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Review

How Can Unmanned Aerial Vehicles Be Used for Detecting Weeds in Agricultural Fields?

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Abstract: Weeds are among the most harmful abiotic factors in agriculture, triggering significant yield loss worldwide. Remote sensing can detect and map the presence of weeds in various spectral, spatial, and temporal resolutions. This review aims to show the current and future trends of UAV applications in weed detection in the crop field. This study systematically searched the original articles published from 1 January 2016 to 18 June 2021 in the databases of Scopus, ScienceDirect, Commonwealth Agricultural Bureaux (CAB) Direct, and Web of Science (WoS) using Boolean string: "weed" AND "Unmanned Aerial Vehicle" OR "UAV" OR "drone". Out of the papers identified, 144 eligible studies did meet our inclusion criteria and were evaluated. Most of the studies (i.e., 27.42%) on weed detection were carried out during the seedling stage of the growing cycle for the crop. Most of the weed images were captured using red, green, and blue (RGB) camera, i.e., 48.28% and main classification algorithm was machine learning techniques, i.e., 47.90%. This review initially highlighted articles from the literature that includes the crops' typical phenology stage, reference data, type of sensor/camera, classification methods, and current UAV applications in detecting and mapping weed for different types of crop. This study then provides an overview of the advantages and disadvantages of each sensor and algorithm and tries to identify research gaps by providing a brief outlook at the potential areas of research concerning the benefit of this technology in agricultural industries. Integrated weed management, coupled with UAV application improves weed monitoring in a more efficient and environmentally-friendly way. Overall, this review demonstrates the scientific information required to achieve sustainable weed management, so as to implement UAV platform in the real agricultural contexts.

Keywords: precision agriculture; unmanned aerial vehicle; weed

1. Introduction

Weeds are significant contributors to the decline in crop yield and quality [1]. Weeds compete with crops in terms of nutrients, water, and sunlight. Weed losses are expected to reach 11 billion USD per year in India, ranging from 13.8% in transplanted rice to 76% in soybean; in which, weeds contribute the highest potential loss, accounting for 34% of all biotic stressors, followed by insects of 18% and diseases of 16% [2]. The high morphological, physiological, and anatomical plasticity of wild species such as weeds makes them more resistant to environmental stressors than crop species [3].

The interaction of weeds with other biological components is; it can damage nearby crops [4]. Due to this reason, weed containing herbicide residuals can cause the accumulation of off-flavour products [5], or in some cases, making them harmful to humans and animal health when they enter the food chain [6]. If consumed, the detrimental health ingredients could cause hepatic failure in humans and farm animals [7]. Herbicides move away in various ways, from the target plants, triggering pollution in the environment. The sorption process binds herbicides to soil particles, resulting in severe soil pollution [8]. Then, herbicides seeping to deeper layers of the soil surface or carried directly to field drains could enhance losses of herbicides in target crops and contaminate the surface and groundwater. This potentially leads to soil and water pollution, putting the above and belowground wildlife biodiversity at risk, including flora, fauna, and microorganism [9]. On the other hand, herbicides applied in farming activities spray drift in the air, and the volatilised, dispersed, and transported of its residues over a long distance facilitates the process of environmental recycling between the atmospheric and terrestrial environments. However, this process creates air pollution in the local environment and adversely impacts the global environment [10]. Thus, alternative weed mitigation strategies must be designed and promoted to mitigate and eliminate the ecological, environmental, and potential social problems with the intensive use of herbicides.

Spraying herbicides is the most common approach to weeding worldwide [11]. Weeding is typically conducted by uniformly spraying herbicides over the field, irrespective of weed density, which results in over-spraying in weed-free areas. This approach of weeding generates herbicide waste and pollutes the agricultural ecological environment. The site-specific weed management (SSWM) approach was suggested to tackle these problems [12]. SSWM is a strategy that consists of varying management of weed within a crop field to suit the variation in density, location, and composition of the weed population [13]. Weed populations are often dispersed irregularly inside crop fields. Therefore, the basis of this control strategy is to provide a guideline of weed spatial information to apply the herbicides with a minimum consumption by adapting it according to actual needs and utilised other techniques, including any use of plant derivatives that comprises of allelopathy effect, i.e., natural herbicides to minimize agrochemical pollution [14], thereby helping to lessen soil, water, and air pollution. By realising these benefits, detailed and resource-efficient approach of herbicide spraying with SSWM in smart farming decreased herbicide consumption by 40% to 60% [15], thus providing better environmental protection, sustainable agricultural production, and increasing economic profits.

The first step in implementing a SSWM strategy is weed detection and mapping (Figure 1). This task includes creating a weed map by integrating the sensor, processing procedures, and the actuation system. On-the-ground or remote sensing technologies can be used to capture weed images or non-imaging data. Previous research has shown that ground-based approaches (also known as proximal sensing) can capture high-resolution images, allowing for the early detection of substantially lower weed densities, and the discrimination of primary plant species [16,17]. Alternatively, traditional remote sensing platforms such as piloted airborne and satellite may investigate wider areas but have lower image spatial resolution [18].

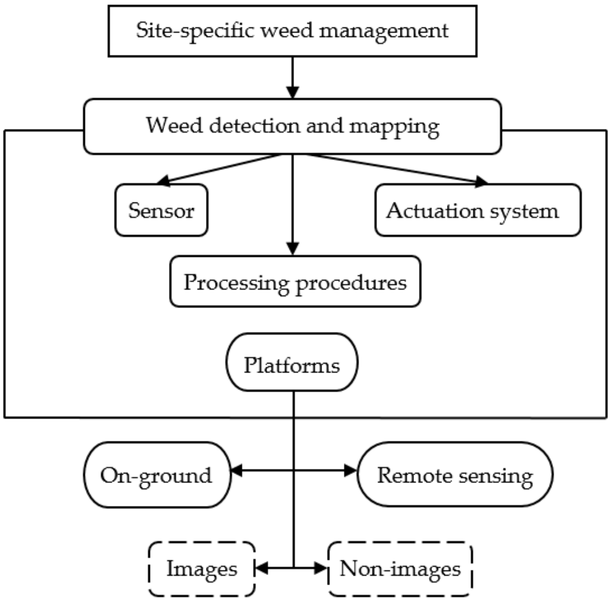

Figure 1. The first step in implementing a site-specific waste management strategy.

The emerging priority of remote sensing in the precise management of weed is to facilitate extracting information relevant for data-driven decisions [19]. A remote sensing technique must meet three requirements: (i) supply cost-effective data, (ii) ability of capturing and providing information promptly, and (iii) have user-defined spectral characteristics to enable crop indication adjustment. Satellites, manned planes, and ground-based platform can be used with remote sensing sensors. Satellite image analysis offers some solutions that could cover the entire fields and solving problems of the applications of herbicides by sampling, but it has a lower resolution and depends on high weed infestation in the absence of clouds to obtain good results [20]. Furthermore, different types of satellites offer some advantages and disadvantages of its features (Table 1). Contrarily, manned aircraft can cover broad areas but are prohibitively expensive. Handheld sensors are very accurate; yet, when compared to aerial remote sensing, their coverage area is incredibly limited [21].

Table 1. Advantages and disadvantages of different satellite features.

Types of Satellites	Advantages	Disadvantages	References
WorldView-3	- High spatial and spectral resolution (panchromatic of 31 cm, multispectral of 1.24 m, short wave infrared of 3.7 m, and 30 m CAVIS) - Broad spectral range i.e., has 29 spectral bands - Precision geolocation without ground control points - Huge collection capacity i.e., more than 25 million km^2 per year - High classification accuracy in terms of visual interpretation and supervised classification	- High resolution of sensor limited to visible and NIR wavelengths	Warner et al. [22]

Table 1. *Cont.*

Types of Satellites	Advantages	Disadvantages	References
Sentinel-2	- Make available data with a minimum spatial resolution of 10 m - Broad acquisition coverage - 13 bands based on visible to Short Wave Infrared (SWIR) - Short time revisits cycle i.e., less than five days globally	- Need to depend on other satellite data before the commencement of Sentinel-2. - Rate of uncertainties in data fusion and downscaling methods	Orlikova et al. [23] and Varghese et al. [24]
Land Satellite (Landsat) Operational Land Imager (OLI)	- High spatial variability even though the time elapsed is one month - Has a push broom configuration generating 16-bit images with at least an eight fold increase in signal-to-noise ratio than previous Landsat missions - Data saturation in sites with high biomass and penetrable canopies in low cover areas generate large uncertainties	- Higher spatial resolution sensor is limited by the temporal resolution when compared to medium-resolution data.	Abascal Zorrilla et al., [25]

Clouds, Aerosols, Vapors, Ice, and Snow: CAVIS.

