MUSHNOMICS

Unlocking data-driven innovation for improving productivity and data sharing in mushroom value chain

D2.3 - Validation of MUSHNOMICS AI algorithms

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Disclaimer

The MUSHNOMICS Consortium is the following:

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1. Introduction

This document constitutes the deliverable D2.3: Validation of MUSHNOMICS algorithms and details the validation process of the models for mushroom detection and cluster tracking, also providing a pixel-wise relative growth index that can be linked to yield. Specifically, the MUSHNOMICS algorithms that previously developed in Task 2.2 on image data taken from the farm trials were validated using the novel MUSHNOMICS substrate compositions of Task 3.1. The production trials were carried out at PILZE premises (Task 3.5). The same DL-based instance segmentation pipeline was implemented including the following distinct steps: data acquisition, data annotation, data preprocessing and instance segmentation. The last step was to evaluate the performance of the Mask R-CNN based model to automatically recognize whole clusters and single mushrooms in images based on domain-specific performance metrics and compare it to the results produced in Task 2.2. The practical aspect of this application is to use the timelapse images, which are passed through the script as a farming aid to track the growth of mushrooms grown in real farms. The mushrooms in these farms are usually grown in large substrate bags or buckets both of which are compatible with our Mask-RCNN-based instance segmentation growth monitoring algorithm. Overall, pixel growth tracking offers a good basis to visualize the growth of the clusters numerically even though it has little application in terms of real-world size at this stage. The growth tracking curves give an indication of the growth rate of mushrooms and serve as a proof of concept for tracking mushroom growth digitally using various substrates.

2. Validation of Mask R-CNN based detection

Following the same experimental set-up and data collection procedure described in D2.2, a new timelapse dataset containing images of white buckets filled with the novel MUSHNOMICS substrate (D3.1) was collected for the validation of the algorithms The production trials were carried out in Task 3.5. Figure 1 shows images of the validation dataset at selected timesteps.

Figure 1. Validation dataset: Production trials of oyster mushrooms grown on the MUSHNOMICS substrates.

Table 1 shows a comparison of the performance of the algorithms for the two datasets obtained from the production trials. A deeper understanding of the performance of each model can be supported by observing the predictions of the models. Hence, some representative detection results are presented in Figure 2, allowing for a visual interpretation of the performance of the Mask R-CNN based model. The performance of the model on the validation dataset was inferior to the baseline model developed in task 2.2. However, it can be observed by examining the Recall values that the model was capable of detecting the majority of the mushroom cluster instances in the images. It should be noted that detection and segmentation of mushrooms in a farm environment involve challenging conditions such as varied lighting conditions, shadows, perspective and scale variability and occlusion among others. In addition, it seems that the model was able to detect mushroom cluster instances of lower quality present in the background of the images which resulted in lower mean average precision (mAP). Also, the color difference between the buckets and the bags might have challenged model's detection capability since this condition was not introduced during its training. To overcome background detections, image post-processing can be applied in order to remove instances that are not part of the targeted foreground. Overall, the models were able to detect the target mushroom instances of the foreground substrates regardless of their color, validating their selection and implementation for mushroom instance detection and segmentation.

Table1. Performance of Mask R-CNN model on different image datasets captured under production trials.

Timelapse Mask R-CNN model	mAP	Recall
Common block substrate (Black bags)	0.774	0.823
MUSHNOMICS substrate composition (White buckets)	0.618	0.789

