

*This paper considers the process of developing a method to recognize the causes of plant growth deviations from normal using the advancements in artificial intelligence. The medicinal plant *Aloe arborescens L.* was chosen as the object of this research given that this plant had been for decades one of the best-selling new products in the world. *Aloe arborescens L.* is famous for its medicinal properties used in medicine, cosmetology, and even the food industry. Diagnosing the abnormalities in the plant development in a timely and accurate manner plays an important role in preventing the loss of crop production yields.*

*The current study has built a method for recognizing the causes of abnormalities in the development of *Aloe arborescens L.* caused by a lack of watering or lighting, based on the use of transfer training of the VGG-16 convolutional neural network (United Kingdom). A given architecture is aimed at recognizing objects in images, which is the main reason for using it to achieve the goal set.*

*The analysis of the quality metrics of the proposed image classification process by specified classes has revealed high recognition reliability (for a normally developing plant, 91 %; for a plant without proper watering, 89 %; and for a plant without proper lighting, 83 %). The analysis of the validity of test sample recognition has demonstrated a similar validity of the plant's classification to one of three classes: 92.6 %; 87.5 %; and 85.5 %, respectively.*

*The results reported here make it possible to supplement the automated systems that control the mode parameters of hydroponic installations by the world's major producers with the main feedback on the deviation of the plant's development from the specified values*

**Keywords:** *neural network, machine learning, hydroponic systems, image recognition, *Aloe arborescens L.**

# DEVISING A METHOD FOR RECOGNIZING THE CAUSES OF DEVIATIONS IN THE DEVELOPMENT OF THE PLANT *ALOE ARBORESCENS L.* USING MACHINE LEARNING CAPABILITIES

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## 1. Introduction

*Aloe arborescens L.* is known as a medicinal plant that is widespread. The favorable conditions for its growth are semi-desert areas with a hot climate. In a temperate climate, cultivating *Aloe arborescens L.* with sufficient healing properties is a challenge. This raises the issue of creating artificial conditions in unfavorable regions for the cultivation of *Aloe arborescens L.*

Turning to the experience of growing crops in unnatural environments, one can note hydroponic technologies. Growing medicinal plants in hydroponic installations is gaining popularity. Work [1] reports a technology that could be used to grow the plant on hydroponics while maintaining the ecological safety of the region's produce.

A study described in paper [2] confirms the fact that medicinal plants grown in hydroponic installations retain all the properties of plants grown in the natural environment. It is also possible to cultivate such medicinal plants as aloe, valerian, motherwort, and others. The process of adapting

some plants to a soil-free growth system was described in [3]. The dry mass of roots and shoots of yarrow, wormwood, starweed, medicinal dandelion, and medicinal valerian many times exceeded the growth rates in the open ground [3].

Growing *Aloe arborescens L.* in hydroponic installations is possible. At the same time, it is advisable to supplement a hydroponic installation with an automatic control system to reduce human participation in this process and improve the quality of products.

Existing automatic control systems for hydroponic installations (systems) are a set of independent, autonomous closed systems that control their individual parameters under a particular program. At the same time, none of the automatic control systems provides feedback on the efficiency of plant growth; the feedback is available only on the parameters that affect this growth. The websites of the world's leading manufacturers recommend making adjustments to growth control programs based on the results of visual observations [4, 5]. That is, they propose providing feedback based on the effectiveness of plant growth through

a person (specialist in agronomy). That makes it impossible to design a fully automated adaptive plant growth control system under hydroponic conditions without retooling existing automatic control systems with devices and algorithms that could provide feedback on plant growth efficiency [6].

One possible way to improve the quality and effectiveness of diagnosing abnormalities in the development of *Aloe arborescens L.* in artificial environments is an automated analysis of parameters, implemented in the form of a computer diagnostic system based on the application of neural networks. The relevance of such studies is predetermined by the high volume of utilization of *Aloe arborescens L.* in the production of various goods, including for medical purposes. That makes it appropriate to use hydroponics to cultivate this plant. In this regard, improving the efficiency of automatic systems that control hydroponic installations for cultivating *Aloe arborescens L.* is a relevant task. Supplementing existing automatic hydroponic control systems with a recognition system for the causes of abnormalities in the development of *Aloe arborescens L.* would increase yields and reduce losses.

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## 2. Literature review and problem statement

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Paper [7] reports the results of a study to determine the ability of bitter melon to produce good yields. The leaves of the plant were categorized into “good” and “bad” by their description. The study used a machine learning algorithm through a convolutional neural network. The training was enabled by the combined capabilities of Keras, TensorFlow, and Python. The study result has proven that a base of 293 images could make it possible for a computer to tell the difference between a good and a bad plant. Both Keras (United States) and MATLAB are equally effective for these purposes, with the only difference being that MATLAB is mostly launched in a local environment while Keras could be downloaded in the cloud, as well as run along with other cloud platforms created by Google [7].

Paper [8] reports the results of research on the detection of plant diseases and pests using the functions of deep learning. The research evaluated performance results using different approaches from nine powerful deep neural network architectures to detect plant diseases. The experiments involved data on real diseases and images of pests from Turkey. The cited research assessed the performance by trying different approaches of the nine most powerful neural network architectures for plant disease identification: AlexNet (Canada), VGG-16 (United Kingdom), VGG-19 (United Kingdom), GoogleNet (United States of America), ResNet50 (United States of America), ResNet101 (United States of America), InceptionV3 (InceptionV3), InceptionResNetV2 (United States), and SqueezeNet (United States of America). Each deep model used has unique features, such as the number of layers, the number of connections, and the types of filters. The estimates have shown that deep learning models produce the best results [8].

