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IOT based Automated Greenhouse Using Machine Learning Approach

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Abstract: Focusing on the effect of universal food insecurity, over 60% of sub-Saharan countries are predicted to be in a state of malnourishment and yet several farming places are under drought state. The climatic condition is believed to be biannual dry seasons which is very difficult for farmers to cultivate crops due to shortage of water and poor soil fertility. Yet heavy rainfall is still a great threat for the farmers since it devastates cash crops. The use of a smart greenhouse with Artificial Intelligence to grow and protect plants in both dry and wet seasons and reduce labor-intensive human tasks and automate pervasive data analytics of daily plant status can surprisingly boost food security. Here we present a fully automated greenhouse system with artificial intelligence embedded in it that uses around 10,000 plant images in it that initially nurture plants under optimum atmospheric conditions by taking real-time decisions, detecting any kind of illness, and interestingly notifying the stage of fruit ripeness. By implementing a neural network-based computer vision approach we were able to keep track of the health status of the plants caused by several microorganisms. The obtained predictions and results accurately verify how machine learning can be used to increase gross national food security by implementing such systems in multiple farming areas without prior human involvement.

Keywords: *Artificial Intelligence, Computer vision, Data-analytics, Machine Learning, Neural Network.*

1. Introduction

Farming has undergone a lot of revolutions over the past decades to overcome several constraints that led to low food production and malnourishment. As a result of this, nowadays digital technology and IoT (internet of things) along with artificial intelligence are being a trending approach to solve the early problems regarding plant status, climate, state of wellness of the plants, and much more [6]. This has stimulated the rise of machine learning to get involved in such domains and bring radical outbreaks [15]. The greenhouse has been one of the most productive approaches in agriculture in the last decades, where the one facet of a greenhouse is nurturing plants in a confined room under meticulous atmospheric conditions. Yet, this goal becomes very hectic and tiresome when considering large greenhouse areas with thousands of hectares. The emergence of IoT (Internet of Things) and the sophisticated networking world, has paved a way for effective interaction with remote devices and storing real-time data measured by the environment in the cloud. With such approaches, being in any part of the world we have the aptitude to monitor and access remote network devices [2]. A fully Automated greenhouse uses different environmental sensors that record timely atmospheric condition and mechanical actuators that replaces the manual care made by humans. Different environmental sensors are subjected to keep track of the optimum condition needed by plants to grow, whenever an unfavourable situation is being detected signal is immediately transferred to the server with the help of brainy microcontrollers, as a result, the server will resend the appropriate decision back to the control unit [12]. With this scheme going on, every measure detected by the sensors and respective move taken is being stored in a central repository which becomes the crude oil for the artificial intelligence to figure out patterns and features from the data and gives the grower accurate trends about the next possible decision. With the help of the AI model, we have built the continuous atmospheric measure and water consumption recorded over a long period can give us a smart conclusion and meaningful pattern on how to operate and what could be the beneficial move in the future. Moreover, a fully autonomous greenhouse uses a computer vision-based deep neural network approach that can be used to detect the health of the plants which might be difficult to identify at early stages with bare eyes [3]. Simultaneously the growth and status of the fruits inside the greenhouse are being monitored and predicted with the help of the Ip-camera. For machine learning models to work functionally they must be trained on vast pre-processed data that can give them the ability to extract meaningful patterns and information. In our case we have collected thousands of images from the internet, the pre-processing scheme held for such data includes binarization, grayscale conversion, noise removal, scaling, augmentation, and annotation. When the dataset is being passed through these stages it becomes pure and very easy for the AI program to learn itself some structure. The next stage is training the model with the pre-processed data, it takes up a lot of resources to train a model with thousands of images. It is unpractical to hold such a training process in a normal pc with CPU architecture, instead, we have used google collab, a web service that gives users access to remote GPU and TPU servers with a minimum subscription fee. After training the models for long hours we came across satisfactory prediction results.

