A Review On Machine Learning And Deep Learning Models For Pest Detection For Precision Agriculture Applications

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Abstract- *Agriculture constantly faces various challenges including attacks from new pests and insects. Often, with large farm sizes and plummeting manpower in the agricultural sector, it becomes challenging to continuously monitor crops for pest infestation. Precision agriculture has emerged as a promising and much sought after technique for automated and quick detection of pests in agricultural farms. With the advent of inexpensive and compact drones, image capturing and processing techniques based on machine learning, automated detection of pest attacks has gained prominence. In this research paper, a specific type of pest attack known as the white fly attack has been investigated which affects a variety of crops. This paper presents a detailed background of precision agriculture based techniques for automated detection of white fly attacks on crops. A thorough investigation of image enhancement, segmentation, feature extraction and classification pertaining to white fly attacks has been resented. Salient features of the contemporary techniques used for the purpose have been cited and evaluated.*

Keywords: Precision Agriculture, White Fly pest detection, Image Processing, Segmentation, Feature Extraction, Machine Learning, Accuracy.

I. INTRODUCTION

Agriculture has seen a tremendous shift in terms of technological use over the last decade. With the increase in the farm size and concentration of crops, the use of technology has come in handful. The major technological aspects however have been mostly mechanical or bio-technological in aspect [1]. However, off late, some of the problems which could not be tackled by mechanical systems or were not efficient are being explored by artificial intelligence and machine learning. One such domain is the use of artificial intelligence and machine learning for crop weed identification. It is basically used for precision agriculture applications. Precision agriculture can be defined as a farming management concept based on observing, measuring and responding to inter and intra-field variability in crops. Precision agriculture has also been enabled by unmanned aerial vehicles which are relatively inexpensive and can be operated by novice pilots These agricultural drones can be equipped with multispectral or RGB cameras to capture many images of a field that can be processed using photogrammetric methods to create maps or photos. These drones are capable of capturing imagery for a variety of purposes and with several metrics such as elevation and Vegetative. This imagery is then turned into maps which can be used to optimize crop inputs such as water, fertilizer or chemicals such as herbicides and growth regulators through variable rate applications. While several applications of precision agriculture can be implemented, one of the most important applications remains is the accurate detection of weeds employing precision agriculture [2]. Pests and weeds grow continuously on the farmlands and consume the resources of the actual crop under interest. In the event of large farm sizes and migration population towards cities, there has arisen a need for automated pest detection or to be more precise, automated pest infestation classification to aid farmers and agriculturists alike. This would however, employ artificial intelligence and machine learning based techniques which can be used to automate the process.

Fig. 1 A typical pest infestation

Whiteflies have a host range of more than 250 plants including cotton, cassava, sweet potato and tomato, which may grow in different site characteristics. The large number of hosts for whiteflies makes them an extremely dangerous pest category which can destroy crops. The whitefly (Bemisia tabaci) is one of the most common pest and plant-viral component responsible for transmitting plant related diseases. Automated detection of whitefly attacks has been an active area of research as design of robust automated techniques is highly challenging due to the variation in the crop, extremely small size of whiteflies and the conditions being extremely site specific [3]-[4].Off late, automated techniques for the detection of whiteflies are being explored with an aim to attain high accuracy of classification. However, it is extremely challenging since a technique developed for one scenario does not necessarily work in another scenario due to differences in the pest site background [5],[6].. This paper presents the various tools and techniques adopted for separation or segmentation, feature extraction and machine learning based automated classification. The paper is arranged as:

Section 1 introduces the concepts of precision agriculture and its need and white fly pest infestation. Section 2 of the paper discusses the various sub-techniques required for processing of the images and classification of images. Section 3 presents a summary of the previous work in the domain highlighting the salient features and also the research gaps identified. Finally, section 4 presents the concluding remarks and future directions of research.

