A REPORT

ON

AI FOR CROP GROWTH MONITORING

BY

Yatish Agrawal	2018B1A40660P
Yash Kumar	2018A7PS0126G
Sarthak Chordia	2018B1A40605P

AT

ALW lightings India Pvt. Ltd.
A practice school-I station of

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE, PILANI

(MAY, 2020)

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Prepared in partial fulfillment of the
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BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE PILANI (RAJASTHAN)
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Abstract:
A Monitoring system which incorporates Artificial Intelligence to keep track of various plant features like leaf count, color index,leaf size, etc. to calculate the health of the plant and make predictions based on the features and growth conditions. It enables people to monitor the effects of their decisions efficiently.

Acknowledgement

I would like to thank BITS for the great opportunity in collaborating with ALW Lighting and giving us this project. I would also thank MR. Tanuj Arora for his guidance as a mentor of the project. I am also grateful to Prof. Lucy and Prof. Rakesh who encouraged us during the course of the project. I am thankful to my colleagues who also helped me in the project. At last I would like to thank my parents for their support during the project.

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INTRODUCTION

Indoor Agriculture is bound to become a big industry as our populations keep increasing and the land for agriculture will be limited even more.The world's population is expected to increase by 2 billion persons in the next 30 years. This requires more living land and so decreases agricultural land even more, even now An estimated 820 million people did not have enough to eat in 2018, as our civilization grows more we need cheaper and abundant food even on smaller land. In such an industry the efficiency and controllability is key and so we combine this with another very fast growing industry, AI and automation.

Indoor agriculture requires delicate control of the growth conditions and accurate measurements which become incrementally more difficult as the scale of operation increases unless it’s automated.We plan to make a horticulture monitoring system using Machine Learning. The system uses a variety of sensors to measure the growth of plants through monitoring many different features like number of leaves and their details using image processing, nutrient levels, humidity and temperature.

Then further algorithms will present the data in easily understandable format so that farmers can monitor their farm conditions precisely and clearly see the effects of any changes they made. Further, it will be able to suggest which lighting conditions will be better for the growth of your farms.

The agricultural field is only apparently refractory to digital technology and the “smart farm” model is increasingly widespread by exploiting the Internet of Things (IoT) paradigm applied to environmental and historical information through time-series. The focus of this study is the design and deployment of practical tasks, ranging from crop harvest forecasting to missing or wrong sensors data reconstruction, exploiting and comparing various machine learning techniques to suggest which direction to employ efforts and investments.

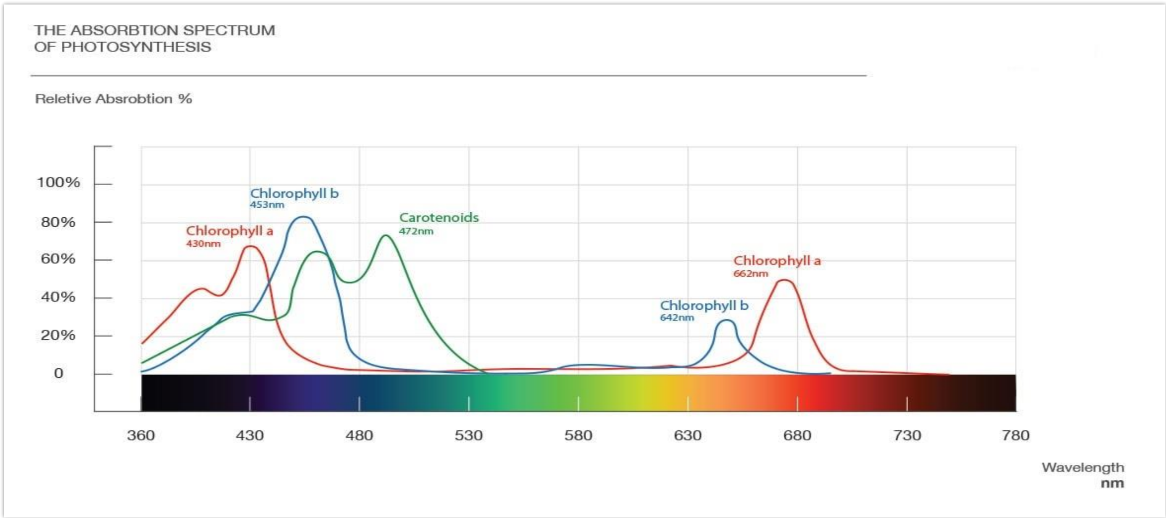
Photomorphogenesis

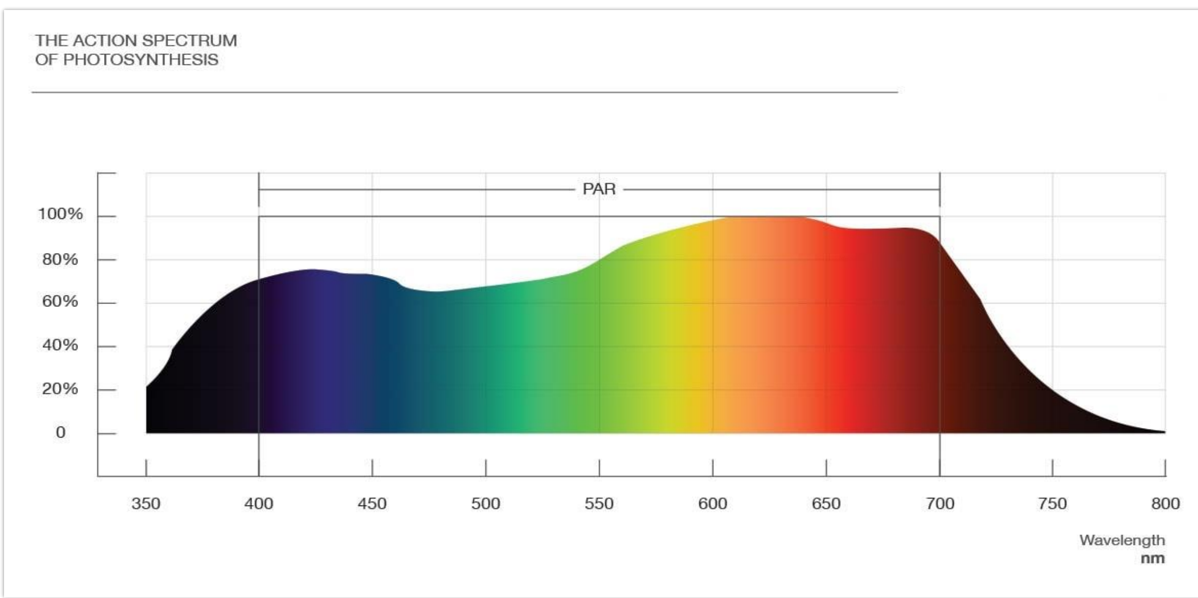
Photomorphogenesis is a phenomenon seen in autotrophic plants where plants develop with light spectra as a means of stimulus. A few inputs determine where along this growth spectrum a given plant will be found, including the quality, quantity, duration, and intensity of light, as well as genetic factors. It is perhaps not surprising that such a complex web of regulation controls photomorphogenesis. As in a natural environment sunlight mediates various plants developmental stages and in indoor setting fluorescent lights and LEDs are commonly used. Using different spectra of light with various intensities can induce faster growth in plants also enriching plants in their nutraceuticals such as phenolic compounds and antioxidants. Phytochromes, cryptochromes, and phototropins are various photochromic sensory receptors that restrict the photomorphogenic effect of light to the UV-A, UV-B, blue, and red portions of the electromagnetic spectrum. The integration of development and physiology, the rapid reprogramming of the genome, large-scale changes in cellular structure and function, and re-wiring of metabolism are major aspects can controlled be by photomorphogenesis
There are three major stages of plant development mediated by photomorphogenesis namely are:

