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Phenological Property Consideration for Crop and Weed Discrimination Technologies: A Review

Jyoti Lahre
Ph.D. Scholar, Department of Farm Machinery and Power Engineering, College of Agricultural Engineering and Post Harvest Technology, Central Agricultural University, Imphal, Ranipool, Sikkim, India.

(Corresponding author: Jyoti Lahre)*
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ABSTRACT: Unwanted plants grow non-uniformly, autonomously in the field, and compete with the major crop called weeds. It competes with the main crop for sunlight, nutrients, water, and space and grows faster. These effects affect the growth rate of crop seedlings, eventually resulting in crop yield reduction. Weed control is very critical to crop production. Several studies have examined the yield loss associated with weed competition. Due to the phenotypic similarity between some crops and weeds as well as changing weather conditions, it is challenging to identify and design an automated system for general weed detection. Many research studies documented various weed discrimination, identification, and control techniques. These recognition mechanisms could be mechanical or physical for intra-row weeding. Image segmentation, height/stalk identification, machine vision systems, sensor-based approaches, RTK-GPS based systems, etc. It is better to control weeds effectively. These advancing technologies promise agriculture improvement with fewer labor-intensive tasks. The more challenging area of intra-row mechanical weeding with manually operated weed control is labor-intensive and time-taking. Along with various discrimination solutions for weed control discovered in industry and the research community, the state of the art in automated mechanical weeding is being explored. An automated technique includes data acquisition and processing. Data processing includes typical plants' morphological trait extraction and estimation based on a multi-level region segmentation method. Automatic morphological traits are compared with manually measured values. The proposed method's robustness and low time cost for different plants, show potential applications for real-time plant measurement and high-throughput plant phenotyping. In this paper, we study different methods or techniques for weed recognition.

Keywords: Crop production, recognition mechanism, RTK-GPS, morphological trait, segmentation, plant phenotyping.

INTRODUCTION

Basic Weed Detection Methods. Plants' morphological traits are indices describing plant physical architecture. They can be used in many fields of agricultural research. Weeds and plants can be distinguished by their morphological characteristics. Weed plants have some major characteristics as they grow before or after the major crop; their height differences, shape, and color, and growing characteristics. Weeds grow faster than the main crop and compete with them for nutrition. In some agricultural research, such as high-throughput phenotype, a large number of samples are needed. Automatic sample selection has become necessary. Nevertheless, various sensors, such as color digital cameras, range cameras, hyper spectral cameras, multispectral cameras, thermal imagers, infrared radiometers, fluorescence sensors, light detection and ranging (LIDAR) sensors, global positioning system (GPS) receivers, laser sensors have been used for plant measurement. Those sensors can generate a large amount of data. Traditional leaf trait measurement that mainly relies on manual measurement methods based on contact tools is not suitable for such a large capacity of data processing. Automatic morphological trait estimation should be carried out and automatic data batch processing is urgently needed. Many researchers have done their experiments on a shape and color basis. For shape and color identification, image analyzer software, sensors, and a simulation algorithm are used. Height and stalk are other characteristics of weed discrimination. Sensor-based weed mapping and machine vision-based technologies are new approaches to weed discrimination.

Shape, Size and Colour Identification

Colour Features. Machine vision is a major key for weed and plant detection using cameras. Assumption and knowledge of the position of the crops may be used in such systems where crops should be grown, such as the position of weeds. Computer vision has been a viable and accurate option in crop-weed identification, especially when shape and color need to be analyzed at high speed (Batchelor and Searcy 1989). Tang *et al.*

(2000) used color image segmentation integrated with a binary-coded genetic algorithm (GA) with Hue-Saturation-Intensity (HSI) color space (GAHSI) identifying the weed in an outdoor field. Three different approaches, shape analysis, color analysis, and texture analysis, were used as effective criteria for weed discrimination. The texture analysis was performed with Fourier spectra, the colour analysis was performed with grey scales of images and shape analysis was done with compactness, eccentricity and three invariant moment measurements (Zhang and Chaisattapagon 1995). Shiraishi and Sumiya (1996) identified plants by using a machine vision technique. Plant morphological parameters (color, aspect ratio, size, radius permutation of plant leaves, complexity, and curvature) were used to classify each plant. Effective discrimination was obtained by using a quasi-sensor fusion combined with a decision-making model. A developed system estimates the weed density between two rows of soybeans (Steward and Tian 1999). An environmentally adaptive segmentation algorithm (EASA) was used for segmentation of plants from background objects. The result in significantly higher quality segmentation based on morphological opening and closing pixel loss over the RGB-rgb transformation. An adaptive scanning algorithm (ASA) was developed and used to detect crops and the number of weeds in the inter-row area. The mean execution time of the ASA was 0.038 s for 0.91 m (3 ft) long inter-row. Ge et al. (2008) used a crop/weed discrimination method that can be divided into the two following steps. 1) a crop row detection was performed from the identification of the vanishing point of the perspective geometry of the scene. An algorithm based on a double Hough transform (DHT) was applied. Afterwards, the discrimination between crop and weeds was done by a region-based segmentation method using a blob coloring analysis. The proposed Genetic algorithms (GA) method with the fitness function of Bayesian classification was applied to calculate the color index for the segmentation. The proposed algorithm of CenterNet, achieved a precision of 95.6%, a recall of 95.0% and a F1 score of 0.953 (Jin *et al.,* 2021).

Shape Features. The shape analysis techniques were proposed to discriminate between crop and weeds and colour information to distinguish between vegetation and background. The shape analysis algorithms achieved 75% with Bayes Rule and k-NN methods (Prez *et al.* 2000). Chi *et al.* (2003) developed algorithms to extract the leaf boundary of selected vegetable seedlings. The leaf boundary of color images was fitted with Bezier curves and geometric descriptors. Leaf features (apex angle, base angle, control line ratios, and fitting error) were subsequently derived from the fitted Bezier curves. The leaf shape was modeled by Bezier curves and contributed a significant data reduction, compared with using discrete boundary points. Søgaard (2005) did the classification of weeds by their shape with image processing. This image processing was based on active shape models. The images have been used as training data for recognizing the young seeding with two leaves and the construction of an active shape model for each species. An algorithm for the identification of weed species has been developed through models. Depending on the weed species, results were obtained by classifying a test set of weed seedlings may vary from 65% to above 90%. Weis and Gerhards (2009) did the image processing by extracted weed images and described shape features. This was helpful to determine the type and number of weeds per image. For the determination, only a maximum of 16 features out of the 81 computed ones were used. Swain *et al.* (2011) followed the automated active shape matching system (AASM) technique. The nightshade plants were identified 90% correctly by AASM. The time required for identifying the targeted plant was approximately 0.053s as a nightshade and a non-identification process required 0.062s with the Linux platform used for eight iterations. Herrera et al. (2014) used a set of shape descriptors (the seven Hu moments and six geometric shape descriptors). Six geometric shape descriptors (perimeter, diameter, minor axis length, major axis length, eccentricity and area) were proposed. Kazmi *et al.* (2015b) integrated leaf edge shapes with KNN and SVM classifiers for weed detection. Multi-scale edge shape detector (TLR) based on color vegetation indices. The surface detector (MSER) was combined with edge and corner based detectors (TLR, Harris Affine and Hessian Affine) to test the combined potential of edge and surface detectors. Hamuda *et al.* (2017) integrated an algorithm based on morphological erosion and dilation and color features of plants. The moment method was applied to determine the position and mass distribution so as to track crops in video sequences. A precision of 99.04% and sensitivity of 98.91% was achieved. Amsini and Rani (2021) integrated a triangular intuitionistic algorithm with spatial type II fuzzy c means. Gray Level co-occurrence matrix statistical features and shape-based features were used for image analysis based on shape and features, and decision-making. The neural network and support vector machine classifier machine learning algorithm was used to classify the image features such as color variations depending on the weed size. The pixel semantic segmentation of crop and weed to balance the features map textual and shape signals. A multi-level feature re-weighted fusion (MFRWF) module was designed based on convolutional weighted fusion (CWF) to reduce possible feature context distortion.

