INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Check for updates

OPEN ACCESS

Received: 24.02.2022

Accepted: 16.03.2022

Published: 19.05.2022

Citation: Chakraborty A, Das S, Mondal B (2022) Integrating Neural Network for Pest Detection in Controlled Environment Vertical Farm. Indian Journal of Science and Technology 15(17): 829-838. https://doi.org/10.17485/IJST/v15i17.353

* **Corresponding author**.

biplob.tezu@gmail.com

Funding: The research was funded by Tezpur University Research and Innovation grant in year 2020-2021

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Integrating Neural Network for Pest Detection in Controlled Environment Vertical Farm

Ayan Chakraborty[1], Suvajeet Das[1], Biplob Mondal[1]*

1 Department of Electronics and Communication Engineering, Tezpur University, 784028, Assam, India

Abstract

Background: An integrated system for creating and maintaining controlled environment ideal for vertical farming prototype is demonstrated. The requirement of optimal artificial light for different growth stages of tomato and chilli plants is studied in detail and CNN model-based method for detection and classification of Leaf disease is also developed. **Methods:** The artificial environment ensuring adequate artificial lighting, moisture, and minerals was create by implanting various sensors and actuators to the plant beds and connected in network through a cloud based remote server. A CMOS image sensor module was used to monitor the various stages of plant growth. **Findings:** The duration and intensity requirement for germination, vegetation and flowering of both tomato and chilli plants are relatively lesser with artificial light condition than with sunlight. At the end of fifth epoch the developed convolution neural network model for detection and classification of leaf disease produced training and validation accuracies of 84.8% and 67.2%, respectively. **Novelty:** For different growth stages of tomato and chilli plants in north eastern India, the requirement of optimal artificial light is studied by exposing them to different light intensities. The study was conducted during summer (May-June) when the average sun exposure in eastern India was ~130-190 hours. The captured images and data generated were used to monitor the status of the crops and identifying diseases with the application of Deep Learning models. Convolutional Neural Network (CNN) model-based method for detection and classification of leaf disease is presented.

Keywords: Convolution Neural Network; Vertical Farming; Artificial Light; Pest Detection; Light Emitting Diode

1 Introduction

Recent developments of Internet of Things (IoT) along with smart sensing technologies, has enables farm land to produce crops with improved quality and yield[1–3]. IoT technologies is predicted to play key role in the advancement of agricultural technology due to its capabilities in cloud-based connectivity of devices, local and remote data acquisition, intelligence, data analysis and decision making etc[4,5]. Availability of low cost and low power consuming sensing and actuating devices boost the process, bringing transformation to farming technologies. For example, limiting light to specific wavelengths might allow huge energy saving as photosynthesis does not require the full spectrum present in white light. The Light Emitting Diodes (LEDs) are capable of producing photon fluxes of specific wavelengths matching the spectral composition required during different growth stages for different types and are widely used in plant growth facilities[(6)]. Ma et al. presented earlier a meta-analysis on the effect of LED light on plant growth, development and traits and found that current researches on LED lights needs further exploration for horticultural production[(7)].

Vertical farming adopts method for growing crops in a closed and controlled environment in which the crops are staked vertically at different levels[(8,9)]. The plant growing condition is controlled through fine-tuning of temperature, humidity, light, carbon-di-oxide (CO_2) concentration, soil pH using varieties of sensors connected in network in an IoT enabled vertical firm. Setting of these parameters at specific levels during different growth stages allows the crop to grow and develop optimally. However, critical analysis is necessary before choosing the optimal ambient conditions. It is worth mentioning that inappropriate choice of ambient condition may alter the plant's metabolism and physiological process. As a matter of fact, elevating the CO_2 concentration increases photosynthesis rate in plants enhancing the growth rate and yield, but at the same time might result in decreased nutritional values including protein concentration, vitamins etc of food crops[(10)]. Rapid expansion in vertical farming research in various academic and industrial workplaces is being carried out due to increased consumer demand of agricultural products and potential for huge business[(8,9)]. Liwal et al. reported on a sustainable and scalable vertical micro-farm with automatic control on environmental conditions. However, authors did not give any information on the type of crop investigated, how the system chose the optimum environmental condition.

Pest management and control is very important to enhance the agricultural yield[(11–13)]. Automatic pest detection using deep learning techniques like convolution neural networks (CNN) model can lead to highly efficient pest management system[(14,15)]. The outstanding performance of CNNs as feature extractors and classifiers in image recognition has ignited researchers to apply idea to agricultural applications in order to accomplish tasks such as disease recognition, pest recognition, fruit and flower counting, crop yield detection, crop classification etc[(16–21)]. The techniques of these kind use machine vision equipment to acquire images and the collected images are used to judge the requirement of pest and disease control through decision making algorithms.