- Seed germination
- Seedling development
- Vegetative to flowering stage switch

Action Spectrum vs Absorption Spectrum

An action spectrum is the rate of a physiological activity plotted against wavelength of light. An absorption spectrum is a spectrum of radiant energy whose intensity at each wavelength is a measure of the amount of energy at that wavelength that has passed through a selectively absorbing substance. The similarity of the action spectrum of photosynthesis and the absorption spectrum of chlorophyll tells us that chlorophylls are the most important pigments in the process.

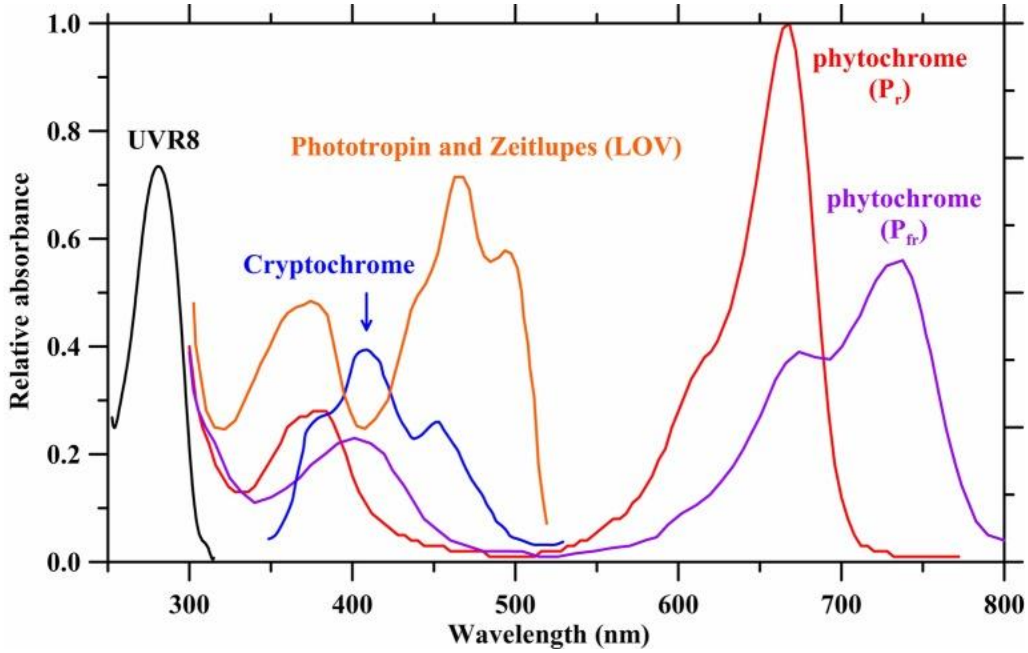




The spectra are not identical, though, because carotenoids, which absorb strongly in the blue, play a role as well. The carotenoids help fill in the absorption gaps of chlorophyll so that a larger part of the sun's spectrum can be used. The energy absorbed by these "antenna pigments" is passed to chlorophyll a where it drives the light reactions of photosynthesis.

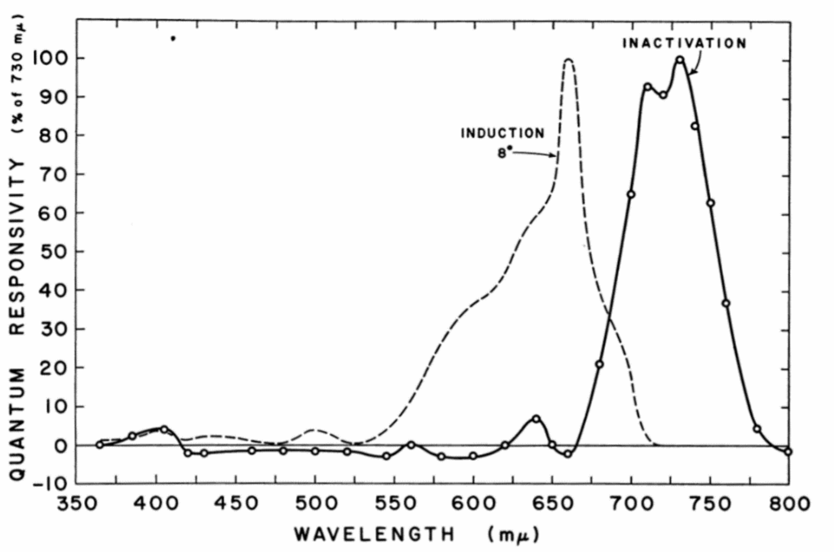
Electromagnetic spectra for growth

Typical wavelengths required by a plant to perform the process vary from plant to plant. But a common spectrum for photomorphogenic induction can be illustrated as below:

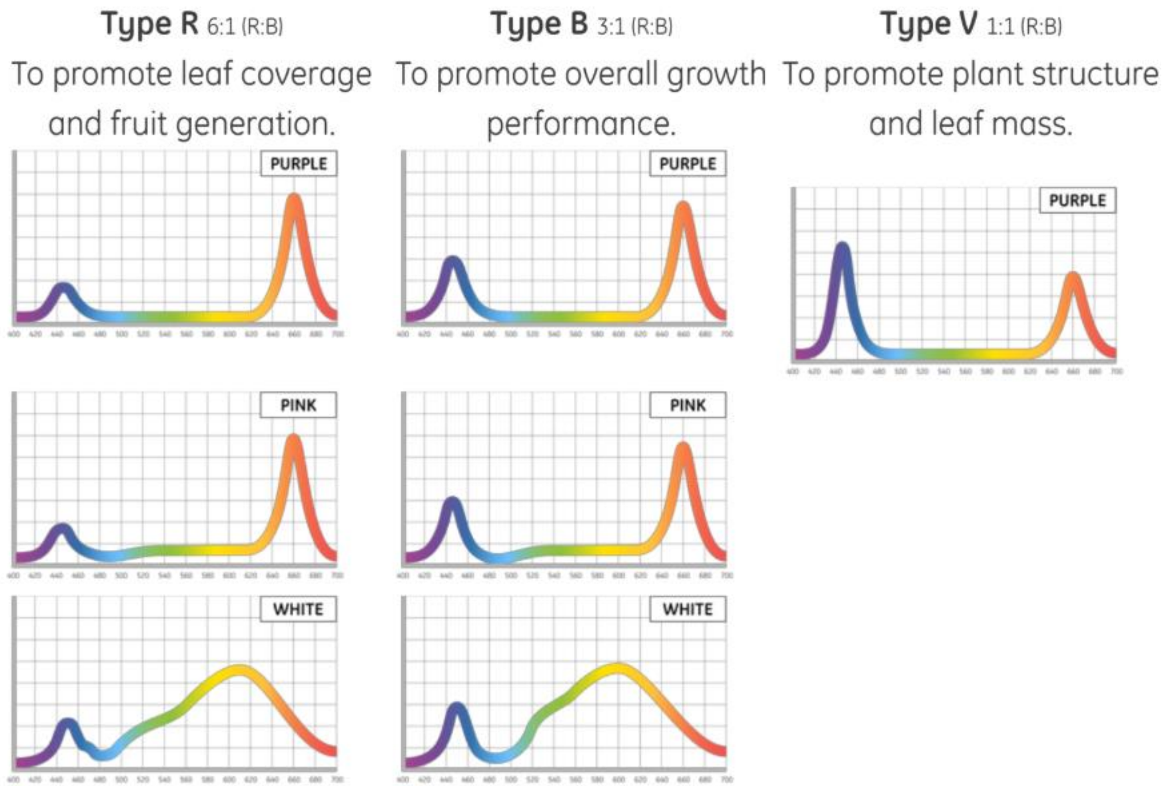


The above curve shows spectra peak for various photoreceptors of plant involved in different functions of growth.

However, if a variation in the spectra for phytochrome of the plant being exposed occurs, the process ceases and thus inhibits plant growth. Shown below is the curve illustrating inactivation and induction spectra for the process. Thus this can occur for all photoreceptors.



Many research conducted related to finding an optimum spectra for growing and thus revealing the following spectra patterns:



The above curves illustrate the various benefits of using different spectra. However, using a combination of above at different stages can yield better results. Function of different light wavelengths specific to its growth are:

- Red and far-red light: Phytochromes are induced in response to it using chromophores. These are responsible for elongation of roots in plants.
- Blue light: There are multiple blue light responsive photoreceptors having different functions major being cryptochromes. It controls stem elongation, leaf expansion, circadian rhythms, and flowering time.
- UV light: It is one of the essential part of spectra needed for plant development. It plays an important role in seed germination. Exposure to UV- light in plants mediates biochemical pathways, photosynthesis, plant growth and many other processes essential to plant development. These response are important for initiating hypocotyl elongation, leaf expansion, biosynthesis of flavonoids and many other important processes that affect

the root-shoot system. Its exposure can also lead to an increase of various nutritions such as antioxidants.

Photoperiodism

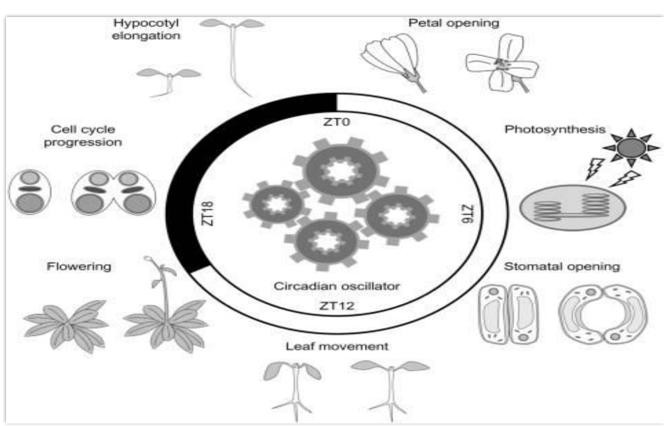
Photoperiodism is an organisms' ability to adjust their physiology and behavior to seasonal changes in the environment according to the length of day. It the developmental responses of plants to the relative lengths of light and dark periods. It also acts as molecular internal clock for plant. Based on photoperiodism we can classify plants in three types namely-

- Long-day
- Short-day
- day-neutral plants

It is used to adjust plants nutraceuticals and flowering and other developmental stages as per need.

Circadian rhythms as growth regulators

Circadian rhythms of plants act as biological clocks for plants. It helps in regulating plant growth and regulating signalling pathways. Important features include two interacting transcription-translation feedback loops: proteins containing PAS domains, which facilitate protein-protein interactions; and several photoreceptors that fine-tune the clock to different light conditions. For eg: The elongation of the stem in the young seedlings is controlled by PIF proteins, whose cellular accumulation depends on sunlight. Thus, light promotes the degradation of PIF proteins during the day. At night, however, PIF proteins accumulate inside the cell promote plant stem growth.



Skotomorphogenesis

It helps in maintaining proper growth of plant and help get ready for next circadian cycle. The activity of the basic helix-loop-helix (bHLH) phytochrome-interacting factors (PIFs) transcription factors and by degrading transcription factors via the ubiquitin-proteasome system. Receptors get supressed in absence of light and thus skotomorphogenesis is induced.

Features for monitoring and predicting growth

Various characteristic features of the plant considered for focusing LEDs for optimising their growth are:

- Shoot length
- Root length
- Leaf cross-section
- Leaf number
- Leaf colour
- Petiole cross-section
- Transpiration rate
- Photosynthetic rate
- Nutraceutical of plant
- Biomass of plant (dry/fresh)
- Content of various pigmentation compounds

Various other features that should also be taken into consideration for optimum growth inside the indoor facility can be:

- Temperature
- Humidity
- Soil nutrient content
- Air composition

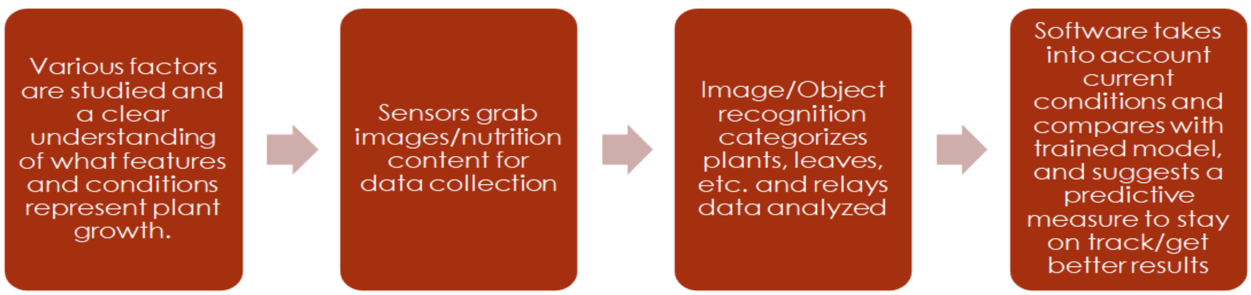
Physical environment for growth

- Optimum temperature and humidity
- Air composition (enriched in carbon dioxide)
- Ponics
  - Aeroponics
  - Hydroponics
  - Aquaponics

- Bioponics

Monitoring and measuring devices

- Humidity sensor
- Carbon dioxide, oxygen and carbon monoxide sensors
- Temperature sensors
- Cameras
- Spectrometers (various ranges)
- Chromatograms



Feature Extraction from Images

The purpose is to interpret the data of images to get some of the required features for further analysis. Some features like humidity and temperature can be used directly from raw sensor data but we can't get raw information on some features like leaf count, average color score, etc. so we use image processing to get that information.

Some of the algorithms and techniques are:

- Image Segmentation
    - Semantic Segmentation
    - Instance Segmentation

- Object detection and classification
    - Region based Convolutional neural networks(R-CNN)
    - Mask R-CNN
    - Fast R-CNN
    - Faster R-CNN
    - YOLO (you only look once), YOLOv2, YOLOv3

Image Segmentation and Mask RCNN

Image segmentation helps us to identify the location of a single object in the given image. In case we have multiple objects present, we then rely on the concept of object detection. We can predict the location along with the class for each object using object detection.It creates a pixel-wise mask for each object in the image. This technique gives us a far more granular understanding of the object(s) in the image.

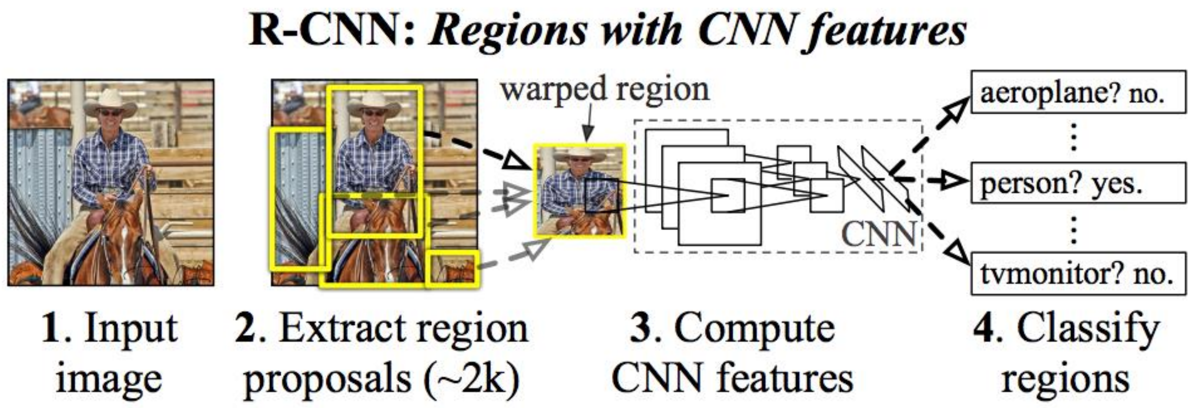
In semantic segmentation each pixel belongs to a particular class (either background or a leaf in this example) and in the representation all the pixels of one class are colored one color. This gives us a location for different classes for further identification.

Instance Segmentation - It uses Mask RCNN to subclassify the overlapping instances of objects of the same classes, it can be quite useful for counting objects in an image which is what we’re trying to do. Mask R-CNN is an instance segmentation technique which locates each pixel of every object in the image instead of the bounding boxes. This technique is very useful for our project as it can differentiate overlapping objects which leaves often are.

Types of CNN for object recognition

Region based CNN selects many possible regions in an image and from those regions similar regions are combined with a greedy algorithm to get 2000 regions for examples. These regions may or may not be accurate bounding boxes and are only called “proposals”.

These proposed regions are then fed into the convolutional neural network and produces a 4096-dimensional feature vector as output. CNN extracts a feature vector for each region which is then used as an input to the set of SVMs that outputs a class label.



There are several shortcomings of RCNN mainly being its very slow and since then many new models have been made such as fast RCNN,faster RCNN, YOLO versions 1 2 and 3.

Fast R-CNN also uses the selective search algorithm but solves the problem of R-CNN being slow by sharing computation of the convolutional layers between different region proposals. In this technique, the image is given as input to CNN that generates a convolutional feature map as the output.

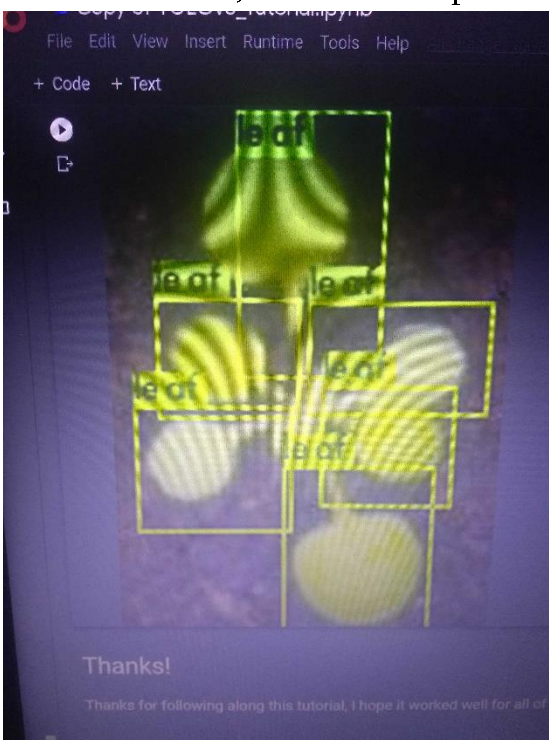
YOLO improves the fast RCNN and is fast enough to be used in real time . with a smaller version being able to process 155 frames per second. It is fast and accurate enough to use in real time object classification.

Currently we are focusing on testing an open source YOLOv3 model with custom data from.

Leaf count using YOLOv3

Leaf count has a direct relation to the health and growth of the plant hence it is one of the most important features to monitor. Leaf count is often used to measure plant age.