Texture Features. Dryden *et al.* (2003) implemented a Bayesian method for segmenting weed and crop textures. Image simulations were applied the posterior distribution considered with the reversible jump Metropolis–Hastings algorithm. Chou et al. (2007) proposed a wavelet packet transformation combined with weighted Bayesian distance based on crop texture and leaf features. Wavelet analysis with Bayes distance resulted in 94.63% accuracy for crop identification. Tellaeche *et al.* (2008) performed image segmentation combined with image processing techniques for extracting cells from the image as low level units. The decision-making computation was based on the posterior probability under a Bayesian framework to determine the cells to be sprayed.

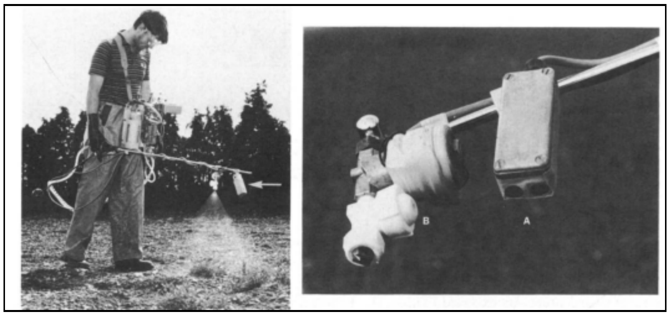
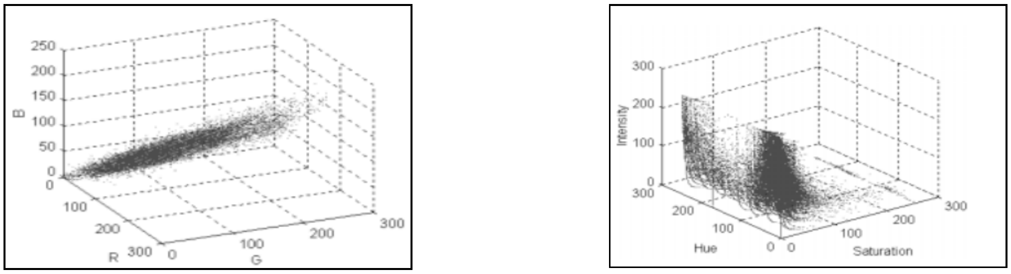


Fig. 1. (Left) View of patch detector coupled to an Oxford Precision Sprayer, (right) close-up of detector (A) mounted on a boom adjacent to a spray nozzle (B) (Haggar *et al.*, 1983).

Polder *et al.* (2007) used textural image analysis. Images were divided into square tiles. In the textural analysis, which was subjected to a 2-D FFT. The algorithm had a success rate of 94%. Paap *et al.* (2008) used photonic-based spectral reflectance sensors as architecture for non-contact spectral reflectance measurements. Plant discrimination was based on the slope of the spectral response between the 635-670nm and 670-785nm laser wavelengths.

Table 1: Weed detection based color texture features.

Architecture	Crop Types	Strengths	Accuracy	References
Color Co-occurrence Method (CCM)	Not specified	HSI color features used to discriminant between soil and weeds, SAS STEPDISC procedure evaluated the CCM texture variable set	93% (hue and saturation statistics)	Burks *et al.* (2000)
LoH, IN, EN and ASM based discrimination models	Grass species	Discrimination models of local homogeneity (LoH), inertia (IN), moment entropy (EN) and angular second moment(ASM),, Color image segmentation using KB Vision	93 and 85% (grass and broadleaf categories of plants)	Meyer *et al.* (1998)
Chromatic coordinates	Weed species	The non-normalized RGB coordinates of individual weed species, Image converting software Leadview® v2.6, HALO® Professional Graphics Kernel System for programming	95% (chromatic coordinateds)	Woebbecke *et al.* (1995)
Gabor wavelets algorithm	Grass with broadleaf	Low-level Gabor wavelets-based feature extraction algorithm with neural network-based pattern recognition algorithm	100% (elapse time with neural network)	Tang *et al.* (2000)
Discrete wavelet transformation (DWT)	Grass with broadleaf	Combination of a Gabor wavelet (GW) and gradient field distribution (GFD) techniques	84% (Gabor wavelets)	Ishak *et al.* (2009)
Color co-occurrence matrices	Weed species	HIS color co-occurrence method (CCM) texture analysis techniques with VC++ computer software program, four texture parameters: Entropy(E), Inertia quadrature (IQ), Angular second moment (ASM), and Inverse difference moment or local homogeneity (IDM), NeuroShell 2 software program	78% (ANN classifier)	Li *et al.* (2008)
Image processing systems using the machine vision	Lettuce	Calibration bars proposed for leaf color analysis and color constancy, PRO DISCRIM of SAS for discrimination equation	80.8%	Lee (2007)
Image segmentation with texture parameters	Corn	SVM and back-propagation (BP) neural-network classifier, Gray Level Co-occurrence Matrix (GLCM)	Accuracy of 100% with SVM classifiers and accuracy of 80% with BP classifier	Wu and Wen (2009)
Wrapping based Curvelet transform and Support Vector Machine (SVM)	Corn	Particle Swarm Optimization (PSO)-based Differential Evolution Feature Selection (DEFS) to select the optimal features, RVM-based classifier, Adaptive Median Filter (AMF) used for filtering the impulse noise, Feature extraction performed to extract the angular texture pattern	99.3 % (SVM classifier)	Prema and Murugan (2016)
Image segmentation and Principal Component Analysis	Sugar beet	Co-occurrence texture features determination for by single-level wavelet transform	96% with wavelet texture features	Bakhshipour *et al.* (2017)
Laws' texture method and Random Forest classifier	Carrot	Texture features extracted from Laws' texture masks for discrimination	94% accuracy with classifier	Kamath *et al.* (2020)



(a) (b)

Fig. 2. Mosaicked image pixel distribution in RGB color space (a) and HSI color space (b), (Tang *et al.,* 2000).

