WEED SPECIES IDENTIFICATION IN DIFFERENT CROPS USING PRECISION WEED MANAGEMENT: A REVIEW

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Abstract

Agriculture plays a vital role in societies and requires research, planning, and execution. It is important to research new trends, scientific methods, and boosters that can give a boost it. The farmer can reduce the amount of workload using some technology which is enhancing the quality of cereal. It is important to identify and growth estimation of weed using deep learning technology in the field of convolution neural networks. This review paper is identifying different types of weeds which are harmful to crop and also identify weed controlling mechanism. It is also useful for researchers to assimilate and clustered the weeds using artificial intelligence techniques and machine learning techniques and to study existing technology of weed detection, which is useful for a researcher can propose new techniques for weed classification and detection. This review paper concise the development of weed detection and classification using the most recent technologies in the field of artificial intelligence and image processing techniques. Concretely, the four procedures, i.e., pre-processing, segmentation, feature extraction, and classification is a part of weed detection and classification were presented in detail. Sooner or later, demanding situations and answers furnished by researchers for weed class and detection inside the subject, together with occlusion and overlap of leaves, varying lighting conditions, and specific growth degrees, have been mentioned.

Keywords

Weed detection; Weed Classification; SVM; Deep Learning, CNN.

1. Introduction

Crop[1] production is an important component of agriculture which is responsible for global food management. It requires proper planning and management. Therefore, it is important to invent new trends, scientific methods, and boosters that give a boost to crop production. One of the boosters in this field is soil fertility and its management. The measurement of soil to the right amount of fertilizers or fertilizers can ensure the best results. Information on how to use fertilizer and how to improve the productivity of grain can be readily available to farmers at the right time. This is possible with the use latest technology and technique based on artificial intelligence (AI), machine learning (ML) and deep learning (DL), etc. [Indian govt. Nitti Aayog in its discussion paper on 'National Strategy for Artificial Intelligence 'https://niti.gov.in/national strategy-artificial-intelligence on 4th June 2018]

Explains that the use of artificial intelligence will increase efficiency at each level of agriculture and also increase the income of farmers along with the productivity of crops. These techniques use 'image recognition' as an underlying technology through 'deep learning models'. The same is very crucial in the field of weed detection which will be very fruitful to take necessary steps to improve crop production. There are different varieties of weed that are harmful to crop production and need to be detected in the early stage of growth. The growth of weeds within the crop will affect the basic resources such as water, soil, minerals, fresh air, sunlight, etc which is the basic need of the crop. In recent studies, it has been found that 35% of crops destroyed just due to the growth of different types of weeds in the agriculture field. The main objective of this paper is to study different tools and techniques used by the authors to detect and classify weeds, which are necessary for the assessment of weeds development. Several other computer-oriented techniques such as artificial intelligence, wireless sensor network, some other techniques which improve the quality of agriculture for research also help to researcher. These research papers also briefly describe and maintain the biological method of Weed control strategy such as computer vision technology implemented on the biological method of weed control. For each method described with deficiencies recognized results on insects and plant bacillus, and examples of, and capacity for, integration with biological manipulate. This complete paper is sub-divided into different sections:

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Section 2 describes related work of the concerned area. The weed classification and control techniques are explained under section 3. Section 4, describes Materials and Methodology. Comparative work is given in section 5 and Section 6 is the conclusive section.

2. Related Work

The recent study and research in the field of agriculture predict the yield of the crop is affected by different factors. The weeds are the foremost factor that could harm crop yield. Therefore, this is the most important task to identify and control the weeds at the early stage of weed growth. This section describes the different types of weeds and their management and control techniques. The weed and control classifications are laid-down below:

