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Quality Management Of Weed Control System By Image Processing Techniques- A Review

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Abstract
Modern sustainable agriculture depends on hybrid approach of combining ecofriendly farming system and precision tools to combat the challenges of farmers. Agricultural image processing is applicable to various real time challenges in the agriculture field. One such challenge is weed infestation which compete with agricultural crops. To feed the global population, innovative promising practices are required to enhance yield rates and promote sustainable farming methods. Hence this paper critically reviews about quality management of weed control system by image processing techniques. Cultural methods can only reduce the weed infestation but still profitable growth of agricultural crops is a critical factor.The available traditional image processing technologies used in weed management are image segmentation, restoration, spatial and frequency domain techniques and traditional image-processing algorithms . Various precision tools such as Precision Weed Management (PWM), emphasizing cutting-edge technologies such as computer vision, Unmanned Aerial Vehicles (UAVs) and autonomous weeding robots were discussed. Thus to implement weed management technologies a smart agricultural field and yield can be focused on precision and sustainability.
Keywords: *Precision farming, weed detection, image processing technologies, CNN ,non CNN , autonomous weeding robot.*

1. INTRODUCTION

Traditional cultural practices like tillage, planting, fertilizer application, irrigation etc., are employed in weed infestation involves time and man power consumption process.Integration of AI, robotics ,innovative sensors and other precision tools in sustainable agricultural system evolves an impact in the advancement of agricultural technologies. Drones and satellites equipped with sensors can monitor crop health, vegetation indices, and soil properties across vast areas(Zou et al.2021; Zhang et al.2022).Synthetic pesticides, herbicides and fertilizers can be curtailed in the organic farming to enhance eco-friendly environment. Water quality and aquatic life can be protected by reducing pollution and pave the way to mitigate climate change due to carbon sequestration. One of the major challenges faced by the farmers is weed infestation.The competitive factors for the weeds and crops are vital nutrients, water, and sunlight which lower crop yields and profits. Conventional weed control techniques like hand weeding and heavy chemical herbicide use, are labor intensive, time-consuming and have negative environmental effects. Hence the modern agriculture introduced precision tools to solve the problems in farming practices.IP techniques has computer vision-based applications along with improved performance and cost-effectiveness when compared to traditional practices.

There is a critical need for weed management to combat the challenges and construct an automated weed-removal system which uses various image processing methods. This involves high-resolution cameras to take real-time pictures of the crop field. These photos are then analyzed using image processing. Reduction in herbicide usage,manual labor,cost and time are the foremost advantages of precision technologies in weed management. The sophisticated imaging technologies utilizing automation tend to improve the sustainable farming practices. Drones and robots equipped with sensors to monitor crop index, health, soil structures and properties enable the farmers to detect various problems at the earlier stages. Due to variable-rate application (VRA) farmers can minimize the cost,wastes and environmental pollution (Okamoto et al., 2004)

The current review paper focused on the Precision Weed Management (PWM), emphasizing cutting-edge technologies such as computer vision, Unmanned Aerial Vehicles (UAVs), and autonomous weeding robots.

Weed Management Strategies

Weed detection with accuracy by RGB imaging has been conducted by Solahudin et al., 2018. Various methods had been experimented to discrimination between crop seedlings and weeds. To recognise carrot (*Daucus carota* L.) seedlings from those of ryegrass (*Lolium perenne*) and Fat Hen (*Chenopodium album*) using digital imaging and AI based neural network by Aitkenhead et al.,2003. An accuracy of 75% was achieved. Pérez et al. (2000) reviewed and reported the results of colour and shape analysis to detect broad-leafed weeds in cereal crops. Hemming (2000) used digital image analysis for identifying weeds amongst cabbage (*Brassica oleracea* L.), achieving an 87% success rate in identification.

Precision Weed Management

Precision weed management encompass advanced technologies with data-driven approaches to identify, target, and manage weeds more effectively. Image processing enables highly accurate, real-time weed detection.

Computer vision involves image processing and deep learning emerges as a key player in automated weed detection alternative to the traditional herbicide methods. UAVs equipped with advanced sensors facilitate high-resolution weed mapping. Laser and thermal treatments showcase targeted and efficient weed control, while autonomous weeding robots exemplify a hands-free, precise approach(Cho et al., 2002).