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2. Related Work

Several studies had been done on a greenhouse-based structure over the past decades. Most if not, all try to address the climatic problems faced by growers and mainly the water supply expected from biannual seasonal rainfall [13]. Weather changes effect cropping methods. Machine learning helps farmers choose more environmentally friendly crops [19]. To solve these and related issues there have been a lot of moves made. The use of a greenhouse to nurture plants is one of them. The design of an affordable greenhouse [11] has been studied in 2012 to address and solve climatic problems faced by farmers by creating an isolated environment. Yet this approach becomes infeasible when it comes to large greenhouse areas, the main issue raised here is the manual manpower used to operate the system. Since this system doesn't use an automation system all the dedicated work is being done by humans which still fails to solve the target plan. "According to Somchoke Ruengittinum and Sitthidech Phongsamsuan [7] IOT field has been an out-breaking move around the world these days, one typical example in using such technique is Thailand which is completely trying to use and integrate with different pillars of its infrastructure". The fundamental idea behind implementing IoT is adding up more and more objects to simplify the way humans interact with their environment. By doing so different devices and items gets sharing information capability. Venlo greenhouse [17] is a famous greenhouse design in central and north European countries using IoT and artificial intelligence. It is built with small mesh windows that prevent the harms such as whiteflies and thrips".

However, these screens degrade the light transmission [14,16,18] and inhibit ventilation. For proper plant growth inside the greenhouse, the use of ventilation is mandatory and unavoidable. The major means of ventilation inside the Venlo greenhouse is natural ventilation. However, this sort of ventilation is not enough for places where the temperature is very high, where actuated cooling systems using fans and extractors are needed [8] such that the warm air inside is replaced with cold. In the last two years, there were many research papers on greenhouses with machine learning inside the greenhouse. [9] Plant disease detection using the VGG model was also a study made on different plant diseases in which the model used for prediction was built using VGG pre-trained CNN architecture. VGG is a pre-trained machine learning model which was trained on millions of images in 2014 and attained magnificent prediction accuracy. It is one of the excellent vision model architectures to date. Since then, people have used this model as their backbone architecture and built their trainable layers on top of it. This approach is very simple and can be implemented within a few lines of code. This project implemented this backbone for the classification of plant diseases. It covers a small domain of plant disease grown inside the greenhouse [1].

3. Methodology

This paper tries to implement the internet of things (IoT) and machine learning in the area of horticulture to solve several productivity issues. The main focus is to build a smart and intelligent greenhouse system that can monitor the different tasks done by humans. In general, the features used in this study are to automate and monitor a portion of the greenhouse. e.g., Drip irrigation, temperature, humidity, fire detection, and security system. On the other hand, the research covers the health aspect of the plants. This is done by collecting images from the Ip-cameras located at different angles of the room and handing them over to the trained model for early plant disease detection which uses machine learning algorithms related to computer vision-based neural networks. Similarly, the issue of looking after the growth and status of the fruit is being done by the system which works in a pretty similar way as that of plant health detection.

Sensors, microcontrollers, and radio interfaces all play important role in the design of the smart intelligent sensor system [20]. The study comprises the implementation of microcontrollers, raspberry pi minicomputers, humidity and temperature sensors, moisture sensors, water flow sensors, Ip-camera, and motors. Figure 1 shows the block diagram of the entire system.

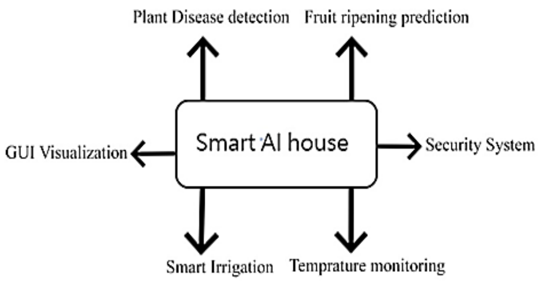


Fig. 1. Block diagram of smart greenhouse

Here are the basic and core hardware components used in the project.

