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Machine Learning Methods for Weed Recognition in Corn Fields: A Review

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Abstract
Herbicide use is a common practice for managing weeds in wheatgrass fields, but it can be costly, raise ecological concerns, and lead to herbicide resistance. A potential solution to this problem is using machine learning models for precise weed identification. This study provides an overview of the key ML techniques utilized in wheatgrass weed identification, including classifying and detecting objects. A performance evaluation measure, such as accuracy in classification and score F1, were also discussed. Furthermore, potential areas for future research are highlighted, such as increasing a data capacity through enhancing data, leveraging passing learning, and enhancing comprehension of artificial neural networks to avoid excessive fitting and boost transparency. Typically, digital images are utilized as input data in ML weed identification, although hyperspectral data is sometimes employed. The majority of current studies utilize support vector machines and neural networks for this purpose.

Keywords: Machine Learning, Vector Devices, Neural Networks, Weeds

1. Introduction

Zea mays, commonly known as corn, is widely consumed globally, including in the United States. During 2020-2021, the U.S. alone accounted for 26% of the world's corn consumption [1]. As the largest producer of corn in the universe, In 2019-2020, the United States accounted for a total of 345 million tonnes of extraction [1]. The exceedingly productive grain maize, is utilized for a variety of commercial and agricultural applications, including feeding animals, sugar substitutes and biofuels. In relation to the USDA's report on US corn cultivation in 2020, a significant portion (46%) was utilised for feeding animals, 27% was utilized for biofuel production, and the remaining 18 percent went abroad primarily to South Korea, Colombia, Mexico, and Japan. Japan and South Korea depend heavily upon the U.S. to provide animal nutrition based on corn. The remainder of the output (approximately 9%) had been utilized to produce merchandise like sweeteners, corn syrups, cereals, corn starches, and liquids [2]. Recently, corn-based items such as icing supplies, inhibitors of corrosion, and coatings have been created, which could increase corn's local market position. Corn, plays the crucial role in the U.S. economy, as evidenced by the Corn Refiners Association study that found that the corn refining industry alone contributed to an economic output of 47.5 billion dollars in the U.S. in 2020 [3].

One of the obstacles to improving corn production is the difficulty in controlling the growth of weeds. Not only do these plants compete with maize for nourishment and supplies, but they to bring viruses, dangerous microbes, and additional virulent microorganisms, leading to substantial yield reductions [4]. A study based on the USDA-NASS 2014 corn yield report found that weed interference in from 2007 until 2013, maize production led to an annual yield loss of 50 percent and an annual economic loss of $26.7 billion. Weed control is often accomplished at the time applying pesticides or elimination by thermal, mechanical, or electrical processes. Among both of these options, a use of pesticides constitute the most common, but it comes with some significant drawbacks. Applying herbicides to a full field can be extremely costly, according to the 2021 University Harvest Expense and Yield Guide, the average cost per acre is approximately $60, corresponding to 10% of the total anticipated maize sales [5]. The overuse using pesticides can have negative effects on the environment, including soil fertility and aquatic ecosystems, as well as being harmful to human health. Additionally, weeds have been known to become resistant to herbicides over time. To address these issues, targeted herbicide application or manual weed removal is necessary, but identifying weeds can be a challenging task. This is where machine learning (ML) techniques can be useful, as they provide precise weed identification and allow for automation of weed control and management. However, manual identification of weeds is not always feasible due to the scale of the problem. This study provides an overview of the various machine learning (ML) methods that have been used for herb identification in fields corn. A paper also provides technical information such as the type of ML task solved, the category of herbs targeted, the facts utilized, and error metrics used to measure performance. The ML methods are classified into three major groups: Support Vector Machines (S.V.M), Networks Neural, Other. Division 3 covers SVM-based approaches, Division 4 covers Network Neural -based methods, Division 5 delves into random algorithms that have been used in the past for weed identification in corn fields. Division 6 highlights the role of Information in ML achievement and metrics utilized for evaluating techniques. Lastly, Division 7 summarizes the study's conclusions and outlines additional studies using machine learning (ML weed identification. The first table contains the acronyms utilized in the present investigation.

Table 1: A list of acronyms

Acronyms	Explanation
AI	Artificial intelligence
ANN	Artificial neural network
ASM	Active shape modeling
BP	Backpropagational network
CSM	Color Co-Occurrence Method
CDC	Canonical Discriminant classification
CNN	Convolutional neural network
DA	Discriminant analysis
DHT	Double hough transform
DT	Decision tree
DWT	Discrete wavelet transform
EOH	Edge of histogram
FFT	Fast fourier transform
FIP	Fast image processing
FLDA	Fisher Linear Discriminant analysis
GA	Genetic algorithms
GAN	Generative adversarial networks
GLCM	Gray-Level Co-Occurrence Matrix
GMM	Gaussian mixture model
HIS	Hue, intensity, saturation
HT	Hough transform
IOU	Intersection over union
KNN	K nearest neighbor
LBP	Linear binary pattern
LDA	Linear Discriminant analysis
LIDAR	Light detection and ranging
LMC	Linear margin classifier
LR	Linear regression
LS-SVM	Least square-support vector machine
MOG	Mixer of gaussian
ML	Machine learning
NDVI	Normalised difference vegetation index
PCA	Principal components analysis
PCANet	Principal components analysis network
PDF	Probability density functions
PNN	Probabilistic neural network
RBF	Radial basis functions
RCRD	Robust crop row detection
RF	Random forest
RGB	Red, Green, Blue
ROI	Region of interest
RVI	Ratio vegetation index
SMH	Shape matrix histogram
SOM	Self-organazing map
SPCA	Sparse principal components analysis
SVDD	Support victor data description
SVM	Support vector machine
SWLDA	Stepwise linear Discriminant analysis
VI	Vegetation indices
WIR	Weed infestation rate

2. Machine Learning

Artificial Intelligence (AI) has a branch known as Machine Learning (ML) that aims to support computers in discovering the connections a relationship within inputs and outcomes in a particular data set, leading to precise forecasts [11]. Algorithms for ML utilize techniques from statistics to gain knowledge about data that is accessible without explicit instructions for programming [12]. The standard ML framework has a workflow as shown in the first figure, which includes the following steps:

- Information Collection - collecting Information from various sources such as Information sets that are open-source., sensors, etc.
- Information Preparation - washing and transforming the information to make it appropriate for the model.
- Dataset Generation - dividing the classification of data into testing, training, and validation collections.
- The process of training the model includes using the instruction set to teach the model, allowing it to understand the suitable output-input connections.
- Applying the model that was trained to the test set and assessing its effectiveness via metrics for accuracy.
- Model Implementation-providing model access to consumers through software and web applications.

