Potentials of Neural Models for Wheat Disease Detection in Precision Agriculture

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Abstract

In this paper, we study the potentials of merging novel technologies, including AI and drone utilization for smart and precision agriculture. The Learning algorithm for real-time assessing the plant states with geomatching is presented. To analyze the potentials of AI-based technologies, we consider and study the YOLO model to identify the signs of wheat rust disease and classify the states of the plants. We consider the version 8, small (YOLOv8s) model as this is known for their use for tasks of real-time signs detection and images classification. The model analysis was done using the next metrics: Accuracy, validation curve, confusion matrix, and PCA-visualization. The analysis of the simulation confirms the benefits of the proposed approach for agricultural tasks.

Keywords

AI, Neural Network, UAV, YOLO model, CNN, innovative technologies, industry innovation, resilient infrastructure, smart and precise agriculture, sustainable agriculture

1. Introduction

The latest and advanced technological developments include robotics, unmanned technologies, Internet of Things (IoT), artificial intelligence (AI), cloud computing. From one side, it opens the prospectives in achieving the goals of sustainable development of many fields of people activity such as sustainable industrialization, cities and agriculture, zero hunger, innovative and resilient infrastructure together with sustainable economic and productivity growth [2-5]. From another side the appropriate study, testing and implementation are required to reach the key goals of community and industry development.

One of the leading branches of industry in Ukraine is agriculture. For example, the 10 percent of global wheat products in 2021 was the wheat from Ukraine [6]. Therefore, the tasks of crop securing and productivity enhancement under the requirements of sustainability is of high importance. The wheat crop failure can be caused by diseases. One of the most distributed wheat diseases is brown wheat rust. In paper [7] the wheat rust is also indicated as a pathogen that restricts the global yields. Therefore, the timely identification of the initial stage of the infection as well as immediate response is important to prevent the disease propagation and crop loss.

The potentials of novel technologies including AI and drone utilization for the range of the tasks are seemed to be promising for precision and smart agriculture [8-11]. This was our motivations to consider and study how the AI-based and UAV-based (unmanned aerial vehicle) technologies can impact into the sustainability and productivity of agriculture.

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We propose to consider AI-based technologies for identification of the wheat states for early identification of infected plants. The UAVs are proposed to use as a multifunctional platform and mobile platform with sensors and cameras to obtain wheat images with precise matching to the position on the field for AI-based processing. The approaches that consider aircraft and particularly UAV as a platform for sensors were considered earlier with the challenges that are faced when such their use [12-15]. Also, UAV can be used as an instrument for immediate response according to the obtained information about state of the plants. These can include fertilizing the plans or chemical treatment against disease.

The requirements to this combined approach for precision and smart agriculture are real time data processing and fast decision-making [16-18]. This also motivates us to consider edge-AI technologies as those that fit to the mentioned requirements.

In this paper we present the federated Learning algorithm for real-time assessing the plant states with geomatching. Also, we study the YOLO (You Only Lives Ones) model to identify the signs of wheat rust disease and classify the states of the plants. One of the tasks when operation with AI-based models is the evaluation of the model correctness to be sure in effective model implementation in the entire system. For this purpose, we make model analysis and consider the next metrics: Accuracy, validation curve, confusion matrix, and PCA-visualization.

2. Materials and Methods

To study the potentials of AI models for real-time wheat state assessment we propose the algorithm of UAV-and AI based edge system that is shown in Figure 1. For proposed approach, the UAV should be equipped with the camera or sensors for crop field scanning to obtain images and microcomputer for AI models for image classification and geomatching of infected areas.

We chose edge AI realization as it allows to make realization on local devices. Moreover, as it is indicated in [17, 20], the developing AI on edge is connected with the following advantages:

- Data processing near the data source that reduces the time delay between data obtaining and results;
- Volume of data is relatively low compare to the AI and cloud- based technologies;
- The operation of the devices does not require the centralized servers, so the autonomy of operations can be achieved;
- Lower energy consumption because of proximity of data source and area of operation;
- More stable connectivity and stability in operation.

The challenges to edge AI also are mentioned in [19-22] and connected with:

- Large-size DL (deep learning) model execution that can be restricted due to limitations of memory and storage devices;
- Deterioration of model performance;
- Energy depletion of edge devices;
- Rather low inerrability;
- Computational restriction of the majority devices.

