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The Use of AI to Determine the Condition of Corn in a Field Robot that Meets the Requirements of Precision Farming

Justyna Stypułkowska
0000-0002-8601-4483
Łukasiewicz Research Network – Institute of Aviation,
al. Krakowska 110/114, 02-256 Warsaw, Poland
Email: justyna.stypulkowska@ilot.lukasiewicz.gov.pl
and
Faculty od Electronics and Information Technology, Warsaw University of Technology
ul. Nowowiejska 15/19, 00-661 Warsaw, Poland
Email: justyna.stypulkowska.dokt@pw.edu.pl

***Abstract*—Artificial intelligence helps to solve numerous problems in modern science and technology. AI-based image recognition allows the detection of specific features. One of the fields that uses AI-based image recognition is precision agriculture. The purpose of the solutions described in this article was to create a system based on artificial intelligence methods and use it in a real project. The article describes the methodology and results of work on tasks related to detection and recognition of corn growth stages, corn hydration levels, and detection and recognition of healthy corn and pathogen-infested corn. Details of the implementation, results and their usefulness for determining selected parameters of corn condition are presented. The developed system makes it possible to monitor the condition of corn, and can be extended to other crops in the future. The presented solution meets the requirements of precision agriculture and is in line with the idea of agriculture 4.0.**

***Index Terms*—AI, image recognition, precision agriculture, determining corn condition parameters, field robot.**

I. Introduction

The MODERN development of AI has significantly influenced the development of precision agriculture.[1] Numerous research and research centers are successfully using AI methods to achieve the primary goals facing modern agriculture [2][3], while providing an indispensable tool for efficient analysis [4], rapid prototyping and detection of selected features (e.g., object recognition in images). The achievements gained are the engine for further development of better and better solutions and implementation of the developed AI methods to more and more new applications. [5]

The present work concerns a real project implemented by the Łukasiewicz Research Network - Institute of Aviation in cooperation with the Łukasiewicz Research Network - Poznań Institute of Technology and the UNIA company titled "Polish robot - Intelligent robot that meets the requirements of precision agriculture", which fits perfectly with the theme of applying AI to modern agriculture. The main task of the aforementioned robot is to realize the assumptions that guide precision agriculture and fit into the idea of agriculture 4.0. [6] Among the numerous functions of the field robot (such as precise weeding of plants, precise fertilization of plants, navigation based on computer vision, automatic movement), of particular note from the AI point of view is the system developed for this project, the purpose of which is to automatically determine the broadly understood condition of corn (this plant was chosen as the subject of research and its cultivation is dedicated to the field robot developed in the project).

The system developed for this purpose deals with detection and recognition of developmental phases of corn, detection and recognition of corn hydration levels, and detection and recognition of healthy corn and corn infected with selected pathogens based on the RGB images acquired. Based on these values, an aggregate parameter for corn condition is determined in the next step. The system is based on the use of deep learning methods, with multiplication of calculations using a graphics card, under field conditions during field work carried out by a prototype field robot in a real time.

The system consists of four key elements: a system sensor in the form of an RGB camera mounted on a prototype field robot, a set of trained deep neural networks, a set of tagged RGB images that were used to train the deep neural networks, and an application for testing the condition of corn, through which transformations are performed using a set of trained deep neural networks.

The system that is the subject of the invention is based on a new and innovative solution that uses existing technologies, namely RGB imaging and a set of trained deep neural networks, in an area that connects agricultural producers and designers of modern agricultural machinery. This area is the support of corn cultivation, which is an important part of the domestic grain crop and an important part of the global grain crop. [7] The developed system fits perfectly into the strategy of agriculture 4.0, by using some of the latest artificial intelligence methods to automatically detect and analyze selected environmental elements.

An important element of the invention characterized by innovation is a proprietary and unique collection of labeled RGB images, containing several hundred labeled corn images in the form of RGB images, allowing neural networks to be trained to detect and recognize the developmental phases of corn and to detect and recognize corn hydration levels.