Yuewei Yang et al. [1] have suggested the using positive enable technique find the exact location of the object and get solution by an encoder-decoder conventional neural network (CNN) were used for fast weed identification of harmful plan like weeds. Further, Chechliński, Łukasz, and Barbara Siemiątkowska. et al. [2] suggested clustering methods like weeds segmentation and classification based on deep learning also explain the benefits, the loss has been discussed. Rasti, Pejman et al. [3] And Inkyu Sa 1,Marija Popovic et al. [4] discuss some techniques for identifying and detect the weed to increase crop production using image processing. Reduce the weeds using automatic robot technique with semantic segmentation CNN (mobile), feature extraction, and recognition. Aji, Wahyu, and Kamarul Hawari et al. [5] Briefly stated by this method exclusively classifies the weed using UAV imaginary and transfer learning with FCN technology. Huang, Huasheng, Jizhong Deng et al. [6] drift the detection of broadleaf weed on various crops. In the weed classification process, an algorithm like multistage scattering transformation was playing an important role, weed detection using convolutional deep learning technique and SVM classifier provide 96.88% accuracy. Zhang, Wenhao, et al. [7] Has suggested a new architecture of RCNN for classification and detection of weed where weed leaf images were classified by PU learning technique, weed characteristic extricates using positive negative problem technique. The development of remark the broadleaf was typical in the crop, VGGNet model useful for various broadleaf identification like amaranths Viridis, boerhavia diffua, anagallis arvenisis,argemone Mexicana. Jalin Ya and Di Cicco, Maurilio et al. [8] The weed categorized accuracies were 70.99%, respectively manually weed detection and identification ware time consuming, using Robot technology implemented Tested is modern deep learning-based image segmentation technique differentiate monocot and die cot weed. Huang, W. et al. [9] Sreelakshmi et al [10] examine 1119 plants 54 test 682 detection and detection accuracy is 0.37% therefore, some weeds are difficult to distinguish visually. Therefore, the category approach insect the pixel-wise object base detection using deep learning VGG 16 FCN technique. Datta et al. [11] demonstrated a framework to classify weed images. Philipp Lotter et al. [12] also use pixel-wise image segmentation photograph sequences allows our system to robustly estimate a pixel-sensible on weed, furnished comparisons to other today's tactics, and display that our device appreciably improves the accuracy of weed segmentation with retraining of the model. Om Tiwari et al. [13] implements an automated approach for the detection of weeds like transfer learning technique reduce the time for determining the weeds using pertained model implemented on some weeds having better accuracy(90%).Heo Choon Ngo et al. [14] implement weed detection using color classification, using an automated image classification system is designed using CNN which is distinguish between weeds and crops, also used the robot Lego Mind storm EV3 which is directly connected to the computer will spray weed directly into the area near or at which time the weeds have been detected. Discussed by compare weed detection, deep learning, 10 and 50 meters and implement on machine learning but the image taken with different space. S.Manvel G.Forero et al. [15]The machine learning technique was obtained 93.23% accuracy as compared to the image processing method. Dyrmann and R. N. Jørgensen et al. [16] get critical analysis of weed image identification, in this research paper approx 17000 weeds images of the wheat crop, this data has been collected by which ATV-mounted camera, for weed detection implement using fully convolution neural network (FCNN).Nima Teimouri and Mads Dyrmann et al. [17] Completely focused on weed growth and implement a deep convolution neural network (DCNN) used for weed growth repugnance's, with the classification of cereal. In this research paper approx 18 weed image species are cover and 9649 images are used for training for the computer system, the computer system can spontaneously, categorized the weed into nine subgroups. That cans performance using of this deep convolution neural network (DCNN) which is estimate 2516 set of images, defluxion of two leaves having 96% accuracy. Andres Milioto, and Philipp Lottes et al.[18] compartmentalization of the crop and weed in sugar beet plant using deep learning. 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3. Weeds classifications and Control Methods

2, 50,000 plant species, weeds are approximately 250 species, primary in agricultural and non-agricultural structures. In recent studies, it has been found that the above-described weeds strongly impact on agriculture system which is the result of heavy loss in the agriculture field. Therefore, it is required to identifying, controlling and reducing their impact on the ecosystem

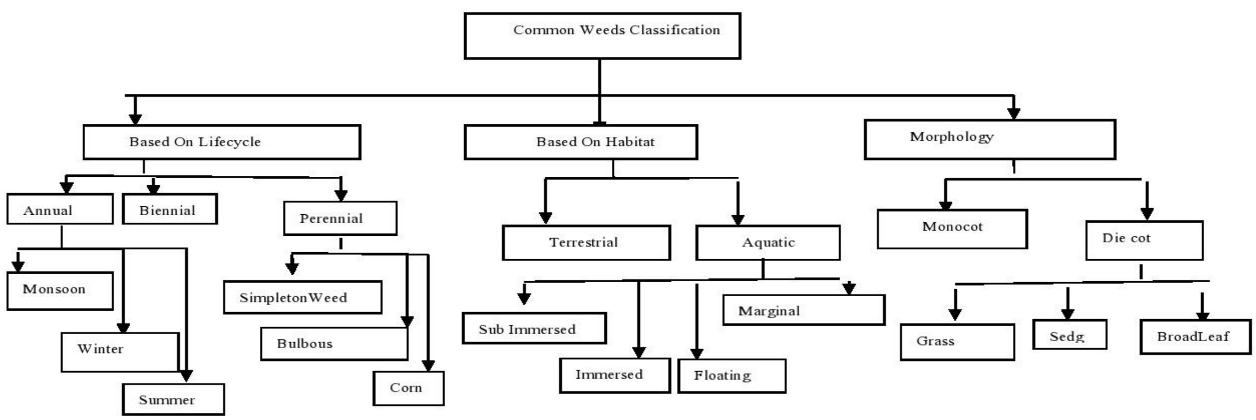

Figure 1: Classification Based on Life-Cycle

3.1 Weeds classifications

The weed is classified into two categories based on life cycle, habitat, and morphology in figure 1 and based on ecology, soil type, and septicity, and noxious weeds.

I. Based on Life span

a) Annual: Annual weeds life cycle is one year. This type of weeds like herbs with shallow roots and stems are weak and propagate through seeds. Annual seed after seeding die away and start the production for the next generation of season. There are some most common annual weeds (Table 1).