Automated Detection of White Fly Infestation

The automated detection of white fly attacks is challenging due to a multitude of reasons which include:

Large variation in the crop size and texture, extremely small size of whiteflies and variation in sizes of child and adult whiteflies, conditions being extremely site specific, variation of pest-crop backgrounds, images being affected by effects of noise and blurring, automated models being non-reusable due to being site and data specific. Hence, prior to classification, data pre-processing is to be invariable employed to facilitate classification. Each of the processes is described subsequently.

2.1 Image Processing:

Prior to computing important parameters or feature of the fundus image, which lays the foundation for the final classification, it is necessary to process the image for the following reasons:

Illumination Correction: In this part, the inconsistencies in the image illumination are corrected so as to make the image background uniform and homogenous. Illumination inconsistencies occur due to capturing the image from different angles which makes the reflection from the retinal image variable rendering inconsistencies. Inconsistencies in the illumination canbe caused due to the position and orientation of the source, the non-homogeneity of wavelengths of the source, the nature of the surface such as smoothness, orientation and material characteristics and finally the characteristics of the sensing device such as resolution, capturing capability and sensitivity [7]. Typically, illumination correction is done based on the computation of the correlation co-efficient given by:

$$Corr2(x,y) = \frac{O(x,y) - D(x,y)}{B(x,y) - D(X,y)}.N \quad (1)$$

Here,
Corr2 represents the 2 dimensional cross correlation,
N is termed as the normalizing factor
O represents the original image
D represents the dark image
B represents the bright image

The normalizing term 'N' is computed as:

$$N = \frac{mean\{O(x,y)\}}{\frac{O(x,y)-D(x,y)}{B(x,y)-D(X,y)}} \quad (2)$$

Here,
Mean represents the average value of the random variables (x,y) which are the pixel values of the images.

Another common approach is the use of low pass filtering which considers the inconsistencies to occur in the low spectral range of the image and are filtered out using a low pass filter (LPF), given by:

$$N_I = O(x,y) - LPF\{O(x,y)\} + mean[LPF\{O(x,y)\}] \quad (3)$$

Here,
N_I represents the normalized image
O represents the original image
LPF stands for the low pass filter

Segmentation: This process of separating the area under interest from the composite image is called segmentation [8]-[10]. The segmentation is typically a threshold based segmentation since the parts to be separated are not generally regular shapes. The segmentation is generally done adopting the sudden change in pixel characteristics given by the gradient:

$$G = max(r, x_0, y_0)\left|K_\sigma(r)\frac{\partial}{\partial r}\oint_{r,x_0,y_0}^{r,x_f,y_f}\frac{I(x,y)}{2\pi r}ds\right| \quad (4)$$

Here,
G is the gradient
(x,y) are the image pixels
r represents the image radius
ds is the surface integral
K is a typically a Gaussian kernel

The gradient based method allows to find the maximum change in the pixel intensities to perform the thresholding so as to separate out the vessels. Further the inpainting can be performed based on the neighbouring pixel information and the stochastic characteristics utilizing the fact that image regions generally comprise of highly redundant values. Considering the region to be inpainted as S and its boundary to be δS, inpainting is performed by computing the stochastic parameters around δS and gradually moving towards S as:

$$\frac{\partial I}{\partial (x,y)} = \nabla(\Delta I).\nabla^{O} I \quad (5)$$

Here,
$\frac{\partial I}{\partial (x,y)}$ represents the partial derivative of the Image w.r.t. x & y
ΔI represents the Laplacian of I
∇^{O} represents the orthogonal gradient.

Finally the optical nerve is normalized to compute the CRD of the image.