UAVs have shown the remarkable potential of low altitude applications in agriculture since they are more cost-effective and easier to use [26,27]. Current UAVs have higher image spatial resolutions, whereby technological breakthroughs in miniaturisation sensors are embedded. The most recent generation of multispectral (i.e., sensors offer from 3 to 7 bands), superspectral (i.e., sensors offer from 7 to 20 bands), and hyperspectral (i.e., sensors offer more than 20 bands) provides an opportunity to create very precise weed maps [28]. Advances in two-dimensional and three-dimensional sensor and camera images, as well as more powerful and efficient computers processing data streams in near real-time, could provide the tools required for real-time SSWM [29]. Nonetheless, those spectral cameras, 3D cameras, and LiDARs are costly. Generally, they are used on broad land- and time scales. Since it is smaller and lighter than other sensors, an RGB camera is a more cost-effective sensor.

In this perspective, it is essential to recognize the published studies attributed to the application of UAVs for the detection of weed to realise the research fields. Furthermore, assessing the advantages and disadvantages of each sensor and its algorithm is crucial to be used by agricultural industries. Although UAV capabilities are well known in agriculture, lack of review articles that structurally extracted and synthesised about the latest and upcoming utilization of this technology for detecting weed in different aspects. Therefore, this systematic review would fill this knowledge gap. The purpose of this review is to describe the current and future trends of UAV applications on weed detection in the crop field. It is organized in the following main aspects: (i) current trend of UAV applications for detection of weed, (iii) advantages and disadvantages for each sensor (iii) advantages and disadvantages for each algorithm, (iv) benefit of UAV to the agricultural industry, (v) future trend of UAV applications for detection of weed (Table 2).

Table 2. Topics reviewed in this article.

Topics of Detecting Weed Using UAV	Review Focuses
Current trend of UAV applications for detection of weed	-Spectral differences of weed detection -Types of remote images on weed detection -Effect of spatial and spectral resolutions on weed detection -Algorithms and classification techniques for weed mapping
Advantages and disadvantages for each sensor	-RGB -Multispectral -Hyperspectral -Thermal
Advantages and disadvantages for each algorithm	-Object Based Image Analysis -k-nearest neighbour classifier -Neural networks -Support vector machine -Decision trees
Benefit of UAV to the agricultural industry	-Wireless sensor networks and artificial intelligence models
Highlighted problems for future trend of UAV applications for detection of weed	-Deep learning algorithm problems -Imaging platform challenges -Computation burdens -Different capability of different devices for UAV flight control detection of unknown weed species -Difficulty in manual labelling labour for labelling images

2. Materials and Methods

2.1. Search Strategy

This systematic review followed the Preferred Reporting Items for Systematic Reviews recommendations (PRISMA) [30] and referred to the Pickering and Byrne [31] systematic quantitative literature review method. A systematic search of the literature was carried out using the electronic databases: Scopus, ScienceDirect, Commonwealth Agricultural Bureaux (CAB) Direct, and ISI Web of Science (WoS) (Figure 2). All searches were conducted on 18 June 2021, using the following Boolean string: "weed" AND "Unmanned Aerial Vehicle" OR "UAV" OR "drone" based on the titles and/or abstracts and/or keywords. This study used various search term combinations according to the criteria or limitations of each database (Table 3). No geographical restrictions were applied to the identification process, and the search period in the databases was from 1 January 2016 to 18 June 2021. Articles identified in the search engine were inserted into Mendeley version 1.19.2 (Mendeley Ltd., London, UK). The articles were screened using guidelines [32] based on the following three categories: (i) not published in English, (ii) non-original research, and (iii) non-full text. Only original articles and conference papers were selected for eligibility.

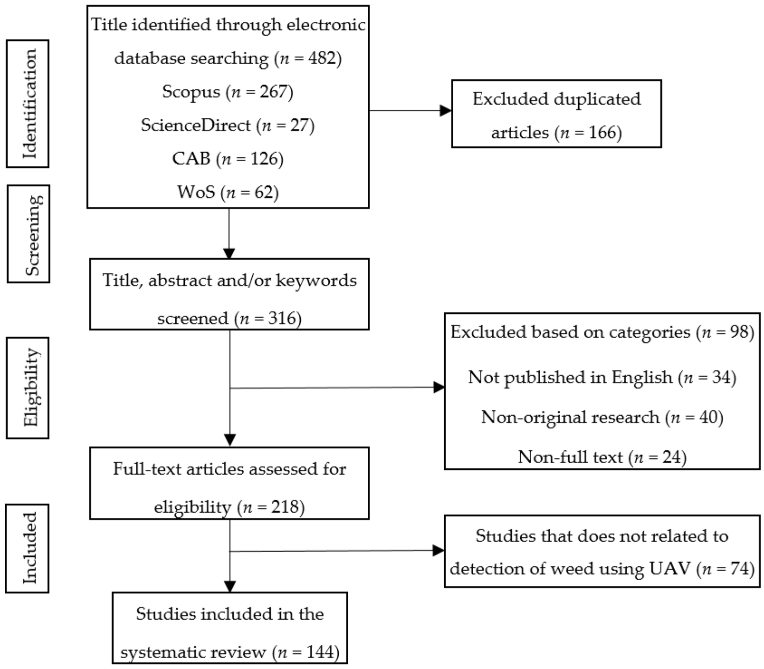

Figure 2. Flow diagram for the study selection.

Table 3. The search strategies.

Database	Search Terms
Scopus	Titles, abstracts, keywords: "weed" AND "Unmanned Aerial Vehicle" OR "UAV" OR "drone"
ScienceDirect	Title, abstract, keywords: weed "Unmanned Aerial Vehicle" Title, abstract, keywords: weed UAV Title, abstract, keywords: weed drone
CAB Direct	Abstract: "weed" AND "Unmanned Aerial Vehicle" OR "UAV" OR "drone"
WoS	(Abstract = "weed" AND Abstract = ("Unmanned Aerial Vehicle" OR "AUV" OR "drone")

2.2. Selection Criteria

Full text of the original articles that meet those three categories was assessed in detail according to inclusion or exclusion criteria: weed detection using UAV, including RGB, multispectral imaging, hyperspectral imaging, and thermal imaging. Therefore, non-weed studies that irrelevant to UAV imaging were excluded. In the end, 144 articles were included in the systematic review, whereby their findings were then undergone data extraction and synthesis.

2.3. Data Extraction

The first author independently extracted the data from all included studies and co-authors cross-checked the findings. The authors identified and gathered common themes, and any inconsistencies were discussed and reconciled. Information about the research in the 144 articles was extracted, including (i) the common phenology stage of crop, (ii) reference data, (iii) type of sensor/camera, (iv) classification methods, and (v) current trend of UAV applications for detection of weed.

2.4. Data Synthesis

The extracted information from the included studies was compiled in a summary. The findings were compared narratively, and the (i) advantages and disadvantages for each sensor, (ii) advantages and disadvantages for each algorithm, (iii) benefit to agricultural industries, and (iv) future trend of UAV applications for weed detection was explored. Then, the gap from earlier studies about weed detection using UAVs were addressed.

3. Results

3.1. Selection of Eligible Articles

The search strategy from electronic databases identified 482 potentially relevant studies, of which 166 duplicated studies were removed. After the primary screening of title, abstract and/or keywords, 316 articles were further screened for eligibility. Then, 218 full-text articles were assessed for detailed evaluation according to the studies that satisfied the inclusion criteria. Ultimately, 144 articles that satisfied inclusion criteria were obtained for the final analysis (Table 4).

Table 4. Studies included in the systematic review.