- Monsoon annual: This type of weed's life duration is only four months. E.g Commelina benghalensis, Boerhavia erecta.
- Winter annual: These weeds grew during winter sessions and propagate through seeds. Seeding dies away. lambs quarter, Chenopodium album e.g. lambs quarter
- Summer annual: Kharif corps. Foxtail.

b) Biennial weeds: Biennial weeds life durations for two years. First-year they are simply Vegetative and next year produce the seed and flower. Biennials example: Alternanthera echinata, Daucus carota.

c) Perennials: These types of weeds' life cycle are more than two years. It has also been categorized into three types.

Simple: Weed born by seed. Eg. Sonchus arvensis

Bulbous: Weed propagated from seeds. Eg. Allium sp.

Corm: Plants breed through cream and seeds. Eg. Timothy (Phleum pretense)

Table 1.Example of weeds based on life cycle

Annual weeds			Biennial weeds		Perennials weeds		
Monsoon Annual	Winter Annual	Summer Annuals	First Year	Second Year	Simple Perennials	Bulbous Perennials	Corm Perennials:
Commelina	Lambs Quarter e.g.	Kharif Annuals e.g. Foxtail	Daucus,	Alternanthera	Sonchus Arvensis	Allium Sp.	Timothy (Phleum Pratense)
Benghalensis	Chenopodium Album	Ravi	Carota, Nulicauls	Echinata,	Bermuda gras	Hedge bindweed	Japanese knotweed
Boerhavia Erecta	Lambs Quarter	Kharif Annuals	Biennials Example:	Daucus Carota	Wild onion	Yarrow	Leafy spurge

II. Habitat weeds

Terrestrial weed:

That type of weed grew on land soil, called terrestrial plants. The examples of some terrestrial plants are as follows: e.g Air potato

Aquatic weeds:

Aquatic weed plants grew under the water and complete at least one or more years in a biological clock called aquatic weeds. It is also divided into four subcategories like submerged, emerged, marginal and floating weeds (Table 2).

Submersed weeds:

In general, weeds have grown under the water and stems and leave underneath the water facial. Example: Lemma, polyrrhiza e.g. Ceratophyllum demersum.Ceratophyllum Australe Griseb, Ceratophyllum demersum L. (rigid hornwort or common hornwort) - cosmopolitan

Immersed weeds:

This type of weeds completely grew up under the water and root in the mud. E.g. Nelumbium speciosum, Jussieua repens.

Floating weeds:

In this type of weeds, the leaves are gaggle and grew on the water floor both independently. A few weeds are partially unfastened float and few mounted on mud, leaves upward push and fall because the water level increments or diminishes expand at the water floor and not linked to the dust base.

e.g echhornia , pistia, nymphaea e.g. Eichhornia crassipes, Pistia stratiotes, Salvinia sp

Marginal weeds:

This can develop in a wet seaboard with a profundity. The root beneath the water and leaves above the water. Anchored weed in water with major foliage on the above surface. e.g Nilumbium speciosum. Typha, Polygonum, Cephalanthus, Scirpus, and so on.

Table 2. Example of aquatic weed.

Aquatic weeds			
Submersed Weeds:	**Immersed Weeds**	**Marginal Weeds:**	**Floating Weeds:**
Utricularia Stellaris,Polyrrhiza Demersum.	Speciosum Jussieu Repens.	Cephalanthus, Scirpus	Echhornia, Pistia ,Nympheea e.gEichhornia crassps, Pistia stratotes, Salvinia sp., Nymphaea pubescens.

III. Classification according to the cotyledonous character of morphology:

The morphological plant of the plants categorized on insignificance, and also it's has categorized into three types.

a) **Grasses:** It is a Poaceae family, approx all weeds come under on this family called grass which has spiral leaves.

Sedges:
The weed is cyperaceous family graminoid, monocotyledonous flowering plant life known as sedges. Approx 5,500 species described but 2,000 are identified.

Broad Leaved Weeds:
This type of weed comes under on dicotyledonous family, for example flavaria australacica, digera arvensis, tridax procumbens.e.g. Rubus Spp., Bramble, Butterfly-Weed etc

IV. Based on ecological affinities

Wetland weeds:
This type of weed are semi-aquatic, it can grow in two types of ecological condition first under the dehydrated and moderately parched situation. The dissemination of wetland by seed.

Irrigation Lands: The land weeds no longer require greater water it will also no longer as dry land weeds.

Dehydrate Lands: Dehydrate or drylands weeds are deep root system, dryland weeds adapt as glutinous nature and hairiness

V. Based on soil type (Edaphic)

Weeds of regur soil:
Those varieties of weeds are grown in the dehydrated situation
Weeds of red clay soils:
It'll consist of special kinds of numerous plants.

Weeds of loamy soils:
Those types of weed produce sewage like conditions e.g. Leucas Aspera

Weeds of lateritic soils:
e.g. Lantana Camara, Spergula arvensis

VI. Based on specificity:

There are some weeds are identified by specificity, it has categorized into three types a). Poisonous weeds, b). Parasitic weeds c). Aquatic weeds.

