Neuromodeling in horticulture and viticulture

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Abstract. The article considers the possibilities of using the artificial intelligence in horticulture and viticulture. At present, the artificial intelligence technologies are actively used in agriculture, which make it possible to effectively determine crop yields, automate the cropping and storage of agricultural produce, determine the condition of the soil, the composition and effective use of fertilizers, identify plant diseases and bring weeds under control using recognition methods. The use of the artificial intelligence methods in horticulture and viticulture has its own specific features: firstly, robotic complexes for harvesting cherries, apricots, apples, peaches and grapes; and secondly, the identification of fruit diseases by means photo recognition using neural networks' machine learning.

1 Introduction

Nowadays, gardeners should be concerned with the formation of gardens' "digital twin", and agronomists should start digital diaries. After all, neural networks first of all require information, and it is often not available. Initially, the artificial intelligence must be trained, and then it, in turn, will prompt what to do. Machine learning (ML) methods make it possible to process a large amount of input data on plant development and, on this basis, carry out very accurate forecasting of crop yields [1].

Firstly, in order to solve the problem of creating a high-quality database for training neural networks for recognizing plant photos, it is essential to create a national database taking into account the regional climatic factors. Secondly, to create applications helping agricultural producers to determine the incidence of fruit diseases and advise on methods for their treatment, it is necessary to use the combined machine learning methods, such as the convolutional neural networks (CNN) and fuzzy neural networks (FNN) [2-15].

2 The purpose of article

The purpose of the article is to discuss the main problems of creating artificial intelligence systems in horticulture and consider neuromodeling as a method for solving them. Considered are neuromodeling using convolutional neural networks (CNN) and fuzzy neural networks (FNN).

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3 Main part

The machine learning (ML) methods facilitate processing a large amount of input data on plant development and, on this basis, carrying out very accurate forecasting of crop yields [16]. In one of the studies, the authors developed a machine vision system for harvesting cherries [1]. The main purpose of this system is to reduce the need for manual labor during harvesting, loading and unloading.

There are several interesting gardening solutions on the market today.

1. Shuttle is a universal robotic platform for organizing intra-garden logistics of inventory, agricultural chemistry, products and waste. A robot of this design can solve all logistical agricultural tasks, and its work will cost much less than any tractor. Manufacturers of universal platforms in Russia are Droneshub and Gumich RTK.

2. Harvesting robot for harvesting marketable apples and mechanical thinning of apple trees. In Russia, robotic solutions for this area are represented by two factories - FGBNU FNATS VIM (Moscow) and KBNTs RAS (Kabardino-Balkaria).

3. Robot pruner — a universal robot for shaping pruning, pruning annual competitors and branches growing at an acute angle, as well as pruning vertically growing branches of the second order (branch on branch) and extension branches that shade the crown of trees. The picker robot is easily transformed into a pruner, it can read the tree skeleton, keep its electronic diary and clearly understand from the tree skeleton where to cut the branch and where to leave it.

4. Forwarding robot - a universal robot for organizing loading and unloading operations. Its task is to take cargo from a shuttle robot, stack it and bring it to a car or storage.

5-7. Sprayer robot, spreader robot, fertigator robot. The first is needed to protect the garden by spraying against diseases and pests, as well as for foliar dressing and chemical thinning. The second is used to apply basic root fertilizers or poison against rodents. The third robot is designed for differentiated watering and fertilization.

8-9. Mower robot and mulcher robot. The mower robot is designed to mow the grass inside the garden spacing, and the mulcher robot performs the work of chopping branches and grading intercellular roads before harvesting.

10. Weeding robot for protecting the garden from weeds near the tree trunks and removing excess root system.

11. Robot-shaper for tying trees to trellis wire with a rubber cambric or metal clip, for tying or breaking the side main base branches in a horizontal position.

