysed a subset of existing studies on image-based insect detection and classification methods. The study [20], one of the earliest papers on insect identification, states that automated species identification was not widely practiced in the early 2000s and discussed various obstacles for applying automated approaches. The study in [25] conducted a literature review on vision-based entomology. This study discussed several computer vision techniques for insect identification including advantages and disadvantages of each technique. In [43], the authors conducted a comprehensive survey on image-based insect classification and discussed the current state of the field covering 44 studies. This study mainly reviews the previous studies in terms of image capturing setups/apparatuses, the feature extraction methods, the classification methods, and the datasets. This study provides a general discussion on the questions that should be focused on future works. The study [32] discussed 33 previous works on insect identification methods using digital images under three main topics. In the first topic, they identified image processing techniques generally used to eliminate noise generated in the image acquisition process. The second topic discussed adapting CNN architectures for insect identification. The final topic focused on various techniques for the treatment of images with overlapping objects.

In [41], authors reviewed recent works in the field of automatic insect detection and monitoring. They analysed how systems built upon different sensors, including infrared sensors, audio sensors, and images, can be used to detect and monitor insect pests, especially on identifying four insect orders: Lepidoptera Pest Species, Sucking Insects, Fruit Flies, Weevils in Palm Trees and Other Borer Insects. The study [29] presented sensor-based monitoring techniques for insects including image-based systems and discussed how deep learning tools can be applied to handle large datasets to drive ecological information.

To the best of our knowledge, a systematic literature review in this research domain has not been conducted. And the scope of the aforementioned secondary studies did not include a detailed analysis in terms of dataset properties (e.g., targeted insect species, crops and data acquisition methods), classification methods and their performance. In recent years, the number of publications in this domain has been gradually increasing. Hence, it is timely to conduct a comprehensive analysis of the existing methods.

## 3. Research methodology

### 3.1. Systematic literature reviews

As defined by [34,36], a systematic literature review (SLR) is a “means of identifying, evaluating and interpreting all available research relevant to a particular research question”. The individual studies contributing to a systematic review are called as **primary studies**. There are several methodologies have been proposed in the literature to conduct an SLR. For this SLR, we followed the guidelines discussed in [34,36], which propose a general guideline for systematic literature reviews appropriate for software engineering researchers. These guidelines can be adapted for our study as research on image-based insect identification is conducted way similar to the software engineering.

### 3.2. Research questions

We defined several research questions and categorised them within the SLR using three headings: (1) Dataset Properties (RQ1); (2) Classification Methodology and Performance (RQ2); and (3) Limitations, Gaps and Future Direction (RQ3).

**RQ1 Dataset Properties**

RQ1.1 What are the insect species, crops and geographic locations considered in the primary studies?
RQ1.2 Do primary studies introduce new image datasets? If so, what image acquisition technique was adopted?
RQ1.3 What are the properties of datasets used in the primary studies? Are the datasets publicly available?

**RQ2 Classification Methodology and Performance**

In this study, we define *image-based insect classification* as an automated process that takes a image of an insect as the input, and then outputs the correct type of the insect from a predefined set of groups with the help of computer vision tools. This process becomes more complex when several insects from different groups are present in an image. We have defined following two research questions under this section to analyse the different classification techniques proposed in the primary studies and their performance.

RQ2.1 What are the techniques used in the primary studies for the insect classification task?
RQ2.2 How is the performance of the proposed models evaluated and compared to chosen baselines?

**RQ3 Limitations, Gaps and a Future Research Roadmap**

RQ3.1 What are the limitations, gaps and key opportunities for future research identified by this SLR?

### 3.3. Search strategy

The process of selecting candidate publications for the SLR was conducted in two stages. In the primary search, a set of relevant queries was adopted to find the initial set of candidate publications from the selected databases. The secondary search was done using backward snowballing - i.e., by identifying articles from the reference lists of the studies selected from the primary search.

For the primary search, a set of key terms (i.e., keywords and phrases) was defined such that it covers the scope of the SLR. Subsequently, the selected key terms were aggregated using AND and OR operations to formulate the basic search query shown below.

*S*1 *AND S*2 *AND S*3 where

*S*1: "*insect*" *OR* "*pest*" *OR* "*beneficial*" *OR* "*pollinators*" *OR* "*biocontrol agent*" *OR* "*natural enemies*"
*S*2: "*detect*" *OR* "*count*" *OR* "*classify*" *OR* "*identify*" *OR* "*recognise*"
*S*3: "*computer vision*" *OR* "*machine learning*" *OR* "*deep learning*" *OR* "*image processing*"

where the key terms in S1 and S2 were used to identify the related publications for insect detection and classification, and the key terms in S3 were used to limit the search scope by eliminating the publications that cover the manual/bio-chemical insect classification approaches. These key terms were initially selected by examining the author defined keywords, title and abstract of the highly cited publications in the field. Afterwards, the key terms were further fine-tuned by iteratively examining the search results from different search engines (e.g., Google Scholar, Springer).

The formulated search query was then adopted to select the initial set of candidate publications from three databases: ScienceDirect[1]; IEEE Xplore[2]; and SpringerLink[3]. ACM and Wiley databases were excluded due to their lack of relevant publications. We also avoided direct searching on search engines like Google-scholar and Web of Science due to their secondary indexing nature which results in a large number of duplications and non-peer-reviewed papers. We introduced some refinements to our basic search query to handle the large amount of existing work and to ensure the quality of the initial candidate publications:

1. Phrase searching, truncation, wildcards and proximity searching were applied for each database search
2. If the database provided the options for a detail search, in this SLR, only the title, abstract and keywords were searched.
3. The date of the primary study publications was limited to between 2010 and 2020
4. The type of documents was limited to peer reviewed journals and conference papers.

### 3.4. Selection criteria for primary studies

The search query had a broad scope intentionally because we did not want to miss any potentially interesting research, which ultimately led to a large number of papers. Hence, we defined selection criteria to filter the most relevant studies out of the resultant publications from the primary and secondary search to include as the primary studies for our SLR.

First, we set boundaries for the SLR using the inclusion and exclusion criteria listed in Appendix B. Those exclusion and inclusion criteria were carefully designed to identify the studies which were directly related to the designed research questions of the SLR at the SLR protocol design stage and revised while selecting the publications.

Initially, the title and abstract of each paper were read. If the paper was related to the objectives of the SLR, then the paper was skim-read to identify if it met the inclusion/exclusion criteria. Eventually, we came up with 69 primary studies (Appendix A) for the SLR, and a summary of the selected papers is given in Table 2.

### 3.5. Quality checklist and procedures

We defined a set of quality attributes for the selected papers according to the questions listed in Appendix B. For each question, we used a coarse scoring mechanism: yes = 1; no = 0; and partially = 0.5. These weightings were accumulated and used when assessing the quality of each study. If the accumulated score for a paper is greater than or equal 4, then it was considered as a high-quality paper to include in the SLR; otherwise, it was excluded from the SLR.

### 3.6. Data extraction strategy

For data extraction, we created a Google Form with pertinent questions that would be helpful to synthesise the research question. This task ensures that each research paper is analysed consistently. We defined the initial set of questions in the form to cover the basic information of the paper, and the questions associated with the research questions of the SLR. Then, we randomly picked three papers from the final pool of selected papers and fine-tuned the questions. Consequently, we came up with 36 questions, which are summarised under 5 categories below (please refer to Appendix B for the full list of the questions):

1. Basic information of the paper (e.g., title, abstract, published year, venue, and aim)
2. Properties of the dataset (e.g., targeted insect species, data acquisition method, and size of the dataset)
3. Detection and classification method (e.g., data pre-processing technique, classification/detection methods, and tool/software)
4. Result (e.g., evaluation metrics and benchmarking method)
5. Discussion and future works (e.g., limitations)

Each paper was assigned a unique ID to make it easier to reference in the SLR. Meta-analysis was carried out to answer each sub-research question using the extracted data. Coding was used to abstract and group common phrases, techniques, insect species, crops and data sets in each primary study.

## 4. Results

### 4.1. Selected studies statistics

Over the study period (2010–2020) there has been an increase in interest in the area (Fig. 1) of image-based insect identification. More than half of the studies (60.9%) were found in Science Direct. IEEE Xplore and Springer account for 21.7% and 13.0% respectively. 11 papers out of 61 are conference articles, the rest are from journals. The most popular venue for relevant research is the journal Computers and Electronics in Agriculture with 26 of 69 studies. The second most popular venue, IEEE Access, published only 6 relevant articles.

[1] https://www.sciencedirect.com/
[2] https://ieeexplore.ieee.org/Xplore/home.jsp
[3] https://link.springer.com/

**Table 1**
List of Abbreviations.

| | | | |
|---|---|---|---|
| BP | - Back Propagation | BoVW | - Bag of Visual Words |
| CNN | - Convolutional Neural Networks | DT | - Decision Tree |
| FFNN | - Feedforward Neural Network | FPN | - Feature Pyramid Network |
| GAN | - Generative Adversarial Network | GLCM | - Gray-Level Co-occurrence Matrix |
| HSL | - hue, saturation, lightness | HoG | - Histogram of Gradients |
| HSI | - Hue, Saturation, and Intensity | HSV | - Hue, Saturation, and Value |
| KNN | - K-Nearest Neighbour | LR | - Logistic Regression |
| MKL | - Multi Kernel Learning | MLP | - Multilayer Perceptron |
| NB | - Naive Bayes | R-CNN | - Region-Based Convolutional Neural Networks |
| RGB | - Red, Green, and Blue | RPN | - Region Proposal Network |
| SDD | - Single Shot MultiBox Detector | SIFT | - Scale-Invariant Feature Transform |
| SLR | - Systematic Literature Review | SURF | - Speeded up Robust Features |
| SVM | - Support Vector Machine | YOLO | - You Only Look Once |

**Table 2**
Overview of search results and study selection.

| Source | Initial pool of papers | After applying selection criteria |
|---|---|---|
| 1. Primary Search | | |
| ScienceDirect | 290 | 38 |
| SpringerLink | 450 | 8 |
| IEEE Xplore | 240 | 13 |
| 2. Secondary Search | 22 | 10 |
| ***Total*** | **1002** | **69** |

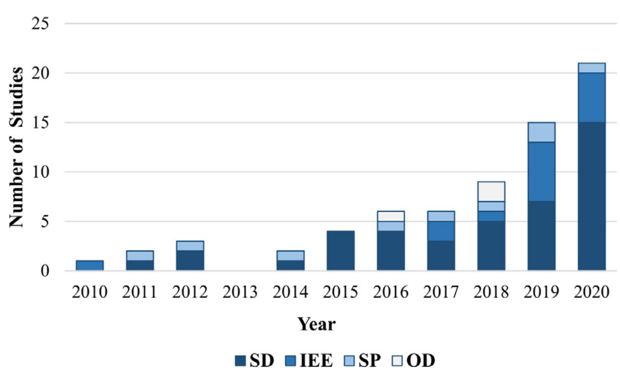


**Fig. 1.** Number of selected primary studies by year: SD for ScienceDirect, IEE for IEEE Xplore, SP for Springer, and OD for Other Databases.

