NEURAL NETWORK TESTING FOR SPOT-APPLICATION OF PHYTOSANITARY SUBSTANCES IN VEGETABLE CROPS USING A SELF-PROPELLED ELECTRICAL SPRAYER

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TESTAREA UNEI REȚELE NEURONALE PENTRU APLICAREA ȚINTITĂ A SUBSTANȚELOR FITOSANITARE ÎN CULTURILE DE LEGUME FOLOSIND O MAȘINĂ DE STROPIT AUTOPROPULSATĂ ELECTRIC

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ABSTRACT

For negative effects minimization generated by agriculture on the environment, there were established a series of measures regarding the reduction of the amount of fertilizers and phytosanitary substances used. Thus, one of the innovative technologies appeared on the market is represented by the usage of some automated equipment for selective spraying of targeted plants, this way significantly reducing the amount of active substances used. The paper presents the usage of a technique specific to artificial intelligence for identification of target crops and their proper treatment. Thus, was developed a convolutional neural network formed of six neuron layers, which was used for analysis of crop field images recorded with a LOGITECH HD Pro C92.0 video camera. The network was developed in C++ programming language, using function libraries from OpenCV, and has run on a Dell laptop, with Intel i8 processor. Following images analysis and targeted plants identification, from laptop there are sent ON/OFF commands through an Arduino microcontroller toward the electrical microvalves mounted on the nozzles of a self-propelled electric spraying machine having a working width of 8 m, with the purpose of spot-spraying the crop plants and reducing the amount of used substances. In this paper are presented the experiments done for testing the neural network efficiency.

REZUMAT

In scopul minimizarii efectelor negative generate de agricultura asupra mediului s-au stabilit o serie de cerințe privind reducerea cantităților de substanțe fitosanitare și fertilizanți. Astfel, una din tehnologiile inovative apărute pe piață este reprezentată de utilizarea unor utilaje automatizate pentru stropirea selectivă a plantelor țintă, reducându-se astfel semnificativ cantitatea de substanțe active folosite. Lucrarea prezintă utilizarea unei tehnici specifice inteligenței artificiale pentru identificarea culturilor țintă și tratarea acestora corespunzător. Astfel a fost dezvoltată o rețea neuronală convoluțională formată din șase straturi de neuroni, care a fost folosită pentru analizarea imaginilor câmpului de cultură înregistrate de o cameră video LOGITECH HD Pro C92.0. Rețeaua a fost dezvoltată în limbajul de programare C++, folosind librării de funții din OpenCV, și a rulat pe un laptop Dell, cu processor Intel i8. În urma analizei imaginilor și identificării plantelor țintă, din laptop se trimit comenzi de PORNIT / OPRIT printr-un microcontroller Arduino către microvalvele electrice montate pe duzele unei mașini de stropit autopropulsată electric cu o lățime de lucru de 8 m, în scopul stropirii țintite a plantelor de cultură și reducerii cantității de substanțe folosite. În cadrul lucrării se prezintă experimentele efectuate pentru testarea eficienței rețelei neuronale.

INTRODUCTION

In the field of conventional agriculture, inputs of chemical substances have been used to increase production. Unfortunately, the use of a significant amount of chemicals (such as fertilizers or herbicides) involves serious problems related to water contamination, health risks (for workers and food consumers), reduced biodiversity and risks of developing weeds resistant to herbicides.

Smart agriculture involves the objective of continuing to use herbicide chemicals but significantly reducing the amount of chemicals to maintain production efficiency by killing weeds (*Latha A. Poojith et al., 2014; Jianlun Wang et al., 2013; Jianshu Chen, 2013; S.J. Rees et al.*).

In order to achieve this objective, one way is to only administer the substances in the area where it is located spatially and in this way the administration of the herbicide to the plant or the soil is avoided. In a similar case, for the administration of a chemical fertilizer, it would only be administered to the plant.

Image classification is a key component in the field of artificial vision algorithms to develop applications such as: surveillance, traffic monitoring, collision avoidance, face recognition, augmented reality, ocular tracking, medical imaging, agricultural industry, etc.

