Performance Comparison of Weed Detection Algorithms

Sarvini T, Sneha T, Sukanya Gowthami G S, Sushmitha S and R Kumaraswamy

***Abstract*— Weed control is essential in agricultural productivity as weeds act as a pest to crops. The conventional methods of weed removal are time-consuming and require more manual labour work. Hence there is a need to automate this process. The objective of the proposed system is to detect weed from crop using machine learning algorithms. The exhaustive dataset is collected for four different commercial crops and two types of weeds such as Para grass and Nutsedge. Excess green method and Otsu's thresholding is used for masking the soil and extract the region of interest. The shape features of an image are extracted to provide distinguish properties between weed and crop. The classification of weed and crop has experimented with three different classifiers: Support Vector Machine, Artificial Neural Network and Convolutional Neural Network. The performance comparison of weed detection algorithms is executed on the Open CV and Keras platform using python language.**

Index Terms-Weed Classification, Shape Features, Support Vector Machine, Artificial Neural Network and Convolutional Neural Network.

I. Introduction

CLASSIFICATION of weed from crop plays a vital role in precision farming as weed act as a pest to crop and competes for space, nutrients, water, light and hinders the growth of crops in the field. The conventional way of eliminating weed is to spray herbicides or manual plucking. The manual weed removal method is a tedious task as it needs huge labour work. Usage of herbicides has an adverse effect on the health of living beings and the surrounding environment. Hence, there is an urge to automate the process of weed identification.

An image processing based approach is proposed in [1] to differentiate crop Eleusine coracana (Ragi) from weeds. The algorithm involves erosion and dilation [2] operation to extract the region of interest and corresponding white pixels are determined. The regions with higher white pixel count than the predefined threshold has been considered as weeds. But, this approach reliance on good and stable illumination conditions which does not make the system to be functioning in real time. Two methods for detecting weeds in the lawns is discussed in [3]. Initially, the captured RGB image is converted into a gray scaled image and edges present in the image is calculated by applying the Sobel edge operator. Local mean and variance of each pixel have been used as features for the Bayes classifier. The second method follows with the morphological operations to discriminate weed pixels from the lawn. But, the system assumes the grass area should contain a group of edges while the weed area consists of fewer edges which render to the false prediction. The machine vision based clustering method has been used to classify crop and weed in a corn field [4]. Excess green segmentation [5] is used for masking the soil. The morphological operation and wavelet transforms are used as features for feature extraction. Based on the similar features, identification of weeds namely Goosegrass and Alligator alternanthera in soybean seedlings has been proposed in [6]. The radial basis function based neural network classifier is trained with one hidden layer to classify crop and weed in which 80% of the samples are classified correctly. In addition to morphological features, the statistical texture features like intensity, mean, energy, entropy, standard deviation and smoothness are also been used to classify crop and weed in maize field mentioned in [7]. Support vector machine classifier is used for training for these features which resulted in an accuracy of 82%. The recognition of weed in the corn field is carried out using Probabilistic Neural Network (PNN) classifier in [8]. Shape features like area, aspect ratio, eccentricity and roundness are used to train the PNN classifier model. In the above mentioned work, weed identification is not suitable for different soil and illumination conditions.
The drawbacks associated with existing approaches are each model is trained only for specific type of crop and weed with several assumptions and fail to identify weeds in real-time images. In the proposed system, sincere attempts are made to address a few of these problems by collecting the data for different crops and weeds which includes data variability and helps to detect weeds irrespective of soil and illumination conditions.

In this paper, the dataset is collected for four different commercial crops and two types of weeds. The morphological features are extracted and the performance analysis for three classifier algorithms like Support Vector Machine, Artificial Neural Network and Convolutional Neural Network is conducted.

The rest of the paper is organized as follows: Section II presents about the database, Section III explains about system architecture, Section IV explains about experiments conducted and their results. Finally, Section V concludes the paper.

