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Pervasive Agriculture: Measuring and Predicting Plant Growth Using Statistics and 2D/3D Imaging

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***Abstract*—The growing of Earth population and the need of food provisioning to remote areas make *pervasive agriculture* the research problem of high priority. In this work, we present a 2D/3D scanning system with the intelligent data processing mechanism which can be easily deployed in a greenhouse. The proposed solution enables finding of correlations between the leaf area and biomass and thereby helps predict the plant metrics including the growth rate and leaf area. This knowledge is of particular significance for actuating the plant growth parameters depending on the context and feedback. Our experimental results conducted on two sorts of tomatoes and salad demonstrate high potential of this approach.**

Keywords*—*3D imaging, growth rate, plant modeling, image-based modeling, pervasive agriculture

I. Introduction

Nowadays, humanity still depends on water and agriculture to survive. Agriculture experiences a high number of difficulties ranging from water shortages to urbanization which has led to the decrease of a great number of farms worldwide. In fact, societal concerns about food safety and environmental impact resulted in a growing interest of the application of artificial intelligence in agriculture [1][2].

Originally the problem of plant growth dynamics assessment in controlled artificial conditions was a crucial point in life support systems development for space and associated ground applications. Although coming from space technologies the development of artificial closed controlled systems for *pervasive agriculture* is in high demand nowadays [2]: it is expected to guarantee food provision for the increasing population of Earth and people living in remote areas or in harsh environments. Indeed, recent achievements in the Internet of Things related technologies [3][4] will make pervasive agriculture reality.

A number of various technologies and techniques have been used for monitoring and studying the agriculture related topics. For example, the wireless sensor network [5] paradigm application to control the climate conditions in a greenhouse is reported in [6]. Tiny sensors were deployed at different height and measured temperature and relative humidity. If threshold values are violated actuators are activated for keeping the predefined settings of the greenhouse. This approach relies on compact sensor nodes which can be deployed anywhere and perform low-power monitoring tasks and send measured data periodically to the user or cloud over the wireless channel. Importantly, the sensor nodes can be deployed in difficult-to-access areas without cabling production. It makes them easy to set up, debug and reduce the maintenance costs for monitoring infrastructure. Recent advances in data science [7] and machine learning for constrained devices [8] are vital for making real-time inference procedures and prediction.

The 2D approach is often used in the case when the plant is characterized by large leafs and simple structure [9]. However, it typically relies on complicated software for performing the analysis and suffers from leaf overlap and concavity. Laser scanning is also used for plant digitization and has been successfully applied to forestry and statistical analysis of canopies [10]. Its application is limited for extracting single plant attributes due to computationally intensive tasks.

Another set of approaches is based on 3D imaging [11]. This approach helps capturing the plant shape in three dimensions and study it. In [12] a 3D scanning system is proposed for taking quick and accurate images. The approach is based on two tilting cameras, methods for camera calibration and background removal. A similar approach is proposed in [13] where the authors use a robotic arm equipped with a 3D imaging system for 3D plant growth measurement. Processing and data recording is a long period of time though. A semiautomatic 3D imaging system for plant modelling is reported in [14]. The bottom line of this research is to combine reconstructed 3D points and the images for guarantying a more effective segmentation of the data into individual leaves. Although the 3D imaging approach is getting popular, the image acquisition for 3D reconstruction is typically carried out manually [15].

Albiol et al. report in [16] on the monitoring of biomass evolution in plant cells. This approach relies on the Kalman filter and is featured with very low volume samples for effectuating monitoring.

In this paper, we propose a methodology for predicting the plant growth dynamics based on statistical data. The novelty of our approach is in the application of both 2D and 3D image acquisition techniques with consequent data processing for getting more accurate results. The outcome of this processing is a prediction of growth rate and leaf area.

The paper is organized as follows: in Section II we discuss the proposed approach in more details. We describe the 2D and 3D based data acquisition and testbeds in Section III and

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Section IV, respectively. The obtained experimental results are present in Section V. Finally, we discuss our future work and provide the concluding remarks in Section VI.