Information	Sub-Information	Percentage of Studies (%)
Phenology stage of crop	Early-stage	21.00
	Vegetative	9.68
	Mature	9.68
	Flowering	8.07
	Seedling	27.42
	Heading	1.62
	Late-season	4.84
	Growing season	11.29
	In-season	6.45
Reference data	Visual from images	84.76
	Visual labelling	3.81
	Digital records	2.86
	Field observations	2.86
	Visual and in situ polygons, points	4.76
	Landsat images	0.95
Type of sensor/camera	RGB	48.28
	Multispectral (broad band)	20.69
	Hyperspectral (narrow band)	4.83
	Thermal	1.38
Weed detection procedure/classification methods	Several pixel-based classifiers	4.20
	Maximum likelihood	6.29
	Spectral angle mapper (SAM)	0.70
	Vegetation index (pixel-based)	18.18
	OBIA	14.69
	Machine learning	47.90
	Fuzzy art map	0.70
	Unsupervised method	8.39
	Supervised method	11.19
	minimum distance	2.10
	Perceptron	2.10
	AlexNet	0.70

The publications were reported in journals and conferences were identified. The articles published in six high-ranking journals were the main source of information for this review. Figure 3 displays only articles that published more than two. Remote Sensing, Precision Agriculture, International Journal of Remote Sensing, Sensors, Computer and Electronics in Agriculture, and PLoS One were the top journals for weed detection using UAV.

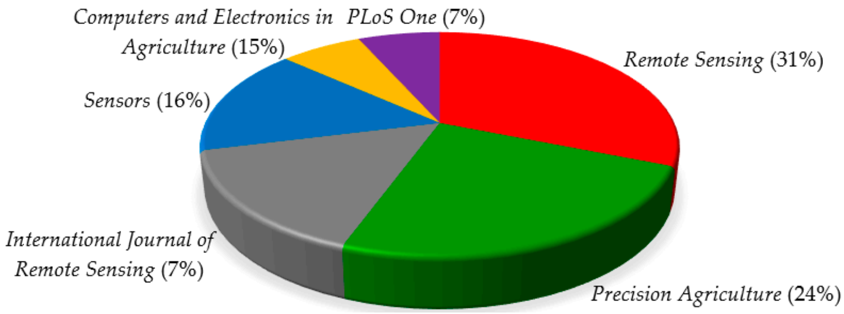

Figure 3. Scientific articles published by researchers from different journals (by 18 June 2021).

Geographical analysis showed that the scientific articles were mainly published by researchers from 14 countries: China, Italy, United States of America, India, Germany, Australia, Spain, Greece, Brazil, Japan, France, Denmark, United Kingdom, and Switzerland. (Figure 4).

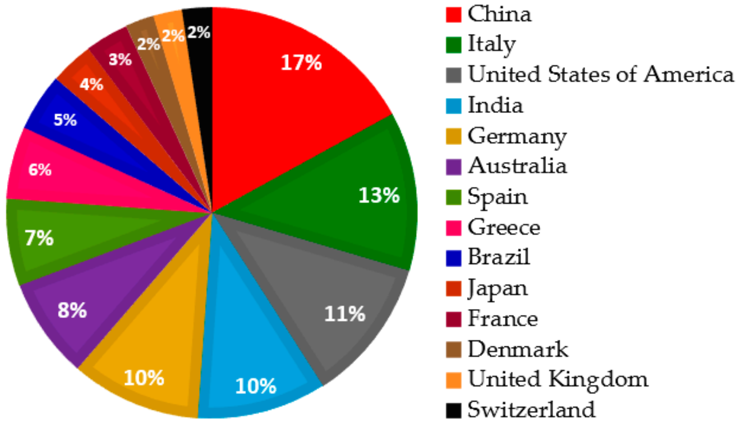

Figure 4. Scientific articles published by researchers from different countries (by 18 June 2021).

Funding sources that are used to support those studies have been listed in Table 5, whereby could give some insight about which region(s) of the world is leading the pioneering role in the relevant research field.

Table 5. Previous studies that received financial support for their research.

Studies	Source of Funding
Jiménez-Brenes et al. [33] Jurado-Expósito et al. [34] de Castro et al. [35]	Spanish Ministry of Science, Innovation and Universities
Jiménez-Brenes et al. [33] de Castro et al. [35]	European Union-European Regional Development Fund (EU-FEDER) funds
Huang et al. [36]	National Key Research and Development Plan: High Efficient Ground and Aerial Spraying Technology and Intelligent Equipment, China
Aharon et al. [37]	Chief Scientist of the Israeli Ministry of Agriculture
Fukano et al. [38]	Japan Society for the Promotion of Science
Smith et al. [39]	Department of Agriculture and Water Resources, Australia
Ahmad et al. [40]	Bahauddin Zakariya University in Multan, Pakistan
Nevavuori et al. [41]	Mtech Digital Solutions Oy, Finland

Table 5. *Cont.*

Studies	Source of Funding
Reis et al. [42]	(i) National Council for Scientific and Technological Development (CNPq), Brazilian Government, and (ii) National Research, Development and Innovation Office, Hungary
Zou et al. [43] Yan et al. [44]	National Key Research and Development Project of China
Veeranampalayam Sivakumar et al. [45]	(i) Nebraska Research Initiative (NRI) Collaboration Initiative Seed, Nebraska Corn Board, and (ii) Nebraska Agricultural Experiment Station through the Hatch Act capacity funding program from the USDA National Institute of Food and Agriculture, USA
Deng et al. [46]	(i) Key Area Research and Development Planning Project of Guangdong Province, (ii) Guangdong Provincial Innovation Team for General Key Technologies in Modern Agricultural Industry, Science and Technology Planning Project of Guangdong Province, China, (iii) National Natural Science Foundation of Guangdong Province, China, (iv) National Key Research and Development Plan, China, and (v) 111 Project, China
Xavier et al. [47]	Gulf Atlantic (Long-term Agro-ecosystem Research) LTAR site of the U.S. Department of Agriculture by the University of Georgia
David and Ballado [48]	Department of Science and Technology-Engineering Research for Development and Technology, Philippines
Huang et al. [49]	(i) Educational Commission of Guangdong Province of China for Platform Construction: International Cooperation on Research and Development of Key Technology of Precision Agricultural Aviation, (ii) Science and Technology Planning Project of Guangdong Province, China, (iii) National Key Research and Development Plan, China, (iv) National Natural Science Fund, China, (v) Science and Technology Planning Project of Guangdong Province, China, (vi) Science and Technology Planning Project of Guangdong Province, China, and (vii) the Science and Technology Planning Project of Guangzhou city, China.
Khan et al. [50]	National Center of Robotics and Automation—Advanced Robotics and Automation Laboratory of UET Peshawar, Pakistan
Lake et al. [51]	(i) United States Department of Agriculture, and (ii) the United States Army Corps of Engineers and South Florida Water Management District, USA
Huang et al. [52]	(i) Guangdong Provincial Innovation Team for General Key Technologies in Modern Agricultural Industry, (ii) Science and Technology Planning Project of Guangdong Province, China, (iii) leading talents of Guangdong province program, (iv) Science and Technology Planning Project of Guangdong Province, (v) Key Area Research and Development Planning Project of Guangdong Province, (vi) Science and Technology Planning Project of Guangdong Province, China, (vii) National Key Research and Development Plan, China, (ix) Science and Technology Planning Project of Guangdong Province, China, Science and Technology Planning Project of Guangdong Province, China, and (x) Science and Technology Planning Project of Guangzhou city, China.

3.2. Current Trend of UAV Applications for Detection of Weed

Research on the application of UAV for weed detection and mapping mainly highlight four issues: (i) spectral differences of weeds detection, (ii) types of aerial images from several sensors and platforms on weed detection, (iii) effect of spatial and spectral resolutions on weed detection, and (iv) algorithms and classification techniques for weed mapping. UAVs have primarily been assessed in different crops such as maize, wheat, sugarcane, cultivar, chilli, onion, vineyard, pistachio, baby-leaf red lettuce, barley, and mixed agricultural field such as pea and strawberry (Table 6). Those are among the world's most widely cultivated crops, and they are highly vulnerable to weed competition, particularly during the seedling stage of the growing cycle. Our systematic review found that the seedling stages of crop contribute the highest, i.e., 27.42% in weed detection. One study [53] proposed that crop images could be taken precisely in the early season, so that specifically color-dependent segmentation can be applied to segment weed patches to achieve the higher accuracy of an algorithm.

Table 6. Example of UAV imaging applications in detecting weed for different crop types.

