Methods for Automatically Determining the Level of Disease Damage to Plant Leaves from Their Raster Image

Stepan Bilan, Georgii Gaina, Oksana Vlasenko, Oleksandr Sutyk and Yevhenii Roiko

Taras Shevchenko National University of Kyiv, Volodymyrska Street, 60, Kyiv, 01033, Ukraine

Abstract

The article is devoted to the consideration of solving the problem of diagnosing and the degree of plant disease using a raster image of their leaves. Methods for visual monitoring of plant diseases based on analysis of leaf images are considered. Methods for automatic analysis of plant diseases using raster images of leaves are proposed. The methods solve the problem of simplifying and reducing the database used for their implementation. The ratios of the R, G and B codes of the components of each pixel are used to highlight the affected areas of the leaves by the disease and determine the degree of damage to the plant. The use of ratio groups made it possible to expand the range of diseases that are diagnosed automatically using the method. In addition, the method allows to select pixels that display areas of leaves that are not affected by the disease, but have already dried out, which allows you to apply the method throughout the entire life development of plants. To identify the degree of leaf damage, which is determined by the voids formed, a method was proposed that made it possible to automatically separate leaf pixels from background pixels in the image to further highlight the affected areas, which makes it possible to automatically determine the percentage of leaves damaged by disease or harmful insects. The method does not allow determining the degree of damage to the edges of leaves, which are subject to complete destruction and disappearance of areas of leaf tissue. Both methods require preliminary preparation of images under special lighting conditions to clearly separate the background from the leaves without the presence of shadows in the image and other image distortions.

Keywords [1]

Raster image, plant disease, leaf distortion, pixels of affected leaf tissue, highlighting voids in the image, thresholding image processing

1. Introduction

Generators of pseudo-random forms and states are the basis of the dynamics of life. All plants in the process of life change their forms and become such as the initial conditions of the plant species are inherent in them. Plants are an integral part of all life on earth. Also, plants and their fruits are an integral part of the diet of people and animals. Many of them became the product of direct cultivation by humans. With the help of humans, new varieties have been bred and new initial states have been established for their growth with the formation of new biological forms. Good harvests of agricultural crops and plants contribute to a favorable life for people on earth. To obtain a good harvest, people create favorable conditions for the growth and maturation of crops and plants. However, plants grown by humans can be susceptible to various diseases, which significantly affect the yield and can significantly reduce it. Modern detection of diseases and determination of their level of development is one of the main tasks of agricultural workers.

As a rule, plant diseases are often determined visually, which makes it possible to determine the degree of development and type of disease. The degree of development of the disease can be determined

Information Technology and Implementation (IT&I-2023), November 20 - 21, 2023, Kyiv, Ukraine
bstepan@ukr.net (A.1); ggaina@knu.ua (A.2); o.vlasenko@knu.ua (A.3); oleksandr.sutyk@gmail.com (A.4); arbokora@gmail.com (A.5)
ORCID: 0000-0002-2978-5556; 0000-0003-0260-0950; 0000-0003-4292-6218; 0009-0008-1572-6329; 0009-0003-4671-7330

directly on the plant and in the places where it grows, as well as in laboratory conditions. Plant diseases are analyzed visually by several experts in this field. This approach often requires a lot of time and also entails errors due to the carelessness of experts [1, 2].

Modern information technologies have made it possible to implement semi-automatic and automatic methods for diagnosing plant diseases using leaf images. Semi-automatic methods use special graphic packages that laboratory workers work with [3]. Such methods can also lead to diagnostic errors, as they require the direct participation of specialists. Although accuracy and speed improve with semi-automated approaches.

Automatic methods for diagnosing and developing plant diseases based on the analysis of raster images of leaves use the principles of automatic image processing, which use image conversion into various color spaces [1, 4 - 7], threshold processing, various image transformation methods (edge detection, segmentation, etc.), texture analysis methods, fuzzy logic and neural networks [8 - 10]. However, all the described methods are applicable to a limited number of diseases. An increase in the number of recognized diseases leads to a decrease in recognition accuracy. In addition, most automatic methods use a large database and the need for preliminary training, which complicates processing processes and reduces performance.