During the development phase of an algorithm, variations in patterns of data as time passes can negatively impact its performance. Making it necessary to update the model and repeat the information collection stage. Additionally, adjusting the worth of the hyperparameters, which is established prior to the learning procedure, can lead to improved results during the evaluation stage. The following serves to regulate the model's general conduct. The placement of the model has evolved a crucial aspect of modern machine learning practices, with a focus on the practical application of ML models. MLOps provides a comprehensive method for deploying deep learning models, and further information can be found in references [6, 7]. ML can also be classified into different categories based within learning of the program's possible developing response type. In guided instruction, the ML algorithms are trained using labeled information to conduct duties such as regression and classification analysis. This type of data includes both the input features, referred to as causal factors, and the corresponding target responses or outcomes, known as variables for output. The objective of classroom supervision understand the connection within their input characteristics and variables that output, in order for future, unseen input features can be predicted with accuracy. Precision agriculture offers various applications for supervised learning as highlighted in [8].

Unsupervised machine learning (ML) involves training algorithms on datasets that are not labeled. The aim of this type of ML is to discover patterns and connections in the data. Some common unsupervised ML techniques include k-means clustering, PCA, and Gaussian mixture models. The implementation of unsupervised acquiring precision industry may be seen in the work of Davis *et al* [9].

Reward training constitutes an automated learning subfield concerned with consecutive making choices in order to attain a specific target. The objective of reinforcement learning is for a computer agent to navigate its environment and make choices that result in maximum incentives. SARSA and Dense Q A system reinforcement learning algorithms. There are resources in [10] for demonstrating the application of reinforcement learning to precision agriculture. Within the following three parts, we give a few words overview widespread ML techniques while thoroughly examine their utilization in the detection vegetation in maize crops.

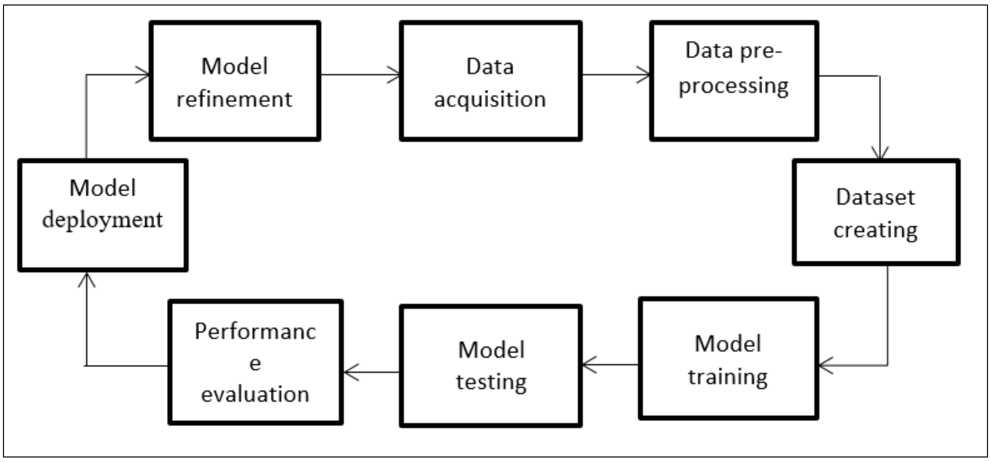

Fig 1: Flowchart of Machine Learning Model Processes

3. Support Vector Devices

One of the supporting product devices representing the linear classifier was first introduced by [11]. The method works by creating hyperplanes to separate data into different classes. The defining characteristic of SVMs is the search for a hyperplane is a structure that optimizes the gap between nearest data points of each class, known as the support vectors. This maximization results in a reduction of generalization error. There are two varieties of edge used in SVMs: Both firm and flexible margins. A firm margin is utilized while the information is uniformly distinct and free of disturbance. But this can lead to overfitting, so a soft margin approach is used to handle noisy data. The soft margin allows some overlap between classes by down weighting the importance of overlapping data points. This approach was introduced by [12] and was applied successfully to recognize handwritten images. Support Vector Devices (SVD) were further enhanced by [13] to handle non-linear classification problems through the utilization of the "Kernel Trick." This approach involves transforming inputs into a higher-dimensional space, allowing linear hyperplanes to effectively separate the data. SVMs have been expanded to also address regression and multi-class classification issues [14]. With its ability to deliver dependable results in tasks such as digital image classification, text categorization, and character recognition, SVMs have become a go-to tool in AI [12, 13, 14]. In precision agriculture, the use of SVMs is also prevalent for identifying weeds [15]. Y. Karimi [16] employed the use of SVMs with a radial basis function (RBF) kernel for detecting prevalent grassy weeds nitrogen toxicity in maize using hyperspectral data. This data comprised of 72 narrow bands, ranging from 408.73 to 947.07 nm, with weed treatment as the major factor and three rates of nitrogen are used as sub-factors. The design SVM achieved a classification precision is 69.2 percent considering the combined vegetation control and rates of nitrogen, but this improved to over 80% when vegetation management and rates of nitrogen have been assessed individually.

In another study, Wu and their colleagues showed the application of using shape characteristics as sources for SVM model to classify maize and vegetation seedlings [17]. The researchers had a collection of 64 photos in RGB, with 40 being employed for teaching and twenty-four test. The quantity of photos for each type of seedling did not disclosed. They transformed RGB photo into HIS (Hue, Intensity, Saturation) space as they believed it would result in better features. Based on these photos, they extracted leaf form variables such as Roundness an R, M, L. These criteria seemed then utilized as inputs for the SVM approach, sigmoid, RBF, and polynomial kernel functions are utilized. The results showed that the RBF-SVM had a classification accuracy of 96.50%, sigmoid-SVM had 67.67%, polynomial-SVM had 90.00%, and ANN (Artificial Neural Network) had 83.20%.

In [18], a weed classification method based on texture was demonstrated. The researchers focused on the deciduous and grassland weed categories. A dataset of 200 colour photos, 100 from every grouping, was used, and process of cross-was performed ten times. The set of data was randomness divided through ten subgroups, with one is employed to evaluate and the remainder to be trained. The LBP (Local Binary Pattern) supervisor was once used encode the images and determine the LBP value for every pixel, resulting in a histogram representing the texture information of the image. The histogram served as the feature vector, which was then fed into an SVM using an categorization using kernel RBF. The classification accuracy achieved was 98.5%.

In the study conducted by Satvini [19], a demonstration of the usage of geometry characteristics for agricultural and weed classification. The study involved the form characteristics such as eccentricities, region, the long of the major direction, boundaries, and duration of the smaller axis. The weeds that were included in the study were Chrysanthemum, Para grass, and Nutsedge. For a purpose of classification, It was utilized by the SVM and RBF and function polynomials. The dataset comprised 2560 images, 1155 of the two categories (crop and weed) was employed to train, and 125 of every class were utilized for validating the model. The SVM's achievement was commendable, As it accurately identified every 125 photos of a field and 104 of the 125 photos of weeds as invasive plants, but incorrectly classified 21 images of weeds as crop. The second table of the research study provides a summary of every project that has engaged SVMs for vegetation identification. Described an approach for classifying monocotyledon and dicotyledonous species in maize seedlings using shape characteristics [20]. A authors utilized a information set consisting of 60 grain 280 weed photo; however, the images' format or nature was not specified. Otsu's threshold was employed, which relies on the Excess green method, to eliminate the background. The authors then area ratio, size ratio, bizarre behaviour, and smoothness were utilized. As shape features to train a probabilistic neural network (PNN) on 20 corn and 80 weed images. They then tested the PNN on 40 corn and 200 weed images, culminating in a 92.4 percent accuracy for maize and a 95 percent accuracy for pest. The creators indicated that a timing collection of images may have contributed to the misclassification. The PNN's performance was compared to that of a backpropagation neural network (The BP system) underwent training and assessment using an identical dataset. The PNN achieved greater results, with maize and vegetation precisions of 87.5 and 93.0 percent respectively, respectively, compared to the BP network.