Although research on leaf disease detection and vertical farming technology is developing rapidly, there are still lots of challenges to be addressed for field-based application giving high economic benefit. Lack of publicly available data set for many crops of vegetables and flora is one of the biggest challenges for the development of uniformly applicable deep learning algorithm for all environments, irrespective of seasonal change across different region of the globe. Also, most of the previously reported study focus on applying decision making algorithm to either field-based data or public domain database for classification and detection in offline mode[(20,22)]. The real time detection of leaf disease is challenging due to small infected area, multiple disease type on same leaf, difficulty in correlating disease site with disease type etc[(23,24)].

An integrated system for creating and maintaining appropriate controlled environment ideal for plant physiological developments in vertical farming system is studied and presented in this work. The artificial environment delivering optimal condition for plant growth is created that ensures adequate artificial lighting, moisture and mineral level. Nevertheless, the appropriate requirement of intensity and spectrum of artificial light for indoor farming is not clear. We therefore studied the requirement of optimal artificial light for different growth stages of tomato and chilli plants. A CNN model-based method for detection and classification of Leaf disease is also presented. The CNN model is trained with data generated from the developed vertical farming beds in addition to the dataset provided by 'Plantvillage' on Kaggle.

2 Methodology

2.1 Fabrication of experimental set up

The artificial environment ensuring adequate artificial lighting, moisture, and minerals was create by implanting various sensors and actuators to the plant beds and connected in network through a cloud based remote server. In addition to the duration of exposure, the intensity of the light also plays a crucial role and hence an efficient, high intensity light source is required in order to maintain stable illumination. LED lights were used as artificial light and Light Dependent Resistor (LDR) was used to measure intensity of sunlight. As for the water requirements of the plants, a prototype of the watering system is built using a 9V DC motor and relay board (8 relay) which is indeed controlled by the Raspberry Pi microprocessor board. Watering of the plants was done with a measured quantity, every day at a fixed time. The FC-28 soil moisture sensor was used to monitor the moisture content in the soil with an Arduino Uno board. The soil moisture sensor consists of two probes which were used to measure the volumetric content of water. A CMOS camera image sensor module was installed inside the chamber to monitor the various stages of plant growth. A Raspberry Pi based local server was used to collect data from various sensors.

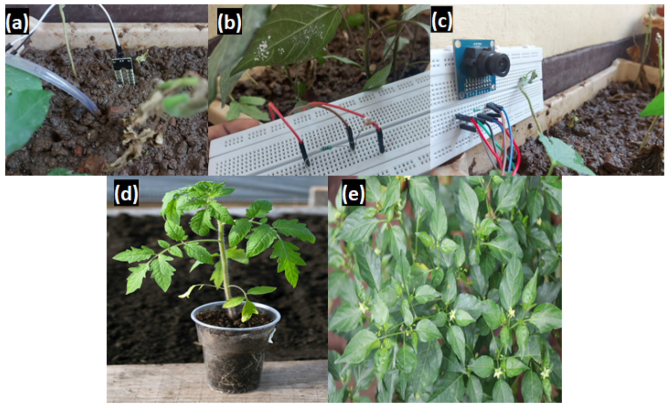

Fig 1. (a) Installed FC-28 moisture sensor, (b)RTD sensor for recording intensity of light (c) installed camera module, (d) fully vegetated tomato plant, (e) chilli plant in flowering stage

2.2 Implementation of CNN model

Providing optimal environments for the crops to grow is not sufficient to ensure the health and quality of the crops. Pest control and crop management is essential, and in close and compact environment it is possible to install equipment to monitor plants growth and health by means of capturing images or videos. The captured data can be used to monitor the status of the crop and identifying diseases with the application of some Deep Learning models. Convolutional Neural Network (CNN) model-based method for detection and classification of leaf disease is proposed in this work.

2.2.1 ***Used data set***

The "Plantvillage" dataset was retrieved from Kaggle which contains over fifty thousand images of healthy as well as diseased plant leaves belonging to various plants. The Tomato Leaf Disease dataset contains a huge collection of images of healthy as well as diseased leaf with diseases like bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, spider mites, two-spotted spider mite, target spot, tomato yellow leaf curl virus and tomato mosaic virus etc. The dataset used for the purpose contains over five thousand images of tomato leaves with ten classes of images, nine of which represent nine different symptoms of diseases along with one image class of healthy leaves. A CNN has been modelled for automatic feature extraction which will in turn be used for the classification process. Colour information has been used, based on RGB components the filters are applied to three channels. Some of the images in the dataset have been added from the plants that were grown by us along with a pre-existing dataset provided by 'Plantvillage' on Kaggle.

