The problem of multiple zones in computer vision, including pattern recognition in the agricultural sector, occupies a special place in the field of artificial intelligence in the modern aspect.

The object of the study is the recognition of weeds based on deep learning and computer vision. The subject of the study is the effective use of neural network models in training, involving classification and processing using datasets of plants and weeds. The relevance of the study lies in the demand of the modern world in the use of new information technologies in industrial agriculture, which contributes to improving the efficiency of agro-industrial complexes. The interest of private agricultural enterprises and the state is caused by an increase in the yield of agricultural products. To recognize weeds, machine learning methods, in particular neural networks, were used. The process of weed recognition is described using the Mark model, as a result of processing 1,562 pictures, segmented images are obtained. Due to the annual increase in weeds on the territory of Kazakhstan and in the course of solving these problems, a new plant recognition code was developed and written in the scanner software module. The scanner, in turn, provides automatic detection of weeds. Based on the results of a trained neural network based on the MaskRCNN neural network model written in the scanner software module meeting new time standards, the automated plant scanning and recognition system was improved. The weed was recognized in an average of 0.2 seconds with an accuracy of 89 %, while the additional human factor was completely removed. The use of new technology helps to control weeds and contributes to solving the problem of controlling them

Keywords: computer vision, image segmentation, neural network model, pattern recognition algorithms

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IDENTIFICATION OF WEEDS IN FIELDS BASED ON COMPUTER VISION TECHNOLOGY

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1. Introduction

Industrial agriculture is one of the industries that bring great benefits to humanity. In the modern world, work is underway to fully or partially automate this industry. There is a growing demand for efficient and safe methods of agricultural production [1]. Traditional methods of agricultural management should be complemented by innovative sensor and mobile technologies, as well as advanced information and communication technologies to accelerate the increase in agricultural productivity. Over the past few decades, computer vision surveillance systems have served as an important tool in rural operations and their use has increased significantly [2]. The growth of weeds, which hinder the growth of crops on agricultural land, is one of the main problems of agronomists. One of the most rational methods is to use information technology in their recognition. For example, Kazakh scientists in weed recognition developed a weed detection system based on the yolov5 architecture as a result of studying the territory of southern Kazakhstan. By the results of the evaluation of k-nearest neighbors classifiers, the accuracy of weed detection, RandomForest and DecisionTree, was 83.3 %, 87.5 % and 80 %. Since weed images differed in resolution and illuminance level, neural network results had corresponding scores ranging from 0.82 to 0.92 for each class [3]. There are different climatic zones in Kazakhstan, so different weed species are found in different regions. This study is based on the recognition of weeds found in the northern region of Kazakhstan. The process of using a neural network model and training images of weeds with their subsequent recognition will improve the quality when scanning plants in the process of weed detection. The joint work of scientists in the agricultural sector and information technology will automate the work of farmers in the search and detection of weeds.

The results of scientists' work in the field of weed recognition by computer vision methods require training with a large amount of data. Initial research by agricultural scientists provides an opportunity to cover all kinds of weeds growing in Kazakhstan and neighboring countries. The resulting IT solution of this study is an integral part of the work of production workers in the agricultural sector. In practice, they can use a neural network-based weed recognition program, which is supplemented with new types of weed images that replenish the database. The software module of the scanning equipment can be easily improved and modified.

The problem of weed control is increasing every year all over the world. To solve this problem, it was proposed to consider such plants as hogweed, kochia, ragweed and crowberry and six types of crops: black bean, rapeseed, corn, flax, soybean and sugar beet [4]. The proposed solutions either did not consider other weeds, limited only to hothouse plants, or used old technologies (Viola-Jones method, gradient histograms, infrared rays). The development of new information technologies in order to save time in data analysis allows you to quickly get more accurate results of data processing, including data on weeds.

The main problem is that the available machine learning databases do not cover all types of weeds, hence the training base is not sufficiently filled with data. The problem of this topic is to identify weeds using computer vision. In particular, to propose a software module of a scanner for recognizing plants and analyzing their images. This process automates and accelerates weed detection.

Based on preliminary studies conducted on the market of Kazakhstan and the world, it was found that the identification and destruction of weeds is a big problem, which can be qualitatively helped by new technologies. If these issues are resolved, private agricultural enterprises and agro-industrial complexes under the jurisdiction of the state register will increase the productivity of arable land.

Thus, from the research conducted on this topic, the use of artificial intelligence in the agricultural sector and the joint work of agricultural scientists and IT technology are relevant. An analysis of research in this area shows that in-depth investigation and selection of the optimal training model for automatic weed detection are required.

