Crop leaves high-resolution images analysis and segmentation by a convolutional neural network under small sampling condition

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Abstract. The authors propose an algorithm for analysing and segmenting high-resolution images of cultivated plant leaves by a convolutional neural network of deep learning in conditions of small samples. The algorithm implemented in the hardware and software complex includes images preprocessing procedures with the elimination of distortions if they are present, data augmentation to increase the number of variations, classification of signs by textural characteristics in order to identify diseases with subsequent segmentation of images of affected leaves.

1 Introduction

Plant diseases have an adverse effect on agricultural production, which negatively affects food security and productivity. Incorrect diagnosis of diseases of agricultural crops leads to the erroneous use of fertilizers, leading to the emergence of resistant strains of pathogens, an increase in the cost of new treatments, an increase in the number of outbreaks with significant economic losses and environmental impact. There are a large number of diseases that affect the yield of plants, which leads to economic and environmental losses, in this regard, the diagnosis of diseases, which gives an accurate and timely result, is of key importance in the field of digitalization of agricultural production. The issues of creation and use of intelligent algorithms and computerized systems implementing them in agricultural production are becoming a fundamental factor in the development of innovation and scientific and technological progress in the industry. One of the primary tasks in the field of application of modern digital technologies is the creation of computerized systems for diagnosing diseases of agricultural crops with the ability to predict their development. In recent years, a number of studies have appeared that address the problems of diagnosing plant diseases, in particular, in [1-2] the problem of diagnosing diseases of cultivated plants using deep learning neural networks is considered, in [3] the problem of implementing a computerized system for diagnosing diseases of fruits of cultivated plants based on the analysis and segmentation of images of their leaves is studied. The development, implementation and adaptation of intelligent diagnostic systems

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makes it possible to use objective diagnostic information, carry out an earlier and sufficiently accurate diagnosis of plant diseases and make a decision on carrying out operational agrotechnical measures for plant protection [4]. The key tool for creating intelligent systems for the diagnosis of plant diseases are methods and algorithms of computer vision and deep machine learning. An analysis of modern research on image recognition [5-9] shows that a number of computerized models for recognition and segmentation have been built and studied in sufficient depth to date [1,10].

Image analysis and segmentation is an important task that is widely in demand in many fields, including agricultural production. There is often a need to process and study such images that do not contain objects of a clearly defined shape. Such images contain randomly arranged extended figures of different shapes, orientations and brightness. One of the classical approaches to the recognition of plant diseases from photographs of leaves is the use of fuzzy logic algorithms in conjunction with feature vectors obtained when calculating the textural characteristics of images [11-14].

2 Materials and methods

Normalization of the original image obtained using technical means of photo-video fixation (including UAVs, mobile devices, etc.) (Fig. 1), as one of the important methods of image processing, should be considered in the form of transformation of the original image to improve the interpretability of information by people and provide favorable conditions for other methods of machine image processing. The operation of the original image in the RGB color palette is considered as one of the fundamental processes of digital image processing in order to increase the contrast of images at the gray level, which facilitates subsequent operations of a higher level, such as detection, identification of objects or the use of various kinds of morphological operations. Color images can be improved in the presence of noise by applying filtering.

a) b)

Fig. 1. Aerial view of a plant (a)-healthy, b)- diseased) obtained using a UAV.

The segmentation procedure is based on the principles of continuity and similarity. Heterogeneity highlights areas with properties of intensity, color, texture, etc. The similarity principle allows you to structure the pixels of the image into groups according to predefined characteristics, which will allow, when detecting leaf diseases, to identify the affected area using the segmentation procedure. Figure 2 shows the result of the implementation of the segmentation procedure of a leaf affected by a fungal disease (powdery mildew).

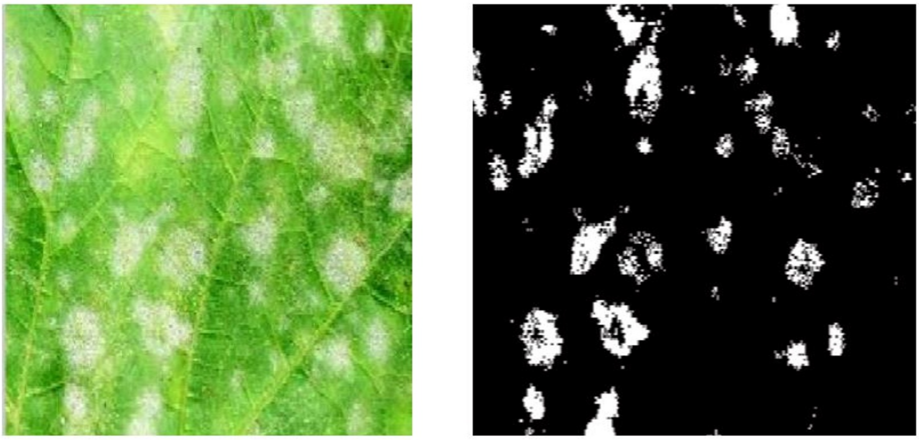

Fig. 2. The results of segmentation of the image of a leaf affected by fungal diseases (powdery mildew) (left - the original image of powdery mildew, right - an image with selected segments of powdery mildew).