### *4.2. Dataset properties (RQ1)*

#### *4.2.1. What are the insect species, crops and geographic locations considered in the primary studies (RQ1.1)?*

**Insect species.** According to the taxonomic ranking of insects, there are around 28 orders of insects [22]. Each order can be further categorised to family, genus and species levels. As insects go through taxonomic ranking from order to species level, inter-specific differences in morphological characteristics gradually fade away, making them harder to differentiate. Hence, to explore the level of difficulty addressed by the studies, we analysed the taxonomic ranking of the targeted insects in each study. Although there are around 28 insect orders, almost all previous studies cover only 10, as shown in Fig. 2 and Table 3 (Primary studies that do not clearly mention a target insect group are not considered in Fig. 2 and Table 3). They can be identified as dominating insect orders in terms of the global distribution of insects, especially Lepidoptera, Hemiptera, Coleoptera, and Diptera orders which account for more than three-quarters of recorded insect occurrences globally[4]. Most studies classified insects belonging to orders Lepidoptera (i.e., butterflies and moths, 36 studies), and Hemiptera (i.e., true bugs, 34 studies). Since, it is difficult to differentiate between insect species belonging to the same order compared to species belonging to different orders, we analysed the number of distinct insect species in each insect order classified by each primary study (Fig. 5). Studies [SP06, IE11] attempted to classify the largest number of insect species belonging to a single order, 100 distinct Lepidopterans. The Thysanoptera (i.e., thrips), Neuroptera (i.e., lacewings), Odonata (i.e., dragonflies and damselflies) and Phasmatodea (i.e., stick insects) received the least attention. No studies attempted to classify multiple species belonging to Thysanoptera or Neuroptera.

Sometimes distinct populations of the same insect species (i.e., same insect species from different geographical locations) can exhibit slight differences in appearance. Hence, studies [SD20 and SD36] attempted to distinguish subspecies of the same insect species.

**Study location.** We analysed the geographical distribution of the species collected by the primary studies as it provides useful information related to location-specific differences of species and active geographical regions for this line of research. In 35 primary studies, the authors mentioned the location/country where they collected insect samples or images. We categorised these study locations by continent as shown in Fig. 3. Around half of them (21 out of 35 studies) were conducted in Asia, and none in Africa.

**Targeted crop field.** The majority of the primary studies (78.3%) aimed to identify crop pests. 27 studies focused on detecting insect pests targeting a particular crop field, as shown in Fig. 4. Most studies aimed to identify the pests of rice and wheat crops. However, only three studies [SD20, SD36 and SD40] particularly focused on identifying beneficial insects (bees and predatory species).

#### *4.2.2. Do primary studies introduce new datasets? if so, what image acquisition technique was adopted (RQ1.2)?*

Table 4 categorises the primary studies by image acquisition technique. A primary study can belong to more than one cell in Table 4 if the study either adopted different image acquisition techniques to construct one dataset or used multiple datasets collected using various image acquisition techniques. Studies [SD01, SD06, SD10, SD13, SD20, SD25, SD35, IE04, IE14] used more than one dataset.

56 primary studies introduced new datasets, and 14 primary studies used existing datasets (Table 4). 50 studies captured images of insects for themselves. These can be further divided into two subgroups based on the image capturing environment: on-site and lab. Additionally, 9 studies downloaded insect images from different search engines to create a new dataset.

**On-site images.** 26 studies out of 69 collected on-site insect images (i.e. collected from an uncontrolled environment such as a crop field and a grain warehouse). We classified their capturing techniques into: 1) handheld camera (a digital camera or mobile phone); and 2) image capture/trap that is fixed in position and operates without human intervention.

14 studies captured images using a digital camera or mobile device during field visits. For example, study [SD35] used colour digital cam-

[4] The Global Biodiversity Information Facility - GBIF

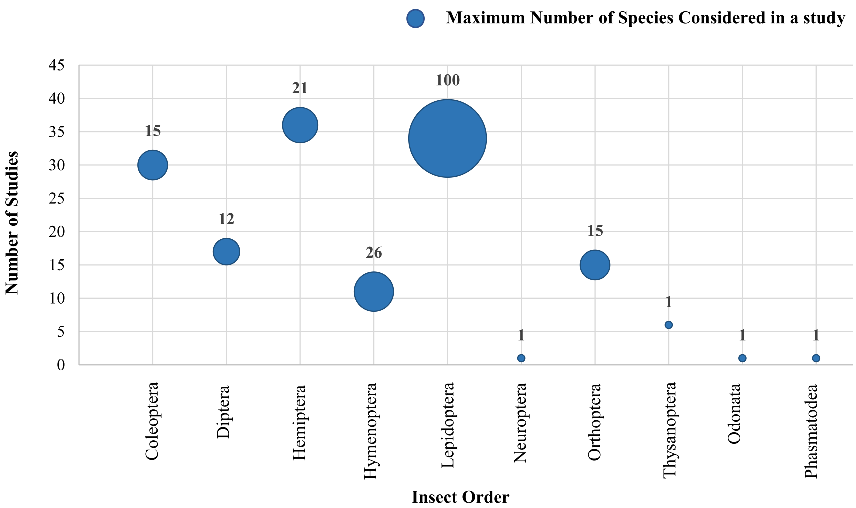


**Fig. 2.** The targeted insect orders across the primary studies. The size of the bubbles represents the maximum number of distinct insect species considered by a primary study for each insect order.

**Table 3**
Insect orders considered in the primary studies.

| Insect order | Primary studies |
|---|---|
| Lepidoptera | SD01, SD04, SD06, SD09, SD10, SD11, SD14, SD18, SD20, SD22, SD25, SD26, SD27, SD29, SD34, SD35, SD39, SD40, SD41, SD42, IE02, IE04, IE07, IE11, IE14, SP01, SP03, SP04, SP05, SP06, SP08, OD01, OD02, OD03 |
| Hemiptera | SD01, SD02, SD03, SD04, SD05, SD06, SD07, SD09, SD10, SD11, SD12, SD13, SD14, SD16, SD17, SD18, SD21, SD23, SD24, SD27, SD28, SD29, SD35, SD39, SD40, SD41, SD42, IE03, IE04, IE07, IE14, SP02, SP03, SP07, OD02, OD03 |
| Coleoptera | SD01, SD04, SD06, SD8, SD09, SD10, SD11, SD15, SD18, SD24, SD27, SD29, SD31, SD32, SD33, SD35, SD37, SD38, SD39, SD40, SD42, IE02, IE04, IE07, IE14, IE15, SP03, SP09, OD01, OD02 |
| Diptera | SD03, SD04, SD06, SD07, SD10, SD21, SD25, SD30, SD35, IE04, IE06, IE09, IE09, IE14, SP03, OD01, OD02 |
| Orthoptera | SD01, SD04, SD06, SD11, SD14, SD19, SD27, SD35, SD39, SD40, SD42, IE02, IE04, OD02, OD03 |
| Hymenopter | SD06, SD09, SD10, SD20, SD21, SD35, SD36, SD38, IE03, IE04, OD01, OD02 |
| Thysanoptera | SD03, SD07, SD13, SD21, SD24, SD28 |
| Neuroptera | SD24 |
| Odonata | SD40 |
| Phasmatodea | SD40 |
| **Other insect orders** | |
| Archaeognatha, Blattodea, Dermaptera, Embioptera, Ephemeroptera, Grylloblattodea, Mantodea, Mantophasmatodea, Mecoptera, Megaloptera, Plecoptera, Psocodea, Raphidioptera, Siphonapter, Strepsiptera, Trichoptera, Zoraptera, Zygentoma | |

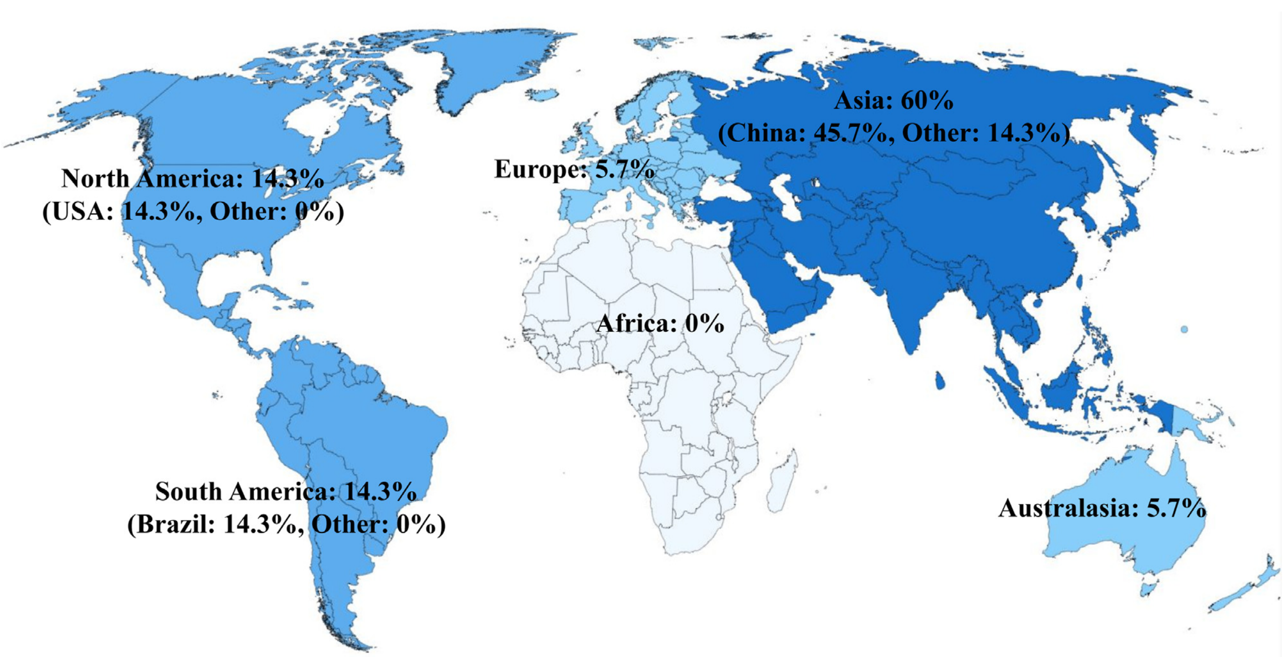


**Fig. 3.** Geographical distribution of study location (based on 35 primary studies).

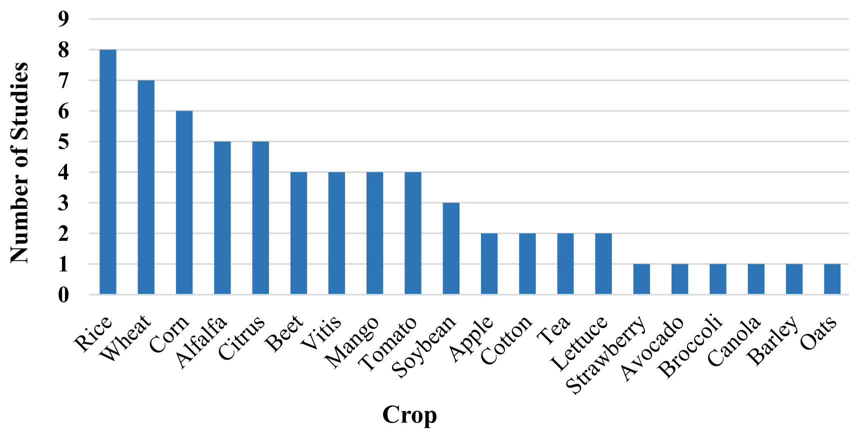


**Fig. 4.** Distribution of target crops (based on 26 primary studies).

**Table 4**
Different image acquisition techniques used in the primary studies.

| | | | |
|---|---|---|---|
| Collected a new dataset | On-site | Handheld camera | SD01, SD10, SD14, SD16, SD18, SD19, SD23, SD27, SD35, SD39, SD40, IE07, SP03, SP07 |
| | | Image capturing system/ trapping system | SD03, SD05, SD07, SD17, SD21, SD22, SD39, SD41, SD42, IE02, IE03, SP01, OD01 |
| | Lab | Simulating the actual environment under lab settings | SD08, SD12, SD15, SD33, IE14, SP02 |
| | | Other methods | SD02, SD13, SD20, SD24, SD25, SD26, SD28, SD30, SD31, SD36, SD37, SD38, IE06, IE09, IE10, IE11, SP05, SP06 |
| | Downloading images using search engines | | SD01, SD04, SD18, SD27, SD40, IE05, IE12, SP08, OD02, OD03 |
| Existing Datasets | | | SD01, SD06, SD09, SD10, SD11, SD32, SD34, SD35, IE01, IE04, IE08, IE13, SP04, OD02 |
| Unavailable | | | SD29, SP09, IE15 |

eras (Canon, Nikon). This allows flexibility to handle camera settings, angle and distance to the subject. However, it does not facilitate changing a subject's visual background. Hence, backgrounds of such images can be cluttered with leaves and other objects, making it harder to locate insects within the frame when compared to lab-based images.