In Russia, the Garden-IoT intelligent system has been implemented - this is a system that receives information from a large number of sources, analyzes it, gives an answer to the person concerned about the operational situation in the gardens - with seedlings, equipment, work. The system allows you to control all production processes, track the current state of each seedling, the history of the seedling itself and cost analytics. Garden-IoT has several modules: gardens, irrigation, agrochemical inspection, warehouses with acceptance and delivery of chemicals, fertilizers, etc., tasks on which reporting is based, a monitoring module, and separately - the history of the seedling

A neural network can distinguish a healthy plant from a diseased one. The system is able to determine the degree of threat to the future crop and suggest the possible ways of solving an urgent problem. In the agro-industrial complex of the Russian Federation, there are a large number of tasks that can be solved using the artificial intelligence. A trained neural network is able to adapt to the agro-climatic features of the regions and individual market agents. In the context of the sector's digital transformation, it is advisable to form a single national database for training neural networks. The ecosystem that Rosselkhozbank is developing for the agricultural business includes the up-to-date digital solutions determining the health status of fruit and field crops by analyzing their photos. These solutions can be adjusted to other types of trees and plants. Obtaining up-to-date and objective information about the health status of plants using the Internet services will improve the data exchange among specialists and expert consultants. As a “smart filter”, the neural network can be used to reap and sort the harvested crop. At the same time, the labor productivity of such a robot is much higher than the efficiency of human labor [1]. According to experts, in order to train neural networks to solve problems in the agro-industrial complex, it is necessary to form a national database containing information on the functioning of leading industries, taking into account the regional specific features. This will facilitate making the right managerial decision in the market subjects of digital agriculture based on the use of neurocomputer technologies.

The detection of plant diseases and pests based on the profound learning of convolutional neural networks is most effectively used in the agro-industrial complex nowadays.

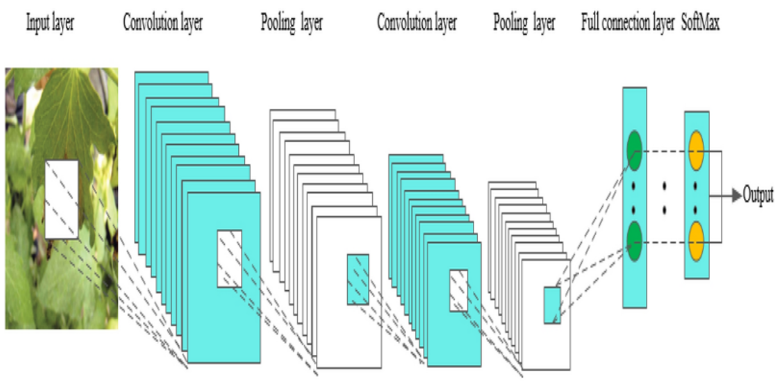

Fig. 1. CNN basic structure

The Convolutional Neural Networks (CNN) feature a complex network structure and can perform convolution operations [17-25]. As shown in Fig. 1, a convolutional neural network model is composed of an input layer, a convolution layer, a pooling layer, a full connection layer, and an output layer. In one pattern, the convolution layer and the pooling layer are interleaved several times, and when the neurons of the convolution layer are connected to the neurons of the pooling layer, the full connection is not required. The CNN is a popular model in the sphere of profound learning. The cause lies in the huge capacity of the model and the complex information generated by the CNN basic structural characteristics, which allows the CNN to have an advantage in image recognition. At the same time, the CNN’s advances in computer vision have fueled the rise of profound learning.

Consider the neuro-fuzzy image classification based on the NEFCLASS neural network, the basic learning algorithm of which was proposed by D. Nauck and R. Kruse in 1994. This learning algorithm is implemented as a fuzzy multilayer perceptron and is used to model the Mamdani-type systems. The learning process uses learning error and can operate with fuzzy rules and sets. This method preserves the structure of the neural network and allows for interpreting the system through fuzzy sets. The task of the NEFCLASS (NEuro Fuzzy CLASSifier) model is to obtain fuzzy rules from a set of data that can be divided into different classes [26].