2.2.2 ***System Specifications***

As per the system requirements of the latest stable release TensorFlow version (ver.2.5.0) which goes with python (ver. 3.6-3.9), The system configurations of the system used for generating the results of this paper are:

CPU: Intel Core i5-10300H, ~2.5GHz
GPU: NVIDIA GeForce RTX 3060
RAM: 8 GB
Operating System: Windows 10.0, 64-bit
TensorFlow Version: ver. 2.5.0

2.2.3. ***Workflow of the model***

The general workflow of a CNN based image classification algorithm has three primary stages. At first the dataset is organised in ten separate directories of healthy and diseased class of leaves and ensure that none of the leaves are located in the wrong directory to avoid chances of any mislabelling of training data and compromise the integrity of the dataset. The segmentation pre-processing is done which includes the process of image segmentation, image enhancement and color space conversion. The pre-processing step involves image resizing using various filters. In our case, a manual image augmentation is done followed by converting each image into an array. The CNN classifiers are built and then after applying the required parameters, they are trained using the augmented dataset, labelled based on the class they actually belong to, in order to build a model capable of identifying diseases in each plant class. The model is ready to use after trained it with a certain number of epochs and achieving satisfactory training and validation accuracy. The model takes input images, one at a time, which also undergoes similar augmentations and resizing steps as used in the training process, after which the previously trained weights of the model classify the image into one of the 10 classes. For building and training the image classifier five thousand images available in the original dataset from Plant village were used and split them into training and testing data in the ratio 7:3. The Keras Deep Learning framework has been used for performing the various pre-processing steps and for building the model. Figure 2 shows the flowchart depicting the workflow of steps involved in building the model.

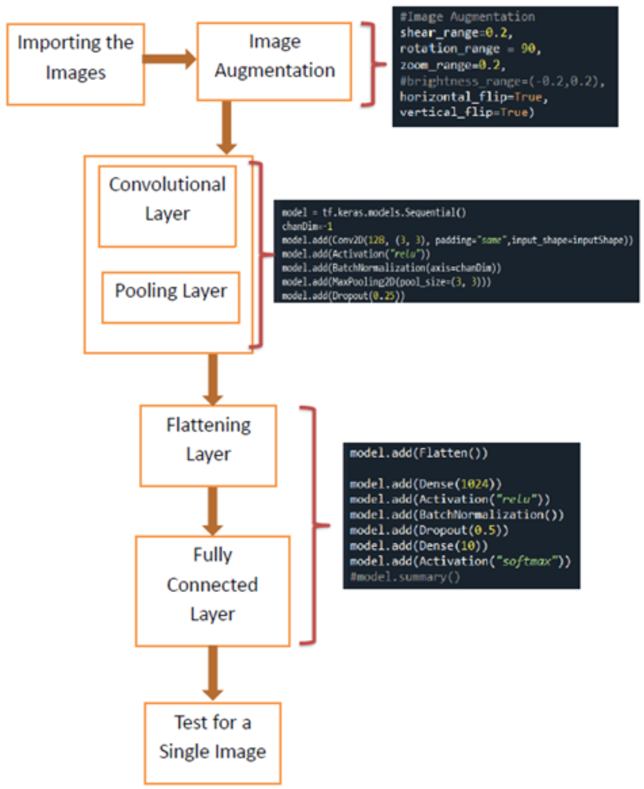

Fig 2. Flowchart representing the workflow of the image classifier mode

2.2.4 Importing and Pre-processing the images

The creation of an effective image classifier depends strongly on an equally good image augmentation process. Despite the fact that datasets may contain a large training sample, this might not be adequate to develop an appropriate model. Various augmentation methods are used which may include: i) Rotation (to rotate a training image randomly over various angles, ii) Brightness (helps the model to adapt to variation in lighting while feeding images of varying brightness during training), iii) Shear (adjust the shearing angle), iv) Zoom range (to obtain cropped/magnified segments of the image), v) vertical and horizontal flip (helps the model to adapt to vertically and horizontally flipped images). These additions help to improve the amount of relevant data in a dataset as shown in Figure 3. The size of each image in the Plant Village dataset is found to be 256 x 256 pixels, which has been resized to 128 x 128 to account for the processing capacity of the GPU and to reduce the training time. The data processing and image augmentation are also done using the Keras deep-learning framework. We further split the current training set into training and validation sets as shown in Figure 4 for cross-validation of the data while training.