Out of 69 primary studies, 13 adopted an image capture/trap system. For example, study [SD21] operated a mobile agricultural robot in a greenhouse to capture images of pests on strawberry flowers. The robot moved along strawberry pots and captured images of flowers using a digital camera (Canon EOS M) mounted on the robot arm end-effector. Study [SD03] used a Raspberry Pi 3 with a Raspberry Pi Camera v2 module to build an automated image capture system for use in the field. The study set up sticky traps in a tomato seedling greenhouse to trap insect pests. Rasberry Pi units were hung above the tomato plants to capture images of the sticky traps periodically. In study [IE02], the authors deployed a device which included a multispectral light trap to attract pests, and a digital camera to take pictures of the trapped insects automatically at regular time intervals. Such automatic image capturing systems enable studies to collect large numbers of insect images with little human intervention. Therefore, this is a suitable technique for collecting large datasets such as might be required to train deep learning-based insect identification algorithms.

**Lab images.** 34.8% primary studies used lab-based datasets. Among them, studies [SD13, SD24, SD25 and SD28] set up sticky traps in crop fields to collect insect samples and transferred the sticky traps to a lab to record images of trapped insects. Studies [SD20, SD30, SD31, SD37, IE06, IE09, IE10, IE11, SP05 and SP06] prepared individual insect specimens in a lab before the images were captured. For example, study [IE06] first prepared specimen of flies to ensure that their shape and colour did not change with age. Then, each specimen was pinned to a stand which connected to a rotating table to shoot images of the specimen from different angles using a digital camera. In general, lab-based approaches are suitable to capture highly detailed images of insects with little background noise. Also, they allow manipulating the posture of an insect as required before taking a photo. This may be more appropriate for accurate identification of morphologically close insect species than the on-site images.

Some primary studies tried to mimic the actual field environment under a lab-setting to test the effectiveness of their insect trapping/image capturing system for the targeted field. Consequently, we categorized such studies under a separate subgroup of the lab-based primary studies (Table 4). For example, study [SD33] attempted to reproduce stored-grain warehouse conditions using Online Insect Trapping Devices (OITD). The study manually added beetle species into OITD containing wheat with or without foreign materials, dockages and broken grains. These lab experiments help to measure the effectiveness of the data acquisition methods under the simulated real environment scenarios and make adjustment as necessary before setting up the systems in the field.

**Images downloaded from search engines.** A few studies downloaded their insect images using different search engines to create a new dataset. For example, study [IE05] relied on widely used image search engines such as Google, Flickr, and Bing. This process is one of the easiest techniques to create a new and diverse dataset, and search queries can make this process faster. However, it may require significant time to filter the downloaded images, and may not be able find enough number of images of the targeted insects with the expected quality.

**Existing image datasets.** 14 studies used existing datasets to test their insect detection and classification algorithms. More details about the publicly available datasets are discussed in Section 4.2.3.

*4.2.3. What are the properties of datasets used in the primary studies? is the dataset publicly available (RQ1.3)?*

In Fig. 5, we present a histogram of the number of insect species classified in the primary studies. It can be seen that most datasets (56.5%) contain between 1–10 species, and 25 datasets among them considered less than 6. The highest number of species that a study attempted to classify is 123 [IE12].

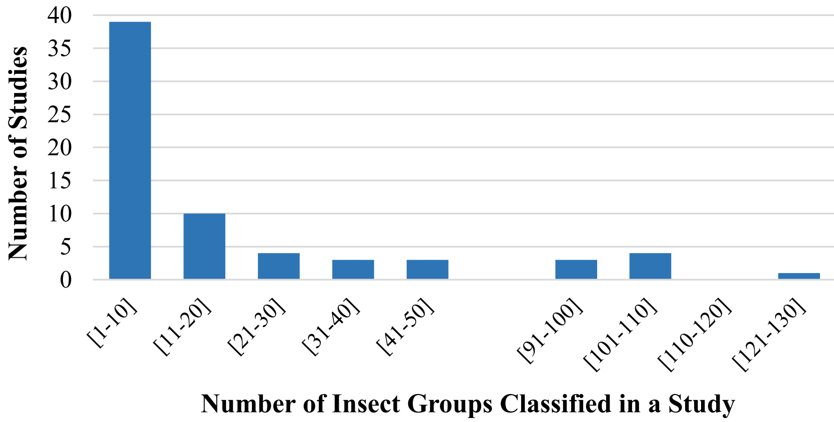


**Fig. 5.** Distribution of the number of insect groups classified across the primary studies.

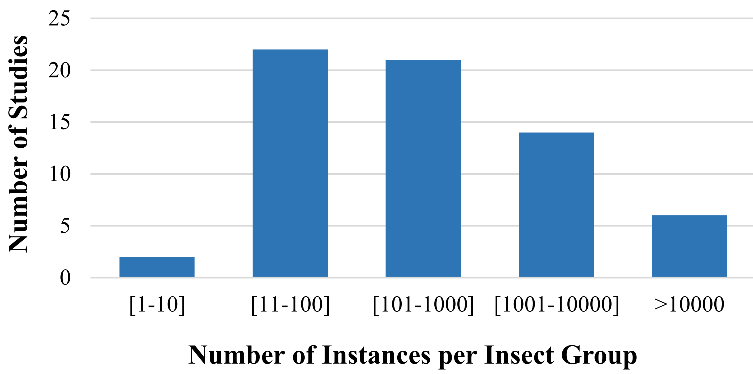


**Fig. 6.** Distribution of the number of instance per insect species across datasets used in primary studies. (In the figure, we assume that the number of data instances of a dataset is equally distributed among all the targeted insect species of that dataset).

Fig. 6 shows the distribution of the average number of data instances per insect species across the datasets – i.e, the number of times, the insects of a given species appear across the dataset. The minimum number of instances per species considered in a study is 4, which is in [IE11, SP06]. Both these studies adopted datasets that contain wing image of 100 lepidopteran insect species taken under lab settings. The maximum number of instances per species in a dataset is 45,424 [SD23]. This dataset comprises 2200 images of aphids captured from different fields such as wheat and corn. Study [IE02] proposed the image-wise largest dataset (Multi-class Pests Dataset 2018 (MPD2018)), which contains 88,670 images captured using a multispectral light trap system. Each image of the dataset contains multiple insects and in total, 582,170 instances belong to 16 different insect species.

A dataset can comprise three types of images: 1) images that contain more than one insect; 2) images with a single insect; and 3) images that contain a part of a single insect. The primary studies can be assigned into one or more of these categories based on the types of images they used (Table 5). Approximately half of studies (49.3%) have collected images that contain multiple insects per images. Many insect species have wings which grow in their later life stages (i.e., adult stage), and a few primary studies explored the possibility of classifying different insect species using their wing images. Six studies used datasets that contain wing images of insects, and one study [SD31] attempted to classify insects based on Elytra. Study [SD37] constructed a dataset including images of body fragments, such as larval skins or fragmented adults, to classify beetle species.

We summarise some of the widely used publicly available datasets and their properties in Table 6. The datasets Xie01 and Xie02 contain the images of insect pests species collected from common crop fields including corn, soybean, and wheat. The largest publicly available dataset is IP102. This dataset includes a set of diverse images downloaded from different search engines. RGBInsect dataset is also relatively large dataset that formed using 10 insect species (species belongs to Coleoptera) in stored-grain warehouses.

**Table 5**
The classification of the studies based number of insects per image .

| Number of insects per image | Primary studies |
|---|---|
| Single insect per image | SD01, SD04, SD06, SD09, SD10,SD11, SD14, SD18, SD19, SD20, SD25, SD27, SD29, SD34, SD35, SD37, SD38, SD39, SD40, IE01, IE04, IE05, IE06, IE08, IE12, IE13, IE15, SP03, SP04, SP05, SP08, SP09, OD02, OD03 |
| More than one insect per image | SD01, SD02, SD03, SD05,SD07, SD08, SD12, SD13, SD15, SD16, SD17, SD21, SD22, SD23, SD24, SD26, SD28, SD32, SD33, SD41, SD42, IE01, IE02, IE03, IE05, IE07, IE08, IE14 SP01, SP02, SP03, SP07, SP08, OD01 |
| Wing (Elytra) | SD20, SD30, SD36, IE09, IE10, IE11, SP06, (SD31) |
| Body Fragments | SD37 |

### 4.3. Classification methodology and performance (RQ02)

#### 4.3.1. What are the techniques used in the primary studies for insect classification/detection task (RQ2.1)?

In this SLR, we divide classification methods into two groups: (1) “shallow” learning and (2) “deep” learning. We categorise existing insect classification techniques that extract predefined hand-engineered features (i.e., manually selecting properties which are derived using algorithms to feed the classification model) from insect images and then adopt machine learning models with fewer hidden layers for image classification, as “shallow” learning methods. In contrast, “deep” learning

**Table 6**
Publicly available datasets.

| Dataset ID | Published In | Dataset Size | Number of Insect Classes | Description | Used In |
|---|---|---|---|---|---|
| Xie01 | SD35 | 1440 | 24 | Insect images collected across several common crop fields including wheat, soyabean, canola and corn. | IE04, OD02, SD06, SD09 (10 classes), SD10, SD35 |
| Xie02 | SD10 | 4500 | 40 | Insect images collected across several common crop fields including corn, soyabean, wheat and canola. Most data were collected from experimental fields of the Anhui Acadamy of Agricultural Science in China. | IE04, SD06, SD10 |
| IP102 | IE05 | 75 222 | 102 | Data collected using search engines, which are mainly divided into two super classes: (1) Field Crop; and (2) Economic crop. Each super class is then split into subclasses: Field crops into Rice, Corn, Wheat, Beet, and Alfalfa, and Economic crops into Vitis, Citrus and Mango. About 19,000 images are available with bounding boxes annotation for object detection. | SD01, IE01, IE05, IE08 |
| RGB2019 | [40] | 3757 (157 287 insects instance) | 10 | Images of stored-grain insects (species belongs to Coleoptera), which are collected using: (1) trapping devices; and (2) smart phones. In these datasets, each image includes multiple insects. | SD32 |

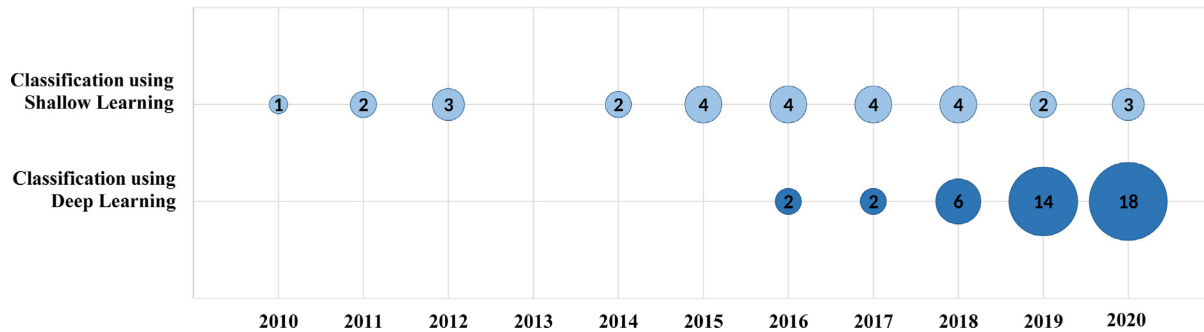


**Fig. 7.** Distribution of the insect classification methods used in the primary studies from 2010 to 2020. Bubble size indicates the number of primary studies per year for each method.

approaches such as Convolutional Neural Networks (CNN), adopt neural network architectures with many hidden layers. These take raw images as their input and automatically extract informative features to predict image labels. 42.0% of studies adopted shallow learning to classify insect groups, while 60.9% studies proposed deep learning approaches. Appendix C summarises the classification techniques and their performance.