2. Literature review and problem statement

Innovative technologies based on artificial intelligence cover all sectors of state industry and economy, including the agricultural sector.

The paper [5] presents traditional methods of agricultural management with innovative sensor and mobile technologies, as well as advanced information and communication technologies to accelerate the increase in agricultural productivity. The results of the research indicate the need to use advanced software systems to increase agricultural productivity. The annual growth of weeds in fields, with the intensive introduction of IT technology, requires the implementation of an automatic solution for their rapid detection, which is one of the most pressing problems. The reason lies in objective difficulties, i.e. the inability to completely destroy the weed and separate it from the crop, to be sure that it will be destroyed. A number of losses are also increasing: acreage inspection, work to ensure that the detected plant is a weed or crop, provision, etc. However, research methods in this direction, expert and intelligent systems based on computer vision algorithms according to the results of the work [2] are a common part of agricultural management. And the technology of agricultural automation based on computer vision is often used in this field to increase productivity and efficiency. In [6], with the development of GPU (GraphicsProcessingUnits) and DBN (DeepBeliefNetworks) technologies, computer vision technology has given farmers many proposals to support decision-making. In the scientific work [7], the result is the application of computer vision technology in the field of agricultural automation, ensuring the efficiency of agricultural production.

We can also note a number of research works that have achieved high results using computer vision in many branches of agriculture. Scientists led by Maharlooei [8], identifying soybean species and making calculations for them, used Rebel T2i, Sony DSC-W80, Panasonic DMC-ZS20 sensors to detect ticks in fields and count them. With the help of such sensors, it was possible to solve other problems in agriculture. In the study [9], when identifying invertebrate pests common in agricultural fields, a result of acceptable accuracy was obtained using the 3D MVC multispectral method. In addition, a number of authors who conducted research on the topic “identification of potatoes and three different weeds” [10] used an expert computer vision system based on a neural network. The result of the expert system showed a recognition accuracy of 98.38 %, and the accuracy indicator showed an average operating time of less than 0.8 seconds.

In [11], the diagnosis of wheat and cotton diseases was carried out, reaching 99 % accuracy. The proposed system was tested for 100 specific crop problems, and its final engine showed excellent performance with 99 % accuracy in predicting the correct disease.

Thus, all the above studies indicate the expediency of conducting research in the field of recognition and identification of weeds in agriculture. The analysis of the studied literature shows that the solutions to the problems in these studies [2, 5–11] do not address the issue of weed recognition and filling data with images of new weed species. The analyzed works do not trace the use of the MaskRCNN neural network model for pattern recognition. So, the problem of recognizing weeds and detecting their localization through the computer vision method remains open.

3. The aim and objectives of the study

The aim of the study is to identify the localization of weeds in the image stream by downloading and analyzing a dataset prepared on the basis of deep learning using computer vision. This will make it possible to control weeds and increase the yield of agricultural products.

To achieve the aim, the following objectives were accomplished:

– weed recognition using the MaskRCNN neural network model;

– development of an operation algorithm of the software module of the weed recognition scanner.

4. Materials and methods

All phenomena and objects are not similar to each other, but similarities by some signs can be found between some of them [12].

In this study, the object is the recognition of weeds. The application of the MaskRCNN neural network model in plant recognition will lead to the accurate identification and recognition of weeds in agriculture.

In the work, changes in the image are allowed to determine the number of petals and the size of the leaves of weeds, but this issue is exhausted during training. When recognizing weed images, they were divided into segments, and objects that did not correspond to this plant (garbage, dead wood, stone, etc.) were removed.

Several methods were used to distinguish images. These methods are selection, deep analysis, recognition with artificial neural networks (ANN), and the expert method.

Three models with 500 manually placed samples were trained for the study. The number of training images was reduced to verify and compare the threshold estimate of the methods used in the trained models. In total, 30 images of 638 weeds were used to train the final models, which is 40 % of the total number of samples.

Table 1 shows the results of evaluating the model performance, which was calculated using precision matrices of the models and its indicators for each crop. The performance results of the models show a good picture.