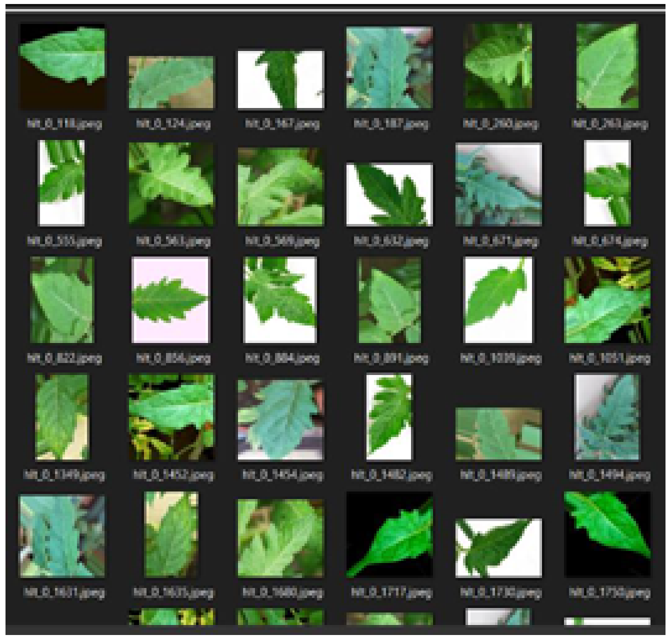

Fig 3. Example of augmented leaf images

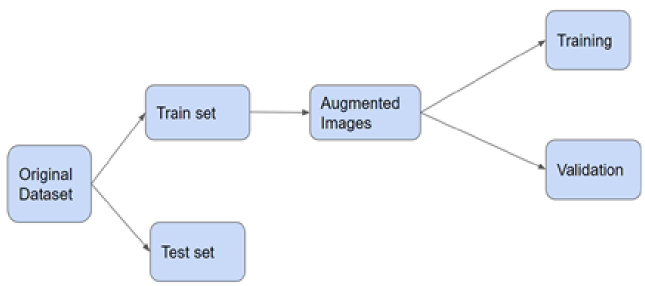

Fig 4. Flowchart representing data splitting

*2.2.5. **The CNN implementation and parameters***

A multi-layered convolution neural network models is built in this work which is responsible for feature extraction and identifying key feature matrices. The Convo2D layer is used to create a convolutional layer with thirty filters, kernels of 3 x 3 size and ReLu activation function which is the linear correction module. A pooling layer is added, for which Max-Pooling is chosen, followed by a batch Normalization layer with channel dimension of one for normalizing the inputs for each mini-batch. This is followed by a dropout layer which is set to 0.25 for an effecting averaging of the neural network. Dropout is a control method that prevents the rectification of complex collaborative data for training, reducing neural network readjustment. In short, dropout randomly sets some weights to zero to be retrained in order to prevent overfitting of the model. Padding enabled multiple layers were used, after which the output of the entire network is flattened so that it can be taken as an input to the ANN layer. The ANN layer is responsible for training the model by updating the weights of the network after each iteration. Adam optimizer was used for our model's optimization and for the loss function, loss function was selected. The batch size was set to 32, the model was trained for 8 epochs.

3 Results and discussion

Although, LED lights are being widely used in the plant growth factories for cultivating various plants, there is still incomplete information available on the lighting conditions required for optimal growth of different plants. For different growth stages of tomato and chilli plants, the requirement of optimal artificial light is studied here, by exposing the crops to different light intensities. Three separate groups of chilli and tomato plants were planted on the upper, middle and low bed of the three-level farming structure and were exposed with light of different intensities. The middle and bottom layers are lighted with LED bulbs of 100 watts and 200 watts respectively. The area of the plant bed in each level is 1350 cm^2. The study was conducted during summer (May-June) when the average sun exposure in eastern India was ~130-190 hours. The plants of the upper bed were exposed to sunlight and the intensity of sunlight was measured with light dependent resistor (LDR) sensor. Table 1 summarizes the exposure duration to different lighting conditions during different stages of the growth of tomato plants, while Table 2 corresponds to data for chilli plants. The Figure 5 indicates the average number of days required for the plants to germinate, completely vegetate and flower with illumination of 13333.00 lux and 26666.00 lux corresponding to 100 watts and 200 watts LED lights. Both tomato and chilli plants take relatively lesser time for germination, vegetation and flowering with artificial light compared to when grown under sunlight. The intensity of sunlight throughout the day is not uniform and its intensity also varies day to day (seeTables 1 and 2), which could the reason among many other for the relatively lower plant growth rate with sunlight. When compared the intensity of artificial light requirement, 200 watts bulb is recorded for faster germination, vegetation and flowering of the crop in all the growth stages. However, the average requirement of light exposure is also much higher with 200 watts bulb, approximately 1.2 to 1.6 times higher as compared with 100 watts bulbs. Nevertheless, the appropriate requirement of intensity and spectrum of artificial light for indoor farming is not clear and depends on multiple factors.Optimal light spectrum requirement varies with geographical locations from crop to crop. As can be seen from the obtained data the requirement of lighting varies during growth stages. Avgoustaki and Xydis conducted similar study to evaluate growth, yield, and quality of basil plants under continuous and intermittent lighting. The experiment was performed in Denmark from October to December in year 2019[(25)]. The authors proposed energy saving protocol in automated indoor farms with artificial lighting solutions. Similarly, Monostori et al. manifested benefit of LED light with increased photosynthetic activity, number of tillers, biomass and yield in wheat[(26)]. The spectral quality and intensity were found to be the factors for optimizing the tillering, flowering, stem elongation phase and metabolism of leaves etc. The obtained results and the observations made in the work presented in this article are in good agreement with findings of the above cited works.