Crop	Research Focuses	References
Maize	Tested a low-cost UAV for weed mapping, evaluated open-source packages for semi-automatic weed classification, and implemented a prescription map-based sustainable management scenario.	Mattivi et al. [54]
Wheat	Optimized a deep residual convolutional neural network (CNN) (ResNet-18) for classifying weed and crop plants in UAV imagery.	de Camargo et al. [55]
Sugarcane	Developed a framework to identify the defect areas in the sugarcane farms.	Tanut and Riyamongkol [56]
Cultivar	Investigated the viability of integrating UAV image with satellite images to improve the classification of different pistachio cultivars and separate weeds from trees.	Malamiri et al. [26]
Chilli	Detected weeds in a chilli field using image processing and machine learning methods.	Islam et al. [57]
Onion	Investigated the late-season weed mapping by surveying dry onions with a simple off-the-shelf UAV, employing several techniques across various spatial resolutions, estimating weed coverage in the fields, and assessing the spatial pattern of weeds.	Rozenberg et al. [58]
Vineyard	Provide UAV and precision agriculture users with a FOSS-replicable methodology that can meet the needs of agricultural operations, as well as operational and management needs.	Belcore et al. [59]
Baby-leaf red lettuce beds	Provided an estimation of the exact weed quantity on baby-sized red lettuce beds using a light drone.	Pallottino et al. [60]
Barley	Evaluated the yield loss of spring barley due to *various C. arvense* infestations in big plots in farmers' fields, and proposed a novel approach to quantifying *C. arvense* infestation in large plots.	Rasmussen and Nielsen [18]
Mixed agricultural field	Developed a deep learning system for identifying weeds and crops in croplands, such as peas and strawberries.	Khan et al. [61]

This review has figured out few types of UAV that being used for weed detection which includes single-rotor, multi-rotor, and fixed-wing (Figure 5). Ahmad et al. [40] used single-rotor as a spraying unit in the target and off-target zones for outer field weed control application. On the other hand, there are two studies that used the multi-rotor on the cultivated rice in China, in which Huang [38] captured imagery on few patches of *Cyperus iric* while Huang [52] captured the *Chinensis*, *Cyperus iric*, *Digitaria sanguinalis*, *Scop*, and

Barnyard grass. In another study, Khan et al. [52] used multi-rotor to obtain imagery for two different crops which is pea and strawberry and *Eleusine indica* on infested weeds in Pakistan. In terms of fixed-wing, Zisi et al. [62] used this type of UAV to capture the images of *S. marianum* and patches of other weeds such as *Solanum elaeagnifolium*, *Avena sterilis* L., *Bromus sterilis* L., *Cav*, *Cardaria draba* L., *Conium maculatum* L., and *Rumex* sp. L. at the field that previously cultivated with cereals in Greece. Also, for fixed-wing that detect other weed types, Barrero and Perdomo [63] has detected *Gramineae* at the rice field in Columbia, whereas Tamouridou et al. [64] has identified *S. marianum*, and other weed types that consist the mixing of *Avena sterilis*, *Rumexsp*. L., *Bromus sterilis* L., *Conium maculatum* L., *Cardaria draba* L., and *Solanum elaeagnifolium Cav* at the field that previously cultivated with cereals in Greece.

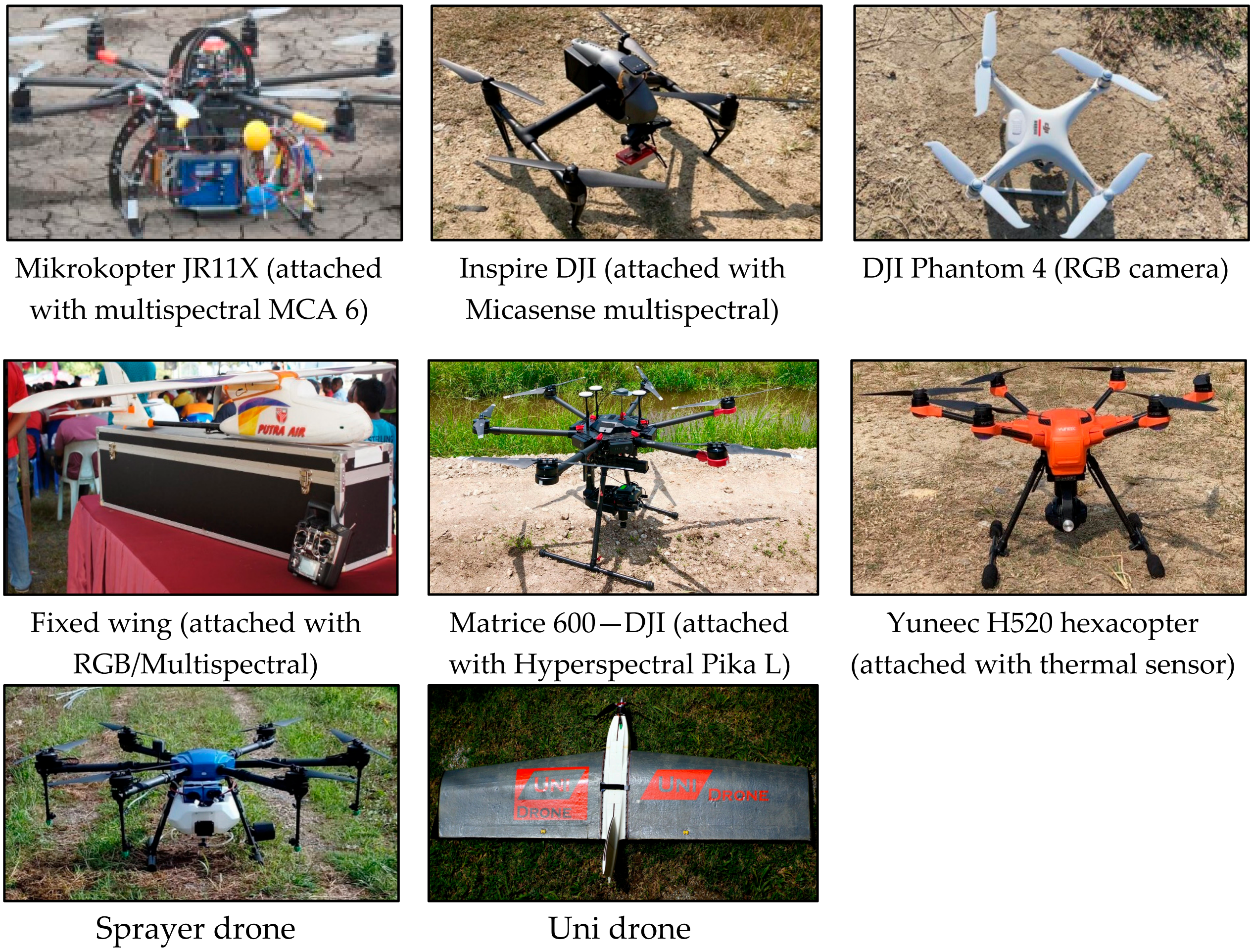

Figure 5. Example of UAV systems used in detecting weed (The pictures were captured by authors).

3.2.1. Spectral Differences of Weed Detection

The basic concept behind weed discrimination is to locate the spectral region or, instead, the vegetation indices that maximise the differences between weed and crop plants, based on the reflectance values acquired in aerial images [65]. At the time of image acquisition, the weed percentage was very low. Using a mosaic of images is often more difficult than using a single image because of distortions and spectral variations between the images. The ability of detecting and identifying weed species is largely influenced by environmental conditions. This is related to the weeds' distribution pattern such as patchy patterns with high inconsistency, their textural phenotype, and spectral signature that visually similar to other vegetation types growing in the same location [66]. Spectral signature can be used in chemical content in the leaves or plants, in which each band represent the condition of the plants.

To evaluate weed identification capacity, spectral signatures were acquired from the upper surface area of the leaves, for example, *from S. marianum* plants and other vegetative species such as *A. sterilis* and *Conium maculatum* [67]. Accordingly, *A. sterilis* and *S. marianum* were found to have similar spectral reflectance characteristics, making weed classification difficult which mainly in the early season. However, these three species were easier to distinguish in the NIR spectrum. This indicates that the NIR zone and other properties (i.e., texture) could be used to enable class separation. Another study [68] that monitored the same species that mentioned previously also observed that *S. marianum* had some similarities with *A. sterilis* in the visible spectrum (400–700 nm) but differ in the near-infrared (700–1100 nm). This shows that the camera's band is one of the essential feature that allows for weed discrimination in the crop field.

Because of challenges regarding indistinguishable spectral signatures between crop and weed seedlings, other characteristics such as different textures and shapes may help to differentiate the two. Also, initial parameters may have an effect on the creation of objects from pixels. Rozenberg et al. [58] applied a single set of parameters, in which the shape and size of the weed patches varied. Due to the significant spectral differences at the phenological stage at which the data was collected, the use of differential parameters was unnecessary.