Spectral Reflectance with Machine Learning. Vrindts *et al.* (2002) used site-specific weed detection and evaluation for sugarbeet and maize. Classification tests were based on spectra reflection between weed and crop in laboratory test. Canopy reflection was measured with 90% of correct identification with a line spectrograph from 480 to 820 nm (visual to near infrared) in the wavelength range. Moeslund *et al.* (2005) determined the 3D pose of cactus leaves on binocular stereoscopic images acquired using Active Shape Model (ASM). This process provides 3D points to find the 3D pose of the leaf. This showed that 84.6% of the 3D poses are found correctly. Barraga´n *et al.* (2007) studied the spectral discrimination by multispectral reflectance. Reflectance data was collected in three phenomenal stages: mid-May, mid-June and mid-July. The resultant hyperspectral reflectance curves were statistically used as significant within and between crop and weed phenological stages, which facilitates their discrimination. The weed seedlings were identified under the natural light conditions. A wavelength band filter combination was based on a quadratic discriminant analysis with a multispectral device consisting of a black and white camera. The best combination of filters was included on the basis of three interference filters, respectively centred on 450, 550 and 700 nm (Piron *et al.* 2008). Burgos-Artizzu *et al.* (2011) used real-time lighting to discriminate between crop rows and weed patches. The computer vision system was divided into two subgroups; fast image processing in real time and slower image processing with accurate results. The system detected 95% of weeds and 80% of crops under the different illuminated conditions. Pena *et al.* (2013) developed a weed map for image processing. They use object-based analysis for unmanned aerial vehicles (UAV). An automatic object-based image analysis (OBIA) procedure was developed on a series of UAV images using a six-band multispectral camera (visible and near infrared range) in an experimental maize field in Spain. The weed map coverage was found with 86% overall accuracy. In experimental work, the weed free area was 23%, and the low weed coverage area (<5% weeds) was 47%. Potena *et al.* (2017) developed an automatic robot which enables an unmanned ground vehicle (UGV) equipped with a multi spectral camera to perform crop/weed detection. Their approach utilizes a pipeline that includes two different convolutional neural networks (CNNs) applied to the input RGB+near infra-red (NIR) images. The weed image segmentation and localization solves four problems related to camera-based weed detection: handling of changing environments and non-green plant stems, segmentation of overlapping weeds and crops, and, for instance, detection in cereal fields (Dyrmann, 2017). Sakthi and Yuvarani (2018) did their experiment on weed detection by image processing. They detected weed density between row and crops. Image segmentation of lines and curves assigns the entire image of the weed.

A significant approach was made with hyperspectral radiometry using spectral reflectance difference (Che'Ya *et al.,* 2013). A handheld spectrometer was used to get spectral signatures with a spectral range of 325 to 1075 nm. A one-way ANOVA and Linear Discriminant Analysis (LDA) were used to get significant resulting wavelengths to discriminate between weeds and crops. Haug *et al.* (2014) used non-segmentation techniques to identify weeds and crops. They used a Random Forest classifier to estimate crop / weed certainty at pixeled positions based on features extracted. These individual sparse pixel results are spatially smoothed using a Markov Random Field. Continuous crop / weed regions are inferred in full image resolution through interpolation in field conditions. Applying the plant classification system to images, an average classification accuracy of 93.8 %.

Kumar et al. (2016) proposed a novel Wrapping Curvelet Transformation Based Angular Texture Pattern Extraction Method (WCTATP) for weed identification. Global Histogram Equalization (GHE) was used to improve the quality of the image and Adaptive Median Filter (AMF) was used for filtering the impulse noise from the image. Wrapping Curvelet transform was applied to the plant image. Feature extraction was performed to extract the angular texture pattern of the plant image. Particle Swarm Optimization (PSO) based Differential Evolution Feature Selection (DEFS) on the approach to selecting the optimal features. An automatic OBIA (object-based image-analysis) procedure was developed which was applied on orthomosaicked images using visible (red-green-blue bands) and multispectral (red-green-blue and near infrared bands) cameras collected by an unmanned aerial vehicle (UAV) that flew on two maize fields. The altitudes of 30. 60 and 100m were taken. The accurate weed mapping was found using the multispectral camera at an altitude of 30 m (Lopez-Granados *et al.*, 2016).

Pulido *et al.* (2017) integrated Support Vector Machine (SVM) with the Radial Basis Function (RBF) into the nonlinear case. Principal Component Analysis (PCA) calculated from Gray Level Co-occurrence Matrices

(GLCM) and the result was above 90%, validated with specificity, sensitivity and precision calculations. Louargant *et al.* (2018) developed an algorithm to discriminate crop and weed image pixels combining spatial and spectral information extracted from the four-band multispectral images. The mean value of the spatial and spectral combination method for weed detection rate was 89%. The individual value of the spatial method was 79% and 75% for the spectral method was recorded. This method was acceptable for intra-row crops and high resolution images (at least 6 mm/pix). Saha (2019) did classification of carrot leaves from weeds. He divided his work into three processes: 1) image segmentation, 2) extraction and 3) decision making. Image segmentation was processed, where images were processed into lower units for extraction. In the extraction process, the images are extracted by the K-method to identify weeds. In the last decision making process, the system uses the support vehicle machine (SVM) to separate weeds from the plants. Liu *et al.* (2019) designed an imaging spectrometer system and used it to discriminate carrots and three weed species. Dimensionality reduction was performed by spectral data based on wavelet transforms; were extracted and used as the classification features in the weed detection model. The results were compared by using spectral bands as the classification feature. With spectral bond (8), the overall classification accuracy was 85%. If the spectral bond increased to 15, accuracy was found to be 90%.

A good crop row detection rate of 93.58% was obtained. A developed strategy for inter and intra-row weed detection in maize fields from aerial visual imagery Gao *et al.* (2018). The Hough transform algorithm (HT) was used to the orthomosaicked images for inter-row weed detection. A semi-automatic Object-Based Image Analysis (OBIA) procedure was applied with Random Forests (RF) combined with feature selection techniques to recognize soil, weeds and maize. An overall accuracy was obtained of 0.945, and Kappa value of 0.912. A non-overlapping multi-camera system was used to provide flexibility for the weed control system (Wu *et al.,* 2020). The system performs naive Bayes filtering, 3D direct intra- and inter-camera visual tracking, and predictive control, while integrating state-of-the-art crop/weed detection algorithms. This algorithm was developed to guide in the detection delays the tools to achieve high-precision weed removal.

