Weed Detection in Farm Crops using Parallel Image Processing

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***Abstract*— Human community are educated about the environmental issues of pesticides and fertilizers used in agriculture. There is a ever-growing demand for food to be met by agriculture producers. To reduce the environmental issues and address food security, IoT based precision agriculture has evolved. Precision agriculture not only reduces cost and waste, but also improves productivity and quality. We propose a system to detect and locate the weed plants among the cultivated farm crops based on the captured images of the farm. We also propose to enhance the performance of the above system using parallel processing in GPU such that it can be used in real-time. The proposed system takes real time image of farm as input for classification and detects the type and the location of weed in the image. The proposed work trains the system with images of crops and weeds under deep learning framework which includes feature extraction and classification. The results can be used by automated weed detection system under tasks in precision agriculture.**

Keywords*— *parallelized weed detection, Graphic Processing Unit, Convolutional Neural Network

I. INTRODUCTION

With existing issues of shortage of manpower and resources for agriculture, development of new crop diseases and weeds, there is advancement in the field of robotic farming and precision agriculture. The problem of efficient weed classification and detection is closely related to the problems of sustainable agriculture and climate change. Research results indicate that climate change can introduce new and hybrid weeds to existent species. Hence, it is important to develop new technologies that help to identify weeds present along with farm crops as they can affect their growth. The detection of weeds is also useful for removal of weeds, thus reducing the usage of pesticides and providing efficient alternatives at the time of harvesting the crops.

The aim of this paper is to present an end to end system which works in real time by taking images of farm crops as input and produces a set of bounding boxes for each type of weed located in the image as output directly. This is challenging one as it needs to distinguish weeds from the farm crops and also to estimate the number of different weeds and their locations appropriately. This paper proposes a deep learning approach that learns from labelled field images and detects the weeds present in test images. Although the existing methods consider prediction or classification as an independent problem and need some pre-processing in the input and post-processing on the detected output, the proposed method does not demand them. The technical contribution of this paper involves defining the metrics for evaluation and comparison of different algorithms in the crop/weed discrimination tasks.

The rest of the paper is organized as follows. The related existing work is surveyed and presented in section II. The architecture and description of the proposed system is detailed in section III. The experimental results are presented in section IV and compared. Section V discusses the results of the proposed system. Section VI concludes the proposed work and mentions the future direction.

II. RELATED WORK

Image processing and computer vision tasks have been used for plant classification and crop/weed discrimination at various levels.

When considering only the plant classification system B. Yanikoglu and E. Aptoula [4] proposed a plant identification system for automatically identifying plants in a given image. C. M. Zhai and J. X. Du [5] developed a machine learning algorithm known as the Extreme Learning Machine (ELM) to classify plants by extracting Gabor texture feature of plant/ leaf. These approaches shared with other work [13,15,10] have a limitation that the input is a plane leaf captured in a uniform background. Further these approaches only concentrate on classification of plants on different methods and have disadvantage of not being applicable in real-time due to problem of segmenting individual leaves from foliage images in fields.

A. Ozdemir and T. Altiler [1] proposed a weed detection system using ground based hyperspectral images of corn crop fields The system involved preprocessing and normalisation steps followed by classification using SVM/LDA. D. Seatovic, H. Kutterer and T. Anken [6] proposed a system using 3D images of the plants and surface patches to identify broad leafs from grasses. A. H. Kargar B, A. M. Shirzadifar [3] developed a new weed detection and classification method using wavelet transform and morphological operations. J. Pan, M. Huang, and Y. He [9] used morphological operations and ANN to discriminate a crop between two weeds similar in shape and colour. S. Haug, J. Ostermann, and R. Bosch [17] proposed a machine vision approach without segmenting the individual leaves. Random Forest classifier is used to classify the features extracted from the sparse pixel positions in image. These approaches with other works [11,12] share common limitations like involving intense computations for either pre-processing or post-processing of images, complexity in image acquisition process, need for manual annotation and restriction to limited number of weeds.