The fuzzy sets and linguistic rules represent an approximation and determine the result of the NEFCLASS system. They are selected from many samples by training the system. This system can be tuned with partial image feature data. The user must determine the number of initial fuzzy sets and set the value of the maximum number of rule nodes that can be created in the hidden layer; the membership functions are used for learning. The advantage of fuzzy logic consists in facilitating working with incomplete and fuzzy data. The fuzzy inference is made by means of the logical inference rules, such as “if, then” and using the fuzzy sets in the form of membership functions. Considered is the basic model of the FNN NEFClass, which uses triangular membership functions and the empirical learning algorithm. In order to organize the NEFClass fuzzy neural network's training, a number of learning algorithms have been developed - the gradient, conjugate gradients and genetic ones, the studies of their effectiveness and comparison with the basic learning algorithm of the NEFClass system proposed by D. Nauck and R. Kruse are presented. The use of the vector criterion made it possible to reduce the minimum number of erroneously classified samples [27]. Combining various methods of image recognition in photographs of fruits, it is possible to reliably classify diseases and provide agricultural producers certain recommendations for their treatment [28-38]. As an example, consider an intelligent service built into a tool for processing big data using modular neural networks [39]. Let us consider the possibilities of an optimal modular neural network, the topological model of which is built using not only the spaces of receptor and axon fields, but also the error space obtained using a vector criterion for processing big data (Data mining technology). In order to self-train an optimal modular network, the construction of modules as neuroagents is investigated. The vector criterion allows for constructing an optimal modular neural network for object recognition, excluding from it the modules that do not affect the recognition process. That is, in the space of receptors, the fields of receptors not significantly affecting the recognition of objects according to a certain rule are excluded.

The rule for excluding a module from the network is as follows: if the vector criterion does not change its value when recognizing a new object on the module, then this module can be safely excluded from the modular neural network.

Applying this rule, we actually construct an optimal modular neural network for recognizing a new object. In a specific implementation of the neural network, each neural module is associated with two linear vector spaces:

the space of receptors;

the axon space.

Suppose we add an error space to them. The error space contains error vectors obtained during the object recognition by the neural module.

For a neural module, the dimension of the receptor space is equal to the number of receptors, and the dimension of the axon space is equal to the number of axons. That is, a neural module is an operator transforming a vector from the receptor space to the axon space. The operator can be specified by introducing bases in the vector space.

Suppose we take vectors as a basis. They are typical representatives of object classes from the training sample. A typical representative of a class of objects is selected from the training sample among the reference samples of objects of this class according to the vector criterion; namely, we select the standard on which the vector criterion is maximum. The vector criterion allows for choosing support vectors for the support vector machine in the training sample among the reference samples. We can also add one more basis, namely, the vectors obtained from the recognition errors of the support vectors in the error space. Proceeding from this basis, we shall be able to calculate the vector criterion in the error space when recognizing a new object, and thereby using the above-mentioned rule to optimize the modular neural network.

The algorithm for finding the error vector of an arbitrary object is described in [12]. The neuroagent model is implemented as a vector machine. Suppose a certain machine can classify m+1 of the g0,g1,…,gm classes (the machine states are the vector criteria for recognizing typical representatives of classes) and a natural series of numbers N. Let us put in correspondence a certain configuration λ1=g0a1a2…an with the recognizable image ai, in which ai € N, i=1,2,…n. If there is a computation for the machine (recognizing a pattern - referring to a certain class) starting in the configuration λ1 and reaching the final configuration λ3, then the number p € N associated with λ3 determines the number of the class. For a Turing machine, if there is no such number p that the configuration λ_3 is final, then it works indefinitely. For the machine under consideration, there always exists a number p (class number) that the configuration λ_3 is final (i.e., there is always a class to which the machine assigns the recognizable configuration λ_3). If the number of classes is limited and the objects differing significantly in input parameters are part of the class, then new classes must be introduced. The distinguished objects are characterized by the vector criteria, which act as vectors of the measure of difference between the recognizable objects in the error space. The smaller the vector criterion, the worse the object is recognized. For such objects, it is necessary to create additional classes with typical representatives of these objects. This can be done automatically by setting the conditions for creating a class according to the vector criterion, i.e. the machine is a self-learning system. The machine is implemented as a neural network module. If the neural network modules are implemented in the form of neuroagents, then we shall get a self-learning modular neural network. This network can not only optimize its structure, but also self-learn when recognizing new objects.

In order to create a new class of recognizable objects, it is necessary to find the minimum among the vector criteria. And the object to which this criterion corresponds should be made a typical representative for the new class. Thus, the basis increases by 1 and the basis in the error space increases accordingly. That is, the neuroagent will be able to classify recognizable objects into a larger number of classes. Thus, the self-learning of the neuroagent occurs. If the self-learning of the neuroagent stops, then the recognizable objects are classified with sufficient accuracy according to the existing classes. That is, an algorithm for solving the problem of pattern recognition is built. Unlike the Turing machine, this process is finite and thus the halting problem is eliminated. A neuroagent, unlike a Turing machine, can develop solution algorithms for a wider range of problems [40].