Work [9] reports the results of a study on the use of convolutional neural networks to identify and categorize banana diseases. LeNet’s self-learning model and a classification model were used to categorize the image set and the ability to match healthy and sick banana leaves. First, the network learns to detect various high-level functions from input images. It consists of a sequence of layers of convolution and unification. The purpose of the convolution is to extract elements from the input image. It consists of a set of training filters. Each filter

is applied to the raw pixel values of the image, taking into consideration the red, green, and blue channels under a sliding window mode, calculating the point product between the filter pixel and the input pixel [9]. The classification phase employs fully connected layers, where each neuron provides a complete connection to all the maps of characteristics released from the previous level in the neural network of the convolution. These connected layers are based on a softmax activation function to calculate class scores. The softmax input data are a vector of the attributes derived from the learning process, and the output data are the probability that the image belongs in a given class. The proposed approach could serve as a decision-support tool to help farmers identify disease on a banana plant. Therefore, the farmer could take a picture of the leaf with the symptoms, and then the system would determine the type of disease [9].

Paper [10] reports the results of research on the classification of the shape of strawberry fruit through machine learning to improve the accuracy of sorting and the introduction of computerization in this field. A total of 2,969 images of strawberry fruit were obtained by a digital camera. Four types of descriptions were acquired from the digital images of strawberries:

1. Measured values, including the length of the contour line, the area, length, and width of the fruit, and the ratio of the width/length of the fruit.
2. Ellipse Likeness Index.
3. Fourier’s elliptical descriptors.
4. Subtraction of chain code.

These descriptors were used for the classification test along with the Random Forest algorithm. The results reported show a high capability of machine learning to accurately categorize fruit shapes [10].

Work describes the results of a study on the development of a real-time wheat classification system for selective herbicides using a broad assessment of wheat in a deep neural network. The main purpose of the cited study was to develop a machine vision system that identifies wheat based on its location. To this end, the researchers developed a real-time robotic system that makes it possible to find a plant in a critical zone by recognizing images and machine vision. Microsoft Visual C++ 6.0 (United States of America) was used as software for system development. Various experiments have been conducted to assess the effectiveness of the proposed algorithm in terms of differences between various types of wheat. In addition, experiments were also conducted under different field conditions. The simulation results show that the proposed algorithms demonstrated a 94 % success in categorizing the wheat population, which consists of 80 samples, of which 40 are narrow and 40 are broad [11].

Paper reports the results proving the applicability of neural networks as classifiers to achieve the identification and categorize plant diseases based on the processing of their images. For the wheat and grape disease samples studied, the best prediction accuracy was 97.5 % and 94.29 %, respectively. Those results were achieved through the use of four types of neural networks: a back-propagation network, the neural networks of radical baseline function, the generalized regression networks, and the probabilistic neural networks [12].

Study [13] reports the results of the recognition of tea leaf diseases. The accuracy of the testing process was 91 %. To achieve the set goal, a special tea leaf disease recognizer and a neural network were used to acquire the attributes. The method proved low-cost and non-destructive, which confirms the validity of the use of neural networks.

Our review [7–15] reveals the effectiveness of machine learning to recognize diseases and pests in crop production. The effectiveness of the use of neural networks for this purpose is also demonstrated. In the studies discussed above, the classification was based on an analysis of the shape and/or coloration (coloring) of leaves or fruits of plants.

However, we found no studies among the sources available on the Internet that would consider the development of a system for the recognition of abnormalities in the development of the plant *Aloe arborescens* L. caused by lack of watering or lighting.

The concept of computer vision combines the theoretical foundations and the set of technologies for automatic image analysis. This line of science and technology uses different methods of processing graphic and video information to obtain descriptions of real objects and scenes. At present, a wealth of practical experience has been accumulated in creating algorithms for automatic detection, classification, and segmentation of objects in images. Since 2012, deep convolutional neural networks have been the undisputed leader in this area in terms of accuracy and speed [14].

Thus, it is advisable to synthesize a classifier model using the deep convolutional neural network (DCNN) apparatus for the following purposes:

- to reduce development time;
- to achieve high-quality performance;
- to save computing resources;
- to possibly unify solving similar problems in the future.

At the same time, we should point to the possible difficulties and disadvantages associated with the use of DCNN for classification. First, the selection of the proper architecture of a neural network is in many ways an empirical search that depends on the experience and qualifications of the researcher. There are no ready-made methods of selecting or constructing the network structure that is most appropriate for a particular task. Second, the DCNN training process is a very long and resource-intensive task, requiring a large amount of training data, expensive computing equipment, and considerable time-consuming costs. Third, in the process of training a neural network, there is a high probability to retrain the model, which would negatively affect its generalizing ability. Fourth, the results of DCNN-based classification are difficult to interpret, which imposes a restriction on the use of neural networks in some computer vision tasks.

Among the common DCNN architectures originally used to categorize images are LeNet [15] and AlexNet [16]. These architectures are relatively shallow, using larger convolutional nuclei in the input layers and smaller nuclei closer to the exit. The most used and more effective activation feature ReLU (Rectified Linear Unit) [17] is only used on the AlexNet network.

The more modern architectures of DCNN include VGG-Net [18] and Inception [19]. For the VGGNet network, there are implementations for 16 and 19 layers, and the main innovation in the architecture could be considered the use of 3×3 convolutional filters. The Inception network was developed by Google and differs from previous networks by a more complex structure. This DCNN contains about 100 different units with a total depth of 27 layers. To better spread the gradient, the authors of this network used auxiliary classification networks on top of some intermediate layers.

One of the deepest neural networks actively used in practice at present is ResNet architecture networks of various modifications [20]. A new concept of deep residual learning

has been applied in a given DCNN class, allowing networks to be trained with hundreds of layers.