2.2 Feature Extraction:

Feature Extraction: The classification of a lead as infested or non-infested is to be done using any automated classifier but machine learning classifiers, which needs to be fed with image features or parameters which can help the classifier to learn the differences between the two classes of data [6]. Typically, the features care stochastic features of the image such as the mean, variance, standard deviation, skewness, correlation etc. The feature extraction is critically important since the classifier would decide based on the feature vector whether any new image is infested or not. Apart from the statistical features, some features can also be computed in the transform domain. Some of the common statistical features for grayscale or RGB images are [12]:

$$M \text{ or } E_1 = \frac{1}{N}\sum_{i,j}^{N} f_{i,j} \quad (6)$$

$$sd = \sqrt{\frac{1}{N}\sum_{i,j}^{N}(f_{i,j} - E_1)^2} \quad (7)$$

$$v = \frac{1}{N}\sum_{i,j}^{N}(f_{i,j} - E_1)^2 \quad (8)$$

$$k = \sqrt[3]{\frac{1}{N}\sum_{i,j}^{N}(f_{i,j} - E_1)^3} \quad (9)$$

Here,
$f_{i,j}$ corresponds to the ith colour component for pixel j
$M \text{ or } E_1$ represent the mean or the first moment of expectation for the image
s.d. represents the standard deviation
v represents the variance
k represents the skewness

For the features in the transform domain, one of the most predominantly used features are the Gabor filters which essentially perform the convolution of the Gabor wavelet and the image under consideration given by:

$$g(x,y) = \frac{1}{2\pi s_x s_y} e^{[-\frac{1}{2}\left\{\frac{x^2}{s_x^2}+\frac{y^2}{s_y^2}\right\}+2\pi j C_x]} \quad (10)$$

Here,
$g(x,y)$ represent the Gabor features
s_x and s_y are the scaling parameters
$C_x$represents the central frequency of the contour

Apart from Gabor features, shape features can are also useful in case of images containing regular shapes such as straight lines, circles, rings or discs etc. Another useful feature extraction method is the computation of histogram oriented gradient or the HOG features. The idea behind HOG features is the fact that images can be differentiated based on image intensity histograms and gradients from which the term HOG derives its name. They differential gradients along x and y are computed as:

$$g_x = \frac{\partial f(x,y)}{\partial x} = \frac{f(x+\Delta,y)-f(x,y)}{(x+\Delta)-x} \quad (11)$$

$$g_y = \frac{\partial f(x,y)}{\partial y} = \frac{f(y+\Delta,x)-f(x,y)}{(y+\Delta)-y} \quad (12)$$

Here,
g_x represents the gradient along x
g_y represents the gradient along y
Δ represents an incremental change

If is often customary to take the incremental change to be unity for HOG features.

The gradient vector's magnitude if a function of the orientation angle $\emptyset$ and is computed as:

$$G_{\emptyset} = f(g_x, g_y, \emptyset) \quad (13)$$

$$|G_{\emptyset}| = \sqrt{g_x^2 + g_y^2 = f(\emptyset)} \quad (14)$$

Here,

$|G_{\emptyset}|$ represents the magnitude of the composite gradient

$\emptyset$ is the orientation angle in the azimuth calculated in the range of $(-\pi, \pi)$ or $(0, 2\pi)$.

Another prominent feature extraction technique is the computation of the gray level co-occurrence matrix (GLCM) features which tries to estimate the probability of occurrence of a pixel 'i' w.r.t. a pixel 'j' at a separation 'l'. Thus it's a joint probability distribution based feature extraction technique over the x-y plane of the image. The GLCM normalization co-efficient 'N' is defined as:

$$N_{i,j} = \frac{X_{i,j}}{\sum_{i=0}^{K-1}\sum_{j=0}^{K-1} * X_{i,j}} \quad (15)$$

Here,

i and j are the pixel indices

$X_{i,j}$ is the pixel value

Some of the probabilistic features computed for GLCM features apart from statistical features like mean, variance, standard deviation etc. are:

Entropy: It is the average amount of information contained in a random variable with elements or entities having associated probabilities of occurrence. It is defined as:

$$E = -P[I_{x,y}]Log_2[[I_{x,y}] \quad (16)$$

Here,

E stands for the entropy

I is the image

P is the probability of occurrence of pixel I w.r.t. pixel j.