II. Approach

In this section we describe a generic approach for predicting plant growth dynamics. It is based on statistical analysis without performing multi parameter modelling of each particular plant. It is done because modelling each plant growth dynamics is a complicated task involving actual modelling of each plant. In our work we use 2D and 3D imaging techniques along with associated image analysis. This allows us getting benefits of both techniques.

Since the experiments on growing plants are time consuming taking several months, we conduct monitoring on the plant growth in an automatic mode using a number of sensors and image acquisition techniques which we present in more details in next sections. Main data acquisition is performed using 2D and 3D imaging whereas the data from sensors introduce the context in which the images are collected. It should be noted that these experiments must be continuous in time and the monitoring system must be robust during the data collection.

For modeling the plant growth dynamics, we identify the following four key steps:

1) Collect 3D data manually to ensure a precise model of each plant. This step is a reference point serving for further automatization of the experiments.

2) Find correlations and general regularities between the leaf area and biomass of the investigated plants in accordance with the context of artificial system parameters, e.g. pH, electric conductivity of feeding solution.

3) Collect data describing the changes of leaf area based on an automotive 2D imaging and processing system with concurrent collection and preprocessing of data from sensors that describes conditions in the artificial soilless system where the plants are growing.

4) Proposing and verification a mathematical model for prediction of plant growth dynamics based on received statistics.

Accomplishment of these steps means that acquisition of 3D data allows finding correlations between the leaf area and biomass. Then collection of relevant statistics about the leaf area results in developing of a prediction model for the leaf area. Using the obtained correlation between the leaf area and its biomass results in the reconstruction and prediction of the plant biomass. For testing of this methodology we conduct two experiments on two sorts of tomatoes and salad leafs in Section III and Section IV, respectively. We discuss the experiments in next sections.

III. 3D Data Collection

A. Testbed

As an artificial soilless system allowing for control of ambient conditions we designed and assembled a hydroponic system with a constant feeding layer. For data collection we used a manual 3D scanner, Artec Space Spyder.

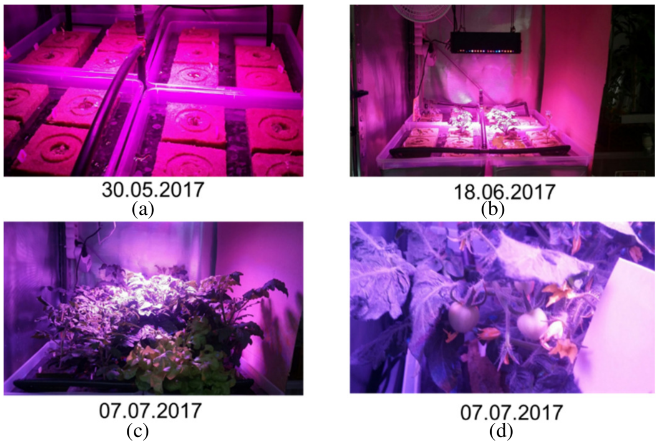


Fig. 1. Hydroponic system showing the tomato growth rate within 1 month and 1 week: germination, (b) vegetation, and (c-d) flowering lifetime.

Below we summarize the features of the hydroponic system shown in Fig. 1:

- System for growing 18 tomato plants,
- 180W multispectral LED light,
- 60 liter tank,
- 0.65 liter rock wool blocks as a substrate,
- 8 W pump (~100 liter/h),
- 1.5 cm of feeding solution layer.

Usage of the rock wool blocks as a substrate for plants cultivation gives an opportunity to inspect and study each plant in the experiment without interruption of the system operation and without damaging the plants. We have chosen this type of hydroponic system due to the rapid system response to changing of parameters, thus guarantying easy control of the experiment. In this case we were able to set the stabilization of pH, electrical conductivity or temperature of the feeding solution in a simple and reliable way. This is highly important for correct setting of the experiment and receiving precise data. Typically, for hydroponic systems of this size, a multispectral light emitting diode (LED) is used. Our calculations demonstrate that 180 W LED satisfied our system requirements well. Also, for satisfying the requirement regarding the 1-2 full recycling of feeding solution per one hour we choose a 60-liter tank and 8 W pump. Fig. 1 shows the performance of the system and acceleration of the physiological processes in the plants in a hydroponic system of this type. In this experiment design it takes around one month from germination to the first flowering.