However, the previously developed model uses one class of weeds, so the precision estimate does not provide sufficient information. This is because the model was evaluated without negative samples. The YOLO [13] and R-CNN [14] models differ in sensitivity and precision. The HOG-SVM model is shown to be very accurate on the basis of clarity [15]. All three models have a high F_1 rating. The F_1 score (F-measure) is a weighted average of precision and recall F_1 is usually more useful than measurement accuracy, especially if the class distribution is uneven. The F_1 indicator is calculated by (1):

$$F_1 = \frac{2}{recall^{-1} + precision^{-1}} = 2\frac{precision * recall}{precision + recall} = \frac{2tp}{2tp + fp + fn}. \quad (1)$$

Table 1

Performance evaluation of machine learning models at the testing stage

Metric	Models for training		
	HOG-SVM	YOLO v3	MaskRCNN
Precision	79 %	89 %	89 %
Sensitivity	83 %	98 %	91 %
Clarity	95 %	91 %	98 %
F1 score	88 %	94 %	94 %

Several non-parametric methods were considered (Nemenyi, Wilcox, Kruskal, Dunn), the use of these methods showed that there are statistical differences over time. As a result, the Wilcox method was chosen [16]. The box diagram (Fig. 1) shows that HOG-SVM and YOLO are more time compatible, while in RCNN time has changed.

The data obtained during the experiment using the MaskRCNN and HOG-SVM models gave almost the same results [17, 18]. And YOLOv3 is slightly inferior to other models in some aspects, such as speed and accuracy. Based on the data obtained during the experiment, it can be concluded that the MaskRCNN model is characterized by a higher operation speed and determination of a more accurate percentage compared to other models [19, 20].

The trained image segmentation model annotates a mask at the pixel level to identify the boundaries of objects in the dataset. For this, the available intuitive model VGG ImageAnnotator (VIA) [21] was chosen, which is presented as a via.html file (Fig. 2).

After completion, the annotation for all images is saved as a JSON file. The data is used separately for the training and test sets.

Fig. 2 shows several similar plants close to each other, the plants are not distinguished at the output, so a mask of pixels marked as cut out is taken. This process is a disadvantage of semantic segmentation. Therefore, the image is presented as an unmarked image and is limited by a box to classify it and create a segmentation mask (Fig. 3).

Further image processing uses a classification and refinement algorithm. Which are K-nearest neighbors (k is the number of classes for the dataset) and softmax for classification, predicting 4 ($4k$) regression targets of the bounded box (x, y, w, h). Where x and y are the centers, and w and h are the height and width of the bounding boxes. This layer is trained using multiclass losses, which are the sum of classification costs (L_{cls}) and regression costs (L_{reg}) of the bounding box (L_{box}) (2):

$$L_{box} = L_{cls} + L_{reg}. \quad (2)$$

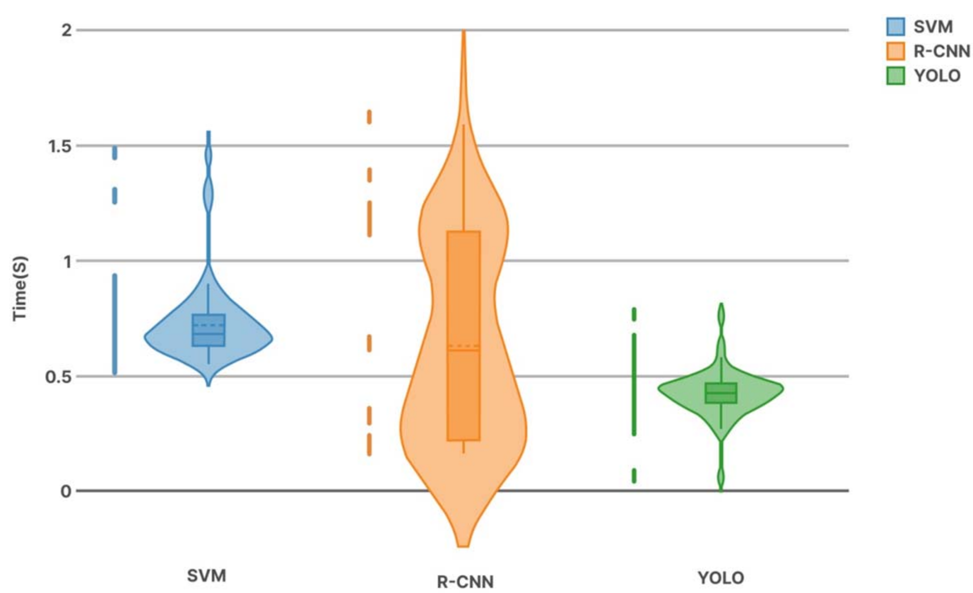


Fig. 1. Execution speed of each model [5]

