Keywords: modeling, production process, multivariate statistical analysis, classification, pattern recognition, cluster analysis, discriminant analysis

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IMAGE-BASED SYSTEM FOR ASSESSING PLANT DAMAGE SEVERITY TO FORM A DIFFERENTIATED APPLICATION RATE OF PLANT PROTECTION PRODUCTS

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Traditional methods of protecting plants against diseases and pests are based on the uniform application of plant protection products over the entire field area at certain stages of plant development. This application pattern is explained by the higher effectiveness of preventive treatment or treatment at an early stage of disease development compared with cases where the disease has already become clearly expressed [1]. This approach simplifies treatment planning, but it may lead to excessive application of plant protection products in areas with a low degree of infection and increase the environmental load. At the same time, the development of systems focused on the use of chemical agents only when economic thresholds are exceeded is often limited by the complexity of organizing regular monitoring [1], [2].

This paper proposes the concept of a system for assessing plant damage severity based on images containing visually noticeable disease symptoms. The result of such analysis is intended to be the formation of recommendations regarding the application rate of a plant protection product depending on the degree of damage. The proposed solution combines two computer vision tasks: automatic identification of the disease class from an image, that is, classical image classification, and quantitative assessment of the degree of damage by calculating the proportion of the affected area relative to the target region, that is, image segmentation. The scheme of the proposed approach is shown in Fig. 1.

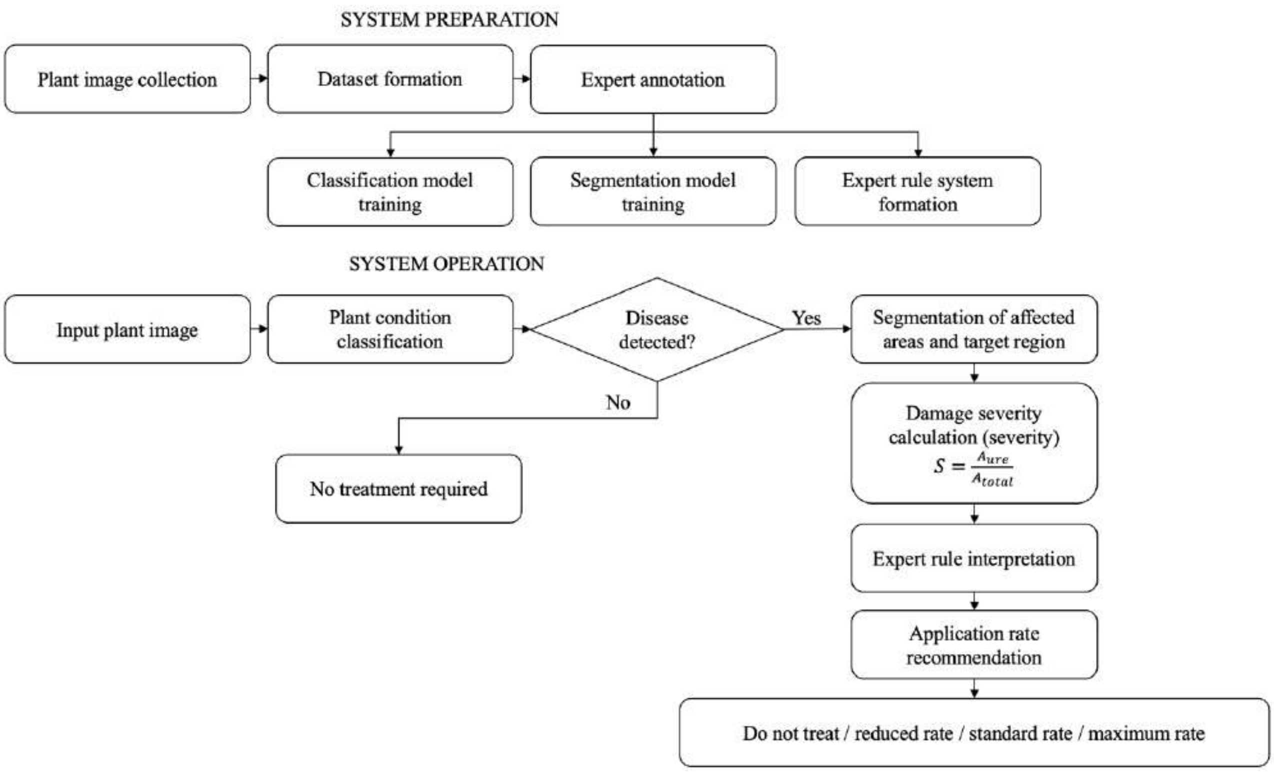

Fig. 1. Framework for assessing plant damage severity and generating recommendations.

