https://doi.org/10.26898/0370-8799-2021-2-13
УДК: 632.38:633.1: 528.8

Тип статьи: оригинальная
Type of article: original

ОЦЕНКА СТЕПЕНИ ПОРАЖЕНИЯ РАСТЕНИЙ БОЛЕЗНЯМИ МЕТОДАМИ КОМПЬЮТЕРНОГО ЗРЕНИЯ

(✉) [1,2]**Алтухов В.Г.**
[1]*Сибирский федеральный научный центр агробиотехнологий Российской академии наук*
Новосибирская область, р.п. Краснообск, Россия
[2]*Новосибирский государственный технический университет*
Новосибирск, Россия
(✉) e-mail: vgaltukhov@gmail.com

Представлены результаты первого этапа исследования в рамках диссертационной работы «Исследование методов и алгоритмов компьютерного зрения в области выявления болезней растений». Проведен анализ работ, связанных с автоматической оценкой степени поражения растений болезнями. Установлено, что для решения задач в данной области перспективными методами являются сверточные нейронные сети, которые в настоящее время по точности превосходят классические методы компьютерного зрения. Для оценки степени поражения используются классификационные и сегментационные архитектуры сверточных нейронных сетей. При этом, классификационные архитектуры способны учитывать визуальные особенности признаков болезней на разных стадиях заболевания, но с их помощью нельзя получить информацию о фактической площади поражения. Решения, основанные на сегментационных архитектурах, позволяют получить информацию о площади поражения, но не проводят градацию степени поражения по видимым признакам болезни. На основании проведенного анализа существующих работ, основанных на применении сверточных нейронных сетей и вариантов их использования, определена цель настоящего исследования: разработать автоматическую систему, способную определять площадь поражения, а также учитывать визуальные особенности признаков заболевания и тип иммунологической реакции растения на разных стадиях развития. Планируется построить систему на основе сегментационной архитектуры сверточной нейронной сети, которая будет производить мультиклассовую сегментацию изображений. Такая сеть способна разделять пиксели изображения на несколько классов: фон, здоровая область листа, пораженная область листа. В свою очередь класс «пораженная область» будет включать в себя несколько подклассов, соответствующих визуальным особенностям заболевания на разных стадиях развития.

Ключевые слова: болезни растений, степень поражения растений, компьютерное зрение, сверточные нейронные сети, классификация, сегментация, разметка датасета

PLANT DISEASE SEVERITY ESTIMATION BY COMPUTER VISION METHODS

(✉) [1,2]**Altukhov V.G.**
[1]*Siberian Federal Scientific Centre of Agro-BioTechnologies of the Russian Academy of Sciences*
Krasnoobsk, Novosibirsk Region, Russian Federation
[2] *Novosibirsk State Technical University*
Novosibirsk, Russia
(✉) e-mail: vgaltukhov@gmail.com

The first stage results within the framework of the thesis “Investigation of computer vision methods and algorithms in the field of plant diseases detection” are presented. The analysis of the work related to the automatic assessment of plant disease severity was carried out. It was established that for solving problems in this field, convolution neural networks are promising methods, which are currently superior to classical methods of computer vision in terms of accuracy. To assess the severity degree, classification and segmentation architectures of convolutional neural networks are used. Classification architectures are able to take into account disease visual features at different stages of the disease development, but information about the actual affected area is unavailable. On the other hand, solutions based on segmentation architectures provide actual data on the lesion area, but do not grade severity levels according to disease visual features. Based on the result of the research into the application of convolutional neural networks and options for their use, the goal of this study was determined, which is to develop an automatic system capable of determining the lesion area, as well as to take into account disease visual features and the type of immunological reaction of the plant at different stages of disease progress. It is planned to build a system based on the segmentation architecture of a convolutional neural network, which will produce multi-class image segmentation. Such a network is able to divide image pixels into several classes: background, healthy leaf area, affected leaf area. In turn, the class "affected leaf area" will include several subclasses corresponding to the disease visual features at different stages of disease progress.