We used an open source YOLOv3 and trained on a darknet framework with custom data taken from plant-phenotyping.org/datasets. We trained for 4 hours on a google colab 12 GB GPU hardware acceleration and got a loss value of 2.34. We used 120 labelled pictures of rosette plants due to availability of the data. The same structure can be implemented on most plants where distinct leaves are visible and with better data, around 2000 pictures, it is expected to give much better accuracy.



YOLO gives out the following information:

1. Centre of the bounding box.
2. Height and breadth of the bounding box.
3. Class of the object detected.
4. The confidence value for the class.

Open source models do not give this information readily, instead they give a new image with the boxes drawn and labeled. So to get the relevant information we have to make some changes in the image.c file as stated in the notebook.
While using the command in the form :
./darknet detector test data/obj.data cfg/yolov3_custom2.cfg /mydrive/yolov3/backup/yolov3_custom2_2000.weights -dont_show < data/train.txt > result.txt

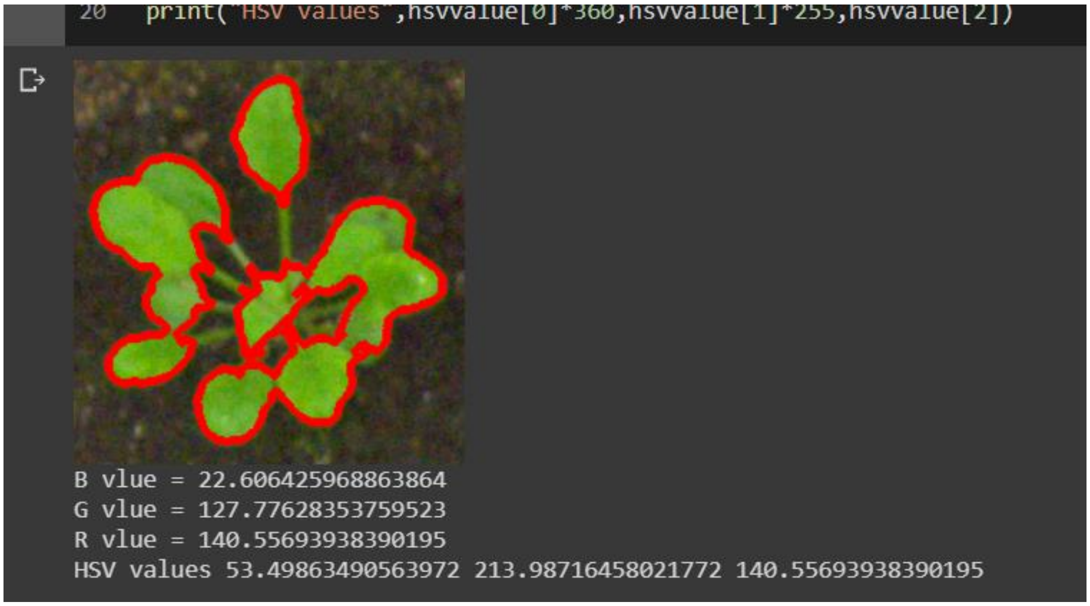
```
result - Notepad
File  Edit  Format  View  Help
net.optimized_memory = 0
mini_batch = 1, batch = 1, time_steps = 1, train = 0

 seen 64, trained: 128 K-images (2 Kilo-batches_64)
Enter Image Path: data/obj/ara2012_plant074_rgb.jpg:
leaf: 100%
leaf: 99%
leaf: 99%
leaf: 100%
leaf: 98%
leaf: 99%
leaf: 91%
leaf: 99%
```

We get a list in the result.txt file which contains the image file name and each object detected with confidence percent. By counting the objects we can get leaf count for each image in the folder.
The limiting factor is usually the training data for these models, so as long as we have reliable labelled data we can use it for most plants.

Average color of leaves

The color of the leaf is an important feature specially for disease detection as the average color will decrease and if we develop the same architecture
more and get localized extremes in color then can detect deviations from the average color, like brown or red spots.
The image of the plant is segmented using a k means clustering CNN in opencv. The function in the notebook segment takes the image and the “K” as inputs.

By segmenting the image multiple times, once with K=3, then K=2 then applying a bilateral filter to smooth the image then once again segmenting with K=2 gives the best result from my observations.
Using the segmented image in gray form as a mask for which pixels are a leaf's pixel and then iterating and averaging over the original image to get the average BGR color then we can use colorsys to convert it to HSV as that is more useful according to the research papers.

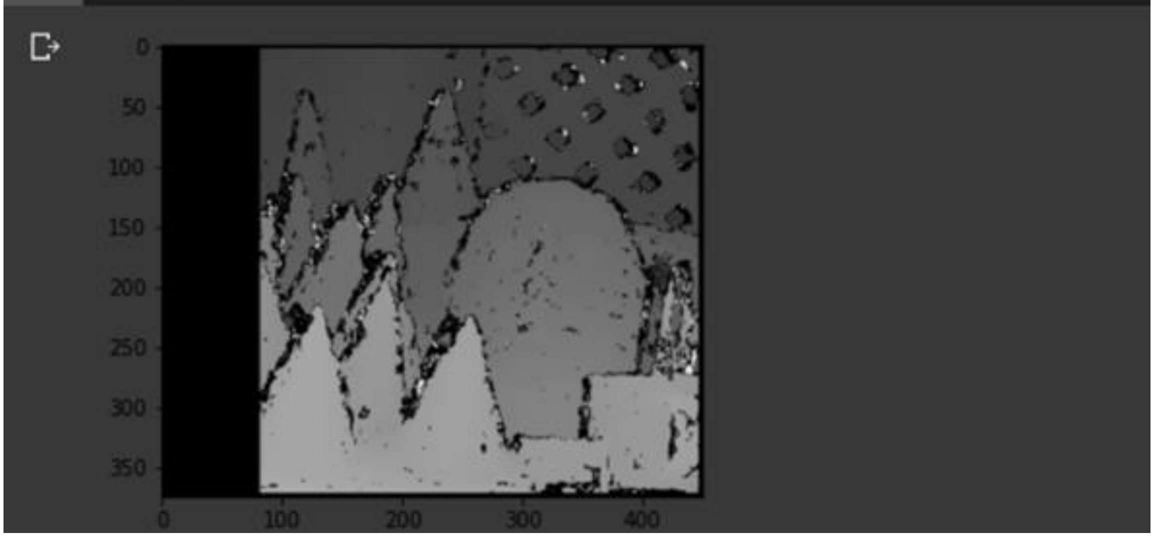


Stereovision for shoot length

Stereo vision systems use 2 cameras and try to mimic the way our own eyes work to get an approx depth, we don't get exact values from our eyes but we do understand the exact depth. Similarly the computer can measure the depth of objects by calculating the shift in object pixels between the two cameras.