The advantages of the edge AI solutions can be effectively used in smart and precision agriculture as they allow to provide real-time processing and immediate actions of farmers if needed. The prompt decision-making is also important in case of automation of particular agricultural missions. The autonomy, lower energy consumption as well as stability are also important for success and efficiency of agricultural missions.

The focus of the paper is the study of the YOLOv8s to identify the signs of wheat rust disease and classify the states of the plants. YOLO belongs to the class of neural networks that use the single-stage convolutional neural network (CNN) and are known for their success in real-time image detection and classification. We study the version 8, small (YOLOv8s) because it is considered as the reliable and stable version of YOLO models with rather good efficiency when small object detection. Despite the fact that there are now newer models than YOLO 8 version (YOLO 11 and YOLO 26), the Ultralytics documentation demonstrates that the YOLO 11 and 26 version models are currently developing towards speed, not accuracy. Also, the analysis of the literature for 2024 -2025 years [23-27] showed us that many studies in areas where the accuracy of the neural network is required prefer

to use the YOLO8 version model. Moreover, our previous study showed that the YOLO11 model works on large objects almost as well as the 8 model, but on small objects this issue requires more detailed research. In this paper, our research focuses more on small objects such as signs on leaves in plants.

It is possible to see from Figure 1 that algorithm consists of the pre-stage that is concluded by the formation of unstructured database. Then the processing for formation of structured data follows. And the stage of real data taking with camera placed at UAV and matching the data with strict geopositioned for further creation of digital picture of field.

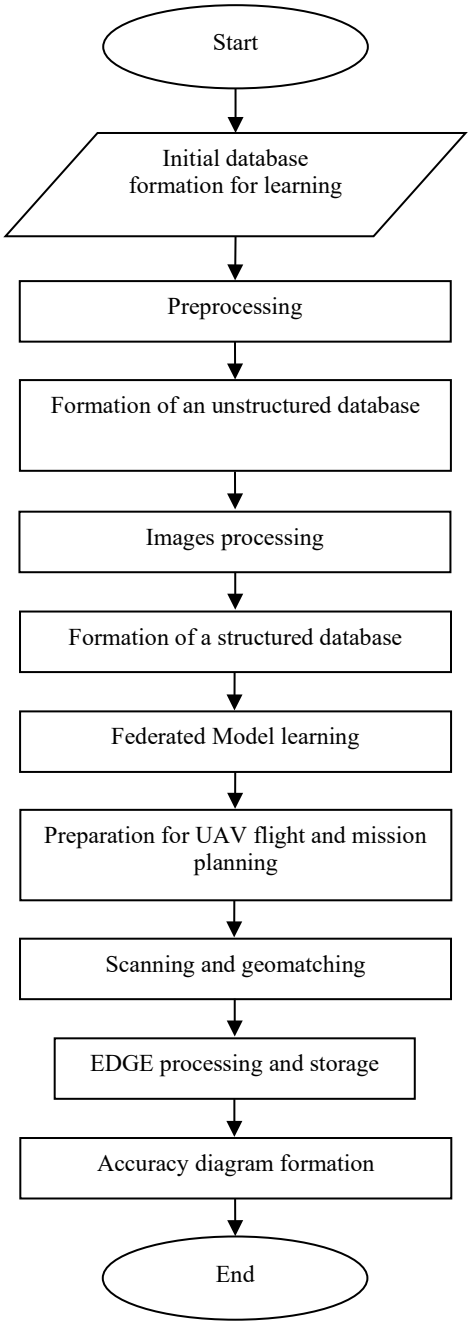


Figure 1: Learning algorithm to assess plant states with geomatching

In Figure 2 the digital picture of the field is shown. The different colors correspond to the different states of the wheat. The state “healthy wheat” is labeled as “0”. The state of wheat at the stage that

requires fertilization is labeled as "1", and "infected wheat" and “treatment is required” is labeled as "2". The example of each state is shown on Figure 3 a, b, c.