B. Data Acquisition

For initial data acquisition, 18 tomato plants were used. These experimental samples were composed of two dwarf tomato sorts: Bonsai Micro (9 plants) and Bonsai (9 plants) were germinated in the optimal conditions and then transplanted to the hydroponic system. The system conditions were monitored manually for the sake of controlling the allowable rates of feeding solution parameters (pH, temperature, humidity, electric conductivity). All of these parameters could be corrected if necessary. Receiving the 3D images of plants was organized in

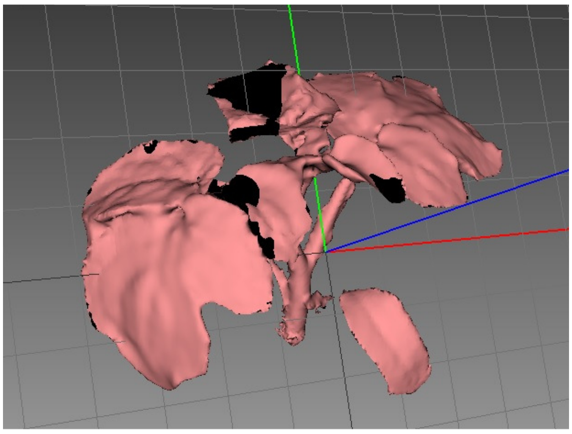


Fig. 2. 3D image of the tomato plant in the beginning of vegetation lifetime.

the following way: we first took out a plant from the hydroponic system, put it on to a rotating table, and scanned it using the 3D scanner with the application of additional green spectrum lamp illumination (because plants reflect this spectrum making the final 3D image more accurate). After receiving the 3D images, their preprocessing, and smoothing, we calculated the main parameters including the leaf areas and their biomass. Smoothing and preprocessing procedures were realized by commercial Artec Studio software which supports the scanner functioning. The preprocessing helps reducing the noise and removing unnecessary parts of scanned image where the parameters were indicated by program recommendations with manual tuning. One of the main functions in the Artec studio and used in this work is “Fusion”. This function enables the creation of a polygonal 3D model based on received clouds of points.

Fig. 2 shows an example of a 3D image of the tomato in the beginning of vegetation lifetime. In total, we received and processed 80 3D images of dwarf tomato plants from germination to the beginning of flowering periods. These images represent the dynamics of plant growth.

IV. 2D Data Collection

A. Testbed

In this testbed, our artificial soilless system with controlled conditions based on hydroponic system relies on a floating table construction when the surface is flooded with 1 cm feeding solution. The testbed also includes the multispectral LED 150 W, 1 cm of feeding solution and rock wool blocks. These components are used due to similar reasons as in the experiment discussed in Section III. The testbed is truly compact: its volume is 0.5 m^3 and it enables conducting the experiments on 9 small plants simultaneously. All system parameters are calculated using traditional algorithms for fitting optimal requirements for plant growth [17]. For receiving 2D images, a XY plotter is assembled and a high resolution camera (1980x1080) is mounted on it. We used extra sensors in the testbed for measuring its parameters automatically: pH, electrical conductivity, humidity, temperature of air, temperature of feeding solution, and flow rate of solution. We used the XY plotter since it is important to avoid the shadowing effect of LED light by the camera when taking images. By mounting the camera on the XY plotter we can take the image of each plant

