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Monitoring System for the benefit of Agriculture using AI Automation Using IoT and Deep Learning

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Abstract

Introduction: The impact of global food insecurity is highlighted by the fact that over 70% of sub-Saharan countries are predicted to be malnourished, even though some farming regions are under drought status. Due to the climate's recurrent dry seasons, farmers have difficulty growing crops there due to water scarcity and low soil fertility. However, floods remain a significant threat to farmers because they wash away valuable crops. An unexpected way to increase food security is to use artificial intelligence (AI)-powered smart greenhouse to grow and protect plants all year round, regardless of the season, while reducing the need for humans to perform labour-intensive tasks and automating widespread daily data analyses of plant status.

Objectives: Using Artificial Intelligence methods, like the Internet of things and Machine learning methods for monitoring agriculture – mainly focusing on Plants.

Methods: Asproposed, show off a greenhouse system powered by artificial intelligence that can analyze a database of almost 10,000 plant pictures to make snap decisionsand detect.Through the use of a neural network-based computer vision technique, this study was successful.

Results: In terms of accuracy, the best accuracy (98%) was achieved by both the CNN model compared withNeural Networks (ANN) model. In contrast, the Convolutional Neural Networks (CNN) model is much quicker. To gather the information – IoT-based devices were deployed to capture the images of the plant's images in real-time.

Conclusions: This method is used tomonitor the crops remotely.Using Artificial Intelligence methods and models, this model fits greenhouse monitoring, particularly in finding a broad spectrum like plant diseases, types, etc.

Keywords: Artificial Intelligence, Green House, Plants Monitoring, Deep Learning, and Internet of Things.

1. Introduction

For the past few decades, agriculture has undergone a series of revolutions to overcome the diversity of issues that lead to historically low food production and widespread famine. These revolutions are being carried out to maximize the yield obtained from a given agricultural land in food production[19]. The following are examples of these worries: As a direct consequence of this, digital technology, the Internet of Things (IoT), and artificial intelligence are currently main ways to address issues linked to plants, climate, plant health, and other essential concerns at an early stage. [An additional citation is necessary] Machine learning is currently experiencing a meteoric rise in popularity, which is evidence that it will continue to thrive in this kind of setting, which will accelerate the diffusion of potentially revolutionary ideas. As a result of this meteoric rise in popularity, there has been an increase in the number of people interested in machine learning. In the most recent few decades, one of the most fruitful methods of farming that has been discovered is growing plants in a controlled environment within a greenhouse. This method involves growing plants in a greenhouse rather than outside. This technique calls for the cultivation of plants inside a greenhouse[20]. This strategy is gaining more and more support from users as time goes on.

However, if tens of thousands of hectares of greenhouse space are involved, this aim's accomplishment changes into a demanding and tiring job[10]. As a result of the development of the Internet of Things (IoT) and the ever-increasing complexity of the networking landscape, it is now feasible to effectively communicate with devices situated in far-flung locations. Additionally, it is now possible to store real-time data obtained from environmental sensors in the cloud[22]. These things have helped pave the way for it to become a reality. Because of the technology at our disposal, we are in a position to supervise and manage nodes in the network located in far-flung parts of the world from any location on the planet. In a completely automated greenhouse, the manual care that the greenhouse normally supplies is replaced with a variety of environmental sensors that record the present atmospheric condition in real-time and mechanical actuators[6]. This makes it possible for the greenhouse to continue to maintain circumstances that are ideal for the growth of plants. These sensors and actuators, which are now installed, are intended to take the role of human involvement[21]. Whenever the clever microcontrollers detect a condition unfavourable to the plants' expansion, they will send a signal to the server with the relevant information. After that, the server will communicate an appropriate determination to the control unit, given the current circumstances. Several sensors maintain a watchful eye on the surrounding region to determine whether or not the conditions are suitable for the development of plants. The farmer now has access to correct trends for the next probable decision based on the data acquired from the sensors and their related actions. These trends are based on the data obtained from the sensors. These patterns have been gleaned from the information obtained from the sensors. Following that, the data are processed to create the crude oil of artificial intelligence[15], which is then applied to the analysis of the data to recognize patterns and characteristics[24]. It is the sensors and the behaviours that correlate to them that provide the information that is acquired. We have developed an algorithm powered by AI that analyses historical data on air quality measurements and water consumption to assist us in coming to insightful conclusions and recognizing patterns that can be acted upon. We did this so that the algorithm couldassist us in coming to these conclusions and recognizing these patterns. This algorithm was employed to construct. In addition, a computer vision-based deep neural network approach is utilized in a fully autonomous greenhouse to identify the health of the plants, which may be difficult to discern in the early stages with bare eyes.