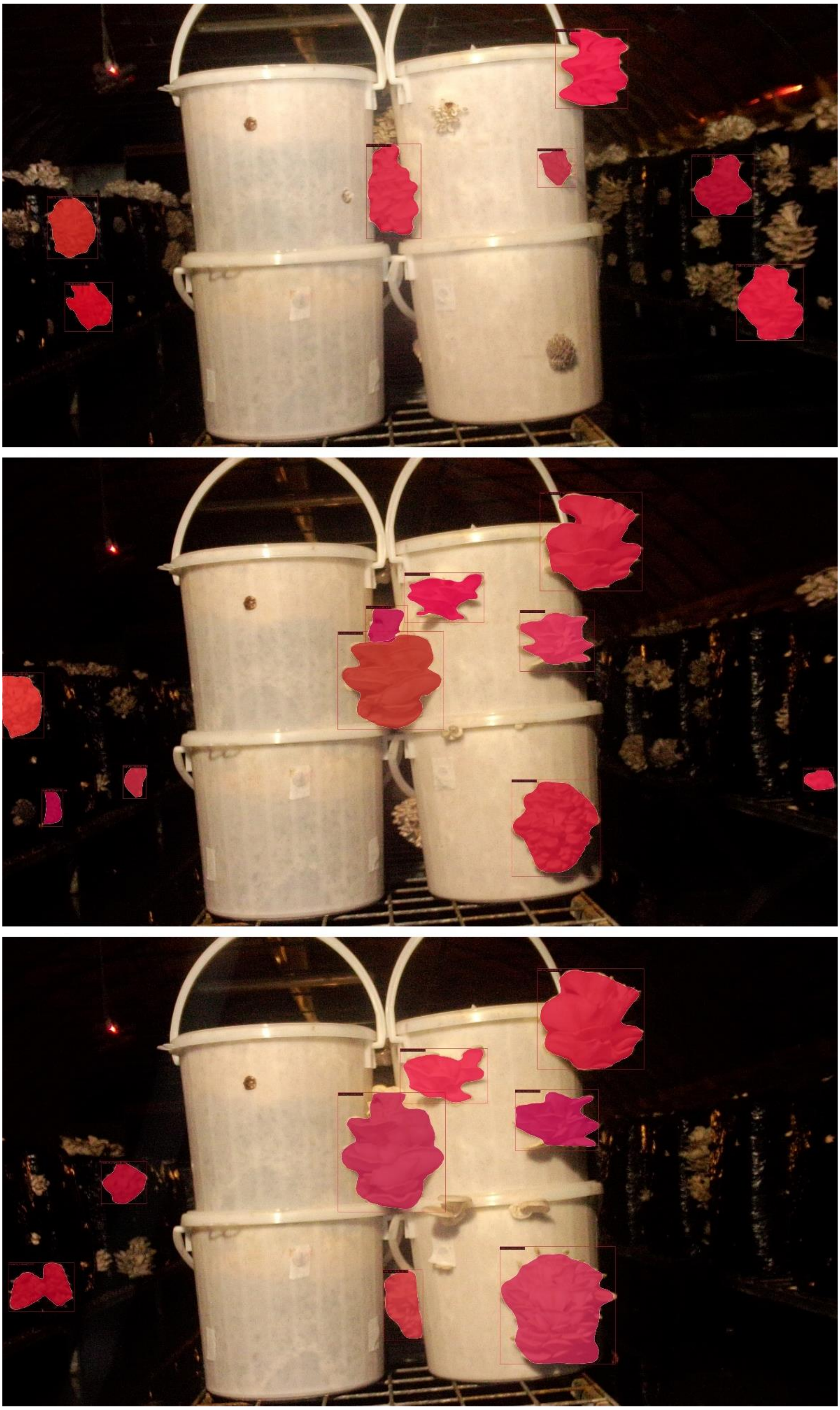

Figure 2. Mask R-CNN based detection of mushroom clusters on a new timelapse dataset for validation.

3. Mushroom cluster tracking and pixel-wise growth monitoring

The timelapse application aims to track the growth of mushroom clusters in a series of timelapse images. The use of pixels as a substitute to "measure" mushroom growth in these images is a promising method of tracking growth. The two image subsets were captured using the same camera and having the same image size (6080 pixels width x 3420 pixels height). However, in order to reduce any discrepancies when comparing between image subsets, the number of pixels per cluster is normalized over the total number of pixels in the images so that the cluster "size" represents a percentage of the total size of the image instead of the absolute number of pixels. The real size of each individual pixel in this case would differ between the two subsets and would not offer insight into the actual size of the mushrooms but an analogue by which to track cluster growth within each subset of images. Figure 3 shows two representative timesteps, with the corresponding numbers of the detected clusters at their center.

Figure 3. Implementation of the tracking algorithm at selected timesteps of mushroom growth.

Figure 4 shows the growth tracking curves of five mushroom clusters grown on white buckets. The mushroom clusters are labelled as small, medium and large to provide an overview on how suitable each cluster is for harvest based on its relative size. The size tracking itself is also rudimentary since it was obtained from two-dimensional timelpase image which does not consider the depth of the mushroom cluster, which may result in untracked growth within the clusters. The sizing is also based on an image taken from a specific angle, which leads to issues of occlusion (e.g., segments of clusters being hidden) as well as distorting the size of the clusters themselves. Additionally, there is sometimes the case of different clusters growing too close to each other being "unified" by the object detection model, which may lead to misrepresentation of the growth and incorrect sizing information. However, this issue is an object detection problem and only consequently affects the efficacy of the pixel growth estimation.