4. Neural Systems

CNNs are a form of deeper neural network that involves convolutional layers has proven highly effective in various computer vision tasks such as image recognition and classification. CNNs imitate the brain's visual cortex in the brain of a person by identifying visual trends while acquiring important characteristics and spatial relationships in photos using little preprocessing. The research [21] discovered in 1962 that complicated tissues in the apparent cortex accomplish spatial consistency via the adding of distinct simple responsive tissues prompted researcher Fukushima [22] to suggest the initial visual comprehension approach, the "recognition." The recognition simulation was made up of both preliminary processing levels, 'S' (Simple) tissues and 'C' (complex) tissues, to resemble [21] results. 1987 saw [23] the introduction of Time Delay neural network algorithms (TDNN), a convolutional-like neural network system created to be shift-invariant to the context of time. Yet, researcher Yang, was the primary person to introduce the design of CNN as we know it today [24]. The proposed CNN, called "LeNet-5," was successful in classifying handwritten digital photos. LeNet-5's segmentation block included maps of features known as 'filters' or 'kernels' and layers for pooling. Despite introducing an intriguing model for machine vision, the paucity of more powerful computational processors and extensive databases of images impeded its development. In contrast, in 2012, [25]. LeNet was effectively scaled up to a more complex and wider system utilizing GPUs and a more extensive imaging collection (Imagenet). A number of sophisticated artificial neural networks, including GoogLeNet [26], VGG-Net [27], and ResNets [28], In general, CNNs are comprised of two squaresboth the convoluted and completely linked brain blocks. The function of the convoluted prevents was to identify important characteristics of images and spatial associations requiring little processing. Images generally appear as 2-D panel matrices containing numerous channels, like RGB photos, that contain three distinct pairs of 2-D panel matrices. The convolutional block operates on the image input matrices, and the information that results is transformed into a character vector with just a single column. By applying a backpropagation procedure, the characteristics collection is subsequently employed to construct an entirely linked artificial neural network. Within the block generative, the matrix images undergo convolution and then pooling have been developed.

To extract features in CNNs, the convolution technique is used. This involves sliding a smaller kernel matrix over the input image matrix to produce a convolved feature map. Pooling is then performed to down sample the feature maps by extracting either the maximum or average value from a smaller window in the feature maps. The resulting features are the data will be input into a layer with full connectivity and taught with a backpropagation procedure. For classification tasks, different activation functions are used in the hidden and output layers.

In their study, [29] introduced a novel neural network architecture called SOM, which utilizes local linear mappings of neurons for differentiating between weed and crop based on Utilizing a scanning spectrograph, the near-inf spectrum of reflectance was acquired. The compilation of data comprised of reflectance spectra from 88 corn samples and 10 different weed species including buttercup, Canada thistle, charlock, chickweed, dandelion, grass, redshank, stinging nettle, wood sorrel, and yellow trefoilThis led to a combined dataset of 766 bands for weeds and 88 bands for corn. To identify the key factors contributing to differentiation, a separability index was utilized. The main elements along with particular bands "(539, 540, 542, 545, 549, 557, 565, 578, 585, 596, 605, 639, 675, 687, 703, 814, and 840)" were Important factors that contribute to distinction.

The dataset was divided through 10 matching pairs using cross-validation, and the SOM artificial brain has been tested and trained via 90 and 10 percent of every set of data, respectively. Categorization precisiongotten from aggregating every test sets' results was found to be 96% for corn and 90% for weeds. The performance of the SOM network was also compared to other classifiers such as PNN, Multi-layer Perceptron, and Linear Vector Quantization, and it was found to be superior with classification accuracies of 85 percent for maize and 77 percent for weeds, accordingly.

Yang and colleagues (reference [30] proposed an artificial neural network (ANN)-based method for classifying different weed species in cornfields. This study examined widespread lambs quarters, quackgrass, yellow nutsedge, and velvetleaf as weeds. The original dataset included images of unspecified number and size, which were rotated by 90, 180, and 270 degrees to enlarge the extent of the dataset. The resulting collection contained 1736 colour photos of maize, 772 colour photos of velvetleaf, 680 colour photos of quackgrass, 752 colour photos of typical lambs quarters, and 1480 colour photos of yellow nutsedge. Green material was extracted in the photos using the measure of green technique, and the photos were subsequently converted to grey.

The ANN model proved trained without the use of cross-validation, as it was found to be unnecessary in the initial stage. The ANN algorithm achieved a recognition rate of 100% for corn, indicating perfect classification accuracy. For the different weed species, the ANN algorithm achieved recognition rates of 92 percent over velvetleaf, 62 percent to quackgrass, and 80 percent to yellow-nutsedge.

Sajad *et al*. [31] demonstrated a wavelet-based application that utilized two-dimensional DWT for wavelet analysis. This method was employed to extract relevant attributes for categorisation, specifically for weed identification in maize, with the assistance regarding an ANN. The compilation of data included 35 images corn and fifty photographs of weed, The weed species examined in this study included Common lambsquarters, Alhagi maurorum, Convolvulus arvensis L, and Amaranthus. For training, a set of 20 corn images and 30 weed images were utilized, while testing involved 15 corn images and 20 weed imagesInitially, the photos were divided via the Extra green gauge, then proceeded with extraction of features using DWT. The features extracted included Contrast, vitality, chaos, a state of in and local uniformity. The accuracy of categorization achieved by the ANN was 98.8%.

Dellia *et al.* [32] demonstrated an application of CNN for object detection, specifically for discriminating between weeds and maize. Vegetation (foxtail) and vegetation-like (yellow nutsedge) vegetation was investigated. The dataset included 224-aerial photographs of cornfields, and that were categorized within three groups: Instruction (158), confirmation (33), and assessment (33) are the components of training. To obtain smaller images for labeling, a structure of 300 × pixels by 300 was placed above enlarged images. The smaller images were then manually labeled as either weed or non-weed. However, there were significantly more non-weed images than weed images, so the authors utilized an information enhancement approach (not defined) to enhance the images of weeds. Subsequently, the set of data was reorganized into test, validation, and training sets. Two additional datasets were created by adding context to the three hundred x 300-pixel square graphic in the center of the screen: Two sets of images were used, one comprising rectangular images with fully extended context, and the other comprising square photo with context extended along the edges. A rectangular images were created by stretching any side of the central image that lacked a 300-pixel border to the outermost point is produced via the large graphic. while square images were generated by only squeezing outwards to three hundred pixels.