3.1. Arduino AT Mega microcontroller

Arduino Atmega2560 is an open-source microcontroller series based on the Atmega2560 AVR development board. An 8-bit microcontroller is used in this work. It uses Microchip technology ATmega16U2. Processing language is used to program this board. The system is composed of 54 digital ports for input and output, 14 of which can be utilized for PWM output and 16 quartz crystal oscillators.

Arduino is a prototyping platform with simple hardware and software. It consists of a programmable circuit board and ready-made Arduino IDE, which is used for writing and loading the computer code into the physical board. This software is used for writing and uploading the computer code. The experimental analysis uses Arduino AtMega2050 which consists of 14 digital I/O pins, 6 analog inputs, and 16 MHZ quartz crystals. Each sensor is connected to Arduino and Arduino is connected serially with raspberry pi using a USB port.

3.2. Raspberry Pi

Raspberry Pi was designed by the Raspberry Pi foundation in collaboration with Broadcom, a line of miniature Single Board Computers (SBCs). In this paper, raspberry pi is used as the central control unit which communicates directly with the Arduino and the backend repository [4]. This is the main part of our system, with the help of socket and multithreading real-time measures from the sensors are being transferred to the server with the help of the raspberry pi. The basic configuration of the entire system including the machine learning part is stored here with SQLite backend.

3.3. DHT11 temperature and humidity sensor

A digital temperature and humidity sensor with extremely low-cost basic DHT11 is available. The surrounding air is measured with a capacitive moisture sensor and a thermistor, and the data pin displays a digital signal. It's easy to use and has a long transmission distance of 20 meters, making it suitable for a wide range of temperatures and humidity levels. We have used this DH11 sensor for sensing both the temperature and humidity.

3.4. IP Camera

The IP camera is a form of digital video camera using the IP network for the receiving of input control and the sending of image data. Images are being taken using an IP camera and directed to the AI model using the network infrastructure. This IP camera is scheduled to take a photo with the help of the raspberry pi at some time interval based on the prior user configuration, then storing the result of the prediction in the repository is also the task done here.

4. Implementation

The system was implemented based on the following steps:

- The sensors and other hardware items are being assigned on their respective position inside the greenhouse.
- Each sensor is connected to the Arduino for two-way communication.
- The Arduino is connected directly to the raspberry pi minicomputer using a serial connection.
- pre-processing: The images are resized to 256 X 256-pixel size and an image augmentation process is used to avoid overfitting.
- Dataset is grouped into 80 % for training and 20% for testing.
- Training is done with the above architecture.
- Convolution layers of the model extract the meaningful features for prediction and classification.
- The trained model is validated/tested using the testing data set.
- Fine-tuning is done by twitching the training hyperparameters.
- The model is exported and integrated with the desktop app for usage.
- The system will make a scheduled image check on the greenhouse.
- This result is sent as a response back to the user.
- The dashboard of the system shows the current status of the room (Figure 2).

Fig. 2. System Dashboard

5. Dataset and Neural Network Training

In this paper, we have used tomatoes as our experiment plant both for the health detection and prediction of fruit ripeness. The Dataset is downloaded from the Kaggle website of the plant village dataset section that is freely available on the web. Generally, we have collected two different sets of data, one is the image of a tomato plant attacked by different viruses and microorganisms, specifically we studied ten different types of diseases are Late blight, Early blight, Bacterial spot, Leaf Mold, Tomato mosaic virus, Target Spot, Septoria leaf spot, Tomato Yellow Leaf Curl Virus, Spider mites Two-spotted spider mite, healthy. For each class, we have collected more than 850 images total of 8,500 images. The other set is images of tomato fruit at different stages of ripeness. We grouped the tomato fruit images into three classes as fully ripened, half ripened, and unripe. The total image size, in this case, was around 1,500. Generally, around 10,000 image data was used to train the model.