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H. Yalcin and S. Razavi [7] proposed a plant classification system using Convolutional neural networks. P. Sermanet et al [14] presented an integrated framework for using Convolutional neural networks for classification, localization and detection. They also proposed a feature extractor called Overfeat. R. Stewart and M. Andriluka [16] developed an end to end approach to detect people in crowded scenes with modified algorithm called GoogleNet-Overfeat. These approaches with other works [2] proved the success of using Convolutional neural networks in image processing applications like classification and object detection. Further, A. Ozdemir and T. Altiler [1] compared various GPU based parallel image processing techniques for analyzing plant growth. In Kyu Park et al [8] evaluated various image processing algorithms on GPU using CUDA.

The proposed approach uses the Convolutional Neural Networks and GPU to solve the existing problems in weed detection and develop a system to work in real time.

III. Parallelised Weed Detection System

The Parallelised Weed Detection System (PWDS) is implemented using Convolutional Neural Networks to develop a robust, scalable and real time weed detection system. The architecture of the proposed Parallelised Weed Detection System is shown in Figure 1.

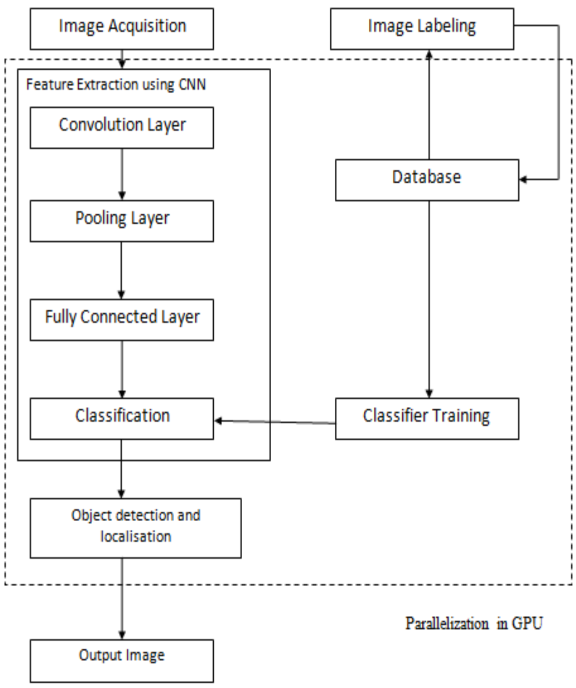

Fig. 1. Architecture of Parallelised Weed Detection System

The image acquisition module in Figure 1 consists of collecting the real time images from the carrot farm without any need for specialized infrared cameras or pre-processing of the images. The image labelling module involves the supervised classification of the images by grouping them into separate directories. The dataset is the labelled directories containing annotated images. The annotation involves identifying the regions were the weeds are present in each image provided in the training set. A bounding box is constructed and the coordinates are saved in JSON file. More than one rectangle can be stored for each image which indicates the regions have the desired object and the machine learns the features from them. Similarly, the output image consists of the predicted bounding boxes which locate the weeds present in the image. A sample output image in which weed detected among carrot crops is given in Figure 2.

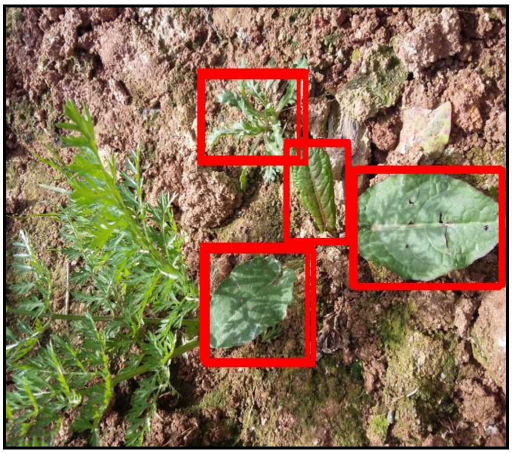

Fig. 2. Weed detection among carrot crop in the natural dataset

The feature extraction module which consists of several modules and layers of Convolutional Neural Network is implemented by using Googlenet-Overfeat model in TensorFlow framework. The details of network architecture are given in [16].

