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AUTOMOISED MOWING, SEEDING AND SPRAYING BY THE ROBOTATO

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ABSTRACT:

Now days, the water wastage is major problem around the world. Installing water flow sensor at every valve and pipes to monitor the establishment's water consumption. The amount water consumed is called based on that the monthly water consumption and cost is calculated. The consumed amount of water and cost can be viewed using webpage. The automated system is used to develop the process of cultivating farming land without the use of human power. Web camera is fixed on the robotic set up, that web camera will continuously monitor the crops. In this project we are designing the agricultural autonomous system which will sense the conditions in real time, we are analyzing the field parameters such as, Temperature, humidity, soil Moisture etc. The robot can be monitored and controlled through web page. Just giving an instruction on web page the robot will move according to the direction also we can give the command to cut the crop, it will automatically cut the unwanted crop. By giving the command on the webpage, fertilizer will be sprayed on the field.

Key words: Sensor, Processor, DC motor, IOT

I INTRODUCTION

In current generation most of the countries do not have sufficient human factor in agricultural sector and it affects the growth of developing countries. So it’s the era of automation to overcome this problem. In India, most of the people are farmers. Here the designing systems like sowing the seed, watering the plant or spraying the fertilizer and navigate the vehicle motion are preferred by this autonomous robot using microcontroller. This system is mainly based on minimizing man power and cost of the equipment, which can be affordable to all farmers. In Existing system, the crop is monitored and the automated unit will cut the unwanted crops. Here, it will go in straight line were direction is controlled manually. Web camera is fixed on the robotic set up, that web camera will continuously monitor the crops. In this project we are designing the agricultural autonomous system which will sense the conditions in real time, we are analyzing the field parameters such as, Temperature, humidity, soil Moisture etc. The soil moisture, Temperature, Humidity sensor is interfaced with the raspberry pi, the sensor will sense the data and it will pass the information to raspberry pi so that it will ON/OFF the DC motor to irrigate automatically. The robot can be controlled through web page. Just giving an instruction on web page the robot will move according to the direction also we can give the command to cut the crop, it will automatically cut the unwanted crop. By giving the command on the webpage, fertilizer will be sprayed on the field.

Fig.1. Aerial view of the field

II PROPOSED METHOD

In this paper, we propose a novel approach for training deep convolutional neural networks (DCNNs) that allows us to tradeoff complexity (e.g. memory size and speed) with accuracy. This is achieved through a three-step process. First, we adapt a pre-trained model (Inception-v3 [5]) to the task at hand which leads to state-of-the-art performance. However, as the pre-trained model has been derived for general object. Classification, using 1 million (1M) images to classify 1,000 objects, the adapted model (Adapted-IV3) is complicated consisting of 25M parameters. This makes it relatively slow and so in the second step we use the adapted model to teach much smaller, or lightweight, DCNNs that can have orders of magnitude fewer parameters. Model compression and "distillation" techniques are used to achieve this. In the third step, inspired by [6], we combine a set of K-lightweight models as a mixture model to further enhance the performance of the lightweight models—this has a linear relationship between the number of models and the resultant model complexity. This approach leads to impressive results for weed segmentation—a critical task for agricultural robots such as AgBot II. The Adapted-IV3 model provides state-of-the-art performance, improving accuracy from 85.9% [7] to 93.9%. However, this model is only able to run at 0.12 frames per second (fps). To make this approach scalable (low memory requirements and fast) while still being accurate, we demonstrate that K = 4 lightweight DCNNs can be learnt and then combined as a mixture model to achieve an accuracy of 90.3%. This model uses just 1/25th the number of parameters of the Adapted-IV3 model and improves the frame rate by an order of magnitude to 1.83fps.

III PROPOSED MODEL

1) We adapt a pre-trained model to the task at hand. In this work we adapt the Inception-v3 [5] model and refer to this adapted model as Adapted-IV3. The process for adaptation is described in Section III-A. 2) The adapted model, Adapted-IV3, is then used to teach (train) a much smaller (lightweight) DCNN. The way in which the adapted network is used to teach the smaller network is described in Section III-B. 3) Inspired by [6], we combine a set of K lightweight models as a mixture model to further enhance the performance of the lightweight models. This involves further training which is described in Section III-C.