5.1. Image Pre-Processing

Images are being pre-processed primarily before being trained. The main reason behind pre-processing is presenting your data into a machine-understandable state where data is cleaned, corrected, and purified such that the data is complete, consistent, and accurate. Since we had two separate sets of datasets, we have used two different pre-processing schemes. Pre-Processing For Plant Leaf Health Detection Here are the most fundamental tasks made in preprocessing. In this paper, we must use the three image pre-processing techniques namely pixel brightness transformations with correction, geometric transformations and image filtering and segmentation.

5.1.1. Image Scaling

The very first step before doing any kind of pre-processing task is to scale the images into a common size. The reason this step is important is that this step will improve the speed and accuracy of the feature extraction process.

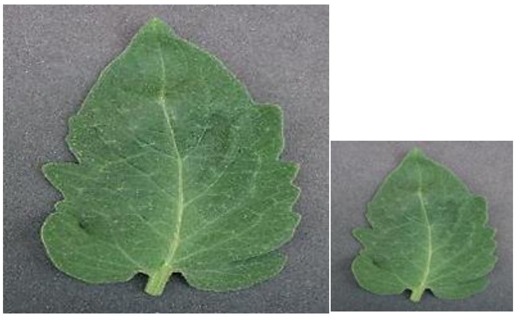


Fig. 3. Original and Scaled image

For a machine learning model to extract features from an image all the images should be resized to the same size unless otherwise, the learning process will be difficult. In most cases, images taken by mobiles and prosumer cameras are typically larger, and directly implementing training tasks on these images will take a much longer time. Hence, to overcome such problems images should be scaled to a common scale of about 250-400dpi (dots per inch). In our case, we resized the images into 256x256 pixels (Figure 3).

5.1.2. Grayscale conversation

Images from smartphones and handheld devices are in colored (RGB) format. In the machine learning process dealing with colored pixels can be hectic and time-consuming. One of the most adaptive ways to overcome this problem is grayscale conversion. Usually, each pixel in any image is denoted with three values red, green, and blue (RGB) in which each value is represented as an 8-bit integer in the range of 0 to 255. Each pixel value in grayscaled images signifies how much that point is bright (white). Ultimately, a pure white is represented with 255 and a pure black with 0. So, by using grayscaled images we can optimize the computation of the deep learning algorithms (Figure 4).

Fig. 4. Original and Gray Scaled image

Segmentation

Dealing with each object in an image might degrade the performance of the learning and prediction tasks. For this reason, it is very advisable to remove the unnecessary subjects in the image so that the algorithm will learn only the target region of interest in the image. Segmentation is the removal of the background color and sometimes the random subjects that appear in the image. By doing this in our case the image will have a dark background with the leaf image in the foreground (Figure 5) [10].

Fig. 5. Original and Segmented image

5.1.3. Augmentation

Training with a low data size is among the most problematic approach in machine learning. Augmentation is the process of enriching the image dataset by changing the orientation of the images. In this method, an image is described in different forms being scaled, rotated, transformed, and zoomed. This enables the algorithm to have multiple viewing angles for the same image. The augmentation practices one of the several transformation methods including simple image rotation, perspective rotation, and affine transformation. The transformation used in the augmentation process is described in Figure 6.

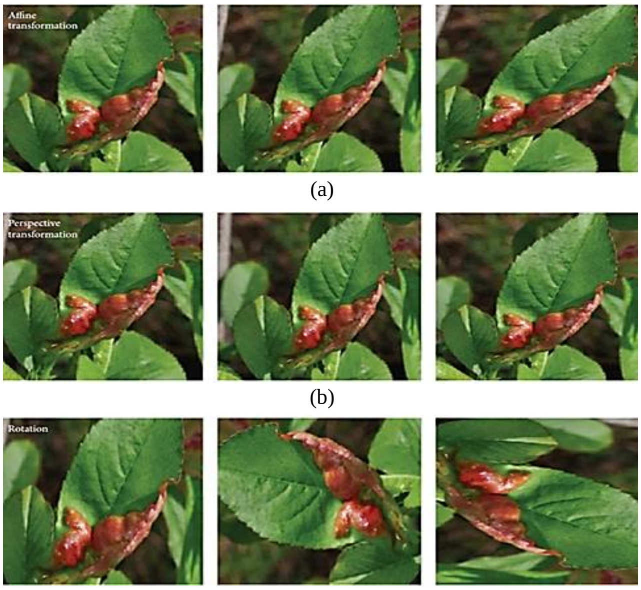
In this stage to automate the augmentation task for the entire image dataset, there is an application developed in C++ implementing OpenCV library with the access to manipulate the parameters related to the transformation during the run-time [6].