The specific challenges associated with each task are described below:

A. Recognizing the growth phases of corn

In this task, the goal was to identify the growth phases of corn, and the international BBCH scale of plant growth, or more precisely its detailing for corn, was used to accurately determine these phases. This scale encompasses several spectra of plant development, and in the conducted research fragments of the scale related to leaf development in plants were used. Thus, on this basis, the BBCH scale [8] was used, ranging from 10 to 19, where the first digit denotes the leaf scale and the second digit denotes the number of developed leaves. Fig. 1 presents an example of determining individual BBCH scale values for the indicated plants.

B. Recognizing corn hydration levels

The task was to determine in which hydration range the corn present in the photos is located. Three levels of hydration were adopted as the basic scale for which the research was conducted: low, medium and high levels of hydration, where low hydration meant exposing plants to conditions of limited access to water, medium hydration was associated with moderate access of plants to water, and high hydration was associated with regular watering of plants and maintenance of optimal levels of plant moisture. The study was conducted under soil conditions characteristic of central Poland, specifically in the village of Borowiec (Tarczyn, Mazowieckie Province).

C. Recognizing healthy corn and corn infected with selected pathogens

This task focused on determining whether the plant was fully healthy or showed some symptoms of infestation with selected pathogens.

The next chapter focuses on the datasets that served as research material for the above tasks.

II. Dataset

An important element of the described system characterized by innovation is a unique collection of tagged RGB images, which was developed strictly for the purposes of the project under implementation. The collection contains several thousand labeled images of corn in the form of RGB images, allowing to train neural networks for detection and recognition of developmental phases of corn, as well as detection and recognition of corn hydration levels.

The collection of images was acquired in the 2021 and 2022 growing seasons on a test plot established in the village of Borowiec (Tarczyn, Mazowieckie Province). Images were acquired in terms of changing developmental phases of corn (images were acquired daily throughout the growing season) and in terms of controlled access of plants to water (here, too, the relative regularity of data acquisition was maintained). In the case of the task related to the identification of healthy corn and corn infested with selected pathogens during the study, there was a problem with the controlled development of fungal infestation of plants, which, due to too low rainfall, did not develop. Therefore, the study used an external dataset [10] containing images of corn infected with selected pathogens (Helmintosporiosis, Common Rust, Gray Spot, Spodoptera Frugiperda caterpillar) and healthy corn were used during the study.

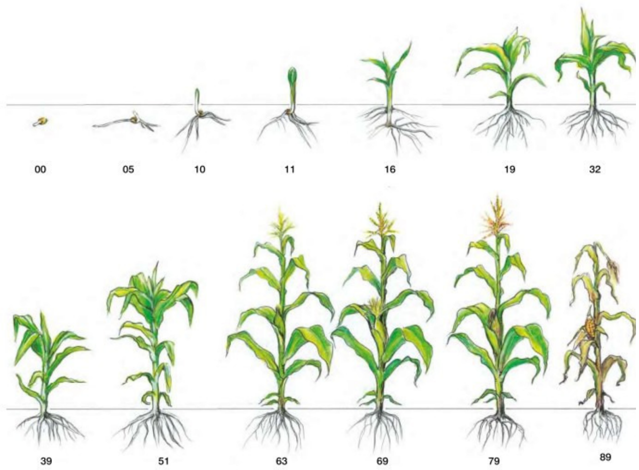

Fig. 1. Example of determining individual BBCH scale values for indicated plants (figure comes from *https://pdf.helion.pl/e_1wwu/e_1wwu.pdf*). [9]

Once the full footage was collected, the next step involved labeling selected crops. The crop concerning corn development stages was labeled using the polygon method, a very precise way, and the output of the labeling process was a .COCO file, which was then used to implement the process of training deep neural networks. The set on corn hydration levels was labeled using the ground truth method. In turn, the set on healthy corn and corn infected with selected pathogens was also labeled using the ground truth method.