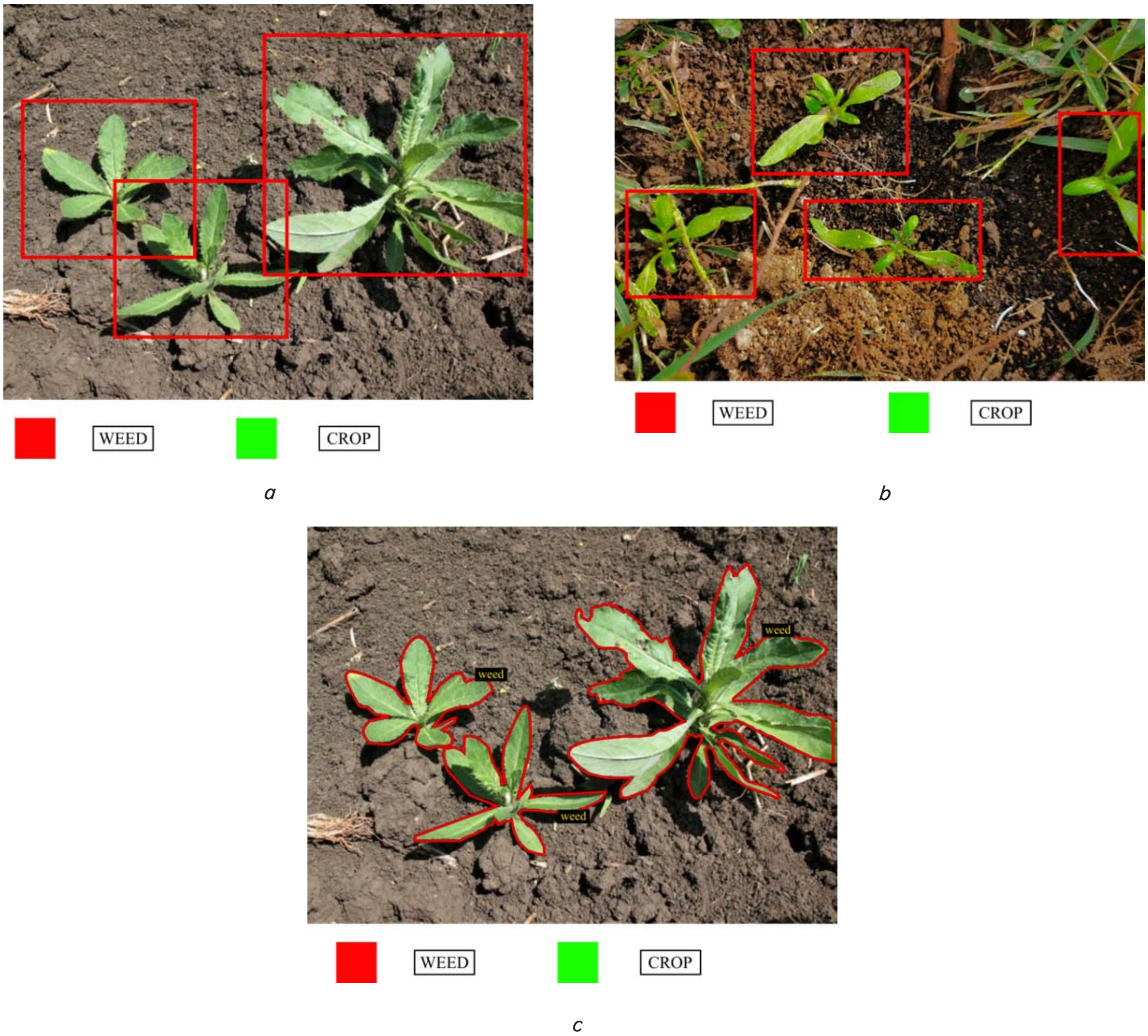


Fig. 2. Identification of objects in the image using VGG ImageAnnotator: *a* – weed found in a dry field; *b* – weed in a wet field; *c* – weed designation