IV. Experimental Results

A. Evaluation Metrics

The proposed system is trained using the standard dataset provided by [17]. It is also used for comparison of the performance with the proposed Parallelised Weed Detection System (PWDS). We defined the metrics for evaluation as

True Positive(TP) : Weed detected by the system

False Positive(FP) : Crop detected by the system

True Negative(TN): Crop not detected by the system

False Negative(FN): Weed not detected by the system

Precision and recall are measures of relevance. Precision is defined as the fraction of relevant instances among the retrieved instances and computed using (1).

$$\text{Precision} = (TP)/(TP+FP) \quad (1)$$

Recall is defined as the fraction of relevant instances that have been retrieved over the total amount of relevant instances and is calculated using (2)

$$\text{Recall} = (TP)/(TP+FN) \quad (2)$$

Accuracy is a statistical measure and it used to measure how correctly a classification test detects a condition. It is the proportion of correctly classified results among the total number of cases examined. Accuracy is computed using(3)

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \quad (3)$$

B. Performance Evaluation

The proposed weed detection system is parallelised and implemented in TensorFlow framework. The experimental results during the training and evaluation of the standard dataset in [17] under the proposed PWDS are shown in Table I.

TABLE I. RESULTS DURING TRAINING OF THE PROPOSED PARALLELISED WEED DETECTION SYSTEM (PWDS)

No. of Iterations	True Positive	True Negative	False Positive	False Negative	Recall %	Precision %
5000	88	33	19	22	80.0	82.2
10000	91	36	14	21	81.2	86.6
22000	90	46	10	16	84.9	90.0
30000	92	47	9	14	86.8	91.1

The precision and recall values of the proposed PWDS system are compared with the results of Plant Classification system for Crop/Weed discrimination in [17] and it is shown in Figure 3.

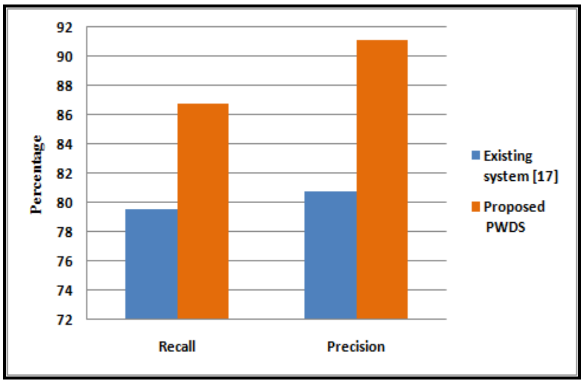

Fig. 3. Comparison of precision and recall

Also the accuracy of weed detection by the proposed PWDS is computed using (3) and is compared with the existing method [17] in Figure 4. Though the accuracy of the proposed system is in par with existing system, it outperforms the existing system in precision and recall.

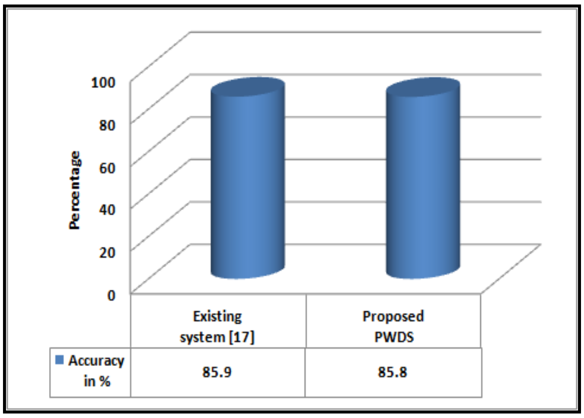

Fig. 4. Accuracy of weed detection

The comparison of training time by the parallelised system implemented using GPU is shown in Table II.