Fig. 2 shows an example of the photos that went into the dataset. In some images plants are not entirely visible. It doesn't affect the results of the algorithm for determining the growing stage, because this is only the case with higher growing stages and in the dataset there are many labeled images on which plants are not fully visible. The photos were taken from the same position of the camera in relation to the rows of plants, which allows to distinguish the structure of individual plants at different stages of development. In addition, plants may have more than 9 leaves and then all cases are still classified as BBCH stage 19, so it is not necessary to count all leaves then. Fig. 3 shows a view of several labeled images that belong to the dataset. There are plans to make the proprietary dataset publicly available in the future, but it depends only on the decision of the management of the Polish Robot project.

Fig. 2. Examples of photos that made it into the dataset.

Fig. 3. Labelled photos that belong to the dataset. The colors: light green, dark blue and light purple mean respectively: phase 14, phase 17 and phase 18 of maize development on the BBCH scale.

III. Methodology

The prototype of the developed system relied on AI methods, in particular deep learning and RGB imaging, which were then used to develop a way of detecting and recognizing the developmental phases of corn, detecting and recognizing corn hydration levels, and detecting and recognizing healthy corn and corn infected with selected pathogens. One of the main goals was for the calculations to be realized in real time. In turn, the primary goal was to improve the field work carried out by the field robot and reduce the amount of crop protection products required.

The developed system is characterized by the fact that:

1) An RGB camera is mounted on the prototype field robot, which acquires images of the objects under study (corn rows). The camera acquires RGB images and is mounted in a position that allows it to acquire images of corn rows from the side, at an appropriate height, so that the places where plants grow out of the soil and whole plants or their parts are visible.

2) Then the recorded data, in the form of images of the plants under study, are sent to the computing unit.

3) In the computational unit, equipped with a corn condition application performing calculations based on a set of trained deep neural networks, analysis of the acquired images is performed. As a result of appropriate processing performed with the help of the application, network responses are obtained.

The set of trained deep neural networks includes the following artificial neural networks (characterized by the set of possible responses to their outputs):

• A network for detecting and recognizing the growth stages of corn by classifying the recognized objects: This network was previously trained on a dataset, so it can classify detected objects and assign them probabilities of belonging to the corresponding classes determined during the process of labelling images from the training set used during the training of the network.

In determining the classes and using them in the process of labelling the dataset images, the international scale of plant growth BBCH and a refinement of this scale for corn were used, resulting in a set of 10 classes as follows: "phase10", "phase11", "phase12", "phase13", "phase14", "phase15", "phase16", "phase17", "phase18", "phase19" corresponding to successive phases of corn growth. The phase numbers additionally allow to determine the moment of corn susceptibility to pathogens and the moment favorable to the use of specific plant protection products and fertilizers, which is important information from the point of view of the farmer.

• A network for detecting and recognizing corn hydration levels: this network has been pretrained on the basis of a dataset, so it can classify detected objects and assign them probabilities of belonging to the corresponding classes determined during the process of labelling images from the training dataset.

In determining the classes and using them in the process of labelling the dataset images, the parameters selected during the seeding and cultivation of corn were used, respectively: "hydration level I", "hydration level II" and "hydration level III" corresponding to low, medium and high hydration levels, respectively.

• The network used to detect and recognize healthy corn and corn infected with selected pathogens: This network was previously trained on the basis of an external dataset available on the network [10], so it can classify the detected objects and assign them a probability of belonging to the corresponding classes determined during the process of labelling images from the training dataset.

A collection of 5 classes was used in labelling the dataset images: "Spodoptera frugiperda", "Helminosporiosis", "Common rust", "Aureobasidium zeae" and "Healthy corn", corresponding to particular types of corn infestation and the case of healthy corn.

The corn fitness application is designed to continuously monitor the folder into which the images coming from the RGB camera are saved. When a new photo is detected, it is loaded by the application and then given input to a set of trained deep neural networks. The artificial neural networks then handle the processing and analysis of the received photo, and the output produces a response in the form of the name of the photo along with its location, sets of parameters calculated by the set of trained deep neural networks, a value for the length of time the photo was processed, and a timestamp value telling the time the processing was performed. These values are saved to a .csv format file with a specific location. For successive images that appear in the monitored folder and are processed by a set of trained deep neural networks, successive rows with processing results are added to the .csv file. This file can then serve as a set of data feeding the database, and being already in the database can be used, for example, to create map visualizations on the condition of corn in a given field.