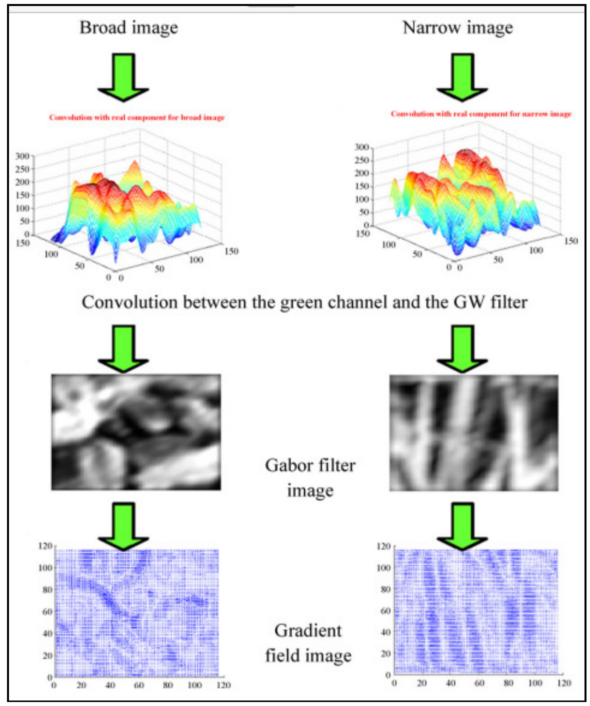


Fig. 3. Gabor filtered image and its gradient field image based on 45◦ orientation (Ishak *et al.,* 2009).

Gao *et al*. (2018) used a novel hyperspectral snapshot mosaic camera for weed and maize classification. Machine learning techniques and image processing were applied for developing the classifier with three different combinations of features. Bah *et al.* (2019) developed a network based an unmanned aerial vehicle (UAV). This "CRowNet" network used a convolutional neural network (CNN) and the Hough transform to detect crop rows in images with SegNet (S-SegNet) and a CNN based Hough transform (HoughCNet).

Table 2: Weed detection based on image spectrograph using structural information.

Datasets	Purpose	Plant	Spectral range	Features	References
Grasses and soil	Sprayer with both regular, artificial patches and irregular, "natural" patches, the effect of various soil conditions on the RRM working performance	Not specified	Near-infrared (750 nm), red (650 nm) radiances	Hand-held reflectance ratio meter (RRM)	Haggar *et al.* (1983)
Crop, weed and soil	Feasible evaluation of crop/weed/soil discrimination using broader filters	Broccoli	680-780 nm, 960-1060 nm and 1320-1420 nm	MONOLITE computerized spectrophotometer, BMDP software for discriminant analysis of the spectral data,	Hahn, 1996
Crop and weed	Performance evaluation of weed detection using spectral reflectance	Corn	400 - 1000 nm	Spectral information analysis using diffraction of the reflected light,	Pollet *et al*. (1999)
Crop, weed and soil	Spectral measurements correspondence to average spectral reflectance	Non-specified	435-1000 nm	Bootstrap procedure for reliability of performance, multilayer neural network with non-linear mapping	Feyaerts and Gool (2001)
Crop, weed and soil	Spatial and spectral methods upon aerial photographies for weed detection and localization	Onion	50-750nm	Principal component analysis (PCA) for crops/weeds discrimination, D-GPS for georectification, Fourier transform of Gabor filter	Vioix *et al.* (2002)

Crop and soil weed	Image processing algorithms with hyperspectral texture images	Cotton	600–820 nm	Spectral component with acousto-optic tunable filter (AOTF), Hyperspectral characteristics of the data for background segmentation	Alchanatis *et al.* (2005)
Crop, bare soil, and weed	Define color indices insensitive to illumination intensity, investigation of feasibility of weed detection based on spectral characteristics	Wheat	Visible (400–750 nm) and NIR (750–1700 nm)	Spectral characteristics of stems and leaves studied using a diode–array spectrometer	Wang *et al.* (2001)
Crop and weed	The discrimination of visual and near infrared spectra from corn sugar beet and different weed species	Corn, Sugar beet	435 and 855 nm	The Self-Organizing Map (SOM) neural network with local linear mappings (LLM), Multilayer perceptrons (MLP), Learning Vector Quantization algorithm	Moshou *et al.* (2002)
Crop and weed	Quantitative image analysis	Maize, sugar beet, winter wheat and winter barley	Not specified	Spatial expansion of images with RL-Imalysis software, description of the phenology of the weed population growth	Krohmann *et al.* (2006)
Crop and weed	The spectral characteristics of several common weed species using NIRS technology and discrimination and identify crop from groups of weeds	Sunflower and wheat stubble	450 and 950 nm	Near-infrared reflectance spectroscopy (NIRS)	Jurado-Expósito *et al.* (2003)
Crop and weed	Evaluation of hyperspectral reflectance for differentiating soybean and six weed species	Soyabean	490 to 700 nm	Principal component analysis (PCA) and linear discriminant analysis (LDA)using vegetation indices	Gray *et al.* (2009)
Crop and weed	The PLS_Toolbox[11] version 5.2.2 under Matlab^{TM}	Corn	UV (327 nm), induced fluorescence spectra (400 to 755 nm)	UV-induced fluorescence for the discrimination between monocots,	Panneton *et al.* (2011)
Crop, soil and weed	Proposed a robust weed recognition model using the low quality colour weed images with these image blurs.	Not specified	Not specified	Calculation of the image-moment-based blur invariant feature, weed recognition with the computed Euclidean distance based on the moment invariants	Peng and Jun (2011)
Crop, soil and weed	Discrimination between crop and weed species based on their spectral reflectance differences	Weed species	435-834 nm	Novelty detection based on one-class classifiers: one-class SOM (self-organising map) classifiers and one-class MOG (mixture of Gaussians)	Pantazi *et al.* (2016)
Crop and weed	The effect of phenologic stages of crops and weeds on crop and weed differentiation, identification of spectral regions,	Yellow nuts edge, soybean, and sweet potato	Visible (350–700 nm), near-infrared (701–1,300 nm), shortwave-infrared I (1,301–1,900 nm), and shortwave-infrared II (1,901–2,500 nm)	Plant phenology, plant spectral reflectance (leaf-level and canopy-level reflectance), plant biophysical characteristics	Basinger *et al.* (2020)

HEIGHT DIFFERENCE/STALK LOCATION IDENTIFICATION

Height Detection. Some techniques are based on height discrimination. This technique was used as "corrected plant height". The accuracy represents a plant's height, taking into account the ground irregularities. Andersen *et al.* (2005) studied the possibility of computing geometric plant characteristics such as plant height and leaf area with stereoscopic images acquired with a binocular camera, on potted plants. They showed that those attributes can be accurately determined using stereovision with three-dimensional analysis. They used simulated annealing for proper use of parameters. Swain *et al.* (2009) presented a low-cost ultrasonic sensor system. Trimble Ag GPS 332 was used with sensors to locate the locations of sensor data points for mapping. Ultrasonic sensor was used to determine forage heights. Forage mass–height relationships were evaluated by static measurements on binary legume–grass mixtures. The prediction accuracy and relationship between ultrasonic sward height and forage mass resulted as 74.8% (Fricke *et al.,* 2011). Piron *et al*. (2011) used active stereoscopy technique based on a time multiplexing coded structured light to discriminate the plant and weed by their height characteristics. The classification accuracy without correction was 66% whereas it reached 83% using the corrected plant height.