5.1.4. Preprocessing Steps for Fruit Ripeness Prediction

In this module, the above-listed pre-processing methods are used with some other additional methods. In this typical prediction model, we have designed the prediction to be in both real-time live video and captured image. Whenever a video is given to this model, it undergoes frame-oriented analysis and predicts the relevant prediction result.

To attain such a feature, the model should be trained with enough awareness of each, and every instance found inside the image. In other words, we should tell our model what the objects and instances within the image are so that in a later prediction task the model doesn't face any problems with the other subjects around the target fruits. such pre-processing method is known as an annotation. [5] Annotation of images means the process by which an image is labeled using text, annotation tools or both to identify data components that the model needs to be analyzed on its own in the machine and deep learning. Annotating an image provides metadata to a dataset. There are several annotation types, the one that has been used in this project is known as instance segmentation.

The occurrence, location, quantity, size, and structure of objects in an image are traced and counted using instance segmentation. We can use instance-based pixel-wise segmentation, which labels every pixel within the boundary. We can alternatively do them using boundary segmentation, which counts only the border coordinates. For this task, there are dedicated tools either web services or standalone applications.



(c)

Fig. 6. Implementation of transformation in augmentation:(a) affine transform; (b)perspective transform; (c) rotation.

5.2. Neural Network Training

Convolutional Neural Network (ConvNet/CNN) and MASK-RCNN algorithms are used to complete the entire learning and prediction task (Figure 7).

Fig. 7. Types of annotation

CNN is one of the most famous deep neural network algorithms applied in the field of image processing. This algorithm assigns important learnable weights that enable the model to extract vibrant features for effective prediction. CNN demands minimized pre-processing steps compared with other algorithms. The extreme target of CNN is to disintegrate the image into a modest form without losing the prior features of the image for obtaining accurate and simplified predictions. CNN architecture is composed of an input layer, output layer, and several hidden layers. The CNN layers do several tasks for the data to adjust with the purpose of feature learning specific to given data. The convolution layer is one of the fundamental layers in CNN drawing an image over a set of convolutional oriented filters each of them stimulating certain features from the given images. Rectified linear unit (ReLU) enhances quicker and more valuable learning by attaching undesirable property values to zero and conserving positive property. These operations are being repeated across thousands of layers having each layer learning to identify several features.

5.3. MASK RCNN Based Object Detection and Classification

There are several linked inter-processes for the identification of fruit being ripened or not. Initially when an image is taken and given to the model the first step is object detection. Out of the entire instances contained within the image, tomato fruit should be identified and detected. Next, the detected fruit should be bounded with some sort of color so that the output of the detection process should be passed for upcoming tasks, such process is known to be instance segmentation. When the detected subject is brought to the next step it is then classified into the respective classes. To make a single prediction all the processes should be undergone. In this project, we have implemented one robust algorithm called MASK-RCNN that does the same task as above.

Mask-RCNN is a deep neural network-based approach for machine learning and computer vision challenges such as segmentation. This means that in an image or a video various item can be separated, and frame-based image analysis is conducted. It offers us an image with boxes, classes, and masks for the object binding. Mask RCNN is divided into two stages. It first creates recommendations for places where an object is presently based on the provided images. Secondly, it predicts the class of the object, refines the bounding box and develops a mask at the pixel level of the object, depending on the proposal from the first stage. The backbone structure is connected to both stages.