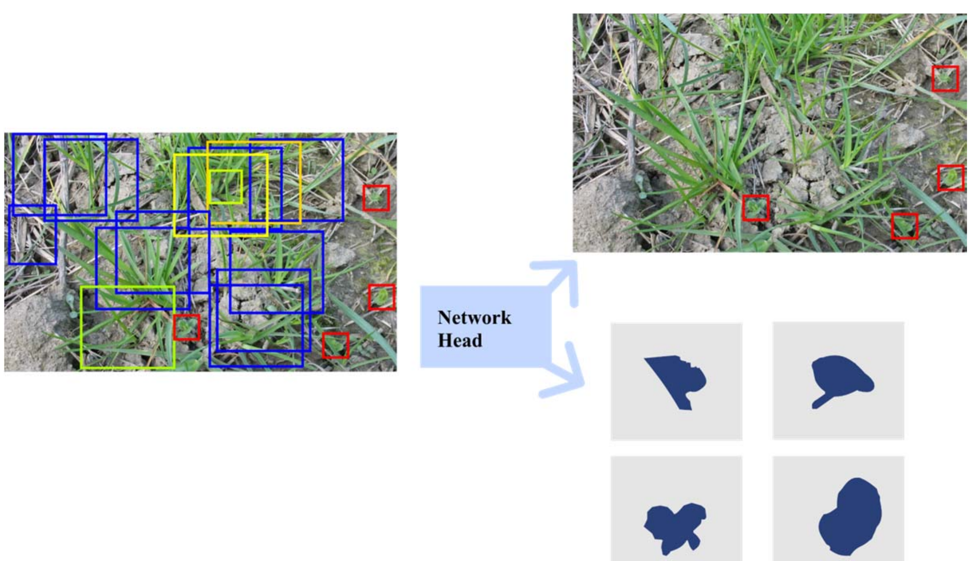


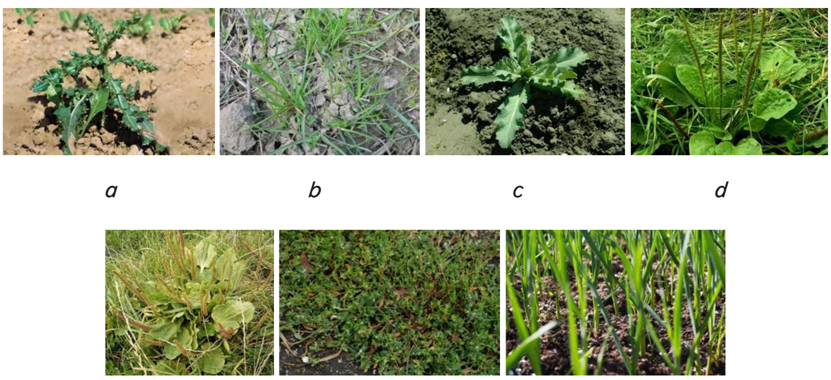
Fig. 3. Result of the network leader algorithm

This direction is fully aggregated and trained using binary cross-entropy loss and mask prediction, while the final loss is calculated from (3):

$$L_{final}=L_{box}+L_{mask}. \quad (3)$$

Mask loss is a binary cross-entropy, but for a given image, a K-mask prediction is obtained for each class in the dataset. The mask is selected for the class for which the cost classification layer is assumed.

To determine the effectiveness of neural network models, trips were organized across the geographical region to collect data. In addition, images were taken of weed species found in the fields of Northern Kazakhstan (couch grass, common couch, broadleaf plantain, dandelion, spurge, common sedge) (Fig. 4).



a b c d

e f g

Fig. 4. Collected species of weeds: *a* – creeping thistle; *b* – field brome; *c* – chickweed; *d* – dandelion; *e* – broadleaf plantain; *f* – spurge; *g* – couch grass

About 210 photos were taken for each species. A total of 1,562 images were collected, of which 1,405 were used for training and 157 for testing.

To analyze the models, 500 samples were selected, experiments were carried out on YOLO, R-CNN, HOG-SVM among the algorithms used, and their results were compared in terms of sensitivity, clarity and precision. Each model has its own features. YOLO and R-CNN are precise and sensitive algorithms, precision is 89 %, sensitivity is 98 % and 91 %, and the HOG-SVM algorithm – 95 %.

After selecting weed species to collect data, visits to the above areas and nearby locations were repeated.

The study used a machine with a 4-core ARM-Cortex processor, 4 GB of RAM and an integrated JetsonNano graphics card. The study measures were described using precision and specificity parameters. When evaluating and comparing performance, the best model was chosen taking into account confusion matrices, coverage values and evaluation time. Later they were implemented in a separate environment with the same characteristics: i. e. a 4-core ARM-Cortex processor and 4 GB of RAM, in an environment without a graphics card. Different programming languages were used to implement each model, the first model used C++, the second model used the Darknet platform for training and Python for evaluation, and the third used Python with TensorFlow library [22–24].