Poisonous weeds

These cause livestock to the animals that are accumulated along with barley and maintain to farm animals or even as grazing the cattle devours this toxic plant life e.g. fastuosa (L.) Danert , Stramonium fastuosum (L.) are noxious to living things. The berries of Withania somnifera and seeds of Abrus precatorius are poisonous.

Parasitic weeds
Parasitic weeds are probably a mixture; the weeds depend entirely on the host plant, the parasites that attack.
Some parasites as given below:

Total root parasite – This type of plant depends on another plant and gets nutrition from them. Dendrophthoe,Orobanche ,Viscum,Santalum Aeginetia, lathrea, cistanche etc.

Partial root parasite – e.g Sandalwood tree, Witch weed, Rhinanthus.
Total stem parasite - e.g Dodder (Cucuta) Cucuta rootless yellow color.
Partial stem parasite - e.g Viscum and Loranthus.

Aquatic weeds:
Aquatic weed plants develop in water and have a life-cycle of at least of years and are classified into four types such as submerged, emerged, marginal and floating weeds.

VII. Noxious Weeds:

A poisonous or noxious weed plant discretionary characterized as being particularly unwanted, inconvenient, and hard to control. The status of a plant as a poisonous weed will shift with the lawful translation of a nation or a state, just as with the advancement of new weed control advances. The toxic weeds have a huge ability to imitate and scatter, and they embrace precarious approaches to resist the man's endeavors to dispose of them. The poisonous weeds are some of the time additionally alluded to as exceptional weeds and offensive weeds. Noxious weeds in India Cyperus rotundus, Cynodon dactylon, Parthenium hysterophorus, Eichhornia crassipes, Solanum elaegnifolium, and Orobanche spp.

VIII. Grassland Weeds:

As the name shows, weeds having a place with this class attack prairie, rangelands, and changeless fields, which offer an unexpected biological condition in comparison to the harvest lands. The significant contrast between the two circumstances, from the viewpoint of perspective on weeds, is that while croplands are much of the time worked and upset, the meadows stay undisturbed for an extensive stretch. The meadow weed species, be that as it may, must withstand visit munching, and cutting, just as stomping on by the creatures. Some grassland weeds are equipped with mechanisms to keep the animals away, like bitter leaves, poisonous foliage, prickly shoots, and hard stems.

3.2 Weeds Prevention Methods:

Farmers increase crop production if they remove the weed farm crop, for this, they use a weed removal technique, which is based on the ecological theme. From crop management to complete weed management. For example, weed management with low nutrient management. -External input system.

These weed identification and control techniques are classified into different categories as given below in Figure 2.

I. Preventive Methods

a) Crop Rotation: The crop rotation is a traditional technique implemented by farmers for increase the productivity and prevents the weed from the crop, simply means different crop grew in the same field known as preventive weed control. There are some weed control method repeated yearly, given in table 3

II. Biological Control Method

The biological influences approach uses naturally occurring enemies of the invasive plant to help minimize its effects. Its objective is to Resume the weeds through its herbal opponents and attain permanent weed management hose herbal images of weeds from field, the weeds image acquisition this parts the weed plant image continuously capture images by the camera with high frame rate and resolution and data pre-processing with output images and feature extraction, detection for use the color analysis use is Hue, Saturation, Value (HSV) computation can be used for categorized to determine the mellowness level of weeds. Even though inside the long run, organic management can be cost-effective and diminish the prerequisite

Control practices, now not all weeds are suitable for organic manipulation.

III. Cultural Control Method:

The cultural method is commonly related to farming systems, even though a few factors apply to landscape and bush care practices. This may include the usage of plant species that overwhelm other plant means poisons.

IV. Physical Control

Physically control is the elimination of the weeds using physical or mechanical machines. The approach used often depends on the place of weeds to be controlled by a mechanical method, burning or with the aid of hand, etc.

V. Chemical control

The farmer can use the chemical to remove the weeds but it will also affect to soil and crop, although the usage of chemicals isn't continually essential, herbicides can be a vital and powerful aspect of herbicides.

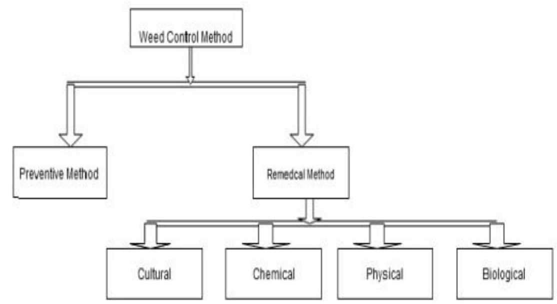

Figure 2. Weed control methods

4. Materials and Methodology

This section laid-down the methodology and techniques of weed recognition and grouping as