Classification is a process of assigning a user-defined class to an object in a scene. Some of the classification methods used on the scale are: Bayes-Naiv Classifier, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Logistic Regression, Neural Networks and other classifiers (*Jain AK et al., 2000; Ian H. et al., 2005; Cortes C. et al., 1995*). The biggest advantage of these classifiers is their ability to perform classification using relatively low computational resources.

The emergence of classification methods based on neural networks has generally resulted in improved image classification accuracy (*Jain et al., 2000*). Algorithms that work using ANN-based classifier networks offer good performance when working with large datasets consisting of hundreds of classes. A fully connected ANN is a core of modern image classification and detection algorithms. The standard architecture of ANN includes an input layer, few hidden layers and an output layer.

There are various approaches and experimental prototypes for the task of achieving intelligent spraying (Figure 1) (*A. Shinde et al., 2014; A. Perez et al., 2000; Sethy P.K. et al., 2019; Knoll F.J. et al., 2018; Patil J.K. et al., 2017*).

Fig. 1 - Experimental spraying systems (*Knoll F.J. et al., 2018; Patil J.K. et al., 2017*)

Since intelligent spray systems will have a low price, it is need to identify low-cost electronic components for the cameras used in such systems. Also, the evolution of cameras on the market and the appearance of new cameras requires us to develop algorithms that produce similar results, regardless of camera brand, in the same quality class. The artificial vision algorithm testing procedure must take into consideration testing on different cameras but also in specific situations that arise in reality.

Regarding optical errors, systems with artificial vision must take into consideration the treatment of the problem of their elimination, caused by the manufacturing precision of the lenses, which in the medium-priced cameras are made of plastic material and not of glass. The importance for identification applications is accentuated in an artificial vision application because the algorithm may fail as a consequence of distortions. High-quality glass lenses do not cause serious errors and are used in practice in computer vision applications, but they are also many times more expensive than optics used in webcams. Ideal lenses refract light rays accordingly so as not to influence light waves. However, even glass lenses are made by polishing glass, which by default means that each lens has unique properties.

The main types of aberrations that appear either due to optics, but especially due to a wrong focus or due to the large relative movement of some portions of the image, according to several authors (*Cortes C. et al., 1995; M. Mustafa et al., 2007*) are:

• Distortion: pixels are mapped to incorrect locations relative to reality, as is the case when an object is moving at a high-speed relative to the camera;

• Spherical aberration: marginal light rays bend more than those near an optical axis, therefore producing two separate images;

• Field curvature: the actual image plane is curved rather than flat since all paraxial rays converge through a single focal point;

• Chromatic: A refractive index depends on the wavelength leading to the bending of the colours of an individual light beam, consequently causing blurring.

An approximate linear correction algorithm can be created even if the exact error model is not known. In this context, linear correction means that the locations of the pixels are changed by determining the coefficient, the size of which depends on the distance from the optical axis. This can work as a first aid for error minimization, but advanced calibration algorithms use high-order polynomial functions due to the non-linear nature of the distortion.

Probably the most famous calibration algorithm was proposed by Tsai (*Shinde et al., 2014*). In that method, the calibration is performed in two consecutive steps (*Perez et al., 2000; Sethy et al., 2019; Knoll et al., 2018*), first solving the rotation and translation parameters and then the remaining ones. Testing the functioning of algorithms must take into consideration real situations, to avoid malfunctioning or blocking of algorithms (*Patil et al., 2017; Hlaing et al., 2014; Zhao et al., 2009; Garousi et al. al., 2016; Moghadam M.H., 2019; Shen et al., 2009; Frommknecht et al., 2014; Perona et al., 1990*).

MATERIALS AND METHODS

The experimental sprayer model used for the experiments consists of three main electrically driven systems, a self-propelled mobile platform, a boom spraying system and the neural network control system. The first system is a mobile platform driven by a 12 kW variable speed electric motor powered by a three-phase controller that converts the electricity from a 96 VDC Li-ion battery into three-phase variable frequency electricity. The advantages of the platform consist of zero toxic emissions due to electric propulsion, increased mechanical torque even at very low speeds and low weight. The li-ion battery can also be charged from renewable energy sources. The system for spraying and biological protection of plants is mounted on the mobile platform and is also an electrical equipment destined for the distribution of phyto-pathological treatments for vegetable crops, driven by a 3 kW motor powered by a 48 VDC battery.

