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Real-Time Wheat Classification System for Selective Herbicides Using Broad Wheat Estimation in Deep Neural Network

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***Abstract*— Identifying seed manually in agriculture takes a long time for practical applications. Therefore, an automatic and reliable plant seeds identification is effectively, technically and economically importance in agricultural industry. In addition, the current trend on big data and data analysis had introduced scientist with many opportunities to use data mining techniques for better decision in various application. Recently, there are various number of applications that use computer-aided in improving the quality in controlling system. Classifying different types of wheat hold significant and important role in agriculture field. An improvement on such kind of system that makes distinctions based on shape color and texture of wheat plantation is crucial. The main objective of this paper is to develop a machine vision system which identifies wheat base on its location. For this purpose, a real time robotics system is developed in order to find plant in sorrowing area using pattern recognition and machine vision. For real-time and specific herbicide applications, the images are categorized in either expansive or precise categories via algorithm following the principal of morphological operation. Different experiments were conducted in order to gauge the efficiency of the proposed algorithm in terms of distinguishing between various types of wheats. Furthermore, the experiments also performed admirably amid varying field conditions. The simulation results show that the proposed algorithms exhibited 94% success rate in terms of categorizing wheat population which consists of 80 samples and out of them 40 are narrow and 40 broad.**

***Keywords*— image processing; wheat detection; real-time recognition; morphological.**

I. INTRODUCTION

Nowadays, wheat controls in the initial stage is an expensive technique and consume more time to be implemented. Therefore the research area in this field is challenging and requires extensive care is needed in making sure that the wheat production is at its optimum. Therefore, many developed countries had used cutting edge technology which includes biotechnology and information technology. The most critical challenges in the growth stage of wheat are the cultivation of the plant because of their leaves make the shadow for emerging wheat. This infection is caused due to their slow development and also because of the use of chemical and mechanical which also affected wheat cultivation. Therefore, it is necessary for utilizing and changing the research in wheat management that are eco-friendly and at the same time can increase the productivity of crops using technologies. Also, the usage of herbicides can cause a risk in potential water contamination and food. Moreover, the use of indiscrimination of herbicide affects the environment where biology is predisposed undesirably [1]. The quality of food can be increased with the help of using herbicides safely, and for this research, we used the tool known as wavelet analysis that can detect the wheat and crops same as Db4 wavelet that has been used for the extraction of wheat and other crops texture features [2].

In agriculture, the workflows are based on crop plants that are placed in a row structure. In a row cereal like wheat and barley, they are placed with no clear structure in rows while in sugar beets, maize and other high-value crops they are kept with clear defined intra-row spacing in rows between crop pants. Crop plant location systems such as Robovator and Garfords Robocop, it controls wheat in the crop by using some information such as plant recognition in robotic weeding applications and sometimes based on machine vision either using shape information/plant morphology properties [3].

Since wheat and crops productivity poses a vital biological constraint such as the extensive use of herbicides, wheat control will result in the appearance of wheat conflict to herbicides. In addition, the environmental problems also occur therefore we need to find out alternative ecological wheat management in cropping system [4].

Manipulating wheat-suppressing facility of crop varieties is a potential and promising option for wheat control where different plant collections, including wheat and rice crops and also a few of crop varieties with wheat suppression effects, are identified. In a natural interference of the crop plants with wheat's, these crop varieties are very much competitive in the field against wheat particularly a crop in the system where there will be used a different kind of wheat. Also, the suppression effect of wheat and its joint action of a competitive factor and ground interactions also affect the performance of crop as comparing above grounded interactions [5].

Recently, artificial neural networks (ANN) had become a popular method used in agricultural. Most of the ANN method was designed and proposed based on the performance of ANN in achieving higher efficiency and vision in cost and production. Multilayer perceptron neural networks technique was used to identifying wheat root and other crops for identification of the specific area of spraying hence decreased the amount of herbicide utilized. Moreover, multilayer perceptron neural networks technique also were used to identify onion and wheat root and specific area for spraying and also the number of herbicides which decreased and utilized [6]–[8].