Keywords: plants diseases, plant disease severity, computer vision, convolutional neural networks, classification, segmentation, dataset markup

Для цитирования: *Алтухов В.Г.* Оценка степени поражения растений болезнями методами компьютерного зрения // Сибирский вестник сельскохозяйственной науки. 2021. Т. 51. № 2. С. 107–112. https://doi.org/10.26898/0370-8799-2021-2-13

For citation: Altukhov V.G. Plant disease severity estimation by computer vision methods. *Sibirskii vestnik sel'skokhozyaistvennoi nauki = Siberian Herald of Agricultural Science,* 2021, vol. 51, no. 2, pp. 107–112. https://doi.org/10.26898/0370-8799-2021-2-13

Конфликт интересов
Автор заявляет об отсутствии конфликта интересов.
Conflict of interest
The author declares no conflict of interest.

During 1980–2020 annual losses of the world harvest due to diseases and pests ranged from 20 to 40% [1]. With the current growth of the world's population, due to the lack of quality food, such trends can lead not only to a deterioration in human health, but also become a threat to the existence of mankind. Carrying out timely control of the state of agricultural crops and selection of plant varieties resistant to various diseases will prevent these negative consequences. In this regard, visual monitoring of plants is required [2, 3]. Currently, such monitoring is performed manually, its quality is subjective and not always qualified by experts. With the development of machine learning and robotics technologies, the implementation of these tasks is possible in the agricultural industry using methods and algorithms of computer vision, including convolutional neural networks (CNN) as artificial neural networks for effective pattern recognition.

Convolutional neural networks are capable of detecting diseases at various stages, as visible signs of disease change over time. It is urgent to create a system capable of detecting a disease throughout the entire cycle of its development and classifying plant damage according to its severity. The solution to this problem is necessary for the early prevention of the development of diseases, to determine the resistance of the variety to pathogens, to maintain crop yields.

The aim of the study is to develop an automatic system for classifying the degree of plant disease damage using convolutional neural networks, to assess the efficiency of the system.

Within the framework of the dissertation research, it is planned to solve the following tasks:

1) to analyze the existing algorithms of convolutional neural networks and options for their use to solve the problems of classifying the degree of damage to plants by diseases;

2) to develop an algorithm for marking up a dataset on images of diseased and healthy plant leaves;

3) to develop a system based on convolutional neural networks for segmentation of diseased plant areas and their classification according to the degree of damage;

4) evaluate the effectiveness of the developed system according to the selected metrics on various data sets.

At the first stage of the research, an analysis of literature sources was carried out with a description of systems for classifying plants according to the degree of disease damage using neural networks.

Computer vision is a set of methods and algorithms that allow the detection, observation and classification of objects, obtaining information from images. There are two main directions in the field of computer vision:

1) classical methods;

2) deep learning[1].

They differ in that classical methods involve the selection of image features manually, by an operator, while deep learning (neural networks) does this automatically. There is a significant difference in the accuracy of these approaches. The best methods of classical computer vision provide an accuracy of up to 80%, while deep learning in some cases - 99% [4]. To ensure high accuracy of the neural network operation, it is necessary to train it (teach to select and generalize features) on a sufficient amount of data. This is important to solve problems of identifying plant diseases [4, 5].

Most of the research that is carried out in this area is related to the identification of plants and diseases. However, the disease in the process of its development has various manifestations and symptoms, which is not always taken into account when developing systems based on the CNN [6, 7]. To determine the degree of damage to plants, two types of CNN architectures are used: classification and segmentation [8]. Classification CNN establish the belonging of the whole image to a certain class. To train them, it is enough to annotate the images with signatures, for example, with a certain degree of defeat. In turn, the segmentation networks classify each pixel in the image, they need masks of the affected areas for training.

The following are some of the existing approaches to assessing plant diseases by degree of damage and methods of data preparation that were used for training.

