Improved image recognition via Synthetic Plants using 3D Modelling with Stochastic Variations

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Abstract. This research extends previous plant modelling using L-systems by means of a novel arrangement comprising synthetic plants and a refined global wheat dataset in combination with a synthetic inference application. The study demonstrates an application with direct recognition of real plant stereotypes, and augmentation via a plant-wide stochastic growth variation structure. The study showed that the automatic annotation and counting of wheat heads using the Global Wheat dataset images provides a time and cost saving over traditional manual approaches and neural networks. This study introduces a novel synthetic inference application using a plant-wide stochastic variation system, resulting in improved structural dataset hierarchy. The research demonstrates a significantly improved L-system that can more effectively and more accurately define and distinguish wheat crop characteristics. **Keywords:** Synthetic plants, Stochastic modelling, L-systems, Global Wheat, Inference

1 Introduction

In 2021 the Global Wheat Challenge (GWC) had a profound impact upon the expansion and extension of the Global Wheat Head Detection (GWHD) dataset, drawing renewed worldwide interest from the computer vision and agricultural science communities [1]. The global focus on improved quality and reduced cost of food production is driven by a rapidly increasing world population [2], [3], [4].

The ongoing pursuit of increased efficiencies in food production has resulted in the rapid growth of research of deep learning approaches towards new discoveries in crops adaptability to suit globally disparate agronomic and climatic conditions [5]. Whilst most of the work in this area has centred on using traditional deep learning approaches and large datasets to establish ground truth, this study demonstrates significant advantages in the application of alternative approaches to deep learning and crop modelling using the APSIM model [6], [7] and [8], or through L-systems [9], [10], and [11].

1.1 Background and Literature

An L-system is a set of rules and parameters which define plant growth, structure, and appearance [12]. This research proposes an extension to an existing L-system (L-NAP) with an improved wheat crop dataset; to add realistic stochastic growth variations; and to introduce a novel and important application in synthetic inference which will directly recognize wheat heads, and wheat characteristics under changing agronomic conditions.

L-systems typically evolve from a mathematical theory of plant and cellular growth [12]. They are based upon the Backus-Naur production rules and allow for extensive application of plant-based synthetic imagery [13], [14], [15].

L-systems are particularly useful in the ability to recognize and measure real wheat plants. Using Python as a language driver, L-system frameworks can be created to form algorithms to characterize and recognize features on wheat heads [16]. They are regularly described by means of small text-based explanations and imageries that require relatively small amounts of storage compared to real imagery [17]. The recognition success is dependent on pixels. An individual person's eyes respond to many light intensity levels. L-NAP must be able to "see" at low resolution and low scale. This increased level of recognition is made possible by refining the dataset to incorporate the range of scale and resolution contrasts.

The aim in synthetic inference is to achieve unabridged corollaries that create a higher level of reasoning for the interpretation of the observed images. The dataset will "carry" images at all growth scales, based on a wide range of grain-counts, which is not the same as image scaling. This is the necessary approach to see smaller images and still accurately recognize plant parts, since

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smaller images are often caused by lower grain-count [18].

This is indeed what stochastic variation means, and it reflects real plant growth variations. This project will push the research envelope to use depth and stereo cameras of higher resolutions in line with improving miniature camera technology. In this sense the evolution of these stochastic augmentations grows in line with advances and upgrades in camera and image capture technologies.

2 Validation of Synthetic Images using the Global Wheat Head Detection (GWHD) dataset.

The Global Wheat Head Detection (GWHD) dataset of 2021 [1] provides renewed confidence in the expectation of improved recognition. In this study, a real wheat neural network was trained on a total of 677 images of the second domain of the GWHD. There were 40 field images in the second domain of around 25 wheat heads each. From these wheat heads two-thirds were used for training whilst one-third were used for validation (See Figure 1.).

This second domain was chosen for its higher quality, in combination with fewer images. It was used to validate the initial synthetic images and was designed to resemble that domain by means of accurate L-system parameter choices, and the stochastic variations of those parameters.

Some larger variations resulted in lower matching scores, while modest variations on the upper images gave higher validation. Here there is an advantage in the use of synthetic data, where this test indicated the best choice of L-system parameters for this domain. These choices in turn allow "domain adaptation" [19], [20] by simple parameter adjustments. These adjustments are guided in a similar test using real data, even if a limited amount, of that domain [21]. This typically demonstrates accurate results even in situations where the real data used to steer the recognition process is drawn from a limited number of real wheat head images.