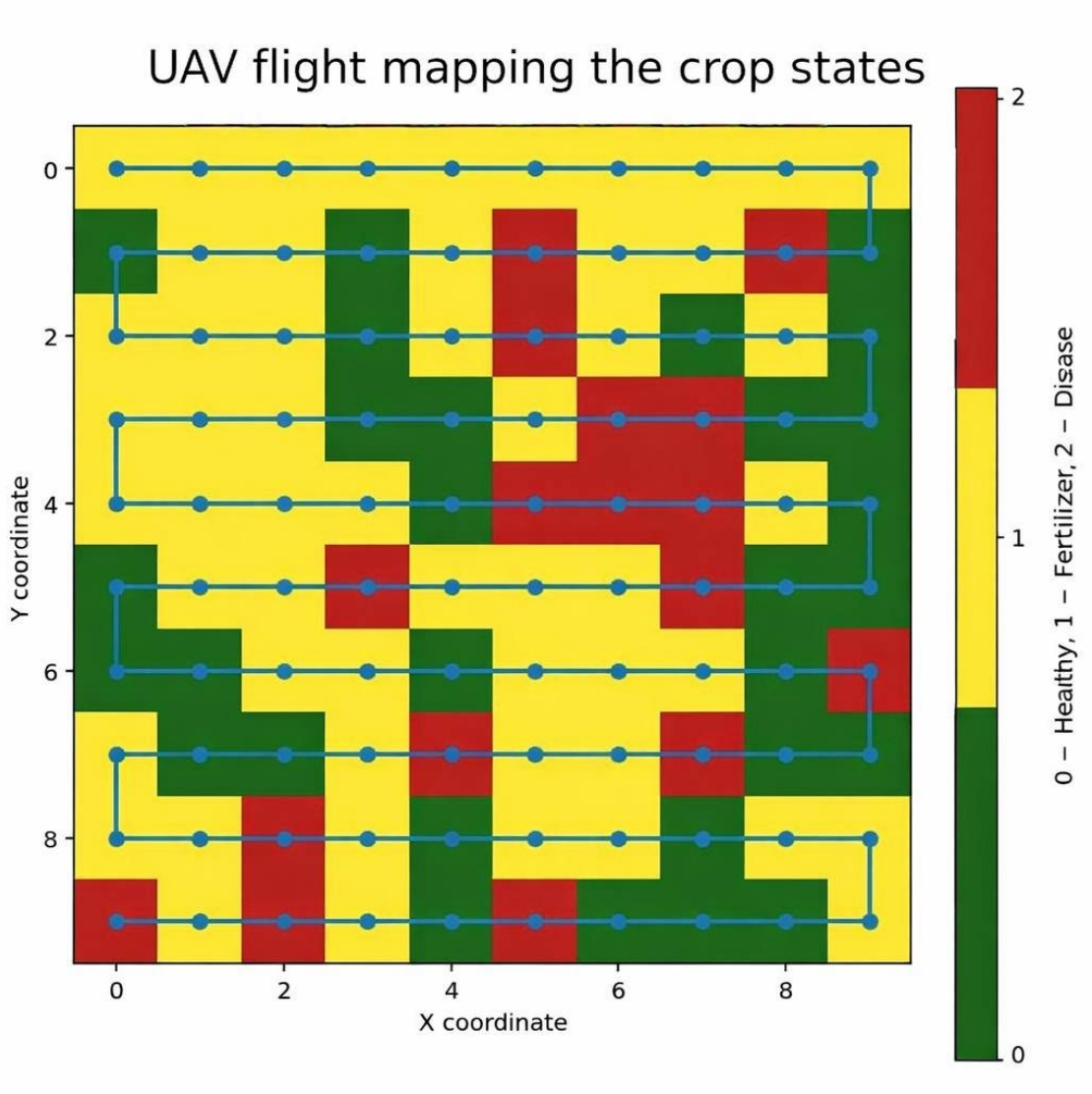


Figure 2: Image of a map obtained during UAV flight and wheat field scanning



a b c

Figure 3: Different states of the wheat:

a) 0 – the healthy wheat; b) 1 – the state of wheat at the stage that requires fertilization; c) 2 – the "infected wheat" and “treatment is required”

3. Simulation results and analysis

The model training to find the signs of wheat rust disease was realized as the 30 epochs scenarios. According algorithm shown in Figure 1, firstly, the dataset was formed after the initial signs of wheat infection. The data of the formed set allows to localize the areas of infected plant on the fields as well as to assess the state of the plants. This helps farmers to take decision which way of plant treatment should be realized.

To demonstrate the classifier operation during the system training we present the dependencies shown in the Figures 4-7. In Figure 4, the learning curve is shown. The curve demonstrates the model accuracy change on number of training samples or epochs.