All experiments were carried out on the JetsonNano platform. The NVIDIA JetsonNano developer kit is a low-cost computer with artificial intelligence. It provides computational performance to run modern artificial intelligence workloads of unprecedented size and saves most power by using only 5 W. The developer kit can be powered by micro-USB and comes with a variety of inputs/outputs from GPIO to CSI. These developers were asked to add different sets of sensors to support many artificial intelligence applications [25].

The trained weed recognition model was implemented in the software module of the scanner (Fig. 5) equipped with RaspberryPi Camera V2, JetsonNano, SD card. This scanner is attached to equipment moving over plants. In the beginning, the sequence of the weed search and detection process implies processing the image that enters the database. Then the image is checked for correspondence to the weed from the database, in the true case, the weed is physically processed, then the search continues. A block diagram of the operation algorithm of the scanner with a software module for searching and identifying weeds is shown in Fig. 9.

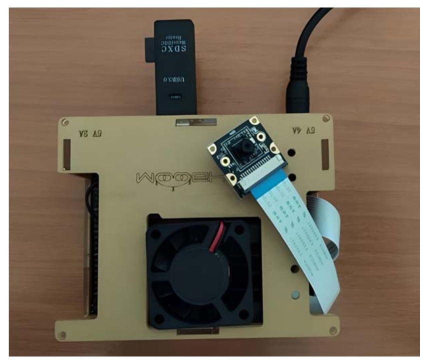


Fig. 5. Plant recognition scanner

A scanner with a software module for plant recognition is very widely used in agriculture. In this case, the trained model written in the scanner software module solves problems of weed identification.

5. Results of weed identification using computer vision

5. 1. Weed recognition using the MaskRCNN neural network model

The main dataset used by MaskRCNN is the MS COCO dataset [26, 27], which consists of 80 classes and 115 thousand training images. The evaluation metrics for bounding boxes and segmentation masks are based on the intersection of the merge (Fig. 6).

a b

Fig. 6. Setting an evaluation mask to a real image (used to calculate the cost): *a* – real image; *b* – masked image

The MaskRCNN model in question was trained on this dataset and used pre-trained weights to train on its own dataset.

It was found that this dataset has different types of weeds that differ in size and shape. Hence, expanding the dataset by adding more images with different types of weeds can improve the accuracy of the model.

The results of weed recognition using the MaskRCNN neural network model are presented in Fig. 7, *b–f*. A colored spray filter and an appropriate mask were applied to the identified weeds (Fig. 7).

After the algorithm finds the mask against weeds in the image/video stream, it sends detailed information about the location of the weeds to the CPU. For example:

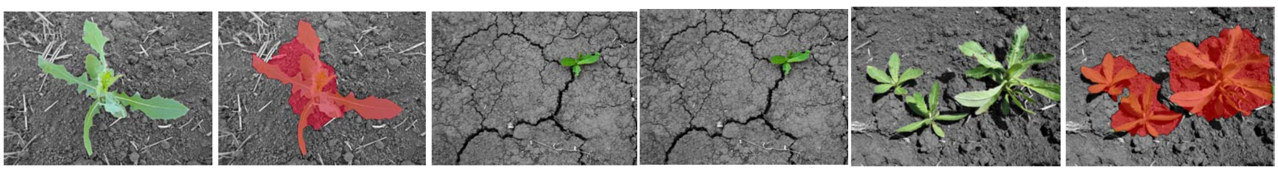
X.Coord==500, *Y.Coord*==350, *Z.Coord*==1000.

Here, *X.Coord* is the *X* coordinate, *Y.Coord* is the *Y* coordinate, *Z.Coord* is the *Z* coordinate. Each coordinate is measured in pixels. The program signals the robot manipulator module and the motion control module to precisely guide the weeder.

The process of training data using the MaskRCNN model took about 1 hour and 30 minutes over 10 epochs, with 100 training packages per epoch and a prediction threshold of 0.8. The training accuracy was 0.98, with a data loss of 1.43 %. This model achieved high accuracy despite the small amount of training.

To visualize the results of the model, the Tensorboard application was used, presented in the form of graphs (Fig. 8).

