Application of neural convolutional networks to identify fungal diseases of strawberry leaves

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Abstract. The ineffectiveness of measures for the prevention and control of diseases of agricultural crops to prevent the spread of pests and diseases on plantations is shown. The necessity of creating automated intelligent systems capable of ground monitoring of the functional state of plants has been substantiated. A convolutional neural network, UNet, has been proposed to solve the problem of recognizing the degree of damage to plant leaves by fungal diseases. Research trials conducted by UNet.

1. Introduction

During the growing season, plants are under constant influence of various biotic agents, such as pests and pathogens (insects, viruses, fungi, bacteria, etc.). In addition, they are influenced by abiotic factors, such as solar insolation, frost, water deficit, soil salinity, chemical poisoning with mineral fertilizers, etc. [1]. It should be noted that plant diseases caused by pathogens lead to disruption of the physiological state of the plant, interrupting and changing its important vital functions. These stresses reduce productivity and lead to significant crop losses [2]. The most widespread group of plant pathogens in the world are fungi (over 20,000 species), which account for 70-80% of plant diseases. Fungi can invade plant tissue or grow on surfaces. Often they are in a dormant state, both on living and dead plant tissues, and await conditions favorable for their reproduction. Spores of fungi easily spread across the territory of neighboring fields by wind, water, soil and small living organisms, intensively infecting them. The spectrum of fungal diseases is large [3]: rust, anthracnose, scab, galls, smut, root rot, spots, ulcers, mold, etc. It should be noted that some types of fungi play a useful role in plant growth due to the formation of mycorrhizal associations with roots host plant.

To prevent the spread of pests and diseases on plantations, measures are taken to prevent and contain diseases of agricultural crops, including treatment with pesticides, the use of genetically modified plants and the timely removal of diseased plants [4]. However, the use of pesticides has the potential to harm humans and the environment. The development of genetically modified organisms makes it possible to obtain transgenic cultures with pathogenic resistance encoded in their DNA. However, the risk of using this approach is not fully understood [5]. Finally, removing infested plants to contain the spread is costly. It is unable to detect an outbreak, making this containment impractical [6].
2. Problem definition
To reduce the loss of agricultural productivity caused by pathogens, which is at least 20% [7], integrated methods of plant protection are needed. Integrated pest and disease management reduces the likelihood of crop losses and reduces the need for pesticides. For this, first of all, it is necessary to develop simple but effective methods for early diagnosis of plant diseases [8]. For effective pest and disease control, it is important not only to diagnose, but also to quantify plant stress, since both of these functions are equally important for phytopathology [9]. In addition, it is necessary to carry out the identification and classification of diseases in order to selectively influence the means of protection on a specific type of disease. Indeed, the main problem in monitoring the functional state of a plant is the correct identification of the symptoms of the main diseases affecting agricultural crops [10]. The traditional mechanized planting methods used in agriculture cannot cover large areas of crops and provide the necessary early information about the state of the plant for decision-making processes [11]. Thus, effective practical automated solutions are needed that are capable of ground monitoring of the functional state of plants. They will provide meaningful data for plant protection decision-making, for example, on the use and correct dosage of pesticides for specific treatment of certain diseases [12].

3. Materials, methodology and result
For the recognition and classification of objects, computer vision is widely used, together with artificial intelligence [13]. It allows you to explore data representations with multiple levels of abstraction, improving the state of the art in object recognition. Among the methods for modeling complex processes and performing image recognition in images in applications with a large amount of data, the most common are convolutional neural networks (CNN) [14]. CNNs represent a subset of machine learning approaches that have emerged as a versatile tool for assimilating large amounts of heterogeneous data and providing reliable predictions of complex and uncertain phenomena [15]. Currently, various CNN models are used to diagnose the disease, on the leaves of tomato, banana, apple, peach, cassava and other crops of cultivated plants [16-20].

We offer CNN with UNet architecture to solve problems of recognizing the degree of fungal diseases affecting plant leaves. This is justified by the following. With the help of UNet, high results are achieved in solving various real problems, especially those related to the creation of biomedical applications [21]. Indeed, UNet won first place at the 2015 ISBI symposium on the segmentation of neural structures in electron microscopic stacks [22]. This network is considered one of the standard CNN architectures for image segmentation and masking tasks, when it is necessary not only to determine the class of the image as a whole, but also to segment its regions by class. Its architecture consists of a contraction path for capturing context and a symmetrical expanding path that allows precise localization. Most importantly, the network is trained end-to-end on a small number of images and outperforms the previous best method (sliding window CNN). It should be noted its high performance (image segmentation 512 × 512 takes less than a second). UNet requires only a few tagged images for training and has an acceptable training time: only 10 hours on a modern GPU [22].