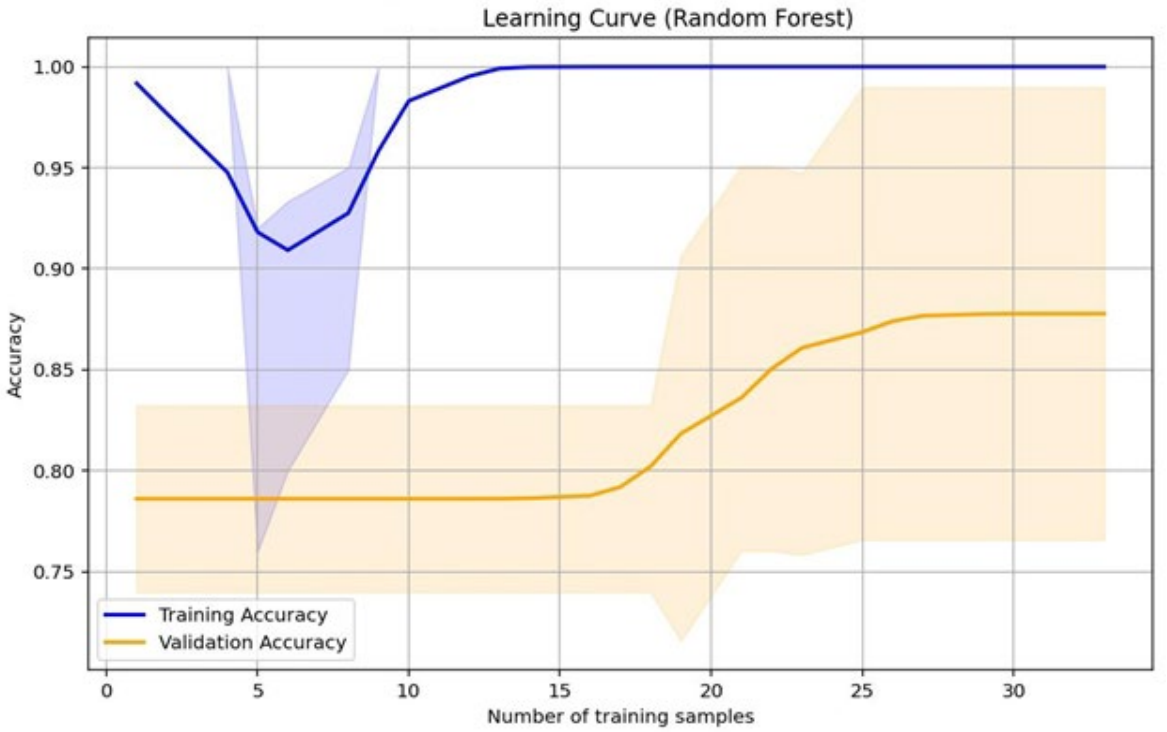


Figure 4: Model accuracy dependence on number of training samples

From the Figure 4 it is possible to see that the curves are rather smooth. This can indicate the gradual model stabilization. At the same time, the difference between training and validation accuracy decreases. Analyzing the Figure 4 it is possible to conclude that the behavior indicates the result of rather long training of the algorithm at the sufficient data volume. The data volume can be used for further training expecting good real-time results and avoiding overfitting.

In Figure 5 the validation curve is shown. The validation curve is a metric that shows the sensitivity between accuracy changes and predefined settings of the model.

The low level of validation curve means underfitting and high level of validation curve means overfitting. The optimal range for our case is on the border of 94%. In this case the training and validation accuracy is the closest to each other.

To evaluate the errors of the algorithm and the system the confusion matrix was built. It is shown in Figure 6.

In Figure 6 it is shown the model classes that are mostly confused. In our case the maximum of confused classes appears when UAV make a transfer from the zone that corresponds to the "fertilizing" to the zone that correspond to the "chemical treatment". This can be explained by the fact that visually these states have the similar characteristics, especially when conditions of field scanning such as angle of photography taking or lighting conditions play important role.