4 Conclusion

The article considers the main problems of creating intelligent systems in horticulture and viticulture and suggests the methods for solving them. For instance, the phenomenon of a digital twin of a garden is completely absent, there are no databases on pests and diseases for recognition by artificial intelligence. Accordingly, there is no precise identification or classification of aims or obstacles, or phytosanitary control data. Therefore, nowadays, gardeners should be concerned with the formation of gardens' "digital twin", and agronomists should start digital diaries

References

1. A.Yu. Dorogov, Politechnica **328,** (2014)
2. P.V. Chetyrbok, *Artificial Intelligence in Distance Education. Distancionnye obrazovatel'nye tekhnologii Materialy III Vserossijskoj nauchno-prakticheskoj konferencii.* In Proceedings of the 3rd All-Russian Scientific and Practical Conference, DET, 91-95 (2018)
3. A.Ju. Dorogov, A.A. Alekseev, *Fast Neural Networks.* In Proceedings of Seventh International Conference on Advanced Computer Systems (ACS-2000) 267-270, October, Szczecin, Poland (2000)
4. Gallini, N.I. Denisenko, A.A., Kamornitskiy, D.T., Chetyrbok, P.V., Motuz, N.S. *Research on the Use of a Neural Network in the Intelligence System of University Research Activities.* Proceedings of the 2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering, ElConRus-2021, pp. 886–890, 9396216 (2021)

5. A.Yu. Dorogov, *Estimation of Multilayer Neural Network Plasticity*. In Eleventh IF AC International Workshop Control application of optimization CAO’2000 Perga-mon An Imprint of Elsevier Science Oxford, 81-85, **VI,** UK (2000)
6. S. Korsakova, V. Korzin, Y. Plugatar, A. Kazak, V. Gorina, N. Korzina, S. Khokhlov, K. Makoveichuk, Inventions **8(3)**, 65 (2023)
7. A. Oblizanov, N. Shevskaya, A. Kazak, M. Rudenko, A. Dorofeeva, Applied System Innovation **6(1)**, 26 (2023)
8. P. Chetyrbok, N. Oleinikov, A. Mayorova, D. Gorobets, E. Ponomareva and E. Sergeeva, E3S Web of Conferences **371**, 06001(2023)
9. D. Kaplun, A. Krasichkov, P. Chetyrbok, ... A. Garg, H.S Pannu, *Cancer cell profiling using image moments and neural networks with model agnostic explainability*: A case study of breast cancer histopathological (breakhis) database. 9(20), Mathematics (2021)
10. A. Kazak, Y. Plugatar, J. Johnson, ..., P. Kaur, T. Kokodey, The Use of Machine Learning for Comparative Analysis of Amperometric and Chemiluminescent Methods for Determining Antioxidant Activity and Determining the Phenolic Profile of Wines Applied System Innovation **5(5),** (2022)
11. F. Rosenblatt, *The perceptron: a probabilistic model for information storage and organization in the brain.* In Psychological review **65(6)**, 386. (1958)
12. C. Saunders, A. Gammerman, V. Vovk, Ridge regression learning algorithm in dual variables (1998)
13. K. Simonyan, A. Zisserman. *Very deep convolutional networks for large-scale image recognition.* In arXiv preprint arXiv:1409.1556 (2014)
14. G. Walz, Journal of computational and applied mathematics **21(1),** 119–123 (1988)
15. L. Jaehoon, X. Lechao, S Samuel et al., Advances in neural information processing systems, 8570–8581 (2019)
16. Md Z. Alom, T. M Taha, Ch. Yakopcic, *The history began from alexnet: A comprehensive survey on deep learning approaches.* In arXiv preprint arXiv:1803.01164 (2018)
17. V.I. Nabokov, E.A. Skvorcov, K.V. Nekrasov, Implementation of robotics in agricultural organizations VIESH Newsletter **4 (33)**, 126–131 (2018)
18. Ing.H.Ney, B.Leibe, Matching Algorithms for Image Recognition (RWTH Aachen University, 2010)
19. L. Bottou, Lecture Notes in Computer Science **7700**, 421-436 (2012)
20. Matthew D. Zeiler, Dilip Krishnan, Graham W. Taylor, Rob Fergus, Deconvolutional Networks in Computer Vision and Pattern Recognition, 13-18 June (2010)
21. Ch. Si, W. Yufei. Convolutional Neural Networks and Convex Optimization (2014)
22. V. Shrivastava, N. Sharma, Signal & Image Processing: An International Journal (SIPIJ), **5** (2012)
23. W. Yangwei, Z. Haouhua, Z. Liqing, *Image Denoising with Rectified Linear Units* in Neural Information Processing. 21st International Conference, ICONIP 2014, 3-6 November,142-149, Kuching, Malaysia (2014)
24. A. Nasonov, K. Chesnakov, A. Krylov, *CNN Based Retinal Image Upscaling Using Zero Component Analysis* in The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, **42**, 27 (2017)
25. D. Page*, How to Train Your ResNet 4: Architecture* (Myrtle.ai, 2012)