Detection of weeds

Detection of weeds through image processing methods involves traditional image-processing algorithms,images of features of plants, spatial and frequency domain techniques. Traditional image-processing algorithms extract crucial features from weeds and profitable plants through one or multiple methods after which a classifier is applied to those features to determine the particular type of weed . Features of plants images such as texture, shape, colour and spectral characteristics (Wu et al. 2021).

Image segmentation relied on standard RGB color images. Each pixel was treated individually and classified as weed or crop making its classification robust to occlusions. Image enhancement techniques improve image quality for visualization and analysis.These methods can be divided into spatial domain techniques that operate directly on image pixels, and frequency domain techniques which use the Fourier transform.

Spatial domain methods include global image enhancement, such as histogram equalization for adjusting global contrast, and local enhancement methods like adaptive histogram equalization and Laplacian methods for edge enhancement.

Image enhancement is a subjective process that manipulates gray level, contrast, noise reduction, edge sharpening, filtering, interpolation, magnification, and pseudocoloring. Image restoration aims to recover the original image from degraded data, focusing on filtering the observed image to minimize the effects of degradations such as motion blurring, information loss, camera misfocus, quantization, and noise.

Restoration differs from enhancement by requiring knowledge of the degradation process and filter design, whereas enhancement emphasizes features for visual appeal without modeling the image creation process. Partitions of images into meaningful regions using methods such as thresholding, edge detection, region growing, watershed, and morphological processing.

Threshold-based techniques segment images by selecting pixels above or below a set intensity value, while edge-based methods detect boundaries by observing changes in pixel intensity.

Region-based segmentation divides images into regions based on criteria like color, intensity, or texture, with approaches including region growing, region merging, and region splitting.

Morphological processing uses operations like erosion and dilation to filter noise and enhance boundaries. The accuracy was affected by variability in image content and the presence of noise

Machine Learning Integration

Traditional machine learning approaches in image processing include classifiers such as support vector machines (SVM) and random forests, which rely on feature-based methods for tasks like segmentation and classification. These methods typically require manual feature extraction, such as color, texture, and shape, followed by feature selection techniques like principal component analysis (PCA) or statistical analysis before classification using machine learning algorithms.

Machine vision spectroscopy methods are based on digital images in which, geometrical, textural or other statistical features are used to detect the weeds.Spectroscopic methods, utilize spectral reflectance or absorbance patterns to discriminate between weeds and crops(Wang et al., 2001, El-Faki et al., 2000).

Deep learning techniques encompass accuracy and efficacy to the maximum .convolutional neural networks (CNNs), have transformed image processing by automating feature extraction and classification. CNNs consist of rectified linear unit (ReLU) to introduce non-linearity and improve training speed. The hierarchical structure of CNNs enables the learning of multilevel representations, from pixel-level features to high-level semantic features, without manual intervention.For feature extraction was done by U-Net with multiscale encoders and decoders for image reconstruction.This enables effective segmentation and restoration tasks.

CSCW-YOLOv7 is a promising tool for the detection of weeds and to locate the weeds of different scales in complex field environments.The Squeeze-and-Excitation (SE) network was added to the Extended Latent Attention Networks (ELAN) module .Concatenation layer in the feature fusion module is used to identify five types of weeds in complex wheat fields. Smartphone ViVO Y52s with an image resolution of 4,000 pixels × 3,000 pixels was adopted to capture the weed images. The weed detection performance of four deep learning models, Faster RCNN, YOLOv5m, YOLOv7, and CSCW-YOLOV7 were compared. CSCW-YOLOV7 is more sensitive to the weed species and achieves more excellent detection performance than other models (Bochkovskiy et al.,2020;Wang et al.,2024).

Spectral reflectance

Researchers were able to discriminate between young crop plants and weeds according to their spectral reflectance in specific wavelengths in the range of 200–2000 nm (Vrindts and De Baerdemaeker, 1996, Wang et al., 2001).

Field studies have also found a potential for distinguishing weeds from agricultural crops according to their relative spectral reflectance characteristics (Goel et al., 2002).

The combination of computer vision with spectroscopic methods yields hyperspectral imaging methods, in which spectral and spatial data are analyzed to aid weed detection (Victor et al.,2005).

Hyperspectral imaging derive mainly from applications of spectroscopy. A hyperspectral imaging sensor consists of a light source and a light-dispersing device coupled with a sensing device(Adhish et al.,2022).