During this period, the IPcamera is being utilized to monitor and create projections regarding the growth of the fruits cultivated in the greenhouse. These fruits are being grown in the United States. All this effort, including monitoring and projection, is being done to guarantee that the fruits are developing correctly. Before being put to use in the real world, models that have been built with the assistance of machine learning must first be educated to recognize patterns and derive conclusions from huge amounts of pre-processed data. Before the models can be used in any way, this training has to be completed first. The steps of binarization, conversion to grayscale, noise reduction, scaling, enhancement, and annotation are included in our pre-processing method for the dozens upon dozens of pictures that were sourced from the Internet that we have accumulated. When these operations are accomplished, the dataset will be clean, and the AI system will be able to use it more quickly and simply learn the structure of the dataset. This will be possible once these procedures have been completed.

After the conclusion of these processes, this activity will take place. After the data have been thoroughly cleaned and processed, the next stage is to train the model by making use of the knowledge that has been accumulated. It takes a large investment of both time and resources to train a model by having them look through thousands of photos. This is a technique that is part of the training process. We made use of Google Collaborator, a web service that, in exchange for a low-cost monthly subscription fee, provides customers with access to remote GPU and TPU computers[23]. This is because carrying out such a training process on a conventional personal computer with CPU architecture would not be very practicable[5]. Instead, we relied on Google Collaboratory. Google Collaborate is an example of a web service. We were rewarded with accurate prediction results after putting in the effort to train the models, which took a few hours worth of work in total.

2. Objectives

1. Deploying Cameras Integrated with Hardware enabled with IP address to capture Images of the Plants.
2. Gathering information from the devices – Camera- Images
3. Processing the Images for monitoring the Plants – Find the diseases – Connecting with the Decision support system (CNN-based model).
4. Monitoring the temperature and related parameters from the agriculture field.

3. Methods

over several years, several investigations of construction based on a greenhouse were carried out. The bulk of these potential solutions, if not all, is centred on ensuring that farmers have access to the water they require in the dry months between the annual monsoon seasons. The weather significantly impacts the ability of a farmer to harvest his food. Agriculturalists now have access to machine learning, which allows them to choose plants with a lower impact on the surrounding ecosystem[17]. A significant number of measures have been implemented to solve these and other problems of a similar nature. Growing plants in a greenhouse are one strategy that can be used. In 2012, researchers examined the possibility of designing a greenhouse that would be affordable and effective in mitigating the effects of adverse weather on farmers. However, this method becomes impossible considering huge greenhouse areas because of the enormous manual labour required to manage the system. This makes it unfeasible. Because it does not use any form of automation, this system is incapable of achieving its objective, despite the greatest efforts of its human operators. An expert on the Internet of Things believes that Thailand is a great example of a country attempting to utilize and integrate this technology with various pillars of its infrastructure. They cite Thailand as an example (IoT). The concept of the Internet of Things, which seeks to simplify human interactions with the physical world, is predicated on connecting an ever-increasing number of disparate devices. This enables numerous tools and gadgets to share information. Countries in northern and central Europe are familiar with the Venlo greenhouse, which is notable for its application of artificial intelligence (AI) and the Internet of Things (IoT)[7]. It has very small mesh windows, so insects like whiteflies and thrips won't be able to get in. However, the amount of light that may pass through is reduced, and airflow is obstructed because of the filters. Ventilation is necessary for the development of robust plants inside the greenhouse. When it comes to cooling and ventilating the greenhouse's interior at Venlo, a significant amount of reliance is placed on natural air movement. To remove the warm air from the inside and replace it with cold air, however, actuated cooling systems that consist of fans and extractors are required in excessively hot situations such as indoor areas. Over the past two years, many articles on artificial greenhouses that house machine learning have been published. Another piece of research looked at the application of the VGG model to the problem of predicting the beginning of plant diseases; this time, several different types of plant diseases were examined.