IV. WORK FLOW CHART

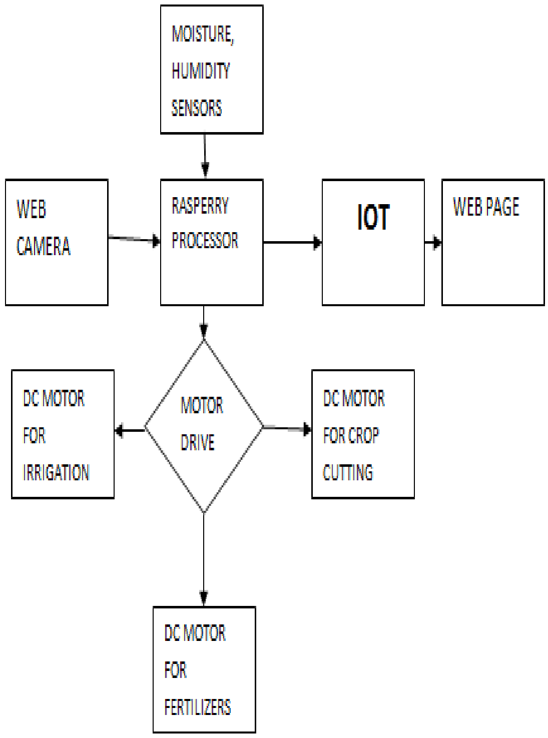

Fig. 2. Workflow chart

- **SELECTIVE HARVESTING**

Selective harvesting involves the concept of only harvesting those parts of the crop that meet certain quality thresholds. It can be considered to be a type of pre sorting based on sensory perception. As these criteria often attract quality premiums, increased economic returns could justify the additional sensing. To be able to carry out selective harvesting effectively, two criteria are needed; the ability to sense the quality factor before harvest and the ability to harvest the product of interest without damaging the remaining crop. Most agricultural equipment is getting bigger and hence not suited for this approach. Smaller more versatile selective harvesting equipment is needed. Either the crop can be surveyed before harvest so that the information needed about where the crop of interest is located, or that the harvester may have sensors mounted that can ascertain the crop condition. The selective harvester can then harvest that crop that is ready, while leaving the rest to mature, dry, or ripen etc.

- **MICRO SPRAYING**

Within the close-to-crop area, great care must be taken not to damage the crop nor disturb the soil. One method of killing weeds close to the crop plants is to use a micro spray that delivers very small amounts directly on to the weed leaf. Machine vision can be used to identify the position of an individual weed plant and a set of nozzles mounted close together can squirt a herbicide on to the weed.

V. EXPERIMENTAL RESULTS

We apply our approach to the problem of weed segmentation for robotic platforms such as Ag Bot II and produce results on the publicly available weed/crop dataset. All of our models were implemented in Tensorflow4. The Adam Optimizer was used with a learning rate of $\lambda = 1e^{-4}$, $\varepsilon = 0{:}1$, a batch size of b = 60 and a dropout rate of 50%. When training the lightweight DCNNs we use the same data as was used to fine tune the complicated (Inception-v3) network.

Fig.3. ROBOTATO

Fig.4 camera for Imaging and distance identification

Fig.5 Image captured by camera

Weed segmentation is key to enabling integrated weed management for intra-row weed management. This task is made challenging by the fact that the weeds can overlap with the crop making accurate classification difficult. To explore the performance of weed segmentation we make use of the publicly available Crop/Weed Field Image Dataset

(CWFID) which consists of 20 training images and 40 testing images; we make use of the agriculture protocol. We compare to the baseline method which trains a random forest classifier on features obtained from shape and pixel intensity information. The parameters for the Mini Inceptions were [64; 96; 128; 192] for the convolutional layers, [240; 480] for the two inception modules (see Table I and Figure 4 for more details) followed by a fully connected layer consisting of 960 neurons. The results in Table II highlight the potential improvements available by using a deep neural network based solution. It shows that all of the presented deep learning solutions.

VI CONCLUSION

In this project we are designing the agricultural autonomous system which will sense the conditions in real time, we are analyzing the field parameters such as, Temperature, humidity, soil Moisture etc. The soil moisture, Temperature, Humidity sensor is interfaced with the raspberry pi, the sensor will sense the data and it will pass the information to raspberry pi so that it will ON/OFF the DC motor to irrigate automatically. The robot can be controlled through web page. Just giving an instruction on web page the robot will move according to the direction also we can give the command to cut the crop, it will automatically cut the unwanted crop. By giving the command on the webpage, fertilizer will be sprayed on the field.

VII FUTURE PROPOSAL

In future model, the number of gears used for seeding is increased. More number of rows can be covered easily. In the next version, dedicated processor for image detection and sowing seeds mechanism will be implemented. The powering system will be changed from12V lead acid battery to high power batteries. Use of solar energy will also be included. This makes the robot more efficient. The robot future model has a display which will be given to the farmer. It deals with the control of robot and also it transmits the video that is been focused by the robot. These changes improve the speed of the robot. This also gives better results than existing technology.

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