Table 1. Exposure duration for tomato plants

Day	**Average Sunlight(lux)**	**Luminance(lux) (100W bulb)**			**Luminance (lux) (200 W bulb)**		
		Plant group 1	Plant group 2	Plant group 3	Plant group 1	Plant group 2	Plant group 3
Germination Phase							
1	10456	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
2	11753	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
3	11777	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
4	12672	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
5	8756	13333.33	13333.3	13333.3			26666.7
6	9921	13333.33		13333.3			
7	10897	13333.33					
Total Intensity:	**76232.00**	**93333.31**	**66665**	**79999.98**	**106666.80**	**106666.80**	**133333.50**
Vegetation Phase							
1	9700	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
2	10700	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
3	7800	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
4	9564	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
5	8905	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
6	12578	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
7	10567	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
8	7891	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
9	6900	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
10	7346	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
11	6146	13333.33	13333.3	13333.3	26666.7		
12	7921	13333.33	13333.3	13333.3	26666.7		
13	10311	13333.33	13333.3	13333.3			
14	11432	13333.33		13333.3			

Continued on next page

Table 1 continued

Total Intensity:	127761	186662	17,3329	18,6662	319992	266,667	266,667
Flowering Phase							
1	10870	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
2	9309	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
3	9450	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
4	9197	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
5	8949	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
6	11893	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
7	14690	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
8	12890	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
9	6290	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
10	8319	13333.33	13333.3	13333.3	26666.7		
11	7812	13333.33	13333.3	13333.3			
12	9348	13333.33	13333.3	13333.3			
13	9822						
14	10254						
Total Intensity:	139093	159999	159999	159999	266667	240000	240000

Table 2. Exposure duration for chilli plants

Day	Average Sunlight(lux)	Luminance(lux) (100W bulb)			Luminance (lux) (200 W bulb)		
		Plant group 1	Plant group 2	Plant group 3	Plant group 1	Plant group 2	Plant group 3
Germination Phase							
1	7862	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
2	8742	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
3	7890	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
4	9561	13333.33	13333.3	13333.3	26666.7		
5	7912	13333.33					
6	10983	13333.33					
7	10236						
Total Intensity:	**63186**	**79998**	**53332**	**53332**	**106664**	**79998**	**79998**
Vegetation Phase							
1	7832	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
2	12873	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
3	15789	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
4	14628	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
5	9721	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
6	10328	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
7	10826	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
8	7289	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
9	7234	13333.33	13333.3	13333.3	26666.7		
10	9854	13333.33	13333.3	13333.3			
11	14579	13333.33		13333.3			
Total Intensity:	120962	146663	133330	146663	239994	213328	213328
Flowering Phase							
1	6732	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
2	8217	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
3	13654	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
4	7612	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
5	8583	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7

Continued on next page

Table 2 continued

6	10096	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
7	10217	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
8	9321	13333.33	13333.3	13333.3	26666.7	26666.7	26666.7
9	8478	13333.33	13333.3	13333.3		26666.7	26666.7
10	9216	13333.33	13333.3	13333.3			26666.7
11	13678	13333.33	13333.3	13333.3			
12	11239	13333.33	13333.3	13333.3			
13	13950			13333.3			
Total Intensity:	130993	159996	159996	173329	213328	239994	266660