TABLE II. COMPARISON OF THE TRAINING TIME OF THE PROPOSED PARALLELISED WEED DETECTION SYSTEM (PWDS) WITH GPU

Number of Iterations	Time taken in CPU(min)	Time taken in GPU(min)	Speed up
10,000	655	340	1.92x
20,000	1279	659	1.94x
30,000	1895	976	1.94x

From the Figure 3, it can be inferred that the proposed system achieves better recall and precision than the existing system in [17]. Further it was found that the system was able to detect weeds which were not even annotated in [17]. This is due to difference in the methods used for detection. The plant classification system for crop/weed detection in [17] uses features both plants' specific information such as length of counter, area, compactness and pixel information such as intensities and their distribution. The plant specific features may vary for every crop in real time which reduces the accuracy. Whereas, the proposed real time weed detection system uses only pixels of input image as neurons and uses the neural network for training and detection of the weeds. The proposed system is not affected by the changes in the size or orientation of weed/crop and it is also not affected by the type of classifier used as in the previous method.

Table I shows that increasing the number of iterations increases the performance of the system. It is notable that the false positives and false negatives are decreased with increase in iterations which is very crucial in implementing the system in real time. Reducing the number of false positives is very important as the system should not detect the crop as weed as it affects the usability of the system. Further it is evident that the precision and recall values increase as the number of iteration increase since it is inversely proportional to the false positive and false negative values respectively. Thus the number of iteration plays an important factor in determining the performance of the system and it is directly proportional to the precision and recall metrics. As the number of iterations increases, the execution time also increases. Hence the parallelised weed detection system is implemented using GPU.

From Table II, it can be observed that there is a notable time difference between the proposed real-time weed detection system under CPU and GPU for the same dataset. It is evident that the time taken for training the system under normal Intel i5 core CPU is almost twice the time taken by the same system supported with GPU. The difference is due to the parallelisation using the CuDNN libraries in Nvidia GeForce GT610 graphics processor.

V. DISCUSSION

A new weed detection system is proposed with an application in carrot crop fields. The results shown in previous section reveals that the system provides a precision of 91.1% for carrot field images in which weeds are close to crops, both are in same size and overlap each other.

Most of the existing works does not address this condition. They fail in recognizing the crop/weed when both overlap. When those approaches try to classify only large non-overlapping weed segments, it results in large loss of accuracy. The per cell-based results are given which are not suitable in real-time mechanical treatment for weed removal.

The proposed system addresses these issues. It does not need to segment plant/leaf before classification. It outputs the image with bounding boxes over the weed. This advantage is possible because the system automatically extracts features from the image without any need of human assistance. Further the system is robust and scalable as such it can learn to detect any new type of weed. The evaluation proves that a real time weed detection system for commercial farm crops is possible with the proposed method and high precision is achieved.

The output of the proposed system can help a robot to plug out the weed selectively. In addition to that, the output helps in finding the coverage of weed, the stage of weed plant (early stage or grown up stage) and crop/weed ratio which may be helpful for the farmers in decision making the techniques to be used or for the devices used in IoT based precision agriculture. The limitation in the proposed system is that the predicted bounding boxes can partly overlap with crops due to very close proximity. However this could not be a disadvantage in weed control in precision agriculture. Here the detection of weeds is most important.

VI. CONCLUSION

A weed detection system that works in real time without need for segmenting plants or leaves is proposed. Feature extraction and detection are instead done using Convolutional Neural Networks without any human assistance. The proposed method can be used in real fields in which weeds crowded with crop plants. The output image of the weed detection system can be used for selective weed treatment.

To evaluate the system, a standard dataset of images provided in [17] and images captured in carrot crop field at different conditions are used. The performance is analysed by training the proposed system with manually annotated input images and comparing the output images with expert labelled ground truth images. The analysis result indicates that the proposed system achieves a precision of 91.1%.

In future, the system will be trained with large datasets of input images to detect different types of weed such that it can be used in real-time.

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