Hyperspectral imaging systems are based on one of three different technologies: electronically tuned spectral band-pass filters; diffraction gratings; and linear variable filters. The potential of multi-spectral sensing for detecting weed infestations in corn and soybean crops was recently examined in an airborne system (Goel et al., 2002). Although several bands were found to have good potential for infestation detection, it was concluded that higher spectral and spatial resolution is needed. (Pantazi et al.,2016).

Charge-coupled devices (CCDs) convert light intensity into electrical signals, and are the most popular sensing devices for image acquisition. CCD arrays are made of silicon and typically respond in the spectral range from 300 to 1000 nm. To include more NIR band (1000–2500 nm) in the sensing range, other imaging devices must be considered.(Lesser,2020).

Robust statistics algorithms are based on local histograms measured for each pixel, over a certain pixel neighborhood. Local histograms are used in many adaptive image-processing algorithms .They described a structural approach to the fast and efficient implementation of a robust statistics algorithm.

Superpixels have become increasingly popular in computer vision applications.Simple Linear Iterative Clustering (SLIC) superpixel algorithm for its ability to stick to a picture border, performance, memory efficiency, and impact on classification results in order to better understand the advantages and risks of current solutions. We then describe Simple Linear Iterative Clustering (SLIC), a new superpixel algorithm that uses a k-means clustering strategy to efficiently construct superpixels. Simple Linear Iterative Clustering (SLIC) is faster and more computationally efficient, increases segmentation efficiency.The Superpixel technique used can hold more data than pixels. Because pixels belonging to the same superpixel have a visual perception. They give a simple and compact visual representation that can be incredibly useful for computationally intensive problems(Lati et al.2021).

Image processing algorithms that are based on image texture in order to detect weeds in a cotton field, at an early stage of crop development. Images from a hyperspectral imaging system processing algorithms that assigned each pixel to the class of crop or weed.

Hyperspectral image acquisition

Hyperspectral image acquisition in agriculture uses sensors on satellites, airplanes, drones, or ground platforms to capture detailed, continuous spectral bands, revealing crop biophysical and biochemical properties invisible to the naked eye or multispectral sensors.

This enables precision management by detecting weeds with high accuracy. The collected data, which

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includes hundreds or thousands of narrow spectral bands.Using AI and machine learning extract actionable insights to enhance sustainability.

To optimize exposure time, the spectral responses of a white reference surface at various exposure times were recorded. The exposure times used ranged from the normal CCIR exposure of 20 ms to 1000 ms, in increments of 20 ms. Exposure of more that 1000 ms was not considered because of the thermal noise of the CCD detector.Exposure of 1 s saturated the CCD detector in the wavelength range of 600–820 nm. In this range, the optimum exposure

An AOTF system was used to capture multiple wavelength images of cotton plants and weeds in the visible and NIR spectral ranges. The system's dynamic range was expanded by means of individual calibration for each wavelength. Two spectral channels were used (660 and 800 nm) to segment weeds and crop plants from the image background. A robust statistics algorithm, based on local histograms, was developed and applied. *Phaseolus vulgaris* and *Spinacia oleracea* are hyperspectrally separable from *Solanum nigrum*, *Solanum tuberosum* and *Datura stramonium* using spectrometer measurements.

Hyperspectral imaging system

A hyperspectral image acquisition system consists of two components: one to select the spectral range and the second to record the spectral response by acquiring the formed image. The selection of the spectral component was done with an acousto-optic tunable filter (AOTF), which acts as an electronically tuned, spectral band-pass filter. Image acquisition used a CCD camera, to translated incident light intensity into electrical signals.

Hyperspectral imaging systems capture a vast amount of spectral information to examine the principles of hyperspectral imaging in weed detection and classification in rice fields based on their unique spectral signatures were reviewed by Sulaiman et al.,2022.

Different populations of crop and weed species were classified using hyperspectral spectrometer measurements and regularized logistic regression (RLR) and a subset of commercial of-the-shelf (COTS) filters were utilized. The authors recommend the use of a high resolution RGB camera to benefit from object-based image analysis to increase classification accuracy. Hyperspectral classification of poisonous solanaceous weeds to discriminate between *D. stramonium*, *S. nigrum* and *S. tuberosum* , *S. oleracea* and *Phaseolus vulgaris*. (Borregaard et al.,2000).

