Intelligent Agriculture

P. Sai Ganesh[1], P. Chandra Naga Prasad[2], V. Gopal Krishna[3], N. Vinod[4]

[1]*Student, EEE Department, pragati engineering college*
[2]*Student, EEE Department, pragati engineering college*
[3]*Student, EEE Department, pragati engineering college*
[4]*Student, EEE Department, pragati engineering college*

Abstract

Farthest, farmers employ traditional methods for sowing seeds which leads to uneven distribution and overcrowding of seeds in fields. Due to these reasons, plants that grow compete with each other and hence they may not receive enough nutrition, which in turn decreases the efficiency of total yield. Manual spraying of insecticides and pesticides by farmers leads direct exposure to body, which may cause immune suppression , hormone disruption, reproductive abnormalities and many ill effects on humans .Excessive use of pesticides leads to decrement of fertility and yield quality. Spraying of pesticides on un desired areas leads to excessive wastage. In this, the total land is divided into identical vertical and horizontal sections and the measurements are taken. The divisions are made such that there is equal distribution of seeds which will avoid overcrowding and uneven distribution of seeds. The trained drone is allowed to fly at a certain height as if there is very less impact of wind .The drone automatically aligns its direction and shifts to adjacent vertical division when the boundary is reached .The programmed drone is allowed to distribute the seeds evenly. A model is trained by artificial intelligence to identify pests and spray the pesticides only in the targeted area. The datasheet of pests is collected and the model is trained by using datasheet which helps to identify the pests. Whenever the model identifies the pest, a pin in an arduino Uno is activated and the pesticide is sprayed in the targeted area.

Keywords: *Arduino, Image Processing, AI technique, learning algorithm.*

1. Introduction

An image recognition algorithm (a.k.a an image classifier) takes an image (or a patch of an image) as input and outputs what the image contains. In other words, the output is a class label(e.g. “cat”, “dog”, “table” etc.). How does an image recognition algorithm know the contents of an image ? Well, you have to train the algorithm to learn the differences between different classes. If you want to find cats in images, you need to train an image recognition algorithm with thousands of images of cats and thousands of images of backgrounds that do not contain cats. Needless to say, this algorithm can only understand objects / classes it has learned.

To simplify things, in this post we will focus only on two-class (binary) classifiers. You may think that this is a very limiting assumption, but keep in mind that many popular object detectors (e.g. face detector and pedestrian detector) have a binary classifier under the hood. E.g. inside a face detector is an image classifier that says whether a patch of an image is a face or background.

Interestingly, many traditional computer vision image classification algorithms follow this pipeline, while Deep Learning based algorithms bypass the feature extraction step completely.

As we move towards more complete image understanding, having more precise and detailed object recognition becomes crucial. In this context, one cares not only about classifying images, but also about precisely estimating the class and location of objects contained within the images, a problem known as object detection.

2. Problem Statement and Formulation

2.1 Problem:

Farthest, farmers employ traditional methods for sowing seeds which leads to uneven distribution and overcrowding of seeds in fields. Due to these reasons, plants that grow compete with each other and hence they may not receive enough nutrition, which in turn decreases the efficiency of total yield Manual spraying of insecticides and pesticides by farmers leads direct exposure to body, which may cause immune suppression, hormone disruption, reproductive abnormalities and many ill effects on humans .Excessive use of pesticides leads to decrement of fertility and yield quality. Spraying of pesticides on undesired areas leads to excessive wastage.

2.2 Drawbacks:

The application of herbicides and fertilizers in agricultural areas is of prime importance for crop yields. The use of drone is becoming increasingly common in carrying out this task mainly because of its speed and effectiveness in the spraying operation system. However, some factors may reduce the crop yields, or even cause damage because of climate condition, wind intensity and direction, and pesticide deposition while spraying. The process of applying the pesticides and fertilizers is controlled by means of the feedback obtained from the wireless sensor network (WSN) deployed on the crop field monitoring. The function is to support short delays in the control loop so that the spraying UAV can analyze and process the information from WSN to further route. We can evaluate an algorithm to adjust the UAV route under changes in wind speed and direction. Moreover, we evaluate the impact of the number of communication messages between the sprayer drone and minimize the waste of pesticides.

2.3 Overcoming from Drawbacks:

Pesticide spraying efficiency is better. Plant protection UAV rotor can produce a large spin force, to promote pesticide droplets on the crops from top to bottom to penetrate, it is conducive to pesticide droplets scattered evenly in all parts of the plant, so that precision spraying in place.