As Fig. 7 shows, shallow learning dominates from 2010 to 2017. Even though the deep learning techniques such as CNN were successfully applied for image recognition around 1998 (e.g., LeNet-5 by LeCun et al.), the key breakthrough in CNN performance happened after the introduction of the AlexNet architecture, which is designed to classify large image datasets into 1000 different categories [35]. Since then, the number of improved deep learning architectures proposed in the literature has increased and been applied in various fields of image classification [35]. Within our primary studies, the first deep learning applications for insect classification appeared in 2016 [SD22, OD03]. Since 2018, deep learning has been more popular for insect classification than shallow learning (Fig. 7).

- Classification using shallow learning.

The shallow learning process typically consists of a sequence of steps including image pre-processing, segmentation, feature extraction and classification. These are discussed next.

**Image pre-processing.** Image pre-processing generally improves image quality. It can consist of steps such as converting images into different colour spaces, de-noising, and normalizing [SD10, SD12, SD25, SD26, SP06, IE11]. These steps are typically used to make calculations of image characteristics more convenient, or to reduce the impact of lighting variation, hardware component variation and shadow effects. For example, The images used in [SD25] were transformed to hue, saturation, value (HSV) colour space before performing segmentation since the hue component is not as sensitive to illumination changes as elements in other colour spaces.

**Image segmentation.** Segmentation removes the background of an image and isolates individual insects in the image when more than one is present. A variety of image processing techniques have been utilised to locate insects and their boundaries within the image. For example, many studies [SD03, SD12, SD13, SD26, SP01, SP02, SP04, SP06, SP09, IE11] adopted thresholding methods such as adaptive thresholding [7] or Otsu's thresholding [49] to separate insects from the background. The Sobel edge detection operator [33] and the watershed algorithm [6] were used for segmentation in studies [SD24] and [SD28] respectively. Once the images are segmented, typically contour detection techniques have been utilised to create bounding boxes around individual insects and to crop insects from the images [SP04, SP06, IE11, SD03].

**Feature extraction.** Feature extraction is an important step in shallow learning as classification results depend on the extracted features to a large extent. The aim of feature extraction is to mine characteristics from the segmented images useful to distinguish target insect groups from each other and from other objects in the image background. Most previous work extracted either one or a combination of the following feature types: (1) colour; (2) texture; (3) shape. When extracting features, studies [SD03, SD12, SD13, SD19, SD21, SD26, SD28, SD29, SD30, SP02, SP04, SP05, SP09, IE11] considered the entire image and extract global features, while studies [SD16, SD27, IE05, IE10] extracted local features using image patches (i.e., a small group of pixels). Some studies [SD17, SD24, SD25, SD34, SD35, SP06, OD01] used a combination of local and global features. For example, study [IE11] differentiated butterfly species using wing images by various colour and texture features. The authors of this study extracted colour histograms

**Table 7**
Primary Studies using shallow learning classification.

| Classification Model | Primary Studies |
|---|---|
| SVM | SD03, SD10, SD16, SD17, SD19, SD21, SD26, SD27, SD36, SD38, IE05, IE10, OD01 |
| KNN | SD24, SD36, SP04, SP06, IE05, IE10, IE11 |
| FFNN | SD13, SD29, SD36, SD38, SP05, SP09, IE10 |
| Thresholding | SD12, SD17, SP02 |
| Adaboost | SD17, SD38 |
| Naïve Bayes | SD36, IE10 |
| Other | SD28, SD30, SD34, SD35, SD36, SD38, IE10 |
| **Cascade classifiers** | SD17, SD25, SP04, IE11 |

in hue and saturation colour components as colour features. And, for the texture features, they extracted energy, entropy, correlation and homogeneity measures using the image Gray-level co-occurrence matrix (GLCM) [24]. Study [OD01] used Histogram of Oriented Gradients (HOG) features [14] that count the occurrences of gradient orientation in localised portions of an image as local features along with different color and shape global features to distinguish six different flying insects.

A few studies [SD10, SD19, SD25, SD34, SD35, IE10] have used mid-level features where they transform low-level descriptors (e.g., Gabor filter responses, SIFT descriptors and HOG features) into global and richer representations of intermediate complexity. For example, study [IE10] classified fruit fly species using mid-level features. The study extracted different local features (e.g., SIFT, SURF) and then used BossaNova [3], a mid-level feature representation based on Bag of Visual Words (BoVW) [11] to transform local features into an intermediate representation.

**Classification.** The primary studies have investigated various shallow networks to classify insects based on extracted features (Table 7). These shallow networks learn a mapping function that transforms the extracted features discussed in the steps above, to insect labels. For example, study [IE10] compared the effectiveness of 9 learning techniques including Multilayer Perceptron (MLP), Naïve Bayes (NB) [46], Decision Tree (DT), K-Nearest Neighbour (KNN) [13], Simple Logistic (SL), and Support Vector Machine (SVM) to identify three fruit fly species. The majority of primary studies adopted SVM as the shallow classifier (Table 7). SVMs learn a linear or non-linear decision boundary in the hyperplane defined by the extracted features to separate insect species.

Two or more shallow classifiers can be combined to create a robust classifier [SD17, SD25, SP04, IE11]. For example, study [SD17] used three-layers of planthopper detection algorithm to detect and count planthoppers in images. The first layer consisted of an AdaBoost classifier [54] which learns an ensemble of weak classifiers to construct a strong classifier to detect planthoppers in the images. To reduce the high false detection rate for planthoppers, the second layer used an SVM classifier to determine whether the sub-windows detected in the first step contain rice planthoppers or not. The final layer adopted a thresholding approach to further reduce the false-positive rate by removing water drops and water reflections.

Studies [SD13, SD29, SP05, SP09, IE10] proposed Feed-Forward Neural Networks (FFNN) [5,58] to learn a mapping between hand-engineered features and labels. The conventional feed-forward neural network (FFNN) architecture consists of one or multiple hidden layers connected in series where each layer consists of multiple hidden neurons followed by a non-linear activation function to define the mapping function of the corresponding layer. For example, study [SP05] implemented an FFNN with 1 hidden layer with 50 neurons to classify 14 species of butterfly. The classification network was trained on five textures features (contrast, correlation, entropy, energy, and homogeneity using GLCM) and three colour features (the mean of R, G, and B colour bands).

- Classification using Deep Learning.

Deep learning techniques have been attracting significant attention recently due to their ability to automatically extract features from raw images with little or no pre-processing instead of relying on hand engineered features. There are several state-of-the-art deep learning-based image classification architectures [45,61] and these have been used widely. Some studies have adopted deep learning models to address insect classification (Appendix C). Most state-of-the-art deep learning models have been pre-trained using large general image datasets (e.g., Imagenet [15] which contains around 3.2 million of images in total). When applying such pre-trained architectures to insect classification, pre-trained weights are used to initialised model parameters rather than randomly initialising model parameters. This process of transfer learning helps the model quickly converge and helps to train a reasonable model using a small training dataset. For example, five different pre-trained CNN models were investigated in [SD04] including VGGNet (VGG-16 and VGG-19) [56], ResNet (ResNet50 and ResNet152) [26] and GoogleNet (Inception-V3) [60] to classify 10 different pest species.

Deep learning methods usually require a lot of data to train a well-performing model due to their complexity. This is a challenge in the insect detection and classification context where resources may be limited. To address this challenge, conventional data augmentation techniques have been used to increase the amount of training data. For example, studies [SD01, SD04, SD06, SD20, SD22, SD39, SD40, IE04, IE13, IE14, IE15, OD01, IE06, IE04, IE03, IE02, SP07, SD32, SD23, SD15, SD14] adopted geometric transformation techniques (e.g., rotation, horizontal and vertical flipping, shifting pixels, and random scaling) in their augmentation processes. Some works used noise adding [SD04, OD02] and intensity transformations [SD15, IE06, SP07, SD15] like brightness variation and image blurring to generate additional samples from small datasets.

Beyond the traditional methods, study [SD07] proposed a deep learning-based data augmentation method using a Generative Adversarial Network (GAN) [2]. This study used a GAN to create a synthesised training dataset from the original training dataset of five insect types. The study showed that improvements could be realised by training the CNN model using both synthesised and original training data. Few-shot learning techniques [57] have also been attracting significant attention recently due to their ability to learn a generalized deep learning model with a few training data instances. Motivated by this trend, study [SD11] applied few-shot learning with a Prototypical network [57] to classify 50 species of cotton pests using only 7 images per species.

Agricultural pest images obtained from the field may be unclear or otherwise of low quality due to constraints such as the cost of employing many in-field imaging sensors, a need to operate devices with low power consumption, or the need to use low resolution images to reduce bandwidth requirements for image transmission [IE04]. The use of low-resolution images can reduce the performance of deep learning classifieres, hence, some studies [SD08, IE04] restored low-resolution agricultural pest images for classification using GAN, and the restored image is fed to the CNN model for insect classification.

Often, images of agricultural pests contain multiple insects. When multiple insects are present in an image, it is important to separately identify each. However, the aforementioned deep learning classification networks do not have the ability to separate insects. Hence, studies [SD01, SD02, SD04, SD06, SD08, SD41, IE07, OD03] extract the area occupied by individual insects from images using image processing-based segmentation, or by manually cropping the relevant area, before feeding the data to classification networks. This process is time-consuming and requires different pre-processing steps for identification and for cropping individual insects. To mitigate these drawbacks, several studies implemented deep learning-based insect detection algorithms with the ability to predict the location and group of each insect in an image (i.e., insect detection) (Table 8). For example, [IE05] evaluated several state-of-the-art object detection methods including Faster R-CNN [53], FPN [42], SDD300 [18], RefineDet [67] and YOLOv3 [52] on the IP102 dataset. Study [IE04] adopted a deep learning-based instance segmenta-

**Table 8**
Primary Studies using deep learning classification.

| Application | Primary Studies |
|---|---|
| Classification | SD01, SD02, SD04, SD06, SD07, SD08, SD09, SD11, SD18, SD20, SD31, SD37, SD39, SD40, SD41, IE01, IE04, IE05, IE07, IE08, IE09, IE12, IE13, IE15, OD3 |
| Detection | SD05, SD14, SD15, SD22, SD23, SD32, SD33, SD42, SP03, SP07, SP08, IE02, IE03, IE05, IE06, IE14, OD01, OD02 |
| Segmentation | IE04 |

tion architecture, Mask R-CNN [27], to segment insects from the image. This is the only primary study which implemented such an approach.