2. Statement of the problem

The objective of this paper is to simplify the methods, which entails reducing the time spent on its implementation by simplifying the operations for processing the color characteristics of each pixel. The methods are aimed at expanding the number of analyzed plant species, as well as the number of diagnosed diseases, without forming a large database and without using additional complex image pre-processing operations.

3. Relative Works

Various methods are used to diagnose plant diseases. A large number of non-visual diagnostic methods are used [11-14]. There are methods that use the polymerase reaction [11], which are characterized by high requirements for laboratory equipment, highly qualified specialists, as well as significant time costs for implementation. Also, to diagnose plant diseases, methods based on immunochromatographic analysis are used [11], which are easily implemented in places where plants grow. These methods do not allow diagnosing a wide range of diseases. Methods that allow one to study plants based on the electrical properties of biological tissues are also widely used [14, 15]. At the same time, electrical methods require the use of high-precision equipment for converting an analog signal, as well as measuring instruments that require constant verification. In addition, electrical methods use various conductive materials, which is not always rational for use outside the laboratory.

The most popular recently are visual diagnostic methods, which are based on the analysis of images of plant leaf tissues. Methods based on the analysis of images of plant leaves are easily automated using various information technologies. Such methods are easily implemented in the form of separate small electronic devices or based on smartphones [3-10]. Modern computer vision methods are used here. Such methods make it possible to both identify the disease and determine the degree of its development, as well as determine the percentage of damage to plant tissues. Many methods use image transformations based on edge pixel detection operators [4] using thresholding. After this, the resulting holes in the sheets were filled. Filled out areas were diagnosed as a disease. The disadvantages of such methods are that after applying selection operators, pixels are selected that may not belong to the edges and are identified as healthy, and after filling they can be assigned to affected pixels, which reduces the accuracy of determining the degree of damage of the plant. There are methods that convert images into different color spaces (RGB, HSV, CMYK, NDVI), which are converted using various pre-processing operations [16 - 18]. Such methods are characterized by the accuracy of disease diagnosis since they use additional calculations when converting and calculating the required threshold. An algorithm has been proposed [7], which is based on comparing the values of the gray channels of the R and G components for each pixel. The $R<G$ ratios determined the presence of the disease and, by growing regions, the affected areas of plant leaves were determined. The method additionally used recalculation

of thresholds, which increases the time spent on its implementation. Methods based on the analysis of structure features and using adjacency matrices are widely used [9, 19]. Such methods consider spatial-frequency, static and structural features. However, they are implemented based on a large number of calculations, which entails greater complexity in implementation. Also, to diagnose diseases, methods based on fuzzy logic are used [8, 20], which require different calculations for each matrix, which may not always provide sufficient accuracy. Methods based on the use of neural networks [1, 21, 22] involve the use of a large database. In addition, the expansion of disease classes and plant species leads to a decrease in the accuracy of diagnosed diseases.

4. Methodology for determining diseased leaf surfaces from their raster images

The proposed methodology for determining the affected leaf surface is based on RGB analysis of raster images of leaves. It includes several stages: a preparation stage for image formation and a stage of automatic selection of image pixels that indicate that an area of a plant leaf is affected by a disease.

The preparation stage for image formation consists of separating the leaves from the plants and placing them on a special surface that displays the background of the image. Leaves located on the surface should not intersect, as the accuracy of determining the affected leaf surface is distorted. In addition, plant leaves should not be placed at an angle, and parts of their surface should not be bent or twisted. An example of the correct (left) and incorrect (right) arrangement of leaves on a special background surface in Figure 1 is shown.

Figure 1: An example of an image of the correct and incorrect arrangement of leaves on a special background surface

At the second stage, pixels indicating the affected leaf surface are selected and the percentage of the plant affected by the disease is calculated. Before selecting a pixel in the image, the color and brightness characteristics of the pixels are established, which reflect healthy and unhealthy leaf surfaces. The healthy leaf surface is determined by its species, and the affected surface is determined by the type of disease, which mainly determines the color and brightness characteristics of the affected leaf surface. In Figure 2 shows an example of an image indicating pixels related to the healthy (in the middle of the figure) and the affected (right in the figure) leaf surface.