Monospecific patches with higher vegetation cover has a unique spectral signature which the classifier can use it to improve its accuracy. Conversely, the spectral reflectance of a mixed community combines the spectral signatures of the plants present in a single location, hiding the target species' signature and lowering classifier performance. In addition, the image resolution was inadequate to give description of pixels indicating pure spectral signatures of spotted knapweed, among other vegetation, and thus pixel-based methods could not be adapted without data from field-spectrometry or a spectral library to provide the spectral signatures of the crop. [69].

Danilov et al. [70] investigated how the form of the spectral signatures of reflectivity for plant items changed based on their current condition, as measured during field surveys. This is the starting of the active vegetation of weeds. The spectral signatures curves of the plants were identified, whereby the (i) distinctive characteristics of reflectivity of some cultivated or weed species is in the visible range of the spectrum between 400 and 680 nm, (i) differences in the average values of the spectral brightness between few plant species are overlapped by the sums of their standard deviations in the NIR region of 800 1100 nm, and (iii) weed is detected by a significant variation in the amplitude of spectral brightness fluctuations between cultivated and weed plants.

3.2.2. Types of Aerial Images on Weed Detection

Our systematic review identified four main types of cameras utilized for weed patches identification: RGB, multispectral, hyperspectral, and thermal cameras. For example, Agüera-Vega et al. [71] used the multispectral (green, near-infrared, red and red-edge) and thermal sensors to discriminate weed images from maize crops. Revanasiddappa et al. [72] stitched weed images to create a weed site map uploaded to the cloud. A study combined simultaneously remotely sensed ground data and aerial imagery to develop models that correlated ground-truth weed densities with image intensity and forecast weed densities in other fields, done by Lambert et al. [73]. The weed effect on canal hydraulic efficiency has also been assessed using ground imagery, UAV images, and high-resolution satellite data [74].

According to the secondary development, a hardware environment for real-time image processing has incorporated map visualisation, image collection, flight control, and real-time image processing on board a UAV [48]. Based on Reis et al. [44], the image generated using LiDAR data had lower canopy cover and higher cover by bare soil and grasses compared to UAV. Differences between LiDAR and UAV may be due to image classification processes, including the existence of shaded areas in UAV camera images and incorrectly categorised pixels in digital image processing that require additional exploration.

3.2.3. Effect of Spatial and Spectral Resolutions on Weed Detection

Weed detection necessitates high spatial resolution in remote image. It is dependent on the sensors and remote platforms used [69]. The average operational parameters of the UAV sprayer on the spray deposition pattern (2.29 L/cm^2) in the target area were found to be the highest when the UAV operates at the higher speed of 2 m/s and a height of 2 m [40]. The weed distribution maps of the UAV imagery were also generated using a semantic labelling technique. An ImageNet with the residual framework was adapted in a fully convolutional version and fine-tuned before being uploaded to the dataset. The field of view of convolutional filters was then extended using atrous convolution; the performance of multi-scale processing was assessed, and a fully linked conditional random field was employed to refine the spatial features [67]. As a result, the ability to differentiate weeds was significantly influenced by the spatial resolution of the image, making the use of higher spatial resolution images more appropriate [75].

Watt et al. [76] discovered that vegetation indices obtained from multispectral UAV data and satellite data were strong predictors of weed metrics, with a spatial resolution of 1 m being optimum. To examine classification performance, the scale of the weed mapping utilizing UAV and multispectral imaging was altered by reducing image resolution, with 1 m resolution yielding the maximum classification accuracy [67]. Mesas-Carrascosa et al. [77] investigated the optimum flight settings for maintaining spatial accuracy in the bundle adjustment, which were 70% to 40% overlap and altitudes above ground level (AGL) ranging from 60 to 90 m. At various flying altitudes, the spatial resolution was relatively similar, allowing us to optimize mission planning, fly at a higher altitude, and increase the area overflow without reducing orthomosaic spatial quality.

Many weed and crop pixels had similar spectral values at higher altitudes, which might increase discrimination errors. Hence, an agreement among spectral and spatial resolution is needed to optimise the flight mission according to the size of the smaller object to discriminate (weed plants or weed patches). As Che'Ya et al. [75] reported the lower flight altitude will determine the highest spatial and spectral resolution of the imagery, they found that at 10 m flight altitude will help to detect weeds accurately at less than 1 cm spatial resolution. The imagery showed the weeds patches more clearly and accurately [78]. The weeds are mostly look alike with the plants. Thus, the high accuracy will help to detect the weeds through the spatial and spectral resolution. Spectral signature can be used to differentiate weeds and plants in the field [75,79]. Not only that, the method to detect the weeds also the main factor to get the accurate classification. Roslim et. al. [80] found that the artificial intelligent (AI) can be used to detect the weeds patches in the rice field. Thus, the used of UAV can help to gain the highest spatial and spectral resolution in the field.

With the small UAVs, such as Phantom 3 Professional (Da-Jiang Innovations, Shenzhen, China) quadrotor, it is possible to map 10 ha in 20 min at 40 m flight altitude, which corresponds to the duration of one battery [74]. The best date for a weed emergence prediction model survey was implemented using a UAV with visible range sensors, resulting in an orthophoto with a spectral resolution of 3 cm, allowing for good weed detection [81].

3.2.4. Algorithms and Classification Techniques for Weed Mapping

Weed discrimination in row crops can be categorised according to crop rows and then detect weed plants as vegetation between the rows. The effectiveness of this approach is attributed to the creation of advanced classification algorithms for analysing UAV images. Researchers used different type of algorithms for weed mapping in their studies. Therefore, this review has categorized the algorithm into several classes as follows: (i) pixel-wise classification vs object-based analysis (OBIA), and (ii) machine learning methods such as ANN, CNN, SVM, RF vs distance or likelihood-based methods.

A pixel-wise was built by Huang et al. [52] which capable of obtaining the position of each pixel and properties of points to train the classifiers. For the pixel-wise classification, fully convolutional network (FCN) has been employed in the deep learning approach, and transfer learning was utilised. In another study by Kerdegari et al. [82], their dataset consist of crop, weed, or crop-weed combination data, and their associated pixel-wise annotated data. Different percentages of pixel-wise annotated images i.e., 50%, 40%, and 30% were used as labelled data to the discriminator during semi-supervised training. In a network developed by Anand et al. [83], two image scales are used for training and three image scales are used for prediction, which referred as a hierarchical model. Using image attributes extracted from the lower scale image, it derived a pixel-wise dense relative attention between the lower and higher image scales. The weights of the attention map could represent the relevance of features at different scales and positions. Thus, the attention module determines the amount of pixel-wise attention to be paid to features at various sizes and positions. This allows for the depiction of attention for each scale by displaying the expected logits.

OBIA also has been applied for weed mapping of the UAV imagery, whereby VGGNet-based FCN has achieved the highest accuracy [84]. The combination of imagery and an Automatic Decision Tree-OBIA Procedure algorithm developed using aerial images allows quick and accurate mapping of weed growing in vineyard cover crops [85]. A semi-automatic OBIA procedure is also being developed with Random Forest (RF)s combined with feature selection techniques for inter-row weed detection. Additionally, the two binary weed masks produced from the Hough transform (HT) algorithm and OBIA were fused for accurate weed mapping [85]. An Automatic RF-OBIA algorithm combined orthomosaics, Digital Surface Models (DSMs), and machine learning techniques for early weed mapping between and within crop rows [86].

Beeharry and Bassoo [87] found that AlexNet algorithms give an accuracy of 99.8% for weed detection compared to conventional ANN algorithm. It is proven in another study [88] that identified weed through colour images along with the GoogLeNet and continuous convolution of Visual Geometry Group 16 (VGG-16) inception models. ANN also being used differentiate between weed, crop, and soil. When compared between ANN and visible atmospherically resistant index (VARI), ANN has higher accuracy of 98.6% and Cohen's Kappa value of k = 83.7 compared to VARI which is 98.1% and k = 72, respectively [81]. However, higher reduction percentage of the sprayed herbicide area that ranged from 65.29% to 93.35% when VARI was used, and from 42.43% to 87.82% when ANN was used. This indicated that ANN has the potential to obtain a reduction in herbicide application and direct advantages for the environment and farming operation cost. In another point of view, when compared between the Counter-Propagation-ANN (CP-ANN) and the XY-Fusion network (XY-F) to recognize *S. marianum* with vegetation, Pantazi et al. [68] found that the accuracy of *S. marianum* identification rates using CP-ANN was higher i.e., 98.87%, compared to XY-F i.e., 98.64%.