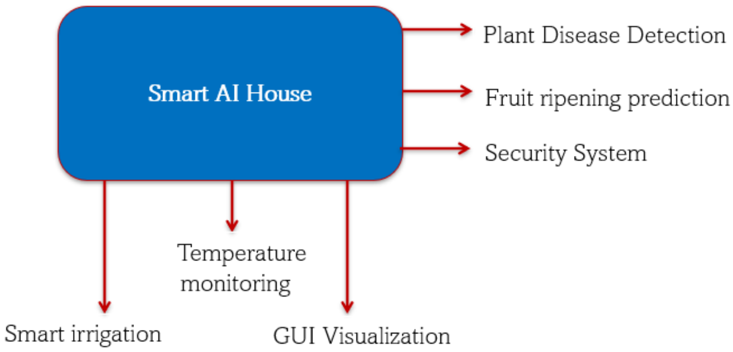

Fig 1. Methodology and modelling base for Green House Monitoring

The model employed the VGGpre-trained CNN architecture to train itself[12]. The VGG algorithm was trained in 2014 using machine learning on millions of pictures to achieve outstanding prediction accuracy. It has one of the most advanced and sophisticated vision model architectures currently on the market. Since then, several people have chosen to use this model as the basis for their design, and they have subsequently added additional layers that can be trained on top of it. This method may be put into action with only a few lines of code, and as a result, it is quite simple to employ. As part of this effort, a framework was established for recognizing and cataloguing various plant diseases. Diseases of plants produced in greenhouses are the only ones affected.An iterative, or "agile," approach is used during the design, development, and testing phases, while a "waterfall" approach is used during the conceptualization, evaluation, and final product stages[9].

Vital Methods

This article investigates how the Internet of Things (IoT) can be combined with machine learning to address various productivity issues prevalent in the horticulture industry. The major objective is to develop anintelligent greenhouse system that can monitor a wide range of human behaviours[24]. This study takes advantage of automated and monitored aspects of the greenhouse. Some examples of this might include a security system, temperature and humidity sensors, and an irrigation system that uses drippers. On the other hand, the study focuses on the positive impact of plants on human health. This is performed by transferring images collected by the IPcameras positioned around the room to the trained model for early plant disease identification. This model utilizes machine learning algorithms related to computer vision-based neural networks[1]. The monitoring of the growth and development of the fruit is handled in a manner that is analogous to how the system determines whether or not the plant is healthy. Sensor data, microcontrollers, and radio interfaces are three components that are extremely important to intelligent sensor systems. Microcontrollers, Raspberry Pi minicomputers, sensors for humidity, temperature, moisture, and water flow, an Internet Protocol (IP) camera, and motors are all components of the inquiry. Fig 1 presents the block diagram for the system in question. The following description will walk you through this project's hardware's crucial and fundamental components [22].

