Weeds classification system for selective herbicides using broad weed estimation

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Abstract**—** Categorizing various types of weeds holds significant technical and economic importance in agriculture. Development of a system that can make distinctions based on color, shape and texture is viable. Primary objective of this research is to develop an automated weed control system which is able to identify weed based on its location. A real time system is developed in order to detect weeds in the surrounding areas using pattern recognition. Different experimentation work is conducted in order to gauge the efficiency of our proposed method in terms of distinguishing between various types of weeds. It also performed admirably amid varying field conditions. The results confirmed that the algorithm exhibited a 94% success rate in terms of categorizing weed samples where a population of 160 samples was used consisting of 80 narrow and 80 broad samples.

Keywords**—**Classification, Weed detection, herbicides.

I. INTRODUCTION

In todays age the skin of fruits and vegetables are significant parameters which determines their quality. In wheat and soybean fields for the detection of weeds, color machine vision is used where they are using color index for weed detection for both preprocessing and statistical different analysis. Different methods are using for discriminating plants from weeds and soil. The important challenge in growth stage is weed control in onion cultivation. Long lineal leaves do no shadow on emerging weeds but the infection is caused by successive invasions due to their slow development. Chemical and mechanical both weeding uses in all cultivation [1].

Weed control is an expensive technique in precision farm field which consumes more time. Science of weeds is a challenging field of research as it is a very vast area. The developed countries use cutting edge technologies such as space technology, biotechnology and information technology. Generally the term weed is used in plants so it is necessary for utilizing and changing the research in weed management of eco-friendly and increasing the role of sustainable crop production and research based technologies. In global scenario the herbicides increases per year in feature. There are potential risk of water contamination and food because of the usage of herbicides. The indiscriminate use of herbicide affects the environment in addition weed biology is influenced adversely. The quality of food increases with the safely use of herbicides, for this we have a popular tool named wavelet analysis used to detect the crop and weed whereas Db4 wavelet has been using to extract the crop's and weed's textures features [2]. Plant recognition in automated weeding applications is sometime based on computer vision either using shape information or similar properties [3].

For crop productivity, weed poses a vital biological constraint. With more use of herbicides, weed control is characterized which results in the emergence of weeding resistance to herbicides in addition in environmental problems so here we need to look for other alternatives that allows ecological weed control in the cropping system. For exploiting weed-suppressing ability of crop varieties themselves, potential is a promising option for weed control. In a cropping system there are actually multiple weeds in addition the suppression effect of weed is a joint action of competitive factors and allelopathy using a mixed-culture of crop-weed design that stimulates a great controversy deal owning neglect of competition. The below grounded interactions affects more performance of coexisting plants as compare to above grounded interactions [4].

II. LITERATURE REVIEW

In some early approaches [10],[11] statistical, color and shape based features were used to detect weeds. According to [5], a new method was proposed which was based on artificial neural networks vision for higher efficiency in cost and production. Multilayer perceptron neural networks technique was employed for identifying weed roots in onion crops that enabled identification of specific areas for spraying, hence decreased the amount of herbicide utilized. Multilayer perceptron neural networks technique was employed for identifying onion crop's weed roots that enabled identification of specific areas for spraying, so the amount of herbicides decreased and utilized. Because of active targeting and identification of infected areas, this method was justified by practical experiments providing very much sufficient evidence regarding saving of resources like herbicides.

In [6], ground based sensors are used for assessing weed levels and weed identification in a crop. The underlying principles, limitations and performance was also discussed.

In research work [7], a machine for new learning mechanism was introduced for distinguishing weed and crop in account with their reflectance differences. They used artificial neural network and mixture of Gaussian techniques in their proposed algorithm. The work [8] deals with sensors of weed deduction system and practical use of them in cereal crops. By employing an ultrasonic distance sensor, the location of weed was identified. As compared to normal areas whether weed containing zones are richer in biomass, the relevant height of plants was compared. Spherical-shaped 40 to 80 samples with varying weed components of two different sets were evaluated at two separate dates. The sensors direction was kept towards the ground to properly assess the heights. Broad-leaved weeds and Grass weeds were removed. The dissimilarities between weed-ridden and weed free zones were analyzed along with dry portion of crop and weed samples. RGB images obtained the weed removal for assessing the area covered by crops and weeds. Analytical techniques based on numerous regression were used to control the coverage of weeds and crops. By the ultrasonic readings, weed containing zones were differentiated from normal zones with 92.8% success rate in addition by utilizing this system, the weed identification cost incurred could be decreased. For limiting the growth of weeds it could also applied in non-selective methods.