Other than ANN, CNN also showed the accuracy of up to 98.8% to identify weed compared using pre-processed images in other high-cost methods. Liang et al. [89] found the best performance in image classification with RGB data than the Normalized Difference Vegetation Index (NDVI) data [41]. Tang et al. [90] applied CNN on *Ipomoea cairica L.* sweets and compared with artificial intelligence, including LeNet, GoogleNet, AlexNet, VGG, and ResNet. A deep learning-based method for estimating the crop and weed distribution from images captured by a UAV leverages the CNN to perform image semantic segmentation and a post-processing step being applied to compute the weed [91]. LeNet, which is based on the CNN methodology, emerged as a promising technique because it used spatial information from UAV images inside that learning framework's architecture. It was operated by enforcing a local connectivity pattern between neurons of adjacent layers to incorporate the spatial relationships between features that comprised the shape of the Lomandra tussocks detected [92]. The Single Shot Detector model's optimal confidence threshold was much lower than that of the Faster RCNN model, which indicated that

Single Shot Detector might have the lower performance of weed detection than Faster RCNN for weed detection in soybean fields using UAV imagery [45].

Chen et al. [93] proposed a SVM to properly segment citrus trees under varying brightness and weed coverage conditions. A chromatic aberration segmentation algorithm and the Otsu threshold approach have been integrated to extract viable fruit tree areas to accurately differentiate them from varying weed coverage backgrounds. The areas' of 14 colour features, five statistical texture characteristics, and local binary pattern features were then calculated to create an SVM segmentation model. Furthermore, the performance of SVM also examined by Islam et al. [57] that detected weeds using images gathered from an Australian chilli crop field, whereby the weed detection accuracy is 94%. In another perspective, SVM has been classified on various type of vegetation such as eggplant, corn, string beans, and grass/weeds, whereby the output map can also be used to update the initial land cover map created from high resolution LiDAR data on a regular basis [48]. Based on above studies, they found that SVM are effective and practical to apply and they can be simply implemented for detecting weed in UAV image.

Another study [94] used classification algorithms based on the RF for weed extraction and unsupervised classification with the K-means algorithm to estimate weeds in non-weed areas. The simple linear iterative clustering algorithm and RF classifier had discriminated rice and weeds with better performance using hue-saturation-brightness than RGB and CIE-L*a*b consumer-grade UAV images, as shown by Kawamura et al. [95]. The images from Canon S110 NIR (green, red, near-infrared) on UAV were also classified by Reis et al. [42] by combining RF and maximum likelihood algorithms. Interestingly, Yuba et al. [96] has tried to integrate OBIA and RF with auxiliary information layers in mapping *P. alopecuroides*, and they found that the combination of these algorithms has increased classification accuracy which is out of bag accuracy = 0.99 and generalized error accuracy i.e., 1.00 from the lowest altitude of 28 m.

The maximum likelihood classifier has been tested by Tamouridou et al. [64] to differentiate *S. marianum* from other weed species, i.e., *Avena sterilis* L. To evaluate classification performance, the size of the mapping was altered by lowering the image resolution, with 1 m resolution yielding the maximum classification accuracy. The overall accuracy of the classification rates obtained was 87.04%, in which demonstrated the viability of operational *S. marianum* mapping with UAV and multispectral imagery. Maximum likelihood also able to generate precise weed maps in onion fields during the late-season, as generated by Rozenberg et al. [58]. In terms of the weed spatial pattern, weed coverage that varied significantly from 1% to 79% was comparable within and between crop rows; and weed pattern was patchy in all fields. In another comparative study that separate weed from vegetation, Malamiri et al. [26] revealed that maximum likelihood has higher accuracy compared to fuzzy artmap. They also overserved that maximum likelihood has a high accuracy in terms of land area and cultivation layout.

Albani et al. [97] has displayed the distance-based exploratory pattern for field coverage and mapping which includes (i) the central cell that represents the agent's position, (ii) the numbers represent the priority of each place, which is determined based on distance, (ii) the momentum of the agent illustrated by vector represents a possible directional bias, (iv) cells in the darkened region are only accepted if no valid cells are discovered in the other semi-plane, and (v) the wrapped cauchy density function with various persistence p values. This technique could maximizes coverage time by minimizing the distance traveled from cell to cell and progressively visiting all cells in the field.

3.3. Advantages and Disadvantages for Each Sensor

Each type of sensor has its advantages and disadvantages. RGB images performed better than NDVI images, indicating that multiple spectral bands expand information content compared to the condensed NDVI image. In terms of utility, RGB cameras are lower cost than multispectral imagery sensors, as they are smaller and lighter than other kinds of sensors. This reason makes RGB the most commercially available UAVs already equipped with decent cameras capable of producing high-resolution images [98], which is affordable for many users [99]. Furthermore, the high-resolution RGB camera saves images on a secure digital memory card and is fixed by an angle fixer, which decreases the high-frequency noise caused by the six high-speed motors [43,93]. Nonetheless, the large spectral bandwidths of RGB cameras limit the pixel-wise of differentiating between weeds and crop based on colour or RGB incidences. Therefore, it could be preferable for the researchers to include the details information regarding the texture, leaf shape, and size in the classification [100].

Multispectral sensors have a slow imaging speed, which limits their use. Unfortunately, the use of multispectral cameras for UAV photography systems is regarded as a disadvantage due to their high cost compared to the lower cost of RGB sensors [101]. Moreover, due to spectral resolution limits, the accuracy of the derived variables is frequently limited, and early signals of plant stresses, i.e., nutrient shortage and crop disease cannot be identified effectively in a timely manner. Hyperspectral imagery efficiently monitors weeds from long-term dynamics elsewhere, allowing management measures to be more precise, faster, and efficient [88]. The hyperspectral images were typically derived through satellite or aircraft, whereby high-resolution spectral data and equipment are expensive. Additionally, data handling of large images is complicated and frequently limited to smaller areas [102]. Some important information in images is also lost when using free low-resolution of spectral data. Accordingly, hyperspectral images are ineffective for monitoring weeds in their early phases [89]. All in all, multispectral and hyperspectral, however, takes a long time to collect images from large-scale areas. When the amount of data is large, it requires a large calculation to analyse the images, making it challenging to create a panoramic weed map of the area [43].

Near-Infrared (NIR) cameras can be easily converted from conventional RGB cameras and thermal functions to cover the majority of all the infrared spectrum. On the other hand, thermal imaging is sensitive to the environmental condition in which the image is captured, such as illumination conditions, canopy architecture, and crop maturity [103]. Furthermore, thermal imaging faced many problems of low pixel resolution caused by environmental variables in an open system, particularly with small uncooled thermal cameras, which are the most common kind employed in unmanned aerial systems [104].

3.4. Advantages and Disadvantages for Each Algorithm

Successful weed management is essential for precision agriculture. The most significant procedure for an automatic system to eliminate the targeted weeds in the crop rows is implementing a reliable sensing approach to establish an accurate differentiation of the weeds and crops at specified locations in the field [105]. This can be achieved by implementing several modelling and algorithm while doing data analysis and interpretation. According to Liu and Xia [106], the dissimilarity between object-based and pixel-based classification procedures can be observed from classification units and classification features. The object-based approach comes with its limitations, i.e., errors that usually exist in image segmentation, including over-segmentation and under-segmentation. The Object Based Image Analysis (OBIA) method produces excellent classification results because it overcomes some of the limitations of pixel-based methods by segmenting images into adjacent pixel groups with homogeneous spectral values and can integrate spectral, topological, and contextual information from these objects to manage complicated classification scenarios [86].

Machine learning assignments are usually classified into several extensive categories based on the learning type (supervised/unsupervised), models learning (classification, clustering, and dimensionality reduction), or the learning models applied in the specific task [107]. There were several excellent classification techniques utilise in agricultural studies, such as Bayesian networks, k-nearest neighbour classifier (k-NN), ANNs, decision trees (DT), and support vector machine (SVM) [108]. k-NN is a standard instance-based learning algorithm used to categorise unknown objects by ranking the objects neighbour among the training data as the output will excellently predict the class of the new objects [109]. Zhang et al. [110] stated that the k-NN technique is quite good as it was easy to apply but could be prolonged if the input data set capacity is quite big.