Image segmentation and classification

This is used to extract and classify based on image attributes. In the first process, the images are captured by a digital camera stored. PNG, JPG, JPEG, etc. The image acquisition involved three steps for pre-processing [20]. The first steps are involved in the RGB image to grayscale images and second, Steps include the resize image and finally filter the image [21]. Segmentation provides the solution to the image problem, each leaf has a separate feature that significant information is completely helpful to the developer which is recognized and classified. The GLCM is the methods used for texture analysis this degree is accomplished to give the characteristics or reputation of each photo on the way to be used for training and testing [22].GLCM is a group of patterns that can be used to discover or classify various capabilities of your application, with the help of a recognition system (for example, an ANN). First converts the RGB picture to HSV. Later, it is important to scale the HSV matrix to values between 0 and 64. It occurs that the co-incidence matrix is computationally viable prefer

Table 3 Common crop rotation technique.

Cultural exercise	Category	Prevailing impact	Instance
Soil Polarization	Preventive Approach	Weed threshold reduction	Use Of Black
Irrigation and drainage system	Preventive Approach	Reduction of weed emergence	Irrigation placement
Cropashes	Preventive Approach	A discount of weed emergence	Suitable cultivation
Crop impartial association	Cultural Method	Development of crop rival, competence	Better seeding price with transparency.
Crop genotype desire	Cultural Technique	Development of crop competitive influence	Soil beret rates in elementary step.

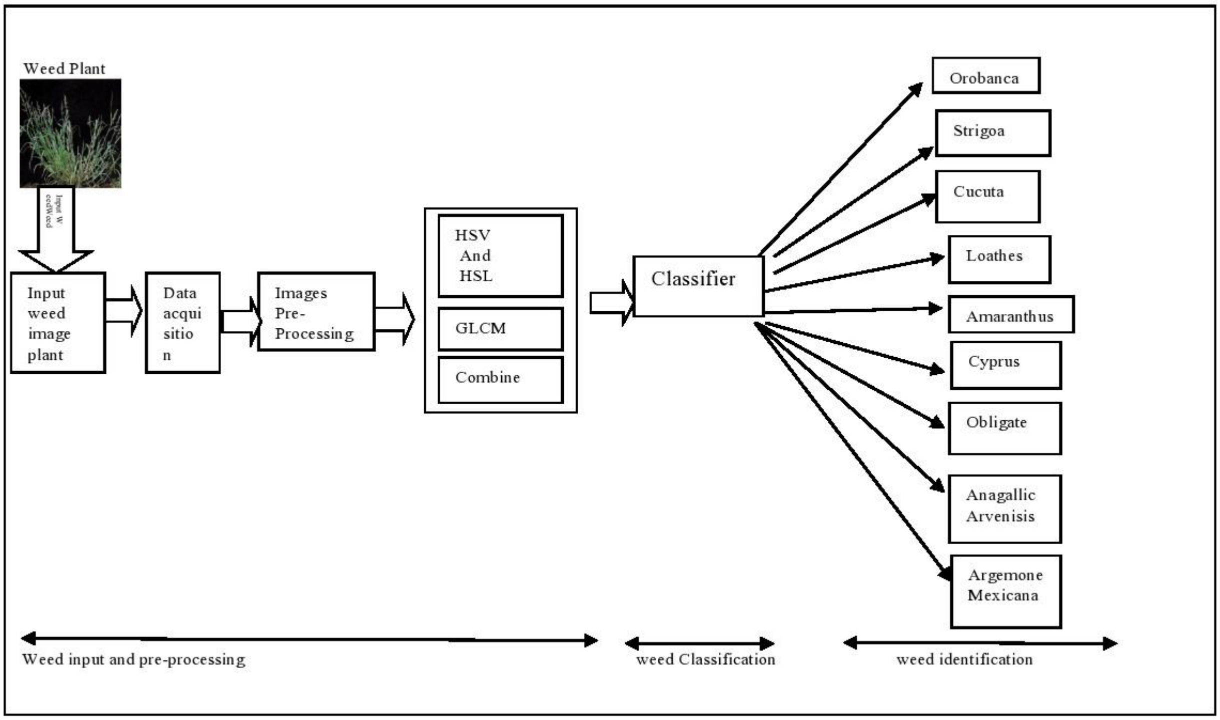

Figure 3: Block diagram of weed classification and detection.

Next, that can compute the co-prevalence matrix for the H, S, and V matrices. Thus, you'll have three co-occurrence matrices, and it could be set parameters (entropy, variance) for each of these matrices. It's far essential to set up correlations between the parameters, to determine which ones are applicable [23]. The GLCM houses of a photo are expressed as a matrix with the identical wide variety of rows and columns gray price in the photograph. The elements of this matrix rely on the frequency of two detailed pixels. Both Pixel pairs can vary relying on their community. These matrix elements consist of 2d-order statistical [24].The implementation of segmented images that can be transformed onto a gray level run length matrix. [25]. Flow chart of GLCM is given below in figure 4.