Another approach was done with ultrasonic sensors and camera vision by Andujar *et al.* (2012). The ultrasonic measured the distance through sound waves from the main crop and weed mixture covering the ground. Weed and crop densities were counted manually and the heights were determined by using a metric rule. The system showed the discrimination of weed presence was correctly predicted in more than 92% of the cases with actual parameter. A hardware and software system was designed to control an intra row weeding operation with a roller mechanism and acquire crop/ weed height data obtained by the ultrasonic sensor (Saber *et al.,* 2013). Results showed that the mechanical weeding machine was satisfactorily worked to uproot weeds. Weeds height were found from 10 cm to 18 cm. The study was continued with LIDAR sensor for height detection of crops/ weeds. A terrestrial LIDAR sensor was used to discriminate the vegetation using distance and reflection measurements. The combined binary logistic regression and Canonical Discrimination Analysis (CDA) method was able to discriminate mostly between soil and vegetation with 95% detection accuracy (Andjar *et al.*, 2013). Assirelli *et al.* (2015) integrated with photoelectric and capacitive sensor for Short Rotation Coppice (SRC) cultivation. Each sensor identified the plant according to its functional parameters. The divergence between the sensor's response and the actual position of the poplar cuttings allowed for the accuracy assessment of detection. Shahbazi *et al.* (2021) focused on weed control methods based on different heights and diameters using artificial targets (representing weeds). The targeted plants at different scanning distances from the LiDAR were directly influenced by the size and orientation of the target toward the LiDAR.

Stalk/Stem Detection. Cordill and Grift (2011) worked on a mechanical weeding machine which located and identified the maize stalk and removed all other plants considered as weeds. They conducted their experiment in two ways: (i) plots without weeds and (ii) plots with weeds. The algorithm was written so that the plants at the bottom 150 mm and no leaves growing from higher than 250 mm considered as weeds. The percentage of fatally damaged plants was 8.8% in without weed plots and reaching 23.7% in heavy weed infested areas with hundreds of weeds per m2. Lottes *et al.* (2019) developed an effective classification system with estimation of the stem location for weeds to perform precise mechanical treatment. Weed features were represented through pixel-wise semantic segmentation and image sequences of local field strips. Deep learning was incorporated with mechanical hoeing with specific sensors to process crop and weed discrimination in real-time. Crop/weed was identified by stem locations in individual RGB images and filtered through an aggregation algorithm (Lac *et al.,* 2022).

LEAF, LEAF AREA INDEX AND VEGETATION INDICES IDENTIFICATION METHODS

Leaf and Leaf Area Index Identification. The relationship between relative weed cover and relative leaf area measured destructively for early growth stages of weeds. Spectral reflectance techniques are realistic alternative methods to estimate the relative leaf areas of weeds without laborious assessments. Introduction of such systems into practice will be enhanced when an accurate method can be used. The simple approach based on relative leaf area would be very powerful if user-friendly methods to detect weed leaf area are available. These methods can be accomplished with tractor mounted weeding tools, self-propelled real-time sensing and autonomous reflectance sensor-based weeding machines. Menges *et al.* (1985) used plant canopy reflectance as a discriminating parameter with the field spectroradiometer. Color infrared (CIR) aerial photography was worked accurately with 0.45 - 1.25 wavelength (WL) of weed species and crops. Lotz *et al.* (1994) integrated the linear relationship between different morphologies of weeds with growth stages based on infra-red reflectance. Manh *et al.* (2001) improved the robustness of the image segmentation stage. The weed leaf segmentation was based on deformable templates fitted with parametric models for the leaf outlines. Two visual methods were used for weed-crop identification (Aitkenhead *et al.,* 2003). The first method was accomplished with a simple morphological characteristic measurement of leaf shape (perimeter2/area), which had varying effectiveness (between 52 and 74%) in discriminating, with the variation dependent on plant size. The second involved a self-organizing biologically plausible neural network. It showed accuracy in discriminating between species exceed 75% without predefined plant descriptions being necessary. Rasmussen (2007) investigated the leaf cover and crop soil cover assessed by visual scores, which were biased and context-dependent. Investigation of vision accuracy was done to evaluate the importance of the directed angle of the camera. De Rainville *et al.* (2014) has analyzed a weed/crop classification method based on subsequent supervised and unsupervised learning methods. The feature extraction process based on spatial localization of vegetation in fields was established. Features from the weed/crop leaf area distribution passed to a Gaussian mixture and a naive bayesian classifier clustering algorithm to discriminate weeds from crop plants.

Vegetation Indices. Panneton *et al.* (2010) demonstrated discrimination between weeds and crops without contact with ultraviolet (UV) induced fluorescence of the plants. The discrimination between plants was based on the blue-green fluorescence yield. Tyystjrvi *et al.* (2011) identified the crop from weed by using chlorophyll fluorescence fingerprinting in variable natural conditions. The measurements consisted of 1s of shading followed by 0.2 s of darkness in between. Merotto *et al.* (2012) evaluated the relationship between reflectance indices of weeds and conventional parameters used for weed interference quantification. These indexes and conventional parameters were measured through the GreenSeeker™ sensor by evaluating the normalized difference vegetation index (NDVI) and the ratio of red to near infrared (Red/NIR). Longchamps *et al.* (2010) evaluated UV-induced fluoro-sensing of green plants for corn-weed discrimination. Linear discriminant analysis was applied to classify spectra on a species/hybrids basis. The classification rate was 91.8%, showing the significant potential of UV-induced fluorescence for discrimination. Le *et al.* (2020) proposed a method using a combination of Local Binary Pattern operators and features extracted by plant-leaf contour masks between broadleaf plants. Mask-based local binary pattern features were combined with a coefficient k and filtered features. Two different spectral sensing systems were combined in order to get digital map weed patches in four different cotton fields. A set of two Crop Circle multispectral sensors and a digital camera were used. Raw recorded data were stored and analyzed in GIS environment, producing spatially interpolated maps of red-edge normalized difference vegetation index

(NDVI) and weed cover percentage values (Papadopoulos *et al.* 2018). Duncan *et al.* (2022) developed a low cost spectral triad sensor with four datasets (Light Intensity, Packet Number, Timestamp and Indicator Index). Data was collected in 18 bands between 410 and 940 nm. The real time threshold was based on triggering according to customized vegetative index. The Weed Warden was used as an open source multispectral sensor to detect live vegetation and send a logic signal to the controller.