2.1 Recognition of Awns

One example of this domain adaptation is in terms of elements such as the length of the awns on the wheat heads. These awns resemble long thin spikes and are predominant on the image set in Figure 2, which can be longer for other domains. Wheat heads represent a critical source of information about the quality of a wheat crop. The accurate recognition of awns is especially beneficial in determining the health of a crop since awns provide rich data about the health, maturity stage, and size of the associated wheat heads.

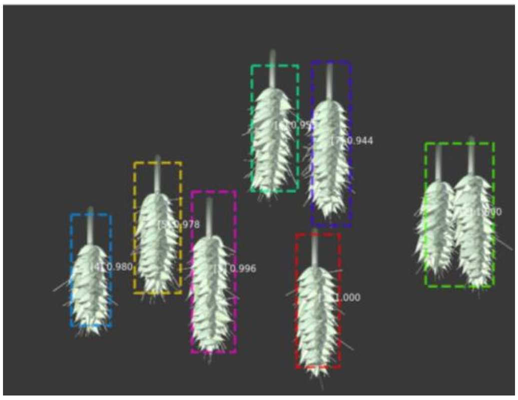

Fig. 1. Validated synthetic wheat with a neural network trained on the GWHD dataset, showing network object recognition errors on overlapping synthetic wheat head images. (Green box on right side of image).

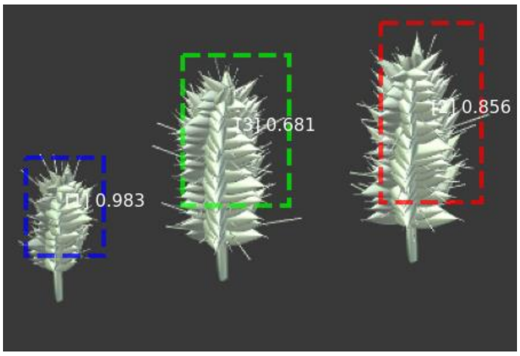

Fig. 2. Validated synthetic wheat with a neural network trained on the GWHD dataset, showing clear recognition of Awns. (Blue box on left side of image).

3 L-NAP System Approach

The previous work of Napier et al (2023) described L-NAP as an application that accurately represented the hierarchy and growth of wheat heads by using synthetic models [16].

L-NAP fully separates an L-system algorithm, describing a synthetic plant, into two files. The first file defines the L-system rules relating to the structure and relation of the plant parts. The second file defines the L-system parameters, relating to sizes, angles, counts, textures, and plant growth. L-NAP communicates these varying parameters as necessary to the rules when the plant is grown, mimicking natural plant processes. The parameter calculations can be complex, but by this separation, they are contained within parameter modules.

Table 1. Steps in L-NAP towards dataset creation, application, recognition, and annotation of real plants.

L-NAP dataset steps		
Step A	Creation of Drawing Commands in an L-system algorithm	
Step B	Create 3D models from commands in Blender	
Step C	Create plant camera views of models	
Step D	Create synthetic dataset	
Step E	Apply dataset to recognise real images	

The L-NAP system has five steps, from A to E, which in turn create drawing commands from an L-system description; create 3D models from these commands; create plant views of the models; create a synthetic dataset from the views; and finally apply the dataset to recognize and annotate real plants (Table 1).

The method of taking this synthetic dataset approach means that the data processing complexity is handled during the dataset creation by the data pipelines, and by the dataset API access functions. The approach demonstrates its completion by the synthetic inference application which employs the synthetic dataset to accurately locate plant instances in real pasture images.

L_NAP has been extended to cover the L-system classes defined in the book “The Algorithmic Beauty of Plants” [12], and to introduce plant-wide stochastic variations, as show in the trees below. Figure 3 demonstrates the use of the L-NAP algorithm (below) which creates the trees by means of a python program.

Fig. 3. A full tree (on the left), and then the same tree re-grown (on the right) with only 80% branch growth, controlled by one L-NAP parameter.

The **complete** L-NAP rules which were used to grow the trees in Figure 3 are defined in this Python program:

```
from L_NAP import *
Tree = L_NAP()
Branch = Tree(Draw, [Turn_left, Branch],
              Draw, [Turn_right, Branch],
              Turn_left, Branch)
Axiom = Tree(Branch)
while Tree.next_stage(Axiom):
    Tree.grow()
```

The separate parameters file gives the number of growth stages (7), the branch length (1.0), width (0.1), and scaling per stage (0.5), the branch turning angle (20 deg.), and the branch growth probability (1.0 or 0.8), and these are applied to each grown branch (See Figure 3).