In [2], by employing an image processing algorithm, weeds and crops were distinguished from one another which utilized “wavelet analysis”. Wavelet transform analyzed the textural properties of weed and crop images. The texture features were extracted from the data related with different parameters like Homogeneity, Contrast, Inertia, Entropy and Energy. By the neural networks, the data collected was then classified accordingly. With the help of herbicides which were sprayed through robotic means, the weed location based on classification and the infected areas was accessed.

In [9], for analyzing the morphological properties of plants; with the classification of small plants for identification proving, depth cameras were deployed for added precision. By employing dual methodology with utilizing RGB (Red, Green, and Blue) height selection, weed, soil and crops can be differentiated. In real life condition by employing Kinect fusion algorithms, the 3D point clouds of weed-ridden crops are reproduced. The models constructed were very much satisfactorily consistent with soil parameters acquired from actual morphological measurements and 3D images. In order to have differences between weeds with the soil and small height micro relief of the samples with weed biomass obtained a correlation of 0.83, RGB recognition is essential. With the volumetric measurements the weed density was well correlated. The results indicated that the volume of accessing could offer precise results by utilizing kinetic methodology that identified weeds and crops and differentiated between them.

Figure 1: ***Real-time recognition system***

III. AIMS AND OBJECTIVES

Narrow leave weeds and Broad leave weeds currently in use are two types of herbicides. We here set a goal for designing an algorithm which can:

- Identify the location and detection of weeds
- Distinguish between the narrow and broad weeds.

IV. PROPOSED FRAMEWORK

The concept of the proposed weed control system is depicted in figure1, which has Central Processing Unit (CPU), Decision Box and Camera used to control dc pumps At 45 degree of angle from the ground the images were taken. Here according to this manner, images size remained the same with high quality of protruding portion of the sprayer captured. The images here are relayed to the CPU and decision box is connected to it through a parallel port which also used for turning on or off the pump purely based on the CPU processing over kind of images. Matlab is used for the software development. The resolution of each image is 240 by 320 pixels.

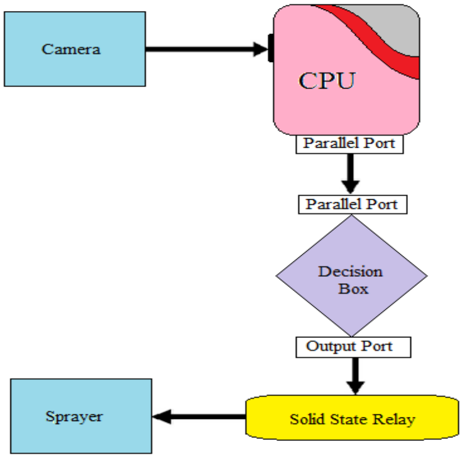

Figure 2: ***Conceptual flow chart***

V. METHODOLOGY

In figure 1, a weed recognition system for real time specific is illustrated and their purpose is to recognize the narrow and broad weeds [8].

In the pre-processing stage we decompose the input image into Red, Green and Blue components create a binary image using the following transformation.

If Gr >Rd and Gr>Bu and Gr>115 then
PI = 1
Else
PI = 0
End if

Where Rd, Gr and Bu are the red, green and blue components and PI is the processed binary image.

We scanned the images horizontally and vertically to find out location of broad weeds in the image by measuring the lengths and heights of objects/weeds.

Narrow weeds as the name suggests are narrower in length than broad weeds so we can differentiate them from broad weeds based on their length and height. By estimating broad weeds with respect to total weed percentage we can classify weeds as either narrow or broad. The classification algorithm is given below:-

If (BroadWeed Percentage >=55 and Weed Percentage>=40)
or (BroadWeed Percentage>60)
Classify category as “Broad Weed”

Else If Weed Percentage>=30
Classify category as “Narrow Weed”
Else
Classify category as “No or Little Weed”
End

VI. RESULTS AND DISCUSSION

The results are represented in table 1 with 95% of the little or no weed and 94% of narrow and broad weeds were successfully categorized. The visual results are depicted in figures 3-6.

