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Autonomous Farmbot: Weed Detection for Smart Farming Using CNN

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ABSTRACT: Today's Modern world has been facing an acute problem of farming. In farming particularly, being more specific it's the cost of production . According to statistical data it has been observed that to maintain the rate of production of grains or any plant in specific ,farmers have to use more fertilizers and pesticides which is cumulatively increasing the production cost . Weed has been continuously dwindling the part of pesticides and fertilizers used by the plants around it. This gives rise to the ever increasing demand of fertilizers. Earlier we were treating each plant equally which increases demand for fertilizers and pesticides . So here we are to cope up with the problem by introducing a notion of AUTONOMOUS FARMBOT, which could treat each plant individually using IMAGE PROCESSING and ARTIFICIAL INTELLIGENCE. Artificial intelligence, specifically deep learning, is a fast-growing research field today. One of its various applications is object recognition, making use of computer vision. FARMBOT will identify the weeds and crops in Farmstead using Computer vision. This technology can be collaborated with SPRAYING MACHINES, which can efficiently use pesticides and fertilizers for weeds and crops respectively. This is done by accessing the images through the FarmBot API(Application Programming Interface), using computer vision for image processing, and artificial intelligence for the application of transfer learning to a CNN that performs the plant identification autonomously.

I . .INTRODUCTION

Agriculture is the backbone of India and the life of many people depends on agriculture for their livelihood. As the Income from agriculture is very less, so to get the maximum benefits maximum productivity should be obtained from the limited resources and minimise the use of sub materials and manual labours. First thing which hinders the farmers to get the profits is weeds in the farm. So to get the maximum profits weed should be removed or use pesticides.But the conventional way to remove weed takes too much time and process will also require more amount of pesticides and other chemicals to kill the weeds if want to do that manually which will increase the overall cost for farmers and also decrease the profit plus it will also cost the manual labour charge. So, if we use an automated method to find the weeds using computer vision, we can spray the pesticides and herbicides precisely only on weeds and can save a significant amount of pesticides to save the money and it will also save the amount used for manual labour thus will effectively increase the profit gain by the farmers. In an automated method, the image is taken by the camera fitted on the autonomous bot. Once the images are captured, it is sent for the preprocessing to remove all the noises and blur due to motion and the features are then extracted. Based on all the features for which the model is trained,the model identifies the actual crops and all the other weeds present in the image. Once the weed is detected, the processor will operate the actuator to spray only on the weed. The rest of this paper describes previously existing work, motivation, methodology, classification and all the experimental results obtained from the setup.

II. LITERATURE SURVEY

Agriculture and farming has always been one of the most important activities for survival. Over the last few decades, and more specifically, over the last 15-20 years, agriculture has been adapted to use mechanised features for effective farming and digitised data. Due to this evolution and all automation, labour flow is almost standardised in most parts of the world. Nowadays, after introducing artificial intelligence and robotics into agriculture there is no need for

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standardization anymore. Robots are learning and working cooperatively with humans and learning as they work with them to understand the basic agriculture tasks such as weed detection in the farms, watering or seeding Weed detection is one of those important agriculture tasks that are being digitised, reducing human intervention will make possible a decrease in the use of herbicides, increasing health care. To achieve this objective, autonomous bots that are able to detect plants and classify them into crops or weeds are now introduced into agriculture. This implementation has been done in multiples studies such as Dankhara, , where Internet of Things (IoT) is applied into an intelligent robot to differentiate crop and weed remotely; IoT is present in the communication between a Raspberry Pi, where the processing is done and the camera and sensors are connected, and the Data Server, where the Raspberry Pi sends the information obtained.

III. CONVOLUTIONAL NEURAL NETWORKS

Convolutional neural network or simply CNN is a class of deep learning, or artificial neural network that has been employ to produce an correct or solid achievement in computer visiontasks, for instance image classification and detection . CNN'sare like traditional neural network, but withmore deeper layers. Ithas biases, weights and outputs through a non-linearactivation. The neurons of the CNN isarranged in avolumetric way such as,width,height and depth.