Another issue arises when comparing clusters of different sizes. Mushroom clusters themselves can differ in the number of single mushrooms produced, which means that even though all clusters start from similar sizes those with more individual mushrooms will gain a much larger size as the cluster matures. The comparison on sizing in this case fails to capture the whole picture since the smaller clusters are fully mature and ready for harvest similar to the larger clusters with the only difference being the number of mushrooms present in the cluster. One method that may be used to resolve this issue is to focus on the rate of growth of each cluster and finding the time it takes for clusters to plateau in growth, which would signify the end of the maturation cycle and optimal harvest time.

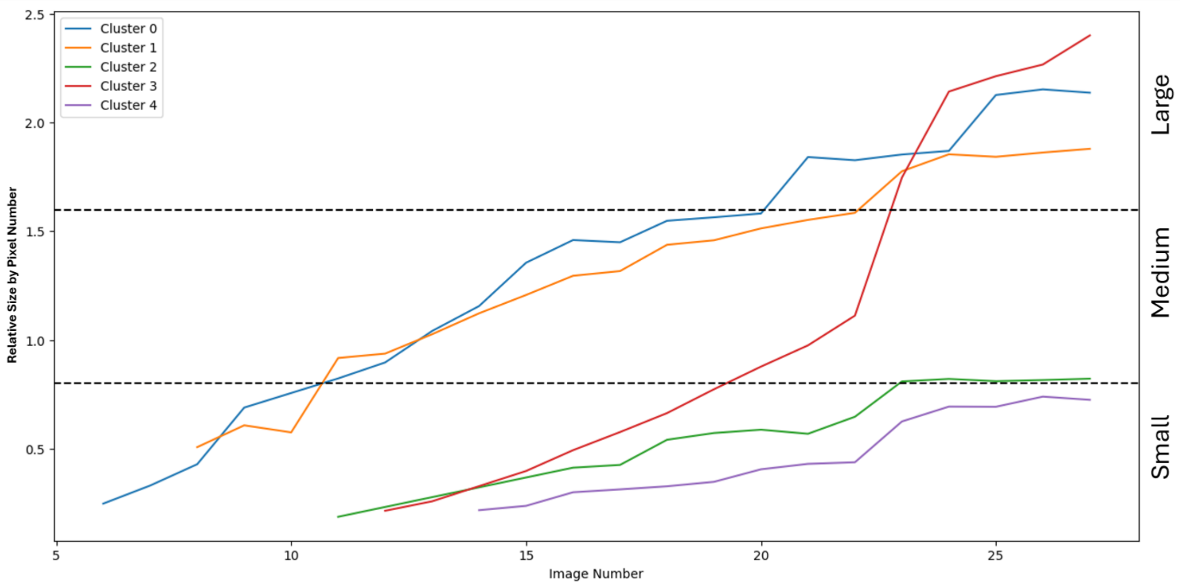

Figure 4. Tracking of mushroom growth using pixel-wise relative growth of individual mushroom clusters.

Overall, pixel growth tracking offers a good basis to visualize the growth of the individual mushroom clusters numerically even though it has little application in terms of real-world size at this stage. The image-based tool developed in MUSHNOMICS is a valid approach to derive growth monitoring curves and through this to calculate the real-time growth rates of mushrooms digitally.

4. Conclusions

Unlike the fruiting bodies of other mushrooms, those of oyster mushrooms grow in clusters, which make their growth estimation a challening task by means of computer vision techniques. This task validated the MUSHNOMICS algorithms on new 2D image datasets developing a practical tool for mushroom growth monitoring, helping farmers with yield estimation. The first task of the system involved mushroom detection, and identification of single mushrooms in a cluster, which provided targets for further actions with respect to growth and yield. A large volume of image data were acquired utilizing low-cost camera-based systems but with certain technical limitations. In the future, a detailed set of information from RGB-D images might be essential to meet the requirements of intelligent applications in mushroom farming such as real-time monitoring and automated selective harvesting. However, the collection of larger and more complex 3D image datasets will require expensive equipment, which may also increase the cost for farm applications dramatically. Finally, the models proposed in the MUSHNOMICS project can detect individual oyster mushroom clusters and track their growth with adequate accuracy under real-life production trials.