Table 1: ***Weed Classification by Broad Weed Estimation***

Image	Weed Percentage	Broad Weed Percentage	`
1	60.94	61.08	Broad Weed
2	56.28	64.00	Broad Weed
3	37.52	48.29	Narrow Weed
4	44.04	47.91	Narrow Weed
5	61.28	64.00	Broad Weed
6	60.94	61.08	Broad Weed
7	44.04	47.91	Narrow Weed
8	56.47	61.66	Broad Weed
9	57.09	61.35	Broad Weed
10	64.48	64.25	Broad Weed
11	23.23	34.44	Narrow Weed
12	20.54	29.11	Little or No Weed
13	44.04	47.91	Narrow Weed
14	56.28	64.00	Broad Weed
15	44.04	47.91	Narrow Weed
16	35.29	45.96	Narrow Weed
17	44.25	47.83	Narrow Weed
18	60.94	62.21	Broad Weed
19	56.07	63.79	Broad Weed
20	41.84	68.56	Broad Weed
21	26.17	55.19	Narrow Weed
22	33.04	51.03	Narrow Weed
23	21.01	44.31	Narrow Weed
24	31.34	57.82	Narrow Weed
25	44.04	47.91	Narrow Weed
26	56.28	64.00	Broad Weed
27	64.48	64.25	Broad Weed
28	21.33	40.07	Narrow Weed
29	23.94	39.83	Narrow Weed
30	13.49	42.07	Little or No Weed
31	28.54	43.81	Narrow Weed
32	61.13	65.65	Broad Weed
33	23.23	44.44	Narrow Weed
34	43.43	53.72	Narrow Weed
35	57.24	65.53	Broad Weed
36	58.70	68.09	Broad Weed
37	56.59	66.20	Broad Weed
38	24.42	46.08	Narrow Weed
39	64.48	64.25	Broad Weed
40	44.04	47.91	Narrow Weed
41	57.24	65.53	Broad Weed
42	45.75	53.42	Narrow Weed
43	53.73	66.27	Broad Weed

44	41.84	68.56	Broad Weed
45	28.68	57.06	Narrow Weed
46	50.02	62.45	Broad Weed
47	44.04	47.91	Narrow Weed
48	53.90	61.45	Broad Weed
49	60.23	64.09	Broad Weed
50	60.94	61.08	Broad Weed
51	8.73	29.95	Little or No Weed
52	2.38	14.64	Little or No Weed
53	57.53	61.41	Broad Weed
54	33.73	42.09	Narrow Weed
55	37.82	43.05	Narrow Weed
56	39.11	43.78	Narrow Weed
57	43.24	46.59	Narrow Weed
58	23.23	34.44	Narrow Weed
59	44.04	47.91	Narrow Weed
60	25.78	40.49	Narrow Weed
61	29.22	39.70	Narrow Weed
62	39.18	45.63	Narrow Weed
63	43.18	49.18	Narrow Weed
64	38.44	52.62	Narrow Weed
65	39.22	51.42	Narrow Weed
66	31.33	49.05	Narrow Weed
67	28.85	42.18	Narrow Weed
68	48.53	62.70	Broad Weed
69	42.33	65.79	Broad Weed
70	26.94	40.64	Narrow Weed
71	31.07	40.05	Narrow Weed
72	22.11	42.15	Narrow Weed
73	48.03	53.67	Narrow Weed
74	33.06	44.76	Narrow Weed
75	33.06	44.76	Narrow Weed
76	35.59	53.03	Narrow Weed
77	28.48	43.50	Narrow Weed
78	35.59	53.03	Narrow Weed
79	25.02	44.73	Narrow Weed
80	35.93	53.90	Narrow Weed
81	26.49	39.92	Narrow Weed
82	38.49	50.10	Narrow Weed
83	32.08	44.77	Narrow Weed
84	34.80	44.66	Narrow Weed
85	32.40	41.38	Narrow Weed
86	31.13	39.92	Narrow Weed
87	25.77	42.01	Narrow Weed
88	23.89	43.15	Narrow Weed
89	35.95	54.42	Narrow Weed

90	37.38	53.51	Narrow Weed
91	39.49	50.25	Narrow Weed
92	32.34	44.72	Narrow Weed
93	51.26	53.98	Narrow Weed
94	36.65	45.93	Narrow Weed
95	32.34	44.72	Narrow Weed
96	34.55	46.53	Narrow Weed
97	34.23	50.12	Narrow Weed
98	28.77	41.64	Narrow Weed
99	27.98	41.91	Narrow Weed
100	39.15	52.80	Narrow Weed
101	29.92	41.32	Narrow Weed
102	35.43	51.04	Narrow Weed
103	26.67	43.46	Narrow Weed
104	34.44	48.28	Narrow Weed
105	39.18	45.63	Narrow Weed
106	39.22	51.42	Narrow Weed
107	58.85	62.10	Narrow Weed
108	26.67	43.46	Narrow Weed
109	57.42	61.46	Broad Weed
110	38.85	47.39	Narrow Weed
111	24.75	48.71	Narrow Weed
112	57.05	65.81	Broad Weed
113	52.82	69.28	Broad Weed
114	52.37	62.36	Broad Weed
115	45.27	52.02	Narrow Weed
116	62.22	70.14	Broad Weed
117	53.35	63.45	Broad Weed
118	56.78	66.26	Broad Weed
119	57.52	63.46	Broad Weed
120	52.37	62.36	Broad Weed
121	43.52	59.46	Broad Weed
122	41.82	60.05	Broad Weed
123	34.34	48.98	Narrow Weed
124	23.23	34.44	Narrow Weed
125	62.22	70.14	Broad Weed
126	27.76	34.67	Narrow Weed
127	36.68	43.26	Narrow Weed
128	34.34	48.98	Narrow Weed
129	35.11	48.81	Narrow Weed
130	34.11	44.09	Narrow Weed
131	30.75	46.19	Narrow Weed
132	21.82	46.38	Narrow Weed
133	27.90	43.43	Narrow Weed
134	22.07	37.81	Narrow Weed
135	32.48	43.32	Narrow Weed