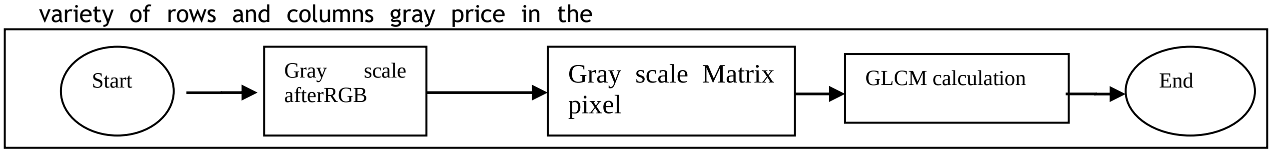

Figure. 4 Flow chart of GLCM

4.2. Convolution Layers

This review paper implements Transfer learning the use with Convolution Neural Network (CNN) for weed detection [13]. Convolutional neural networks use to perform some operations on images and extract some useful information for rained the model. The neural networks are a collection of layers of neurons that are interconnected and the outcome represents the estimates. A Convolution neural network is different and contains three dimensions such as width, height, and depth [14].

a) Network Architecture:

The CNN includes three different layers such as convolution, pooling, and classification. Conventional neural network (CNN) is comely assist to deep studying network. CNN's are typically it's far used to become aware of the phototype from an actual photograph. In this is research paper CNN apply to pick out the weed with the category. there are many exclusive forms of photo category technique consist of a huge wide variety of facts set like photograph net[11], The pre-trained networks which include the VGGNet [8], AlexNet [9], GoogLeNet [10], ResNet [11] [17]. Some other image data set provided by a digital camera set on (MAV) Micro Arial Vehicle [1], Unmanned Arial Vehicle (UAV) [2], TAV mounted camera, which generates the digital image of weeds, transfer learning use with CNN for weed image classifier, some example listed as in table 4.1

Table 4. Weed data execution using CNN

Serial no	Steps	Explanation
1	Data acquisition	Weed plant image acquisition by the camera with a high frame rate and resolution
2.	Images Pre-Processing and techniques	Feature extraction, detection for use of the GLCM, and HSV method provide high evaluation correlation and homogeneity of pictures.
3.	Classifiers	Conventional neural network (CNN), Pooling, flattering, transfer learning to use with CNN for weed image classifier
4.	Classified Weed	It can classify die cot and monocot and broadleaf crop weed, for example, Cyprus, Amaranth

Hue Saturation Value (HSV) color has 3 elements, known as Hue (H), Saturation (S), and cost (V) [19]. The HSV consists of 3 elements, wherein Hue represents coloration, dyeing for saturation brightness and fee degrees, dominance and brightness degrees. [20]. The second segment of weed detection recalls the classifiers, the weed diction is two-step trouble i.e. weed and grain plant. [27].Another classification method also includes K-nearest neighbor (KNN), Complex Tree, and Logistic Regression [36]. There are transfer methods for the switch of knowledge among human beginners. Transfer learning is ordinarily utilized in computer imaginative and prescient and herbal language processing obligations like sentiment evaluation due to the huge amount of computational power required [37].

4.3. Transfer Learning Approach

a) Training to reuse
b) Using a Pre-Trained Model
c) Feature Extraction

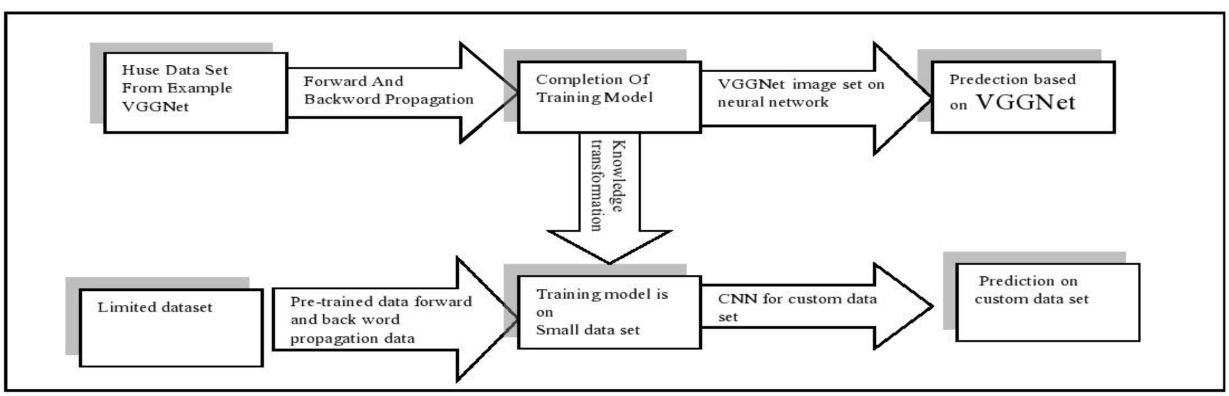

Figure. 5 Transfer learning for weed detection

Transfer learning isn't sincerely a device gaining knowledge of approach but may be visible as a "layout technique" within the subject, as an instance, active getting to know. It's also now not a one-of-a-kind part or takes a look at-place of device mastering [38]