Hardware Unit - Microcontrollers, Raspberry Pi, Sensing and Communication Devices

AT Mega microcontroller The Arduino Atmega2560 open-source microcontroller family is built on top of the Atmega2560 AVR development board as its primary component. To do this task, an 8-bit microcontroller was utilized. Microchip's ATmega16U2 microcontroller is the one that gets put to use here. Processing is the computer language used to write the code for this board. The hardware includes sixteen quartz crystal oscillators and fifty-four digital input/output interfaces (14 of which can be used for PWM output). Arduino is a prototyping platform with a low entry barrier because it is easy to use both in terms of its hardware and software. The two most important parts are an Arduino-compatible programmable circuit board and an Arduino Integrated Development Environment (IDE) that has already been pre-built. This application is utilized in the process of writing and uploading computer code. For the experimental investigation, an Arduino AtMega2050 is utilized. This board possesses 14 digital I/O pins, six analogue inputs, and 16 MHZ quartz crystals. Each sensor is connected to Arduino by a USB cable, which runs from the sensor to Arduino. Arduino, in turn, is connected to the raspberry pi via a serial USB connection[3][2].

Raspberry Pi is the brand name of a family of very small single-board computers that the Raspberry Pi Foundation developed in conjunction with Broadcom (SBCs). A Raspberry Pi is used as the "brain" of the operation on this particular piece of work. It can communicate with an Arduino and a database stored in the cloud. The Raspberry Pi, which uses socket and multithreading, serves as the system's brain and transfers data in real-time from the sensors to the server. This is where the system's SQLite backend stores the configuration settings that are considered the most important. In particular, these are the parameters relevant to the component dealing with machine learning. Raspberry Pi is the brand name of a family of very small single-board computers that the Raspberry Pi Foundation developed in conjunction with Broadcom (SBCs). A Raspberry Pi is used as the "brain" of the operation on this particular piece of work. It can communicate with an Arduino and a database stored in the cloud. The Raspberry Pi, which uses socket and multithreading, serves as the system's brain and transfers data in real-time from the sensors to the server. This is where the system's SQLite backend stores the configuration settings that are considered the most important. In particular, these are the parameters relevant to the component dealing with machine learning[16].

There is a digital sensor that measures temperature and humidity and uses the very affordable and widespread DHT11. The ambient temperature and humidity are evaluated by a capacitive moisture sensor and a thermistor, which output a digital signal on the data pin. It is possible to use it in a wide variety of environments, including ones with varying degrees of heat and dampness, due to its low complexity and broad 20-meter transmission range. Both temperature and humidity readings were taken with the help of the DH11 sensor that was used.

IP cameras are a special kind of IP-enabled digital video camera that can receive and send control information and imagery over a network. These cameras are also known as "IP cameras." An IP camera captures the images, then they are transferred via IP to an artificial intelligence model for analysis. The user of the raspberry pi configures the IP camera to take a photo at predetermined intervals, and the raspberry pi is responsible for taking the picture and storing it in the repository when it has been taken.

Implementation – Modeling

The following steps were carried out to put the system into operation:

Identifying specific areas within the greenhouse in which to install the various sensors and other pieces of equipment.

- Every sensor has a connection that can go in both directions to the Arduino.
- The Arduino can communicate with the Raspberry Pi minicomputer in a straight line thanks to a serial connection.
- During the preprocessing stage, image sizes are reduced to 256 by 256, and enhancements are made to prevent overfitting.
- A training set and a testing set comprise 20% of the dataset.
- To train, the framework described above is utilized.
- The model's convolution layers collect significant features for classification and prediction.
- The testing data set is utilized to determine whether or not the trained model accurately represents the data.
- The hyperparameters of the training can be adjusted to achieve a finer tuning of the training.
- It is possible to use the model after exporting it and importing it into the desktop program.
- The system is going to take images of the greenhouse at regular intervals that have been set.
- The user will receive a response which will include this outcome.