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II. Field Survey

A. Data Collection

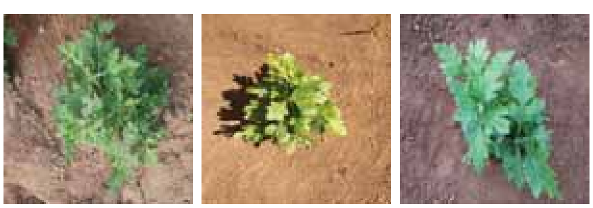
The dataset for weed and crop classification is unavailable which initiated to collect the exhaustive data for different crops and weeds.
Before starting to collect data, the field survey is undertaken in nearby villages of Tumakuru to know the threats in the farm field which are pests for the yield of crops and the adverse effects of herbicides on cultivating land. By this survey, weed is a major hazard to crop growth. It also provided information about the availability of various crops and weeds. Through field survey the weeds namely Para grass, Nutsedge and Parthenium are seen as pests for different crops such as Brinjal, Chrysanthemum, Chilly, Ragi, Onion and Turnip. Finally, crop Chrysanthemum and weeds namely Para grass and Nutsedge are chosen for classification. Data has been collected for 3 months in different fields having constraints like single frame containing only crop, only weed and crop with weed. 2560 images are collected in such a way that either crop or weed is present in one frame of the image.

Some of the procedures are employed during data collection and are as follows:

- 10MP digital camera is used for image acquisition.
- Top view of an image is taken at a distance of 50-70cm.
- Uniform soil background with different soil conditions as shown in Fig. 1 for Para grass.
- Images are taken at various illumination conditions and at different growth stages of crop and weed. Fig. 2 and Fig. 3 shows the above-mentioned conditions for chrysanthemum.

(a) Dry (b) Wet

Fig. 1. Soil condition



(a) Morning (b) Afternoon (c) Evening

Fig. 2. Illumination variation

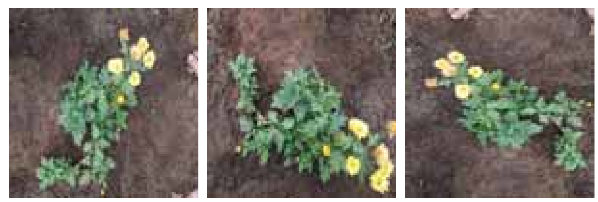
B. Data Preparation

Images are resized to 250x250. Data augmentation is been carried out to enhance the variability among the collected data [9]. Fig. 4 shows data augmented images. Following are the operations performed on the images.

(a) Initial (b) Intermediate

Fig. 3. Growth stages of plant

- Rotation: Rotation of the image by an angle of 45^0 and 90^0.
- Flipping: horizontal and vertical flipping of image.
- Contrast enhancement: multiply each pixel of image by a factor 0.9.
- Noise addition: Noises like salt and pepper and Gaussian is added.



(a) Original Image (b) Rotated by 45^0 (c) Flipped

(c) Contrast Enhancement (d) Noise added

Fig. 4. Data Augmentation

III. System Description

The rise of Artificial Intelligence (AI) has caused the world of agriculture to explore new innovations in precision farming. To ease the process of weed removal, the AI based weed classification system is proposed. Fig. 5. illustrates the overview of weed identification system.

A. Pre-Processing

Noises like Salt and Pepper and Gaussian is removed using Median and Gaussian filter respectively [10]. The preprocessing helps in extracting the green part from the frame using excess green method using equation 1. Then, it is converted into a binary image using Otsu's thresholding [11] [12] which tries to find a threshold value t which minimizes

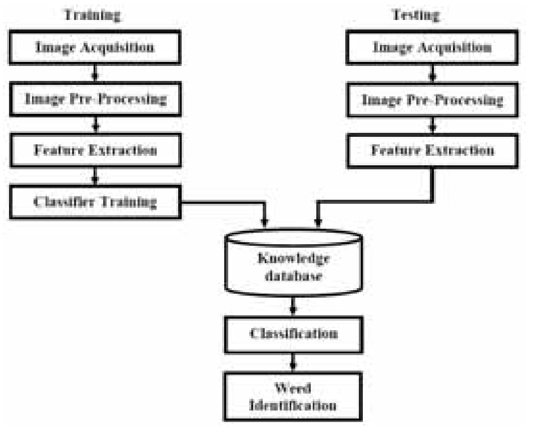


Fig. 5. Block Diagram of the proposed system

the weighted within class variance given in the equations 2 and 3. The summary of pre-processing is shown in Fig 6.

$$y = 2g - r - b \tag{1}$$

where r, g and b represents normalized colour of image in RGB colour space.

$$\sigma_w^2(t) = W_0(t)\sigma_0^2(t) + W_1(t)\sigma_1^2(t) \tag{2}$$

$$W_0(t) = \sum_{i=0}^{t-1} p(i) \ , \ W_1(t) = \sum_{i=0}^{L-1} p(i) \tag{3}$$

where, weights $W_0(t)$ and $W_1(t)$ are probabilities of the two classes separated by a threshold t, $\sigma_0^2(t)$ and $\sigma_1^2(t)$ are variances of these two classes, and L represents the number of bins in histogram.