Neural networks have been widely utilised in agricultural data analysis. However, lots of aspects need to be considered in establishing a neural network for resolving a particular problem, such as the learning algorithm, the architecture, number of neurons per layer, number of layers, data representation, and they were pretty sensitive towards noise appearance in the training data [111]. In the current advances of machine learning, there was enhancing interest in time series classification, which employed deep convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which can take advantage of neural networks for time series end-to-end classification [112]. RNNs approaches can be utilised for pixel-based time series procedures and offer models to precisely control temporal dependencies between data, for example, long short-term memory (LSTM) [113].

SVM is one of the most prevalent data classification and regression techniques. According to Prabakaran et al. [114], SVM aims to formulate a hyperplane that can be utilised to expand geometric margin limits of their classification error when given in two classes of linear differentiable problems. It is the most valuable system which intensely optimising structural risk assessment of real-time data. However, SVM cannot perform well for skewed imbalance datasets due to its difficulty obtaining the optimal separation hyperplane. The disadvantages of SVM include parameters selection, algorithmic complexity that influence the training time of substantial data sets classifier, and multi-class problems in developing optimal classifier [115].

3.5. Benefit of UAV to the Agricultural Industry

Developments of UAVs to detect weeds for precision agriculture have influenced the revolutionisation of the agricultural industry. The recent approaches of combining wireless sensor networks and artificial intelligence models to detect weed could increase agricultural efficiency. As opposed to traditional agricultural methods that require more time, effort and eventually lead to inaccurate outputs and losses, modern agricultural approaches including artificial intelligence and the internet of things will assist farmers in making better decisions and increasing the total of crop yield and efficiency [116]. For example, U-Net, a deep semantic segmentation neural network, was observed to detect weed in crops better. It could produce good results with a small number of training samples [43].

With the help of technology, performance of plant monitoring may be improved, and thus weed issues in agricultural industry can be solved. Farmers' concerns were that precision weeding techniques overcome the vast number of crops lost during the weeding activity. These autonomous UAVs not only increase productivity, but they also eliminate the need for unwanted herbicides and pesticides. Aside from that, farmers may effectively spray herbicides and pesticides on their farms with the help of UAVs, whereby plant monitoring is no longer a burden. For starters, shortages of resources and jobs in agribusiness can be recognized with the help of man-made brain power [117]. In conventional approaches, a large amount of labor was necessary to obtain the crop characteristics such as plant height, content, and soil texture; as a result, manual testing need was carried out which was time-consuming.

3.6. Future Trend of UAV Applications for Detection of Weed

New insights into crop competition are needed to apply low altitude remote sensing approach (e.g., UAV) in agricultural contexts, allowing only harmful weed species to be identified and eliminated. With the intention to this, there is a need to suggest the researchers to use UAV on detecting weeds based on the published studies. The future trend of UAV application was elaborated to highlight problems as follows: (i) deep learning algorithm problems, e.g., short of training data, precise model inference ability, and robust applicability over different scenarios; (ii) imaging platform challenges, e.g., camera parameters and air drone flight parameters; (iii) computation burdens, e.g., cloud computing and edge computing, (iv) different capability of different devices for UAV flight control, and (v) detection of unknown weed species, and (vi) difficulty in manual labelling labour for labelling images.

Future research need to solve the deep learning problems in order to automatically obtaining effective features for weed and crop classification in outdoor scenarios and comparing different sensors and platforms of weed detection [85]. Therefore, it is worth of quantifying various aspects such as aircraft altitudes and ideal resolution for creating accurate weed maps. Additionally, it would be interesting to address the evaluation using a larger image dataset containing a broader range of variables, such as different image acquisition sites and spatial resolution [118].

There is a short of training data and its limited scale for deep learning algorithm, making it difficult to include all the plants that could exist in the UAV image. This problem was seen by Xi et al. [88] that found MmNet's-based on a deep CNN identification of the phorophyte is less reliable since the phorophyte training data which includes a variety of plants in the field mostly unknown. Hence, the developed algorithm could be built to be robust and operate in all expected situations because it used a large amount of training data for the algorithm classification while maintaining high classification accuracy. In addition, using semi-supervised generative adversarial networks could provide pixel-by-pixel classification for all captured images. It will comprised of a generator network that creates photo-realistic images as additional training data for a multi-class classifier that acts as a discriminator and is trained on relatively small amounts of labelled data.

Another problem discovered in the previous studies were the capability of precise model inference, whereby researchers may use cloud computing or edge computing technology for model inference. The time span between data analysis and spraying tasks may be considerably decreased using the real-time processing platform, improving the practicability in real SSWM applications [84]. To differentiate weed pixels from soil and crop, one-class or binary classification algorithms might be examined. A trained model may be slightly adjusted to fit the new data better, and this method could give better results at the expense of low computational effort. Therefore, it may be interesting to investigate the incremental learning paradigm. In this case, a trained model could be slightly modified to fit new data better, and this approach could ideally result at the expense of a low computational load [119].

The problem on applicability of robust application over different scenarios has also been identified by the researchers. The algorithm developed for detection of weed must be highly robust because very similar seedling crop and weed plants mixed within the crop row. Therefore, supervised machine learning technique could be used for creating a model of detecting weed. The future studies could consider previous findings and tries to deal with some of the problems that have been identified when using OBIA. It was an approach that have may enhance better performance than the pixel-based method in preliminary output. Furthermore, a method for enabling robust image classification that does not rely on the user spending significant time drawing new polygons defining classes for each new image is required. To that purpose, a semi-automatic method for re-training the classifier for each new image could be designed, and combining unsupervised and supervised categorization.

Different camera parameter is one the challenges for imaging platform. The influence of model compression techniques and approximation algorithms created for neural networks can be examined to evaluate the edge computing limit in-field and near real-time weed detection. However, the algorithm's performance could be caused by poor image quality [90]. In order to overcome this problem, researchers must configure the UAV camera's parameters and determine the optimal distance between the UAV and the weed for optimum image quality. Furthermore, size of the image could influence not only model accuracy but also monitoring accuracy. Some weeds were misclassified as crops, and some crop edges were incorrectly segmented as weeds. As a result, the weed density assessed by

UAV was slightly higher than that assessed by manual observation [43]. A more precise crop segmentation algorithm can be explored in the future to improve evaluation accuracy.

The target of the novel deep convolutional neural network (ICSNet) developed by Tang et al. [90] has accurately identify *Ipomoea cairica* L. sweets and non-Ipomoea *cairica L.* sweets in the wild. The components of *Ipomoea cairica* L. sweets depicts several improperly identified samples, whereby they are diverse but their quantity are quite small. This is the reason why the algorithms identify them inaccurately. Because the samples are relatively dark, the misidentification is acceptable. In order to overcome the problem, future studies must consider two factors which are configure the UAV camera's specifications for high-quality image acquisition and determine the optimal distance between the UAV and the *Ipomoea cairica* L. sweets for high image quality. Additionally, a clustering method was used to address image object recognition produced from a digital camera. Based on this clustering approach, an algorithm was developed to extract clusters from real images corresponding to various types of weeds [120]. In addition to the real clustering, this approach entails pre-processing the measured image, which includes filtering and adjusting the brightness histogram. Therefore, cluster centre positions could be iteratively adjusted in the future.

Air drone flight parameters is a critical environmental problem during aerial application. The greater deposition volume on the zero mark of the UAV sprayer's central line was caused by the higher kinetic energy of the droplets at the moment of droplet ejection from the nozzle. The development principle of the vortex on both sides of the spray lance and the airflow at the wingtips in the sprayer process by a comparatively large helicopter was identified by Ahmad et al. [40]. The vortex created by the rotor-wing on both sides of the spray lance has altered the droplet's original trajectory and morphology, resulting in a higher distribution of coarse droplets on both sides of the spray lance. In the future, the relative stable airflow profile under the structure of the UAV may be produced by rotor-wing, which could aid in the deposit of coarser droplets in the target at a relatively quick speed.