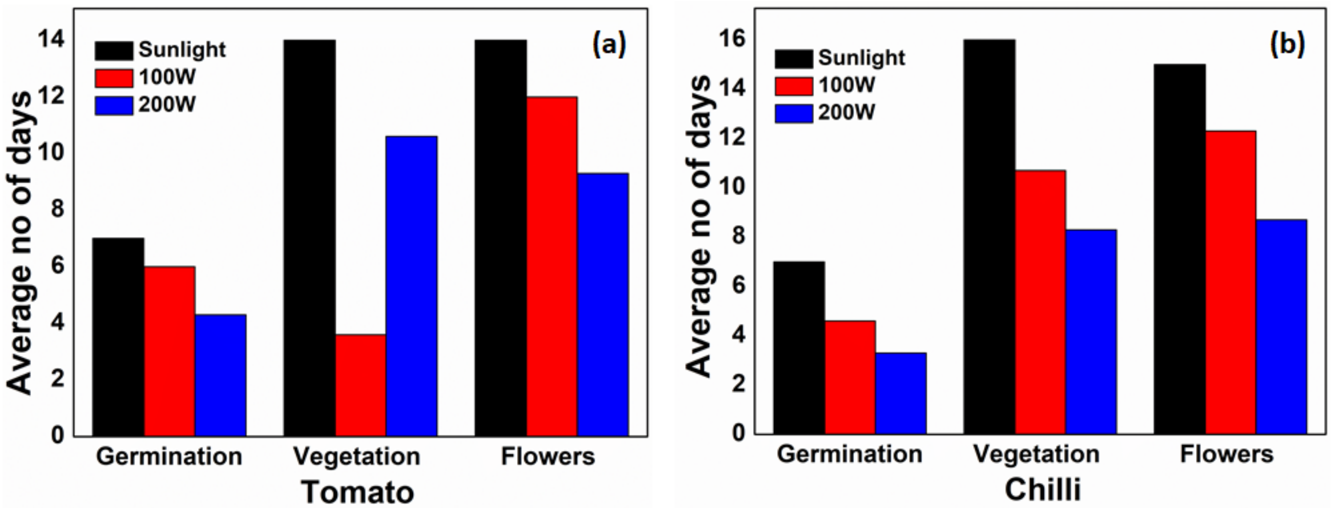

Fig 5. Comparison of average number of days required for tomato and chilli plants to germinate completely vegetate and flower

The accuracy and loss curves of the model are show in Figure 6, that represent the training loss, training accuracy, validation loss and validation accuracy achieved by the model at different stages of the training. From the curves shown in Figure 6, it can be observed that the training accuracy ranges from 70.2% (after the end of the 1st epoch of training) to 88.7% (at the 8th and final epoch of training). On the other hand, the training loss ranges from 96.4% (after the end of the 1st epoch) down to 34% (after the 8th epoch). This is as expected from the model, to have an increment in accuracy and decrement in loss with the number of epochs. But, as we look into the validation accuracy, we can observe that the graph is fluctuating, initially beginning from 19.2% reaching as high as 59%, and then again dropping down to 43.5% and so on, which is due to the dropout layer that was incorporated into the CNN structure to prevent overfitting. Validation accuracy is expected to be lower than the training accuracy, but too large of a difference will lead to our model function inefficiently. Our goal is to achieve such a stage where the validation accuracy is as close to the training accuracy as possible. From Figure 6, we can observe that when the training accuracy is at its peak of 88.7% in the final epoch, the validation accuracy has dropped to 20.6% which is not a suitable stage for our model to end its training on, so it would be more efficient to train the model further until such an epoch where the differences between the training and validation accuracies is found to be minimum or we can choose to end our training after the 5th epoch where the training and validation accuracies are 84.8% and 67.2% respectively and hence the difference between the two are relatively lower. Table 3 summarized the accuracy and loss data during training epoch. In a similar work, Moreno-Revelo reported 2D-CNN-based methodology for crop classification with satellite images with overall accuracy of 81.20%[27].

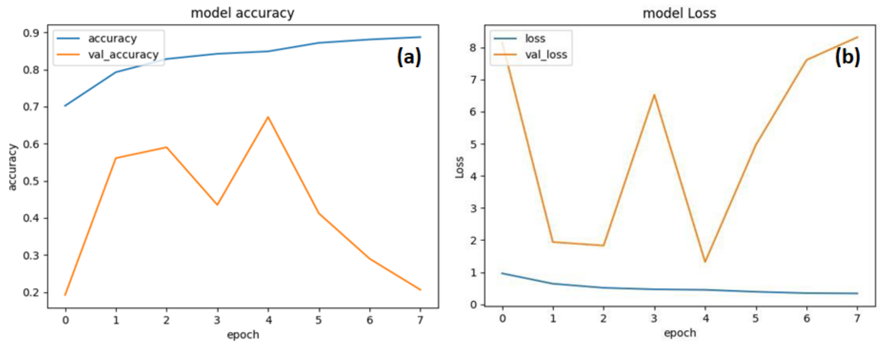

Fig 6. Model accuracy (a) and loss (b) curve

Table 3. Model accuracy and loss table

Epoch	Training Accuracy (%)	Training Loss (%)	Validation Accuracy (%)	Validation Loss
1	70.22	96.49	19.22	8.1647
2	79.27	64.25	56.11	1.9398
3	82.83	51.52	59.03	1.8294
4	84.23	46.79	43.50	6.5257
5	84.87	45.26	67.20	1.3193
6	87.18	39.25	41.22	4.9630
7	88.08	35.02	29.00	7.6073
8	88.72	34.02	20.63	8.3128