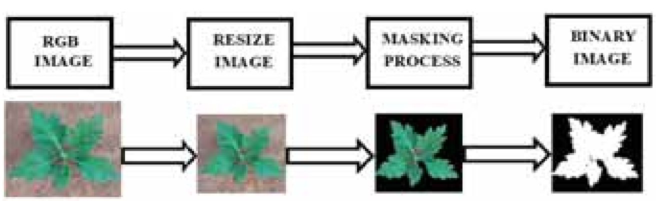


Fig. 6. Pre-processed Image

B. Feature Extraction

Image feature extraction comprises of shape, color and texture of the plant [13]-[15]. The shape features like area, perimeter, eccentricity, major axis and minor axis length extracted from binary image provided distinguishing properties between crop and weed. Area is obtained by the summation of the number of white pixels. Calculating the distance between each adjoining pair of pixels around the border of the region gives perimeter. Eccentricity is determined using equation 4.

$$Eccentricity = \sqrt{1 - (b/a)^2} \tag{4}$$

where a is major axis length and
b is minor axis length

C. Classifiers

1) SVM: It is a supervised learning models which analyses the input morphological feature matrix, recognise the patterns and aims to find an optimal hyperplane separating two classes [16]-[18]. SVM first transforms the input data into a higher dimensional space by means of a kernel function and then construct a linear optimal hyperplane separating the two classes in the transformed space as shown in Fig. 7.

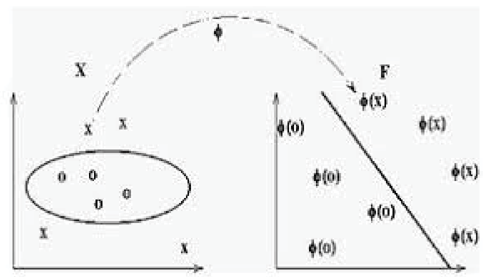


Fig. 7. SVM plot

2) ANN: The input layer of ANN is provided with shape feature vector followed by the hidden layer which is used to locate the pre-eminent features of the classes [19] [20]. The values at each node estimates or approximates using non linear function. Feed Forward Back Propagation algorithm finds error at the output layer between the predicted and targeted output. The error propagates and updates the weights to minimize the error and confirm its capability to distinguish between crop and weed. Fig. 8. explains the ANN architecture for weed recognition.

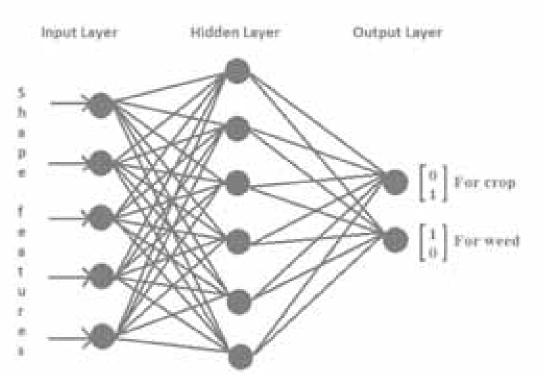


Fig. 8. ANN Architecture

3) CNN: The CNN uses successive convolutional layers with a non linear ReLU function for storing the features of an image having a specific dimension [21] [22]. Maxpooling layers are used for down sampling. The fully connected layer multiplies the input by a matrix with a sigmoid activation function and adds to a bias vector which contains the feature map. The stochastic gradient descent optimiser provides the filter weight updation at the mentioned learning rate. Fig. 9 depicts the overview of the proposed CNN architecture.

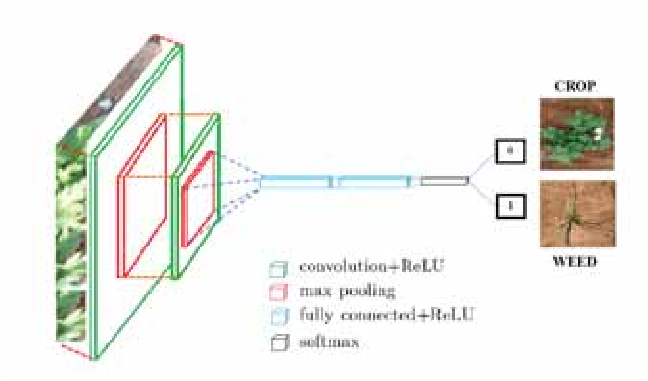


Fig. 9. CNN Architecture

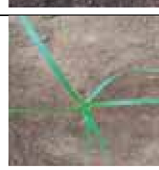
IV. Experiment and Results

The section provides detailed description about the database used for training the model and analysis of results for the experiments conducted using SVM, ANN and CNN.