The RGB camera used in the research and development of the overall system uses an array that captures the visible range, which includes the ranges:

1) blue (VIS) with a range of 400 - 500 nm
2) green (VIS) with a range of 500 - 600 nm
3) red (VIS) with a range of 600 - 700 nm

The camera during the collection of images for the dataset and during the collection of images during the operation of the field robot should be mounted at a height of about 30 cm from the ground and pointed from the side towards the row of corn at a distance of about 40 cm at an angle of 30 degrees, without the possibility of shifting.

The resulting file in .csv format contains the following columns:

1) Column 1 - "Filename"
2) Column 2 - probability of detecting level I of hydration
3) Column 3 - probability of detecting level II of hydration
4) Column 4 - probability of detecting level III of hydration
5) Column 5 - probability of detecting infestation with Spodoptera frugiperda
6) Column 6 - probability of detecting infestation with Helminosporiosis
7) Column 7 - probability of detecting infestation with Common rust
8) Column 8 - probability of detecting infestation with Aureobasidium zeae
9) Column 9 - probability of detecting healthy corn
10) Column 10 - probability of detecting growth phase 10
11) Column 11 - probability of detecting growth phase 11
12) Column 12 - probability of detecting growth phase 12
13) Column 13 - probability of detecting growth phase 13
14) Column 14 - probability of detecting growth phase 14
15) Column 15 - probability of detecting growth phase 15
16) Column 16 - probability of detecting growth phase 16
17) Column 17 - probability of detecting growth phase 17
18) Column 18 - probability of detecting growth phase 18
19) Column 19 - probability of detecting growth phase 19
20) Column 20 - value of "processing time"
21) Column 21 - value "timestamp"

The application has an image processing frequency of about 1 Hz. The application is installed on a control unit with libraries that are not expected to change during the lifetime of the system, has a permanently assigned path for downloading RGB images that does not change during the lifetime of the system, and a permanently assigned path where the output file in .csv format is saved. The adopted structure of the output file in .csv format is invariable, which guarantees that the order of columns that can feed the database at a later stage is invariable.

Below is a schematic of the data transmission in the system

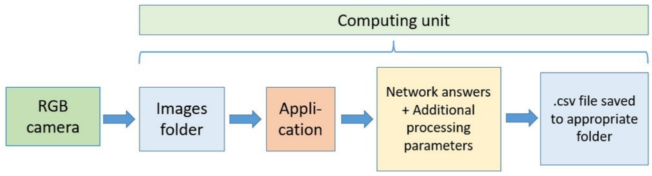

Fig. 4. Schematic of data transmission in the system.

The application was tested using the Gradio library [11], which allows visual operation of a set of trained deep neural networks, i.e. loading selected images into the inputs of individual networks, processing and analyzing the images by individual networks, and displaying the results of the networks in textual and graphical form. The trained deep neural networks for detection of corn hydration levels and corn infestation with particular pathogens produce reflections in the form of detection probability values for each class. In turn, the neural network for detection of developmental phases of corn generates responses both with regard to the value of the probability of detection of individual classes (developmental phases) and the masks visible in the image, along with the assigned value of the class and the probability of recognition of the class. The images that are processed by neural networks should be saved in typical graphic formats (e.g. jpg, png, tiff). The output of an application run through the Gradio library [11] produces numerical data and images in .jpg format with drawn masks (as opposed to an application that outputs results saved as a .csv file). Fig. 5 shows the images in the application's output, with the detected objects labeled and assigned classes and probability values.

The system can be used during the entire growing season of the tested corn crops, i.e. from April to October, depending on the region of Poland, Europe and the world. The optimal range of application of the system is to achieve plant growth from the germination period until reaching stage 19 according to the BBCH scale. The range of hydration levels that are determined by the system is from low (dry corn), through medium, to high (optimal) hydration levels.

When it comes to determining corn hydration levels, individual soil classes are key, some of which guarantee higher levels of hydration, while others don't allow as good water retention. An additional factor in determining hydration levels is the frequency and amount of precipitation and the possibility of artificially irrigating fields.