Drymann and colleagues (2021) [33] developed a modified version of VGG16 using a convolutional neural network to classify crops and weeds pixel-by-pixel. The study focused on maize crops, but did not specify the weed species, only that they included 23 different types. The authors created simulated field images by arbitrarily arranging plant segments on above the soil photos, and used ground truth segmented images labeled as blue (weed), red (soil), and green (plant) pixels to generate these simulated images. They used 8340 and 301 segmented plant and soil images, respectively, to create the modeled images. They generated training data employing eighty percent of plant photos and data for testing with the leftover twenty percent. The photos were then scaled to eight hundred x eight hundred pixels, yielding a trained collection of 3463 photos and a verification collection of 123 photos. Two manually segmented actual photographs were used to assess the performance of the crop segment method in this study. The first photograph originated from an ideal maize farm that had few plants coincide, whereas the other one was captured in an area with fewer plants of maize and a greater weed presence. In both instances, the algorithm effectively identified both weeds and crops, with precise categorization of 98.3% and 94.4% for the first and second images, respectively. However, because there were greater number of earth pixels than cropland or vegetation pixels. pixels, the writers calculated intersection over union for every category. For the first image, the crop, soil, and weed IOUs were 0.92, 0.97, and 0.78 subsequently, for this second photograph, they were 0.71, 0.93, and 0.70, respectively. Table 3 provides a summary of studies that have used neural networks to identify weeds.

Wu *et al.* conducted a study on the classification of weeds and maize seedlings because of features textural, wavelet features, and dimensions of fractals. The study aimed to classify weeds into ranks according to their forms and harmful effects. The ExG-ExR colour index was used to convert 84 digitized colour photos (35 of maize and 49 of vegetation) to grayscale versions. The Wavelet function was subsequently utilized to derive features that include the approximating element (A2), precision aspects "(H1, V1, D1, H2, V2, D2)", and values for energy "(eA2, eH1, eV1, eD1, eH2, and eD2)". The resulting energies have been put through a BP system, resulting in a 100% accuracy in separating the weed species, despite not for Maize and plants. When only the electrical features had been utilized, the classification accuracy was 77.14%, while using fractal dimensions alone resulted in 80% accuracy. Combining both features resulted in 94.28% increased classification precision. The BP network also utilized form constraints for weed identification. Wu *et al.*'s work was published in [34, 17, 35].

Table 2: Provides an overview of studies that used SVMs to identify weeds

Study	Research problem	Dstaset	Accuracy
[16]	weed and nitrogen stress in corn detection	In a study, 9 treatments with 20 data points each and 4 replicates per treatment were analyzed, yielding a dataset with 720 entries. Half of the data was designated for training and the other half for testing. The analysis was conducted using a Compact Airborne Spectrographic Imager as the hardware device.	A 10-fold cross-validation method was employed to evaluate the performance of the model (with a portion of the data set designated for testing). The SVD showed accuracy ranging from 66% to 76% when considering both weed and nitrogen application rates together. When the weed and nitrogen treatments were considered separately, the 57accuracy increased to 73% to 83% and 83% to 93%, respectively.
[20]	Textural properties for weed and corn seedling classification	Sixty-six color photographs were taken, comprised of 30 pictures of corn seedlings and 36 pictures of weeds. The split for usage was 60% for training and 40% for testing purposes. The device utilized was a digital camera with a 640x480 pixel resolution.	The Support Device Machine (SVD) generated accuracy rates between 92.31% to 100% with varying feature selections.
[17]	Using shape criteria, you can spot weed and corn seedlings in fields.	A total of 64 color photographs were taken, with 40 images designated for the training set and 24 for the testing set. The images were captured using a digital camera with a resolution of 640×480	The following accuracy rates were achieved using Singular Value Decomposition (SVD): Sigmoid - 96.5%, RBF - 67.67%, and Polynomial - 90%.

		pixels	
[18]	examining regional binary patterns for weed categorization software	The dataset used in this study consisted of a total of 200 images, with 100 images each of broadleaf and grass, respectively. To facilitate training and testing, the dataset was divided into ten subsets, with one subset being designated as the testing set and the remaining nine subsets utilized for training. The hardware employed for capturing the images was a digital camera with a resolution of 1200×768 pixels.	SVD: 98.5%
56	Performance evaluation of weed identification algorithms	A total of 2560 images were captured, with 1155 images taken for each class of weed and crop for training purposes, while 125 images per class were utilized for model validation. The images were captured using a 10-megapixel digital camera	100% SVD for the crop and 83.2% for the we
19	classifying weeds and corn	A total of 1000 images were utilized in the study, consisting of 500 images of crops and 500 images of weeds. Among these, 450 images of each class were used for training, while 100 images were reserved for testing purposes. Unfortunately, the hardware used in the study was not specified.	82.1%
46	Using Wavelet Transform to categorize photographs of marijuana	A total of 1200 images were utilized in the study, consisting of 500 images in the broad category, 500 images in the narrow category, and 200 images in the unknown category. Among these, 600 images were used for training, including 250 images of broad leaves, 250 images of narrow leaves, and 100 images of unknown weeds. The remaining 600 images, which included 250 images of broad leaves, 250 images of narrow leaves, and 100 images of unknown weeds, were used for testing purposes.	Family of Symlet wavelets: 98.1%

Table 3: Contains summaries of experiments using neural networks to identify weeds

Study	Research problem	Dstaset	Accuracy
[29]	neural network-based classifier for plants	A total of 888 plant samples were included in the study, with 88 samples of corn and 800 samples of various weed species, including 77 samples of buttercup (Ranunculus repens), 79 samples of Canada thistle (Cirsium arvense), 75 samples of charlock (Sinapis arvensis), 73 samples of chickweed (Stellaria media), 76 samples of dandelion (Tarraxacum officinale), 80 samples of grass (Poa annua), 78 samples of redshank (Poligonum persicaria), 75 samples of stinging nettle (Urtica dioica), 78 samples of wood sorrel (Onalis europaea), and 75 samples of yellow trefoil (Medicago lupulina). The hardware used for the study was not mentioned.	The accuracy of the different machine learning models for crop and weed identification were reported as follows: PNN achieved 93% accuracy for corn and 85% for weed, Multi-layer Perceptron achieved 96% for corn and 71% for weed, SOM achieved 89% for corn and 77% for weed, and Linear Vector Quantization achieved 92% for corn and 84% for weed.
[30]	Using ANN to spot weeds in cornfields	The researchers captured 1736 color images of corn, 772 of velvetleaf, 672 of quackgrass, 752 of common lambsquarters, and 1480 of yellow nutsedge using a digital camera, specifically a Kodak DC50.	The artificial neural network (ANN) achieved accuracy rates of 100% for corn, 92% for velvetleaf, 62% for quackgrass, and 80% for yellow nutsedge.
74	Textural characteristics for weed, corn, and categorization	A total of 66 color images were captured, comprising 30 images of corn seedlings and 36 images of weeds. The images were taken using a digital camera with a resolution of 640×480 pixels. The dataset was split into a training set consisting of 60% of the images and a testing set consisting of the remaining 40%.	The SVM algorithm with various feature selection techniques achieved accuracies ranging from 92.31% to 100%. On the other hand, the Backpropagation (BP) algorithm achieved an accuracy of 80%.
[35]	Using wavelet characteristics and fractal dimension, weed or corn identification	35 images of corn and 49 of weed were captured using a digital camera with a resolution of 640x480 pixels. For training, 49 images were used, consisting of 20 images of corn and 29 images of weed. The remaining 35 images, comprising of 15 images of corn and 20 images of weed, were used for testing purposes.	The backpropagation (BP) network achieved 77.14% accuracy when trained with seven wavelet energy parameters. When the network was trained with wavelet energy parameters and fractal dimension as input, the accuracy increased to 94.28%.
[34]	identifying individual corn or weed seedlings in fields using shape factors	Two hundred images were taken, consisting of 100 images of broadleaf and 100 images of grass. The dataset was divided into ten subsets, with one subset used for testing and the remaining nine subsets for training. A digital camera with a resolution of 1200x768 pixels was used.	The application of SVD resulted in accuracies of 96.5%, 67.67%, and 90% for three different tasks, while ANN achieved an accuracy of 83.2%.
[20]	Identifying weeds in a field of corn	The dataset consists of 60 color images of corn and 300 images of weed. The dataset was randomly divided into	The PNN achieved a recognition rate of 92.5% for corn seedlings and 95% for weeds.