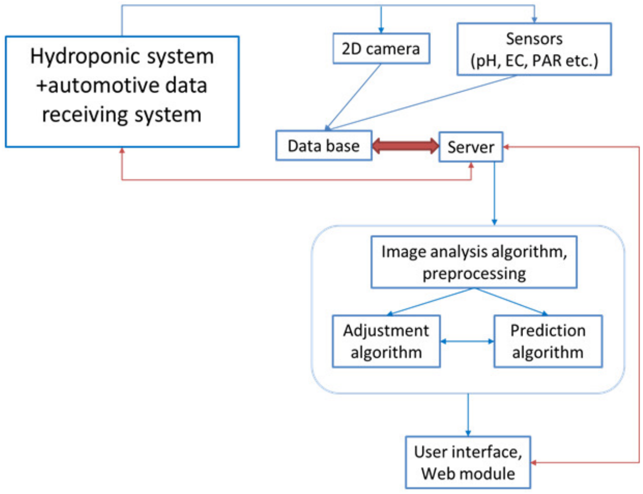
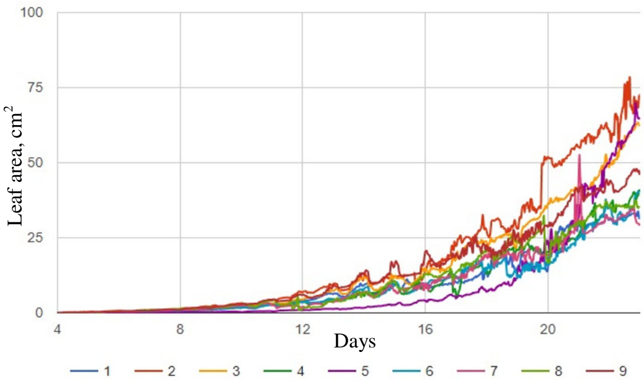


Fig. 3. System architecture for 2D data acquisition and processing.

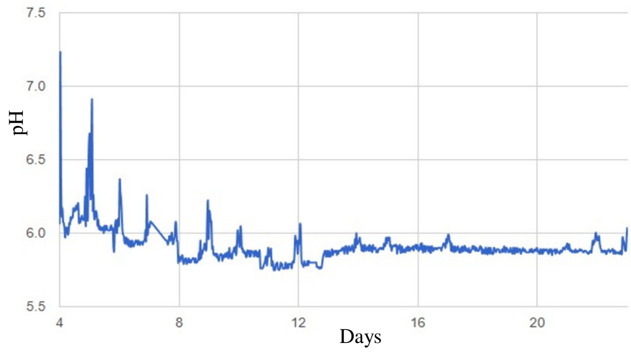
separately in high resolution. Moreover, there is no need to do corrections of the angle parameter of camera view. The LED system is constructed as a part of the whole testbed and it can be controlled as well. All sensors are calibrated and tested before launching the long term experiment.

B. Data Acquisition

Fig. 3 shows the system architecture and relations among the testbed subsystems. By using hydroponic system and automatic data receiving system we received data which describe the plant growth dynamics (2D images) and system parameters. Next we put them into a database, then a server processes it, calculates the leaf area, and predicts the leaf area growth based on the model. Red lines indicate the semi-automatic control effectuated between two blocks. For collecting and processing data automatically, we developed a custom software for a desktop PC and smartphone (see Fig. 3). The developed software is flexible: the user can easily integrate new sensors in the monitoring system. Also, the proposed system showed its robustness to the power interruption: the plotter is automatically re-calibrated in case of power shut up. It is realized via a custom made script developed in Python and C programming languages. We successfully performed a continuous experiment on the plant growth and collected the data set for more than a month. For this experiment we developed and managed to debug the software for hardware control, e.g. stepper drivers on the XY plotter and controllers for LED, and software for data receiving and processing. Both pieces of software must be synchronized properly. During the experiment, 2D images of plants were taken every 30 minutes within approximately one month. In parallel, we collected remaining system parameters, which were measured automatically, organized and recorded to a database. A high-precision algorithm for calculating the leaf area of plants was developed and successfully implemented in the experiment. The developed algorithm relies on a reference point - the red square object (see Fig. 5) with known area for performing the calibration, i.e. calculation of a specific pixel size: area/pixel. Then the algorithm performs the calculation of a number of green pixels which belong to the plant. A pixel is identified as green in its RGB value if it is in the certain bounds which are set up before the experiment starts. We used white background to