Image Based Weeding Machine. Remote sensing is a multispectral aerial imagery provision which gives accurate weed maps, especially at late weed phenological stages. Whereas images from high spatial resolution satellites and unmanned aerial vehicles must still be analyzed. Hyperspectral images produce highly accurate maps at early and late phenological stages at a farm scale or medium spatial scale. Stafford *et al.* (1996) developed a hand-held data logger equipped with GPS. A compact hand-held data logger, with a palm-top PC linked to a differential Global Positioning System (GPS) system, has been developed to help the farmer during field walking. It records weed information and position, which displayed on a screen map on a PC. Borregaard *et al.* (2000) applied two line imaging spectrometers to record reflectance spectra covering the visible (VIS) and near-infrared (NIR) wavebands in the wavelength range 660-1060 nm. Spectra from sub-areas discriminated through linear and quadratic discriminant analysis, principal component analysis. An extended Kalman filter (EKF) based tracking algorithm was used for mapping in real time. A covariance matrix describing the confidence in grid position, allowed plant features to be classified on a probabilistic basis (Tillet *et al.,* 2001). Naeem *et al.* (2007) used two dimensional weed coverage rates (2D-WCR) for weed detection. The classification accuracy of analysis resulted as 98% with broad and narrow leaf weeds. Wiles (2011) investigated the vegetative cover with GIS for weed mapping. Weed cover was estimated with 96% accuracy for images. Dammer and Watenberg (2007) developed an online sensor to detect weeds for herbicide application. Field trials were conducted with a sensor-controlled field sprayer. A ground-based weed mapping system was designed to determine weed intensity and distribution in a cotton field (Sui *et al.,* 2008). The weed mapping system includes WeedSeeker® PhD600 sensor modules to locate the presence of weeds between rows. Wenhua *et al.* (2009) proposed a weed detection method using the color features of corn seedlings. Saturation of the centre zone was used to extract the centre zone of corn seedling with the green-red index. They found that the classification rate of weed was mainly affected by weed leaves and the occluding degree of corn. Muangkasem *et al*. (2010) approached machine vision under natural illumination conditions. The near-ground images were captured using a web camera without any assistant light diffuser for shadow robustness. Agrawal *et al.* (2012) performed a spraying operation based on texture-based recognition. Linear discriminating analysis observed 69% to 80% accuracy coupled with predictive discriminating analysis. A GPS receiver used to provide spatial information. The PhD600 sensor module was used in a weed mapping system. The value of spectral relative reflectance values of both leaf and canopy were obtained by field spectroscopy for four plant categories (Shapira *et al.,* 2013): wheat, chickpea, grass weeds, and broadleaf weeds. Total reflectance spectra of leaf tissues were successfully classified by general discriminant analysis (GDA). The overall classification accuracy for >5% vegetation coverage in a wheat field of 87 ± 5.57% was achieved. Table 1 listed several image processing and listages based on weed detection and identification. Parts of datasets contain image segmentation and species identification.

A significant analysis was performed with erosion and watershed segmentation algorithm for weed classification (Siddiqi *et al.,* 2008). Classification was based on machine vision and spectroscopic methods using image analysis. Xia *et al.* (2013) proposed an in situ weed detection method of multiple leaves with overlapping. A multi-layer perception (MLP) was used to classify partial boundary images of pepper leaves. Active shape models (ASMs) were subsequently built to employ the images of entire leaves with 63.4 and 76.7% detection rates.

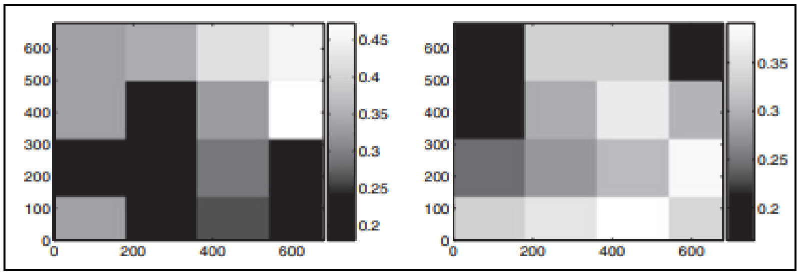
(a) (b) (c)

Fig. 4.

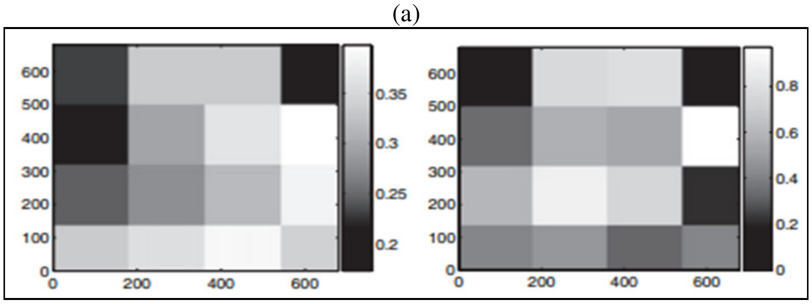
An overview of the Robovator (a), a close-up of the portable knife blades (b), and a diagram illustrating the size threshold and minimum protect safety parameters (c) (i.e., the non-cultivated area around the crop plant). In the circle is a burning nettle (*Urtica urens* L.) plant; the significant size difference between the weed and the crop allow the machine to differentiate between small weeds and the crop (Lati *et al.,* 2016).

Pérez-Ruiz *et al.* (2012) used a real time kinematic global positioning system (RTK-GPS) system to detect the crop planting geo-positions and remove the weeds with a pair of adjustable knives. Barroso et al. (2017) designed an optical sensing unit which detects the presence of green plant matter in plants and assesses the weed mapping in the harvesting period. The spectrum of Chlorophyll in green plant matter was detected by a Global Positioning System (GPS) receiver.

Sodjinou *et al.* (2022) found a solution to the severe presence of weeds as the complex mixture of crops and weeds makes the segmentation more difficult or impossible. K-Means clustering and superpixel algorithms proposed accurate segmentation with the maximum accuracy of equivalent to 99.19% representing the true classification rate of crops and weeds.