The entropy value helps to compress images and is also used for noise removal or inpainting since redundancies of the image can be found and discarded without losing vital image information. The level of similarity is also computed based on the joint probability of occurrence of pixels given by:

$$H = \sum_{i,j}^{M,N} \frac{P_{i,j}}{1-(i-j)^2} \quad (17)$$

Here,

H stands for Homogeneity

P stands for the joint probability .

The value of homogeneity quantifies the nature of distribution of the pixel values which be bear similarity or dissimilarity. A similar parameter evaluating the closeness of stochastic properties of pixel regions is the two dimensional correlation given by:

$$Corr_{2D} = \sum_{i,j}^{M,N} \frac{(i-m_x)(j-m_j)P_{x,y}}{sd_x sd_y} \quad (18)$$

Here,

$Corr_{2D}$ is the two dimensional correlation

M and N are the number pf pixels along x and y

m_x is the mean along x

m_y is the mean along y

sd_x is the standard deviation along x

sd_y is the standard deviation along y

The GLCM features thus help to evaluate the co-occurrence of the pixel values in an image and hence can be used to judge the similarity or redundancies in the image pixel regions.

2.3 Classification:

Based on the image processing and feature extraction, the classification is done. Automated classification requires training a classifier with the pre-defined and labelled data set and subsequently classifying the new data samples. Off late machine learning based classifiers are being used for the classification problems. Machine learning can be crudely understood as the design of automated computational systems which mimic the human behaviour and can be trained in the sense that they can learn from data fed to the system. Primarily machine learning is categorized into three major categories which are [13]-[15]:

1) Unsupervised Learning: In this approach, the data set is not labelled or categorized prior to training a model. This typically is the most crude form of training wherein the least amount of apriori information is available regarding the data sets.

2) Supervised Learning: In this approach, the data is labelled or categorized or clustered prior to the training process. This is typically possible in case the apriori information us available regarding the data set under consideration.

3) Semi-Supervised Learning: This approach is a combination of the above mentioned supervised and unsupervised approaches. The data is demarcated in two categories. In one category, some amount of the data is labelled or categorized. This is generally not the larger chunk of the data. In the other category, a larger chunk of data is un-labeled and hence the data is a mixture of both labelled and un-labeled data groups.

Some other allied categories of machine learning are:

4) Reinforcement Learning
5) Transfer Learning
6) Adversarial Learning
7) Self-Supervised learning etc.

While these learning algorithms can be studied separately, however they are essentially the modified versions of unsupervised, supervised and semi-supervised learning architectures. A more advanced and useful category of machine learning is deep learning which is the design of deep neural nets with multiple hidden layers.

Machine learning based classifiers are typically much more accurate and faster compared to the conventional classifiers. They render more robustness to the system as they are adaptive and can change their characteristics based on the updates in the dataset [16]. The common classifiers which have been used for the classification of pests are:

Regression Models: In this approach, the relationship between the independent and dependent variable is found utilizing the values of the independent and dependent variables. The most common type of regression model can be thought of as the linear regression model which is mathematically expressed as [15]:

$$y = \theta_1 + \theta_2 x \qquad (19)$$

Here,
x represents the state vector of input variables
y represents the state vector of output variable or variables.
ϴ1 and ϴ2 are the co-efficients which try to fit the regression learning models output vector to the input vector.

Often when the data vector has large number of features with complex dependencies, linear regression models fail to fit the input and output mapping. In such cases, non-linear regression models, often termed as polynomial regression is used. Mathematically, a non-linear or higher order polynomial regression models is described as:

$$y = \theta_0 + \theta_1 x^3 + \theta_2 x^2 + \theta_3 x \qquad (20)$$

Here,
x is the independent variable
y is the dependent variable
$\theta_1, \theta_2 \ldots\ldots \theta_n$ are the co-efficients of the regression model.