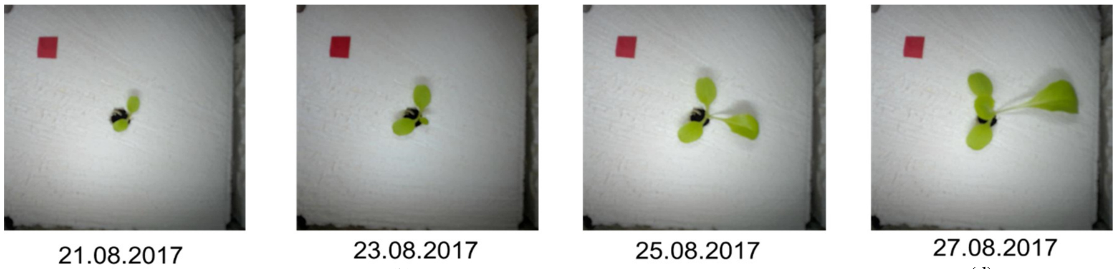


a)



b)

Fig. 4. Sensor data: (a) diurnal fluctuation in relative location of leafs (9 samples), (b) pH level.



(a) (b) (c) (d)

Fig. 5. Examples of images of the salad leafs collected within 6 days.

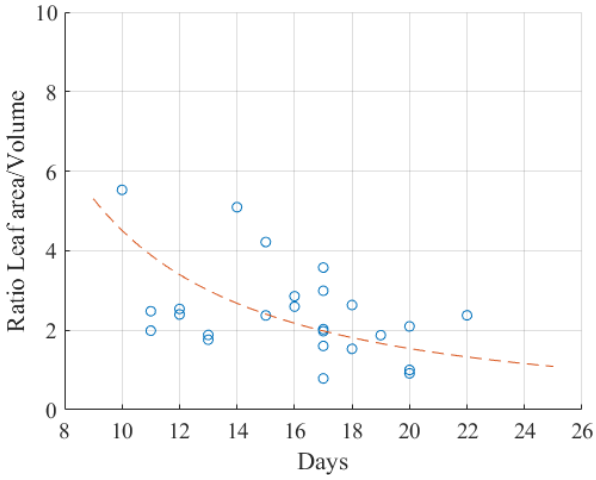


Fig. 6. Correlation for Bonsai tomato sort.

avoid the noise capture, e.g. green pixels not belonging to the plant. We recorded diurnal fluctuations in the relative location of leafs while the plants were tiny in the range of 1-2 cm^2 For online monitoring of the experiment we developed a custom web-interface.

We demonstrate 2 out of 5 performance metrics in Fig. 4. Assessment of dynamics of leaf area growth also brings additional information about the plant growth, e.g. diurnal fluctuation in relative location of leafs (see Fig. 4a) or correlation between these fluctuations and the pH level (see Fig. 4a and Fig. 4b). The proposed system architecture and online monitoring open up wide vista for the entire system (testbed, plants) identification and finding hidden dynamics of plant growth. During this experiment more than 10,000 images were received and processed. Although we carried out the experiment on salad leafs, our approach can be easily scaled to other plants. We selected the salad leafs since they can grow quickly and are unpretentious. This amount and quality of data is enough for its usage as training samples in machine learning algorithms. Fig. 5 presents the examples of received images of the salad leafs collected within 6 days.

The advantages of our approach include the in-situ analysis, scalability, user friendly web-interface and iterative control.

V. Experimental Results

A. *Correlations between leaf area and biomass and general regularities*

Following the methodology, that was discussed in Section II, for further reconstruction of the biomass using leaf area it is important to find correlations between of them. Correlations for two sorts of dwarf tomato: Bonsai Micro (see Fig. 6) and Bonsai (see Fig. 7) for the period of 15 days were found. These correlations were found by using data after preprocessing of the images. The ratio between leaf area and volume decreased in time and tended to remain constant, similar in both cases. We tend to think that this result means that for young plants the ratio between leaf area and volume is higher, and this result fits to plant physiology. However, it is the subject for further research.