Increasing the depth of convolutional neural networks could improve the quality of classification and process the increasingly complex objects and scenes of the image. It should be noted, however, that the quality of the classification does not change much with the multiple increases in the number of layers [21]. In addition, the analysis of images of the plant *Aloe arborescens* L. within the framework of our task does not require the search for complex geometric shapes and various classification characteristics. Therefore, in a given case, it is more reasonable to use networks of non-deep architecture such as VGGNet. The more complex DCNNs are already very demanding of hardware resources, both in the learning process and in the process of subsequent use.

Another fact in favor of choosing the architecture of VGGNet is also that it is possible to use the pre-trained DCNN based on transfer learning technology in order to:

- save time to prepare a training sample and train the network;
- reduce computing and hardware requirements.

One can find in the public domain [22] the values of weights of the already trained VGG16 network on the ImageNet dataset (USA) [23]. A given set contains images for 1,000 classes, split into three sets: training (1.3 million images), validation (50,000 images), and testing (100,000 images). All images are three-channel sized 224×224.

As a result, the use of the pre-trained VGG16 network would significantly reduce the time spent developing the classifier and avoid a series of shortcomings associated with the use of neural networks.

The above review [15–23] shows the effectiveness of the use of neural network machine learning technologies to recognize diseases and pests of a series of plants. Based on this, it becomes obvious that the accumulated knowledge in the field of deep learning should be applied to a new and sought-after subject area for cultivating plants in hydroponic installations. Therefore, it is reasonable to conduct a study on the possibility of adapting the pre-trained DCNN to build a model of the classifier of abnormalities in the development of the plant *Aloe arborescens* L. based on its photographs. Our analysis of the scientific literature on the use of DCNN architectures for the classification of images has revealed that this study task could be resolved by the architecture of VGG16.

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### 3. The aim and objectives of the study

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The aim of this study is to modify the VGG-16 neural network output layer prediction function to effectively address the problem of automatic classification of the plant *Aloe arborescens* L. That would complement the existing systems of automatic control over hydroponic installations with the main feedback on deviation in the development of the plant. The presence of such main feedback could reduce the influence of the “human factor” on the process and improve the yield and quality of the plant *Aloe arborescens* L.

To accomplish the aim, the following tasks have been set:

- to develop a classifier model that allows the use of the VGG16 neural network to solve the problem of automatic classification of the plant *Aloe arborescens* L.;
- to prepare a set of images of the studied plant to acquire informative classification attributes and train the modified neural network;

– to test the developed classifier model during an experiment to detect any abnormality in the normal growth of *Aloe arborescens L.*

#### 4. The study materials and methods

##### 4.1. Developing a classifier model for the automatic classification of the plant *Aloe arborescens L.*

The most common errors in the cultivation of *Aloe arborescens L.* is the lack of light and watering while this plant is quite demanding to these parameters. Consider the main visually distinct external attributes that could be observed in *Aloe arborescens L.*

– *Aloe arborescens L.* belongs to the class “Normal development”, has a fairly saturated dark green color with long dense, and fleshy leaves. They are convex at the bottom; on top, more concave; arranged alternately. The plant develops well in height and width;

– the plant *Aloe arborescens L.*, categorized in the class “Lack of light”, tends to have a faded (with a smooth transition from pale green at the base to pale yellow on the tip) color of leaves. The plant becomes quite weak, the leaf is less juicy, smaller, could fall for no apparent reason. Overall, there is a marked upward trend;

– the brown color of the tips of the leaves is the main external sign that *Aloe arborescens L.* lacks moisture, the class “Lack of watering”. One could also notice that the leaves begin to curl, becoming thinner. This trait is observed both at the end and from the sides of the plant. The edges of the leaves are pricklier, compared to the plant, developing in favorable conditions. Falling leaves are not observed.

To determine deviations from the normal development of the plant *Aloe arborescens L.*, its visual examination is used in practice. Fig. 1 shows visual differences of the tips of the leaves of the normally developing plant *Aloe arborescens L.* from the tips of plant leaves growing with a lack of water or light. In this regard, it seems very reasonable, in order to implement the main feedback in automated hydroponic systems, to use modern computer vision technologies.

A big advantage of deep learning when solving classification tasks is the ability to use it effectively with small

amounts of training data. A DCNN, trained on a large enough set of images, could be seen as a generalizing model of the visible world. Such a pre-trained network could then be used to categorize objects that were not originally represented in the training sample.

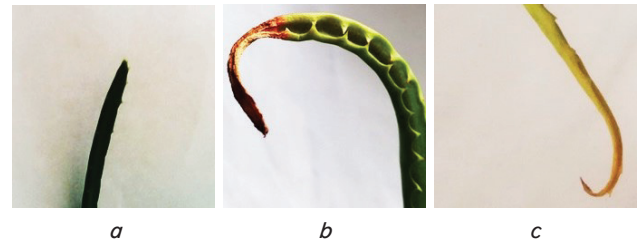


Fig. 1. Visual manifestations of abnormalities in the development of the plant *Aloe arborescens L.*: a – normal development; b – lack of water; c – lack of light

Fig. 2 shows the structure of the VGG16 network, which is used in this work as a pre-trained network.

The convolutional base of the VGG16 network consists of units I–V, shown in Fig. 2. The attributes maps, obtained by the network’s convolution base, are universal and contain general information about the presence of generalized concepts in the images. At the same time, the most common local attributes are highlighted in the initial layers, and, closer to the output, already more abstract elements. At the same time, output fully-connected layers (unit VI in Fig. 2) generate representations that correspond only to the predefined set of classes. In other words, the pre-trained VGG16 network contains a classifier in unit VI that reproduces the probability of the presence of 1,000 classes in the image from the ImageNet dataset [23] on which it was trained.