*4.3.2. How does the performance of the proposed model compare to chosen baselines (RQ2.2)?*

The performance of classification models proposed by the primary studies has been evaluated against a set of baselines. There are general model evaluation measures [1,28] such as accuracy, precision, recall, F1-score, G-mean and average precision (AP) (for object detection task) to measure the performance of a classification model. However, it is challenging to compare the performance of the models across the primary studies due to inconsistencies in the classification process such as targeted insects, dataset properties, image pre-processing steps and design of the experiments in each study. Other application dependent factors such as memory consumption, data processing time, and the number of data required to train the model must also be considered. To indicate something of value on classification performance to readers, we selected three widely used insect image datasets, Xie01, Xie02 and IP102 (Table 6), and discussion in detail the classification performance achieved by the primary studies that used these datasets (Appendix D). Appendix C provides details of the performance of models proposed by the primary studies and the baselines that each study used.

- **The datasets: Xie01 and Xie02.**

As shown in Table 6, Xie01 and Xie02 contain 1400 images and 4000 images belonging to 24 and 40 insect species respectively. There are 6 primary studies [SD35, SD09, SD10, SD06, IE04 and OD02] that utilised Xie01. Among them, three primary studies [SD10, SD06 and IE04] tested their classification approaches on Xie02. A summary of their proposed approaches, baselines and performances are presented in Appendix D. From them, studies [SD35 and SD10] proposed shallow learning techniques for insect classification. The rest used deep learning.

Study [SD09] implemented two shallow learning techniques (SVM and Back Propagation (BP) Neural Networks) and three deep learning models (AlexNet, ResNet101 and ResNet50) for insect classification. The study tested these classification models on 10 insect groups from Xie01. ResNet-101 achieved the highest classification accuracy (98.67% accuracy). By contrast, SVM and BP yielded poor performance (<50% accuracy). Study [SD06] proposed a customised CNN architecture that consists of 6 convolutional layers for effective field crop insect classification instead of using a general deep learning classification model. The study compared the performance of the proposed architecture on Xie01 and Xie02. The proposed CNN architecture achieved 97.47% accuracy for Xie01 and 95.97% accuracy for Xie02. Their experimental results show that the proposed CNN architecture outperformed general deep learning classification models (AlexNet, ResNet-50, ResNet-101, VGG-16, and VGG-19). The second-best accuracy was recorded by VGG-60 (96.25%) for Xie01 and ResNet-101 (93.99%) for Xie02. The results also show their model achieved higher accuracy than shallow learning methods proposed in [SD35, and SD10] (Appendix D). Study [IE04] attempted to restore the images in Xie01 and Xie02 using a GAN-based image-upscaling model named PSRGAN. The restored images were used for insect classification using various deep learning models. Image upscaling improved classification accuracy by as much as 3.17% and 2.32% for Xie01 and Xie02 respectively.

Due to the small size of Xie01, the authors of [OD02] expanded it by manually collecting more insect images from internet search engines. They proposed an insect detection model that consists of an improved deep-learning network architecture based on VGG19 and RPN. The proposed architecture achieved a higher mean average precision (mAP), 0.8922, than the widely used object detection models–i.e., Single Shot Multibox Detector (SDD) and Fast R-CNN networks which had mAP scores of 0.8534 and 0.7964 respectively.

- **The dataset: IP102.**

As illustrated in Table 6, IP102 is a large insect image dataset of 75,000 images across 102 insect species. IP102 is quite different from Xie01 and Xie02 datasets as it includes both on-site and lab-based images collected using several search engines, and an image can contain one or multiple insects belonging to a particular category. Furthermore, each category in this dataset consists of images from all life stages of an insect (e.g. egg, larval, pupal/nymphal and adult stages). It is challenging to classify the life stages of insects as being from a single category, as different life stages usually have very distinct features. IP102 is an imbalanced dataset and image classifiers trained on such a dataset may be biased towards classes with more training samples.

Study [IE05] reports the results of several shallow and deep learning methods using the IP102 dataset. For shallow learning methods, the study extracted several handcrafted features including Color Histogram (CH), LCH [59], Gabor, GIST [48], SIFT, and SURF, and adopted SVM and KNN classifiers for insect classification. 16.5% was the best recorded F-score. This was reported for KNN with Gabor features (Acc. 19.2%, Prec. 22.0%, recall 14.9%, and G-mean 9.1%). This work also reported the performance of four CNN-based deep feature extraction models namely AlexNet, GoogleNet, VGGNet-16 and ResNet-50, with various downstream classifiers (e.g., SVM, Logistic Regression (LR) (i.e., softmax classifier), KNN). According to their experiments, the deep features improved results by as much as 157% $((49.5-19.2)/19.2)$ in F1-score, which verifies that deep features are more informative than shallow features for insect classification. They have also found that tuning the parameters of the pre-trained models for insect classification, instead of training the models from scratch, can improve the F1-score by 16.19% $((49.4-44.4)/44.4)$.

Studies [IE01, IE08] proposed improved CNN architectures based on residual blocks, FR-ResNet and DMF-ResNet. For IP102, the FR-ResNet model achieved an F1-score of 54.18%. DMF-ResNet improved this value by 7.7%. Both studies compared the classification performance of the proposed architectures with several deep learning-based classification models including AlexNet, ResNet-50, ResNet-101, VGG-16, and DenseNet-121. The proposed models in both studies outperformed the baselines, and DenseNet-121 achieved the second-best performance. The authors of [SD01] applied different saliency techniques [31] to images of IP102 to highlight the most relevant regions of each image. The pre-processed images were then fed to several deep learning models for classification. The highest classification accuracy was achieved by the DenseNet-201 model, 61.93% (F1-score: 59.2%). This is a 5.4% accuracy improvement over the sole use of original images.

IP102 contains 18,983 annotated images. Study [IE05] investigated the performance of five state-of-the-art deep learning-based object detection methods: Faster R-CNN, FPN, SSD300, RefineDet and YOLOv3 using IP102. FPN with ResNet-50 backbone achieved the highest average precision of 54.93% (for IoU = 0.5). The second-best performance was AP 50.64% with YOLOv3.

## 5. Limitations, gaps and a future research roadmap (RQ03)

Based on our findings above and the gaps and future work suggested in the primary studies we analysed, we have identified several challenges as follows:

• **Most existing datasets cover few insect species and/or natural habitats. This limits possibilities for learning a unified model for insect detection and classification.** To address this challenge, some studies [SD02, SD31, SD06, SD17, SD18, SD19, SD13, SP06, SP09, OD03, OD02] suggest enlarging datasets with images of more species, or with images of the same insect species collected from different habitats. There are at least six publicly available datasets for insect classification; four contain less than 5000 images. The datasets used in our primary studies only cover a limited number of insect orders (10 orders out of 28) as shown in Table 3. The majority of the studies (78.3%) were aimed at identifying crop pests, with only three being specific to beneficial insects. Clearly, identifying beneficial insects is valuable to the agricultural sector and therefore the coverage of these insects (e.g., pollinators, predatory insects and parasites of agricultural pests) is an important omission to note. Further, we found that more than half of the existing datasets have been collected in Asia (Fig. 3). None were collected in Africa, a continent of unique biodiversity. Hence, introducing a comprehensive public insect image dataset that covers not only the breadth of insect orders, a range of insect body conditions, and more fully spans the diversity of insect habitat, would be a substantial contribution to research.

• **There is no publicly available dataset suited to use for classification of morphologically similar insect species.** This is another omission to consider when constructing new datasets. Furthermore, the primary studies we explored typically used images of full insects, or their undamaged wings, to extract features for classification. However, in any real application, insect images may include deteriorated insects with damaged body parts and altered colouration. None of the studies attempted to classify insects using such images.

• **The insect distribution in particular ecosystems is often unbalanced.** However, the majority of publications used a balanced dataset in their research. Learning a model from a balanced dataset may result in poor generalization of the test samples taken from a particular ecosystem. As a solution, insect classification models could be trained using datasets that reflect the actual insect distribution in a particular ecosystem. Unfortunately, conventional objective functions used to learn classification models are typically unsuited to imbalanced datasets. Thus, exploring other sophisticated objectives specific to imbalanced datasets [19,62] may be another promising future research direction. Insect distributions in ecosystems are also known to be time-dependent, another factor adding complexity to the situation. This suggests the development of methods to update the bias of insect classification models to capture temporal changes may warrant research.

• **The number of insect species to be found in a particular ecosystem is often unknown.** Even when an ecosystem is understood in some detail, it may be infeasible to create a dataset covering all insect species known to be present. Thus, insect detection models should successfully identify novel insect species when they arise (at least as a negative sample) that did not appear in training data. Study [SD20] suggests novelty detection and outlier detection techniques as a promising solution to this challenge.

• **Several studies have identified challenging cases for automated insect detection and classification systems**. One challenge is to separately identify insects in images when their bodies lie close or overlap [SD02, SD03, SD32, SP01, and SP03]. This especially happens when insect density is high. Studies [SD20, SD28, SP02] state that dealing with overlapping insects should be a focus of research to improve the performance of existing systems. Sometimes insect species belonging to the same order may be very similar in appearance - their minute morphological differences may be hard to distinguish visually, even to experts. This is very commonly the case for microscopic insect species (e.g., thrips). In this SLR, we found that there are no primary studies focusing on classifying morphologically similar microscopic insect species. One the other hand, some insect species show significant *intra*-species variation (e.g., variation in body size and shape between sexes, life stage, or among individuals responsible for different divisions of labour among the social insects). Study [IE12] suggests image-based identification of these species to be another valuable future direction. A few studies have attempted to detect and classify insects throughout their life stages. This can be challenging since insects often dramatically change physical appearance, body size and colour during their lives. They may also inhabit different physical locations as they develop. Such variations may reduce the performance of a classification model [SD16, SD17, IE05], something to be addressed in the future. A potential solution is to treat such different phases of same insect species as distinct classes of the classification model [SD19].

• **Capturing photographs of active, fast-moving insects is challenging**. Rapid movements can result in blurred images that may affect the performance of insect detection and classification procedures. External factors, such as lighting conditions, may also add noise to images and further obstruct insect recognition. Such challenges highlight the importance of restoring images to remove noise or blur before use with classification models. Adopting sophisticated image enhancement methods like Deblur GAN [37] and DnCNN [66] to address this need has been suggested in the literature [SD24].

• **The studies we assessed focused on species-level insect classification but ignored other potentially useful information**. For instance, all the studies in this SLR rely on images to correctly predict insect species (i.e., flat classification) and ignore higher level insect taxonomy. However, a hierarchical classification technique [17,23] can be used to inject information about the structure of insect classes into the process, instead of relying on a flat classification method. Incorporating such knowledge into classification models would improve performance while allowing the hierarchical classification algorithm to classify insects at any appropriate level in the taxon hierarchy, depending on the predictive power of the available data. Also, study [SD20] suggests that incorporating external knowledge, such as insects' geographic distribution, as features to classification models may help to achieve a robust classification model instead of relying solely on image features. In addition, predicting categories that are not within the taxon hierarchy, like sex and life stage, would greatly enhance any classifier's utility too [SD20, SD37, OD02].