The system in which the discussed system works is schematically illustrated in Fig. 6 (this is a side view of the field robot). The system for detection and recognition of developmental phases of corn, detection and recognition of corn hydration levels, and detection and recognition of healthy corn and corn infested with selected pathogens is composed of:

• RGB camera 1 located on the field robot and directed from the side towards the corn row,

Fig. 5. View of the image on the output of the application.

• computational unit 2 connected to the RGB camera and becoming the analysis center of the system (the computational unit also takes care of placing the images coming from the RGB camera in a specific file folder),

• An application that determines the condition of corn 3 loading data from the RGB camera and performing calculations based on a set of trained deep neural networks, as well as additional calculations on the parameters and time of the performed calculations, and creating an output .csv file with the results of processing and placing it in the specified location.

The operation of the system is based on the use of an RGB camera 1 on the field robot, which acquires RGB images at a frequency of about 1 Hz. The images thus acquired are then sent directly to computing unit 2 (a computer mounted on the robot's platform), which saves the received images in an appropriate file folder. An application for determining the condition of corn is installed on the computing unit, which analyzes the acquired images. The basis of the application's operation is a set of trained deep neural networks, which have been trained using a dataset. The result of the system's operation is an output file in .csv format, which is a report of the results obtained from the output of the neural networks, which forms the basis for determining the developmental phases of corn, corn hydration levels and detection of corn infestation with selected pathogens. The generation of a .csv file makes it possible, at a further stage, to transfer the data to a suitable database and then to process them, for example, to display the results as depictions on a map. Fig. 7 shows a schematic diagram of the system, including the objects at the input of the system in the form of a row of corn 4 and the objects at the output of the system in the form of a file in .csv format 5.

IV. Results

Once the image tagging stage was completed and a complete dataset was created, it was possible to prepare and test with the dataset the selected deep neural network architectures in order to obtain the best possible results. The programming language used for this purpose was Python with appropriately selected libraries. The tests used selected architectures of artificial neural networks, the most effective of which were the following:

- Hybrid Task Cascade (HTC) with ResNet50 as a backbone
- Hybrid Task Cascade (HTC) with ResNet101 as a backbone
- Hybrid Task Cascade (HTC) with ResNeXt101 as a backbone
- Mask2Former [2021.12]

Of these, the best performance was the HTC network with ResNeXt101 as a backbone.

Fig. 8 shows a summary of the results obtained for the task of detecting and recognizing the developmental stages of corn on the BBCH scale.

Fig. 8 shows a plot of the average precision metric mAP obtained during training of deep neural networks (where the y-axis is the average precision values from all classes, and the x-axis is the successive training steps). Fig. 9 shows the results of the network with the detected objects in the form of corn, along with the identification of their developmental phases and the assignment of their class membership probability values.

The results obtained are satisfactory and allow accurate detection and recognition of developmental phases of corn. The fields drawn by the algorithm are comparable with manual marking of images, which is a great success and proves the high accuracy of the obtained solution.

A further study dealt with the identification of corn hydration levels. In this case, a collection of photos taken in a test plot was used, where hydration levels were kept under close control throughout the corn growth period. The downloaded images were divided into appropriate subsets and labeled us-

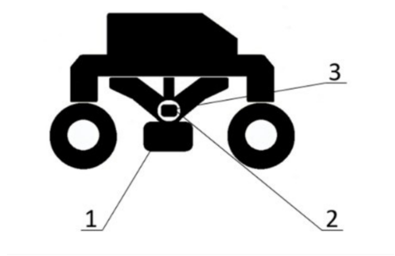

Fig. 6. Schematic view of the system mounted on a field robot.