The main technical characteristics of the electrically driven spraying machine are:

Table 1

Main technical characteristics of the electrically driven spraying machine

Characteristic	U.M.	Value / Characterization
Rear wheels Gauge	mm	1320
Wheelbase	mm	2600
Electric drive motor	kW	12
Li-ion battery	VCC	96
Solution tank capacity	l	400 l
Tank material	-	glass fibre reinforced resin
Pump motor	kW	3
Maximum flow rate of the pump	l /min	86 l/min
Maximum working pressure	bar	20 bar
Line filter	-	with self-cleaning and discharge on hydraulic agitator
Agitation system	-	with hydraulic stirrer
Boom length	m	8
Number of boom sections	-	3
Number of nozzle holder	-	32
Pressure and flow regulator	-	3 way
Capacity of the clean water tank for human operator	l	10
Solution indicator	-	through transparency
Platform structure	-	galvanized steel

In order to achieve the targeted application of phytosanitary substances on crops, microvalves were fitted for each port-nozzle support of the dosing system boom. The solenoid valve coil works in an ON/OFF manner at 12 VDC. The system thus created allows the individual control of each nozzle separately by means of electromagnetic microvalves controlled by a central computer, based on an algorithm to identify cultivated vegetables using real-time images taken from an RGB video camera, processed using a neural network. After identifying the cultivated plants, the microvalves located above them are commanded so that the substances are applied only to the respective plants.

Fig. 2 – Electric self-propelled spraying machine - experimental model

The neural network used was a multi-layer convolutional neural network (CNN) type that consists of two different types of layers, i.e. convolution layers (c layers) and pooling layers - p layers. C layers and the p layers are alternately connected and form the middle part of the network. As shown in Figure 3, the input image is convolved by successive filtering to produce feature maps in the first layer c. The network architecture used consists of 4 hidden layers and of course an input layer and an output layer. The 4 layers are convolutional, pooling and two fully connected layers. The convolution layer is the building block of the CNN, which bears the main responsibility for the computation. The input layer accepts three-dimensional input, represented by an image in the spatial form of the size (width × height) of the image, but also the third dimension represented by the colour channels (in this case RGB (Red, Green, Blue). A proprietary set of 200 weed images and 100 crop plant images were used for training. The C++ language was used for the development of the program, the library of functions intended for the processing of OpenCV and AI platform Caffe images.

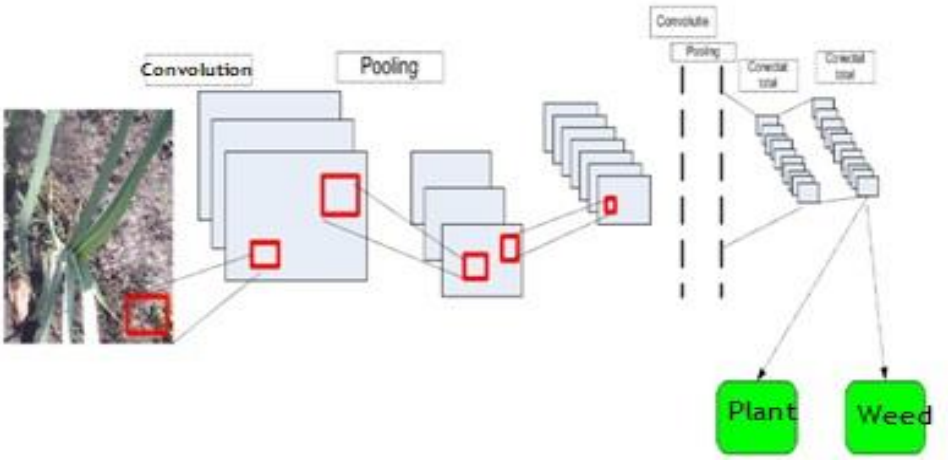

Fig. 3 - The network architecture used

The camera used was a LOGITECH HD Pro C92.0 webcam. The recognition process takes about 100 - 50 ms per image (or 10 - 20 fps) to detect a weed target before a new image is captured and ready for processing, which allows the data to be processed to enable command in real time for real situations.