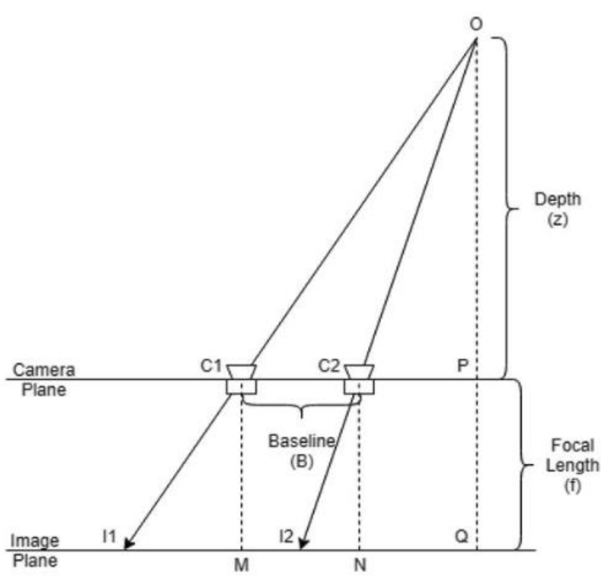
Pixel to pixel matching is the core of stereo vision, we get the shift and that is the disparity values. This image is what's called a disparity map.

```
stereo = cv2.StereoBM_create(numDisparities=80, blockSize=7)
disparity = stereo.compute(imgL,imgR)
plt.imshow(disparity,'gray')
plt.show()
```



Depth estimation:

- Conventional method: we use the geometric principles and calculate the depth Z by using the formula
  $Z=f*B/d$
  Where Z is depth, f is focal length , B is the baseline distance between the cameras and d is the disparity value.



Using openCV to get the shift in pixels i.e. disparity for each pixel in image. Then using the geometry of stereo vision we calculate a depth for each pixel in both real measurements and pixel lengths. By finding the centers of leaves from the leaf count and running depth perception of each of those we can get the distance from the camera plane for all the leaves and from those the closest leaf can be equated to the shoot length.

- Deep learning method: With the rapid development of deep neural networks, monocular depth estimation based on deep learning has been widely studied recently and achieved promising performance in accuracy. Meanwhile, dense depth maps are estimated from single images by deep neural networks in an end-to-end manner. In order to improve the accuracy of depth estimation, different kinds of network frameworks, loss functions and training strategies are proposed subsequently and this can soon become the norm.

Future improvements can include:

- Using YOLOv3 trained on disease datasets we can locate the plants even in large farms.
- By improving the stereo vision system we can possibly get approx. leaf areas in pixels and then use the same to get real values.
- It is even possible to get a 3D point cloud with stereo images, this will make almost a virtual model of the plant trays.

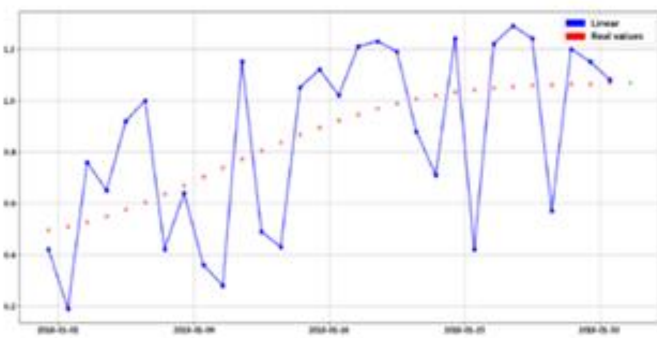
Graphing, Predictive Growth and Suggestive Model

Innovative technologies can be useful to face problems such as environmental sustainability, waste reduction, and soil optimization; the gathering and the analysis of agricultural data, which include numerous and heterogeneous variables, are of considerable interest for the possibility of developing production techniques respectful of the ecosystem and its resources (optimization of irrigation and sowing in relation to soil history and seasonal cycles), the identification of influential and non-influential factors, the possibility of carrying out market analysis in relation to the forecast of future hard-predictive information, the possibility of adapting crops to specific environments, and finally the ability to maximize technological investments by limiting and predicting hardware failures and replacements.

The software takes into account current conditions and compares them with trained models, and suggests a predictive measure to stay on track/get better results. The graphing is done by following a mathematical concept of K-nearest Neighbours, alongside neural networks for retraining of the model.

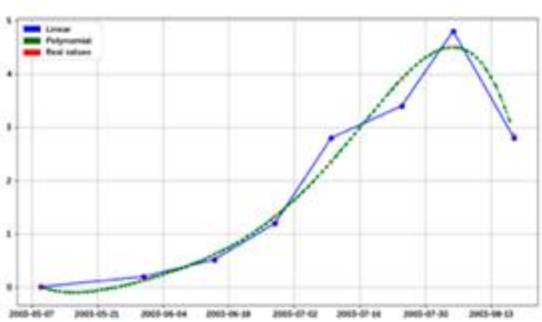
Example Graphs:

During training of model



Sensor real-values (red dots) and their still insufficient linear predictive model (blue lines-at-step) employing a training time of Thirty Days.

Leaf growth chart after model has been trained.



plot comparison between real-values (red dots), the linear (blue), and polynomial (green) predictive model on the CNR scientific agrarian dataset

Variables to consider while evaluating the growth of plant:

- Solar Radiation Incidence (or in this case, the LED luminescence)
- Wavelength of Light
- Humidity and Temperature
- Leaf Count / Colour / Area
- Height
- Bud Count / Size
- Petal Colour / Area / Count
- Plant Nutrients – Nitrogen, Magnesium, Iron, Calcium, Sodium, Potassium

The ones marked in blue are those which we wish to control, the ones in green are supposed to be constant since it's an indoor farm, but we still measure them to see minor fluctuations, and the ones in red are those we want to effect via indirect means of lighting. These are the factors which are the main plot in growth.

The main reason for the proposed tasks using different machine learning techniques is that an exploratory and highly experimental work has been employed; the Information Fusion together with the related optimization of methods and results is expected in future work, where new experiments and tasks exploit other sensor types and datasets will be designed and performed to meet the great heterogeneity of agri-companies and of the hardware sensor market. The intelligent systems developed with machine learning algorithms (supervised and non) have to manage fault tolerance and hardware malfunction prediction, and, in this way, they require designing of integrated tools, user-interfaces, and machines that easily adapt to a contexts subjected to natural events not as easily predictable as the agricultural one. Finally, smart systems that provide real-time suggestions and make long-term forecasts based on user choices and preferences must be studied and tested.