Previously, for the successful implementation of the second stage, it is necessary to determine the pixel codes that belong to the affected leaf surface and the pixel codes of the unaffected surface. It is also necessary to determine the value of the code that indicates the background threshold. By applying the value of the background threshold, the pixels that form the surface of the leaves in the image are separated from the background pixels. As a rule, the background is presented in color tones and in brightness approaches light tones, and in color approaches white (code 16777215). The threshold value (for example, 10000000) is set. All pixels whose codes did not exceed this threshold value were selected as those that belong to the surface of the leaves in the image. All other pixels were considered to belong to the background. An example of separating an image from the background in Figure 3 is shown.

Figure 2: An example of an image of leaves affected by the disease

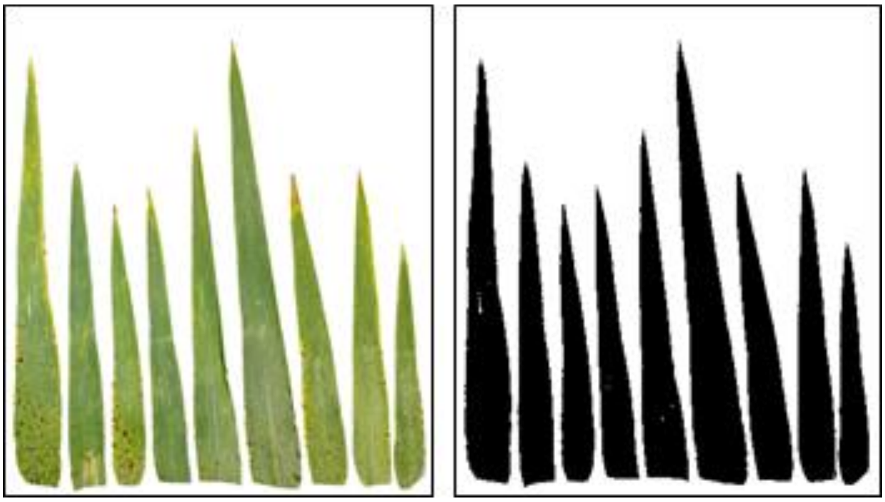

Figure 3: An example of a binary image of leaves separated from the background. The threshold value corresponds to 10000000

The background threshold value was determined experimentally. Lighting and means of photo recording were taken into account. Several experimental images were analyzed and the threshold value was determined.

After carrying out the preparatory procedures described above, the pixels that belong to the image of the unaffected (healthy) leaf surface are selected. To do this, the image obtained in the previous stages is formed as a raster image in RGB format. If the image was generated using other video recording devices and is presented in a different format, then using mathematical formulas it is converted to the RGB format. The code of each pixel is divided into three components R (red), G (green) and B (blue). For each type of plant healthy leaves, a ratio is established, with the help of which you can display the healthy color of the leaves in the image

$$\left\{\frac{R}{G}, \frac{R}{B}, \frac{G}{B}\right\},$$

where R, G and B are quantities that encode the red, green and blue components of the colors in each pixel, respectively.

These relationships for each plant variety are set into inequalities with given threshold values: P_{RG}, P_{RB} and P_{GB}. The P_{RG} value is the threshold value for the ratio $\frac{R}{G}$, P_{RB} – or the ratio $\frac{R}{B}$, and the P_{GB} value is the threshold value for the ratio $\frac{G}{B}$. To select healthy surface pixels, ratio values can be determined to be greater or less than the corresponding threshold value. Threshold values for each plant variety are determined experimentally at the preliminary stage.

Inequalities for the ratios of codes of one pixel are grouped. There may be several and different. Since the color gamut of the healthy surface is different, several groups of threshold ratios with different threshold values and different inequalities can be used to select one pixel of the healthy leaf surface in the image. For example, to select pixels from images of healthy leaf surfaces, several groups can be used, such as,

$$\langle \frac{R}{G} < P_{RG}^{1}, \frac{R}{B} < P_{RB}^{1}, \frac{G}{B} < P_{GB}^{1} \rangle,$$
$$\langle \frac{R}{G} > P_{RG}^{2}, \frac{R}{B} > P_{RB}^{2}, \frac{G}{B} < P_{GB}^{2} \rangle.$$

Such groups of threshold ratios set boundaries that allow to select only specified pixels with the corresponding color gamut. If the used inequalities are satisfied, then the pixel is selected as one that displays (belongs to the image) the undamaged surface of the leaves in the raster image. This pixel is assigned a logical “1”, and the remaining pixels are assigned a logical “0” code. In this way, a binary image is formed in which pixels with a logical code of “1” display the undamaged surface of the leaves. In the resulting binary image, pixels that have a logical state of “1” are counted.