Dataset and Data Modeling using Neural Networks

Tomatoes have played dual roles in this study as the disease-detection test subject and the reference standard for ripening prediction[13]. The dataset can be downloaded from Kaggle's plant village dataset page without cost. September Leaf Spot We have collected two main types of data: the first is a visual record of a tomato plant being

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attacked by numerous pathogens; we concentrated on ten different diseases: late blight, early blight, bacterial spot, leaf mould, tomato yellow leaf curl virus, tomato mosaic virus, target spot, and spider mites. A two-spot spider mite is a typical form. We have collected over 8,500 images, with over 850 in each category. One set shows unripe tomato flowers, while the other shows ripe tomato fruits[4]. Tomato fruits in pictures were sorted into three categories—ripe, overripe, and unripe—for further research. Somewhere between 1,500 and 2,000 images were taken. The model was average, trained using around 10,000 photos.Before any actual training can commence, the vast bulk of the time is devoted to preprocessing images. Eliminating errors and ensuring that everything is consistent and complete are the key focuses of pre-processing, which has as its primary objective the delivery of your data in a form that can be interpreted by a computer. Because we began with two separate collections of data, we have utilized two different pre-processing algorithms to accommodate this. The following procedures constitute the most fundamental phases involved in the preprocessing stage to determine the state of health of plant leaves. As part of this investigation, we will utilise three forms of photo preparation: image filtering and segmentation, geometric transformations, and pixel brightness alterations with correction.

The first thing that needs to be done in any pre-processing procedure is resizing all images to have the same proportions. The process of extracting features is made more accurate and efficient by utilizing this strategy, which is one of the primary reasons it is so important. Before beginning the training process, you need to ensure that every image is scaled to the same size. This should be done before commencing the process itself. The process of extracting features from a picture will be made much less complicated due to this change. Any training activities dependent on larger images, such as those frequently obtained by mobiles and consumer-grade cameras, will require a significant amount of additional time to implement. This additional time will be required. It is advised that photographs be scaled down to a standard size of between 250 and 400 dpi to avoid problems comparable to those experienced in the past (dots per inch). We were required to reduce the size of the images to 256 pixels on each side to comply with the specifications.

Fig 2. Original Images

Fig 3. Original Image and Grayscale Image

Full-colour images can be captured using a mobile device such as a cell phone or other portable camera (RGB). Processing coloured pixels could be a laborious and time-consuming task during the machine-learning procedure. Converting to grayscale is one approach that offers the greatest degree of flexibility in resolving this issue. A number between 0 and 255 is assigned to every pixel in a picture for each of the three primary colours that compose it: red, green, and blue (RGB). In a grayscale image, a pixel's value represents the brightness level in the corresponding area (white). In the end, the value 255 is used to represent white, and the value 0 is used to represent black. The processing of deep learning algorithms can be sped up with the help of grayscale photographs Fig 2 and 3. If each picture component had to be processed separately, learning and prediction abilities might be negatively impacted. Because of this, it is strongly recommended to clean up the image by removing any items or individuals that aren't necessary from the picture so that the algorithm can concentrate on the target area[14]. The segmentation process involves removing the background of the image and, in certain instances, other objects at random. If we go ahead and accomplish that, the result will be a dark background, which will make the image of the leaf stand out more,as shown in Fig 3, and the diseases stage based on the leaves shown in Fig 4.

Fig 4. Stages of Tomato Plant leaves - Monitoring

One of the most challenging aspects of this study area is the training procedure of a machine-learning model with inadequate data. One method of augmenting image datasets that can be utilized to improve image datasets is by rotating the images included in the image dataset. It is possible to define an image according to a wide range of parameters, some of which include its dimensions, rotation, transformation, and magnification, amongst others. Because of this, the algorithm is in a position to make use of a variety of perspectives on the same image. A wide variety of transformations, such as simple picture rotation, perspective rotation, and affine transformation, are performed on the data throughout the augmentation process to create desired effects. This is done to obtain the intended results. Figure 6 depicts the modification that was made as part of the improvement procedure that was carried out. Currently, an application programmed in C++ and using the OpenCV library has been developed to automate enhancing the entire image collection[11]. Users of this program can make changes to important parameters while the transformation is still being carried out.