Typically, as the number of features keep increasing, higher order regression models tend to fit the inputs and targets better. A typical example is depicted in figure 2

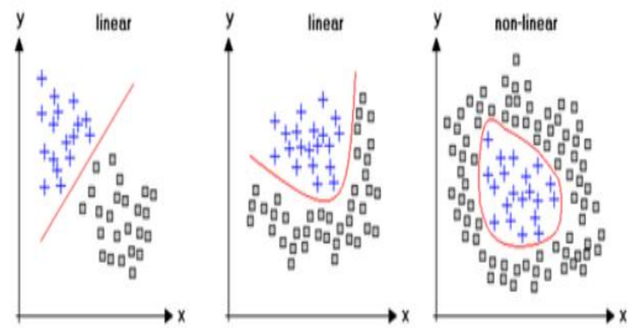

Fig. 2 Linear and Non-Linear Regression fitting [14]

Support Vector Machine (SVM): This technique works on the principle of the hyper-plane which tries to separate the data in terms of 'n' dimensions where the order of the hyperplane is (n-1). Mathematically, if the data points or the data vector **'X'** is m dimensional and there is a possibility to split the data into categories based on **'n'** features, then a hyperplane of the order **'n-1'** is employed as the separating plane. The name plane is a misnomer since planes corresponds to 2 dimensions only but in this case the hyper-plane can be of higher dimensions and is not necessarily a 2-dimensional plane. A typical illustration of the hyperplane used for SVM based classification is depicted in figure 3.

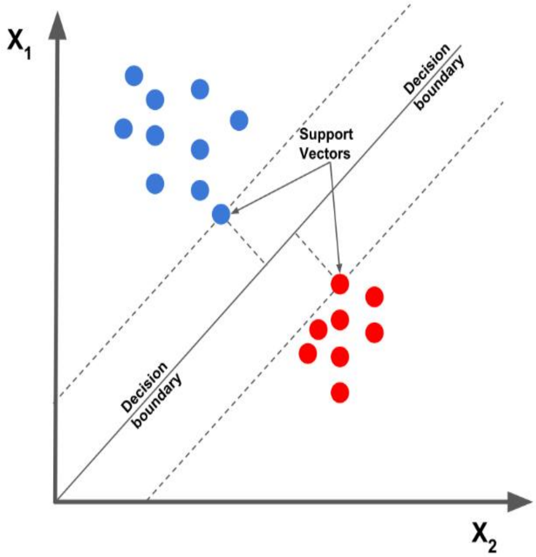

Fig. 3 Separation of data classes using SVM [15]

The selection of the hyperplane H is done on the basis of themaximum value or separation in the Euclidean distance d given by:

$$d = \sqrt{x_1^2 + \cdots \ldots \ldots . x_n^2} \quad (21)$$

Here,

x represents the separation of a sample space variables or features of the data vector,

n is the total number of such variables

d is the Euclidean distance

The (n-1) dimensional hyperplane classifies the data into categories based on the maximum separation. For a classification into one of **'m'** categories, the hyperplane lies at the maximum separation of the data vector **'X'.** The categorization of a new sample **'z'** is done based on the inequality:

$$d_x^z = Min(d_{C1}^z, d_{C2}^z \ldots d_{C2=m}^z) \quad (22)$$

Here,

d_x^z is the minimum separation of a new data sample from **'m'** separate categories

$d_{C1}^z, d_{C2}^z \ldots d_{C2=m}^z$ are the Euclidean distances of the new data sample **'z'** from m separate data categories.

Neural Networks: Owing to the need of non-linearity in the separation of data classes, one of the most powerful classifiers which have become popular is the artificial neural network (ANN). The neural networks are capable to implement non-linear classification along with steep learning rates. The neural network tries to emulate the human brain's functioning based on the fact that it can process parallel data streams and can learn and adapt as the data changes. This is done through the updates in the weights and activation functions. The mathematical model of the neural network is depicted in figure 4.