Extraction of pixels that display a damaged leaf surface in the image is carried out using a similar procedure as for pixels of a healthy leaf surface. The difference is that different threshold values P'_{RG}, P'_{RB} и P'_{GB} are chosen for such pixels, as well as other inequalities according to the disease being analyzed. After selecting pixels that represent the affected leaf surface in the image, single pixels are counted, multiplied by the pixel area and the area of the affected surface is determined.

Having determined the number of pixels of the unaffected surface, the percentage of the plant leaf surface affected by the disease is calculated. To more accurately determine the percentage of the affected leaf surface, it is important to accurately select threshold values for both pixels representing the unaffected surface and for pixels representing the affected surface. When selecting each group separately, situations may arise when pixels remain that do not fall under the implementation for all groups of inequalities. In this case, it is necessary to assign these pixels to one of the analyzed groups of pixels by analyzing their color characteristics. Such an analysis is carried out by a specialist and specified in advance in the program. Examples of identifying such groups of pixels in Figure 2 are presented. Additionally, there is also the problem that you cannot divide by zero. A situation may arise when the code of the green or blue components is zero. In this case, uncertainty arises for pixels that have such codes. To eliminate such situations, before forming the ratios, for all pixels whose G and B components are equal to zero, one is added to the codes of the green and blue components of such pixels. Such code of one does not significantly affect the distortion in the ratios.

To confirm the correctness of the technique for analyzing images of plant leaves affected by the disease, an experiment was conducted in which leaves of plants of different varieties were used. Various diseases were also considered that distort the color of the leaf surface and signal the development of a disease on the plant. In addition, each group of pixels for each image was selected separately, which made it possible to determine the percentage of pixels that were not subject to analysis using this method. For the example shown in Figure 2 The percentage of damage to barley leaves is 2.4%. In this case, the lesion is determined for leaves that are in the growth and full development stage at the green leaf stage. This situation makes it possible to set threshold values for images depicting living leaf tissue. During the period when barley leaves should be green. In this case, disease damage leads to changes in the color and structure of the leaf, its drying out and wilting. Mainly for barley for the one shown in Figure 2 disease lesions result in yellow and brown lesions on the leaf surface, which become larger and wider over the entire leaf surface as the disease progresses. For this example (Figure 2), the following threshold ratios $\langle \frac{R}{G} > 1, \frac{R}{B} > 3, \frac{G}{B} > 2 \rangle$ are established.

However, there is a situation when leaves are plucked for analysis at different periods of the year. There is also often a period when the leaves stop growing, dry out and wither. They grow old. An example of such a picture in Figure 4 is shown.

At this stage, several threshold values are applied to separate dead leaves and diseased areas. For the example shown in Figure 4, in the first iteration thresholds were applied $\langle \frac{R}{G} > 1{,}01, \frac{R}{B} > 1{,}3, \frac{G}{B} > 1{,}2 \rangle$, which made it possible to separate the yellow areas in the leaf image. In the second iteration, thresholds were applied $\langle \frac{R}{G} > 1{,}35, \frac{R}{B} > 3, \frac{G}{B} > 3 \rangle$. The results of this approach in Figure 5 are presented.

Figure 4: Example of an image of barley leaves affected by disease and having large areas of yellowed surface due to aging

