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CROP WEEDS DETECTION USING NEURAL NETWORK MODELS

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Abstract: Weeds are one of the most important factors affecting agricultural production. Environmental pollution caused by the application of herbicides over the entire agricultural land surface is becoming more and more obvious. Accurately distinguishing crops from weeds by machines and achieving precise treatment of only weed species is one possibility to reduce the use of herbicides. However, precise treatment depends on the precise identification and location of weeds and cultivated plants. The aim of the work was to describe and point out the importance of deep learning models for the detection and classification of weeds, in order to enhance their application in real conditions.

Keywords: agriculture, image processing, artificial neural network, weed detection, weed control

Introduction

Nowadays, there is an initiative to automate, speed up and synchronize many processes with the help of new smart technologies. As in other areas, it happens in agriculture as well. In this way, the reduction of labor consumption is achieved while at the same time increasing the productivity of agricultural production (O'Donoghue et al., 2011, Wu et al., 2021). The aforementioned progress is due to the introduction of new technologies in agricultural production (GPS, robots, etc.).

Trends in agriculture today are directed towards food production in an ecologically acceptable way while simultaneously preserving the environment. On the one hand, the demands are to increase agricultural production with greater competitiveness, and on the other hand, the production of health-safe food with less use of chemicals is required. All the stated goals are difficult to fulfill, but it is possible, especially if the concept of precision agriculture that optimizes the use of resources is included in the production process.

The precise weed control systems developed so far cannot yet completely replace conventional systems, but they are striving for them and achieving their

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partial replacement. The basis for further progress is the cooperation of agronomists, information technologies, and mechanical engineers (science, technology, engineering, and mathematics).

One of the most important steps in the adequate application of precise weed control systems is the precise detection or classification of weeds in the field. This implies the precise determination of weed and cultivated species and the detection of the place where the plants are located. On the basis of these data, further decisions are made about the way of working of precise constructions of machines for their suppression (Wang et al., 2019).

For the purposes of weed detection, various deep learning models are very useful. They can be divided into two categories: conventional machine learning-based classification and deep learning-based classification. Machine learning refers to a group of computerized modeling approaches that can learn patterns from the data so as to make decisions automatically without programming explicit rules (Singh et al., 2016; Wang et al., 2019).

The aim of the work was to describe and point out the importance of deep learning models for the detection and classification of weeds, in order to enhance their application in real conditions.

Deep learning model

Detection of crops from captured images is performed by a pre-trained deep learning model. Deep learning is a part of artificial intelligence that focuses on solving problems using neural networks which are trained using large amounts of data. A neural network consists of artificial neurons organized in layers, where there is an input layer, one or more hidden layers, and an output layer. Each layer contains artificial neurons, known as nodes, which are connected with the nodes in the next layer. Each node has two parameters weights and threshold, where weight is defined during the training phase. The weights parameter for each node is updated for every known input and output data during training and represents a learning mechanism. During the training, the accuracy of the neural network improves until it reaches sufficient accuracy to predict the output or to cluster and classify new input data.

Our proposed model was defined as a neural network for classification images implemented with the Keras framework. Keras has a high level of abstraction, which is relatively easy to use due it is written in Python programming language. Keras build on top of the TensorFlow framework and could easily use all its capabilities and cover every aspect of the learning workflow. TensorFlow is an open-source platform for machine learning that has an entire ecosystem of tools and libraries with adequate community support. All these resources allow the development of applications based on machine learning by data scientists and data engineers (Keras, 2023).

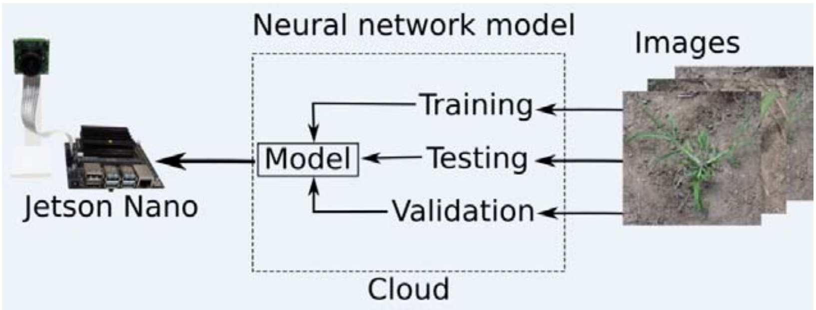

Figure 1. Prepering Neural network model for Jetson Nano

The weeds images are split into the images for the training set and two smaller set for testing and validation, which were loaded into the model using Keras framework. Usually some preparation of data is necessary which would be input to the first layer in implemented neural network. Then the parameters of the neural network are defined and training process is conducted. The entire model finding process should take place in the cloud using an infrastructure with sufficiently high performance. After training phase, model was tested against unused data to check accuracy of obtain model. If the result of testing phase is satisfactory then train model could be used to classify weeds or recognize weeds or benefit crops. Then entire model is saved in appropriate format than it could be transfer to field devices used to detect weeds (Figure 1).