	seedlings	training and testing sets. The training set consists of 120 images (20 of corn and 100 of weed), and the testing set consists of 240 images (40 of corn and 200 of weed). A digital camera with a resolution of 640×480 pixels was used to capture the images.	
[31]	Crop detection and classification using wavelets	The ANN model was built using 20 images of corn and 30 images of weeds (all vegetation except corn). The model was then evaluated using 15 corn images and 20 weed images. The digital images were obtained using a Canonixus digital camera.	Classification accuracy of 98.8%.
[32]	weed detecting software for aerial images	The dataset consisted of 224 aerial images captured using a Sony A6000 camera mounted on a drone. The images were divided into three categories: no context, full stretched, and edge stretched data	The accuracy of the validation was 97.1% for the edge-stretched category, 94.6% for the no-context category, and 96.3% for the full-stretched category.
[33]	Pixel-by-pixel crop and weed categorization using CNN	The researchers had 8340 and 301 segmented images of plants and soil, respectively. They used 80% of the plant images for generating training data and 20% for generating testing data. No hardware was used in the process.	In the first image, the intersection over union (IOU) values were 0.93 for crop, 0.98 for soil, and 0.79 for weeds. In the second image, the IOU values were 0.71 for crop, 0.93 for soil, and 0.70 for weeds. For the first image, the crop had an IOU of 0.93, the soil had an IOU of 0.98, and the weeds had an IOU of 0.79. In the second image, the crop had an IOU of 0.71, the soil had an IOU of 0.93, and the weeds had an IOU of 0.70. IOU values for the first image were 0.93 (crop), 0.98 (soil), and 0.79 (weeds), while the second image had IOU values of 0.71 (crop), 0.93 (soil), and 0.70 (weeds).

5. Models of Several Types for Weed Identification

Other machine learning methods were utilized to identify weeds in corn besides SVM and NNs. This section outlines these approaches. In one study, the same authors employed discriminant analysis (DA) and decision tree (DT) for the same classification task [16, 36]. Utilising SAS's STEPDISC function, the most important bands were selected from 71 wavebands. The STEPDISC algorithm was utilized for all the three categorization issues, yielding a series of bands for the beginning of growth, the tasselling of the platform, and the completely developed state: teams 34-42-42, teams 26-32-31, and teams 28-19-19, respectfully. For each of the three classification problems, DT selected a smaller number of wavebands. The variety of occurrences where misclassified divided due to the number of instances utilized in the categorization, danger estimation values had been generated. A lower estimating risk indicated a higher classification accuracy. In comparison to ANN, DA gave an accuracy rate for classification of 75 percent over the initial categorization issue, whereas ANN and DT only obtained 58 percent and 60 percent, correspondingly. The categorization precision for the subsequent problem was 87 percent, 76 percent, and 68 percent, whereas the classification precision for the third problem was 83 percent, 81 percent, and 69 percent, correspondingly. DT had the biggest precision in the classification of 71 percent to feed the initial problem with classification during the tassel the platform, whereas ANN had the highest classified precision of 88 percent for the remaining two problems with classificationAt the mature stage, DA enjoyed the greatest results (79 percent) in the combination instance. In addition, ANN enjoyed the greatest results for the remaining two scenarios: nitrogen (88 percent) and weeds (85 percent). DA had the best performance over any of the three problems with classification during the initial stages of development.

Hossein and colleagues [37] presented an early work demonstrating the use of FFT to stay the identification of Millet (pigweed) in maize in real-timemoment.. The authors obtained images from cornfields that contained the weed and then preprocessed the images by applying the Euclidean distance algorithm for color segmentation (utilizing green and red pixel values), Change to monochrome and border detection employing the distinction between the greyish levels of pixels next to it. They then used two-dimensional FFT to segment the images into based on regularity and weight, origins, crop, and greenery, followed by a post-processing stage to examine misunderstandings and merge the regions through a singular figure for plant classification. When the suggested approach was applied to eighty photos of cornfields, FFT revealed an accuracy in classification of 92.8 percent. The writers have additionally discussed the potential of implementing this technique is implemented on an agricultural robotic that includes an electronic camera over taking photos, followed by weed categorization and removal using herbicide sprayers, cutting blades, and other methods.

Gee and colleagues (2004) proposed a method to distinguish among produce and vegetation and determine inter-row the WIR for actual time weed management. The investigation included the sunflower, wheat, and maize harvests, but did not specify the weed species. The study employed two kinds of photos: three hundred agronomic photos and fifty photos for every WIR score of zero, ten percent, twenty percent, thirty percent, forty percent, and fifty percent) produced by an engine for simulation and one hundred wide-view perspectives RGB photos recorded from the sunflower (about 35 photos), grain (35 photos), and grain (30 photos) areas, subsequently processed using the Matlab programme 6.5 software processing. Excess Evergreen thresholds was carried out on the RGB images, and only the green channel was considered as it was not affected by the light source's angle or intensity. A DHT was employed to detect rows of crops in the graphic, and conventional glob colouring evaluation, a region-based separation method, was applied to distinguish between field and vegetation [38].

In another study, [39] presented a wavelet-based approach for distinguishing between crop and weed. The authors used two sets of images: 1530 synthetic grayscale images generated with a simulation engine and an unspecified number of RGB images. The synthetic images were modeled with three Geographical distributions of weeds (Neyman-Scott, Poisson, and mixture) resulting in thirty image series, each with seventeen synthetic images representing various Inter-row the WIR levels ranging between zero percent and eighty percent. The clustering method k-means was used to combine the RGB photos. The authors analyzed 33 ripple is transformed by six ripple basic operations and selected the two best performing wavelets. A genuine bidimensional filter is known as Gabor was used to detect crop rows. The authors compared each of the three wavelet filters is employed for Random filtering. By analyzing the confusion matrix, which included four terminologies (False modification, Real Crop, Artificial Weed, Real Weed). They calculated several metrics, including Initial WIR, Initial Planting Speed, Observed WIRinter-row, CR, TWDR, TCDR and mistaken harvest and vegetation identification error rates.