3.1 Modelling using Light Absorption

An important feature of the L-NAP framework is that since it is an L-system defined in a Python class, it may be extended with extra functionality, to create a new L-system framework of a new name, which for example, could have math functions, which depend on external light conditions, to guide the tree growth.

One such extension relates to the work of Renton et al, (2005) that considers modelling in relation to light [22]. This study concludes that new tree growth of (mountain birch) trees can be determined solely by absorbed light. Such a system can become an extension of the L-NAP framework.

In a similar fashion the L-PEACH framework [23], which has source-sink interaction functionality and is described as complex, could benefit from L-NAP. Such a framework could be further be extended to other tree types. The study on MAppleT [24] also constitutes a useful tool for simulating apple tree development in terms of the interaction with gravity. This tool demonstrates a strong alignment with the functionality of the L-NAP framework in terms of integration. The reflection, absorption, and transmission of light are considered to underpin the three principal steps that a light ray goes through upon arriving at the surface of a leaf [25].

4 The Synthetic Inference Approach

Synthetic Inference is a term introduced in this research to describe its novel plant recognition and measurement approach. It differs from traditional approaches in that synthetic inference does not require neural network training. Instead, a synthetic dataset is created as distinct parts preserving the structured knowledge of synthetic plant data and metadata in 2D, 2D + depth, and 3D representations.

Tu [26] (2020) and Li [27] discuss neural network image depth and stereo processing. This structured knowledge maintains the form and hierarchical structure of the plant parts and can be directly and efficiently accessed in synthetic inference applications. The dataset structure combines multiple views, representing positions and orientations of each 3D model, allowing the concept of the matching to individual plant models, and the user interface allows specified variations of these models in the recognition and measurement process. This contrasts with the "pooling" operations performed during neural network training, where individual details are assimilated and combined into a complex but problematic representation, as described by Hinton [28].

A dataset contains separate sections for different regions and different plant varieties, whereas there exist a common set of procedures to store and retrieve the data, and particular combinations of data and metadata, and orientations which match features in a real plant image. For example, to perform a grain-count measurement in synthetic inference, a set of wheat head images with the same orientation but with increasing grain-count can be requested from the dataset, to achieve a better recognition of a given real plant image. A test system was developed with twelve rotations of each view. This is effective in terms of improved image recognition.

5 A Synthetic Inference Application

An important synthetic Inference application was developed to harness the synthetic models, image data, and metadata and its hierarchal structure which is present on the created wheat head dataset.

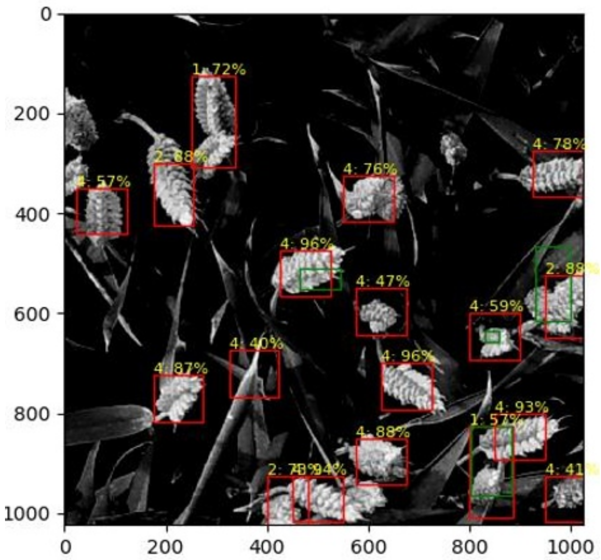

Fig. 4. A Global Wheat dataset image, annotated by synthetic inference, indicating the best synthetic model numbers and matching IoU scores.

The dataset has 100, stochastically varied 3D models. Further, the dataset had 25 2D views of each model. The synthetic inference method directly locates wheat heads on Global Wheat pasture images, using this dataset with high visibility and clarity (See Figure 4).