5. Comparative Analysis

Article name	Problem description	Deep learning architecture	Deep Learning model.	Overall Accuracy	Reference no
Object detection using faster RCNN and PU Learning (positive unlabeled)missing data image. (11 Feb. 2020)	Demonstrate that our proposed PU type loss outperforms the same old PN loss on PASCAL VOC and MS COCO throughout a number label missing, as well as on visible Genome and Deep Lesion with complete labels.	Faster RCNN, PU learning Picks due to the fact filters inner that acts as feature Detector.	ResNet101 Faster R-CNN using both PN	Detector performance Accuracy is 88.9%	[7]
Weed classification in grasslands using convolutional neural networks. (sept. 2019)	Computerized identification and selective spraying of weeds (such as dock) in the grass can provide very considerable long-time period ecological and cost advantages. Although the device imaginative and prescient (with the interface to appropriate automation) affords a powerful means of achieving this, the associated demanding situations are bold, because of the complexity of the pics.	Feedforward Neural network for leaf sickness detection CNN(mobile)	V-Net, mobile-nets, DenseNet and ResNet architecture	An effective system for detection and Classification Detect the weed 47 -67%	[3]
Localization And classification of weed using a scattering transformation (26 Jan 2019)	Any weed Localization And classification of weed using a scattering transformation Detection of weeds inside the direction of extreme density existence plant life from the pinnacle view in-depth snapshots. An annotated artificial statistic-set was positioned underneath the size of an employer and a simulator is proposed for a reproducible technique.	Use DCNN for Weed classification also implantable performance	Classification based on SVM Classifier, V-Net architecture.	The superiority of the scatter set of rules with a weed detection Accuracy of around ninety-five% on a different single scale and multi-scale strategies.	[5]
Broadleaf weed using DL CNN and data collect using VGGNET (22 Jan 2019)	Detection of extensive grass weeds in turf grass the use of VGGNet became an exquisite model for detecting various broad floor weeds that develop in Bermuda grass and the detection of cutleaf knight-primrose (Panthera laciniate Hill) in Bahia grass. DatetechNet changed to a high-quality version to be carried out. The mastering fee coverage exponentially decays.	Deep learning CNN (DL-CNN) models and Faster R-CNN	ResNet101 using both VGGNet-16 and Google net, ResNet, DetectNet.	Those fashions carried out excessive F1 rankings (> 0.99) and ordinary accuracy (> 0.99) with recall values of 1.00 inside the test dataset.	[7]
Weed segmentation and classification using Deep neural network Image taken by UAV(Unmanned Arial Vehicle) (7 Sep 2018)	Use image data taken from the unmanned aerial car (UAV) for mapping the weed and crop with a deep neural network (DNN).	DNN, an encoding part with VGG16 layers. DNN, an encoding part with VGG16 layers	Signet, MAV (Macri Arial Vehicle Under the Curve (AUC) with VGGNet-16	Accuracy of crop = 68%, weed = 57%	[2]
Use FCN (Fully Conovional Nural Network)	Weed And Crop Identification on rice field transfer learning and for image use UAV(Unmanned Arial	Transfer learning Patch base CNN And pixel base	Classifier, patch, and pixel base CNN and	The accuracy of the FCN method is 0.935 and weed recognition was	[4]

transfer learning and for image use UAV(unmanned Arial vehicle) (26 April 2018)	Vehicle)	FCN(Fully convolution network), Bayesian		0.883.	
A study on Image-based Broadleaf identification weeds analysis and system implementation based on SVM, and machine learning (2018)	Identification of Broadleaf weeds analysis and system implementation based on SVM. The critical component within smart sprayers image-based weed detection.	Cascaded CNN and SegNet, MAV (Micro Arial Vehicle)	SegNet, MAV (Macri Arial Vehicle Under the Curve (AUC)	Achieve _ 0.8 F1-score and get 0.78 regions underneath the curve (AUC) class metrics	[6]
'WeedNet: implemented to era sizeable Semantic video type the usage of multispectral photo and MAV for clever farming '(11 September 2017)	Selective weeding measures are a critical step in self-sufficient crop control associated with crop health and yield. but, an important venture is to discover dependable and correct weeds to limit harm to the encompassing plants. In this paper, we gift a method for dense semantic weed sorts with multispectral pix amisped through a micro aerial automobile (MAV).	Cascaded CNN and SegNet, MAV (Micro Arial Vehicle)	SegNet, MAV (Macro Arial Vehicle Under the Curve (AUC)	Achieve _ 0.8 F1-score and get 0.78 regions underneath the curve (AUC) class metrics.	[1]
Using KNN and GLCM, HSV color space techniques in the tomato plant.	In tomatoes leaf has one-of-a-kind maturity level; consequently, it's far necessary to apprehend the proper Sample to decide the extent of maturity. Texture evaluation may be processed with the use of the grey level Co-incidence Matrix (GLCM) technique.	K-NN, GLCM, and HSV	GLCM and HSV color space technique	Use color space techniques like GLCM and HSV color space technique accuracy rate 100%.	[11]
Using machine vision and image process techniques: Weed discrimination	This analysis more increased weed detection employing a ground-primarily based mostly system ingenious and anchoring and image processing techniques	Weed discrimination using CNN	Weed identification and discrimination from the crop plant	Using DCNN got 94% accuracy.	[13]
Weed Classification	Crop weed image mapping using water shade method with different species.	CNN and SegNet, MAV (Micro Arial Vehicle	Keras(Tensor Flow FW)	91%	[14]
Weed Classification	Weed Maps, using thresh holding method for weed control in early climates, inflicting star reflections and troubles.	CNN and SegNet, UAV (Unmanned Arial Vehicle	VGG-16, DenseNet-	90.08% (DenseNet)	[15]
Weed Classification	Crop and weed classification in the soybean plant	CNN EfficientNet	SVM: 98%	(CAFFE FW) 98%	[16]
In-depth study for weed detection: Deep sensory neural network architecture for the plant classification	In most cases, weed management within the traditional method depends on manual labor. This method takes time, contributes to high costs, and vital yield losses. The standard application of chemical weed management, however, goes against the hassle of sustainability. To handle this use of laptop computer imaginers and anchors, preciseness agricultural researchers have used remote sensing Weed Maps,	Deep convolutional neural networks (DCNN)	VGG-16, DenseNet	90.08% (DenseNet)	[17]