(a)



(b)

Fig. 5. Weed intensity maps for X1 (left) weed coverage per region at t - 1 and X2 (right) weed seed production per region at life cycle t (a), Intensity maps X3 (left) for weed seeds patches per region at life cycle t and X4 (right) surface infested by grass weeds at life cycle t-1 per region (b) (Bressan *et al.,* 2008).

Singh (2022) approached semantic segmentation based on deep learning for weed detection in his thesis work. Semantic Segmentation models performed pixel-wise labelling of the detected weed and weed were located with UAV images. LinkNet and UNet used as two Semantic Segmentation models. Sapkota *et al.* (2022) performed CNN and YOLOv4 based weed detection model. Mean Average Precision (mAP) and Average Precision (AP) were calculated to assess the performance of weed species detection and weed detection.

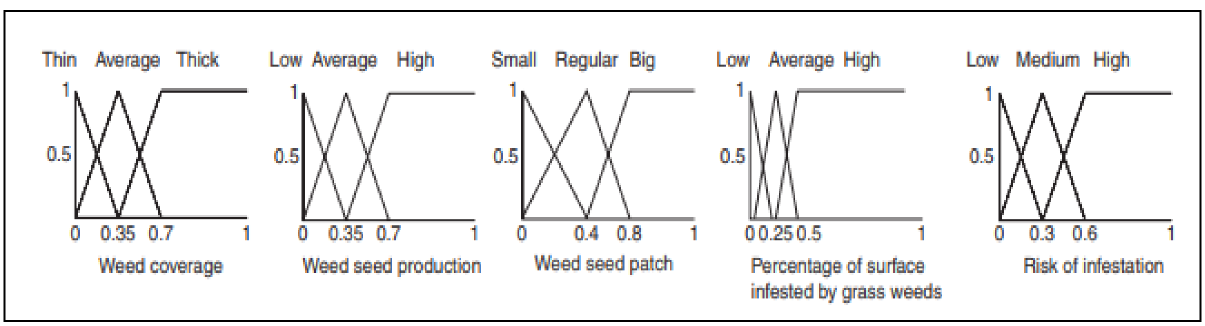


Fig. 6. Membership functions for the inputs and output of the fuzzy classifier normalised in [0, 1] (Bressan *et al.*, 2008).

Rani *et al.* (2021) differentiated weed and crop using speeded-up robust features and histogram of gradients. The logistic regression and support vector machine algorithms were used for classification and accuracy of 83% has been achieved. Albraikan *et al.* (2022) proposed a Modified Barnacles Mating Optimization with Deep Learning based weed detection (MBMODL-WD) technique. This technique applied with the Gabor filtering (GF) technique for the noise removal process. For automated weed detection, MBMODL-WD technique combined with the DenseNet-121 model as feature extraction with the MBMO algorithm as hyper parameter optimization and resulted as maximum accuracy of 98.99%.

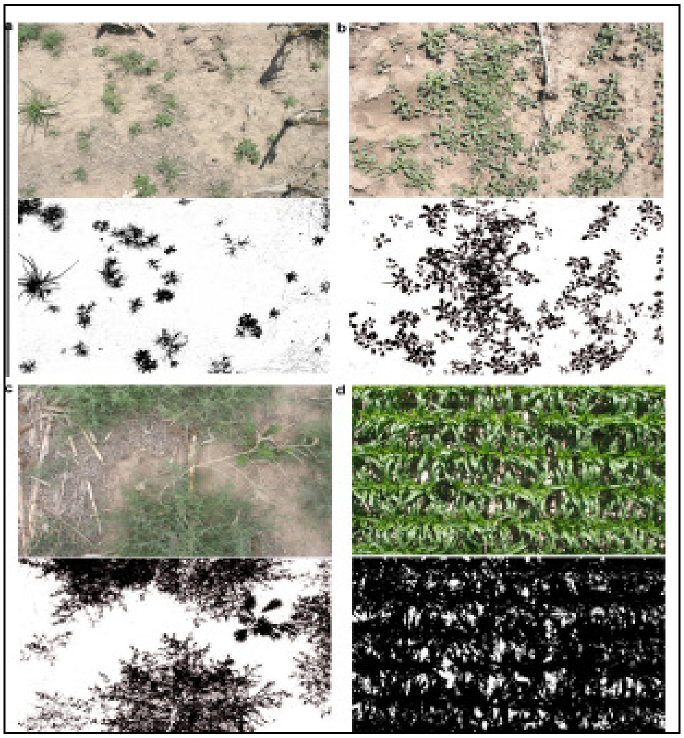
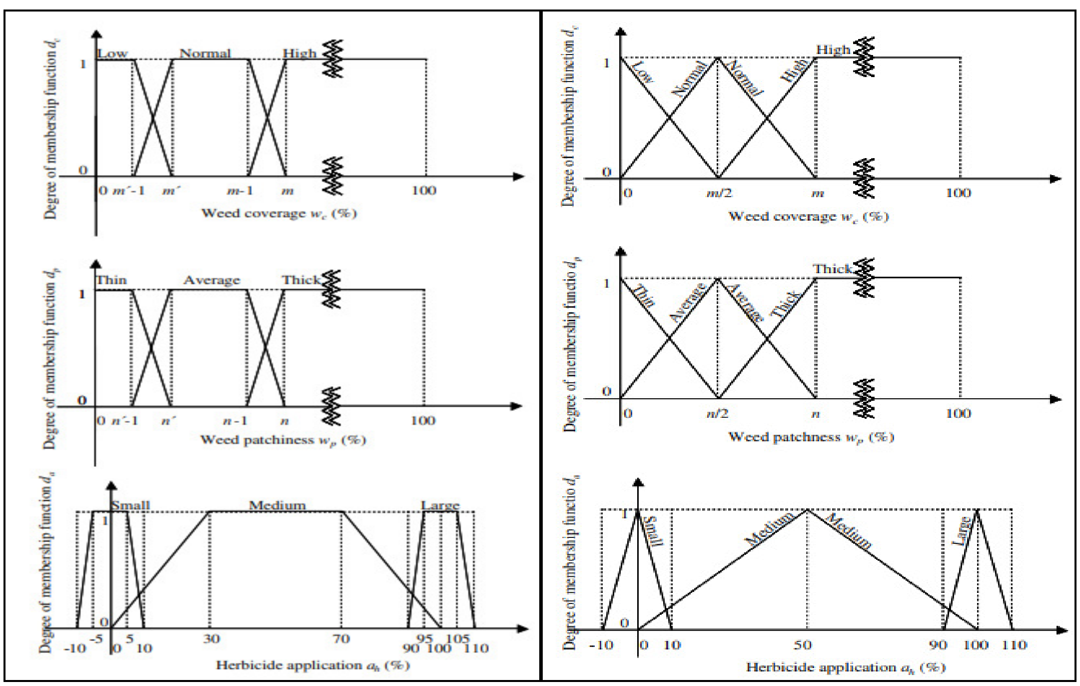


Fig. 7. Small weeds are detected and vegetative cover of different species was estimated with 96% accuracy in images without shadow. Cover estimates are (a) 9%, (b) 21%, (c) 34% and (d) 86% (Wiles, 2011).