It is important to discuss the significance of IoU scores using L-systems for synthetic images [19], [29], [30] and [31]. The Intersection over Union (IoU) is a standard object recognition metric. It is the intersection area divided by the union area of two objects, where area relates to 2D image pixels. Intersection is the common area of overlap, and the union area is the sum of both object areas less the common area, thus:

```
IoU = I / (A1 + A2 - I),
where the two objects have areas A1 and A2
and their intersection area is I.
```

The highest IoU score indicates the best matching synthetic wheat head at each real wheat head position. As a separate measure of overall success in matching a wheat field: Currently, 17 of the 23 wheat heads, are recognised on this one image, giving a score of 17/23 => 74%. This is preliminary since many refinements must be performed.

This synthetic inference application uses direct pixel comparisons between synthetic and real wheat image data. This is a novel approach to demonstrating an accurate method that saves time training neural networks.

6 The L-NAP Dataset

The L-NAP dataset gathers the plant data and makes it available to applications in a structured and relational manner. It follows the standard Detectron2 formalism [32], which uses a JSON file [33] describing the dataset contents. The data format is based on Microsoft COCO [34]. In the case of the Global wheat head recognition project, the dataset was stored in terms of its directory configuration (Table 2).

Table 2. Directory Contents

Meta	Metadata of synthetic wheat heads annotated in JSON files, referring to View and Model files.
Model	3D models, held in object and material files, referenced by JSON files
View	2D image view files, referenced by a JSON file

Each metadata JSON file describes a synthetic wheat head or several related wheat-heads, located on named 2D synthetic view files, as views of 3D models in a Wavefront format [35]. The wheat heads are described to be within given bounding box(es) on the view file, and within bit-mask segmentation(s), each defined by a list of Run-List-Encodings [36].

Each wheat head has categories defining its grain-count, orientation, scale, and partial-image class, and other possible classifications. When there is more than one wheat head defined on a JSON file, then the wheat heads are closely related, such as several orientations of a single view, or a range of wheat heads with increasing grain-count at the same orientation.

This JSON file is used in the synthetic inference application to access the synthetic wheat pixel data and to create relational information, which guides the application. The Model directory holds the original 2D wheat head models. It will be used in future applications to create digital representations of real pasture scenes. The View directory contains the pixel data named in the JSON file.

Note that the plant recognition system from Pl@ntNet.at [37] uses an image dataset that has been annotated by expert botanists. This system has achieved 88% plant recognition accuracy. This level is much higher compared to the lower scores for neural network-based mobile phone plant recognition systems, which generally have poorly annotated data. An algorithmic ranking of viable plant candidates was a key feature of their dataset.

7 Conclusion

This research demonstrates the advantages of using synthetic plants and 3D modelling to accurately recognize real plants by means of an L-systems approach. The study shows the efficacy in two key areas. Firstly, this paper shows the benefits of stochastic variations and the ability to gain a more accurate system of recognition. The second benefit is the ability to save time because this approach allows for synthetic mapping without the need to further train neural networks.

An innovative synthetic inference application has been successful in the accurate recognition of selected wheat head varieties of the Global Wheat dataset of 2021 [2]. This application is an alternative to the neural network application. Synthetic inference will be extended with higher accuracy to cover multiple wheat head varieties and multiple plant types. The stochastic variation method will be extended to allow the creation of increasingly realistic plants.

Research discovered that a smartphone plant recognition system from Pl@ntNet.at uses a dataset of images, categorised by botanists, to achieve 88% plant recognition [37] compared to much lower scores for neural network-based mobile phone plant recognition systems, which generally have poorly annotated data. An algorithmic ranking of possible plant candidates was a key feature. If we note that in the Global Wheat Competition of 2021 the best score was 84% [1], then we can confidently suggest that this type of L-systems approach will allow for image recognition training on a significantly smaller set of synthetic images. In future, the dataset must be refined, and experiments performed to create the best dataset interface, and the data for the best object recognition.

It is one task to find the best L-systems rules and parameters for a given plant, and this has been achieved. It is a separate task to introduce a suitable range of parameter variation within the dataset. To achieve this improvement requires that successful image matching is recorded and fed back to the L-NAP framework to allow it to adapt its L-system parameters and their variational ranges to a new domain or to a related plant type. Such a self-adaption would be a milestone in L-NAP development [38].

The use of stochastic variations is an important improvement in the ongoing research endeavour to create image recognition systems that can be trained on nature-based datasets without the need for enormously large numbers of images. They allow for a more robust set of validations that are helpful in terms of recognition in critical areas such as wheat heads. Stochastic variations represent important inclusions to the development of L-systems because they permit and develop greater flexibility and realism in modelling complex structures. The benefits of these inclusions are essential to food security in terms of resilience given the climatic challenges that are influencing global staples such as wheat.