In 2017, Kersten et. al. [9] described the main advantage of their method and it showed that the active targeting and identification of infected area and the performance of this method is also justified by the partial experiment which provides very much sufficient evidence regarding saving of resources like herbicides. Voisin in 2016 proposed a system that dealt with sensors of ground-based that could be used for assessing wheat levels and identifying wheat in a crop. Here the underlying principles, limitations, and performance of the current system were discussed [10].

Wenzl proposed one machine for new learning mechanism was introduced for distinguishing wheat and crop in account with their reflectance differences. The proposed mechanism introduced an approach for learning through a combination of incremental class augmentation and novelty detection. Classifiers of one class had been constructed by neural networks which provide basics for the novelty detection. Mahayuddin et al. support the effectiveness of the machine by comparing it with a control system in multirotor unmanned aerial vehicle navigation [11]. For the one-class SOM (self-organizing map) and one-class MOG (mixture of Gaussians) classifiers, the best results were obtained for active learning when compared with the auto-encoder network and one-class support vector machines. The success rate for MOG was 98% from 31% which was experimented in various species, the same results are shown at 94% from 53% for SOM.

According to Lahmiri and Boukadoum a sensor node that used for security and control where those methods also used for wheat deduction system and crop monitoring [12].

According to Momtahan [13] in 2016, two sets of the wheat field were selected from the collection of wheat and sensor node was used for their monitoring. Spherical-shaped 40 to 80 samples with varying wheat components of two different sets were evaluated at different separate dates. The sensor node was adjusted at a specific angle to monitor the height of wheat, and narrow wheat during this monitoring are removed, and the analytical technique was used. The dissimilarity was measured between wheat rode and wheat zones along with dry crop with the simple picture which is selected through the machine. RGB images were taken due to removing assessing area that covered by wheat and other product. Analytical techniques based on numerous regressions were used to control the correlation between ultrasonic readings and the coverage of wheat and crops. In the end, wheat-ridden and normal samples were observed at the differences in heights.

The image and the employment of the processing algorithm used in wheat and crops are distinguished from one another by utilizing wavelet analysis. Wavelet transform was used for analyzing the textural property of wheat and crop images. Whereas, the texture feature is mined from the data with a different parameter like energy, entropy, inertia contrast homogeneity with the help of the herbicides which were sprayed through robotic. Where the wheat position was based on organization and the plague-ridden areas was accessed [14].

Wheatfield is selected for the collection of wheat and the sensor node is used for their monitoring. Spherical-shaped 40 to 80 samples with varying wheat components of two different sets were evaluated at different separate dates. The sensor node is adjusted at a specific angle to monitor the height of wheat, and narrow wheat during his grass are removed, and the analytical technique is used. The dissimilarity was measured between wheat is ridden and wheat zones along with dry crop with the simple. RGB images are taken due to removing assessing the area covered by wheat and other product. Analytical techniques based on numerous regressions were used to control the correlation between ultrasonic readings and the coverage of wheat and crops [15]. The real-time machine for wheat is shown in Figure 1.

Fig 1: Real-time machine

Wheat is kind of crop which can affect grow in subtropical climate and wheat is one most reliable source of carbohydrate in the world . Wheat also contains protein minerals and vitamins [16]. All picture with longitude and altitude information were mosaicked and processed with the help of NDVI software [17].

Therefore, the main objectives of this paper are to design a methodology that proposes an algorithm which can identify the location and recognize the presence of wheat and as well as can distinguish between the narrow wheat and broad wheat.

II. MATERIAL AND METHOD

In this section, we discuss data collection area selection, weight, and height of the wheat. The verified wheat was randomly selected at various wheat fields. The data were collected from different week and days, different area and then they are classified into different place. Whereas, the frequency (F) is used to find the survey area to find the wheat by the real system. Figure 1 shows the real time machine.

$$K_P \frac{\sqrt{y1}}{n} \times 100 \quad (1)$$

Where K_p are the wheat in the area y_1 and the present of wheat and yo is the other plant and n the number are searching by the real system.