A. Database

1155 images of each class is used to train the classifier model. 125 images of per class is used to validate the trained model. Shape features with their corresponding labels are used to train SVM and ANN model as shown in Table I.

TABLE I
Index Table

Name	Images	Label
Crop		0
Weed		1

B. Experiments

Python is a widely used high level programming language which has a dynamic type system and automatic memory management and supports multiple programming paradigms including object oriented, imperative, functional programming and procedural styles. The experiments are conducted in python software using OpenCV and Keras packages.

1) SVM: The extracted shape features has non linear separable data. The SVM model is evaluated with different nonlinear kernel functions such as the Radial Basis Function (RBF) and Polynomial Function. Polynomial due to its optimal separating hyperplane gave better prediction compared to RBF as shown in Table II.

TABLE II
SVM Accuracy

Type of Kernel	Classification Accuracy
RBF	80.4%
Polynomial	87.6%

2) ANN: ANN consists of 5 input nodes and two output nodes to classify crop and weed. The number of neurons in the hidden layer is varied from 2 to 10 and their results are shown in Table III. The better result is obtained for 5-6-2 architecture.

TABLE III
ANN Accuracy

Network Architecture	Validation Accuracy(%)	Test Accuracy(%)
5-4-2	95.2	92.8
5-6-2	94.7	93.2
5-8-2	95.4	91.2
5-10-2	95.4	91.6

3) CNN: CNN uses input layer with dimension of 250x250x3. CNN architecture shown in Fig. 9 is used for training and validating the model. The optimiser is used at a learning rate of 0.001 for 10 epochs with a batch size of 231 images. Training and Validation plot for CNN is shown in Fig. 10.

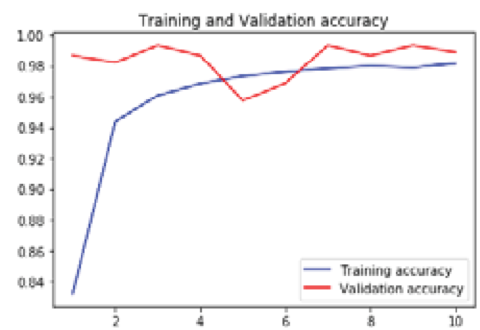


Fig. 10. Training and Validation accuracy plot

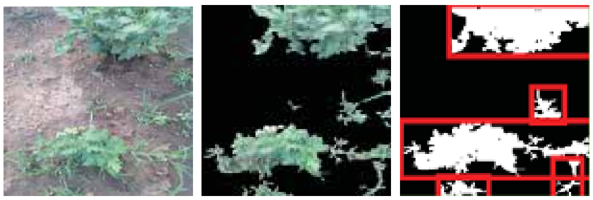
C. Analysis of Result

The confusion matrix shown in Table IV provides validation of crop and weed classification for different classifiers. Confusion matrix helps to understand the uncertainty in recognizing the classes. It shows that the weeds are recognised as crops more in SVM and ANN compared to CNN. The ambiguity may be due to illumination, background and similarity of patterns between crop and weed. The accuracy of SVM and ANN may be enhanced by applying more robust feature extraction methods in the recognition system.

If the image contains crop and weed in one frame, then the required Region of Interest (ROI) is extracted and given to the model to predict whether the ROI is crop or weed. Fig. 11(a) represents the captured field image. Masking of the soil is shown in Fig. 11(b). Using connected component analysis, the number of objects are determined and the bounding box is drawn as shown in Fig. 11(c). Each object is given to the CNN model to predict whether it is a weed or crop.

TABLE IV
Confusion matrix for SVM, ANN and CNN

	SVM		ANN		CNN	
	Crop	Weed	Crop	Weed	Crop	Weed
Crop	125	0	116	9	125	0
Weed	21	104	11	114	4	121



(a) (b) (c)

Fig. 11. Prediction for real-time image

V. CONCLUSION

Weed and crop classification is used for the identification of weed and helps to automate the weed removal process. The shape features provide distinct attributes to categorize weed and crop. The performance of SVM, ANN and CNN based classifiers are analyzed. It is observed that CNN gives better performance compared to SVM and ANN because of its deep learning ability to learn relevant features from the image.

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