Farmers recently claimed that using sprayer drones reduced the pesticide use on farm by 30% because they can spray to all levels of the crop. This improved efficiency could go some way to allaying fears about the environmental damage that overuse of pesticides and fertilizers can cause, such as reduced biodiversity and the poisoning of aquatic life when chemicals run off into rivers after rain.

Spray more evenly. In the process of pesticide spraying, the UAV to take automatic obstacles to avoid and automatic cruise alarm of the new technology, when the pesticide runs out, drone automatically cruise back to the initial position, after the staff add pesticides, according to the location of the return, back to the previous spray area continue to spray, will not cause repeated spraying and endanger crops.

Operating is safety. Eliminate pesticide poisoning incidents occurring in sprayers.

The agricultural spraying drone, each sort can continuous working 10-15 minutes, every drone single-day operation area is 40-60 acres, pesticide utilization increased by 40% or more, also can save a lot of pesticides and labour cost compared to traditional spraying methods.

The agriculture sprayer drones protect farmers from poisoning and heat stroke, while spraying liquid pesticides, fertilizers and herbicides on agricultural land.

Environmental pollution is severely reduced with the fixed position and orientation method.

2.4 Block diagram:

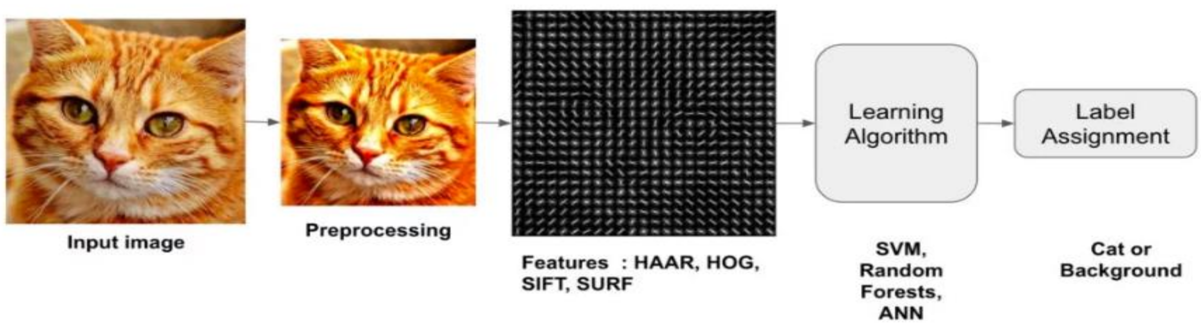

Fig1: Block Diagram

2.5 Working:

In this, the total land is divided into identical vertical and horizontal sections and the measurements are taken. he divisions are made such that there is equal distribution of seeds which will avoid overcrowding and uneven distribution of seeds. The trained drone is allowed to fly at a certain height as if there is very less impact of wind .The drone automatically aligns its direction and shifts to adjacent vertical division when the boundary is reached .The programmed drone is allowed to distribute the seeds evenly.

A model is trained by artificial intelligence to identify pests and spray the pesticides only in the targeted area. The datasheet of pests is collected and the model is trained by using datasheet which helps to identify the pests. Whenever the model identifies the pest, a pin in an arduino Uno is activated and the pesticide is sprayed in the targeted area.

3. Hardware Implementation:

3.1Schematic Diagram:

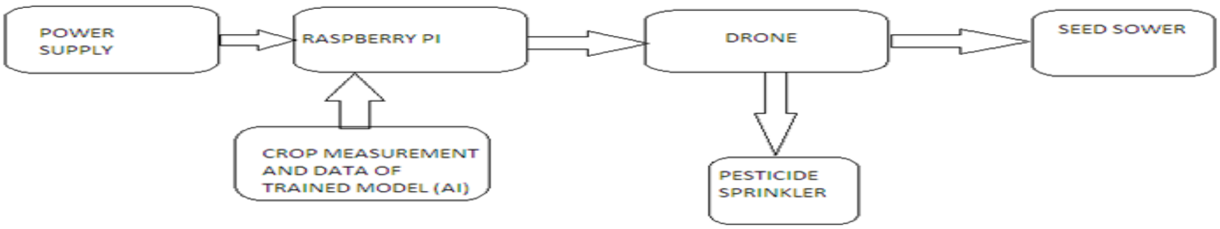

Fig2: Schematic diagram

3.2 Components:

3.2.1 Arduino Uno:

The Arduino is a microcontroller board based on the ATmega. It has 14 digital Input/Output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16MHz ceramic resonator, USB connection, a power jack, an ICSP header and a reset button. It contains everything needed to support the microcontroller; simply connect it to computer with a USB cable or power it with a AC-to-DC adapter or battery to get started. The Uno differs from all preceding boards in that it does not use the FTDI USB-to-serial driver chip. Instead, it features the Atmega16U2 programmed as a USB-to-serial converter.