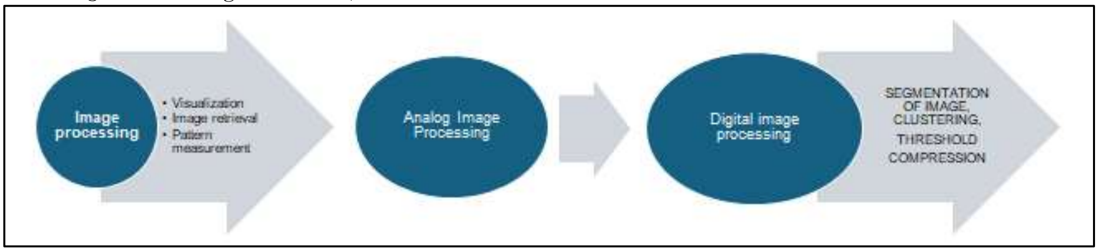

Figure 1: Techniques of Image Processing

Digital image processing

In this technique processing of images are done by digital computers. Firstly via scanner-digitizer images are converted into digital form and then further processing is done on the images. Digital image processing uses many techniques like as correction, formatting of the data, enhance procedure to create picture with better quality.

Basically, there are mainly four operations used in digital image processing like as image preprocessing, segmentation of image, feature extraction, classification of images.

Segmentation of image

This processing method use electrical signals for any change required in the picture. Analog processing includes two dimensional analog signals. In this approach images are modified by changing the electrical signal. It is mainly used for printing/ photography.

Segmentation means partitioning of image into various parts and divides the image in to pixels. Image segmentation divides the image in such a way so that it becomes very accurate.Segmentation is aimed to modify the demonstration which is significant and easy to evaluate.

Table: 1. Traditional techniques in image processing

	References
Segmentation -Shape extraction (region-based and contour-based).	Aktas 2012

Spectral feature and Texture extraction	Ferreira et al. 2017
Colour feature extraction	Pandey et al., 2016
Statistical characteristics	Wu et al. 2021
Simple linear iterative clustering (SLIC)	Adhish et al.,2022;Pauline Ong et al. 2023

Region and Edge Based Segmentation

Region based segmentation technique is a similarity based segmentation. The borders are recognized to perform segmentation. For processing , color and texture of the image is altered and then a vector is created from the edge flow. In this technique every step takes at least one pixel. To recognize pixel values edges are drawn and then these edges are compared with other pixel. The information about edges are extracted and then labeling is done for pixels.

Feature Based Clustering

An image is transformed into histogram and clustering is performed on it . Pixels of the color image are clustered for segmentation using an unsupervised technique fuzzy C. This is applied for ordinary images. If it is a noisy image, it results to fragmentation.

Thresholding

Thresholding changes a gray scale image into binary image wherever the two points are allocated to pixels. These points are below and on upper side of the definite threshold value. Thresholds are obtained from histogram of the original image. The value of the histogram is calculated by detection of edges. So threshold value is accurate only if the detection of edges is accurate. Segmentation perform via thresholding has lesser calculations related to other methods. This technique not provides appropriate results in complex environment .

Model based technique relies on Markov Random Field(MRF). For color segmentation inbuilt region constraint are used. MRF is joined with edge detection for accuracy. This method contains the relations amongst color components.

Image compression signifies compression of the records among the digital images . Image compression eliminates duplication of the data so that it will be stored and transmitted in an effective way.To implement these technologies efficiently ,a smart agricultural field and yield can be focused on precision tools.

Site-specific weed management (SSWM)

Site-specific weed management (SSWM) encompass targeted and timely control measures for each weed in crop field. An advanced technology emerged with accuracy to species-level weed identification during the early growth stage is effective.This is implemented by integrating unmanned aerial vehicles (UAVs), imagery with standard convolutional neural networks (CNNs) models such as VGG16, Resnet152 and Inception- Resnet-v2. Inception- ResNet-v2 achieved over 90% accuracy with 400 labels, while ResNet152 and VGG16 required 600 and 800 labels, respectively, for similar accuracy.

Shape descriptors like etc. can be used to study the shape information in images. Ferreira et al. (2017) grouped pixels according to comparable colour and spatial closeness using super pixel segmentation. Using this technique, the images were divided into sections that featured multiple soy and target weed leaves.