Thus, it is obvious that it is proper to apply transfer training technology on the pre-trained VGG16 network to develop the plant *Aloe arborescens L.* image classifier model. To this end, its architecture should omit the output fully-connected layers (unit VI in Fig. 2). Instead, somebody has to develop and train own optimal structure of a given piece of the network according to the class of objects. In addition, it is possible to improve the quality of classification by “re-training” the layers of unit V of the convolutional base (Fig. 2) on the existing data set.

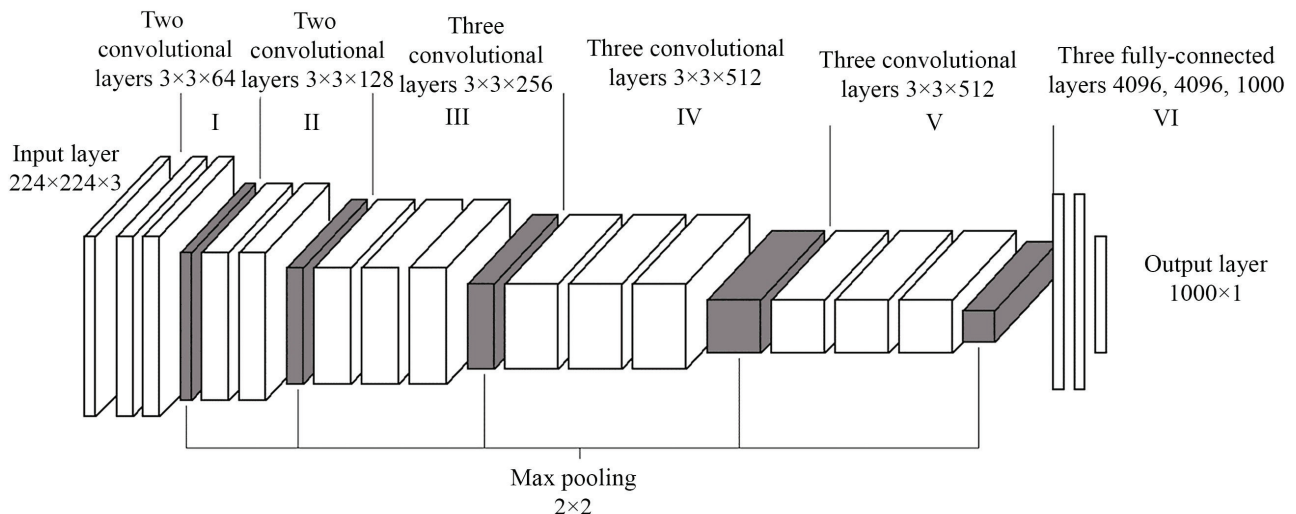


Fig. 2. VGG16 DCNN structure showing the dimensionality of input and output layers and convolutional operations



The following designations have been used to identify the new fully-connected layers:

- flatten is the transition layer from a matrix data structure to a vector structure;
- dense 1 is a fully-connected layer of 256 neurons with the ReLU activation function described by the following functional dependence:

$$h(z) = \max(0, z), \quad (1)$$

where  $z$  is the weighted amount of neuron inputs;

- dropout is the layer of regularization to reduce the retraining of the model. Every second block of data is discarded here because, when training, the images are submitted to the network input in blocks;
- dense 2 is the output layer of three neurons by the number of classes. SoftMax activation function at  $C=3$  is used to obtain the detection probabilities of a certain class:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{c=1}^C e^{z_c}}, \quad (2)$$

where  $i$  is the coordinate of the output vector.

#### 4.2. Preparing the original data set and training a modified neural network

At the initial stage of our study, a set of *Aloe arborescens L.* images was built to recognize abnormalities in its development.

200 digital color photographs of the tips of leaves were prepared:

- normally developed plants;
- plants with visual attributes of lack of watering;
- plants with visual attributes of lack of lighting. The tips of the leaves were photographed (in “color photo” mode) against a white background from different angles and under different lighting (with artificial lighting, with natural light, using a built-in flash).

The prepared images  $I$  were compressed, that is, they were redefined on a rectangular medium:

$$\Omega = \left\{ (x, y) : \begin{array}{l} 0 \leq x \leq n \\ \wedge 0 \leq y \leq m \end{array} \right\} \subset Z^2, \quad (3)$$

where  $n=224$  is the number of columns, and the number of rows is  $m=224$ .

The counts at points  $(x, y)$  have a vector shape of  $u=(u_k)$  at  $k=3$  by the number of channels of the RGB color model. And  $u_k=\{0, 1, \dots, 2^a-1\}$ , where  $a=8$ .

Over the obtained images  $I(x, y, u)$ , preprocessing was performed – a normalization operation, in which the components of the vector  $u$  were reduced to the range  $[0, 1]$ ;

$$\hat{u}_k = u_k / (2^a - 1). \quad (4)$$

The resulting set of images of the plant *Aloe arborescens L.* was used to train the classifier model. This involved the deferred sampling method. All data were randomly split into three groups: 70 % for model training, 20 % for validation, 10 % for final testing.

An augmentation procedure is used to increase the number and diversity of samples. The increase in the amount of data includes a set of methods used to generate new training samples from the original data sets through the use of random “perturbations”:

- horizontal and vertical reversal;
- turn at a random angle from 0 to 40°;
- random shifts in width and height ranging from 0 to 20 % of the image size;
- accidental zoom in the range of 0 to 20 % of the image size.

As an example, Fig. 3 shows a sample image of the plant *Aloe arborescens L.*  $I(x, y, u_k)$ , grown under normal conditions. Fig. 4 demonstrates variants of the same image, which underwent the procedure of augmentation.

Image augmentation and subsequent construction and training of the DCNN-based classifier model were carried out on free software. The Keras 2.3.1 [24] Machine Learning Library was used, written in Python 3.7.9. The Keras library makes it possible to operate high-level functions to design deep learning models. It implements the low-level tensor differentiated and manipulated operations based on specialized and optimized tensor support software libraries (TensorFlow [25], Theano [26], and Microsoft Cognitive Toolkit (CNTK) [27]).