A laptop receives the data flow from the cameras and, depending on the identification of the weeds, commands the central controller of the machine, connected to the relays for actuating the microvalves of the spray nozzles.

Special problems that appear in the field of image processing are known, but especially in the case of real-time recognition tasks, due to variations in light intensity. If in the case of industrial applications this problem is solved by the fact that in the controlled environment in which artificial vision systems work, the properties of light can be controlled in detail, in the case of applications that work in a natural environment, the light intensity varies during the day in a significant manner.

Various developments have used coating systems to allow the control of light intensity (Figure 4). This method, however, does not allow the elimination of the problem of light intensity variation, because due to the condition that the covering screen must be placed at a distance from the ground in order not to hit the plants, natural light penetrates through this space. This type of system has multiple disadvantages, namely that it needs to be repositioned and adjusted for each crop, and in the case of certain crops it leads to a disadvantageous flow of sprayed substances.

Fig. 4 - Smart spraying system equipped with canopy (*Patil J.K. et al., 2017***)**

Identification algorithms should provide high accuracy under all conditions, so they must also be tested for light intensity variability. The following figure shows the stages of testing the robustness of the neural network algorithm.

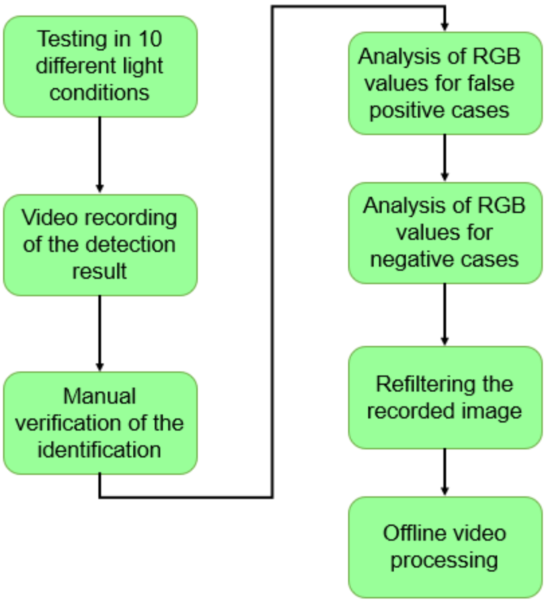

Fig. 5 - The stages of testing the robustness of the algorithm in different lighting conditions

RESULTS

With the experimental model of the spraying machine, the same rows of onion plants were tested for 4 consecutive days, in different luminosity conditions. Although the position relative to the camera for the same plant location is different, in the 10 passes performed, due to the fact that the same trajectory cannot be reproduced every time and because the plants change their position due to weather factors, as well as the fact that plants grow within the 4-day test interval, it is considered useful to test the algorithm in this way to check robustness to brightness variation.

It can be noticed that the capture conditions (height and viewing angle) emulate real situations when the light intensity varies, but also the distance from the camera to the ground due to the appearance of some vertical movements in the machine.

The videos were always captured during daylight hours and the wind speed was very low or zero to avoid the occurrence of technical problems regarding the appearance of drops on the camera. The lux meter used to measure the brightness was LX 1010B.

Table 2

Results obtained from the experiments using the electrically driven spraying machine

No.	Luminosity (lux)	Neural network identification accuracy (%)	False positive (%)
1	5000	92.11	8.12
2	8590	91.98	10.11
3	12456	93.23	9.12
4	45890	91.16	11.12
5	90456	89.16	9.11
6	125600	95.30	7.9
7	130567	91.26	9.67
8	14786	91.36	10.2
9	225786	92.51	11.21
10	250456	91.06	11.12

Testing in different condition

As shown in the figure below (Figure 6), even when dry plant remains appear in the scene, and the crop plant (onion) is partially dry, the algorithm works without causing false-positive identifications.