4. Results

Data Pre-Processing Steps for Fruit Ripeness Prediction

This module makes use of several different pre-processing techniques, including those that have been discussed previously. This standard prediction model was designed to function properly with both live videos and photos taken in advance. Our intention was for it to be able to do both. To offer an accurate forecast, this model goes through films and analyses each frame individually. To achieve such a capability, the model must be trained with comprehensive information regarding every event in the image.

To put it another way, we need to supply our model with information about the items and instances that are present in the image so that it can make correct predictions about the target fruits without being distracted by unimportant information that is present in the background. The term that is used to refer to this kind of preprocessing procedure is "annotation." In machine learning and deep learning, the term "picture annotation" refers to the labelling of an image using a language, annotation tools, or both to identify data components that the model needs to evaluate the image on its own. This can be done either manually or automatically. The metadata added to photos during the annotation process is useful for the datasets containing those images. Instance segmentation is the kind of annotation that's used here out of all the several kinds that are possible. The process of tracking and measuring the existence of objects in an image using a method known as instance segmentation is called instance tracking and quantification. We can make use of instance-based pixel-wise segmentation to categorize all of the pixels that are contained within the border. We could utilize boundary segmentation, which relies solely on the coordinates of the borders, if that's what you prefer. For this exact objective, there are web services and desktop programs that are offered specifically.

Neural Networks Training

To carry out the totality of the learning and prediction, an algorithm known as MASKRCNN is utilized. This algorithm is employed in conjunction with Convolutional Neural Networks, also known as ConvNet/CNN. The field of image processing uses many techniques for deep neural networks, and CNN is one such way. Additionally, it is one of the most well-known examples[18]. This approach entails the application of considerable learnable weights to the characteristics in question to facilitate the effective extraction of valuable characteristics by the model and the formulation of correct predictions.

In comparison to other algorithms, the CNN algorithm only needs a limited number of pre-processing stages to function properly. To generate reliable and uncomplicated forecasts, CNN's objective is to breakdown the image into a more condensed form while simultaneously eliminating the image's historical qualities from the process. This will allow CNN to achieve its goal. In addition to the layers that are input and output, as well as any other levels that may be visible, the architecture of a CNN includes several layers that are concealed from view. The data are in charge of carrying out various tasks to bring the CNN layers used for feature learning up to current. A convolutional neural network comprises several layers, one of the most essential of which is the convolution layer (CNN). This layer is created by drawing a picture while running it through a series of convolutionally orientated filters. Because it reduces negative property values to zero while maintaining positive property values, the rectified linear unit, also known as ReLU, enables faster and more effective learning. This is because it retains positive property values. Train each layer to recognize a new set of features. This procedure is done thousands of times[8].

To determine whether or not a fruit is ready to eat, one needs to carry out several steps that are all connected in some way. The first thing the model does when provided with an image is looking for objects already present within that image. It ought to be able to single out tomato fruits and identify them as such amidst all of the other objects presented in the photo. In the following stage, which is called instance segmentation, the recognized fruit will be given a colour border so that the results of the detection technique may be used in further phases. This will allow the results to be used in subsequent stages. After a subject has been recognized, the subsequent step is to categorize it following the standards outlined in the various possibilities. It is not possible to generate even a single prediction without first completing every one of these steps. This research uses a single algorithm referred to as MASKRCNN, which is extremely effective, to accomplish the goals stated earlier in the introduction. Segmentation is only one example of machine learning and computer vision difficulties that may be conquered with the neural network-based technique Mask-deep RCNN delivers. Other examples include recognizing faces in images and recognizing faces in videos. As a result of this advancement, item-level segmentation can now be performed on still photographs, as well as frame-based image analysis on moving video. Both types of media can also be combined. A graphic that includes several binding boxes, class names, and masks is displayed at the beginning of the presentation.