• **Dealing with the enormous data required to train deep learning models**. Although deep learning-based techniques achieve superior performance for insect detection and classification, they typically require a large, quality, labelled image dataset to learn a robust model. Collecting and labelling such dataset is time-consuming and labour-intensive. Several studies have demonstrated that traditional and GAN-based augmentation methods can improve performance of CNN classifiers for small datasets. However, study [SD07] noted that when the number of real images increases the augmentation methods barely improve the classification performance as the data augmentation methods can not provide additional information to the CNN. In [SD01], active learning techniques [55] were suggested as a potential solution to deal with large numbers of unlabelled images. In general, active learning strategies initially train a model using a small labelled dataset. Next, they adopt strategies to select informative samples to annotate the unlabelled images based on the predictions made by the initial model. Finally, they retrain the initial model using both initial and subsequently annotated data. These steps are usually performed iteratively to learn the final model. Studies on active learning [55] have shown that the approach may reduce the number of samples required to train a deep learning model.

• **The explainability of deep learning models can be an issue.** By analysing the performance for [Xie 01], [Xie 02] and [IP102] datasets, it is apparent that deep learning methods are superior to shallow learning. However, deep-learning methods are not typically "explainable". To address this limitation, explainable deep learning techniques [16] have been attracting attention recently. However, none of the models used in the primary studies were extended in this way to address insect detection and classification.

• **Several obstacles hinder real-world application of insect classification systems.** Much previous work operates on images collected within controlled environments (e.g., greenhouses and laboratories). As identified in [SD02, SD08, SD12, SD13, SD28, SP08], automated insect detection and classification systems trained on this data may not extend to images collected in uncontrolled environments. The aforementioned studies suggest that classification models should consider other variable factors such as illumination, insect density, insect pose, and plant growth stage. An additional obstacle relates to the impact of dust and other non-insect airborne particles that must be accounted for when designing models that operate using images taken in uncontrolled environments. Study [SD10] identifies context-aware feature learning techniques as a potential solution to learn a model that works well for images with variable backgrounds.

Most insect classification methods are only practical for offline insect detection and classification, although some studies [SD10, SD06, and SD09] aim towards future real-time operation. Online learning techniques that can update models in real-time have been identified as a solution to this problem [OD03]. Further, existing classification systems might be incorporated into complete tools for deployment in the field, perhaps as mobile application which is widely used (e.g., Seek by iNaturalist [5]), but still fairly mature technology for species identification. As found by [SD09, SD12, IE09, IE10 and SP01], it would be worth investigating how to extend the proposed models to assist user decision making.

## 6. Threats to validity

The potential for selection bias in our survey was considered throughout. Consequently, a comprehensive search using the databases commonly used by other secondary studies in the area was conducted and we followed Kitchenham's guidelines [34,36] to standardise our process. The selected databases support their own search strategies and differently limit the length of search queries. Hence, the need for variants of our basic query added to the challenge of identifying relevant studies. To manage this complexity, we formulated a basic search query derived from our SLR's research questions, then tested a variety of search strings built upon the basic query for each database. From these we selected a search string specific to each database that returned the most studies for that particular database.

We assessed each paper's quality on its own merits, whilst keeping in mind the general quality of the journal in which it was published. Citation count alone can be a poor metric to assess publication quality, especially for new papers, and hence we didn't use this metric. We are aware that local journals with low Impact Factors and other metrics may nevertheless contain extremely valuable insights and we did not specifically exclude articles based solely on their venue. If a journal was not indexed in our databases then implicitly we may have excluded some potentially relevant articles from consideration. If we did miss any studies, we believe the number to be small, especially since we explicitly excluded articles published outside of the range 2010 to May 2020.

Assessing the relative performance of the classification methods proposed in the literature so as to minimise bias was also challenging. Our data extraction strategy handled this issue by focusing only on the best reported result of a model, even though sometimes several model configurations were provided within a single study. To minimise the loss of detail, our SLR also presents the overarching benefits and drawbacks of each method where possible.

[5] www.inaturalist.org

## 7. Summary

Insect identification is a vital component of several processes in agriculture and environmental management. However, it remains a challenging, labour-intensive task and therefore there is growing interest in developing image-based systems for rapid and reliable insect identification to replace much of the human labour traditionally required. Motivated by this, we conducted this SLR to identify and assess literature in the area.

Our study revealed that only 10 insect orders (out of 28) have been examined by the primary studies and that the majority of the research was conducted in Asia. Almost all of the studies focused on classifying insect pests or general insect species in their research and only three specifically targeted beneficials. Data acquisition methods adopted were spread across diverse techniques that capture images using a variety of setups (e.g., handheld devices, fixed devices and traps), download images from the internet, or use pre-existing datasets. We analysed dataset properties (e.g., dataset size, number of insect groups, and insects per image) and listed publicly available datasets for future reference.

We comprehensively explored: 1) shallow learning techniques; and 2) deep learning techniques. The results show that there is a recent trend toward applying deep learning techniques. The shallow learning process typically consists of sequence of steps including image pre-processing, segmentation, feature extraction, and classification. The selection of the best approaches for each step in shallow learning classification process are highly depend on dataset properties and data acquisition methods. And, there are number of different techniques that have been introduced in the literature to conduct these steps. Hence, it is difficult to identify the most effective approach for the targeted insect species without conducting tedious trial and errors. Moreover, these shallow learning processes could fail under more complex image backgrounds and also for a diverse dataset [IE05]. Hence, deep learning techniques have been attracting significant attention recently due to their ability to automatically extract features from the raw images with little or no pre-processing instead of relying on the hand engineering features. We also analysed the performance of the insect identification methods proposed in each study. Since comparison of performance across primary studies using different datasets is infeasible, we evaluated their classification performance for three publicly available datasets. The results reveal that the deep learning techniques outperformed shallow learning. Finally, we provided a set of recommendations for future research based on the gaps our survey identified.

This SLR provides insight into the current state-of-the-art and indicates promising future directions for image-based insect identification. The survey will assist readers to identify suitable methods for their own applications. Extending the survey beyond 2020 as the field develops is an important, ongoing task as image-based insect identification methods are adopted and continue to diversify.

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## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A: List of studies included in the SLR

**Table 9**
List of studies considered in the SLR and their corresponding sources. Here SD, SP and IE acronyms stand for ScienceDirect, SpringerLink and IEEE Explorer respectively.

| ID | Paper |
|---|---|
| SD01 | Loris Nanni, Gianluca Maguolo, and Fabio Pancino. Insect pest image detection and recognitionbased on bio-inspired methods. Ecological Informatics, page 101089, 2020 |
| SD02 | Elison Alfeu Lins, João Pedro Mazuco Rodriguez, Sandy Ismael Scoloski, Juliana Pivato, Marília Balotin Lima, José Maurício Cunha Fernandes, Paulo Roberto Valle da Silva Pereira, Douglas Lau, and Rafael Rieder. A method for counting and classifying aphids using computervision. Computers and Electronics in Agriculture, 169:105200, 2020 |
| SD03 | Dan Jeric Arcega Rustia, Chien Erh Lin, Jui-Yung Chung, Yi-Ji Zhuang, Ju-Chun Hsu, and Ta-Te Lin. Application of an image and environmental sensor network for automated greenhouse insect pest monitoring. Journal of Asia-Pacific Entomology, 23(1):17-28, 2020 |
| SD04 | Yanfen Li, Hanxiang Wang, L Minh Dang, Abolghasem Sadeghi-Niaraki, and Hyeonjoon Moon. Crop pest recognition in natural scenes using convolutional neural networks. Computers and Electronics in Agriculture, 169:105174, 2020b |
| SD05 | Victor Partel, Leon Nunes, Phil Stansly, and Yiannis Ampatzidis. Automated vision-based system for monitoring asian citrus psyllid in orchards utilizing artificial intelligence. Computersand Electronics in Agriculture, 162:328-336, 2019 |
| SD06 | K Thenmozhi and U Srinivasulu Reddy. Crop pest classification based on deep convolutional neural network and transfer learning. Computers and Electronics in Agriculture, 164:104906, 2019 |
| SD07 | Chen-Yi Lu, Dan Jeric Arcega Rustia, and Ta-Te Lin. Generative adversarial network based image augmentation for insect pest classification enhancement. IFAC-PapersOnLine, 52(30):1-5, 2019 |
| SD08 | Huiling Zhou, Haiwei Miao, Jiangtao Li, Fuji Jian, and Digvir S Jayas. A low-resolution image restoration classifier network to identify stored-grain insects from images of sticky boards. Computers and Electronics in Agriculture, 162:593-601, 2019 |
| SD09 | Xi Cheng, Youhua Zhang, Yiqiong Chen, Yunzhi Wu, and Yi Yue. Pest identification via deep residual learning in complex background. Computers and Electronics in Agriculture, 141:351-356, 2017b |
| SD10 | Chengjun Xie, Rujing Wang, Jie Zhang, Peng Chen, Wei Dong, Rui Li, Tianjiao Chen, and Hongbo Chen. Multi-level learning features for automatic classification of field crop pests. Computers and Electronics in Agriculture, 152:233-241, 2018 |
| SD11 | Yang Li and Jiachen Yang. Few-shot cotton pest recognition and terminal realization. Computers and Electronics in Agriculture, 169:105240, 2020 |
| SD12 | Mohammadmehdi Maharlooei, Saravanan Sivarajan, Sreekala G Bajwa, Jason P Harmon, and John Nowatzki. Detection of soybean aphids in a greenhouse using an image processing technique. Computers and Electronics in agriculture, 132:63-70, 2017 |
| SD13 | Karlos Espinoza, Diego L Valera, José A Torres, Alejandro López, and Francisco D Molina Aiz. Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci and frankliniella occidentalis on sticky traps in greenhouse agriculture. Computers and Electronics in Agriculture, 127:495-505, 2016 |
| SD14 | Yi Yue, Xi Cheng, Di Zhang, Yunzhi Wu, Yang Zhao, Yiqiong Chen, Guohua Fan, and Youhua Zhang. Deep recursive super resolution network with laplacian pyramid for better agricultural pest surveillance and detection. Computers and Electronics in Agriculture, 150:26-32, 2018 |
| SD15 | Yu Sun, Xuanxin Liu, Mingshuai Yuan, Lili Ren, Jianxin Wang, and Zhibo Chen. Automatic in-trap pest detection using deep learning for pheromone-based dendroctonus valens monitoring. Biosystems Engineering, 176:140-150, 2018 |
| SD16 | Tao Liu, Wen Chen, Wei Wu, Chengming Sun, Wenshan Guo, and Xinkai Zhu. Detection of aphids in wheat fields using a computer vision technique. Biosystems Engineering, 141:82-93, 2016a |
| SD17 | YAo Qing, Ding-xiang Xian, Qing-jie Liu, Bao-jun Yang, Guang-qiang Diao, and TANG Jian. Automated counting of rice planthoppers in paddy fields based on image processing. Journal of Integrative Agriculture, 13(8):1736-1745, 2014 |
| SD18 | Adão Nunes Alves, Witenberg SR Souza, and Díbio Leandro Borges. Cotton pests classification in field-based images using deep residual networks. Computers and Electronics in Agriculture,174:105488, 2020 |
| SD19 | LU Shuhan and Si-jing YE. Using an image segmentation and support vector machine method for identifying two locust species and instars. Journal of Integrative Agriculture, 19(5):1301-1313, 2020 |
| SD20 | Keanu Buschbacher, Dirk Ahrens, Marianne Espeland, and Volker Steinhage. Image-basedspecies identification of wild bees using convolutional neural networks. Ecological Informatics,55:101017, 2020 |
| SD21 | MA Ebrahimi, MH Khoshtaghaza, Saeid Minaei, and B Jamshidi. Vision-based pest detection based on svm classification method. Computers and Electronics in Agriculture, 137:52-58, 2017 |
| SD22 | Weiguang Ding and Graham Taylor. Automatic moth detection from trap images for pest management. Computers and Electronics in Agriculture, 123:17-28, 2016 |
| SD23 | Rui Li, Rujing Wang, Chengjun Xie, Liu Liu, Jie Zhang, Fangyuan Wang, and Wancai Liu. A coarse-to-fine network for aphid recognition and detection in the field. Biosystems Engineering, 187:39-52, 2019a |
| SD24 | Luis O Solis-Sánchez, Rodrigo Castañeda-Miranda, Juan J García-Escalante, Ramón G Guevara-González, Celina L Castañeda-Miranda, and Pedro D Alaniz-Lumbreras. Scale invariant feature approach for insect monitoring. Computers and Electronics in Agriculture, 75(1):92-99, 2011 |
| SD25 | Chenglu Wen and Daniel Guyer. Image-based orchard insect automated identification and classification method. Computers and Electronics in Agriculture, 89:110-115, 2012 |
| SD26 | YAO Qing, LV Jun, Qing-jie Liu, Guang-qiang Diao, Bao-jun Yang, Hong-ming Chen, and TANG Jian. An insect imaging system to automate rice light-trap pest identification. Journal of Integrative Agriculture, 11(6):978-985, 2012 |
| SD27 | Limiao Deng, Yanjiang Wang, Zhongzhi Han, and Renshi Yu. Research on insect pest image detection and recognition based on bio-inspired methods. Biosystems Engineering, 169:139-148, 2018 |
| SD28 | Chunlei Xia, Tae-Soo Chon, Zongming Ren, and Jang-Myung Lee. Automatic identification and counting of small size pests in greenhouse conditions with low computational cost. Ecological Informatics, 29:139-146, 2015 |
| SD29 | Piotr Boniecki, Krzysztof Koszela, Hanna Piekarska-Boniecka, Jerzy Weres, Maciej Zaborowicz, Sebastian Kujawa, Arkadiusz Majewski, and Barbara Raba. Neural identification of selected apple pests. Computers and Electronics in Agriculture, 110:9-16, 2015 |
| SD30 | Narin Sontigun, Chutharat Samerjai, Kom Sukontason, Anchalee Wannasan, Jens Amendt, Jeffery K Tomberlin, and Kabkaew L Sukontason. Wing morphometric analysis of forensically important flesh flies (diptera: Sarcophagidae) in thailand. Acta Tropica, 190:312-319, 2019 |
| SD31 | Leihong Wu, Zhichao Liu, Tanmay Bera, Hongjian Ding, Darryl A Langley, Amy Jenkins-Barnes, Cesare Furlanello, Valerio Maggio, Weida Tong, and Joshua Xu. A deep learning model to recognize food contaminating beetle species based on elytra fragments. Computers and Electronics in Agriculture, 166:105002, 2019a |