Table-2. Comparison of Traditional techniques and DL in image processing

Traditional Image Processing	Deep Learning
Image transformation (Lens distortion correction, view changes)	Image classification (OCR and Handwritten character recognition)
Image Signal Processing (ISP)	Object detection/ identification
Camera calibration	Semantic segmentation
Industrial inspection – Defect detection	Instance segmentation
Stereo image processing	Image synthesis
Automatic panorama stitching	Image colorization
3D data processing	Image Super-resolution
Calculating geometries	Scene understanding

Weed detection software and technologies

Successful weed management depends on automated, time saving and cost effective technologies that can

be implemented to enhance the crop productivity. WeedRemeed, a cloud-based system utilizing drones and
AI/ML for effective weed management (2pi software 2024); an automated weed detection system utilizing image processing and machine learning deployed on field robots; a weed recognition system involved image processing techniques for targeted interventions (Bhongale and Gore 2017)

The integration of drone and sensor technology for site-specific weed management, all aimed at reducing herbicide use, improving crop yields, and promoting sustainable agriculture (Esposito et al. 2021).

Random Forest classifier for the weed and crop identification employed trained offline with a proprietary dataset and then tested in the field. Agrochemical spraying utilized a PWM-based fluid flow control system guided by vision-based feedback for precise application (Alam et al. 2020)

Hence integration of precision technologies projecting productivity of crops and the promising weed management based on cost-effective image processing techniques. To feed the global population, innovative promising practices are required to enhance yield rates and promote sustainable farming methods.

CNN-based DL techniques for weed identification and Non-CNN approaches for weed identification

Due to prominent advancements, CNNs for detection of weeds DL refers to neural networks characterized by deep layers or intricate structures (Zhao et al. 2019).There are multiple layers encompass convolutional layers, pooling layers, dropout layers, rectified linear unit layers (ReLU) and fully connected layers.In this approach ,feature extraction is not necessary and can improve weed identification.Crop and weed differentiation by utilizing differences in semantic and spatial features (Wu et al. 2021).

Types of CNNs to detect weeds

AlexNet, SoftMax, ReLU, VGG16, ResNet-101 are the CNNs widely used for weed detection and classification. Potena et al. (2017) employed two distinct CNNs, referred to as sNet and cNet, for the rapid and precise categoriza tion of weeds and crops based on NIR and RGB images. Vegetable segmentation was made easier with the light weight sNet's one convolutional layer, ReLU activation function, and max pooling layer. In contrast, pixel-wise crop and weed classification was done using the deeper cNet.

Beeharry and Bassoo (2020) conducted a study examining the effectiveness of AlexNet and artificial neural networks (ANNs) in classifying soybean, grass, broadleaf weeds and soil using UAV-based images. The AlexNet algorithm demonstrated an impressive accuracy of 99.8% in classification, surpassing the ANN algorithm (50%).

Graph Convolution Networks (GCNs) represent a modified version of CNNs designed to operate on data structured as graphs (Kipf and Welling 2016). Jiang et al. (2020) employed a combination of GCN and a feature extractor based on ResNet-101 to enhance weed detection, particularly when dealing with limited datasets. Using semi-supervised learning, they combined characteristics from a weed CNN with their corresponding Euclidean metrics to generate a GCN graph. The method demonstrated significant accuracy, ranging from 96% to 99% across four weed types, outperforming cutting-edge approaches like VGG16, ResNet-101 and AlexNet.

Bah et al. 2018 applied an unsupervised training dataset and CNN to detect weeds in fields of spinach and beans. There is a 6% difference in the area under the curve (AUC) for the bean field and 1.5% for the spinach field. Non-CNNs such as Region Proposal Networks (RPN) showed a prominent efficiency in weed and object detection.

Bakhshipour and Jafari (2018) explored the implementation of two wide ly used algorithms, Support Vector Machines (SVM) and ANNs for automated weed detection in a field of sugar beet.The findings indicated that ANN outperformed SVM in crop-weed discrimination.

Ma et al. 2019 introduced a resilient image segmentation approach utilizing SegNet, a fully Convolutional Neural Network, for semantically segmenting weeds and rice seedlings in paddy fields.

When compared to traditional semantic segmentation techniques like U-Net and FCN models, the SegNet-based approach produced a high precision of 92.7%, while the lat ter techniques produced accuracy rates of 89.5% and 70.8% respectively.

Hu et al. (2020) presented Graph Weeds Net, a novel semi-supervised deep framework. The network showed an amazing 98.1% accuracy on the Deep Weeds dataset, efficiently extracting weed patterns from various graphs and evaluating the connections between graph vertices.

Fully Convolutional Network (FCN) was used on datasets containing over seventeen thousand annotations to identify weeds in colour images that characterized by significant occlusion (Dyrmann et al. 2017).