4 Conclusion

A vertical farming prototype integrated with Raspberry Pi controlled sensors and actuators for maintaining appropriate artificial environment ideal for tomato and chilli plants is presented in this work. The requirement of optimal artificial light for different growth stages of tomato and chilli plants is studied. The obtained results infer that the average requirement of light exposure is approximately 1.2 to 1.6 times higher with 200 watts bulbs as compared with 100 watts bulbs. However, the germination, vegetation and flowering of the crop is also faster with 200 watts. The duration and intensity requirement for germination, vegetation and flowering of both tomato and chilli plants with artificial light is also relatively less than with sunlight. A CMOS image sensor module was used to monitor the various stages of plant growth. Convolutional Neural Network (CNN) model-based method for detection and classification of leaf disease is also presented. At the end of fifth epoch the training and validation accuracies achieved are 84.8% and 67.2%, respectively. The results demonstrate that the proposed model can detect the diseased lead with high accuracy.

5 Acknowledgement

The research was funded by Tezpur University Research and Innovation grant in year 2020-2021.

References

1) Ayaz M, Ammad-Uddin M, Sharif Z, Mansour A, Aggoune EHM. Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk. *IEEE Access*. 2019;7:129551–129583. Available from: https://dx.doi.org/10.1109/access.2019.2932609.
2) Katiyar S, Farhana A. Smart Agriculture: The Future of Agriculture using AI and IoT. *Journal of Computer Science*. 2021;17(10):984–999. Available from: https://dx.doi.org/10.3844/jcssp.2021.984.999.
3) Farooq MS, Riaz S, Abid A, Abid K, Naeem MA. A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming. *IEEE Access*. 2019;7:156237–156271. Available from: https://dx.doi.org/10.1109/access.2019.2949703.
4) Gour MS, Reddy V, Vishuvardhan, Ram VT. IoT based Farming Techniques in Indoor Environment: A Brief Survey. *2020 5th International Conference on Communication and Electronics Systems (ICCES)*. 2020;p. 790–795. doi:10.1109/ICCES48766.2020.9137950.
5) Ruscio F, Paoletti P, Thomas J, Myers P, Fichera S. Low-cost monitoring system for hydroponic urbanvertical farms. *International Journal of Agricultural and Biological Engineering*. 2019;13:267–271. doi:10.5281/zenodo.3566357.