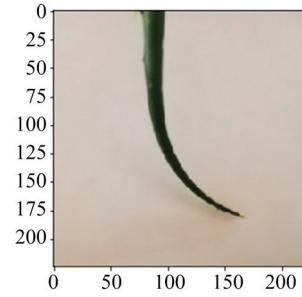


Fig. 3. Sample image of the plant *Aloe arborescens L.* grown under normal conditions

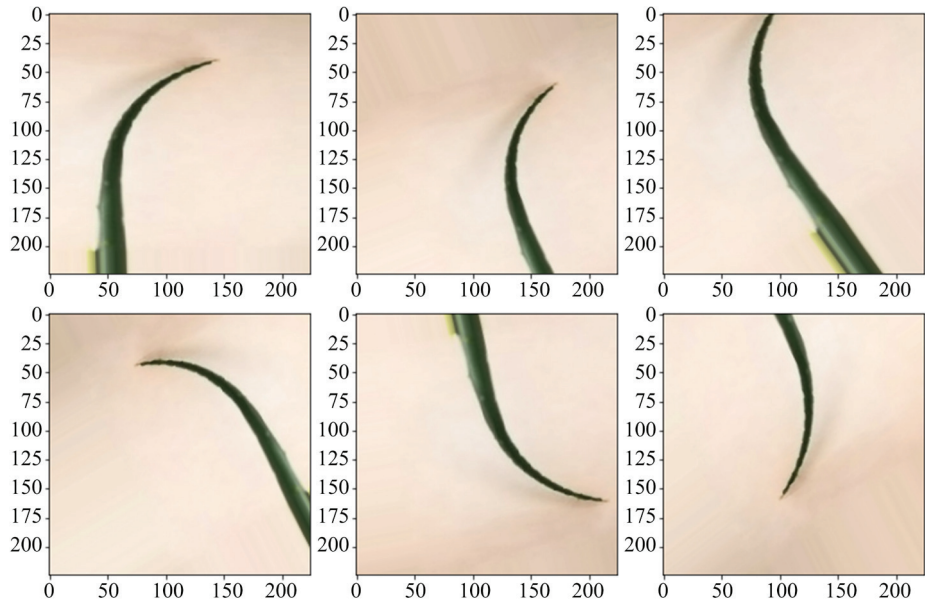


Fig. 4. Augmentation of the plant *Aloe arborescens L.* image

In our study, a program code using Keras was run with the TensorFlow library. Tensing calculations were made on the NVIDIA GPU using the NVIDIA CUDA Deep Neural Network (cuDNN) library [28].

**4. 3. Testing the developed classifier model**

The results of our experiment were evaluated by analyzing classification errors in the process of identifying belonging in a particular class. A combination of accuracy, completeness, and F-measure metrics is used to assess the effectiveness of the proposed system. The numerical values of these metrics were obtained by calculating the error matrix or measuring performance for the classification task during machine learning (Table 1).

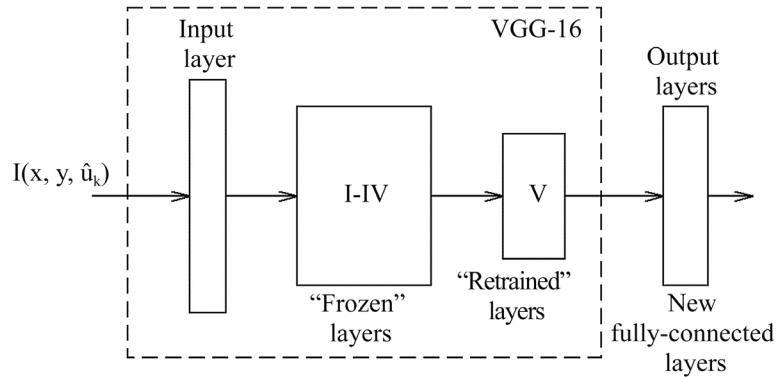


Fig. 5. The structure of the VGG16-based classifier model

Using a test sample from the dataset, it was possible to optimize the output structure of the neural network (Fig. 5) to obtain maximum recognition quality. Various variants of the structure of the fully-connected layers have been explored. The result, given in Table 2, demonstrates the final architecture of the resulting classifier model.

Table 1

Different combinations of predicted and actual values

True label	Recognized label		
	Lack of water	Healthy plant	Lack of lighting
Lack of water	$a_{11}=16$	$a_{21}=2$	$a_{31}=3$
Healthy plant	$a_{12}=0$	$a_{22}=20$	$a_{32}=1$
Lack of lighting	$a_{13}=2$	$a_{23}=0$	$a_{33}=19$

Using numerical data from Table 1 helped calculate the completeness, accuracy, and F-measure:

1. Calculations for a plant with signs of water shortage:

$$\text{Completeness}=(a_{11}/(a_{11}+a_{12}+a_{13}));$$

$$\text{Accuracy}=(a_{11}/(a_{11}+a_{21}+a_{31})).$$

2. Calculations for a healthy plant:

$$\text{Completeness}=(a_{22}/(a_{21}+a_{22}+a_{23}));$$

$$\text{Accuracy}=(a_{22}/(a_{12}+a_{21}+a_{32})).$$

3. Calculations for the plant with signs of lack of lighting:

$$\text{Completeness}=(a_{33}/(a_{31}+a_{32}+a_{33}));$$

$$\text{Accuracy}=(a_{33}/(a_{13}+a_{23}+a_{33}));$$

$$\text{F-measure}=(2*\text{Completeness}*\text{Accuracy}/(\text{Completeness}+\text{Accuracy})).$$

Table 2

A classifier model architecture

Structural elements of the classifier model	Network structural elements	Data dimensionality	Number of trained parameters
Model VGG-16	Units I–V (Fig. 5)	(7, 7, 512)	14,714,688
New fully-connected layers	Layer flatten	25,088	–
	Layer dense 1	256	6,422,784
	Layer dropout	256	–
	Layer dense 2	3	771

Table 2 gives the dimensionality of the data and the number of trained parameters of network structural elements with appropriate activation functions (expressions 1 and 2).