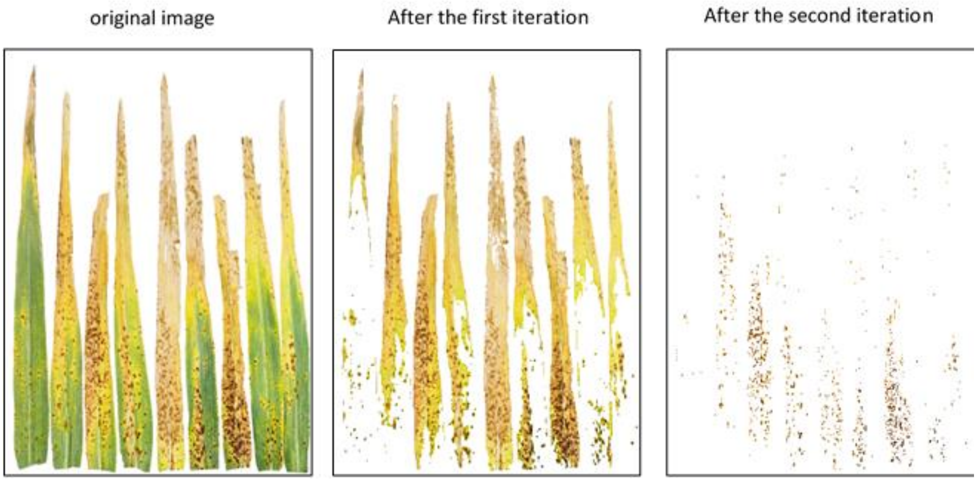

Figure 5: An example of applying several successive groups of threshold values to image barley leaves affected by disease and having large areas of yellowed surface due to aging

Using a combination of groups of threshold values, it is possible to identify only dry areas of leaves, as well as only disease-affected areas. In this situation, it is easy to determine the presence of the disease even after the death (drying) of the leaf mass, but difficulties arise in accurately determining the percentage of the plant affected by the disease. As can be seen in Figure 5, dried leaves have different colors, which does not affect the result of identifying disease-affected areas.

Situations are also possible when healthy leaves have different colors (Figure 6). In this case, a set of groups of threshold values is selected to cut off the unaffected surface in the raster image.

The use of threshold processing along with the ratio of the values of the red, green and blue components makes it possible to expand the number of recognized plant diseases, as well as reduce the size of the database used to automatically determine the level of plant disease damage.

5. A technique for determining voids on leaves affected by disease or after exposure to pests using their raster image

There are a number of plant diseases, after exposure to which voids of various shapes and sizes are formed on the leaves. Also, such voids can form as a result of the influence of harmful insects, which in large numbers can completely destroy the crops in the fields and gardens. Together with the voids, the leaves are also affected along the edges, which is quite easily determined by specialists. However, to automate the process of determining such damage to the leaf mass from a raster image, various methods are used, which differ in varying computational complexity and accuracy in calculating the percentage of damage to a plant by insects or disease. An example of leaf damage, after which voids form, in Figure 7 is shown.

Figure 6: Example image of healthy leaves with different colors areas

Figure 7: An example of an image of leaves with voids resulting from damage by disease or harmful insects.

As can be seen from Figure 7, the edges of the leaves and their inner surface are damaged. The symmetry of the leaves relative to the central line forming the leaf is broken, and there are also voids inside the leaf mass. First of all, to determine the level of leaf damage, it is necessary to select a leaf in the image by separating it from the background. To do this, you need to set the same code to all pixels belonging to the background. The most suitable code is 16777215, which displays the color white. The background in the image is not uniform because the background pixels encode light tones that are close to white. Such a background is created under special lighting conditions at the preliminary stage of image preparation. For our example, the codes of the pixels that form the background in the image vary from 10000000 to 16777215. With this background coding, a condition is set for each pixel code>10000000, which indicates that the pixels belong to the background.

Background pixels are detected using the following algorithm.

1. The outermost pixels of the image that belong to the background are set to code 0 or another code that is not present in the controlled image.
2. At the next iteration step of the algorithm, those pixels that satisfy the following condition (1) go to the zero state:

$$b_{ij}(t+1) = \begin{cases} 0, if\ b_{ij}(t) > 10000000\ and\ D = 0 \\ b_{ij}(t), in\ anothe\ case \end{cases}, \tag{1}$$

where $D = b_{i-1j-1}(t) \vee b_{ij-1}(t) \vee b_{i+1j-1}(t) \vee b_{i-1j}(t) \vee b_{i+1j}(t) \vee b_{i-1j+1}(t) \vee b_{ij+1}(t) \vee b_{i+1j+1}$,

$b_{ij}(t)$ - pixel code with coordinates (i,j) at time t.

In this case, at each iteration step of the algorithm, eight neighboring pixels of each pixel are analyzed to see if its code is equal to zero. If there are such codes, then pixels in which at least one of the eight neighboring pixels encodes 0 go to the zero state. This analysis continues until all background pixels begin to code 0. An example of such separation of a plant leaf from the background in Figure 8 is shown.