CNN classification architectures are used in the works [9–12]. Annotation of the data was carried out manually by specialists; a caption was added to each image: a healthy organ, a diseased organ at different stages of the severity (initial, medium and severe) [9–11]. The authors of other works proposed to annotate images of leaves of various plants automatically [12]. The background, leaf and affected areas were highlighted using classical computer vision methods. The degree of severity was determined by counting the number of pixels of the affected area relative to the number of pixels of the entire leaf. As a result, as in the case of manual marking, each sheet image was annotated with a caption. Then, CNN were trained on these data and the accuracy with which they carried out the classification was assessed.

There are also studies based on segmentation architectures of neural networks. A system for automatic assessment of the resistance of wheat varieties to Fusarium head blight has been developed and the efficiency of its work has been evaluated [13]. The input data were photographs of ears of wheat taken in the field. The marking was done manually. In each image of the ears, the affected area was highlighted. The resulting masks and images were used to train the CNN. As a result of the training, the neural network generated masks, according to which the degree of severity was determined by calculating the area of the affected zone relative to the area of the entire wheat ear. It was proposed to segment the affected areas of cucumber leaves with powdery mildew using CNN in [14]. Preliminary processing (marking) of images was carried out using classical methods of computer vision, as a result of which masks of the affected areas were obtained. The efficiency of the CNN was assessed.

[1] O'Mahony N., Campbell S., Carvalho A., Harapanahalli S., Hernandez G. V., Krpalkova L., Riordan D., Walsh J. Deep Learning vs. Traditional Computer Vision // Proceedings of the 2019 Computer Vision Conference (CVC), 2019, vol. 1, pp. 128–144. DOI: 10.1007/978-3-030-17795-9_10.

Classification architectures can take into account the visual features of signs of diseases at different stages of the course of the disease, but information on the actual area of the severity is not available [9–14]. Segmentation architectures allow us to solve the problem of determining the area of the severity, but do not take into account the visual features of the signs of diseases and the type of immunological reaction (assessment of the degree of resistance) at different stages of development.

Within the framework of this study, the author plans to develop a system based on the CNN segmentation architecture, which, in addition to the affected area, will take into account the visual signs of damage to wheat leaves. Multiclass segmentation of the leaves affected by leaf rust images taken from a publicly available dataset[2] will be performed. There is a known scale for assessing the reaction and the degree of leaf rust infestation of wheat varieties, divided into five gradations[3]:

1) healthy leaf;
2) resistance;
3) average resistance;
4) average susceptibility;
5) susceptibility.

Moreover, on each of them, except for the first, the disease has the corresponding symptoms and the percentage of leaf damage. One more class is added to these classes - the background. As a result, three classes were defined for training CNN: background, healthy leaves and leaves of four degrees of infestation. CNN will allow you to distinguish both objects of different classes (background, diseased leaf, healthy leaf) and objects belonging to a specific class. This will determine the degree of leaf rust infestation on the leaves. This task is called Instance Segmentation [15]. To provide the neural network with training samples, software for automated marking of dataset images will be developed.

The analysis of the literature shows that the issue of automatic classification of the degree of damage to plants, taking into account their visual characteristics and the type of immunological reaction (assessment of the degree of resistance) is a promising area of research. In this regard, a goal was determined and tasks were set to be performed within the framework of the author's dissertation work. Research results and software products developed on their basis can be used in environmental monitoring of crops and in the development of optimal plant protection measures that reduce pesticide consumption, improve product quality, and automate the work of breeders to create resistant varieties of plants.