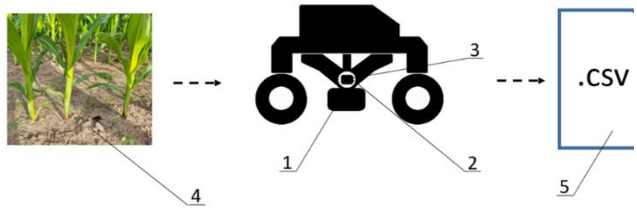

Fig. 7. Circuit schema with input and output components.

ing the ground truth label, and then the creation of the model and the training of deep neural networks were handled. A diagram of the solution concept is shown on the Fig. 10. The input shows a sample input image, then the images are fed to the input to the convolutional deep neural network, and the output gives the individual responses of the network, along

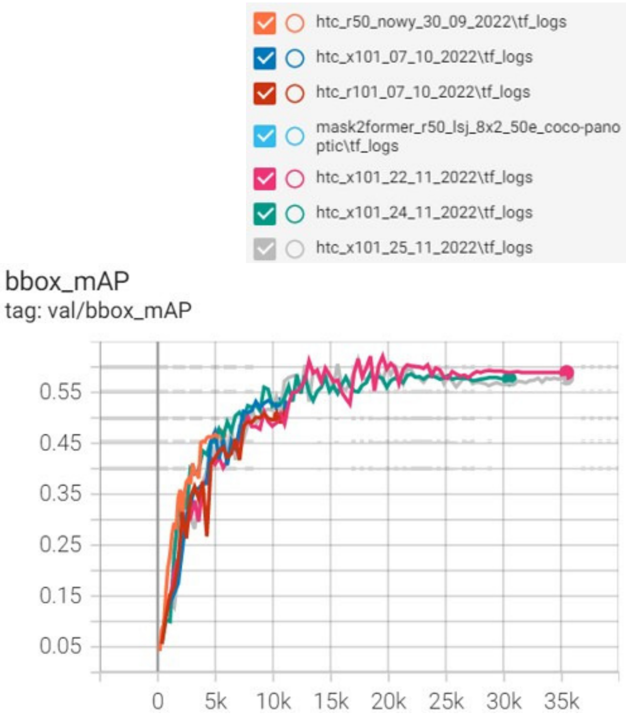

Fig. 8. Diagram of mAP average precision metric obtained during training of deep neural networks. Diagram provides a chart of mean average precision performance vs. number of training epochs.

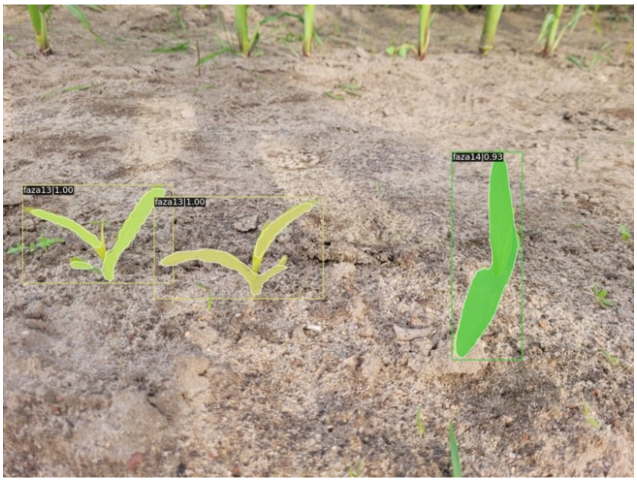

Fig. 9. Results of the network with the detected objects in the form of corn.

with the assigned probability levels of the detected object belonging to each class. These classes are: "hydration level I", "hydration level II" and "hydration level III" corresponding to: low, medium and high levels of hydration. The best results were achieved using the ConvNeXt Small architecture network for classification.

The next stage of the study was the recognition and detection of healthy corn and corn infested with selected pathogens. The images used to train the deep neural networks were of healthy corn and corn infected with selected pathogens (the study used a set of 5 different pathogen infestations, where in

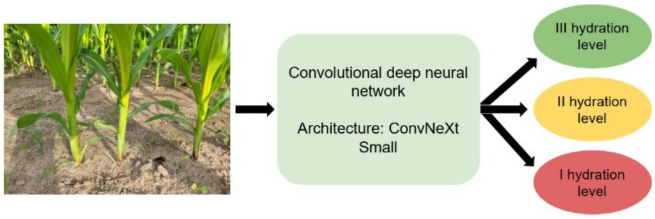

Fig. 10. Schematic of the concept for solving the problem of determining corn hydration levels.