The proposed algorithm for recognizing diseases of plant leaves includes the following steps:
1. Preprocessing of the received images by mobile means of photovideofixation, in order to eliminate the initial distortions.
2. Augmentation of data in order to increase the number of their variations using geometric transformations and increase the intensity (contrast, brightness, saturation, etc.).
3. Image segmentation (decomposition of a digital image into numerous fragments to extract artifacts of other relevant data from the original image, including detection along the perimeter of the sheet, characteristic boundaries of the accumulation of artifacts, etc.).
4. Extraction of features by color, texture and shape of the cluster;
5. Preliminary classification of diseases using convolutional neural network architecture.

3 Results

To form a training convolutional neural network dataset, a data augmentation procedure was carried out, which consists in creating an additional training sample based on artificial geometric transformations of the original high-resolution images. A fragment of the implementation of the augmentation procedure is shown in Figure 3.

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```
Exception="Image.jpg"
def multiply_image(image,R,G,B):
        image=image*[R, G, B]
        cv2.imwrite(Folder_name + img_file_name + "Multiply-"+str(R)+str(G)+str(B)+Exception, image)
def gausian_blur(image, blur):
        image=cv2.GaussianBlur(image,(5,5), blur)
        cv2.imwrite(Folder_name + img_file_name + "GaussianBlur-"+str(blur)+Exception, image)
def averageing_blur(image, shift):
        image=cv2.blur(image,(shift, shift))
        cv2.imwrite(Folder_name + img_file_name + "AverageingBlur-"+str(shift)+Exception, image)
def rotate_image(image, angle):
        rows, cols, pixs = image.shape
        M = cv2.getRotationMatrix2D((cols / 2, rows / 2), angle, 1)
        image = cv2.warpAffine(image, M, (cols, rows))
        cv2.imwrite(Folder_name + img_file_name + "Rotation-" + str(angle) + Exception, image)
def crop_image(image, size_h, size_w):
        size_h_ = round(size_h/2)
        size_w_ = round(size_w/2)
        x, y, _ = image.shape
        center_x = round(x/2)
        center_y = round(y/2)
        image = image[center_x-size_h_:center_x+size_h_, center_y-size_w_:center_y+size_w_, :]
        cv2.imwrite(Folder_name + img_file_name + "Crop-" + str(size_h) + 'x' +str(size_w) +
Exception, image)
```

Fig. 3. A fragment of the procedure for implementing an algorithm for constructing and augmenting images of agricultural crops.

The algorithmic structure of the software and hardware complex for analyzing and segmenting images of leaves of cultivated plants in order to identify diseases is shown in Figure 4.

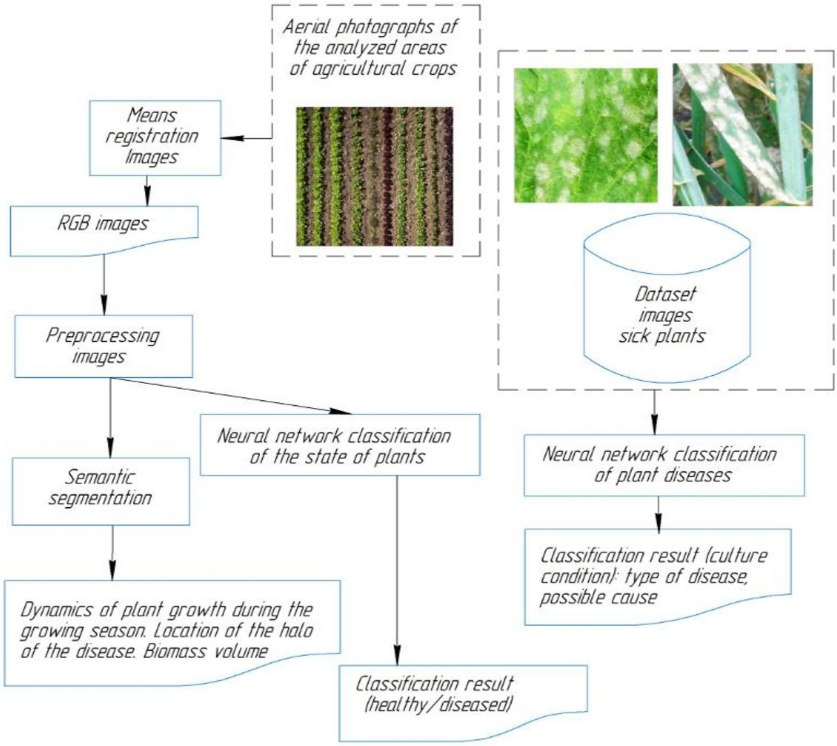

Fig. 4. The algorithmic structure of the software and hardware complex for analyzing and segmenting images of leaves of cultivated plants.

4 Conclusion

The ongoing research on the problems of identifying diseases with convolutional networks of deep learning will allow, in an operational mode, using technical means of photo-video fixation, to identify the degree of damage to the leaves of agricultural crops, including fungal diseases, by the ratio of the total area of the leaf mask to the area of the mask of segmented areas affected by the pathogen fungus. In addition, according to the obtained ratio of the two masks, conduct early ground diagnostics on the plantation according to control crops, as well as solve the problems of classifying diseases by selected segmented sites using a convolutional network of modified architecture for classifying leaf diseases.

The further direction of the implementation and adaptation of the developed set of programs for segmentation of plant leaf images, identification of diseases and the degree of paralysis is the introduction into autonomous UAVs, integration with mobile devices, etc., which will automatically recognize the damaged pathologies of cultivated areas sown with various cultivated plants.

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