СПИСОК ЛИТЕРАТУРЫ

1. *Zhang N., Yang G., Pan Y., Yang X., Chen L., Zhao C.* A review of advanced technologies and development for hyperspectral-based plant disease detection in the past three decades // Remote Sensing. 2020. Vol. 12 (19). P. 3188. DOI: 10.3390/rs12193188.
2. Методы фитосанитарного мониторинга и прогноза: монография. СПб.: ВИЗР РАСХН, 2013. 128 с.
3. *Попова Л.И.* Своевременный мониторинг – основа успешной защиты растений // Защита и карантин растений. 2018. № 4. С. 8–10.
4. *Singh A.K., Ganapathysubramanian B., Sarkar S., Singh A*. Deep Learning for Plant Stress Phenotyping: Trends and Future Perspectives // Trends in Plant Science. 2018. Vol. 23(10). P. 883–898. DOI: 10.1016/j.tplants.2018.07.004.
5. *Singh A., Ganapathysubramanian B., Singh A.K., Sarkar, S*. Machine Learning for High-Throughput Stress Phenotyping in Plants // Trends in Plant Science. 2015. Vol. 21(2). P. 110–124. DOI: 10.1016/j.tplants.2015.10.015.
6. *Barbedo J.G.A*. A review on the main challenges in automatic plant disease identification based on visible range images // Biosystems Engineering. 2016. Vol. 144. P. 52–60. DOI: 10.1016/j.biosystemseng.2016.01.017.
7. *Saleem M.H., Potgieter J., Arif K.M.* Plant Disease Detection and Classification by Deep

[2]Sunny A., Biswabiplab S. Wheat nitrogen deficiency and leaf rust image dataset // Mendeley Data, DOI: 10.17632/th422bg4yd.1.

[3]Koishybaev M., Mumindzhanov H. Methodological guidelines: monitoring of diseases, pests and weeds on grain crops // Food & Agriculture Org. 2018. P. 42.

Learning // Plants. 2019. Vol. *8(*11). DOI: 10.3390/plants8110468.

8. *Guo Y., Liu Y., Oerlemans A., Lao S., Wu S., Lew M.S.* Deep learning for visual understanding: A review // Neurocomputing. 2016. Vol. 187. P. 27–48. DOI: 10.1016/j.neucom.2015.09.116.
9. *Liang Q., Xiang S., Hu Y., Coppola G., Zhang D., Sun W*. PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network // Computers and Electronics in Agriculture. 2019. Vol. 157. P. 518–529. DOI: 10.1016/j.compag.2019.01.034.
10. *Wang G., Sun Y., Wang J*. Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning // Computational Intelligence and Neuroscience. 2017. Vol. 2017. DOI: 10.1155/2017/2917536.
11. *Picon A., Alvarez-Gila A., Seitz M., Ortiz-Barredo A., Echazarra J., Johannes A.* Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild // Computers and Electronics in Agriculture. 2019. Vol. 161. P. 280–290. DOI: 10.1016/j.compag.2018.04.002.
12. *Fang T., Chen P., Zhang J., Bing W.* Crop leaf disease grade identification based on an improved convolutional neural network // Journal of Electronic Imaging. 2020. Vol. 29. N 1. DOI: 10.1117/1.JEI.29.1.013004.
13. *Su W.-H., Zhang J., Yang C., Page R., Szinyei T., Hirsch C.D., Steffenson B.J.* Automatic Evaluation of Wheat Resistance to Fusarium Head Blight Using Dual Mask-RCNN Deep Learning Frameworks in Computer Vision // Remote Sens. 2021. Vol. *13(*1). DOI: 10.3390/rs13010026.
14. *Lin K., Gong L., Huang Y., Liu C., Pan J.* Deep Learning-Based Segmentation and Quantification of Cucumber Powdery Mildew Using Convolutional Neural Network // Frontiers in Plant Science. 2019. Vol 10. DOI: 10.3389/fpls.2019.00155.
15. *Hafiz A.M., Bhat G.M*. A survey on instance segmentation: state of the art // International Journal of Multimedia Information Retrieval. 2020. Vol. 9. P. 171–189. DOI: 10.1007/s13735-020-00195-x.