More than 50 varieties of strawberry leaves were the subject of research. The choice of the object of research is associated with its prevalence in the world, high nutritional value, valuable medicinal properties. However, its leaves damage more than 20 types of pathogens and more than 10 types of pests, but most diseases (about 80%) are caused by fungi [23] (white, brown, angular spots, powdery mildew; gray rot, etc.).

The method for detecting plant diseases consisted of the following techniques:

a) pre-processing of images, in order to eliminate unintentional initial distortions and update the presentation of images;

b) enlargement to expand the dataset and include more variations in the data, for example, using geometric transformations (resizing clipping, rotation, mirroring, etc.) and intensity transformations (contrast, brightness and saturation);
c) image segmentation, that is, dividing a digital image into numerous fragments, in order to extract artifacts of other relevant data from a digital image (detection of the sheet perimeter, characteristic boundaries of artifact accumulations, etc.);

d) feature extraction based on the color, texture and shape of the cluster;

e) classification of diseases based on CNN UNet.

Let us consider in more detail the specific steps of generation in the implementation of the proposed method for detecting plant diseases.

At the first stage, images of strawberry leaves were taken from PlantVillage Datasets [24], and 774 images of leaves affected by brown spot and 442 healthy leaves were selected from them.

Then a general set of 1216 images was generated and masks were prepared for it using the hasty.ai service [25]. As a result, the following masks were obtained for the original images (figure 1).

![Figure 1. An example of the implementation of the masking procedure for a leaf of garden strawberry.](image)

Based on these masks, CNN Unet was trained, which receives an image on a uniform background as input, and gives a leaf mask at the output (figure 2).
Figure 2. Examples of CNN training sequence when masking a leaf of garden strawberry: Diseases_contour - the image fed to the input of the neural network; Diseases_mask - mask for training the neural network; Disease_Predicted - mask obtained using a neural network; Disease_Predicted_binary - a mask obtained using a neural network, with unnecessary discarded pixels, if the probability of a pixel falling into the mask is below a threshold of 0.5.

The next step was the segmentation of the leaf by applying the resulting masks to the original images (figure 3).

Figure 3. Implementation of segmentation of a leaf of garden strawberry.
Figure 3 shows that defects in the form of shadows obtained during the formation of the original image are excluded.

Further, for a segmented leaf, using colorimetric features, masks of the affected leaf areas were made (figure 4). Because the areas affected by the disease have characteristic color differences (brown and purple spots), then pixels were searched for in a specific range of colors.

![Implementation of the procedure for masking the areas of the leaf of garden strawberry affected by the fungal disease.](image)

Because the areas affected by the disease have characteristic color differences (brown and purple spots), then pixels were searched for in a specific range of colors.

A next, using masks, a neural network was trained, which segments the affected area of the leaf (figure 5).

![An example of CNN training on segmentation of an affected area of a leaf of garden strawberry.](image)

Thus, the following sequence was built: an image of a leaf on a uniform background is fed into the input, then, using the first CNN, a leaf mask is built for it and applied to the original image, as a result of which we get a segmented leaf; on the segmented leaf, using the second CNN, we look for the affected
areas and, at the output, we obtain a mask of the leaf areas affected by the fungal disease. It should be noted that the original set of images has been increased due to data argumentation (rotations, mapping).

4. Conclusions

Thus, the studies carried out make it possible using a smartphone:

- to determine the degree of damage to a plant leaf by a fungal disease by the ratio of the total leaf area (leaf mask area) to the mask area of the selected areas affected by the fungus pathogen;
- to carry out, according to the obtained ratio of these two masks (less, for example, 5%), early diagnosis of diseases on plantations (using control plants);
- to classify plant diseases according to the available segmented disease areas using another CNN.

This approach can be transferred to the backend and, through the API, receive the necessary information from the smartphone by making a request to the backend. Those. the client makes a request with the image, the backend processes the resulting image and transmits data on the occurrence of the disease, the probable degree of damage, the characteristic distributions of areas and their concentration near the leaf veins of the plant inherent in specific diseases, etc. The information obtained will allow a qualified user-client with a higher probability to identify dominant disease and plan for future protective measures.

Acknowledgments

This work was supported by the budget project of the Siberian Federal Scientific Centre of Agro-biotechnology of the Russian Academy of Sciences No. 0533-2021-0007.

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