26. A. Rahimi, B. Recht, Advances in neural information processing systems, **37**, 1177–1184 (2008)
27. V. I. Nabokov, E. A. Skvorcov, K. V. Nekrasov, *Kadrovaya problema i vnedrenie robototekhniki v sel'skom hozyajstve.* In Personnel problem and robotics introduction in agriculture Finansovaya ekonomika **7,** 89–91 (2018)
28. Yu.P. Zajchenko, F. Sevaee, K.M. Titarenko, N.V. Titarenko, *Issledovanie nechetkih nejronnyh setej v zadachah makroekonomicheskogo prognozirovaniya*. In Research of fuzzy neural networks in macroeconomic forecasting problems, Sistemni doslidzhennya ta informacijni tekhnologiï, **2**,70-86 (2004)
29. YU.P. Zajchenko, Osnovi proektuvannya intelektual'nih system (Basics of Designing Intelligent Systems, Textbook, Kiev, 2004)
30. R. Fuller, *Introduction to Neuro-Fuzzy Systems* in Advances. In Soft Computing Series. Springer — Verlag, Berlin, (1999)
31. D. Nauck, *A fuzzy perceptron as a generic model for neuro—fuzzy approaches.* In Proc. Fuzzy-Systeme'94, Munich, October (1994)
32. D. Nauck, R. Kruse, *NEFCLASS – A Neuro-Fuzzy Approach For The Classification of Data*. In Applied Computing, (1995)
33. D. Nauck, R. Kruse, *What are Neuro-Fuzzy Classifiers.* In Proc. Seventh International Fuzzy Systems Association World Congress IFSA'97, **IV**, 228-233, Academia Prague (1997)
34. D. Nauck, U. Nauck, R. Kruse, *Generating Classification Rules with the Neuro-Fuzzy System. NEFCLASS* in Proc. Biennial Conf. of the North American Fuzzy Information Processing Society (NAFIPS'96), Berkeley (1996)
35. I.M. Petrosyuk, YU.P. Zajchenko, *Porivnyal'nij analiz nejro-nechitkih sistem klasifikaciï v umovah info-rmacijnoï neviznachenosti.* In Comparative Analysis of Neuro-fuzzy Classification Systems inder the Conditions of Information Uncertainty], NVCH ta optichni informacijni tekhnologiï, **1**, 22-25, Kiev (2005)
36. R.A. Fisher, *The use of multiple measurements in taxonomic problems.* In Annual Eugenics, **7(Part II)**:179 188, (1936, also in: Contributions to Mathematical Statistics, Wiley, New York, 1950).
37. YU.P. Zajchenko, F. Sevaee, K.M. Titarenko, N.V. Titarenko, the Macroeconomic Forecasting Context, Sistemni doslidzhennya ta informacijni tekhnologiï, **2**, 70-86 (2004)
38. Sajmon, Nejronnye seti: polnyj kurs. (Neural Networks: Complete Course, 2nd ed.: Transl. from English, Moscow, 2006)
39. P.V. Chetyrbok, *Preliminary systemic decomposition of big data for their classification using vector criteria dynamic management model of innovations generations*. In 2017 XX IEEE International Conference on Soft Computing and Measurements (SCM), pp. 762 – 764 (2017)
40. D.A. Abramov, V.L. Tokarev, Modern information technologies and IT education, **18 (4),** 878-888 (2022)