REFERENCES

1. Zhang N., Yang G., Pan Y., Yang X., Chen L., Zhao C. A review of advanced technologies and development for hyperspectral-based plant disease detection in the past three decades. *Remote Sensing*. 2020, vol. 12, no. 19, p. 3188. DOI: 10.3390/rs12193188.
2. *Methods of phytosanitary monitoring and forecast.* St. Petersburg, VIZR RASKhN Publ., 2013, 128 p. (In Russian).
3. Popova L.I. Timely monitoring – the basis for successful plant protection. *Zashchita i karantin rastenii = Board of Plant Protection and Quarantine*, 2018, no. 4, pp. 8–10. (In Russian).
4. Singh A.K., Ganapathysubramanian B., Sarkar S., Singh A. Deep Learning for Plant Stress Phenotyping: Trends and Future Perspectives. *Trends in Plant Science*, 2018, vol. 23, no. 10, pp. 883–898. DOI: 10.1016/j.tplants.2018.07.004.
5. Singh A., Ganapathysubramanian B., Singh A.K., Sarkar, S. Machine Learning for High-Throughput Stress Phenotyping in Plants. *Trends in Plant Science*, 2015, vol. 21, no. 2, pp. 110–124. DOI: 10.1016/j.tplants.2015.10.015.
6. Barbedo J.G.A. A review on the main challenges in automatic plant disease identification based on visible range images. *Biosystems Engineering*, vol. 144, pp. 52–60. DOI: 10.1016/j.biosystemseng.2016.01.017.
7. Saleem M.H., Potgieter J., Arif K.M. Plant Disease Detection and Classification by Deep Learning. *Plants,* 2019, vol. *8*, no. 11. DOI: 10.3390/plants8110468.
8. Guo Y., Liu Y., Oerlemans A., Lao S., Wu S., Lew M. S. Deep learning for visual understanding: A review. *Neurocomputing*, 2016, vol. 187, pp. 27–48, DOI: 10.1016/j.neucom.2015.09.116.
9. Liang Q., Xiang S., Hu Y., Coppola G., Zhang D., Sun W. PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network. *Computers and Electronics in Agriculture*, 2019, vol. 157, 518–529. DOI: 10.1016/j.compag.2019.01.034.
10. Wang G., Sun Y., Wang J. Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning. *Computational Intelligence and Neuroscience*, 2017, vol. 2017, DOI: 10.1155/2017/2917536.
11. Picon A., Alvarez-Gila A., Seitz M., Ortiz-Barredo A., Echazarra J., Johannes A. Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. *Computers and Electronics in Ag-*

riculture, 2019, vol. 161, pp. 280–290, DOI: 10.1016/j.compag.2018.04.002.
12. Fang T., Chen P., Zhang J., Bing W. Crop leaf disease grade identification based on an improved convolutional neural network. *Journal of Electronic Imaging*, 2020, vol. 29, no. 1. DOI: 10.1117/1.JEI.29.1.013004.
13. Su W.-H., Zhang J., Yang C., Page R., Szinyei T., Hirsch C.D., Steffenson B.J. Automatic Evaluation of Wheat Resistance to Fusarium Head Blight Using Dual Mask-RCNN Deep Learning Frameworks in Computer Vision. *Remote Sens,* 2021, vol. 13, no. 1, DOI: 10.3390/rs13010026.
14. Lin K., Gong L., Huang Y., Liu C., Pan J. Deep Learning-Based Segmentation and Quantification of Cucumber Powdery Mildew Using Convolutional Neural Network. *Frontiers in Plant Science,* 2019, vol. 10, DOI: 10.3389/fpls.2019.00155.
15. Hafiz A.M., Bhat G. M. A survey on instance segmentation: state of the art. *International Journal of Multimedia Information Retrieval*, 2020, vol. 9, pp. 171–189. DOI: 10.1007/s13735-020-00195-x.

Информация об авторе

(✉) **Алтухов В.Г.,** младший научный сотрудник, аспирант; **адрес для переписки:** Россия, 630501, Новосибирская область, р.п. Краснообск; СФНЦА РАН, а/я 463; e-mail: vgaltukhov@gmail.com

Author information

(✉) **Viktor G. Altukhov,** Junior Researcher, Postgraduate Student; **address**: PO Box 463, SFSCA RAS, Krasnoobsk, Novosibirsk Region, 630501, Russia; e-mail: vgaltukhov@gmail.com

Дата поступления статьи / Received by the editors 19.01.2021
Дата принятия к публикации / Accepted for publication 16.04.2021
Дата публикации / Published 25.05.2021