Liu *et al.* (2022) achieved a rapid and accurate detection of weeds in maize seedling stage based on lightweight YOLO v4-tiny model. The proposed maize weed detection model was combined with mechanism and a spatial pyramid pooling structure. The effectiveness of the proposed method, five different deep-learning algorithms, including the Faster R-CNN, the SSD 300, the YOLO v3, the YOLO v3-tiny, and the YOLO v4-tiny were compared. Jin *et al.* (2023) implemented site-specific weed detection strategy with ResNet demonstration. Weeds were detected and distinguished by their susceptibility to herbicides and achieved excellent F_1 scores (≥0.995) and MCC values (≥0.994) in the validation and testing datasets.



(a) (b)

Fig. 8. (a) Triangular fuzzy logic herbicide application model, (b)Trapezoidal fuzzy logic herbicide application model (Yang *et al.,* 2003).

Table 3: Image analysis based weed detection with machine learning.

Datasets	Image analysis methods	Purpose	Targeted plants	Features	Evaluation metrics	References
Machine vision with color features	Two artificial neural-network (NN) classifiers	Development of statistical classifier-based and neural network-based weed detection algorithms	wheat and soybean	Relative color indices formed by RGB gray levels, statistical classifier based on discriminant analysis (DA)	54.9% for soybean and 62.2% for wheat	El-Faki *et al.* (2000)
Vision system with radial symmetry	Fast Radial Symmetry Weed Classifier	Real-time vision applications to differentiate between broad leaves weeds and narrow leaves weeds	Weed species	The classifier based on Fast Radial Symmetry	95% classification accuracy	Naeem *et al.* (2007)
Vision system with MATLAB	Artificial neural network (ANN)	Back propagation artificial neural network (ANN) model to distinguish young com	Corn	ANNs created with MATLAB	80% for weed and 100% for corn plants	Yang *et al*. (2000)
Vision system and major crop simulation	Nearest neighbor classifier	Shape and size analysis of treated plants and performance evaluation of vision system	Maize	C++ programming language for image acquisition, Open CV for image processing, Fast Fourier Transforms for image templates matching, Binomial distribution for experimental support for a given normal growth fraction hypothesis	Accuracy: 94%	Midtiby *et al.* (2011)
Vision system with STEPDISC discriminating method	Artificial neural network	Shape features analysis for detection of weeds using ANN	Radish	The neural network model with regularization method (STEPDISC option)	92% for radish and 98% for weeds	Cho *et al.* (2002)
Statistical properties of the histogram with different texture features	Support vector machine (SVM)	Evaluate the classification rate with SVM as the classification model	Chilli	Automated machine vision system (support vector machine (SVM))	Accuracy 97%	Ahmed *et al.* (2012)
Image dataset with feature descriptors	nonlinear SVM	Weed recognition framework based on state-of-the object/image categorization methods with advanced encoding and machine learning algorithms	Weed species	Bag-of Features (BoF) model, Spatial Pyramid Matching (SPM), DoG feature detector	81.02±1.21% (k-d tree) 81.49±1.29 (ScSPM) 84.11±0.88 (LLC)	Wong *et al.* (2014)
Machine vision with color images	Multilayer Perceptron Neural Networks	artificial neural network vision based onions roots discrimination	onion	Multilayer perceptron neural networks technique	95% of accuracy	Tannouche *et al.* (2015)
Plant-level datasets with pictures at leaf level	Image-Net dataset, the version 2.1.6 with Tensor-flow 1.13.1	Investigate the fine-tuning of deep neural networks on agricultural datasets	Not specified	Pre-trained on agricultural datasets (AgFT), pre-trained on ImageNet (ImFT).	99.54% to 90.74% Xception-AgFT, (8,84% performance reduction), 98.70% to 85.90% Densenet-AgFT (12.96% performance reduction)	Espejo-Garcia *et al.* (2020)
Binarize grayscale image	Otsu method (OTSU), UNet	pixel-level classification based on deep convolutional neural	Soyabean	improved UNet structure and an embedded channel attention mechanism SE module, ResNet34 used as the backbone network	96.11% average pixel recognition rate	Yu *et al.* (2022)
Image datasets by artificial images	Convolutional neural network (CNN)	The fidelity of synthetic image with t-distributed stochastic neighbor embedding (t-SNE) visualization plots	Maize	Support vector machine (SVM) and linear discriminant analysis (LDA), generative adversarial networks (GANs)	96% for SVM and 96% for LDA model	Divyanth *et al.* (2022)
Image and custom dataset	Deep Neural Networks	Implemention of Deep Neural Networks (MobileNet, ResNet50) for weed detection.	Soyabean	Five deep learning models including: ResNet50, MobileNetV2, and three custom Convolutional Neural Network (CNN) Models	97.7% of detection accuracy	Razfar *et al.* (2022)
Weed Det network based on RetinaNet	Standard mini batch stochastic gradient descent (SGD)	Algorithm for locating the weed in paddy.	Paddy	PASCAL VOC for images labeling, ResNet-50 and VGG-16 for better classification accuracy	94.1% of accuracy	Peng *et al.* (2022)

CONCLUSION AND FUTURE SCOPE

Weed identification and removing is major challenge for intra row crop field. Most of weeds have same characteristics of main crop plant, which is major problem for site specific weed management. In farmer's point of view, the reduction of herbicide uses by different intercultural practices, and investment in relative expensive and complex equipment, without an expectation of increased yield, there should be an acceptable technology used. The main benefits are the savings in production means (herbicide costs) and improved autonomy. Therefore, the introduction of new systems needs to be properly supported and maintained in order to successfully introduce them to farmers. The image segmentation, color and shape identification, active shape models and UAV imagery are satisfactory at their work. Height and stalk location are complex but precise at results. Ground-level sensors offer very high spatial resolution, and therefore the potential ability to apply classification to classes comprising only one plant species It appears possible that small innovative companies may be the primary source of new weed management technology in the future. Based on the vast improvements in robotics and processing, it would appear that the future of automation in weed control is very promising. Given the high-level performance in this paper, it was demonstrated that the reviewed methods are suitable for the ground-based weed identification in vegetable plantation under various conditions, including varied illumination, complex backgrounds as well as various growth stages and has application value for the sustainable development of the vegetable industry. Future work will be conducted to identify weeds in in-situ videos. Meanwhile, it would also be interesting to evaluate the accuracy reached in the detection of vegetables by optimizing the deep learning model.

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