6) Liwal KK, Vohra M, Sheikh H, Al-Khatib O, Aziz NA, Copiaco C. Implementation of a sustainable and scalable vertical micro-farm. *Journal of Applied Horticulture*. 2020;22(1):3–7. Available from: https://dx.doi.org/10.37855/jah.2020.v22i01.01.
7) Ma Y, Xu A, Cheng ZM. Effects of light emitting diode lights on plant growth, development and traits a meta-analysis. *Horticultural Plant Journal*. 2021;7(6):552–564. Available from: https://doi.org/10.1016/j.hpj.2020.05.007.
8) Ares G, Ha B, Jaeger SR. Consumer attitudes to vertical farming (indoor plant factory with artificial lighting) in China, Singapore, UK, and USA: A multi-method study. *Food Research International*. 2021;150:110811–110811. Available from: https://dx.doi.org/10.1016/j.foodres.2021.110811.
9) Van Gerrewey T, Boon N, Geelen D. Vertical Farming: The Only Way Is Up? *Agronomy*. 2021;12(1):2–2. Available from: https://dx.doi.org/10.3390/agronomy12010002.
10) Ebi KL, Anderson CL, Hess JJ, Kim SH, Loladze I, Neumann RB, et al. Nutritional quality of crops in a high CO2 world: an agenda for research and technology development. *Environmental Research Letters*. 2021;16(6):064045–064045. Available from: https://dx.doi.org/10.1088/1748-9326/abfcfa.
11) Bari BS, Islam MN, Rashid M, Hasan MJ, Razman MAM, Musa RM, et al. A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. *Peer Journal of Computer Science*. 2021;7:e432–e432. Available from: https://dx.doi.org/10.7717/peerj-cs.432.
12) Gaetani R, Lacotte V, Dufour V, Clavel A, Duport G, Gaget K, et al. Sustainable laser-based technology for insect pest control. *Scientific Reports*. 2021;11(1):11068–11068. Available from: https://dx.doi.org/10.1038/s41598-021-90782-7.
13) Ishengoma FS, Rai IA, Ngoga SR. Said Rutabayiro Ngoga,Hybrid convolution neural network model for a quicker detection of infested maize plants with fall armyworms using UAV-based images. *Ecological Informatics*. 2012;67:519–537. Available from: https://doi.org/10.1016/j.ecoinf.2021.101502.
14) Ngugi LC, Abelwahab M, Abo-Zahhad M. Recent advances in image processing techniques for automated leaf pest and disease recognition – A review. *Information Processing in Agriculture*. 2021;8:27–51. Available from: https://dx.doi.org/10.1016/j.inpa.2020.04.004.
15) Kasinathan T, Singaraju D, Uyyala SR. Insect classification and detection in field crops using modern machine learning techniques. *Information Processing in Agriculture*. 2021;8(3):446–457. Available from: https://dx.doi.org/10.1016/j.inpa.2020.09.006.
16) Zhou G, Zhang W, Chen A, He M, Ma X. Rapid Detection of Rice Disease Based on FCM-KM and Faster R-CNN Fusion. *IEEE Access*. 2019;7:143190–143206. Available from: https://dx.doi.org/10.1109/access.2019.2943454.
17) Wang XF, Wang Z, Zhang SW. Segmenting Crop Disease Leaf Image by Modified Fully-Convolutional Networks. *Intelligent Computing Theories and Application*. 2019;11643:646–652. Available from: https://doi.org/10.1007/978-3-030-26763-6_62.
18) Wang Q, Qi F, Sun M, Qu J, Xue J. Identification of Tomato Disease Types and Detection of Infected Areas Based on Deep Convolutional Neural Networks and Object Detection Techniques. *Computational Intelligence and Neuroscience*. 2019;2019:1–15. Available from: https://dx.doi.org/10.1155/2019/9142753.
19) Liu B, Ding Z, Tian L, He D, Li S, Wang H. Grape Leaf Disease Identification Using Improved Deep Convolutional Neural Networks. *Frontiers in Plant Science*. 2020;11:1082–1082. Available from: https://dx.doi.org/10.3389/fpls.2020.01082.
20) Mónica Y, Moreno-Revelo L, Guachi-Guachi J, Gómez-Mendoza JB, Revelo-Fuelagán DH, Peluffo-Ordóñez. Enhanced Convolutional-Neural-Network Architecture for Crop Classification. 2021;11:4292. Available from: https://dx.doi.org/10.3390/app11094292.
21) Dhaka VS, Meena SV, Rani G, Sinwar D, Kavita K, Ijaz MF, et al. A Survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases. *Sensors*. 2021;21(14):4749–4749. Available from: https://dx.doi.org/10.3390/s21144749.
22) Gao J, French AP, Pound MP, He Y, Pridmore TP, Pieters JG. Deep convolutional neural networks for image-based Convolvulus sepium detection in sugar beet fields. *Plant Methods*. 2020;16(1):29–29. Available from: https://dx.doi.org/10.1186/s13007-020-00570-z.
23) Wang Q, Qi F, Sun M, Qu J, Xue J. Identification of Tomato Disease Types and Detection of Infected Areas Based on Deep Convolutional Neural Networks and Object Detection Techniques. *Computational Intelligence and Neuroscience*. 2019;2019:1–15. Available from: https://dx.doi.org/10.1155/2019/9142753.
24) Jiang P, Chen Y, Liu B, He D, Liang C. Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks. *IEEE Access*. 2019;7:59069–59080. Available from: https://dx.doi.org/10.1109/access.2019.2914929.
25) Avgoustaki DD, Xydis G. Energy cost reduction by shifting electricity demand in indoor vertical farms with artificial lighting. *Biosystems Engineering*. 2021;211:219–229. Available from: https://dx.doi.org/10.1016/j.biosystemseng.2021.09.006.
26) Monostori I, Heilmann M, Kocsy G, Rakszegi M, Ahres M, Altenbach SB, et al. LED Lighting – Modification of Growth, Metabolism, Yield and Flour Composition in Wheat by Spectral Quality and Intensity. *Frontiers in Plant Science*. 2018;9. Available from: https://dx.doi.org/10.3389/fpls.2018.00605.
27) Moreno-Revelo MY, Guachi-Guachi L, Gómez-Mendoza JB, Revelo-Fuelagán J, Peluffo-Ordóñez DH. Enhanced Convolutional-Neural-Network Architecture for Crop Classification. *Applied Sciences*. 2021;11(9):4292–4292. Available from: https://dx.doi.org/10.3390/app11094292.