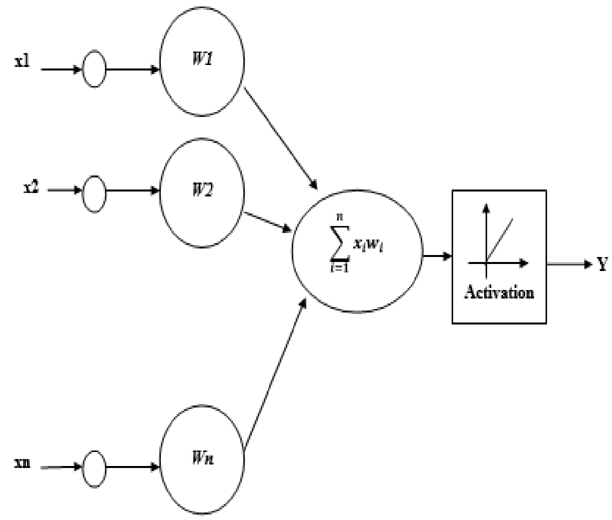

Fig. 4 Mathematical Model of Single Neuron [13]

The mathematical equivalent of an artificial neuron is depicted in figure 4 where the output can be given by:

$$y = f\left(\sum_{i=1}^{n} x_i w_i + b\right) \quad (23)$$

Here,

x denote the parallel inputs

y represents the output

w represents the bias

f represents the activation function

The neural network is a connection of such artificial neurons which are connected or stacked with each other as layers. The neural networks can be used for both regression and classification problems based on the type of data that is fed to them. Typically the neural networks have 3 major conceptual layers which are the input layer, hidden layer and output layer. The parallel inputs are fed to the input layer whose output is fed to the hidden layer. The hidden layer is responsible for analysing the data, and the output of the hidden layer goes to the output layer. The number of hidden layers depends on the nature of the dataset and problem under consideration. If the neural network has multiple hidden layers, then such a neural network is termed as a deep neural network. The training algorithm for such a deep neural network is often termed as deep learning which is a subset of machine learning. Typically, the multiple hidden layers are responsible for computation of different levels of features of the data. Several categories of neural networks such as convolutional neural networks (CNNs), Recurrent Neural Network(RNNs) etc. have been used as effective classifiers [17] .

Previous Work

This section cites the various contemporary approaches employed for automated pest and weed detection in plants. The salient features of each approach in terms of the technique adopted, performance metrics obtained and detected research gaps or limitations are also mentioned for a quick analysis of the contemporary techniques employed in the domain.

Table I. Previous Work.

Authors	**Approach Used**	**Performance**	**Limitations**
W Li et al. [1]	Deep Learning based on Recurrent Convolutional Neural Networks (RCNN)	F-1 Score of 0.944	Separate image enhancement not employed.
KRB Legaspi et al. [2]	Classification of white fly and fruit fly infestation using YOLO algorithm.	Accuracy of 83.07% achieved.	Comparatively low recall and more localization error compared to CNNs
G Pattnaik et al. [3]	Histogram of Oriented Gradient (HOG) and Local Binary Pattern techniques (LBP) along with SVM.	Accuracy of 97% achieved for used dataset.	The Support Vector Machine (SVM) suffers from performance saturation.
G Pattnaik et al. [4]	Convolutional Neural Network (CNN) with transfer learning	Accuracy of 88.83%	Convolutional Neural Networks are prone to overfitting thereby negatively impacting transfer learning models.
QJ Wang et al. [5]	CNN, R-CNN and Yolo algorithms applied for classification.	Accuracy of 62%, 73.7% and 62.5% achieved.	No separate pre-processing or dimensional reduction performed. Initial low level features and processing done by starting layers.
DJA Rustia et al. [6]	Integrated camera modules and an embedded system as the sensor node in a wireless sensor network, for pest counting.	Average accuracy achieved for automated pest counting was 93%	Only pest counting and monitoring was done. Automated classification not employed.
L Liu et al. [7]	Region proposal network (RPN) that is adopted by fusing the channel-spatial attention (CSA) module and CNN	Classification Accuracy of 75.46% achieved.	Fully connected layer replaced with bounding box regression with suffers from performance saturation with increasing data size.
CJ Chen et al. [8]	Alexnet and CNN used to evaluate crop damage	Mean Accuracy of 82% achived.	The Alexnet deep learning framework doesn't perform well for low light or noisy conditions.
L Deng et al. [9]	bio-inspired Hierarchical Model and Scale	Accuracy of 85.5% achieved.	Separate denoising not performed.