The uniform (U) is designed to find in percentage:

$$U_P = \frac{\sum_1^n \sum_1^m MXij}{m \times n} \quad (2)$$

Where U_p up is the uniform wheat in the field and, X_i is the ununiform product is the field total will be $M = N$ and D = is the density each product in the fields.

$$D_{PI} = \frac{\sum Zj}{m} + 4 \quad (3)$$

Where D_{PI} is the density of the field and can be express as number /m2, NZ and j are the numbers of the product.

$$MFD_K = \frac{K\,1 D_{KI}^{N}{}^{+4}}{n} \quad (4)$$

Where MFD_K, is the mean density of the filed used. The above four education is used to find the wheat at different level [16].

$$\Pr oduct = AI_k = U_P + D_{PI} + MFD_K \quad (5)$$

After the selection of an area in the field the following wheat data are collected as shown in Table 1.

TABLE I
DATA COLLECTION FOR 6 WEEK

Image	Wheat Density	Broad wheat Density	Type
1	60.94	61.08	Broad wheat
2	56.23	64	Narrow Wheat
3	37.52	48.29	Broad wheat
4	44.04	48.29	Broad wheat
5	56.47	67.45	Broad wheat
6	60.56	45.55	Broad wheat
7	56.67	34.56	Broad wheat
8	44.67	78.67	Narrow Wheat
9	20.54	56.67	Narrow Wheat
10	44.56	67.67	Narrow Wheat
11	56.28	68.90	Narrow Wheat
12	35.29	78.56	Narrow Wheat
13	42.56	45.67	Narrow Wheat
14	44.67	67.67	Broad wheat
15	47.78	76.45	Broad wheat
16	67.56	56.78	Broad wheat
17	45.67	67.67	Broad wheat
18	56.66	78.56	Broad wheat
19	56.55	56.78	Broad wheat
20	67.75	67.78	Broad wheat
21	78.78	67.56	Broad wheat
22	60.94	61.08	Broad wheat
23	56.23	64.00	Narrow Wheat
24	37.52	48.29	Broad wheat
25	44.04	48.29	Broad wheat
26	56.47	67.45	Broad wheat
27	66.56	45.55	Broad wheat
28	56.67	34.56	Broad wheat
29	44.67	78.67	Narrow Wheat
30	26.54	56.67	Narrow Wheat
31	44.56	66.67	Narrow Wheat
32	56.28	68.90	Narrow Wheat
34	47.56	45.67	Narrow Wheat
35	40.67	67.67	Broad wheat
36	47.78	76.45	Broad wheat
37	67.56	50.78	Broad wheat
38	45.67	67.67	Broad wheat
39	56.66	78.56	Broad wheat
40	56.55	56.78	Broad wheat
41	67.75	67.78	Broad wheat
42	78.78	67.56	Broad wheat
43	60.94	61.08	Broad wheat
44	56.23	64	Narrow Wheat
45	37.52	48.29	Broad wheat
46	44.04	48.29	Broad wheat
47	56.47	67.45	Broad wheat
48	60.56	45.55	Broad wheat
49	56.67	34.56	Broad wheat
50	44.67	78.67	Narrow Wheat
51	20.54	58.67	Narrow Wheat
52	44.56	67.67	Narrow Wheat
53	56.28	69.90	Narrow Wheat
54	35.29	78.56	Narrow Wheat
55	42.56	40.67	Narrow Wheat
56	40.67	67.67	Broad wheat
57	47.78	70.45	Broad wheat
58	67.56	56.78	Broad wheat
59	45.67	67.67	Broad wheat
60	56.66	78.56	Broad wheat
61	56.55	56.78	Broad wheat
62	67.75	60.78	Broad wheat
63	78.78	67.56	Broad wheat
64	60.94	61.08	Broad wheat
65	58.23	64	Narrow Wheat
66	39.52	48.29	Broad wheat
67	44.04	67.29	Broad wheat
69	56.47	67.45	Broad wheat
70	60.56	45.55	Broad wheat
71	56.67	34.56	Broad wheat
72	67.67	78.67	Narrow Wheat
73	20.54	56.67	Narrow Wheat
74	44.56	67.67	Narrow Wheat
75	56.28	68.90	Narrow Wheat
76	67.29	78.56	Narrow Wheat
77	42.56	45.67	Narrow Wheat
78	44.67	67.67	Broad wheat
79	47.78	66.45	Broad wheat
80	57.56	76.78	Broad wheat

Table 1 shows the data which are collected in the different week with the help of real-time machine. Due to the above manner images and their size are remained the same with high quality of the protruding portion of the sprayer captured. In Figure 2, the diagram demonstrated the images are related to the CPU, and decision box are connected through the parallel port and used for turning off the pump purely on based of on the CPU processing over kind of images.