The stochastic variations explored in this paper demonstrate the ability to save significant amounts of time. The 18 domains of wheat could easily be matched using this stochastic method. Having mapped one domain, this system would allow for the same application to map the other 17 global wheat domains. A further benefit is the significant value of recognising awns. Such an approach allows for a system of recognition using synthetic wheat and generating reliable mapping without the need to spend additional valuable time in individual domains.

7.1 Limitations and Future research

One of the limitations is the use of mono recognition of images. A future direction for this recognition approach will be to use a stereo image approach to determine a sharper image in terms of the quest for greater detail in wheat head characteristics. This is an important consideration given that synthetic data is highly applicable to stereo imagery, providing synthetic data that can be generated as 3D models.

This approach is transferrable to recognition in other plants. A new approach is being considered in terms of coffee to investigate the benefits of an L-systems approach for the classification and grading of coffee beans using synthetic modelling.

8 References

1. E. David, M. Serouart, D. Smith et al, *Global Wheat Head Detection 2021: An improved dataset for Benchmarking Wheat Head Detection Methods,* Plant Phenomics, Volume 2021. (2021).
2. Y. Kassem, H. Gokcekus, E. Alassi. *Identifying most influencing input parameters for predicting cereal production using an artificial neural*

 https://doi.org/10.1051/bioconf/20238006004

network model. Modelling Earth systems and Environment, Volume 8. (2022).

3. T. Khan, J. Qiu, M. Qureshi, and M. Iqbal, *Agricultural fruit prediction using deep neural networks,* Procedia Computer Science, Volume 174, Science Direct. (2020).
4. H. Yalcion, and S Razavi, *Plant classification using convolutional neural networks,* 2016 Fifth International Conference on Agro-Geoinformatics (Agro-Geoinformatics), IEEE Explore. (2016).
5. J. Ubbens, M. Cieslak, P. Prusinkiewicz, and I. Stavness. *The use of plant models in deep learning: an application to leaf counting in rosette plants.* Plant Methods, Volume 14, 6. (2018).
6. D. Holzworth, N. Huth, J. Fainges, et al, *APSIM Next Generation: Overcoming challenges in modernising a farming systems model.* Environment Modelling and Software, Volume 103, pages 43 – 51. (2018).
7. J. Hyles, M. Bloomfield, J. Hunt, R.M. Trethowan. *Phenology and related traits for wheat adaptation*. Heredity, Volume 125, pp 417 – 430. (2020).
8. H. Brown, N. Huth, and D. Holzworth, Crop *Model Improvement in moderning and farming systems model,* European Journal of Agronomy, (2018).
9. J. Hanan, *Parametric L-systems and their application to the modelling and visualization of plants*. Dissertation University of Regina, Department of Computer Science, (1992).
10. R. Mech, *Modelling and simulation of the interaction of plants with the environment using L-systems and their extensions,* PhD Thesis, Computer Science Department, University of Calgary, (1997).
11. R. Rokhana, W. Herulambang, and R. Indraswari, *Machine Learning and Polynomial – L System Algorithm for Modelling and Simulation of Glycine Max* (L) Merrill Growth, International ElecLindentronics Symposium, (IES), pages 463 – 467, (2020).
12. P, Prusinkiewicz, A. Lindenmayer, and J. Hanah, *The Algorithmic beauty of Plants,* Springer Verlag, (2004).
13. N. Chomsky, *Syntactic Structures*, The Hague, Mouton and Co. (2002).
14. J.W.Backus, *The Syntax and semantics of the proposed international algebraic language of the Zurich ACM-GAMM Conference*. Proceedings of ICIP, UNESCO, pp. 125-132. (1959).
15. B.G. Fitch, P. Parslow, and K. Lunqvist. *Evolving complete L-systems: using genetic algorithms for the generation of realistic plants*, in Lewis, P.R. Headland C.J., Battle, S., and Ritsos, P.D. (Eds) Artificial Life and Intelligent Agents. Pp 16-23, Springer. (2018).
16. C. Napier, D.M. Cook, L. Armstrong, and D. Diepeveen, *A synthetic wheat L-system to accurately detect and visualise wheat head anomalies,* Proceedings of the 3rd International Conference on Smart and Innovative Agriculture (ICOSIA), (2023).
17. J. Bernard and I. McQuillan, *New techniques for inferring L-systems using genetic algorithm.* In Proceedings of the 8th International Conference on Bioinspired Optimization Methods and Applications. Lecture Notes in Computer Science, pp 13-25. Springer, (2018).
18. J. Guo, H. Jiang, B. Benes, O. Deussen, X. Zhang, D. Lischinski. And H. Huang. *Inverse Procedural Modeling of Branch Structures by Inferring L-Systems,* ACM Transactions on Graphics, Vol, 39, No. 5. (2020).
19. Z. Hartley, and A.P. French, *Domain adaptation of synthetic images for wheat head detection,* Plants, Volume 10, Issue 12. (2021)
20. A.Farahani, S.Voghoei, K. Rasheed. *A brief review of domain adaptation,* Advances in data science, Springer (2021)
21. D. Kuznichov, A Zvirin, Y. Honen, R.Kimmel. *Data augmentation for leaf segmentation and counting tasks in rosette plants,* Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, (2019).
22. M. Renton, P. Kaitaniemi, and J. Hanan, *Functional–structural plant modelling using a combination of architectural analysis, L-systems and a canonical model of function,* Ecological Modelling.Volume 184, Issues 2–4, (2005).
23. M.T., Allen, P. Prusinkiewicz, and T.M. DeJong, *Using L-systems for modelling source–sink interactions, architecture, and physiology of growing trees: the L-PEACH model*. New Phytologist, Volume 166: 869-880. (2005).
24. E. Costes, C. Smith, M. Renton, Y. Guédon, P. Prusinkiewicz, and C.Godin. *MAppleT: simulation of apple tree development using mixed stochastic and biomechanical models*. Functional Plant Biology Volume 35, 936-950. (2008).
25. F. Grisafi, T.M. DeJong, and S. Tombesi. *Fruit tree crop models: an update*. In Tree Physiology Volume 42, pp 441 – 457. (2021).
26. S. Tu, J. Ping, H. Liu, N. Zhuang, Y. Chen, C. Zheng, H, Wan, and Y. Xue. *Passion fruit detection and counting based upon multiple scale faster R-CNN using RGB-D images.* Precision Agriculture, Volume 21. Pp 1072 – 1091. Springer Link. (2020)
27. D. Li, L. Xu, C. Tan, E.D. Goodman, D. Fu, L. Xin. *Digitization and Visualization of Greenhouse Tomato Plants in Indoor Environments.* Sensors.; 15(2):4019-4051. (2015).
28. G. Hinton, S. Sabour, N. Frosst. *Matrix capsules with EM Routing.* Google Brain, Toronto, Canada, International Conference on Learning Representations (ICLR). (2018).