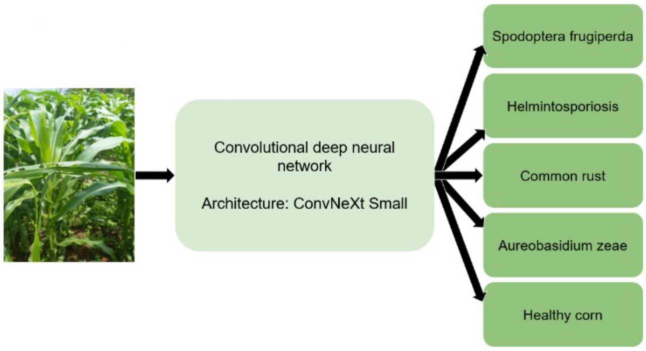

Fig. 11. Schematic of the concept for solving the problem of detection of healthy corn and pathogen-infected corn.

each crop the corn was infested with only one of the selected pathogens and there was no infestation with several pathogens simultaneously). The input to convolutional deep neural networks was given an input image, and the output received five responses with assigned probability levels for detection of individual pathogen infestations or a healthy plant state without pathogen infestation. A diagram of the solution concept is presented below. The best classification results were achieved using a network with the ConvNeXt Small architecture.

The approaches that were developed were then subjected to performance tests of all algorithms from the test set on the same single image. The results confirmed the validity of the approaches. The conclusion of the experiments confirms that the algorithms can successfully operate simultaneously with high detection and recognition accuracy.

The generalization ability of the trained algorithms has been tested also on a different corn fields than the one of the test site. The results of the developed system were tested on a robot prototype in a larger corn field. The conducted research confirmed the correctness of the adopted concepts and after confrontation of the obtained results with the analysis carried out using the human eye, the correctness of the obtained results was confirmed. Thanks to this, the use of the developed system in the prototype version of the robot was accepted and will be continue in the product version of the robot.

V. Discussion

The subject of corn cultivation supported by the application of modern solutions in the field of field robots and information technology (with particular emphasis on AI) is a fairly new topic, but already has a large number of implemented solutions. [12] The subject is constantly developing rapidly, and the research is a driving force for the introduction of better solutions and development of this branch of science and technology. [13] The analysis of the state of the art has been carried out focusing on the main tasks that the system in question performs, and attempts have been made to find other ways of approaching the same subject.

The first task analyzed was the detection and recognition of corn growth levels consistent with the BBCH scale. In the collection of available scientific articles, one has not come across an approach identical to the one discussed in this article. Determination of developmental stages is usually done manually, i.e., by a person who has to look at the plant to ascertain its developmental level. The BBCH plant growth scale has been developed for this purpose and detailed for the case of corn, but it is usually used for manual identification of developmental stages, and no one has yet carried out this identification in an automated manner. The prepared collection of labeled RGB images in the form of a dataset containing, among other things, a collection of images of corn with the designation of its individual growth stages according to the BBCH scale is therefore a unique thing. In addition, it was used to realize the process of automatic determination of developmental phases of corn with very high efficiency thanks to appropriately selected architecture of deep neural networks and training of these networks based on the collected dataset. The developed solution can run both on a standard computer in the office, using images taken in the field, and directly in the field as a solution applied to a computing unit mounted on a field robot. It is a fast method, which eliminates the laboriousness of the previous manual approach to this subject, and in addition it is characterized by high accuracy and allows to obtain a data set with results on many individual plants collected in a single file, which can input to the database.