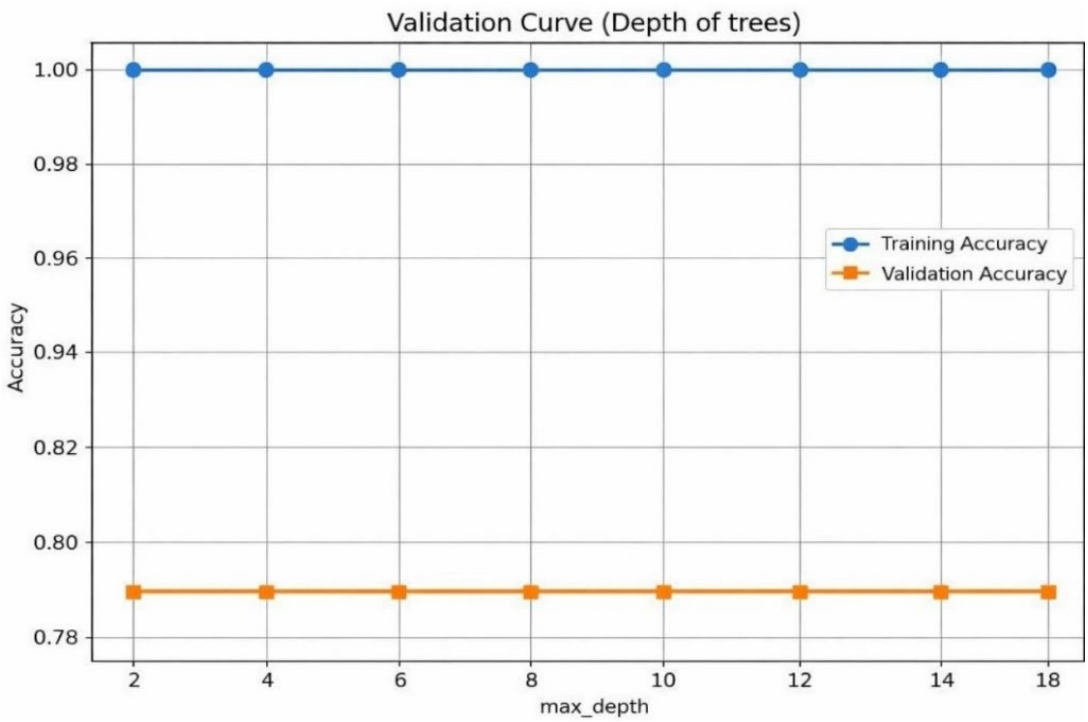


Figure 5: Model validation curve

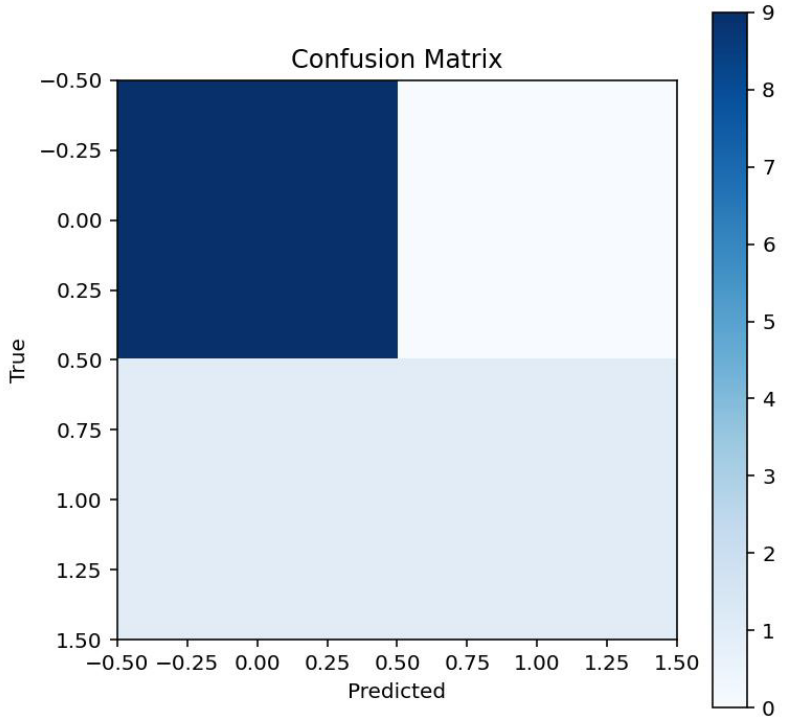


Figure 6: Confusion matrix for wheat states

To visualize the location of wheat states classes in a simplified manner we use the method of principal component analysis (PCA). This method is used to decrease the number of signs and present the data in two-dimensional domain. This is the way to transform the multidimensional data to the two-dimensional domain and keep the general structure recognizable. It is obvious that part of the information is missed when such transformation, but the general structure is kept. The two-dimensional visualization is shown in Figure 7.