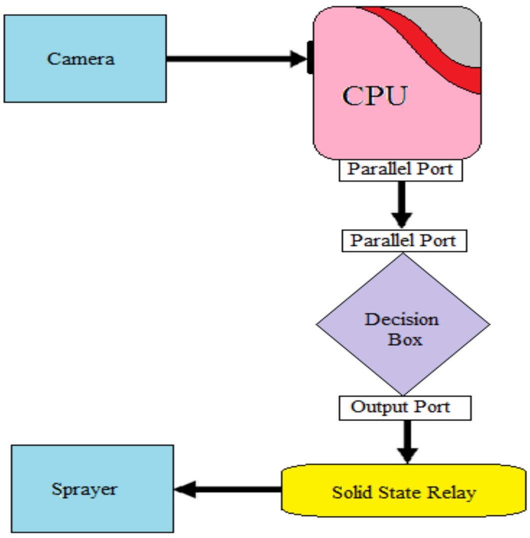

Fig.2: Conceptual flow chart

Figure 2 illustrates the image relayed to CPU, and then decision box makes a decision make off the pump or on because it connected to the CPU through parallel ports .with the help of it CPU process images.

Microsoft Visual C++ 6.0 is used as the software to develop the system. Moreover, the GUI design is with the resolution of 240 pixels of the image by rows and 320 pixels by columns, the standard and mean deviation between the altered image and the actual image is calculated. Figure 2 showed the wheat recognition system for real-time and demonstrated their persistence in recognizing the narrow and broad wheat by implementing the algorithm in the morphological operation.

The classification algorithm is given as follows:

```
If (Broad Wheat Percentage >=55 and
    Wheat Percentage>=40) or (Broad
    Wheat Percentage>60)
    Classify as “Broad Wheat”
Else If (Wheat Percentage>=30)
    Classify as “Narrow”
Else
    Classify as “No or Little”
End
```

Where 55, 40 and 60 are threshold values that were taken from previous literature [12]–[14]. In the start of the image preprocessing operation, the input image is decomposed into red, green and blue components to create a binary image using the following transformation.

```
If G>R and G>B and G>115 then
   PIMG = 1
Else
   PIMG = 0
End if
```

Where R, G, and B are the red, green and blue component sand PIMG is the processed binary image. The resulting binary image will have wheat in bright pixels and background in dark pixels. Next technique is classification based online based segmentation wherein this technique different image of wheat scanned horizontally and vertically to find out their location. Their length and height measure image. In broad wheat, the length and height are more than other wheat in the field. Narrow wheat the case change in here the length and height are small then other wheat. After collecting the data, we classify narrow wheat from broad wheat and get the percentage of the total fields [18],[19].

Next, the output variable in is this case is a scalar value, the threshold to be used in the banalization whose value ranges from 0 to 1. However, in the real system, the output value is a W. The adaptation, in this case, is straight forward. The output value will be a weighted average of the threshold of the k neighbors selected in the previous step. The weight assigned to the threshold of a given neighboring histogram (hp with p = 1, k) will be inversely proportional to the distance between itself and the W whose threshold is unknown (hx) equation as follows:

$$W_p = (d(hp, hx) + w) \tag{6}$$

$$W_p = (d(hp, hx) + w) \tag{7}$$

$$Tx = \sum_{1}^{KP=1} WP_T \quad PA \tag{8}$$

Where Pt is the threshold value of the, neighboring hp. In order to avoid infinite values caused by zero distances, the value of the threshold for a given histogram x will be estimated as follows [18].

III. Results and Discussion

This section will discuss further the next process once the data were collected. Next, the process of selecting the threshold and wheat were classified into a different category with the help of the given program:

```
Total images= 80
Failure in = 100
So 80-10=70
Now 10/80*100=80%(Accuracy)
Without considering ambiguous images
total =80
Error occurred in=10
80-10=70
10/80*100=95%(Accuracy
The above loop selection algorithms
run and generate the result.
```

According to the above algorithm, the result is almost 94 % accurate in the selection of a different kind of wheat. The result is then generated and shown below in graphic form.