Thus, the results of the trained MaskRCNN neural network model showed good results that contribute to the high quality of weed recognition.



a *b* *c* *d* *e* *f*

Fig. 7. Representation of a mask of various weeds based on the MaskRCNN model:
a – real image; *b* – mask image; *c* – real picture;
d – mask image; *e* – real picture; *f* – masked image

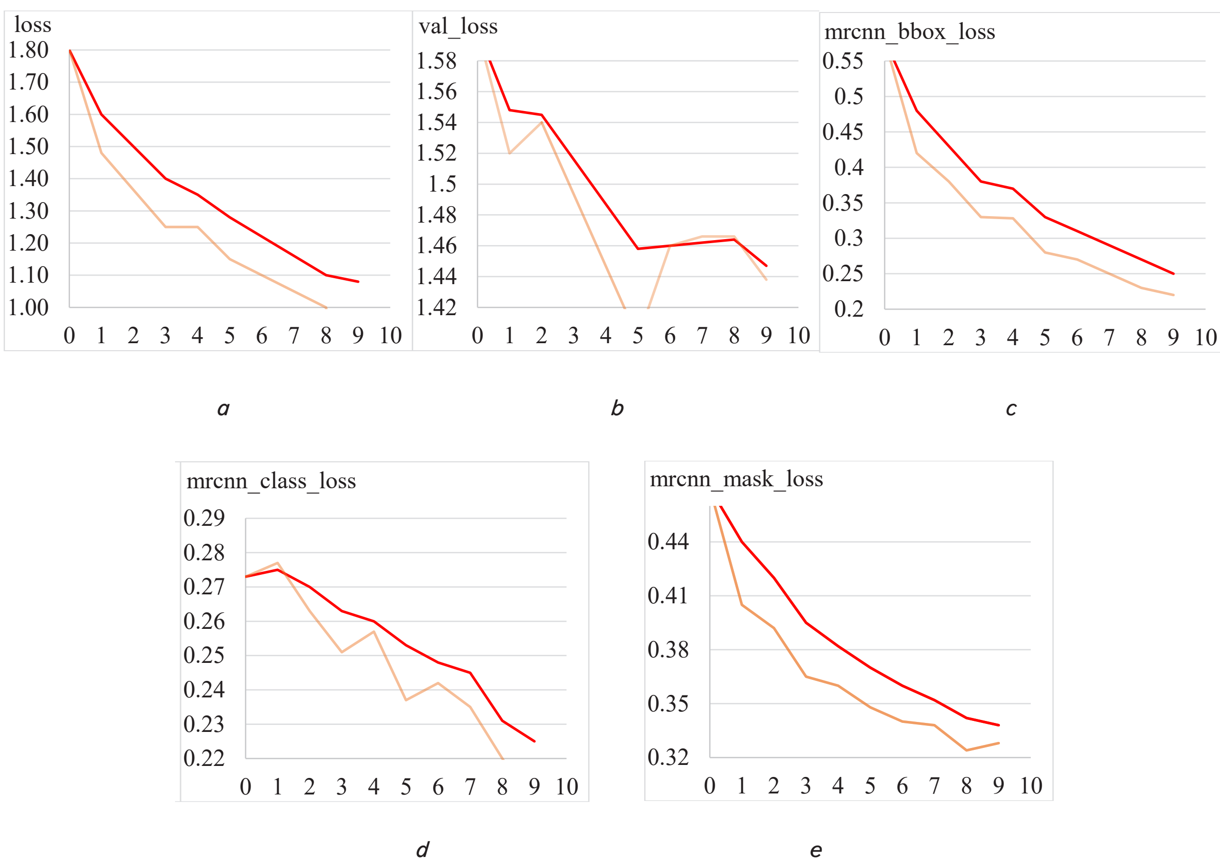


Fig. 8. Indicators of the loss function when training the database trained MaskRCNN model, shown using the Tensorboard tool:
a – loss in the first layer; *b* – val loss in the integration layer;
c – loss in the processing layer; *d* – loss when dividing into classes;
e – masking loss function

5. 2. Operation algorithm of the software module of the weed recognition scanner

The trained neural network model was used in the software module of the weed recognition scanner. The plant recognition process involves processing the resulting images with noise removal and masking. Then, the obtained image is segmented and candidate regions are identified. After that, it is checked whether there is a weed in the picture, if so, then information about it is collected in a separate database, if not, the picture is deleted.

The scanner operation algorithm implies the following steps:

1) image capture;

2) saving in the database;

3) search for weeds in the image (when interacting with the trained model);

4) if a weed is found, it is physically removed, otherwise, the next section is scanned.

A block diagram of the operation algorithm of the software module of the scanner for searching and identifying weeds is shown in Fig. 9.