Simple RNN Model using CuDNNLSTM in Backend for Time Series Analysis

(WILL REQUIRE GPU, PREFERABLY NVIDIA LISTED FOR BETTER PERFORMANCE)

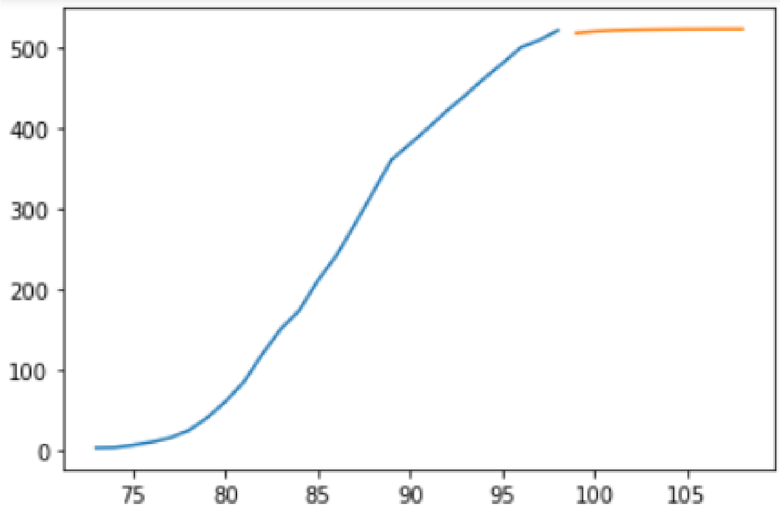
Static Attributes in the Programme

- age of plant (will vary with type of plant)
- number of attributes that are fixed: obs_num, plantage and wavelength
- folder location
- file name for training
- test name (this file only has obs_num, plantage and wavelength as its inputs, for prediction purposes)

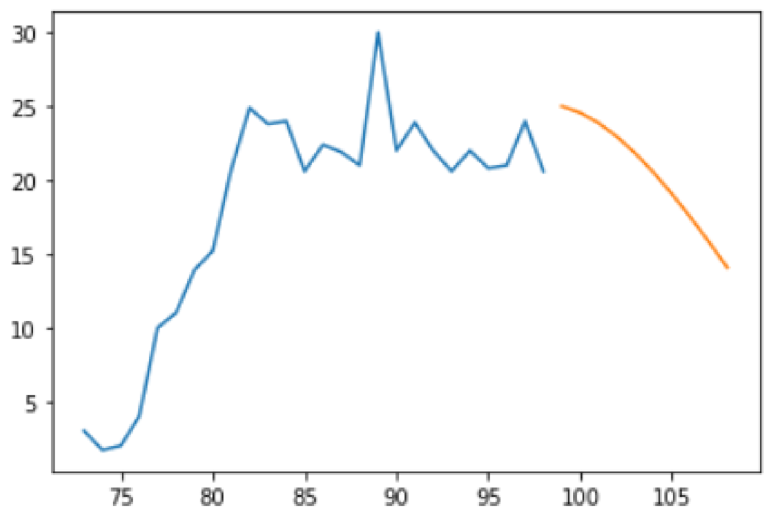
The dataset we will use will be of 2-D shape, but RNN models always take 3-D inputs, therefore we will have to reshape the array after converting it into a numpy array. Also, it is highly recommended to standardize these values to reduce processing time, which was not done in this model since the model training size was small.

We use the LSTM model with CuDNNLSTM Architechture (since there is no activation function, it automatically picks up CuDNN (for TensorFlow new versions, otherwise you have to specify within imports)). The function must be modified according to usage, these are default weights/values set
You might need to download CUDA libraries for this to work, and an NVIDIA Graphics Card is necessary for this. The reason to use this library is that it makes the processing a lot faster, especially for larger datasets for training. And since we are using a looped training (mentioned below), it is logical to opt for stronger processing power.
For the model, since the model.predict() command combines all the values, we used a loop to train the model for a specific value of predicted attribute and then store it in a separate array, for which we can plot the graph separately as well.
For the retraining part, the values will have to be loaded into the monitoring part of the programme, back into the training set and then run the RNN programme again.

Leaf Area

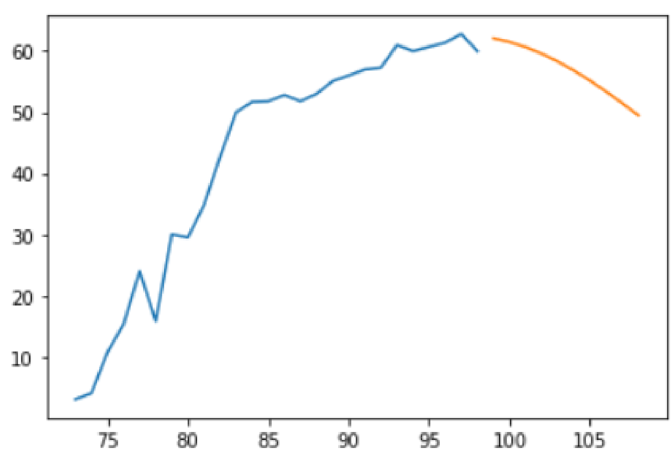


Leaf Count



Legend: Orange – Predicted Growth
Blue – Actual Growth of the plant
X-Axis : obs_num

Shoot Length



In the test file, we removed the values we wanted to predict, but took a screenshot of the values we added. Obviously, due to lack of available data, this was manually entered. However, the error came out to be low even with less data present in the training model.

Actual Values

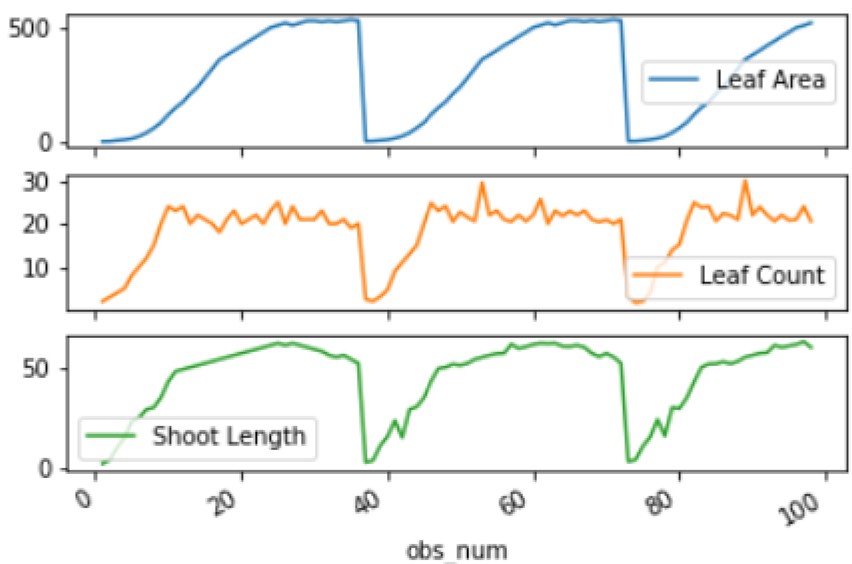
obs_num	plantage	waveleng	Leaf Area	Leaf Coun	Shoot Length
99	27	1	511.7	23.8	62.7
100	28	1	521.6	20	60.1
101	29	1	530	22	60.9
102	30	1	531.7	22.7	61
103	31	1	526.9	23.6	59
104	32	1	531.3	22	57.4
105	33	1	525.8	20.7	55
106	34	1	530.5	21	57
107	35	1	535	20.6	55.2
108	36	1	530.5	22	53