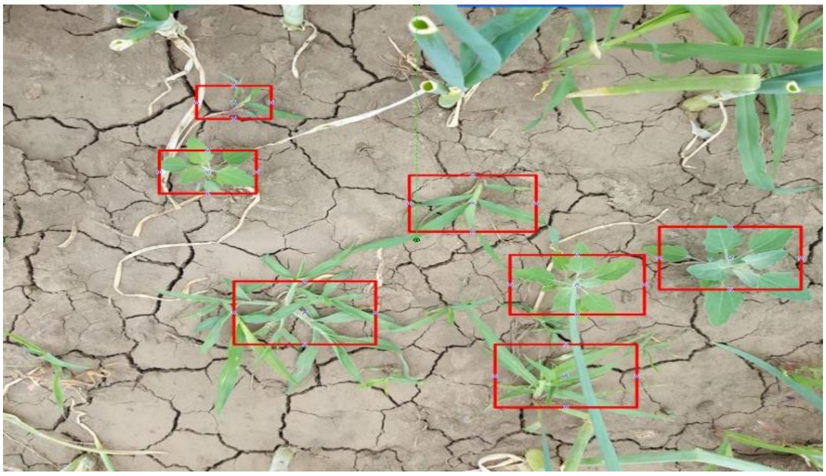

Fig. 6 - Identification in the case of the existence of plant remains

In the figure below (Figure 7) the operation of the algorithm can be seen even in the conditions where, due to a misalignment of the row, the camera is not positioned above the intervals between the rows of plants, but is positioned above the row. This situation occurs frequently in real situations when, due to some technical conditions of the ground, the row is not straight. The developed algorithm works with very good results even in this situation.

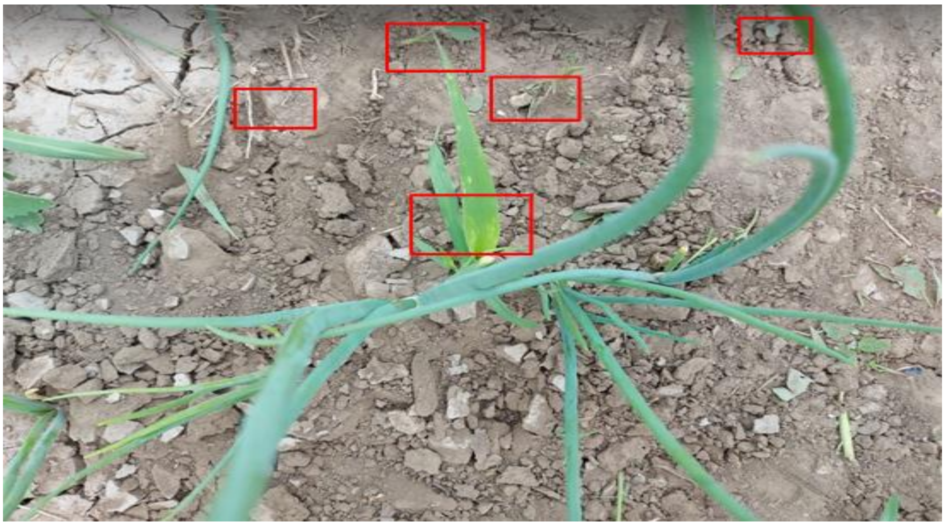

Fig. 7 - Identification in the case when the camera is above the crop plant

For the case when the plant is so close to the camera that a certain portion of it is not in focus, as shown in the figure below (Figure 8), the algorithm has a good detection rate.

Fig. 8 - Identification in the case when a certain area in the scene is out of focus

In the case when the plant is very close to the central area of the camera, as seen in Figure 9, due to the fact that the image is blurred, the weeds are not identified with a very good accuracy. In position 1, the top of the plant is observed to be weakly focused.