136	28.82	37.95	Narrow Weed
137	32.08	38.82	Narrow Weed
138	24.86	38.38	Narrow Weed
139	28.01	42.11	Narrow Weed
140	32.08	38.82	Narrow Weed
141	34.62	42.37	Narrow Weed
142	24.30	45.49	Narrow Weed
143	25.93	50.15	Narrow Weed
144	5.74	17.27	Little or No Weed
145	22.03	51.13	Narrow Weed
146	29.42	47.90	Narrow Weed
147	28.65	46.53	Narrow Weed
148	30.77	43.73	Narrow Weed
149	26.41	41.09	Narrow Weed
150	31.27	46.14	Narrow Weed
151	36.89	49.72	Narrow Weed
152	25.27	40.48	Narrow Weed
153	50.15	53.22	Narrow Weed
154	49.46	51.51	Narrow Weed
155	55.26	54.90	Narrow Weed
156	44.24	48.91	Narrow Weed
157	28.55	38.01	Narrow Weed
158	34.61	41.78	Narrow Weed
159	33.93	40.02	Narrow Weed
160	34.24	43.47	Narrow Weed
161	25.93	50.15	Narrow Weed
162	25.26	31.89	Narrow Weed
163	27.43	34.60	Narrow Weed
164	23.23	34.44	Narrow Weed
165	32.08	38.82	Narrow Weed
166	26.36	35.62	Narrow Weed
167	26.17	35.10	Narrow Weed
168	25.77	33.14	Narrow Weed
169	24.43	32.45	Narrow Weed
170	23.23	34.44	Narrow Weed
171	31.95	40.30	Narrow Weed
172	29.02	37.62	Narrow Weed
173	33.48	39.65	Narrow Weed
174	37.22	48.28	Narrow Weed
175	31.90	40.95	Narrow Weed
176	33.97	42.02	Narrow Weed
177	33.38	44.35	Narrow Weed

VII. Conclusion

A real weed-control system incorporating with vision recognition system is designed and various experiments are conducted by using it for isolated spraying for limiting weed growth. The system is based on an identification and other characteristics is developed for identifying and categorizing of weeds. The images which were caught by a video camera are categorized with high rates of success.

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Figure 3: Broad Weed Type

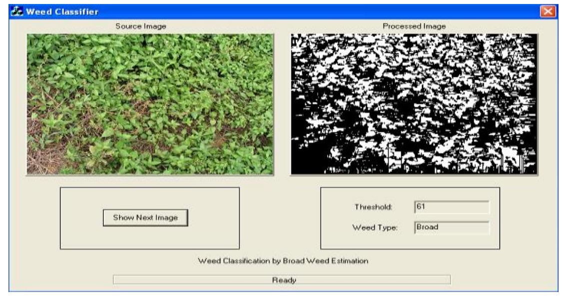

Figure 4: Broad Weed Type

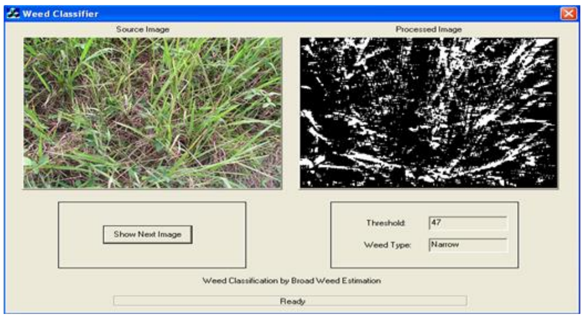

Figure 5: Narrow Weed Type

Figure 6: Little Weeds Type