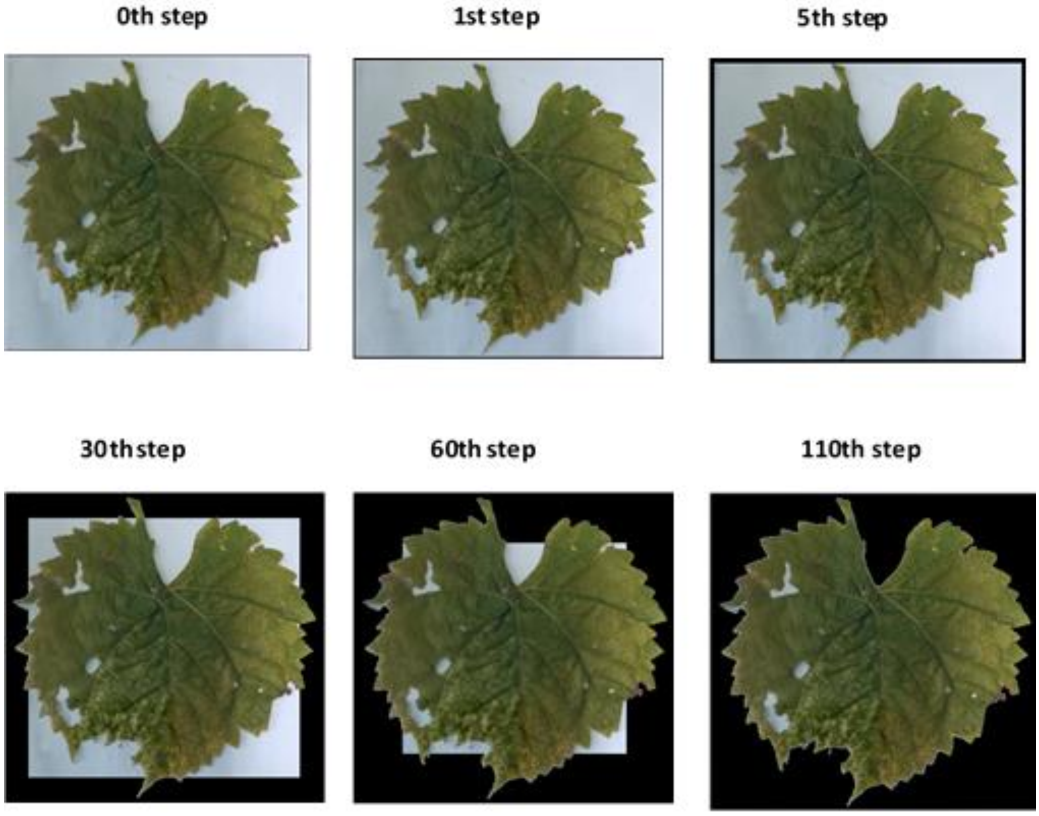

Figure 8: An example of separating a plant leaf from the background in a raster image.

In Figure 8 shows the process of spreading black pixels across the background pixels from the edge pixels of the image. In this case, the pixels representing the sheet holes remain in the codes of the original background. In principle, it is possible to distribute not only the code 0 over the background pixels. The best option is to analyze all pixels for the absence of numbers encoding one of the colors on the image. The analysis is preliminary carried out to determine the code number, which is not present in the control image. This number is selected to be distributed across the background pixels. This approach eliminates erroneous filling, formed voids on the leaves.

After all the pixels have the same code, pixel areas are selected that represent voids. As a rule, such pixels have codes corresponding to the codes of the original background, i.e. their codes contain values in the range from 10000000 to 16777215. These codes are acceptable for the presented example (Figure 8). If the lighting conditions and photographic recording are preserved for all leaves, then this range is preserved for other obtained images of leaves. After this, thresholding is applied to the pixels of the entire image in accordance with the condition

$$b_{ij}(t+1) = \begin{cases} 1, if\ b_{ij}(t) > 10000000 \\ 0, in\ other\ case \end{cases}. \qquad (2)$$

In accordance with this condition, a binary image of selected voids is formed, which have different shapes as shown in Figure 9. In a binary image, voids are represented by codes of one, and the remaining pixels are coded by zeros. By counting ones, the degree of leaf damage can be determined. The shape of each void can be determined using projection analysis and Radon transformations [23, 24].