(*continued on next page*)

**Table 9** (*continued*)

| ID | Paper |
|---|---|
| SD32 | Jiangtao Li, Huiling Zhou, Zhongming Wang, and Qingxuan Jia. Multi-scale detection of stored-grain insects for intelligent monitoring. Computers and Electronics in Agriculture, 168:105114, 2020a |
| SD33 | Yufeng Shen, Huiling Zhou, Jiangtao Li, Fuji Jian, and Digvir S Jayas. Detection of stored-grain insects using deep learning. Computers and Electronics in Agriculture, 145:319-325, 2018 |
| SD34 | Linan Feng, Bir Bhanu, and John Heraty. A software system for automated identification and retrieval of moth images based on wing attributes. Pattern Recognition, 51:225-241, 2016 |
| SD35 | Chengjun Xie, Jie Zhang, Rui Li, Jinyan Li, Peilin Hong, Junfeng Xia, and Peng Chen. Automatic classification for field crop insects via multiple-task sparse representation and multiple-kernel learning. Computers and Electronics in Agriculture, 119:123-132, 2015 |
| SD36 | Felipe Leno da Silva, Marina Lopes Grassi Sella, Tiago Mauricio Francoy, and Anna Helena Reali Costa. Evaluating classification and feature selection techniques for honeybee subspecies identification using wing images. Computers and Electronics in Agriculture, 114:68-77, 2015 |
| SD37 | Manjree Agarwal, Thamer Al-Shuwaili, Anupiya Nugaliyadde, Penghao Wang, Kok Wai Wong, and Yonglin Ren. Identification and diagnosis of whole body and fragments of trogoderma granarium and trogoderma variabile using visible near infrared hyperspectral imaging technique coupled with deep learning. Computers and Electronics in Agriculture, 173:105438, 2020 |
| SD38 | Midori Tuda and Alejandro Isabel Luna-Maldonado. Image-based insect species and gender classification by trained supervised machine learning algorithms. Ecological Informatics, 60:101135, 2020 |
| SD39 | Everton Castel*ão* Tetila, Bruno Brandoli Machado, Gilberto Astolfi, Nícolas Alessandrode Souza Belete, Willian Paraguassu Amorim, Antonia Railda Roel, and Hemerson Pistori. Detection and classification of soybean pests using deep learning with uav images. Computers and Electronics in Agriculture, 179:105836, 2020 |
| SD40 | Jin Wang, Yane Li, Hailin Feng, Lijin Ren, Xiaochen Du, and Jian Wu. Common pests image recognition based on deep convolutional neural network. Computers and Electronics in Agriculture, 179:105834, 2020a |
| SD41 | YAO Qing, FENG Jin, TANG Jian, Wei-gen XU, Xu-hua ZHU, Bao-jun YANG, L*ü* Jun, Yi-zeXIE, YAO Bo, Shu-zhen WU, et al. Development of an automatic monitoring system for rice light-trap pests based on machine vision. Journal of Integrative Agriculture, 19(10):2500-2513,2020 |
| SD42 | Qi-Jin Wang, Sheng-Yu Zhang, Shi-Feng Dong, Guang-Cai Zhang, Jin Yang, Rui Li, and Hong-Qiang Wang. Pest24: A large-scale very small object data set of agricultural pests for multi-target detection. Computers and Electronics in Agriculture, 175:105585, 2020b |
| SP01 | Wenyong Li, Meixiang Chen, Ming Li, Chuanheng Sun, and Lin Wang. Automated counting of sex-pheromone attracted insects using trapped images. In International Conference on Computer and Computing Technologies in Agriculture, pages 40–53. Springer, 2017 |
| SP02 | An C Tran, Nghi C Tran, and Hiep X Huynh. An approach to detecting brown plant hopper based on morphological operations. In International Conference on Nature of Computation and Communication, pages 52–61. Springer, 2016 |
| SP03 | Hong-Wei Pang, Peipei Yang, Xiaolin Chen, Yong Wang, and Cheng-Lin Liu. Insect recognition under natural scenes using r-fcn with anchor boxes estimation. In International Conference on Image and Graphics, pages 689–701. Springer, 2019 |
| SP04 | Fan Li and Yin Xiong. Automatic identification of butterfly species based on homsc and glcmoib. The Visual Computer, 34(11):1525-1533, 2018 |
| SP05 | Yılmaz Kaya and Lokman Kayci. Application of artificial neural network for automatic detection of butterfly species using color and texture features. The Visual Computer, 30(1):71-79, 2014 |
| SP06 | Le-qing Zhu and Zhen Zhang. Insect recognition based on integrated region matching and dual tree complex wavelet transform. Journal of Zhejiang University SCIENCE C, 12(1):44-53, 2011 |
| SP07 | Bohan Liang, Shangxi Wu, Kaiyuan Xu, and Jingyu Hao. Butterfly detection and classification based on integrated yolo algorithm. In International Conference on Genetic and Evolutionary Computing, pages 500–512. Springer, 2019 |
| SP08 | Yue He, Zhiyan Zhou, Luhong Tian, Youfu Liu, and Xiwen Luo. Brown rice planthopper (nilaparvata lugens stal) detection based on deep learning. Precision Agriculture, 2020 |
| SP09 | Shahrul Nizam Yaakob and Lakhmi Jain. An insect classification analysis based on shape features using quality threshold artmap and moment invariant. Applied Intelligence, 37(1):12-30, 2012 |
| IE01 | Fuji Ren, Wenjie Liu, and Guoqing Wu. Feature reuse residual networks for insect pest recognition. IEEE Access, 7:122758-122768, 2019 |
| IE02 | Liu Liu, Rujing Wang, Chengjun Xie, Po Yang, Fangyuan Wang, Sud Sudirman, and Wancai Liu. Pestnet: An end-to-end deep learning approach for large-scale multi-class pest detection and classification. IEEE Access, 7:45301-45312, 2019 |
| IE03 | Rui Li, Rujing Wang, Jie Zhang, Chengjun Xie, Liu Liu, Fangyuan Wang, Hongbo Chen, Tianjiao Chen, Haiying Hu, Xiufang Jia, et al. An effective data augmentation strategy for cnn-based pest localization and recognition in the field. IEEE Access, 7:160274-160283, 2019 |
| IE04 | Qiang Dai, Xi Cheng, Yan Qiao, and Youhua Zhang. Agricultural pest super-resolution and identification with attention enhanced residual and dense fusion generative and adversarial network. IEEE Access, 8:81943-81959, 2020 |
| IE05 | Xiaoping Wu, Chi Zhan, Yu-Kun Lai, Ming-Ming Cheng, and Jufeng Yang. Ip102: A large-scale benchmark dataset for insect pest recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 8787–8796, 2019b |
| IE06 | Yantong Chen, Xianzhong Zhang, Weinan Chen, Yuyang Li, and Junsheng Wang. Research on recognition of fly species based on improved retinanet and cbam. IEEE Access, 2020 |
| IE07 | Everton Castel ao Tetila, Bruno Brandoli Machado, Geazy Vilharva Menezes, Nıcolas Alessandro de Souza Belete, Gilberto Astolfi, and Hemerson Pistori. A deep-learning approach for automatic counting of soybean insect pests. IEEE Geoscience and Remote Sensing Letters,2019 |
| IE08 | Wenjie Liu, Guoqing Wu, and Fuji Ren. Deep multi-branch fusion residual network for insect pest recognition. IEEE Transactions on Cognitive and Developmental Systems, 2020 |
| IE09 | Matheus Macedo Leonardo, Tiago J Carvalho, Edmar Rezende, Roberto Zucchi, and Fabio Augusto Faria. Deep feature-based classifiers for fruit fly identification (diptera: Tephritidae). In 2018 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI), pages 41–47. IEEE, 2018 |
| IE10 | Matheus Macedo Leonardo, Sandra Avila, Roberto A Zucchi, and Fabio A Faria. Mid-level image representation for fruit fly identification (diptera: Tephritidae). In 2017 IEEE 13th International Conference on e-Science (e-Science), pages 202–209. IEEE, 2017 |
| IE11 | Le-Qing Zhu and Zhen Zhang. Auto-classification of insect images based on color histogram and glcm. In 2010 Seventh International Conference on Fuzzy Systems and Knowledge Discovery, volume 6, pages 2589–2593. IEEE, 2010 |
| IE12 | Yoon Jin Park, Gervase Tuxworth, and Jun Zhou. Insect classification using squeeze-and-excitation and attention modules-a benchmark study. In 2019 IEEE International Conference on Image Processing (ICIP), pages 3437–3441. IEEE, 2019 |
| IE13 | Suchang Lim, Seunghyun Kim, and Doyeon Kim. Performance effect analysis for insect classification using convolutional neural network. In 2017 7th IEEE International Conference on Control System, Computing and Engineering (ICCSCE), pages 210–215. IEEE, 2017 |
| IE14 | Zhichao Shi, Hao Dang, Zhicai Liu, and Xiaoguang Zhou. Detection and identification of stored-grain insects using deep learning: A more effective neural network. IEEE Access, 8:163703-163714, 2020 |
| IE15 | Zhou Dongmei, Wang Ke, Guo Hongbo, Wang Peng, Wang Chao, and Peng Shaofeng. Classification and identification of citrus pests based on inceptionv3 convolutional neural network and migration learning. In 2020 International Conference on Internet of Things and Intelligent Applications (ITIA), pages 1–7. IEEE, 2020 |
| OD01 | Yuanhong Zhong, Junyuan Gao, Qilun Lei, and Yao Zhou. A vision-based counting and recognition system for flying insects in intelligent agriculture. Sensors, 18(5):1489, 2018 |
| OD02 | Denan Xia, Peng Chen, Bing Wang, Jun Zhang, and Chengjun Xie. Insect detection and classification based on an improved convolutional neural network. Sensors, 18(12):4169, 2018 |
| OD03 | Ziyi Liu, Junfeng Gao, Guoguo Yang, Huan Zhang, and Yong He. Localization and classification of paddy field pests using a saliency map and deep convolutional neural network. Scientific Reports, 6:20410, 2016b |