**5. 2. Results of preparing the initial data set and training the modified neural network**

The result is the acquired set of images of the plant *Aloe arborescens* L., normal and at a deviation in development  $\{I_j(x, y, \hat{u}_k), \theta_j\}_{j=0}^{l=600}$ ,  $\theta_j \in \{0,1,2\}$ , dimensionality  $l$ , marked into three classes. In this case,  $\theta_j$  is a sign description and class label for the  $j$ -th image: “0” – a plant with no watering, “1” – a plant under normal conditions, “2” – a plant with no lighting.

To increase the number and diversity of samples, an augmentation procedure was used. Applying augmentation ensures that data class labels do not change. The goal of data augmentation is to improve the generalizability of the model.

DCNN training with the architecture given in Table 2 was performed on the sample training group using an error backpropagation algorithm [29]. To this end, at each step of the training, the error function  $Q$  is optimized by finding its gradients from the received weights  $w$ . The optimization task is solved by the method of stochastic gradient descent through mini-blocks of data using the algorithm Adam [30].

A categorical cross-entropy is used as a function of error:

$$Q = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^C 1[\theta_i \in C_c] \log p[\theta_i \in C_c]. \tag{5}$$

**5. Research results on the development of a model for the plant *Aloe arborescens* L. automatic classification by the type of abnormality in its development**

**5. 1. Results of the development of a classifier model for the automatic classification of the plant *Aloe arborescens* L.**

Fig. 5 shows the structural scheme of the proposed model of the classifier based on DCNN. Roman numerals indicate the corresponding units of the VGG16 network in Fig. 2.

The “frozen” units from I to IV are not involved in the training process, but the layers of unit V are being retrained.

In expression (5),  $N$  is the sample size;  $p[\theta_i \in C_c]$  is the probability of categorizing the  $i$ -th image to class  $c$ ;  $I[\theta_i \in C_c]$  is the indicator function. Expression (5) is a logarithmic loss function, which is characterized by convergence and efficiency of calculation. For these reasons, it is used as an error function.

As a result, the learning process is to find the optimal weights  $w^*$  of the neurons for which the network error becomes minimal:

$$w^* = \arg \min_w Q(w). \tag{6}$$

### 5. 3. Results of testing the developed classifier model during the experiment to detect deviations in the normal growth of *Aloe arborescens L.* from normal

A combination of accuracy, completeness, and F-measure metrics was used to assess the effectiveness of the proposed system. The results for experimental configurations are given in Table 3.

Table 3

Accuracy, completeness, and F-measure evaluation (aggregated parameter for accuracy and completeness) for appropriate experimental configuration

Examined class and parameter	Accuracy	Completeness	F-measure	Number of samples
Lack of water	0.89	0.76	0.82	21
Healthy plant	0.91	0.95	0.93	21
Lack of lighting	0.83	0.90	0.86	21
Accuracy	–	–	0.87	63
Total average of obtained results	0.87	0.87	0.87	63

Additional test samples of photographs were examined to check the quality of neural network training. The results of the study of these test samples are given in Table 4.

Table 4

Results of studying test samples

Classification attribute	The credibility of the classification to one of the classes, u. f.			Credibility of the correct classification, u. f.
	Class «healthy plant»	Class «lack of water»	Class «lack of lighting»	
Healthy plant	0.9155848	0.0191234	0.06529175	0.9155848
	0.88159305	0.06798921	0.05041769	0.88159305
	0.97951835	0.00543664	0.01504505	0.97951835
Average value	0.9255654	0.03084975	0.04358483	0.9255654
Lack of water	0.00458096	0.9771553	0.01826373	0.9771553
	0.05824844	0.6864041	0.25534746	0.6864041
	0.00548201	0.9604281	0.03408988	0.9604281
Average value	0.02277047	0.8746625	0.102567023	0.8746625
Lack of lighting	0.01505669	0.00631772	0.97862554	0.97862554
	0.00445156	0.00396815	0.9915803	0.9915803
	0.05040942	0.35360035	0.59599024	0.59599024
Average value	0.02330589	0.121295407	0.855398693	0.855398693

The numerical data in the above Table showed averages for three test images. For each of the classes under consideration, the following data were obtained: 92.6 %, 87.5 %, and 85.5 % for a “healthy plant”, a plant with a lack of water, and a plant with a lack of lighting, respectively.

## 6. Discussion of results obtained in the development of a system to recognize the plant *Aloe arborescens L.* deviations from normal growth using machine learning algorithms

Our analysis of the quality metrics of the proposed image classification process by specified classes (Table 3) has demonstrated a high reliability of recognition: for a normally developing plant (class “healthy plant”) – 91 %, for a plant without watering (“water deficiency” class) – 89 %, and for a plant without lighting (class “lack of lighting”) – 83 %.

Our analysis of the validity of the recognition of the causes of abnormalities in the development of *Aloe arborescens L.* for three groups of test samples (three photographs for each classification type) has shown similar reliability of the plant’s classification to one of three classes: 92.6 %, 87.5 %, and 85.5%, respectively (Table 4).

Thus, a photograph of the tip of an *Aloe arborescens L.* leaf against a white background could be used to determine with a high probability the fact of lack of either lighting or watering. At the same time, it is also highly likely to distinguish between a plant with a lack of lighting from a plant with a lack of watering. Our results confirm the effectiveness of the chosen method for recognizing the causes of abnormalities in the development of *Aloe arborescens L.*, based on the deep learning of the VGG-16 convolutional neural network.