The considered method has a fairly high accuracy provided that the conditions for high-quality image formation are met. The method is not applicable to images formed at different distances and at different angles. Almost all internal voids are detected if the image is of high resolution. However, the method does not allow determining damage to the edges of leaves, which can be quite large.

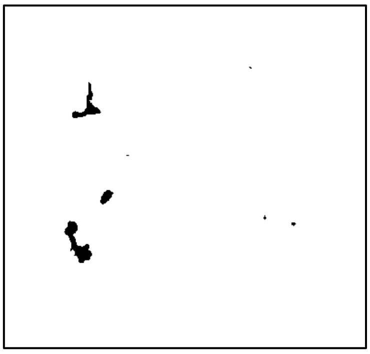

Figure 9: An example of highlighting voids in leaf images for the example shown in Figure 8 and the formation of a binary image. The shapes of the resulting voids are highlighted in black.

6. Conclusion

The paper discusses and studies methods for identifying plant diseases based on the analysis of leaf images. Based on the proposed RGB - analysis of images of plant leaves, the method allows you to automatically identify diseases and determine the degree of damage to plants. The use of the relations R, G and B of the component codes has expanded the range of diagnosed diseases, and the implementation of the method requires a small number of calculations. The proposed approach makes it possible to separate tissues that are affected by the disease from healthy tissues and from the dried part of the leaves, which makes it possible to use it throughout the entire period of plant growth, as well as in the autumn, when leaf tissues begin to die. For plants whose leaves have voids formed as a result of their disease, a method has been proposed that makes it possible to separate the pixels displaying the surface of the leaves from the background pixels, which effectively identifies areas formed by voids in the image. The method does not allow determining the presence of marginal leaf lesions. The methods used do not use large databases, which significantly reduces the time spent on its implementation. Unlike the use of artificial neural networks, the method allows to increase the number of classes without reducing the accuracy of disease identification. At the same time, modification of approaches in threshold processing of raster images based on the relationships of color characteristics makes it possible to expand the number of analyzed plants and their diseases, which significantly increases the efficiency of solving the problem and claims scientific novelty in threshold processing methods. Also, unlike the use of artificial neural networks and deep learning methods, the proposed methods can significantly reduce the number of computational operations such as addition, multiplication and other operations that in large quantities require a lot of computing resources. There may be especially inaccuracy in the results in cases where the forms of distortions vary sharply, and there is also a high probability of overtraining the network, which does not always lead to the desired results. To solve this problem, there is no need to create a large number of references and form a large training sample, which is not always possible to do in real conditions. In further studies, the authors plan to use analysis of the geometric structure of leaves to determine edge distortions.

7. References

[1] Barbedo, J. 2014. An Automatic Method to Detect and Measure Leaf Disease Symptoms Using Digital Image Processing. Plant Dis. 98:1709-1716.

[2] Bock, C. H., Poole, G. H., Parker, P. E., Gottwald, T. R. 2010. Plant disease severity 2 estimated visually, by digital photography and image analysis, and by hyperspectral 3 imaging. Crit. Rev. Plant Sci. 29:59-107.

[3] Boese, B. L., Clinton, P. J., Dennis, D., Golden, R. C., Kim, B. 2008. Digital image 6 analysis of Zostera marina leaf injury. Aquat. Bot. 88:87-90

[4] Weizheng, S., Yachun, W., Zhanliang, C., Hongda, W. 2008. Grading method of leaf spot disease based on image processing. Pages 491-494 in: Proc. IEEE Int. Conf. Comp. Sci. Soft. Eng., China.