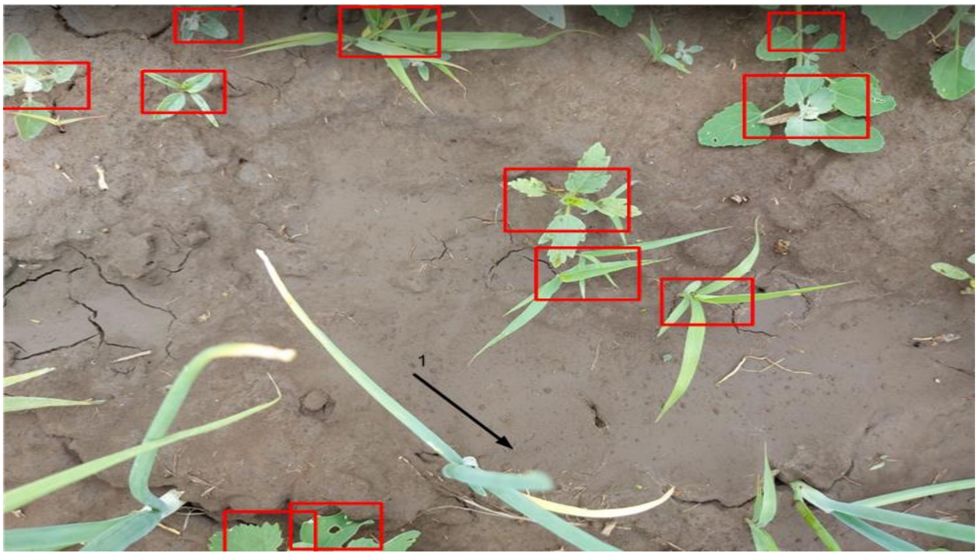

Fig. 9 – Identification in the case when the plant is near the camera

For the case when there are weeds with a considerable length in the scene to be analysed, as is the case below, the algorithm worked with a good detection rate (Figure 10).

Fig. 10 – Identification in the case when the weeds have a considerable length

As shown in the images below (Figure 11), the algorithm developed works for any kind of soil texture, which translates into a distinctly different colour and appearance between tilled, wet or dry soil.