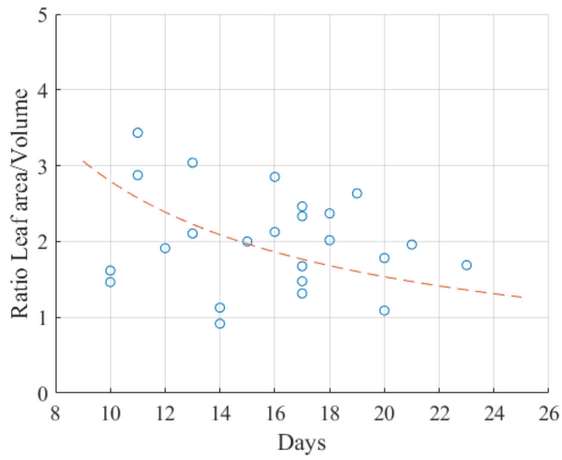


Fig. 7. Correlation for Bonsai Micro tomato sort.

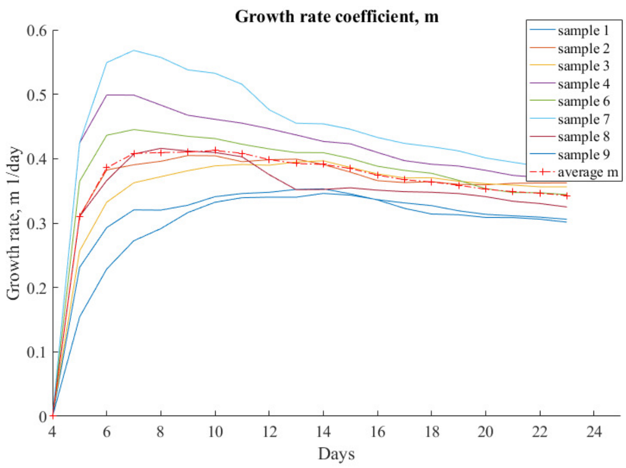


Fig. 8. Evaluation of growth rate.

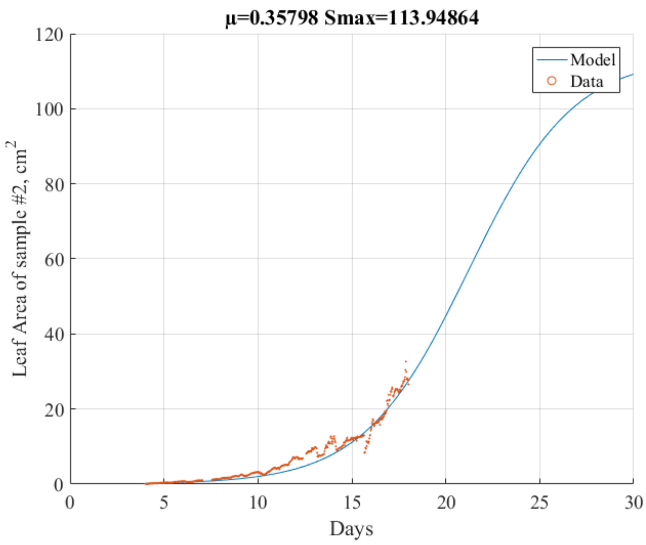


Fig. 9. Prediction of growth dynamics.

B. Math Model Verification

In this section we develop and verify a mathematical model for prediction of the dynamics of plant growth based on a statistical approach. As the basis we take the Verhulst model or logistic growth curve (1). This equation describes the population growth and can also be used for describing the dynamics of plant growth.

$$\frac{dS}{dt} = \mu S\left(1 - \frac{S}{S_{\max}}\right) \tag{1}$$

where S is the leaf area (cm^2), μ is the growth rate (1/day), S_{max} is the maximal leaf area (cm^2), t is the time (days).

Integrating (1) leads to (2) as follows:

$$S(t) = S_{\max} \cdot \frac{S_0 e^{\mu t}}{S_{\max} + S_0\left(e^{\mu t} - 1\right)} \tag{2}$$

where S_0 is the initial leaf area.