Pin out: added SDA and SCL pins that are near to the AREF pin and two other new pins placed near to the reset pin, the IOREF that allow the shields to adapt to the voltage provided from the board. In future, shields will be compatible with both the board that uses the AVR, which operates with 5v and with the Arduino due that operates with 3.3v.

"Uno" means one in Italian and is named to mark the upcoming release of Arduino 1.0. The Uno and version 1.0 will be the reference versions of Arduino, moving forward. The Uno is the latest in a series of USB Arduino boards, and the reference model for the Arduino platform; for a comparison with previous versions, see the index of Arduino Boards.

Fig3: Over view of Arduino

- Microcontroller ATmega328 specifications
- Operating Voltage: 5V
- Input Voltage (recommended): 7-12V
- Input Voltage (limits): 6-20V

- Digital I/O Pins: 14 (of which 6 provide PWM output)
- Analog Input Pins: 6
- DC Current per I/O Pin: 40mA
- DC Current for 3.3V Pin: 50mA
- Flash Memory: 32 KB (of which 0.5 KB used by boot loader)

Result:

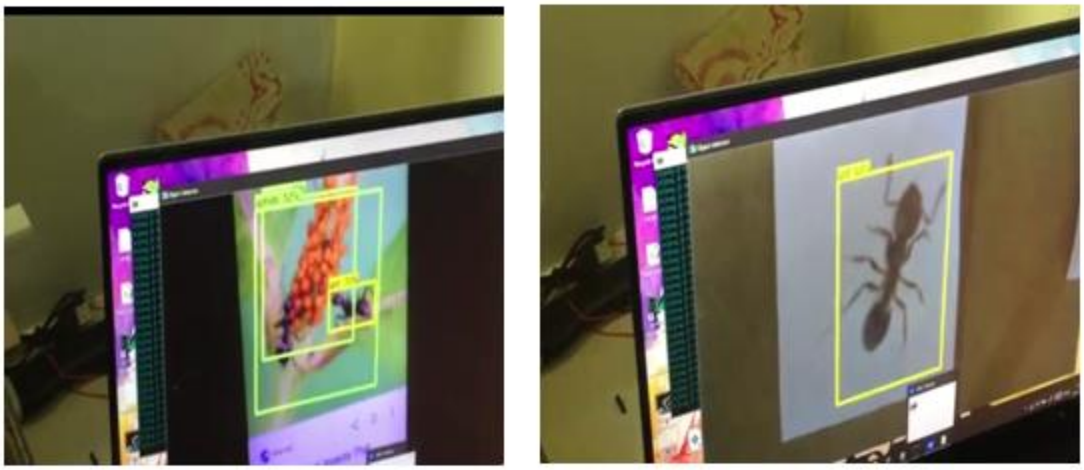

Fig4: Detection of Pest in live field

Conclusion:

In this work we leverage the expressivity of DNNs for object detector. We show that the simple formulation of detection as DNN-base object mask regression can yield strong results when applied using a multi-scale course-to-fine procedure. These results come at some computational cost at training time – one needs to train a network per object type and mask type. As a future work we aim at reducing the cost by using a single network to detect objects of different classes and thus expand to a larger number of classes.

Thus, dronetech allow the farmers to monitor and control the use of pesticides properly. This allows minimizing the environmental impact of pesticides. The drone can survey the crops for the farmer periodically to their wish. Weekly, daily, or even hourly, pictures can show the changes in the crops over time, thus showing possible “trouble spots”. Having identified these trouble spots, the farmer can attempt to improve crop management and production. With the data that drone’s record from the crops the farmers are able to analyze their crops and make educated decisions on how to proceed given the accurate crop information. By this, farmers have more time to focus on the big picture of production instead of spending time surveying their crops.

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