The cloud computing problem for computation burdens could be solved in the future. For example, the researchers may use cloud computing or edge computing technology for prediction model inference in weed mapping of UAV imagery using OBIA and deep learning approaches. The time period between data analysis and spraying operations may be considerably decreased using the real-time processing platform, which may improve the viability of this work in real SSWM applications [52]. Researchers could also obtain additional UAV images for model training and validation. In addition, integrate lightweight network architecture system with variable spraying technology for weed mapping tasks is proposed. The classification results of images can offer sprayers with decision-making information, which can help maintain pesticide effects while minimizing chemical use [46].

Different UAV devices have their own capability for flight control which could be improved in the future. This task conducted at various altitudes should be carried out on low computational power devices such as standard laptops and mini-PCs (e.g., Raspberry Pi) for UAV flight control. This would help to understand the capability of using these devices for on-farm, near real-time data processing and actuation. Researchers can assess the performance variation of different models using different devices in various weed species. For example, Sivakumar et al. [45] suggested that the performance of Faster Region-Based CNNs at various altitudes can be evaluated by resampling high-resolution images to low-resolution images.

There were some limitations of detecting unknown weed species to the Optimized Deep Learning model in a previous study [55]. When the model precision was increased from 16 to 32 bits, there was no improvement in classification accuracy but a significant decrease in speed performance, especially when a larger number of filters was utilized in the ResNet-18 model. Future research should focus on integrating the mapping process on UAV platforms, autonomously guiding UAVs for mapping purposes, and enabling model transferability to other crop areas. The neural network should also be used to more hyperspectral maps of herbicide-susceptible and -resistant weeds among crops to evaluate the model under various field settings that includes unknown weed species. In future study, these maps should include data from the field to explore the efficacy of weed detection by varying the crops, mixed pixels, weeds, lighting, imager distance from plants, and environmental conditions [121].

There is a difficulty in manual labelling labour for labelling images. A Fully Convolutional Network is a fully supervised algorithm, and the network's training and updating rely on a considerable number of labelled images, which necessitates substantial manual labelling labour. Therefore, in the future, researchers could develop weak-supervised learning i.e., limited, noisy, or imprecise sources are employed to provide supervision signal for labelling large amounts of training data in a supervised learning setting, and helps to reduce the burden of collecting manual-labelled data sets which can be expensive or impractical) and unsupervised learning algorithms to minimize manual labelling work and improve application efficiency [84].

4. Discussion

To the best of our knowledge, there were no standard techniques for extracting previous studies systematically that focusing on weed detection using UAV. The goal of this systematic review article has been accomplished by providing a concise and comprehensive overview of the current application the UAV-based imaging in weed detection and future research aspects of this technology for precision agriculture. There is information in the previous section which extract and synthesis a total of 144 original articles from 1 January 2016 to 18 June 2021, and the articles were published in a broad range of journals and conference papers. These previous studies elaborates the spectral differences, types of remote images, effect of spatial and spectral resolutions, and types of algorithms and classification techniques in weed detection. Most of the applications were utilized during seedling stage of crop and used visual from image analysis as a reference data.

With the knowledge of how the weed and crop data are gathered and processed through UAV, it will be easier to highlight the pro and cons of each sensor, therefore could be beneficial for researchers to use what type of sensor based on the different purpose of application in the field. Despite the advantages and disadvantages for each sensor, we found that RGB cameras was the most commonly used compared to other types of sensor because it has (i) lower cost, (ii) smaller and lighter in terms of its features, (iii) can easily be mounted and integrated; and (iv) has capability of generating high-resolution images.

Following the pro and cons for different algorithm types, this review will provide insight on their classification accuracy on analysing UAV images. When we compared each algorithm, we found that the machine learning techniques were widely used because, it (i) has high-performance computing that generate new possibilities to unravel, quantify, and recognise data-intensive procedures in farming operational environments, and (ii) comprises of diverse type of models. Nonetheless, many aspects need to be considered because this technique requires massive data sets to train on and sometimes must wait for new data to be generated. Additionally, the major challenge is the ability to accurately interpret results generated by the algorithms and is highly susceptible to errors, which could results in biased predictions that came from a biased training set. In the future, more specific algorithms need to be developed to handle weed removal. However, faster classification algorithms and more efficient computational hardware are still needed to improve machine vision.

The recent approaches of integrating various type of sensor and specified classification algorithm could increase the efficiency of weed detection. The use of UAV would give benefits to agricultural industries, which indirectly provide opportunities for employment to those who has expertise on using this technology and a good prospect for their career in precision agriculture field. Furthermore, UAV also solve the farmers' problems, in which the weeding techniques overcome the huge number of crops lost during the weeding activity. The UAVs not only increase crop yield and production, but they able to eliminate the unwanted pesticides and herbicides. Other than that, farmers may effectively spray herbicides on their farms using UAVs, whereby plant monitoring is no longer a burden.

UAVs have many unique characteristics that keep them at the forefront in agricultural industries compared to (nano) satellites with very high spatial and spectral resolution. Aside from their low cost, UAVs (i) provides centimetre resolution, (ii) combining crop height and orthophoto information, (iii) providing multi-angular data (especially from snapshot cameras), (iii) enabling high-quality hyperspectral data acquisition, and (iv) sensor flexibility. Transferring weed information obtained from UAVs into everyday practice, on the other hand, would necessitate a change in a scientific approach. The current requirement for practical and technical expertise for flight operation and data processing impedes the routine use of UAVs in weed detection, mainly for thermal and hyperspectral data [122,123].

There is no doubt that UAV technology will continue to advance, potentially expanding its use in weed detection. We anticipate that the current trend of growing UAV sensor quality and user-friendliness will continue, eventually allowing RGB, multispectral, hyperspectral, and thermal sensors for routine operation by non-expert users. Although it is not yet possible, the future research should (i) could develop unsupervised learning, (ii) configure the UAV camera's parameters and determine the optimal distance between the UAV and the weed, (iii) examine the influence of model compression techniques and approximation algorithms created for neural networks, (iv) adjust iteratively cluster centre positions from algorithm, (v) use cloud computing or edge computing technology for model inference, (vi) investigate deep learning methods for automatically obtaining effective features for weed and crop classification in outdoor scenarios, and (vii) consider two factors such as configure the UAV camera's specifications for high-quality image acquisition and determine the optimal distance between the UAV and weed for higher image quality.

One of the benefit of UAV is its ability to mount and test several sensors simultaneously, which is one of their unique features. However, data fusion should not be limited to fusing two or more sensors on the same UAV. Combining information from the tools of the within-field spatial variance in the management decision-making phase is promising [84], but it has yet to be established and should be a top priority. This is proven by Che'Ya et al. [75] that used RGB, multispectral and hyperspectral sensors in UAV platform to detect weeds in the field. Hence, ground data is very important to crosscheck the imagery. They counted manually the actual weeds to check the real weeds in the field. Berahim et al., [124] also collected the ground and agronomic data and related with the aerial imagery. They found that physiological responses similar to the aerial imagery in rice field monitoring. The end user also is important to use the imagery, in which Roslim et al., [125] found that Padi2U mobile apps helps end user to get access the aerial map to monitor their field. They also used the ground data such as soil plant analysis development (SPAD) data to correlate with the multispectral imagery through the NDVI map. Similar findings also been observed by Yuhao et al. [126] that used SPAD meter and NDVI, Normalized Difference Red Edge (NDRE), Soil Adjusted Vegetation Index (SAVI), and Optimized Soil Adjusted Vegetation Index (OSAVI) map to correlate with the ground data. They found that NDRE was highest correlation in rice monitoring in the field.

When combined with weed management preparation, the knowledge gathered from remote imaging analysis will help to improve weed management in the future. Furthermore, imaging analysis may aid in studying weed dynamics in the field and their interaction with the crop, both of which are required steps in developing new weed management strategies based on interspecific crop–weed interactions [127].

5. Conclusions

UAVs allow for the accurate identification of weed patches in a plantation area, in which increasing weed management sustainability. UAVs' crop patch detection will aid in integrated weed management, reducing selection pressure against herbicide-resistant weeds, and herbicide diffusion in the environment. Once combined with weed management preparation, the information acquired from remote imaging analysis will strengthen weed management sustainably. Furthermore, AI integrated with imaging analysis may help in studying weed dynamics in the field and their interaction with the crop, both of which are required steps in developing new weed management strategies based on interspecific crop–weed interactions. Different machine learning techniques would provide an accurate overview of the degree and form of infestation. In light of this review, it can be stated that UAVs are a suitable technique for weed mapping, providing the perfect platform for flying a medium-size field with a reasonable spatial resolution and leaving open a broad line of future research.

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