	however, this has become mostly useless for weed control in early climates, inflicting star reflections and troubles. Satellite imagination includes cloud cowls.				
Crop and weed image mapping using machine learning UAV remote sensing	Weed control pest on rabi crop session weeds using image segmentation method for dense semantic weed sorts with multispectral pix through a micro aerial automobile (MAV).	R-CNN machine learning Deep learning CNN (DL-CNN) models and Faster R-CNN Machine learning,	DNN has SegNet architecture, an coding dispense with VGG16	96.08%(SegNet)	[19]
Using Deep CNN find the Weed growth competition from the crop.	This looks at situ images involving 18 weed species grown within a Time,8000 leaves of these drawings were used for the trained of the weed statistics is taken from the rabi crop.	Deep learning CNN (DL-CNN) models and Faster R-CNN Machine learning,	Our DNN has SegNet architecture an encoding part with VGG16 layers.	78% Maximum accuracy	[8]
Growth of weeds in young coffee plants using CNN.	Competition of weed in flower plants using ResNet-50 in CNN architectures study technique of interference between flowers.	Statically analysis of data taken from the field	Different coffee plants using ResNet-50	Convolutional neural network using inceptionv3 model on 2000 pictures tested, which also are several in cropping.	[10]
Multiclass weed Species data set Dataset for Deep learning: Deep Weeds	Soil types, photograph judgments, and lighting fixtures situations. The common ordinary performance of this method met the maximum accuracy of 90.79%	Deep Learning CNN (DL-CNN) model and quicker R-CNN machine learning,	CNN architecture Inception-V3	ResNet-50Validity accuracy of 96.7% and 97.6%.	
Weed classification: using Image Net	Survey paper measure completely different views equivalent to implications for regulation of weeds, terrestrial weeds, and annual weed	Survey paper on Weed classifications	Mini tab on vex platform weed science.	Researchers for weed detection inside the discipline has been discussed	[12]
Weed Management in the transition to Conservation Agriculture: a Review	The weed management practices used by farmers in conservation agriculture and the modifications initiated thru its adoption.	Deep Convolutional Neural Networks (DCNN)	VGG-16, DenseNet-	In 425 French farm with (Dense Net) 96.09%	[18]
Applications of Computer Vision in Plant Pathology:	Real-time selection support gadgets can beautify crop or plant boom, consequently, increase their productivity, best and financial value. It also permits the North American nation to serve the character by watching plant growth in equalization the surroundings. pc inventive and presenter technology has valid to play a vital place among the degree of programs equivalent to medicine, defense, agriculture, remote sensing, enterprise analysis, etc.	Deep learning CNN (DL-CNN) models and Faster R-CNN	ResNet101 using both VGG-16 and GoogleNet, ResNet, DetectNet	(CAFFE FW) 98%	[20]

6. Conclusions

This paper explains different categories of weeds and control methods used in crops. This paper also explores different techniques that are used for weed management such as artificial intelligence, machine learning, and deep learning with their pros and cons. This paper explains different steps to detect and analyze weed-based images. The steps are pre-processing, Classification,

identification of crop weed and cereal categorization using image processing, artificial intelligence, and deep
Learning processes techniques. In this paper, the evaluation and assessment of various methodologies are mentioned. The emerging approach CNN with transfer learning ideas can be included right into a speaking device that could similarly help farmers in identifying crop weeds of plants. The precise category model allows in predicting the species of pest. Deep learning-based destiny work can gain to farmers. In this review, the paper assists the researcher in further weed identification and detection.

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