Weed management by Robotics

Weed management methods by robotic technology has provided an alternative approach to SS Weed management. This type of precision agriculture eliminates the need for human presence (Rao 2021).

An agricultural weeding robot has both hard ware and software components. It is an unmanned, self-steered platform equipped with various weed detection units.

Currently, a diverse range of robotic machines and systems has been developed globally, such as Hortibot, EcoRobot, Ladybird, Robocrop, Robovator Hoeing Ro bot, Thermal Hoeing Robot, Bonirob, AgBot, Swarmbots, IC-Cultivator, RIPPA, and more (Rao 2018).

A prototype robotic system with a mechanical device to remove weeds within the crop rows was designed by Astrand and Baerveldt (2002). The robot employs a system based on colour vision for recognizing weeds and a vision system utilizing gray-level for guiding within the rows.

The Intelligent Autonomous Weeder (IAW) is a robot platform designed for automated weed control in maize fields, utilizing mechanical drivers (Bakker et al. 2010). It autonomously weeded 18 parallel tramlines, each 40 meters in length at a speed of 0.5 meters per second.

Raja et al.,2020 aimed to remove weeds within rows near to tomato and lettuce plants using completely automated system to manage weed knives with an accuracy level of 83%.

Sellmann et al. 2014 , employed a mechanical ramming rod (Bonirob) to crush weeds in carrot cultivation experiments using decision tree learning to differentiate between plants and weeds based on parameters like leaf colour, shape and leaf size. This mechanism claims 90% effectiveness in weed elimination.

Carbon Robotics, a company based in Seattle, engineered a laser weeder characterized by sub-millimeter precision, capable of covering 2 acres per hour at a speed of 1.6 kilometer per hour (Carbon Robotics 2023). While commercial weeding machines are entering the market, their limited applicability to specific crops and high costs hinder widespread adoption.

Detection through deep learning algorithms

Earlier methods for weed and crop differentiation involved extracting features using image processing and employing an ML classifier for pixel classification. The limited improvement in ML accuracy stems from the requirement for prior knowledge in manually designing features. In contrast, neural networks, empowered by increased processing capabilities and abundant training data, autonomously learn features and optimize weights across layers, significantly enhancing DL performance (Zhang et al. 2022).

DL is a subset of ML with a unique learning approach, involving the quantity and data type each algorithm utilizes. It has found uses in various fields that involve computer vision. It is applied in industrial robots, autonomous cars, UAVs and robots for object detection.DL has seen widespread application in agriculture, encompassing weed detection (Garibaldi-Márquez et al. 2022)

Types of CNN and Accuracy rate

Vegetable segmentation was made easier with the light weight sNet's one convolutional layer, ReLU activation function, and max pooling layer.Pixel-wise crop and weed classification was done using the deeper cNet. The cutting-edge approaches like VGG16, ResNet-101 and AlexNet demonstrated significant accuracy of four types of weed detection ranging from 96% to 99% (Jiang et al. 2020).

Traditional semantic segmentation techniques like U-Net - accuracy rate is 89.5% . FCN models recorded accuracy rate of 70.8%. SegNet-based approach produced an accuracy rate of high precision of 92.7%.

Graph Weeds Net, A novel semi-supervised deep framework showed 98.1% accuracy on the Deep Weeds dataset and AlexNet algorithm demonstrated an accuracy of 99.8% (Hu et al. 2020) .

Challenges, Present and Future perspectives in India

In recent years various technologies applied in India to enhance agricultural practices. Internet connectivity is essential to implement precision farming technologies effectively in India especially to the small farms. Internet access and electricity, to support the use of advanced technologies like sensors and drones to rural areas of India are not reliable. Furthermore fragmented farms /pieces of land may not access the precision farming technologies. Awareness and training to the farmers on these viable precision farming technologies may lead to knowledge them.

CONCLUSION

Yield potential of the profitable crops depends on the removal of weeds which compete for nutrients with the crops. Hence weed discrimination from the crops by traditional and advanced techniques were discussed and reviewed. High costs and knowledge demand, unavailability of precision tools/ services may lead to loss in agriculture sector of developing countries . To sum up this review implementation of an automated tools to detect weeds as target that helps to decide the herbicide management. Integration of image processing techniques with real-time control mechanisms will effectively targets weed infestations which ensures an efficient precision and sustainable agriculture.

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