Asif and colleagues [40] developed a computer vision system for guiding an automated robot to detect and remove weeds. The color segmentation was performed using k-means clustering, and a region of interest (R-O-I) were selected consequently. Afterward, the photos were changed to monochrome, and Sobel edge detection was applied to detect the edges. A technique called the Hough Change was utilized to identify field margins, and guide the robot to follow them. The ROI had been broadened if the high-throughput (HT) refused to discern the field borders following a certain amount of tries. In addition, the HT supplied monitoring metrics which showed the position and orientation of each of the cropping lines relative to the image's center. The system successfully detected and tracked the crop boundaries, with errors of less than ± 5 pixels and ten cents for localization and position, on synthetic images.

Xavier and colleagues [41] developed a real-time computer vision system to detect and classify weeds in maize. The study included four types of weeds. The dataset contained six videos, with each video having an average length of 12 seconds or 300 frames, resulting in a total of 1800 frames. Binary images were obtained by segmenting the images based on a threshold, separating the areas representing foliage in those that did not. The system comprised two independent subsystems, RCRD and FIP, which operated concurrently. RCRD was utilised for recognising cropped grid frames, and by performing the AND operator, it merged all binary frames to create a single image. For images that contained large weed patches, FIP utilized field divisions produced by the RCRD. The small areas of the image's trim row, if they coincided with the positions marked by FIP, and The remainder was destroyed. On average, the algorithm detected eighty-five percent of all vegetation and 69 percent of the actual crop when evaluated on multiple maize videos to various fields and decades. The technology behaved admirably according to various conditions, including changing lighting, soil moisture, and hazy conditions, and even while the crop and weed were in very difficult growth stages.

Longchamps and colleagues [42] examined the potential of LDA for differentiating maize and according to their UV-induced luminescence. The study included various plant species, including “Corn mixtures (Monsanto the disorder 26-78, the company Syngenta N2555, and the wealthy 60T05), monocot/grass mixtures (Echinochloa crus-galli (L.) Beauv, Digitaria ischaemum (Schreb.), the species Setaria glauca (L.) Beauv and Panicum capillare (L.), as well as diatoms mixtures (Ambrosia artemisiifolia (L.), the album (L.), Capsella bursa-pastoris (L.) Med, and It retroflexus (L)”. The researchers collected 1440 firefly signatures in spectra from several comparable studies conducted at various points in time, but owing to lost spectra, just 1361 spectral identities had been accessible. Employing PCA, the most vital data was determined. The researchers then utilized LDA via the botanical genus and the initial five main elements as variables and carried out cross-validity, yielding a matrix of confusion with a 37 percent error in prediction. They then performed another categorization by clustering the mixtures together, which produced a matrix of confusion with an estimated error of 8.2 percent and a success rate of 91.8 percent for classification. 9 and 49 grass spectra were incorrectly categorized as Maize and algae, accordingly, out of 388 grassland spectra; the rest of them were properly categorised.

Montalvo and colleagues [43] developed a method to detect crop rows in high weed pressure maize fields. The dataset included 300 RGB images of maize, with 200 photos displaying dense vegetation growth and 100 images having exceptionally high weed densities. To separate the crop and weed, Initially, the photos were converted to monochrome via the Excessive The author Indicator and then subjected to a double Otsu approach. Using a regression method employing sum minimum squares, the horizontal lines related to the agricultural plots were determined. The authors compared the efficiency of linear regression with regard to though transform for photos of different decisions (1390 × 1044, 696 × 522, 720 × 576, and 360 × 288). LR outperformed HT for all resolutions, with the highest effectiveness percentage achieved for images with a resolution of 1390 × 1044, where LR scored 95.5% and HT scored 89.3%. The weed species involved in the study were not mentioned.

Gao and colleagues [44] investigated the possibility of identifying weeds and hyperspectral imaging of maize. The research included three types of weeds: Cirsium arvensis, Rumex, and Cirsium arvense, and 25 images of maize. The authors used ROIs from the leaves of each plant, with a total of 79, 80, 80, and 84 ROIs over specifically, Rumex, Cirsium arvense, and maize, Cirsium arvensis, in that order. Reflectance calibration was performed for each band, and NDVI and RVI values were calculated for each ROI. Principal component analysis was then applied to reduce redundancy, and the initial five main elements were analysed in greater detail. Random forest detectors were built about multiple spectral character combinations and an accuracy-focused reduction of features method was used to select the 30 most important features. The RF models were evaluated using A single set is used to evaluate and a total of four to serve as training in a five times a cross-valid. The results showed a precision and recall of 94% and 100%, respectively, for maize, 70.3% precision for Rumex, 65.9% precision for Cirsium arvense, and 95.9% precision for Cirsium arvensis. The optimal RF model was found to outperform KNN, as determined by a McNemar test 0.05 at the reliability stage.

Liu et. al. [45] presented a fatal object detection approach that utilized SVDD to distinguish between corn and weeds. RGB images were initially collected, 75 smaller photos (256 256 frames) of maize and 43 smaller photos (256 256 frames) of vegetation have been obtained using a 256 256 pixel photograph. The specific type/species of weed was not mentioned. The photos had been then converted to grayscale and binary utilising the surplus green indicator. Next, wavelet decomposition was applied to draw out physical and energy-based characteristicsA multiresolution dimensional investigation separated frequency components into low and high frequencies. The images were decomposed into four groups: low-frequency component A1, high-frequency components H1, D1 (in x, y, and xy directions). RATE, where RATE is defined as the quantity of properly categorized items reduced by the overall amount of items, was utilized to evaluate the model's success. The SVDD model with the highest efficacy was validated 88.2 percent of the time. When T was the input vector. The study chose several morphologies and 5 wavelet-based characteristics that had a RATE>60% followed by generated SVDD predictions using every possible combination of those attributes for further analysis.

Shubham [46] presented a method for distinguishing between crops and vegetation in a field of corn. The study utilized a collection of sixty RGB photos of a corn area, yet the vegetation type/species wasn't mentioned. The green indicator has been utilized to transform those photographs into cyan, magenta, and yellow. To distinguish between cereals and plant growth, the dual thresholding Otsu method was utilized. In regions of dense vegetation growth, the PCA technique was used to differentiate between crops and weeds across each crop row. The PCA technique achieved a classification accuracy of 91.67% by correctly identifying 55 out of the 60 images as either crop or weed.

A. and A. [47] presented a weed-control automaton that uses pixel classification to identify weeds in cornfields. The dataset included 73 images of a cornfield, with no mention of the type/species of weed. The Surplus green procedure was applied for obtaining plant elements in the initial pictures, before auto-clustering. Clustering was applied to the colour level of a photo, and morphological operations were performed. Wavelet reshape was utilised in order to derive spatial and frequency characteristics, which were then utilised for identifying. the LabVIEW program was employed to carry out the entire procedure, and the algorithm used for classification identified 70 of 73 photos with a 95.89% precision rate. Once vegetation sections were determined, an interface made of hardware was employed to provide spraying instructions to the robot's nozzles.