Fig. 3: Broad Wheat Type for Threshold 29

Figure 3 shows the selection of broad wheat in the specific area. According to the result, the threshold is 29% at each area which means that every 29 wheat is there will be narrow wheat. In Figure 4, the narrow wheat is 61% as shown in the threshold. This means that at each 61 narrow wheat there will be one broad wheat in that specific area. According to Table 2, 96.3% of that area is narrow wheats which means that in a specific area there are 96.3% wheat are the same size and shape.

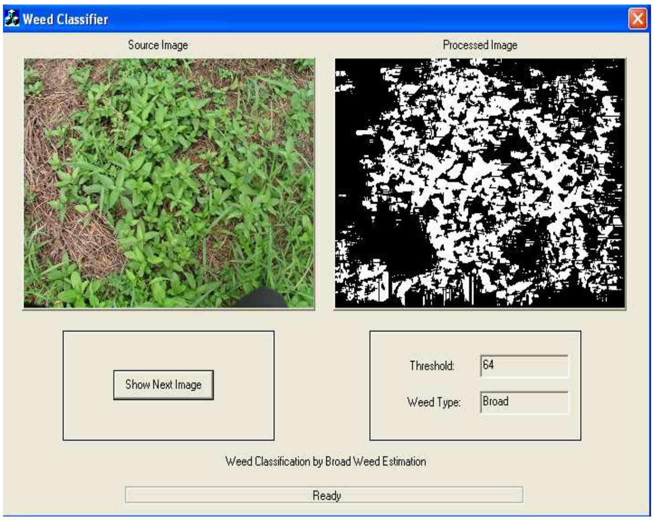

Fig. 4: Narrow Weed Type for Threshold 61

In Figure 5, the black section shows the result after the processing. According to the result, 64% are a threshold which means that after each 64 broad wheat we found 1 narrow wheat. From Table 2 it shows that the result is 95% indicate broad wheat in the specific area which is selected for the process.

Fig. 5: Broad Wheat Type for Threshold 64

Fig. 6: Narrow Weed Type for Threshold 61

In Figure 6 the narrow wheat is 43% as shown in the threshold. This means that at each 43 narrow wheat there will be 1 broad wheat in that specific area. According to Table 2, 89% of that area is narrow wheats which means that in a specific area there are 89% wheat are the same size and shape.

Figure 6 shows that that the green clour is before process, and the black color is after process, and according to the result the threshold is 43 where after each 43 narrow wheat there will be 1 broad wheat hence according to the Table 2, almost 89 % of wheat in that specific area is broad wheat which is selected for process.

TABLE II

RESULT AFTER PROCESSING

Type of wheat	Threshold value	Results in percentage
Broad Wheats 1	29	84.5%
Broad Wheats 2	64	92.0%
Narrow Wheats 1	47	95.2%
Narrow wheat 5	43	89%
Wheats	80	94%

Table 2 contains the simulation results. According to the result, narrow wheats is 89% and 95.2%, and broad wheat are 84.5% and 92% so overall result we get after multiplying these number with a threshold is 94% it means that the proposed design system is working accurately.

IV. Conclusion

The simulation results had shown that the classification through this system could be proved very effective as far as the images are concerned which contain only one prevalent wheat type. However, it is very difficult to categorize the wheat types which contained more than one prominent, so extensive research is required for categorizing such crop areas. A promising method for achieving that would be to divide wheat to any given population into smaller ones in order to diminish the possibility of there being more than one species of wheat in these smaller components. Moreover, based on the above scenario, this research had designed a real-time system which used for classification of two kinds of wheat (narrow and broad wheat). According to the result, almost 94% of the proposed system work appropriately in finding the result, but there is still some works need to be done for improvement in getting an outstanding result for classification of wheat. Overall, as compared to pervious work the result demonstrates an improvent of 2%. This work can be further explored for improving classification with the help of real-time system by introducing an improvement on the algorithms and real-time system on different wheat plant classification.

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