The Mask RCNN process can be broken down into two separate steps. Based on the photographs supplied, it initially makes some educated guesses as to the potential locations of the object at this point. In the second stage, it takes the suggestion generated in the first step and uses it to build a prediction about the object's class. This prediction is based on the proposal generated in the first phase. After that, it will adjust the bounding box and produce a mask at the pixel level. Each of the Acts has some connection to the Main Structure of the story. The most encouraging and surprising result we noticed when carrying out this experiment was that by using MASK-RCNN, we could push the different levels in the neural network architecture to learn informative patterns and features with varying sizes and ROI Align. This was the most surprising result that we noticed. The Mask-RCNN algorithm will begin by generating a region proposal surrounding the things to be categorized. This region will be centred on the objects that are to be categorized. After that, the relevant masks will be applied to the regions of interest, and the objects will be labelled.

Fig 5. Stages of Tomato Plant leaves - Monitoring

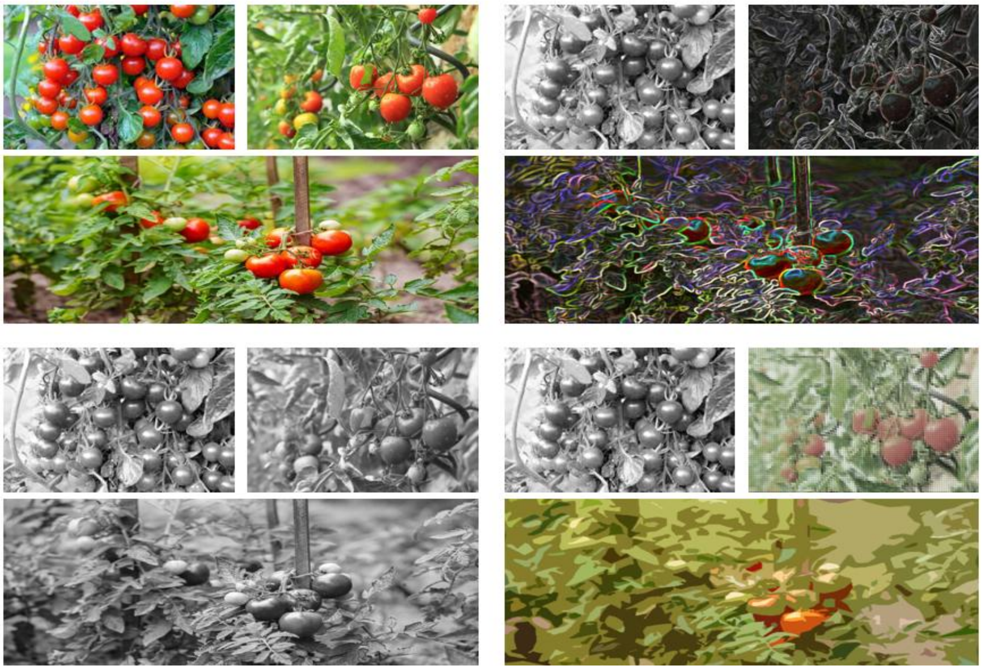

Fig 6. MASK-RCNN Modeling

It is possible that even a slight tweak to the architecture's hyperparameters could significantly improve its learning performance. You can complete this work on your own or utilize specialized tools that come pre-configured with the appropriate settings already applied. Either way, you have options. Models that have been fine-tuned can learn much faster and in a much shorter amount of time than models that have been trained from the beginning. A brand-new, ground-up version of the SoftMax classifier was constructed with the help of the backpropagation approach and the information given in Section 4. This version was trained from scratch. According to the preliminary findings of the training, the plant disease classification model displayed characteristics of overfitting behaviour. Because the model cannot generalize, it has demonstrated a capacity to memorize patterns. This is because it cannot be generalized[25].