Deep learning applications are based on matrix computations which require computers with high processing power. Field devices, on the other hand, have a set of spatial and power consumption constraints, so they need to be energy efficient to execute such high-performance deep learning applications. Raspberry PI single-board computer was first used in such applications, but its real-time performance in image processing applications was very limited to less than one frame of video per second. The main reason for the poor performance of Raspebby PI’s dual-core ARM processor is that it was not designed for fast matrix operations. Raspberry Pi performance was slightly improved in such applications using Intel Neural Compute USB Stick, which was used to offload the processor from matrix intense operations. Graphical processing units have dozens of cores, which makes them more suitable for matrix operation when compared to the central processor. NVIDIA, a leading manufacturer in graphics processing units, launched the Jetson Nano computer board with a built-in 128-core Nvidia GPU for accelerating deep learning applications. Jetson Nano has quad-core ARM central processor which with assistance of integrated 128-core NVIDIA Maxwell GPU could reach performance level of 472 GFLOPS, or 472 billion floating point operations per second. Such performance levels are dozen times better when compared to Raspbeery PI, which makes Jetson Nano suitable for real-time image processing applications as shown by Assunção et al. (2022). Jetson Nano has small dimensions of 100x79 mm and power consumption of 5-10W so it can be powered by rechargeable battery. It runs Linux operating system which is preloaded onto the SD memory card.

Application of deep learning models in agriculture

Weeds are one of the most important factors affecting agricultural production. Their control is carried out using herbicides that affect environmental pollution. The reduction in the use of herbicides has so far mainly been reduced to compliance with the recommended doses of application as well as to the harmonization of their application with the measures of mechanical weed control. Today, there is a trend to develop smart systems that first perform precise weed detection. The collected data is then precisely processed. In the end, a precise application of herbicide in a certain amount is carried out only in those places where there are weed plants. The goal is to apply the minimum amount of herbicide, in the right way in the right place, and at the right time (Šćepanović et al., 2018, Wu et al., 2021).

The prerequisite for choosing the most effective herbicide or their combination is the determination of the weed flora in the field. The correct determination of weeds is particularly important in the earlier stages of development, that is, in the stage of development of cotyledons and the first leaves, because the application of herbicides in these stages enables the use of lower concentrations. In this way, a reduction in the amount of herbicides introduced into the environment is achieved.

The correct determination of weeds is the basis for the application of the DSS (decision support system) model, and the weed germination forecast model, which indicates to the producer which herbicide, in what dose, and at what time, should be applied.

Determining weeds in the stage of cotyledons and first leaves is the most difficult to do in practice. This is especially demanding with monocotyledonous weed species (grasses) which are morphologically very similar. In order to make the determination of weed species easier and faster for agricultural producers, various applications are being developed for the automatic digital recognition of weed species. The idea of these applications is to provide the agricultural producer with the help of modern technology (ordinary smartphones) information about which weed species dominate the field.

Various morphological characteristics of plants are used to identify weeds, such as the shape of cotyledons and leaves, color, surface structure and texture, shape of edges and leaf surfaces. The algorithm compares such information with features "learned" from the photos used to create the algorithm. As an output, the model suggests a series of species for which the algorithm has calculated a high similarity to the photographs. The result is transmitted back to the user's device (smartphone) and provides information about the weed species represented. Until now, only applications have been developed for the determination of dicotyledonous weed species, which is expected due to the high level of difficulty in recognizing monocotyledonous species (Šćepanović et al., 2018).

Santel i sur. (2018) state that such applications for some weed species that have specific leaves gave very high precision of identification, while for species that have more complex and denser leaves, it is less reliable.

According to the results of Razfar et al. (2022) using a deep learning model can positively influence the efficiency, application time, and total soybean production with high accuracy.

The mentioned models can be of special interest in the Republic of Serbia and similar countries. Namely, our conditions are characterized by a large number of small, fragmented individual farms that do not have direct contact with experts in the field of plant protection. In such conditions, this technology facilitates the detection of conditions on the ground, and on the basis of this data, it is easier to find the right solutions that should be applied in weed control in accordance with current trends.

Conclusion

The main aims of modern plant protection are the optimal intake of resources while maintaining high yields and crop quality and reducing environmental pollution and degradation. In order to succeed in this, one of the solutions is to reduce the application of herbicides to a minimum while maintaining high efficiency with the help of precision agriculture. Robotic weed control with targeted herbicide application can reduce the use of herbicides by up to 90%. Choosing the right herbicide, time, and place of application can be facilitated by new technologies for determining weed species such as deep learning models. These models can then be transferred to smaller field devices such as the Jetson Nano suitable for image processing.

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