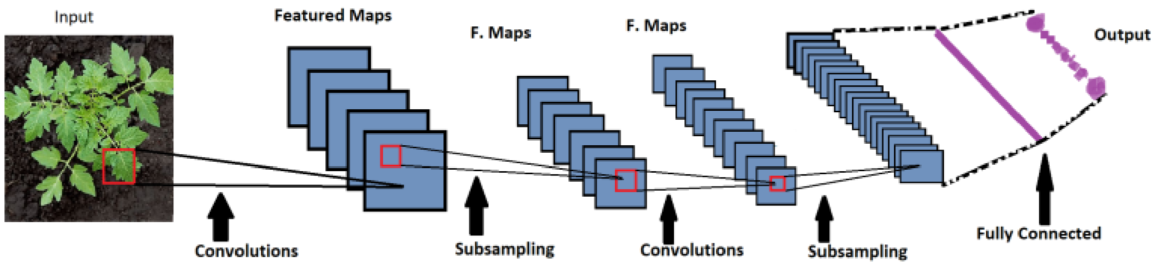

Fig 1 CNN Architecture

Fig. 1 displays the model's CNN architecture, it is made up of convolutional layer, pooling layer and fully connected layer. Pooling layer and Convolutional layer are typically interchange and the intensity or depth of each filter increases from left to right while the output size which is height and width are diminishing. The fully connected layer is the last stage which is similar to the last layer of the conventional neural networks.
The input is an image that holds pixel values. It has 3 dimensions which is width, height and depth – RGB channels example is [150 x 150 x 3].The convolutional layer will calculate the output of neurons that are interconnected to nearest regions in the input. The layer's parameters are made up of a set of learnable filters or kernels, convolved across the width and height of the input, extending throughout its depth, calculating the dot product between all the entries of the input and the kernel. This produces a Two-dimensional activation map of that kernel and as a result, the network learns kernels that trigger when it idetifies any particular type of feature at any spatial position in the input. The function called Rectified Linear Unit or simply ReLU layer will perform element wise activation function. ReLU function is defined as

$$f(y) = \max(0, y)$$

This function is 0(zero) for values less than zero and grows linearly for values greater than zero. This will not have any effect on the volume size. The pooling layer outputs the maximum activation in a small region. This function down samples the spatial dimensions of input, such as height and width. The output layer of the CNN is a fully connected layer which is comparable to the final layer of the CNN. This layer utilized commonly used softmax activation function to output probability distributions over the number of output classes.

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IV. BLOCK DIAGRAM

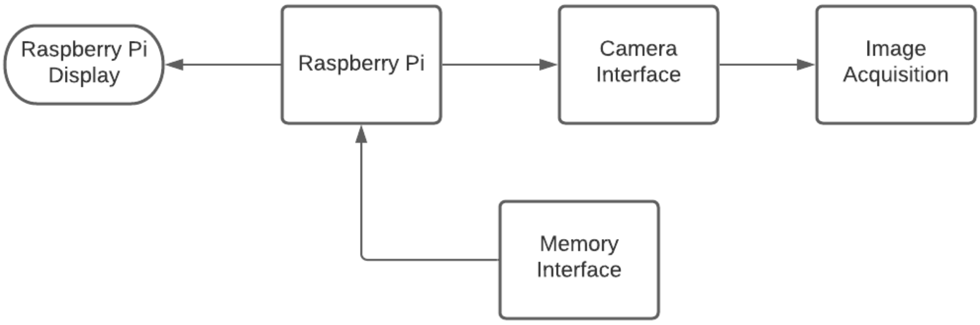

Fig 2 Block diagram showing all components with connections.

V. WORKING

The input for this device is Camera. The controller used is Raspberry pi 4 Model B. The Input image captured by camera is sent for the image processing and data related to plants are extracted in python and opencv. Extracted data is used in CNN tensorflow model for weeds and crop differentiation. The Model is trained to identify the respective crops and other plants growing in the fields will be marked as unwanted plants or simply weeds. Thus the farmbot will be able to identify if there is a weed growing in the farm and it will display the output in the output devices.
For the model we are using ssdmobilenet which we trained using our custom dataset of tomato plants on the googlecolab online IDE which provides the free GPU support for the high processing required at the time of training. SSD mobilenet is tensorflow object detection model develop by google for the object detection and image classification . It requires comparatively low processing power compare to other open source detection model. After the model is trained using the datasets, it is then converted into a tensorflowlite model which can run into raspberry pi device which uses limited resources. Trained model use CNN technique to detect the crop from the preprocessed image which was captured by the camera.