We use nonlinear regression for identifying parameters: μ and S_{max} consistently. In Fig. 8 we represent a reconstructed growth rate μ for each of 9 salad samples (the 5-th was not included as its germination took longer time), S_{max} is constant. We can see that in average after the 7-th day the growth rate coefficient becomes close to linear. It means that the coefficient μ becomes predictable along with dynamics of plant growth. Analysis of (2) shows that for small values of t, the value of μ impacts the value S more than S_{max} does. For larger values of t, the value of μ impacts value S much less than S_{max} does. Thus, experimental data for the first 7-8 days are used for reconstruction of coefficient μ and other data are used for prediction of S_{max} with using of reconstructed μ.

Fig. 9 shows the prediction of S for the 30-th day by using data for period of 14 days. The first 4 days are not included in the prediction as this period is for germination of seeds. For estimating μ, data for the first 8 days of measurements are taken, the remaining data are taken to predict S.

For comparison, Fig. 10 and Fig.11 show the prediction of S for the 30-th day by using data for a period of 16 and 20 days, respectively. The first 4 days are not included as this period is for germination of seeds. For estimating μ, data for the first 8 days of measurements are taken, the remaining data are taken for predicting S. It can be seen that in this case the coefficient S_{max} has changed while μ remains stable. It happens due to the fact that we used more experimental data for the prediction procedure. Calculations for remaining 8 samples showed that experimental results have a good fit to the reconstructed theoretical curve and this makes the prediction of plant growth dynamics possible.

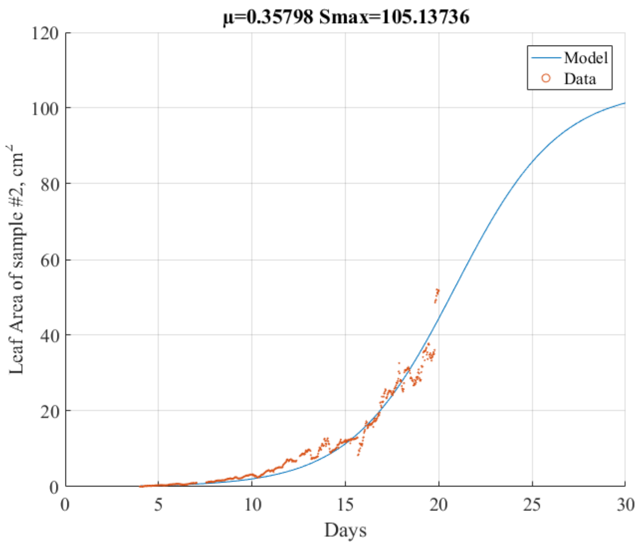


Fig. 10. Prediction of growth dynamics.

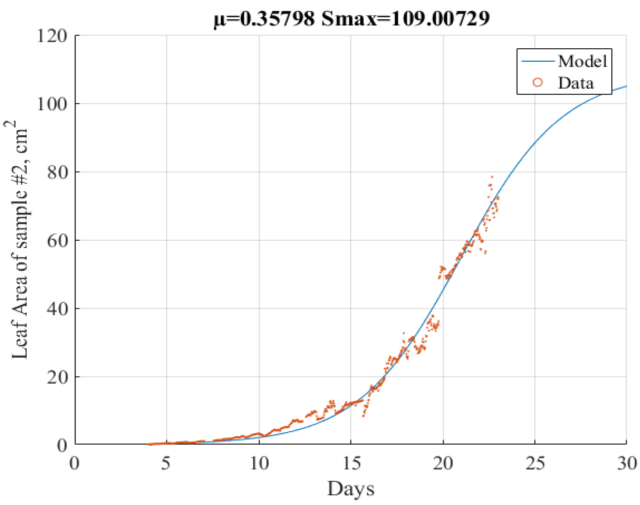


Fig. 11. Prediction of growth dynamics.

VI. Conclusions

In this work, we present a 2D and 3D based system enriched with machine learning for plant modelling and predicting plant growth. The imaging system is supported with extra sensors helping to position the collected images in the right context.

Within the experimental period we managed to collect and process more than 10^4 data samples. While conducting research we found correlations between leaf area, biomass and general regularities which together with the statistics helped in predicting the plants growth rate.

Our future work includes the deployment of the proposed system in greenhouses and a large-scale deployment.

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