

Digital monitoring of crops in grain ecosystems

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Abstract. In the conditions of rapid global population growth, resource depletion, and increasing demand for grains, an efficient agricultural management system becomes a crucial element for ensuring food security in Russia and worldwide. The foundation of such management is an intelligent grain production monitoring system, where diagnosing grain crop diseases serves as a critically significant subsystem. This article presents an approach based on the utilization of neural networks, specifically the U-Net architecture for semantic segmentation, adapted for the analysis and detection of helminthosporium through images of maize leaves. Quality evaluation of segmentation employs metrics like Intersection over Union (IoU) and Dice coefficient, computed from a held-out dataset, ensuring an objective assessment of results. The research demonstrates high accuracy and similarity between the model's predictions and expert annotations, while also showcasing the convergence of loss function during neural network training. A notable advantage of the proposed approach lies in the lightweight nature of the suggested architecture and the ability to utilize trained models as cores for decision support systems, including on local devices without network connectivity.

1 Introduction

According to the United Nations data, the world's population surpassed the 8 billion mark in the year 2023, and forecasts predict that by 2050, this number will reach 9.7 billion. The Earth's land-based humus resources are not only limited but are gradually depleting due to population growth and the increasing demands for food, energy, and materials. This necessitates a reevaluation of existing production processes and the maximization of their efficiency. In the face of continuously growing grain demand and limited resources, the development and utilization of innovative technologies become a critically important step in ensuring the sustainability of future agricultural development.

Digital technologies contribute to the enhancement of production efficiency, increased volume and quality of grain crop yields, as well as the optimization of resource utilization [1, 2]. The integration of digital platforms, intelligent systems, and services into grain production will provide accurate and timely monitoring of grain production, which, in turn, forms the foundation for the entire industry management system [3]. Therefore, when

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establishing a grain production management system, the initial step involves organizing the monitoring of the controlled system, with the ongoing control of the phytosanitary condition of grain crops being a crucial operational measure to ensure its functioning. Phytosanitary monitoring is an integral part of modern grain production, and based on its results, strategies and tactics for protective measures in fields are justified.

In this context, it is important to ensure both vertical and horizontal scalability. Vertical monitoring in this case tracks the stages of the production process, starting from the germination phase of plants and ending with the harvest. Vertical scalability entails variability across crop types, varieties, various diseases and pests, types of variety resistance to pathogens, and so on. Such detailed depth in the system contributes to adaptation to changing conditions and emerging issues at the level of a specific geographical region.

At the same time, spatial localization has its own specifics. Climatic conditions, cultivated crops, soil characteristics, water resource availability, seasonal variations, and more can vary across different zones of grain cultivation. Horizontal monitoring entails the collection, processing, and analysis of data from various farms, districts, regions, and areas, leading to a comprehensive overview of the industry's state as a whole. This contributes to identifying common trends, comparing different factors in various regions, and facilitating the exchange of expertise between farmers and industry specialists.

Such adaptation of the observation system both «horizontally» and «vertically» can be achieved through the utilization of intelligent information systems, at the core of which advanced models and machine learning algorithms are employed.

The present study describes the experience of utilizing intelligent technologies in diagnosing corn diseases, focusing on the example of helminthosporium. Corn leaf blight (*Helminthosporium maydis* Y. Nisik. & C. Miyak) is one of the dominant pathogens in the corn ecosystem, both in southern Russia and worldwide. Helminthosporium is a highly damaging disease of corn, causing not only a reduction in grain yield (up to 40%) but also affecting the green mass [4, 5]. In addition to potential crop losses, fungal infections can contribute to the development of stem rot and lodging of plants.

This is a significant problem for agriculture and the economy at large, as corn is a crucial crop and one of the four major cereals (alongside wheat, rice, and sugarcane) that collectively contribute to over half of global agricultural production [6]. In 2020, corn became the second most produced crop globally (first among cereals), with a total production volume of 1,148,487 thousand metric tons. The United States accounts for more than 30% of the world's corn grain production (347,087 thousand metric tons), followed by China (260,958 thousand metric tons) and Brazil (101,139 thousand metric tons). For Russia, this figure was 13,900 thousand metric tons in 2019 [6, 7].

To combat this disease, various phytosanitary measures are employed, including cultivating resistant hybrids, implementing agronomic practices, seed treatment, and spraying crops with fungicides. However, not all of these approaches prove to be effective. Agronomic practices might only slow down the disease's progression but do not guarantee complete crop protection. Seed treatment also often proves to be insufficiently effective.

Guaranteed preservation of the crop can only be achieved through the application of fungicides effective against leaf blight. However, selecting the right fungicide requires taking into account disease development conditions, such as variety, weather, and agronomic practices. The optimal decision is made based on the degree of disease threat, determined by the economic injury level. In the case of corn helminthosporium, this threshold stands at 15% disease development [8].