29. D. Li, L. Xu, C. Tan, E.D. Goodman, D. Fu, L. Xin. *Digitization and Visualization of Greenhouse Tomato Plants in Indoor Environments. Sensors*. 2015; 15(2):4019-4051. (2015).
30. E. Fiestas, O. Ramos, and S. Prado, *RPA and L-System based Synthetic Data Generator for Cost-Efficient Deep learning Model training.* 3rd IEEE Eurasia Conference on IOT, Communications and Engineering, (2021)
31. L. Du, R. Zhang, & X. Wang. Overview of two-stage object detection algorithms. In *Journal of Physics: Conference Series* (Vol. 1544, No. 1, p. 012033). IOP Publishing. (2020).
32. Y. Wu, A. Krillov, F. Massa, W.Lo, R.Girshick, *Detectron2*. https://github.com/facebookresearch/detectron2, (2019).
33. T. Bray. *The JavaScript object notation (JSON) data interchange format.* (2014).
34. TY. Lin, M. Maire, S. Belongie, L. Bourdev, R. Girshick, P. Perona, D. Ramanan, C.L. Zitnick, and P. Dollar. *Microsoft COCO: Common Objects in Context. CoRR*, *abs/1405.0312*. (2015).
35. W. Carlson. *History of Computer Graphics and Animation.* Ohio State University, (2017).
36. A. Apostolico, G. M. Landau and S. Skiena, "Matching for run-length encoded strings," *Proceedings. Compression and Complexity of SEQUENCES 1997 (Cat. No.97TB100171)*, Salerno, Italy, pp. 348-356, (1997).
37. Pl@nt.Net.at (PLoS One, doi.org/j479)
38. T. Bureš. *Self-Adaptation 2.0.* In 2021 International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS) pp. 262-263. IEEE. (2021).