Pantazi and colleagues [48] developed a novel dynamic education method to distinguish among corn as well as various weed organisms by analyzing the differences based on their infrared projection. Ten species of weeds were included in the study: The genus Ran returns, Urtica dioica, Medicago among, Po annual, Cirsium arvense, the Oxalis plant europaea, Stellaria the press, Taraxacum officinale, Sinapis arvensis, and the genus Poly persicaria. A hyperspectral visual scanner installed on a vehicle served to gather spectral characteristics, which required albedo computation, plant choice, NDVI, resolution in space, and spectral evaluation. Diffuse banding selected had been 550, 580, 660, and 830 nm. One-class classifiers were used to identify and remove the weeds as outliers, and the remaining weed species were included in a fresh multiclass classifier that could detect any novel kinds of plants that emerged. This procedure continued as long as the multi-class predictor contained all marijuana classes. Machine learning methods for the identification of the vegetation species, we utilized SVMs, self-encoder MOG, as well as SOM. On 110 maize plant spectrum, decision-making was carried out, leading to a collection of 110 specimens, each with a vector formed containing four properties. This process was repeated iteratively for each new weed species. The first-class MOG and SOM obtained a 100 percent produce identification rate. whereas the highest rates of identification over weed taxa are observed in were achieved by MOG and SOM for Cirsium arvense (98.14 percent SOM as well as 98.15 percent MOG), Sinapis arvensis (90.74 percent SOM), Stellaria media (94.44 percent MOG and 92.59% SOM), Tarraxacum officinale (90.74 percent SOM), Poa annua (94.44 percent SOM), Polygonum persicaria (94.44 percent SOM), Urtica dioica (94.44% SOM), and Medicago lupulina (94.44 percent SOM). Good identification rates were achieved for Medicago as lupulin (83.33 percent), Oxalis also europaea (85.19 percent), Taraxacum beneficial (79.63 percent), and Poa annua (85.19%) using the autoencoder, SOM, and SOM, correspondingly.

6. Measures of Performance, Data Augmentation, Transfer Learning, and Dataset Size

O train a classification model with high accuracy, a substantial amount information and powerful calculating equipment are usually required. The quantity and quality of the dataset can significantly affect the ML model's performance in image classification. Research studies [49, 50, 51] have established that smaller datasets lead to lower classification accuracy. Multiple variables, including the number of segmentation groups, the level of detail of the characteristics of the image to be categorized, and class imbalance, determine the quantity of the set of ideas necessary to achieve the intended precision. As an instance [51]. Found which to achieve 90% accuracy, a 6000-image collection was examined. needed for three classification categories, while 40,000 was required for eight categories [52]. Using a small dataset may cause the model to overfit [53], which means the model memorizes variability and fundamental interactions, and scores unfavorably on potential data sets [54]. However, in some domains, it may not be feasible or cost-effective to gather a large training dataset.

Table 4: Contains summaries of studies that used various models to identify weeds

Study	Research problem	Dataset	Accuracy
[36]	Weed and nitrogen stress in corn detection	A data set of 720 entries was created with 20 data points of 9 treatments, each with 4 replicates. For training purposes, 50% of the data was used, while the remaining 50% was used for testing. The hardware employed was a Compact Airborne Spectrographic Imager (CASI).	The classification performance of three different models was evaluated for two different classification problems at different growth stages. For the first classification problem at the tasseling stage, the DT model achieved a 71% accuracy, while the ANN model achieved the same accuracy level. For the third classification problem at the full growth stage, the DA model achieved a higher accuracy of 79%
[37]	Classification of weeds and corn using FFT	The study utilized robotic cultivators, equipped with a digital camera for image capturing, and pre-processing techniques were employed to obtain RGB images.	The researchers employed 80 images of corn fields to assess the accuracy of the classification. They detected 5927 blocks labeled as weeds and 3217 as crops, out of a total of 8579 blocks that were correctly classified. The accuracy of the model was 92.8%
[38]	Crop and weed differentiation in agronomic photographs	The experiment used a total of 400 images, consisting of 300 simulated images and 100 in-field images. Among the in-field images, there were 35 of wheat, 35 of sunflower, and 30 of maize.	In the case of simulated images, the classification accuracy was 100% for crops with low WIR, while for medium WIR, the accuracy was 94% and 92% for two different types of crops. For high WIR, the accuracy was 89% and 82% for the same two crop types. For the 100 in-field RGB images, the accuracy was 88% for 30 images of maize with low WIR.
[39]	Utilizing the wavelet transform, distinguish between crops and weeds.	1530 pictures were taken using a CANON Ixus 330 digital camera.	The accuracy for Daubechies 25 was 80.7% while for Discrete approximation Meyer wavelets it was 80.6%.
[40]	autonomous weed detection using vision	No data information available Equipment used: not brought up	To ensure accurate results, the allowable error for translation and orientation is set to be no more than ±5 pixels and ±10 degrees, respectively.
[42]	Based on their UV-induced fluorescence spectral signature, crops and weeds are classified.	No data information available Equipment used: not brought up	LDA over PCA: 91.8%
[41]	Real-time image processing for crop and weed differentiation	The study employed six video segments, each lasting an average of 12 seconds (equivalent to 300 frames), yielding a total of 1800 frames. The hardware utilized for data acquisition included Sony DCR PC110E and JVC GR-DV700E cameras, which captured images at a resolution of 720×576 pixels.	The system was able to achieve a weed detection rate of approximately 95% and a crop detection rate of around 80% across varying environmental conditions.
[45]	Utilizing SVDD to identify photos of weed and corn	A total of 118 color images were captured using an Olympus FE-280 digital camera, which has a resolution of 1280×960 pixels. For training purposes, 40 images of corn and 10 images of weeds were used, while 35 corn and 33 weed images were used for testing.	95.59% SVDD (eH2, eV2, T) 95.59% SVDD (eH2, eV2, C, D, and T).
[55]	Using LIDAR to distinguish between weeds and corn	1558 sample units Use of hardware not specified	The overall accuracy for CDA was found to be 72.2%. The accuracy for dicots was 64.5%, while the accuracy for crops was 74.3%.
[47]	Automatic weed and corn identification	The study used 73 images captured by a digital camera, specifically a normal webcam. RGB images were obtained at a size of 640×480 pixels.	95.89%. 3 photos were improperly categorised.
[44]	Hyperspectral imaging was used to differentiate between weed and maize.	A set of 110 spectra obtained from maize plants were used for feature selection, resulting in 110 representative samples. One-class classifiers were then evaluated to identify new species by testing 54 additional samples of maize plants and 54 samples of a single weed species as outliers. The imaging technique employed was hyperspectral, and the hardware used for data acquisition was Inspector V9, which incorporates a 10-bit integration charge-coupled device.	One-class classifiers based on MOG and SOM achieved 100% accuracy. For the MOG-based classifier, the accuracy ranged from 31% to 98%, while for the SOM-based classifier, the accuracy ranged from 53% to 94%.