This is generally consistent with the results reported in [7–13] on the use of machine learning to develop methods for the recognition of plant diseases and pests. In addition, the results reported here supplement the above studies with the method for recognizing the causes of abnormalities in the development of *Aloe arborescens L.* due to lack of watering or lighting.

There are several shortcomings related to the VGG16 architecture that should be noted. In the first place, a given DCNN contains a relatively large number of parameters for the predefined number of layers. This is due to the size of the 3×3 filters used, which slows down the learning speed and increases the required storage space for the model. However, these features are not critical when solving the task set for this work as the automatic plant recognition system is not designed for deployment on mobile platforms with limited resources and does not require real-time operations.

The limitation of a given method is the need to photograph the tip of a leaf against a white background. Thus, it is necessary that the back wall of the hydroponic installation should be white. This would make it possible to get pictures of several leaves in each plant against a white background, with the automatic movement of the camera over the guides located on the front side of the hydroponic installation. It is preferable to take a camera with a great depth of field so that at one photograph one gets a high sharpness of the image of all the visible tips of the leaves of *Aloe arborescens L.* Acquiring photographs of the tips of *Aloe arborescens L.* leaves against a white background in a fully automatic mode is a technical challenge, given the chaotic location of the leaves in space. It is obvious that not all tips of leaves could be photographed against a white, or on some other monochrome background. In addition, there is an issue of how to cut images of the tips of leaves automatically from the received photograph against a white background of the predefined size. Therefore, in order to integrate the developed system of recognition of the causes of deviations in the development of *Aloe arborescens L.* into the system of automatic control over the modes of a hydroponic installation, it is necessary

to develop specialized software (SSW). Such SSW would have to provide a consistent solution to a series of challenges:

- automatic detection of all the leaves' tips visible in the photograph of the plant *Aloe arborescens L.*;
- determining the contours of the identified tips of leaves;
- cutting out of the original photograph of square-shaped fragments containing the contoured tips of the leaves optimal for length recognition;
- replacing everything on each fragment that is outside the highlighted contours with white;
- uploading all fragments to the *Aloe arborescens L.* recognition system of growth deviation causes;
- adjusting the system of automatic control over a hydroponic installation in case of detecting developmental abnormalities.

The development of such SSW, as well as the additional training of the developed system to recognize other causes of abnormalities in the development of *Aloe arborescens L.*, including diseases and pests, is the direction of further research.

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## 7. Conclusions

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1. A classifier model has been developed to enable the VGG-16 neural network to be used to solve the task of automatic classification of the plant *Aloe arborescens L.* This classifier model was developed using transfer learning technology based on the pre-trained VGG-16 network, consisting of 6 units. To this end, the output fully-connected layers (unit VI) were removed from its architecture and, instead, we developed and trained the optimal structure of this piece of the network according to object classes. In order to improve the quality of the classification, it was possible to “post-train” the layers of unit V. At the same time, the “frozen” layers of units I–IV did not participate in the training process. The optimization of the VGG-16 DCNN architecture was carried out in accordance with the principles of transfer training. The neural network output layer structure has been optimized to maximize recognition by using a test sample from the dataset.

2. A set of images of the plant under study was prepared for training the VGG-16 neural network in order to produce informative classificational attributes. We produced 200 digital color photographs of the tips of *Aloe arborescens L.* leaves: normally evolved plants, plants with visual signs of lack of watering, plants with visual signs of lack of lighting. The tips of the leaves were photographed in the “color photo” mode against a white background from different angles and under different lighting (with artificial lighting, with natural light, using a built-in photo flash).

The images were compressed to 224×224 pixels and normalized. The augmentation procedure was used to increase the number and diversity of the samples. The application of data augmentation improves the generalizability of the model, and data class labels do not change.

A deferred sampling method was used to train the classifier model. All data were randomly split into three groups: 70 % for model training, 20 % for validation, 10 % for final testing.

3. We have tested the developed model of the classifier during the experiment to identify deviation from the normal growth in *Aloe arborescens L.* The analysis of quality metrics of the proposed image classification process by specified classes has shown high reliability of recognition: for a normally developing plant (class “healthy plant”) – 91 %, for a plant without watering (class “lack of water”) – 89 %, and for a plant without lighting (lack of lighting) – 83 %.

Our analysis of the validity of the recognition of the causes of abnormalities in the development of *Aloe arborescens L.* based on three groups of test samples has demonstrated similar reliability of the plant's classification to one of three classes: 92.6 %, 87.5 %, and 85.5 %, respectively.

The developed system for recognizing the belonging of the plant *Aloe arborescens L.* to the corresponding class could be used as the main feedback of the automatic control system of a hydroponic installation. This would reduce the impact of the “human factor” on the process and increase the yield of *Aloe arborescens L.* In addition, the developed approach to solving the task set provides an opportunity to retrain the model of automatic classifier for the relevant tasks of recognition other known causes of deviations in the development of aloe.