The structure of the proposed solution consists of four sequential stages. As shown in Fig. 1, the first step is the formation of a dataset for diseases for which the combined approach is appropriate, particularly those for which differentiated dosing of plant protection products is possible [3]. Such a dataset may have a structure typical of most image classification tasks, with directories corresponding to plant and disease classes. With the involvement of an expert agronomist who can determine the boundaries of affected areas, the dataset can be transformed from a classification dataset into a segmentation dataset by annotating disease zones in the images [4]. In addition, a system of expert rules can be formed to determine the recommended spraying level depending on the degree of plant damage.

At the second stage, automated recognition of the plant condition from an image is performed in order to determine the class, namely a healthy state or disease class, and to identify localization features of the infection. Since segmentation is considered a computationally expensive task, it is reasonable to activate it only after the presence of a disease has been detected, that is, after standard classification has been performed. Therefore, to improve computational efficiency, a cascade scheme is proposed: primary classification performs image classification, after which, for confirmed disease cases, a segmentation submodule is activated. This submodule generates a mask of the affected areas and, if necessary, a mask of the target organ, such as a leaf or canopy, as shown in Fig. 1, for further quantitative assessment. This approach is consistent with common two-stage models for assessing disease severity [5], where object separation from the background precedes the identification of pathological zones.

At the third stage, severity is calculated as the ratio of the area of affected pixels to the area of the target region obtained from the segmentation masks. The calculated indicator may be interpreted as a continuous value or discretized into severity levels according to an accepted scale. The corresponding equations describing the logic presented above are given in formulas (1)–(2).

$$S = \frac{A_{ure}}{A_{total}} \times 100\% \tag{1}$$

$$D(S) = \begin{cases} 0, & S > T_1 \\ 1, & T_1 \le S < T_2 \\ 2, & T_2 \le S < T_3 \\ 3, & S \ge T_3 \end{cases} \tag{2}$$

Accordingly, the fourth module performs the function of generating recommendations, where the results of stages 2–3, namely the disease class, severity estimate, and confidence indicators, are integrated into the expert rule system to form a recommendation regarding the spraying rate class and/or treatment priority. The expert layer takes into account regulatory restrictions on the use of plant protection products, as well as time-related limitations of effectiveness, for example, the preventive nature of many fungicides [1] and the decrease in effectiveness when they are applied after clearly visible symptoms have appeared. This ensures the correct interpretation of severity as an indicator for decision support in a precision agriculture system [2], [3]. Discrete recommendation classes may reflect the treatment intensity depending on the degree of infection. In other words, they define the need for treatment and its intensity: "do not spray / reduced rate / standard rate / maximum rate" within regulatory limits. Obviously, at the technical level, such a system must take into account the technological limitations of the sprayer and safety requirements for the use of plant protection products.

However, it should be emphasized that, according to expert comments from practicing agronomists, an approach based on preventive spraying cannot be fully replaced by methods based on visual indicators for a number of diseases due to their specific characteristics, for example, rapidly spreading diseases, as well as the economic complexity of organizing regular visual monitoring [1]. Therefore, for agricultural crops and, accordingly, their diseases, where focal or spatially stable disease manifestations are more typical, such differentiated treatment may reduce the amount of product used while maintaining effectiveness. This approach belongs to precision agriculture and requires more advanced methods for its implementation compared with standard whole-field treatment: the creation of a dataset with expert annotation, including disease class and/or infection masks for the segmentation task, and the definition of disease severity levels and treatment recommendations according to an accepted scale.

Keywords: computer vision, plant diseases, segmentation, damage severity, precision agriculture, spraying.

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OPTIMIZATION OF PRODUCTION SYSTEMS

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The basis of the modern approach to determining machinability in an automated mode is the use of regulatory and technical data; mathematical models development based on them in order to assess the machinability of new materials based on their belonging to known groups; using the information about the real cutting process to find the parameters' values of the cutting system; creation of effective methods for assessing the materials' machinability based on the most important technological parameters of machining; calculation of a complex machinability index. In this case, it is necessary to ensure sufficient adequacy and accuracy of mathematical models, physical validity for the selected informative parameters of the processes that occur in the cutting zone and in the technological processing system

Instrument-making is developing in the direction of integrating all production structures and creating intelligent production systems. This process is directly dependent on the automation level of production technological preparation and, first of all, on the effective automated determination of metal machinability. Knowledge of metal machinability allows solving the most important problem of the production's technological preparation complex - the appointment of rational processing modes,