MobileNet is a deep neural network architecture. It is light-weight architecture designed for embedded vision applications and mobiles by google's Machine Learning Team. The core layers of this architecture is built on depth-wise separable filters or kernels. Only the first layer is an exception is a full convolution. SSD (Single Shot object) detection takes one single shot for the detection of multiple objects within the picture. The SSD way is based on a feed-forward technique that produces a fixed-size set of bounding boxes and score or percentage for the presence of object class type in those bounding boxes. It's made up of two parts:

1. Extraction of feature maps, and
2. Applying the convolution filter to detect objects from the image.

To further remove the practical constraints of running power-consuming and high resource neural networks on low-end like a Raspberry Pi devices in real-time running applications, MobileNet was combined with the SSD framework. Due to this, it is known as MobileNet SSD.

Thus mobilenet detects the crop using extracted features using the depthwise technique. After the crops are identified in the image it this the removed from the background using masking techniques and then further using the shape color and sizes of the plants weeds are extracted and marked in the image giving all the possible coordinates where weeds can be found. Thus the setup is able to detect the weeds in the farm.

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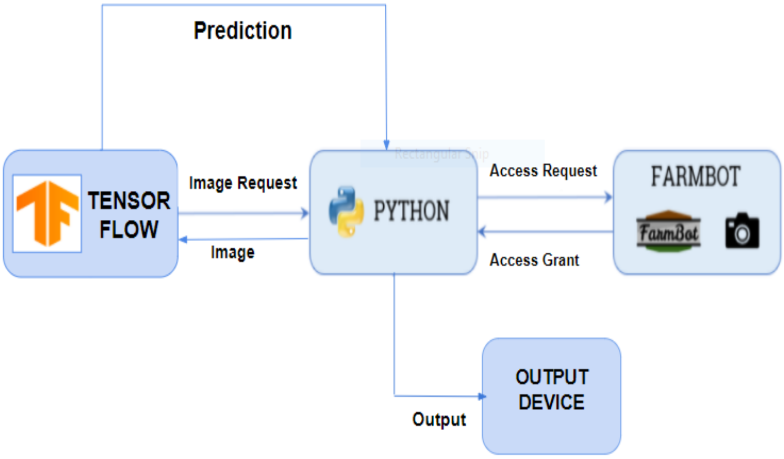

Fig.3. Flow Chart

When raspberry pi gets started it will start capturing the image and send it for pre-processing to remove all the noises. After pre-processing it will be sent to tensorflow model for further detection and after the crop is detected it will return for the crop and weed classification in the python programmed code.

A. Input : Input is taken from a megapixel pi camera which captured the images at a resolution of 2592 x 1944 pixels.

B. Processing : Processing work is done by the 1.5GHz 64-bit quad-core Arm Cortex-A72 CPU, with 2GB RAM in the Raspberry Pi 4 model B. Raspberry Pi runs all the scripts at the start and also displays the result in the wireless device like a remote computer.

C. Displaying Information : A 7 inch Raspberry Pi Display is used to display the result.

VI. HARDWARE

1. Raspberry Pi 4 Model B :
2. Picamera
3. RPI LCD display

The components used are explained as follows:

1. Raspberry Pi-4 Model B:

- Broadcom BCM2711, Quad core Cortex-A72, ARM v8, 64-bit
- 2GB RAM
- 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless, Bluetooth -5.0, BLE
- Gigabit Ethernet
- Two USB-3.0 ports; Two USB-2.0 ports.
- Raspberry Pi standard 40-pin General Purpose Input Output header
- Two micro-HDMI ports
- 2-lane display port
- 2-lane camera port
- 4-pole stereo-audio and composite-video port
- OpenGL ES 3.0 graphics
- Micro-SD card slot for loading operating system and data storage
- 5Volts DC via USB-C connector (minimum 3Aampere)
- 5Volts DC via GPIO header (minimum 3Ampere)

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2. Picamera:
- Compatible with Raspberry Pi 4 Model B
- 5MP
- Still image Resolution is 2592 x 1944
- Video Supports 720p at 60fps, 1080p at 30fps
- 20 x 25 x 9mm
- Weight - 3g

2. RPI LCD display:
- Resolution - 320 x 480 Pixel
- Touch Screen Type - Resistive
- Backlight - LED
- LCD Interface - SPI
- Aspect Ratio is 8:5
- Touch Screen Controller is XPT2046