The significance of bigger data sets for better categorization is regularly emphasized. In many situations, accuracy by itself is insufficient for assessing the efficacy of a machine learning model. Additional performance measures, including the F1-s recall, precision, matrix of confusion, loss- log, and AUC-ROC, are commonly used to assess the performance of a model [56]. Accuracy, defined as the ratio of when the information being collected is unbalanced, comparing the number of precise forecasts to the entirety of forecasts can be deceiving. To be able to achieve fully comprehend the use of other performance metrics, it is necessary to understand fundamental terminologies including accurate positive tests, erroneous positives, exact adverse effects, and inaccurate negatives Table 5 outlines the meanings of the aforementioned phrases, while Table 6 provides the numerical meanings of frequently utilized metrics for performance.

The matrix of confusion gives a summary of the advantages and disadvantages anticipated through the algorithm, but it is not an indicator of performance per se. Fig 2 illustrates a confusion matrix for binary classification. Pinpoint gauges the proportion of correctly anticipated signals relative to the overall amount of projected positives, with greater accuracy showing fewer errors in the algorithm. In circumstances in which false alarms are extremely undesirable, it is useful. Memory, sensibility, or real-positive rate quantifies the capacity of a model to foresee genuine positives relative to the total number of true positives. A greater memory rate is essential for identifying illnesses. The F1 indicator assigns erroneous positives and erroneous negatives to the same weight and is the average of both recall and accuracy. The rate of false positives or miss percentage is the cumulative opposite of susceptibility and assesses the percentage of identified denials relative to the entirety of expected negatives. Log-loss is often employed in binary sorting to quantify the variation between the anticipated likelihood of a situation falling into a class and the actual likelihood (typically 1).

Table 5: Classifier prediction definitions

Terminology	Definition
False Positive FP	An instance was incorrectly assigned to a specific class
True Positive TP	correctly attributed a particular instance to a class
False Negative FN	An instance that was incorrectly classified as a member of a class
True Negative TN	An instance that has been correctly identified does not belong to a certain class.

Table 6: lists the definitions of performance metrics in mathematics

Performance indicator	Definition
Precision (P)	TP/(TP+FP)
Specificity (S) / True Negative Rate (TNR)	TN/(TN+FP)
Recall (R) / True Positive Rate (TPR)	TP/(TP+FN)
F1 Score	2PR/(P + R)
Miss Rate / False Positive Rate (FPR)	FN/(TP+FN)
Log Loss (for one-hot coded vectors)	-log p
Note that 'p' refers to the probability of an instance being classified in a particular class.	

Signal		Anticipated class	
		-	+
Actual Class	_	Number of True Negatives	Number of False Positive
	+	Number of False Negative	Number of True Positive

Fig 2: Shows the confusion matrix for a binary classification task

The receiver working characteristic (ROC) graph is defined as widely used as a performance metric for categorization binary algorithms with unequal sets of data [57]. This graph compares the percent of true positives (Y line) with the rate of false positives (X line) for various categorization criteria (the likelihood thresholds). It is essential to note that a classifier model aims to strike a balance between authentic findings and erroneous positives. A randomised classifier geared to produce more true positives may also generate false positives at the same rate. Therefore, arbitrary segmentation in such cases followed by 45-degree ROC horizontal line via an AUC (area under the curve) of 0.5. A classifier with subpar performance lies below this horizontal line and possesses an AUC level below 0.5. Therefore, an effective predictor has to have an area under the curve via an AUC score larger than 0.5 that lies above this straight line.

7. Conclusion and Future Research Directions for the Identification of Weeds in Corn

In the present study, that we conducted an analysis of 35 research studies focusing on maize identification of weeds. Twenty-seven investigations towards of a total of thirty-five research. Were dedicated to the problem of classification, whereas seven tackled the issue of recognising an object. Additionally, dual documents addressed each of these issues. Fig 3 depicts the placement of those pieces by algorithms and problem type. In these studies, three machine learning SVM, Artificial Neural Networks, and various methods (such as networks Bayesian, trees of decisions, Evolutionary Algorithms, etc.) were utilized Eight of the offered articles employed SVM as an artificial learning technique, ten employed artificial neural networks, and seventeenth employed other techniques. Fig 4 demonstrates the placement of articles based on the ML technique employed. Upon closer examination, It had been discovered It was found that the SVM via RBF function in the kernel was the least popular SVM kind, whereas the one using BP was the majority popular neural network type, nevertheless, CNNs had been extensively utilised. Popular in the Assorted methods were Fourier evolves, as well as DT, PCA, tailored vision systems, etc. Color data (images and videos) was the most commonly used type of data, accounting for eighteen of the submitted articles, data from spectroscopy (including hyperspectral information, absorption wavelengths, and luminescence wavelengths, among others) was also utilized. Fig 5 depicts the arrangement of papers according to the data category concerned. The papers discussed an array of vegetation pertaining to various groups, such as grassy, governing grassy, broadleaf, narrow-leaf, monocotyledonous, dominant broad-leaf, dicotyledonous, etc.

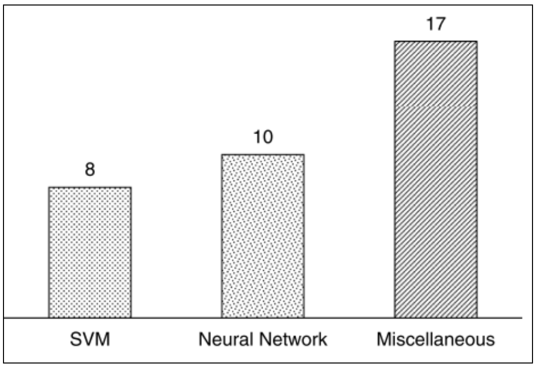

Fig 3: The distribution of Machine learning techniques used for weed detection in corn fields

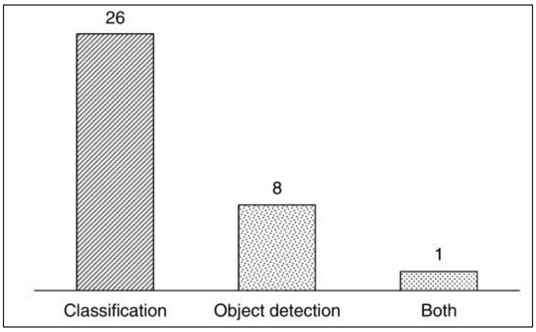

Fig. 4: Displays the distribution frequency of machine learning tasks used for detecting weeds in corn fields

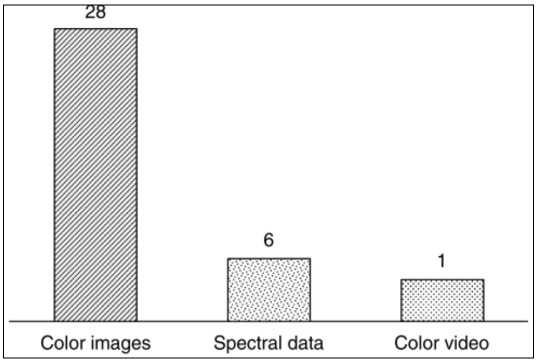

Fig 5: Illustrates the frequency distribution of different data types utilized in the detection of weeds in corn fields

8. References

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