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## References

1. Tikhomirova, L. I., Bazarnova, N. G., Il'icheva, T. N., Sysoeva, A. V. (2016). Process for the preparation of medicinal plants of *Potentilla alba* (*Potentilla alba L.*) under hydroponics. *Chemistry of Plant Raw Material*, 3, 59–66. doi: <https://doi.org/10.14258/jcprm.2016031228>
2. Vardanyan, A. P. (2009) Sopryazhennyy metod kul'tury in vitro i gidroponiki dlya sohraneniya prirodnyh resursov *Hypericum perforatum*. *Flora, rastitel'nost' i rastitel'nye resursy Armenii*, 17, 108–110. Available at: <http://takhtajania.asj-oa.am/392/>
3. Dorais, M., Papadopoulos, A. P., Luo, X., Leonhart, S., Gosselin, A., Pedneault, K. et. al. (2001). Soilless Greenhouse Production of Medicinal Plants in North Eastern Canada. *Acta Horticulturae*, 554, 297–304. doi: <https://doi.org/10.17660/actahortic.2001.554.32>
4. Ustanovka “Podsolnuh”. Available at: <https://gidroponika.com/content/view/330/142/>
5. AeroFlo 14. Available at: <https://www.gidroponika.su/g/gidroponnye-ustanovki/ghe-sistema/aeroflo-14-kupit.html>
6. Kim, G., Demyanenko A. (2019). A review of automated hydroponic systems of the main world manufacturers. *VESTNIK KazNRTU*, 4 (134), 370–376. Available at: <https://official.satbayev.university/download/document/12092/%D0%92%D0%95%D0%A1%D0%A2%D0%9D%D0%98%D0%9A-2019%20%E2%84%964.pdf>
7. Villanueva, M. B., Salenga, M. L. M. (2018). Bitter Melon Crop Yield Prediction using Machine Learning Algorithm. *International Journal of Advanced Computer Science and Applications*, 9 (3). doi: <https://doi.org/10.14569/ijasca.2018.090301>
8. Türkoğlu, M., Hanbay, D. (2019). Plant disease and pest detection using deep learning-based features. *Turkish Journal of Electrical Engineering & Computer Sciences*, 27 (3), 1636–1651. doi: <https://doi.org/10.3906/elk-1809-181>
9. Amara, J., Bouaziz, B., Algergawy, A. (2017). A Deep Learning-based Approach for Banana Leaf Diseases Classification. Conference: *Datenbanksysteme für Business, Technologie und Web (BTW 2017)*. Bonn: Gesellschaft für Informatik e.V., 79–88. Available at: <https://dl.gi.de/bitstream/handle/20.500.12116/944/paper09.pdf?sequence=1&isAllowed=y>



10. Ishikawa, T., Hayashi, A., Nagamatsu, S., Kyutoku, Y., Dan, I., Wada, T. et. al. (2018). Classification of strawberry fruit shape by machine learning. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-2, 463–470. doi: <https://doi.org/10.5194/isprs-archives-XLII-2-463-2018>
11. Ullah, A., Mohd Nawi, N., Arifianto, A., Ahmed, I., Aamir, M., Khan, S. N. (2019). Real-Time Wheat Classification System for Selective Herbicides Using Broad Wheat Estimation in Deep Neural Network. *International Journal on Advanced Science, Engineering and Information Technology*, 9 (1), 153. doi: <https://doi.org/10.18517/ijaseit.9.1.5031>
12. Wang, H., Li, G., Ma, Z., Li, X. (2012). Application of neural networks to image recognition of plant diseases. *2012 International Conference on Systems and Informatics (ICSAI2012)*. doi: <https://doi.org/10.1109/icsai.2012.6223479>
13. ChandraKarmokar, B., Samawat Ullah, M., Kibria Siddiquee, M., Md. Rokibul Alam, K. (2015). Tea Leaf Diseases Recognition using Neural Network Ensemble. *International Journal of Computer Applications*, 114 (17), 27–30. doi: <https://doi.org/10.5120/20071-1993>
14. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S. et. al. (2015). ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision*, 115 (3), 211–252. doi: <https://doi.org/10.1007/s11263-015-0816-y>
15. Lecun, Y., Bottou, L., Bengio, Y., Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86 (11), 2278–2324. doi: <https://doi.org/10.1109/5.726791>
16. Krizhevsky, A., Sutskever, I., Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, 60 (6), 84–90. doi: <https://doi.org/10.1145/3065386>
17. LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. *Nature*, 521 (7553), 436–444. doi: <https://doi.org/10.1038/nature14539>
18. Srivastava, R. K., Greff, K., Schmidhuber, J. (2015). Training Very Deep Networks. *arXiv*. Available at: <https://arxiv.org/pdf/1507.06228.pdf>
19. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D. et. al. (2015). Going deeper with convolutions. *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. doi: <https://doi.org/10.1109/cvpr.2015.7298594>
20. He, K., Zhang, X., Ren, S., Sun, J. (2016). Deep Residual Learning for Image Recognition. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. doi: <https://doi.org/10.1109/cvpr.2016.90>
21. Du, W., Rao, N., Liu, D., Jiang, H., Luo, C., Li, Z. et. al. (2019). Review on the Applications of Deep Learning in the Analysis of Gastrointestinal Endoscopy Images. *IEEE Access*, 7, 142053–142069. doi: <https://doi.org/10.1109/access.2019.2944676>
22. VGG16 model for Keras. Available at: <https://gist.github.com/baraldilorenzo/07d7802847aaad0a35d3>
23. Large Scale Visual Recognition Challenge 2012. Available at: <http://image-net.org/challenges/LSVRC/2012/>
24. Keras. Available at: <https://keras.io/>
25. TensorFlow. Available at: <https://www.tensorflow.org/>
26. Theano. Available at: <https://github.com/Theano/Theano>
27. The Microsoft Cognitive Toolkit (2017). Available at: <https://docs.microsoft.com/en-us/cognitive-toolkit>
28. NVIDIA cuDNN. Available at: <https://developer.nvidia.com/cudnn>
29. Nikolenko, S., Kadurin, A., Arhangel'skaya, E. (2018). *Glubokoe obuchenie*. Sankt-Peterburg: Piter, 480.
30. Kingma, D. P., Ba, J. (2014). Adam: A Method for Stochastic Optimization. *International Conference on Learning Representations*. *arXiv*. Available at: <https://arxiv.org/pdf/1412.6980.pdf>