VII. RESULTS AND DISCUSSIONS

The TF model used for training and detection was SSD with MobileNetV2. The total number of training images was 130 and total number of testing images was 50. The total number of steps in the training was 30,600 steps. Fig. 3 shows the total loss vs number of steps of the training of model using TensorBoard (visualization tool for ML). The max.and min. loss was 19.67 and 1.21 respectively. Minimum loss is covet and a decreasing value indicates the model is learning while being trained. Training can be stopped anytime whenever we want if the loss is not declining anymore. Throughout the training, it periodically saves a checkpoint at each five minutes. This checkpoint is used to export graph that contains graph variables frozen as constants. Fig. 4 shows the total loss vs Number of steps in the training.

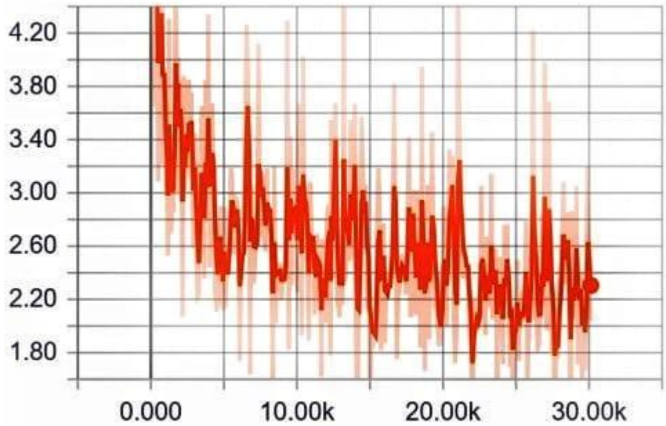

Fig.4. Total loss vs number of steps

Fig. 5 shows the total loss vs time. Training this model took about 8 hours using Google colab which provided the GPU support. This training time will vary depending on the GPU power of the computer on which it is trained.

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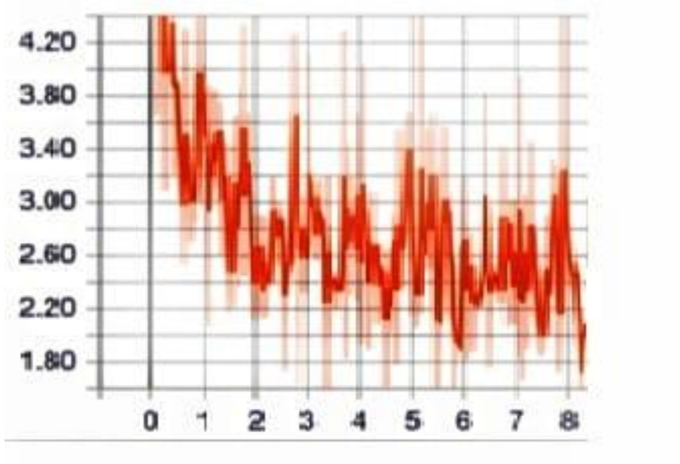

Fig.5. Total loss vs time (hours)

Fig. 6 shows the sample detection of crop and weed in an image. The SSD with MobileNetV2 failed to detect few of the weeds. Although this SSD mobilenet model has large loss, but due to its high speed detection it can be applied in real-time application for the weed detection

Fig.6. Screenshot of testing of weed detection

The output display shows and locates the crops with a bounding box and weeds using a red colour and also labels the crop as a plant. Model was able to identify most of the crops and weeds from a fixed distance from the ground.

VIII. CONCLUSION

Identifying the crops and weeds using CNN with images captured by the FarmBot. The accuracy is little less right now due to shortage of images, but after some more the network should be able to differentiate well enough the different types of plants it has been trained on. It was able to detect the object using a raspberry pi device. Low frame rates due to less processing power of raspberry pi. Low Power consumption as raspberry pi consume very less power

IX. ADVANTAGES

- Can run 24 x 7 without manual labour.
- Can be used in crops after changing the training set to the desired crops.
- Research on the FarmBot programming environment and weed detector
- Research on computer vision and image processing

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- Research on deep learning and its implementation in Python
- Develop the code to take the pictures on FarmBot
- Active contribution step towards Digital India

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