## Appendix B: Exclusion / Inclusion Criteria, Quality Assessment Criteria and Data Extraction Form

**Table 10**
Exclusion / Inclusion Criteria.

| Exclusion criteria | |
|---|---|
| ID | Criteria |
| E01 | Workshop articles, papers present in symposiums, posters, books/book chapters, Gray literature (theses, technical report and unpublished work) and non-peer review articles. |
| E02 | Work-in-progress studies, discussions, proposals and opinion papers are excluded if they do not provide a proper methodology and outcomes. |
| E03 | Secondary or review studies |
| E04 | Studies beyond the scope, not related to the research question set for this SLR, or do not include a considerable amount of information to extract. |
| E05 | Short papers (pages less than 5) and low-quality papers[a] |
| E06 | Studies do not provide clear information about the dataset, experimental setup, methodology and results |
| E07 | Studies written in other than English |
| E08 | Studies that propose an indirect method for insect identification (e.g., detect insect by analysing the images of damaged leaves) and ruled-based system |
| E09 | Papers without full text available |
| | **Inclusion criteria** |
| **ID** | **Criteria** |
| I01 | Conference papers and journal articles which propose an image-based insect detection or classification method |
| I02 | Primary studies that benchmark one or more existing image-based classification methods |
| I03 | Selected cited references |
| I04 | Studies published during the year range 2010–2020 |

[a] elaborate under quality criteria

**Table 11**
Quality assessment criteria.

| ID | Question |
|---|---|
| Q01 | Is the paper highly applicable to the objective of the SLR? |
| Q02 | Does the paper provide adequate information regarding the data acquisition method and dataset properties? |
| Q03 | Does the paper clearly state the insect classification/detection method that they have implemented? |
| Q04 | Are there any solid findings/results and a benchmark with the previous works? |
| Q05 | Does the paper provide a conclusion and any limitation/future works? |
| Q06 | Is the paper published in a quality venue (i.e., A, B ranking in core ranking portal or Q1, Q2 in SJR portal or listed in the quality conference and journal list provided by Faculty of IT, Monash University)? |

https://www.core.edu.au/conference-portal https://www.scimagojr.com/journalrank.php.

*Data Extraction Form*

1. Paper ID
2. Paper Title
3. Authors of the Paper
4. Authors' affiliation
5. Published Year
6. Source of the publication (ScienceDirect/SpringerLink/IEEE Xplore/Other)
7. Type of the study (Conference Paper/Journal)
8. Name of the Conference or Journal
9. Abstract
10. Authors' keyword
11. Number of Citations
12. BibTex
13. What are the key research problems addressed in the study?
14. What is the data acquisition method used in the paper?
15. Explain the data collection setup and apparatus
16. Research Environment (Open Field/ Green House/ Lab/Stored-grain warehouse/ other)
17. What are the target insects' species in the study?
18. Is there any particular target field/weed/plant covered in the paper?
19. Does a data instance (in the dataset) represent an individual insect or a collection of insects? (One Insect/ Multiple Insects/ Part of an Insect)
20. Size of the dataset?
21. Is dataset publicly available?
22. What is the country in which the research is conducted?
23. Application of the proposed method (Classification/ Detection)
24. What are the data pre-processing and data augmentation techniques that have been used in the study?
25. What are the segmentation techniques that have been used in the study? (Only if the system is image-based)
26. If there is any specific features used in the study for classification, please mention here.
27. Detailed explanation of the proposed methodology for insect detection and classification?
28. Tools and software used in the study
29. What is the evaluation metric used in the study? e.g., mean average precision.
30. Performance of the proposed method
31. What are the baselines used in the paper for evaluation?
32. What are the limitations/future works identified/proposed in the study?
33. Are there any important references cited in the study?
34. Please add if there is any important diagram or table?

## Appendix C: Summary of the models used in each primary study.

you can find the a summary of classification/detection models used in the primary studies in the Excel Workbook provided under the link: https://drive.google.com/summaryOfModels. It summarises the pre-processing techniques, data augmentation techniques, features extraction techniques, classification/detection models, baselines used and the classification performance in the primary studies.

The Excel Workbook contains three sheets:

1. Shallow Learning Methods: This contains a table that summarises the shallow learning techniques adopted by the primary studies for insect classification.
2. Deep Learning - Classification: This contains a table that summarises the deep learning techniques adopted by the primary studies for insect classification.
3. Deep Learning - Detection: This contains a table that summarises the deep learning techniques adopted by the primary studies for the insect detection task.

## Appendix D: Performance comparison for datasets: Xie01, Xie02 and IP102.

**Table 12**
Performance comparison for datasets: Xie01 and Xie02.

| insect classification | | | |
|---|---|---|---|
| Study | Proposed Method | Baselines | Best Performance of the proposed method |
| SD35 | multiple-task sparse representation and multiple-kernel learning (MKL) | Classification methods proposed in [21,30,38,63–65,68] and SD25 Two general classifiers (nearest subspace classifier (NSC) and linear SVM) | Xie01: Accuracy 81.0±2.4 using SIFT features as low-level features. (multiple-task sparse representation generated using two or more features were outperformed the classification accuracy of single feature alone) |
| SD10 | multi-level learning features and multiple-level fusion classification | Image classification methods proposed in [ [21,65], SD25, and SD35] | Xie01: Accuracy 90.0±1.7% Xie02: Accuracy 89.3± 2.8% |
| SD09 (only 10 classes) | AlexNet, ResNet101, ResNet50 | Back Propagation (BP) Neural Network and SVM | Xie01: Alexnet - Accuracy 86.67%, ResNet50 - Accuracy 94.67%, ResNet101 - Accuracy 98.67% |
| SD06 | Customized CNN architecture with 6 convolutional layers | Deep learning models: AlexNet, ResNet-50, ResNet-101, VGG-16, and VGG-19 The results of the previous studies that used the Xie01 and Xie02 datasets: [SD35, SD10, SD09] and [10] | Xie01: Accuracy 97.47% Xie02: Accuracy 95.97% |
| IE04 | PSRGAN, an image upscaling model based on generative adversarial network (GAN) to pre-process the images. AlexNet, VGG-16, Inception-v3, ResNet-101, ResNeXt50, DenseNet-121, MobileNet V2, ShuffleNet V2 as classification models | Feeding raw images, and pre-processed images using different image restoration methods to the classification models | Xie01: Accuracy 94.15% by ResNet101 and MobileNet V2. Xie02: Accuracy 99.10% by MobileNet V2 |
| | | **insect detection** | |
| **Study** | **Proposed Method** | **Baselines** | **Best Performance of the proposed method** |
| OD02 | An improved network architecture based on VGG-19 with RPN | Single Shot Multibox Detector (SSD) and Fast Region-based Convolutional Neural Network (R-CNN) | Xie01: mPA 0.8922 |

**Table 13**
Performance comparison for IP102.

| Insect classification | | | |
|---|---|---|---|
| Study | Proposed Method | Baselines | Best Performance of the proposed method |
| IE05 | Features: Color Histogram (CH), LCH, Gabor, GIST, SIFT, and SURF.<br>Classifiers: SVM and KNN | | Accuracy 19.5%, F1-score: 4.7%, precision 28.2%, recall 7.3%, and G-mean 0.9 for SVM with SURF features. |
| | Features: Deep features extracted from AlexNet, GoogleNet, VGGNet- 16, and ResNet-50 Classifiers: SVN and KNN | | Accuracy 49.5%, F1-Score 40.6%, Precision 43.6%, recall 39.1%, and G-mean GM 31 48.7% for deep features from ResNet-50 and SVM classifier |
| | Training the deep learning models from scratch:AlexNet, GoogleNet, VGGNet- 16, and ResNet-50 | | F1-Score 33.3%, Accuracy 41.4%, G-mean 25.5% for VGGNet-16 |
| | Fine tuning pre-trained deep learning models (Trasfer learning): AlexNet, GoogleNet, VGGNet- 16, and ResNet-50 | | F1-score 40.1%, Accuracy 49.4%, G-mean 31.5% for For ResNet-50 |
| IE01 | FR-ResNet (Feature Reuse Residual Network) which consists of an improved residual block structure based on the original residual block in ResNets | ResNet-50, ResNet- 101, AlexNet, GoogLeNet, VGG-16 and DenseNet-121 | F1-score 54.18%, Accuracy 55.24% |
| IE08 | Deep Multi-branch Fusion Residual Network (DMF-ResNet), which consist of improved residual blocks to learn multi-scale representations | AlexNet, ResNet-50, ResNet-101, Pre-ResNet-50, VGG-16, Densenet-121 | F1-score 58.37%, Acc.59.22% |
| SD01 | Saliency techniques [31] to highlight the most relevant regions in an image before feeding the image to the classification model Classifiers: AlexNet, GoogLeNet, ShuffleNet, MobileNetv2, DenseNet201 | Compare the results after a fusion between different saliency methods and CNN Compare the results with previous work which used IP102: IE05 and IE01 | Accuracy 61.93%, F1-score 59.2%, and G-mean 75.5% for Densenet201 |
| | | **Insect Detection** | |
| **Study** | **Proposed Method** | **Baselines** | **Best Performance of the proposed method** |
| IE05 | Deep learning object detection models: Faster R-CNN (FRCN), FPN, SSD300, RefineDet, and YOLOv3 | | Average precision (for IOU 0.5) 54.93% for FPN with ResNet-50 CNN architecture as the backbone feature extraction network |

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