While doing this experiment the most inspiring and surprising result we have found about MASK-RCNN is that we can surprisingly force the different layers in neural network architecture to learn informative patterns and features with different scales and ROI Align, instead of treating layers as a black box.

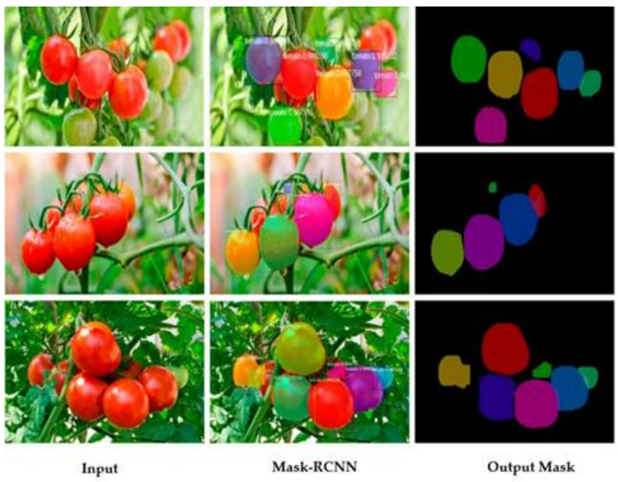


Fig. 8. MASK-RCNN bounds region of interest

Figure 8 below shows how this algorithm treats an image given to it. In the first step, Mask-RCNN algorithm will draw a region proposal around the target objects next the target regions will be covered using an appropriate mask and lastly classified.

5.3.1. Fine-Tuning

Tends to boost the effectiveness of the learning process by making small changes in the hyperparameters of the architecture. This can be done either manually or using some dedicated tools with pre-configured settings. Fine-tuned models seek less learning rate and are much faster than that learning from scratch. To start the tuning process, the new SoftMax classifier was trained from the scratch using the backpropagation algorithm with data described in section 4. In our first training results, we observed overfitting behavior in the plant disease classification model. The model has lost the ability of generalization rather it has shown memorizing trends. The main factor for such a result was the dataset size used on the first try was small thus the model was unable to extract meaningful full patterns. After the entire dataset was loaded and trained, we have seen some changes in the performance of the model but still, that was not enough. Next, we have twitched some hyperparameters like the epoch, batch size, learning rate, optimizer, and dropout. Adam optimizer was used as the best optimization parameter with a 0.0001 learning rate.

6. Result and Evaluation

We present the result of our findings. Figure 9 shows loss versus epochs and precision versus epochs.

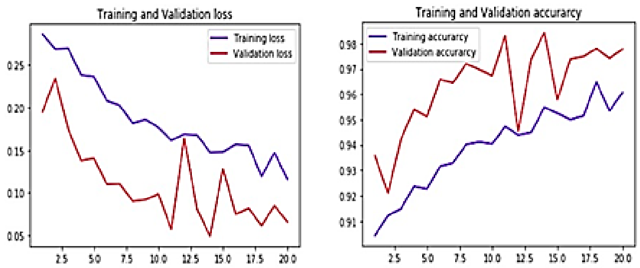


Fig. 9. a) Loss vs epochs b) Precision vs epochs

In this paper, total 10 types of diseases and 3 fruit stages are being addressed. The overall evaluation of the model is being calculated using Precision, Recall, and F1-score. F1-score combines both precision and recall in a single term. The higher the F1 the better the model. The average accuracy and weighted class are obtained to be 0.91 and 0.93 respectively.

7. Conclusion

The greenhouse is one of the most trending approaches being implemented in several developed countries to produce high food production output. Integrating smarter techniques of IoT and artificial intelligence to automate the labor-intensive manual task made by humans greatly enhances crop production. Here a new trend of deep learning methods was implemented on IOT based greenhouse with the ability to detect and classify several kinds of diseases seen inside the room and monitor the growth and development of fruit along with the overall management needed to operate the system fully functional without the involvement of human being. In future, additional datasets will be used to increase performance even further with ensemble novel machine learning techniques.

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