[5] Camargo, A., Smith, J. 2009a. An image-processing based algorithm to automatically identify plant disease visual symptoms. Biosyst. Eng. 102:9-21.
[6] Ohta, Y., Kanade, T., Sakai T. 1980. Color information for region segmentation. Comp. Graph. Image Proc. 13: 222-241.
[7] Pang, J., Bai, Z.-Y., Lai, J.-C., Li, S.-K. 2011. Automatic segmentation of crop leaf spot disease images by integrating local threshold and seeded region growing. Pages 590-594 in: Proc. IEEE Int. Conf. Image Analysis Signal Proc., Wuhan, China.
[8] V.S. Tutygin, Al-Windi Basim H.M.A. A method for recognizing plant diseases by texture characteristics using fuzzy logic. Engineering Bulletin of the Don, No. 3, 2019: 2007-2019.
[9] Bianconi Francesco, Harvey Richard, Southam Paul, Fernandez Antonio. Theoretical and experimental comparison for color texture classification. URL: pdfs.semanticscholar.org/31a0/cf98ca459ab6e4676ac45 700cc2485358347.pdf.
[10] Aung C.H., Tant Z.P., Fedorov A.R., Fedorov P.A. Development of algorithms for image processing by intelligent mobile robots based on fuzzy logic and neural networks // Modern problems of science and education, 2014, No. 6. URL: scienceeducation.ru/ru/article/view?id=15579
[11] Fedorenko V.F., Mishurov N.P., Nemenushchaya L.A. Promising technologies for diagnosing pathogens of agricultural plants: scientific. analyte review.-M.: FGBNU "Rosinformagrotech", 2018. - 68 p.
[12] Wang Y.Q., Zhao P.F., Fan L.F., Zhou Q., Wang Z.Y. Determination of water content and characteristic analysisin substrate root zone by electrical impedance spectroscopy // Computers and Electronics in Agriculture. 2019. Vol. 156. P. 243-253
[13] A.S. USSR 31123586, IPC A01G 7/00 Method for determining plant resistance to changes in environmental factors / F.G. Oloyer, V.N. Lysikov. publ. 11/15/1984; Bull. No. 42
[14] Meiqing L., Jinyang L., Hanping M., Yanyou W. Diagnosis and detection of phosphorus nutrition level for Solanum lycopersicum based on electrical impedance spectroscopy // Biosystems Engineering. 2016. Vol. 143. pp. 108-11
[15] Alejnikov A.F., Cheshkova A.F., Mineev V.V. Choice of impedance parameter of strawberry tissue for detection of fungal diseases / AGRI-TECH-III - 2020: III International Conference on Agribusiness, Environmental Engineering and Biotechnologies(Krasnoyarsk,June 18-20, 2020) // IOP Conference Serie: Earth and Environmental Science. 2020. Vol. 548: 032005. DOI: 10.1088/1755-1315/548/3/032005
[16] Guan Wang, Yu Sun, and Jianxin Wang. Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning. Computational Intelligence and Neuroscience Volume 2017, Article ID 2917536: 1-8.
[17] Patil, S. B., Bodhe, S. K. 2011. Leaf disease severity measurement using image processing. Int. J. Eng. Tech. 3:297-301.
[18] Sekulska-Nalewajko, J., Goclawski, J. 2011. A semi-automatic method for the discrimination of diseased regions in detached leaf images using fuzzy c-means clustering. Pages 172-175 in: Proc. Perspective Tech. Meth. MEMS Design, Polyana, Ukraine.
[19] Denisyuk V.S. Algorithms for identifying features in images for the purpose of classifying plant diseases. URL:iis.nsk.su/files/articles/sbor_kas_16_denisyuk.pdf.
[20] Faouzi D., Bibi-Triki N., Draoui B., Abène A. Greenhouse Environmental Control Using Optimized, Modeled and Simulated Fuzzy Logic Controller Technique in MATLAB SIMULINK //Computer Technology and Application. 2016. No. 7. P. 273–286.
[21] M. Ya. Braginsky, D. V. Tarakanov. Estimation of plants health using convolutional neural networks. Вестник кибернетики. 2021. № 1 (41): 41-50
[22] J. Arun Pandian, V. Dhilip Kumar, Oana Geman, Mihaela Hnatiuc, Muhammad Arif and K. Kanchanadevi. Plant Disease Detection Using Deep Convolutional Neural Network. Appl. Sci. 2022, 12, 6982: 1-17.
[23] R. L. Motornyuk, S. Bilan. The Moving Object Detection and Research Effects of Noise on Images Based on Cellular Automata With a Hexagonal Coating Form and Radon Transform. Handbook of Research on Intelligent Data Processing and Information Security Systems. Handbook of Research on Intelligent Data Processing and Information Security Systems. Edited by Bilan, S. M., & Al-Zoubi, S. I. Hershey, USA: IGI Global(2019): 330 – 359.
[24] Bilan, S. Identification of rolling stock of railways based on multi-projection image processing methods. Vol. 2845, 2021: 33-42.