Predicted Values

```
[[517.82043]  [[25.00376 ]  [[62.09261 ]
 [519.9157 ]   [24.568716]   [61.494785]
 [521.0887 ]   [23.87319 ]   [60.656483]
 [521.7715 ]   [22.944937]   [59.586643]
 [522.1884 ]   [21.811989]   [58.30036 ]
 [522.4546 ]   [20.503778]   [56.819164]
 [522.6309 ]   [19.05042 ]   [55.169918]
 [522.7508 ]   [17.480024]   [53.381588]
 [522.83356]   [15.816   ]   [51.48102 ]
 [522.8908 ]]  [14.076044]]  [49.489307]]
```

Root Mean Squared Error:2.4851405371946163
(for average values of the Predicted Model vs the Actual Values, calculated using scikit-learn library, sklearn.metrics.mean_squared_error function)

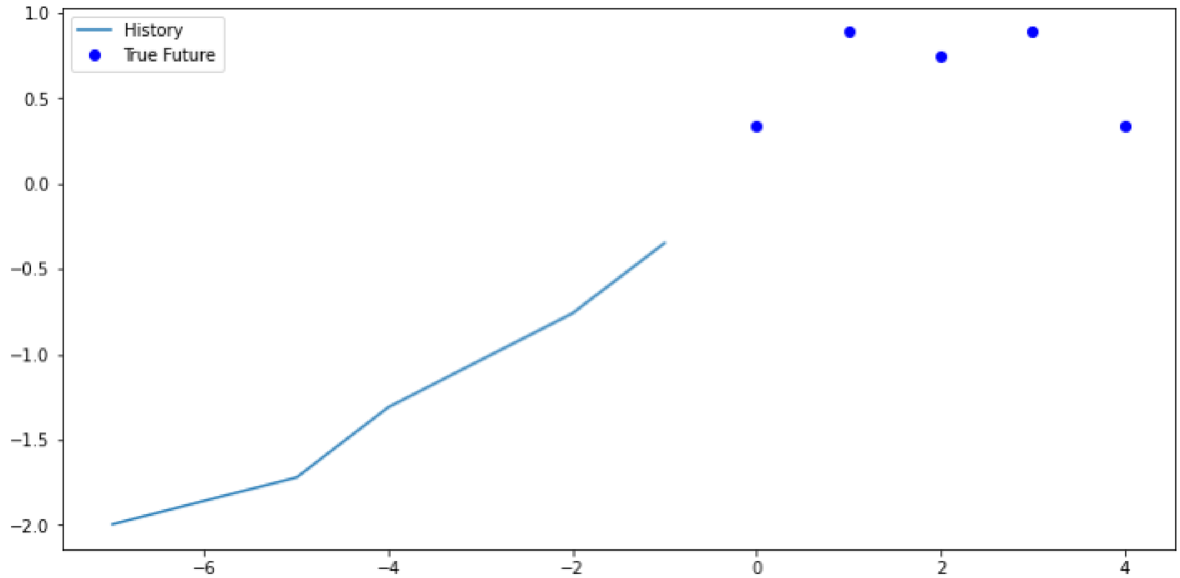
Another model considering Time Series Model by Tensorflow tutorial



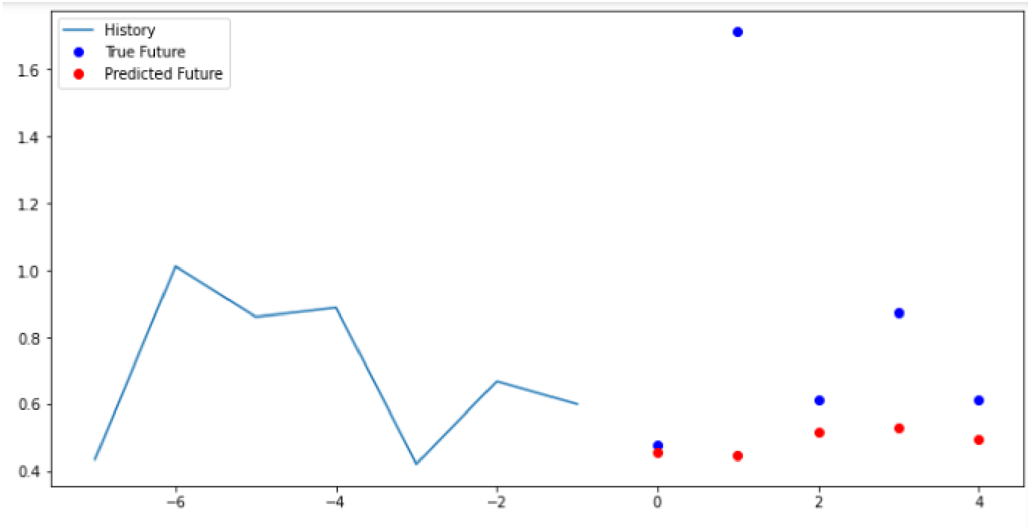
Here, we specify the values we want to work with, thus it must be explicitly mentioned. The graphs above represent the cycles of plant growth with different attributes mentioned, in this case, 'Leaf Area', 'Leaf Count', 'Shoot Length'. The more the number of observations, the more repetition graphs this will display, where each segment is a plant cycle.

In this prediction, we use multivariate data training and a multistep plot to predict the future (as given on TensorFlow's website for time series)

Plot for 5 predictions



Plot for 5 predictions vs true valuations



CONCLUSION

The System will use carefully selected features, based on prior research, which will be extracted autonomously with a variety of sensors and AI to monitor plant growth and Predict future growth patterns using statistical and machine learning analysis.

The benefit of this type of structure is that it can be an incremental production. Considering the small timeframe of the internship it's highly unlikely to make a marketable product but we can set the groundwork and it can be developed further. Further enhancements could include disease detection, Pest detection, custom light recipes based on reinforced learning, and much more.

The better these systems are made the greater profits can be made possible which will not exploit any element in the food production process. Better systems could increase quality and yield of the production which enables the producers to get better profits and the system to justify a higher cost. More yields might even decrease the retail cost of individual units, essentially from an economic point of view if the systems are made good enough they could bring higher standards of food and still be reachable for everyone.

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