	Invariant Feature Transform (SIFT) were used for feature extraction and classification was done using the SVM		SVM suffers from performance saturation.
MA Ebrahimi et al. [10]	SVM method with difference kernel function was used for classification of parasites and detection of thrips.	The MSE, RMSE and MAPE were computed. The best classification MAPE was 2.25%	The system doesn't employ technique for image denoising or feature optimization. Moreover SVM suffers from overfitting and saturation.
P Rajan et al. [11]	Segmentation employed, color features used to train the SVM to classify the pest pixels and leaf pixels.	The classification accuracy was 95%.	Color features are often degraded by effect of Gaussian and Poisson noise. Moreover SVM suffers from data saturation.
Pérez-Ortiz et al. [12]	Semi-supervised learning approach for weed mapping in sunflower crops.	The MAE for Semi-supervised SVM (SS-SVM) approach was 0.1268	The SS-SVM approach suffers from under fitting and hence the classification accuracy suffers for large testing datasets.
C Potena et al. [13]	Lightweight CNN used for crop weed classification.	Highest Accuracy of 96% achieved	No separate feature extraction done. Dimensional optimization also not employed.
E Omrani et al. [14]	A combination of K-Means clustering and SVM used for crop disease detection.	Accuracy of 93% achieved	The SVM is prone to performance saturation for large datasets. Image filtering and denoisingnot employed.

The performance metrics of the classifiers are generally computed based on the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values which are used to compute the accuracy and sensitivity of the classifier, mathematically expressed as:

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \quad (24)$$

$$Se = \frac{TP}{TP+FN} \quad (25)$$

$$Recall = \frac{TP}{TP+FN} \quad (26)$$

$$Precisiosn = \frac{TP}{TP+FP} \quad (27)$$

$$F - Measure = \frac{2.Precision.Recall}{Precision+Recall} \quad (28)$$

The aim of any designed approach is to attain high values of accuracy of classification along with other associated parameters. The computation complexity of the system often evaluated in terms of the number of training iterations and execution time is also a critically important metric which decides the practical utility of any algorithm on hardware constrained devices.

III. CONCLUSIONS

This paper explains the need for precision agriculture with its possible applications Moreover, the various tools and techniques adopted for pest and weed detection have been evaluated in terms of the technique uses, the performance achieved and the limitation of the technique. Different stages of the data processing and segmentation have been enlisted. The significance of different image features and extraction techniques have been clearly mentioned with their utility and physical significance. Various machine learning based classifiers and their pros and cons have been highlighted. The mathematical formulations for the feature extraction and classification gave been furnished. A comparative analysis of the work and results obtained has been cited in this paper. It can be concluded that image enhancement and feature extraction are as important as the effectiveness of the automated classifier, hence appropriate data processing should be applied to attain high accuracy of classification.

Some of the future directions of work can be separate image enhancement and data optimization to avoid both over fitting and under-fitting, moreover, employing separate image denoising to extract features more accurately. Solely computing feature based on deep learning architecture can be compared with statistical feature extraction. This would make the system application to a large variety of datasets. Moreover, classifiers which do not saturate in terms of performance with increasing sat size can be employed.

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