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The initial dataset size was insufficient, which prevented the model from recognizing useful full patterns and resulted in an unsatisfactory output. This was because the model was unable to identify entire useful patterns. There was some improvement in the model's performance after we loaded and trained on the entire dataset; however, this improvement was not even close to being sufficient to justify labelling the activity as a success. After loading and training the entire dataset, there was some improvement in the model's performance. Our group has also altered some of the hyperparameters, including the epoch, the batch size, the learning rate, the optimizer, and the dropout. These are only some examples. According to the findings of our investigation, the Adam optimizer with a learning rate of 0.00001 offered the best overall performance for our company.

5. Discussion

Greenhouse agriculture is gaining ground as a feasible practice in an increasing number of industrialized economies, to increase overall food production as one of its primary benefits. Greenhouse agriculture is gaining ground as a feasible practice in many industrialized economies. Implementing smarter strategies based on the Internet of Things (IoT) and artificial intelligence (AI), which automate labour-intensive manual tasks that humans currently perform, is one method for increasing crop yields. This method is one of several ways to increase crop yields. This investigation made use of a novel approach to deep learning methods and applied those methods to a greenhouse that utilized the Internet of Things (IoT). In addition to monitoring fruit growth and development and the general management required to run the system, this enabled the automatic detection and categorization of a large number of different types of illness within the region. Because of the availability of this technology, it was able to accomplish this goal. In the not-too-distant future, new ensemble machine learning algorithms will be used to integrate additional datasets to achieve even bigger increases in performance. These improvements will be achieved by combining additional datasets.

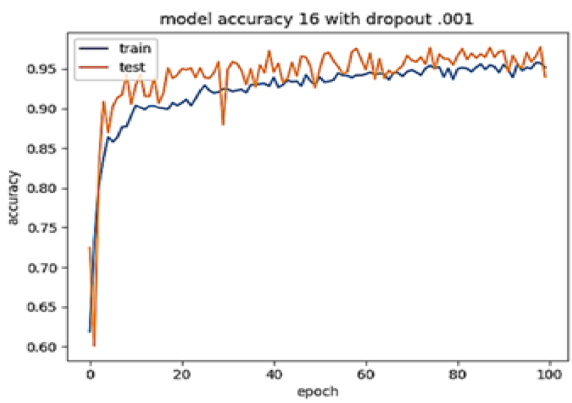

Fig 7. Algorithm training and testing.

Table 5 displays the performance of each RGB channel as well as the overall performance of the combined RGB channels for image-level categorization. The results demonstrate that the Bagged and Complex trees produce superior outcomes on RGB colour features. Compared to Fine CNN, it is subpar regarding the histogram features of the R channel. The image-level accuracy for the H, S, and V individual channel features and the combined HSV features. Fine CNN, Bagged tree, and Complex tree performs admirably regarding the HSV colour features.On RGB colour properties, it Demonstrates that the Bagged tree ensemble approach performs better than the Boosted tree ensemble approach, and the analysis demonstrates that the Bagged tree ensemble approach performs better than the Boosted tree ensemble approach. The Bagged tree ensemble approach performs better than the Boosted tree ensemble approachesin the diseaselevel accuracy on the H, S, and V individual channels and the combined HSV. When it comes to HSV colour features, the performance of the Complex tree is superior to that of Fine CNN. In the same heatmaps, the precision of the disease level on the LBP features is also represented. The accuracy of the Complex Tree is improved with the addition of LBP features.Overall, we can see that using histogram features helped reduce the amount of overfitting for the Rus target class. Despite this, the regular class is still overfitted in this scenario with a perfect accuracy score.

Similarly, the TPR was brought down to 87% with the Can target class. Using cubic support vector machine analysis, the HSV histogram feature vectors provide a different solution to this phenomenon with an accuracy of 98.5%.In a similar vein, the accuracy of the LBP feature vectors for the Can class is the lowest among all classifiers, with an accuracy of less than 70%. On the other hand, the TPR rate tends to increase by 100% when the GLBP channel and the Complex Tree are involved.

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