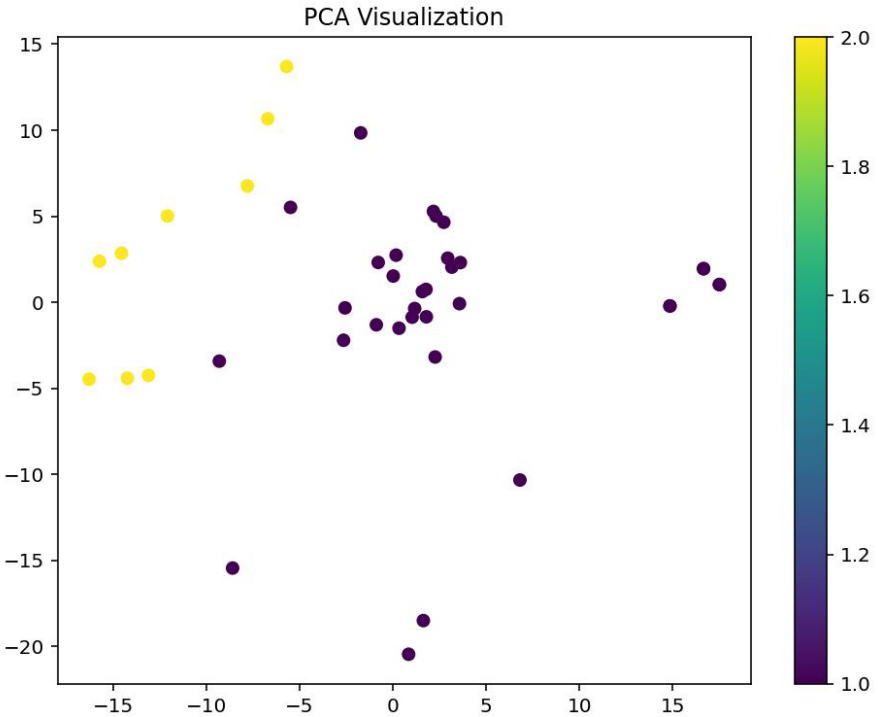


Figure 7: PCA Visualization

It is possible to see from Figure 7 that some dots create compact clusters. The other dots are sparsely distributed. This is the evidence that the model has enough information to differentiate the plant states. At the same time, it is possible to see the areas with intersection of classes. This can be caused by the range of the factors. Some of them can include:

- similar conditions of lighting,
- or shadows from the plants or some other objects (birds, low clouds etc.)
- different angle of camera
- soil heterogeneity.

The real conditions of environment are almost important to control. They can vary from case to case. Therefore, such intersection of classes can be considered rather normal situation.

Generally, the PCA visualization helps to estimate the next characteristics:

- Clearness of plant classes separation;
- Whether data has Nature clustering or not.

Analysis of Figure 7 allows to conclude that in our case, data has not chaotic structure and samples from certain groups. This is the evidence of the fact the model operation is based on real signs and patterns that are present in images.

Practically, this result can be interpreted as the prevalence of healthy plants over those requiring fertilization within the analyzed area. The proposed classification algorithm enables a clear visual and quantitative distinction between vegetation states. Healthy plants are represented by violet dots, indicating sufficient nutrient levels and normal physiological condition. In contrast, yellow dots correspond to plants exhibiting signs of nutrient deficiency, which require additional fertilization. Such a representation allows decision-making for precision agriculture applications, enabling targeted fertilization and reducing unnecessary resource usage.

4. Conclusions

In this paper we studied the potentials of novel technologies including AI and drone utilization for the agricultural task of wheat states classification for early identification of infected plants.

The Learning algorithm for real-time assessing the plant states with geomatching was presented and analysis of the YOLO model to identify the signs of wheat rust disease and classify the states of

the plants was done. The model potentials and correctness were studied on the base of the next metrics: accuracy, validation curve, confusion matrix, and PCA-visualization.

Analysis of the simulation shows that rather sufficient data volume was used for training as the difference between curves that correspond to the training and validation accuracy decreases. The data volume can be used for further training and we expect good real-time results without the overfitting. The validation curves for training and validation accuracy are not too far from each other that also demonstrates quite good results.

The confusion matrix shows the maximum of confused classes when UAV make a transfer from the zone that corresponds to the "fertilizing" to the zone that correspond to the "chemical treatment". We explain this by the similarity of the plant conditions caused by conditions of field scanning that influence the image characteristics.

The visualization of the location of wheat states classes with method of principal component analysis demonstrates the model operation that is not chaotic but is based on real signs and patterns of the images.

It is our plans for future research to continue the study taking into account the latest progress in the AI-based models for image classification. We plan to focus on model selection and strategy of model validation to make effective choice for the proposed approach for tasks of smart and precision agriculture.

5. Declaration on Generative AI

The authors have not employed any Generative AI tools.

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