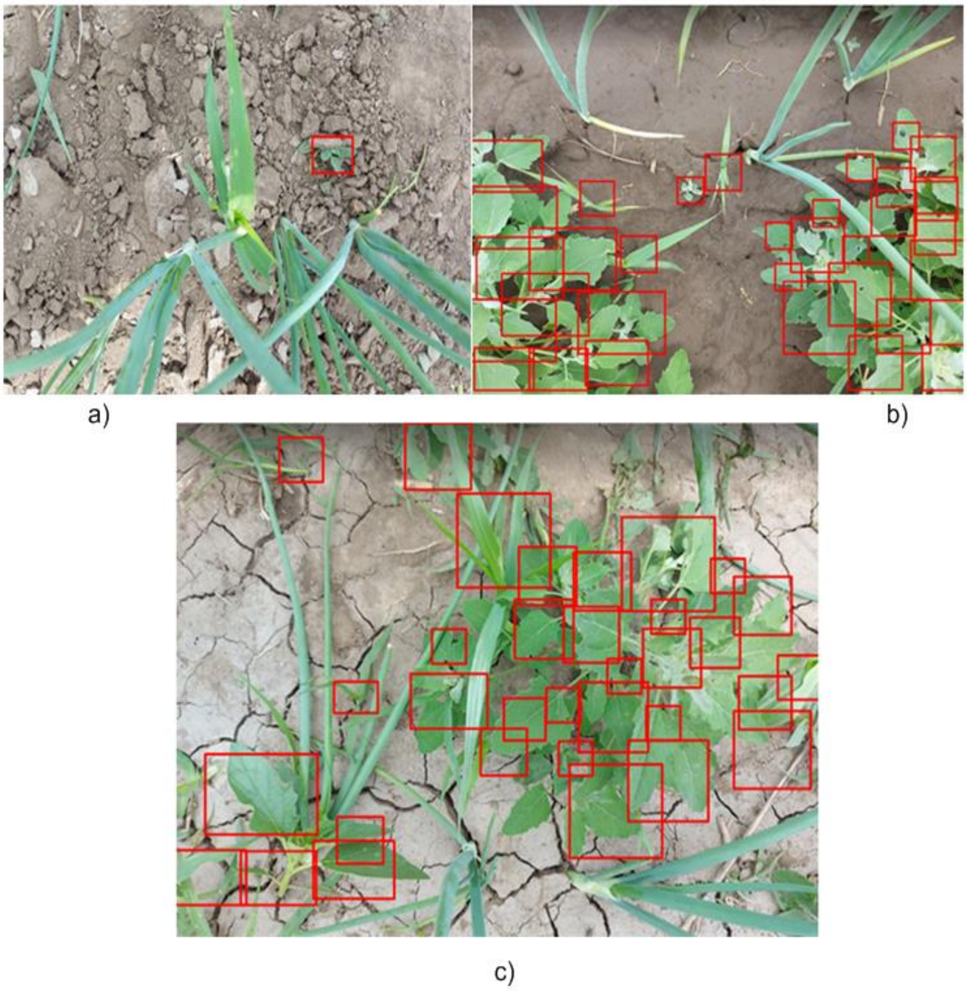

Fig. 11 - Identification of weeds in scenes with different soil texture: a) texture for tilled land, b) texture for wet land, c) texture for arid land

Due to the proximity to the camera of a leaf that occupies a considerable area in the scene, the camera focuses on the nearest considerable area, as is the case below. In the tests considered, there were only 7 positions with this situation, but the detection was at a good rate.

Fig. 12 – Identification in the case when weeds occupy a considerable area in the scene

Night time functionality testing was done to test the capabilities of the algorithm. Unfortunately, due to the artificial lighting and the characteristic of the LED light, the results decrease, and in the areas where there is less light, due to the positioning of the lighting system, it is obvious that the weeds cannot be identified at a high rate. The identification accuracy is 40%.

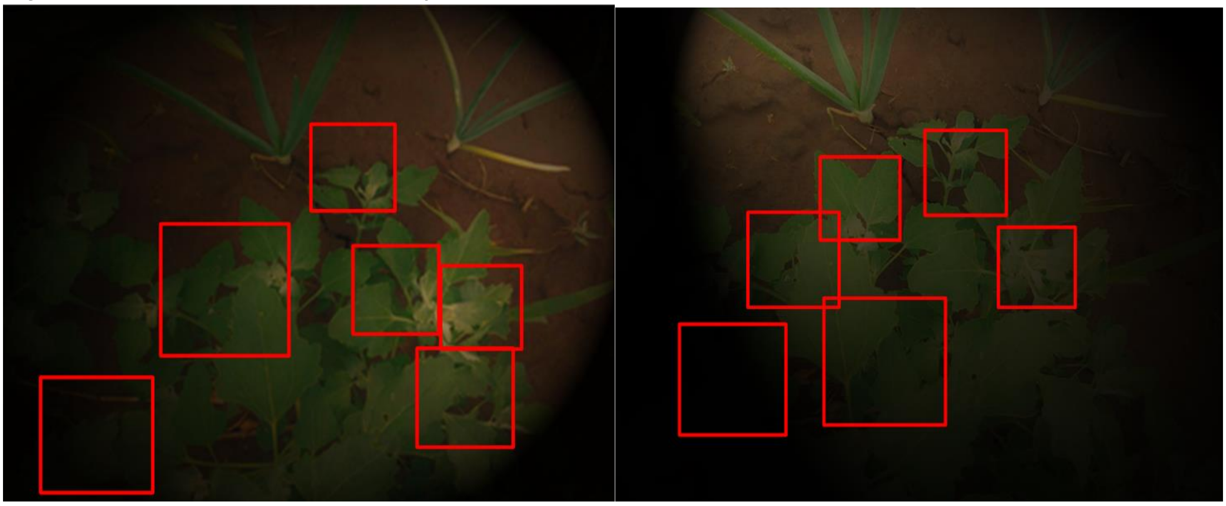

Fig. 13 - Tests carried out at night using LED lighting

CONCLUSIONS

Following the tests carried out, the following can be stated:

- the neural network algorithm is robust even in conditions of variable luminosity;
- at night, using LED lighting, the identification accuracy partially decreases, especially since the lighting system does not make the image visible in its entirety;
- several situations from reality were taken into consideration, such as: different texture of the soil, weak focus, the existence of plant residues in the scene;
- the algorithm works even if the camera takes information above the plant or above the interval between crop rows.

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