Another of the tasks was the recognition and detection of corn hydration levels. A detailed analysis of the current state of the art indicates that this is also a unique solution. There are solutions that use deep learning to determine and predict soil moisture. [14][15][16][17] Machine learning is further used to predict soil properties in terms of permeability and water retention. [18][19][20] However, in no case has an approach been found that is consistent with the one developed in the present invention application. The dataset created, which also contains an image collections of corn characterized by different levels of hydration, is unique in terms of developing an approach based on training deep neural networks based on images of corn characterized by different levels of hydration. In addition, the developed solution allows efficient determination of corn hydration levels based on individual photos, and this process can be carried out both on a standard computer (e.g., in the office or at home) and directly in the field as a tool mounted on a field robot. As in the first task, here, too, the resulting data is made available in the form of a text file that can be an input to a database.

The third of the tasks, which is carried out with the help of the solution, is the recognition and detection of healthy corn and corn infected with selected pathogens. In this case, an available collection of labelled images [9] was found on the web that show pathogen-infected corn and healthy corn. AI-based solutions are also available that can begin to identify pathogen-infected plants.[21][22][23][24][25][26] However, the solution presented in this application is characterized by the use of additional deep neural network architectures, and the entire solution is composed with simultaneous determination of developmental phases of corn and recognition of corn hydration levels, which is unique. In addition, the adopted solution easily aggregates the data collected during the measurements into a .csv text file, which can conveniently be an input into the database. Thus, the solution demonstrates the several-track analysis of single images and allows the determination of parameters that are not realized by other available studies.

VI. Conclusions

The use of the system in question to support the cultivation of corn will affect the emergence of the possibility of accurate and rapid monitoring of the condition of individual plants, including: the determination of corn growth stages; corn hydration levels; and precise identification of the threat from typical corn pathogens. Such accurate identification is made possible by linking output data with data from a GPS transmitter, which can work simultaneously with the described system. Linking data from the .csv output file with data from the GPS transmitter is not complicated and can be done at the database.

The main goals that will be achieved after the implementation of the system in the actual project will be beneficial not only for the manufacturers of modern machinery used in precision agriculture, but primarily for the producers of agricultural crops, whose goal is to accurately monitorize their crops, the desire to reduce the amount of plant protection products and fertilizers used, as well as to obtain high yields of plants with minimum consumption of pesticides.

The developed approach may affect: the possibility of early detection of infestation by disease-causing pathogens attacking corn crops, the ability to accurately determine the hydration levels and development phases of corn, so that it will be possible to determine the moment of necessary application of necessary plant protection and fertilization products in a very precise way. As an additional effect, thanks to the data obtained with the system, it will be possible to visualize the field in terms of the occurrence of specific developmental phases of corn, specific levels of hydration and corn infestation with selected pathogens.

The practical use of the discussed system will translate into considerable benefits for manufacturers of agricultural machinery for precision farming: increasing the efficiency and accuracy of detection of plant pathogen infestation, speeding up the process of detecting corn development stages, and automating the determination of corn hydration levels without the need for additional soil sensors. The AI input will allow to reduce the production costs of highly specialized agricultural machinery, and will also allow to extend the developed solution to other crop species.

The system will also bring benefits to corn crop producers. These include the possibility of simultaneous and early detection of plant pathogen infestation, determination of hydration levels and precision determination of corn growth phases with the accuracy of individual plants. This will give a chance to react early to pathogen threats and overdrying of crop fields. This will directly reduce the usage of crop protection products. The process of automation of the crop field inspection will reduce the financial outlays necessary for the implementation of this process by standard means. Early response to pathogens, detection of insufficient hydration, as well as detection of differences in growth phases between plants in different parts of the fields will allow to achieve higher yields and increase income of agricultural producers.

In addition, the system will provide benefits for consuments and the environment. With early detection of pathogens, alarmingly low levels of hydration, and identification of areas of crop fields where plants are characterized by slower growth, it will be possible to decrease the use of crop protection products and fertilizers, which will directly reduce the release of harmful chemicals into the natural environment and food, thereby positively affecting human health.

The system under discussion, which will be well received by precision farming machinery producers and agricultural producers, will have tangible benefits for both these groups and for consumers themselves. This solution will be able to find interest not only in Poland, but also in the rest of Europe and around the world. In addition, the described system is easily transferable to other crop species than just corn, and can be an invaluable aid to the implementation of modern precision agriculture in many key plant food crops in the world.

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