The traditional approach to diagnosing corn leaf blight relies on visual assessment, a method that demands highly skilled experts and can be challenging, especially for small-scale farms where timely expert visits might not always be feasible. A novel and promising approach in disease diagnosis could be the application of computer vision technology for

automated pathogen recognition and determining its severity from images or a series of images. Contemporary computer vision methods exhibit object detection quality on par with, and in some cases even surpassing, human capabilities. This opens up new possibilities for more effective diagnostics and combating the helminthosporium disease in corn.

2 Materials and Methods

To gather data in the Krasnodar region during the period from 2020 to 2023, systematic field observations and plant studies were conducted over a span of three years. These studies were carried out on crops grown in experimental fields of the second plant cultivation department of the educational-experimental farm «Kuban». The focal maize hybrid under investigation is the Krasnodarsky 291 AMV, a high-yielding hybrid, modified from the FAO 290 group, with a vegetation period spanning 106-108 days. This hybrid was developed by scientists at the National Grain Center. The mature plant attains a height of 180-200 cm, with the main stem bearing 19 leaves. The cylindrical-shaped cob is formed at a height of 60-80 cm and features 14 rows of grains with an oblong shape. The grain yield during threshing amounts to 80% - 82%. The Krasnodarsky 291 AMV hybrid exhibits strong resistance against stem rots and head smut, displays excellent drought resistance, and is well-suited for mechanized harvesting. It showcases high potential and stability.

The size of the experimental plot was 105 square meters, with a triple repetition. The preceding crop was winter wheat. The primary soil preparation involved chiseling to a depth of 35-40 cm, followed by pre-seeding cultivation to a depth of 7 cm, and then harrowing before germination. The sowing direction was aligned with the last cultivation. The seeds were planted at a depth of 5-6 cm using the «Kvernerland Optima Tfmaksi» seeder. The seeding rate was set at 70,000 germinating seeds per hectare. Seed treatment was conducted using the Maxim Gold preparation at a rate of 1 liter per ton. Herbicide treatment was performed with a combination of Milena at 1.5 liters per hectare and Egyda at 0.35 liters per hectare.

Pathogen infection occurred due to the presence of a natural infectious background. The assessment of plant infection by leaf blight was conducted under controlled conditions following existing methodological guidelines [9].

Photographs of affected leaves displaying signs of the disease were taken under artificial lighting on a white background at a 90° angle, from a distance of 30-50 cm from the subject. The resolution of each photograph was 1024 by 682 pixels. The collected dataset consisted of 320 images. Manual annotation was performed to mark the areas of helminthosporium infection on the images.

Figure 1a illustrates the general field conditions for data collection. Figures 1b and 1c depict the object of the training dataset before and after expert annotation, respectively.

To detect leaf blight and determine its severity, a segmentation model based on the U-Net architecture was utilized [10, 11]. Unlike previous fully convolutional networks where spatial information is lost due to bottlenecks between layers and sharp tensor size increments with resolution increase, U-Net-based models perform upsampling more smoothly.

The U-Net architecture consists of two main parts: an encoder that compresses the image by extracting semantically meaningful features and a decoder that operates in the reverse direction, gradually increasing the tensor's dimensionality to restore it to its original size. Horizontal connections between symmetric blocks in the encoders and decoders are employed in the U-Net model to preserve the accuracy of pixel data and spatial information.

Thus, the U-Net model efficiently detects helminthosporium and determines its severity, ensuring result accuracy and the preservation of spatial characteristics in the image.

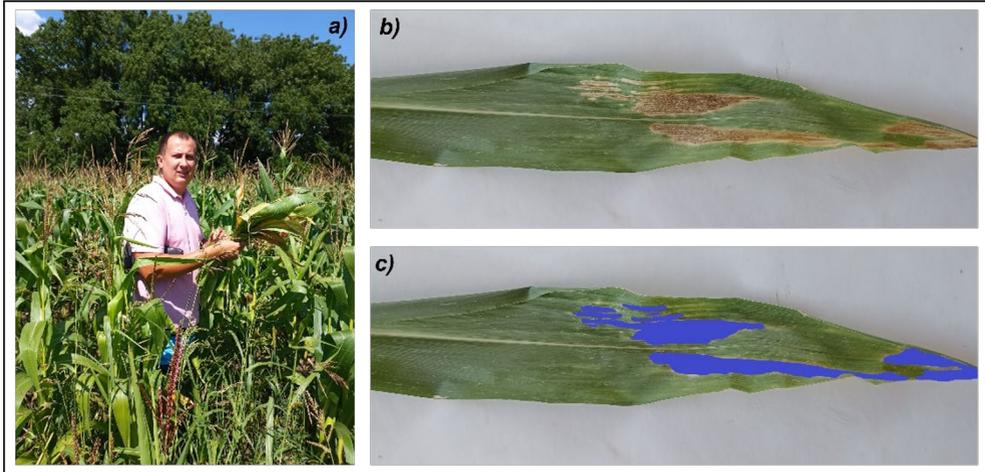


Fig. 1. Formation of the training dataset a) in field conditions b) under controlled conditions c) based on expert annotation

3 Results and Discussion

For training the neural network, we utilized the PyTorch framework version 2.0.0, which has gained widespread usage due to its simplicity and functionality. The neural network was trained on a desktop computer with the following configuration: Intel Core i7, Nvidia GeForce RTX 3060 8 GB.