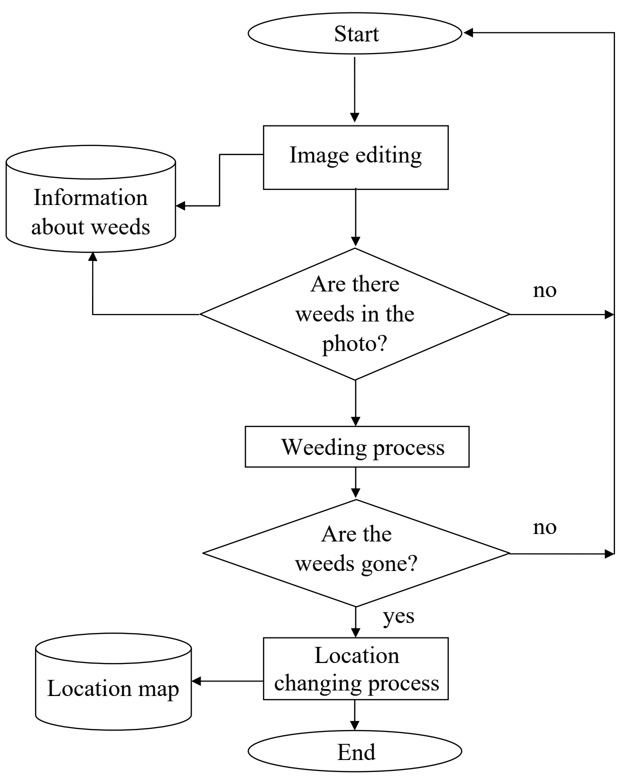


Fig. 9. Operation algorithm of the software module of the scanner for searching and identifying weeds

Capabilities of the weed recognition model:

– speed – the device very quickly recognizes and transmits information about the weeds found to the platform – 0.2 seconds;

– reliability – average identification accuracy achieved when experimenting with models – 98 %;

– ease of use, which may be limited by a customized database and a suitable illuminance level (about 35,000 lux).

6. Discussion of the results of research on the use of computer vision in weed recognition

The trained neural network model using MaskRCNN is used in computer vision technologies, weed identification and is one of the most advanced and rational technologies in modern information technology. Thus, the proposed hypothesis of weed detection based on the MaskRCNN neural network model gave a positive result, as can be seen in Fig. 8, *b*, *d*, *f*. The results obtained were due to the use of this trained neural network model.

The advantage of this work is the wide application of the proposed software module for the weed scanner. Previously, the MaskRCNN neural network model was not used to recognize weeds. The MaskRCNN model is characterized by simplicity and quality of prediction compared to other neural networks. The result of training based on the MaskRCNN neural network model is considered to be the best compared to neural networks with Backbone, Neck, Head layers [13, 22, 23], and the accuracy result showed 89 % (Fig. 9).

The proposed neural network model has achieved a high result in the time of rapid information recognition and learning – 0.2 seconds. Weed images in the collected dataset have low resolution, so being able to economically identify objects is one of the advantages of the system.

The limitation of the trained neural network model is the processing of images of only weeds in the Northern region of Kazakhstan. In order to eliminate these shortcomings, further research is planned to supplement the growth stages and species of weeds and other plants, as well as to optimize the MaskRCNN neural network model.

One of the disadvantages of the trained neural network model can be its application only for the Northern region of Kazakhstan. In the future [28], it is planned to use the tomato recognition system when detecting weeds in all regions of Kazakhstan and improve the work on distinguishing harmful plants from cultivated ones.

There are opportunities to further improve the neural network model by increasing the number of training iterations and increasing the number and quality of images. The complexity of this study lies in the need to detect all weeds. Since plants can be modified over the years relative to natural and climatic conditions, and thus new species of weeds can appear.

7. Conclusions

1. The process of weed recognition using the MaskRCNN model is described and 1,562 images are obtained. With the help of special new software, it became possible to automatically detect weeds. The software recognizes the weed in 0.2 seconds and completely eliminates the additional human factor. Of all the images, 1,405 were used for training and 157 for testing. The weed recognition model has a learning accuracy of 0.98, with a data loss of 1.43 %.

2. A block diagram of the operation algorithm of the softe ware module of the weed recognition scanner is proposed. This algorithm differs from previously existing algorithms in that it makes it possible to process and recognize an image with an illuminance level of 35,000 lux in 0.2 seconds. It allows detecting weeds in the image and transmitting information for weeding. In this algorithm, the recognition process

includes trained data on the MaskRCNN neural network model. The algorithm shows the operation of the software module and control of a weeding machine in agriculture. The scanner and the weeding mechanism are controlled by the software module, which, after detecting weeds, gives a command to weed them. This process is repeated until all weeds are destroyed.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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The study was carried out with the authors' own funds.

Data availability

The manuscript contains related data in the data warehouse.

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