The dataset was split into a training and testing set in an 80/20 ratio, where 80% of the data was used for training the model and 20% for evaluating its performance on new data. This allowed us to assess the generalization ability of the neural network and prevent overfitting, where the model memorizes the training data well but fails to generalize to new data. To achieve a stable level of model quality, 30 epochs of training were required (approximately 2 hours on the aforementioned hardware configuration). Figure 2 depicts the loss function plots for the training and testing sets. Within a relatively small number of epochs, the loss values plateaued close to zero. Для оценки результатов семантической сегментации используются метрики *IoU* (Jaccard Index) (1) и *Dice* (Sorensen coefficient) (2) [12].

$$IoU = \frac{|A \cap B|}{|A \cup B|}, \quad (1)$$

$$Dice = \frac{|A \cap B|}{(|A| + |B|)}, \quad (2)$$

where A represents the ground truth annotation and B represents the segmented area by the model.

The IoU metric represents the ratio of the intersection area between the ground truth and predicted regions to the union area of these regions. The closer the IoU value is to 1, the more accurate the segmentation result is considered. The Dice metric also calculates the similarity between areas by computing the ratio of twice the intersection area of their masks to the sum of their individual areas. The Dice value can also range from 0 to 1, where 1 corresponds to perfect overlap. In the U-Net segmentation result, the values of these metrics were 0.77 and 0.87, respectively.

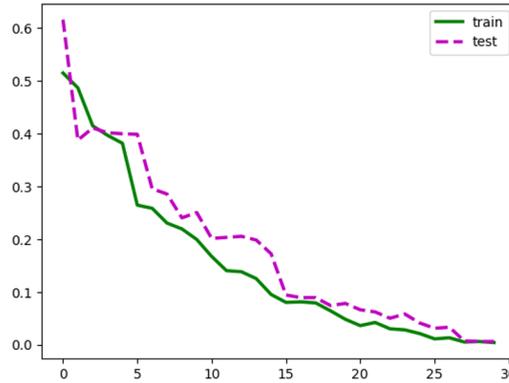


Fig. 2 – Loss functions on the training and testing datasets

In Figure 3, the results of semantic segmentation obtained using the neural network for an object from the testing dataset are presented. The first image in the figure represents the original photo captured under controlled conditions from the testing dataset. The second image illustrates the result of manual expert annotation carried out by a specialist. The third image displays the segmentation results achieved using the trained U-Net model.

Visual analysis of the images indicates that the U-Net model has demonstrated predictions comparable to those achieved through manual expert annotation. This confirms that the numerical results of the modeling, such as the convergence of the loss function to zero and high metric values, indeed correspond to the quality of object segmentation in the images.

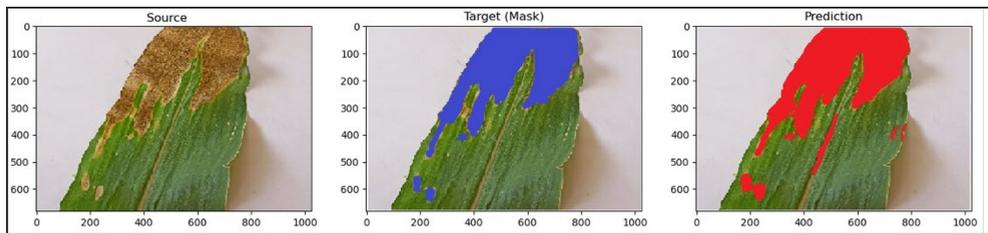


Fig. 3. Comparison of modeling results with expert annotation

4 Conclusion

In discussing the results of maize segmentation obtained using the proposed approach, several key aspects can be highlighted. The numerical values of segmentation quality metrics, such as the Sorensen coefficient and IoU metric, indicate a high accuracy of the model's predictions and similarity to expert annotation. This suggests the effectiveness and reliability of the proposed approach for solving the task of maize disease segmentation. Additionally, the convergence of the loss function during neural network training is observed. This important observation indicates that the model quickly and consistently learns from the provided data, providing further confidence in the segmentation results. Visual analysis of the modeling results demonstrates that the model's predictions are comparable to expert annotation and accurately delineate areas affected by helminthosporium on the maize leaf photos. This confirms the effectiveness and suitability of the proposed toolkit for practical phytosanitary monitoring tasks and its potential for decision support systems.

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