Remote Sensing, Monitoring and Classification of Agricultural Land Using Artificial Neural Networks

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REMOTE SENSING, MONITORING AND CLASSIFICATION OF AGRICULTURAL LAND USING ARTIFICIAL NEURAL NETWORKS

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Abstract. The results of an analytical review of the use of artificial neural networks (ANN) in agricultural production are presented. Results of remote sensing of agricultural land in the form of color images can be obtained using unmanned aerial vehicles (UAV). UAV can be used as aerial robots that perform aerial photography functions, transport technological components such as plant protection products, and perform other similar functions. Other functional equipment can be installed on the aircraft: thermal imagers, multispectral and IR cameras, etc., using the data obtained from the UAV, you can create an orthophotoplane or a 3D model of the area, make a map of heights, determine the state of fields, crops and determine their vegetation indices NDVI. A classification of UAV application areas in agricultural production is proposed, which involves ordering the UAV application areas in agriculture. To obtain and process remote sensing data from UAVs in different parts of the spectrum, a conceptual model of the software package has been developed. The software package is intended for receiving and processing the results of monitoring and subsequent analysis of the set of calculated vegetation indices. The main research tasks solved by the software developer and determining its structure are formulated. To predict productivity, a method of applying the results of aerial photography in combination with experimental data on the biological development of agricultural crops has been developed. For practical use of the developed methodology, a database for each culture is formed. The results obtained from UAV are used to construct regression and matrix mathematical models of the relationship between optical-spectral characteristics and crop yields.

1. Introduction

Solving the problems of ensuring food security through the industrialization of agricultural production requires the creation and research of new technologies and technical means for obtaining information on-line [12, 20, 22]. The expansion of the scope of unmanned aerial vehicles (UAVs) in agricultural production is due to the need to obtain timely reliable information on the status of agrocenoses over the entire growing season.

The range of UAV use in agricultural production is very wide: monitoring of agricultural lands and pastures, assessment of the amount of work and control of their implementation, protection of farmland [1, 2, 5]. Currently, there are many types and types of UAVs on the market: aircraft type, helicopter type, unmanned balloons, hybrid subclasses of vehicles [10, 11, 15, 19]. The analysis of the use of UAVs in agricultural production showed that they are often used as aerial robots that can perform the function of both aerial photography and for the delivery of plant protection products and perform other functions. Quadrocopters can also be used to create 3D models of various objects (buildings, technological

structures, reclamation facilities and hydraulic structures), or small areas of fields with an area of less than 0.8 hectares.

The study of structural schemes and settings of the UAV in agricultural production devoted to the work of scientists Yakushev V. P., R. A. Poluektova [6] Mikhailenko I. M. Petrushina, A. F., Yakushev V. V.[10,7] Frohlich H., Walter E.,[16] Joseph G.[18] and other Researchers have noted the possibility of a detailed assessment of the nature and extent of the impact on productivity of the actual soil-climatic, agrometeorological and other aspects, including the possibility of obtaining informative indicators of vegetation indices, remote receive in different bands of the reflectance spectra of plants [14].

A separate problem is the rapid processing of information from video cameras and radiometric sensors placed on mobile media. Domestic and foreign publications in the field of building and improving the architecture of artificial neural networks (ins) (J.-S. R. Jang, L.-X. Wang, J. M. Mendel, T. Takagi, M. Sugeno, R. Fuler, O. Nelles) show wide possibilities of their adaptation to the features of the subject area. Geostatistical methods of estimation allow to use large data sets and to compare with each other different productivity areas of the field and the field as a whole with each other, based on a very specific variation of the yield. Modern it allows to analyze and identify the role of specific factors and their groups [17], affecting crop yields and land productivity, to clarify the standards of mineral nutrition and application of meliorants, taking into account crop rotations, which allows to identify patterns and use them to form sustainable crops [9].

2. Materials and methods

In the analysis of methodological approaches to assessing the level of crop productivity, the following methods and private methods were used. To justify the system of indicators based on enlarged groups of factors, it is advisable to use the expert method of analyzing hierarchies using statistical indicators structured using a relational database. Based on the obtained system of indicators, the formation of the infological and information models in the form of structure, relationships and membership functions for a fuzzy-multiple description is carried out. providing. A significant amount, heterogeneity by types and types, and the dispersion of the initial data required the use of artificial intelligence technologies (AI or AI) to collect, systematize and directly evaluate and predict the level of crop productivity.

Among the basic approaches and tools were selected, as more focused on the subject area of assessing the productivity of crops, artificial intelligence (AI) methods, including deep machine learning [17], cognitive modeling (construction and parameterization of fuzzy cognitive maps) [23, 21] modeling based on artificial neural networks (ANNs) [4, 8, 13], as well as image classification methods.

3. Results and discussion

Figure 1 shows the systematization of the UAV application areas in the agricultural sector, depending on the purpose of use.

According to the scheme, it is possible to use UAVs in animal husbandry, land reclamation, agroecology, in the field of monitoring and land conservation, in the construction of hydraulic structures, etc.

Practice shows that satellite images can give distorted data [2]. In fact, they are influenced by atmospheric conditions that affect the light transmission and its reflection. Satellite data are not calibrated depending on weather conditions. When shooting is done on a drone (quadrocopter), two people work in the team: a pilot and a ground specialist, whose duties include conducting atmospheric calibration, which allows us to compare the images regardless of the conditions in which they were taken.
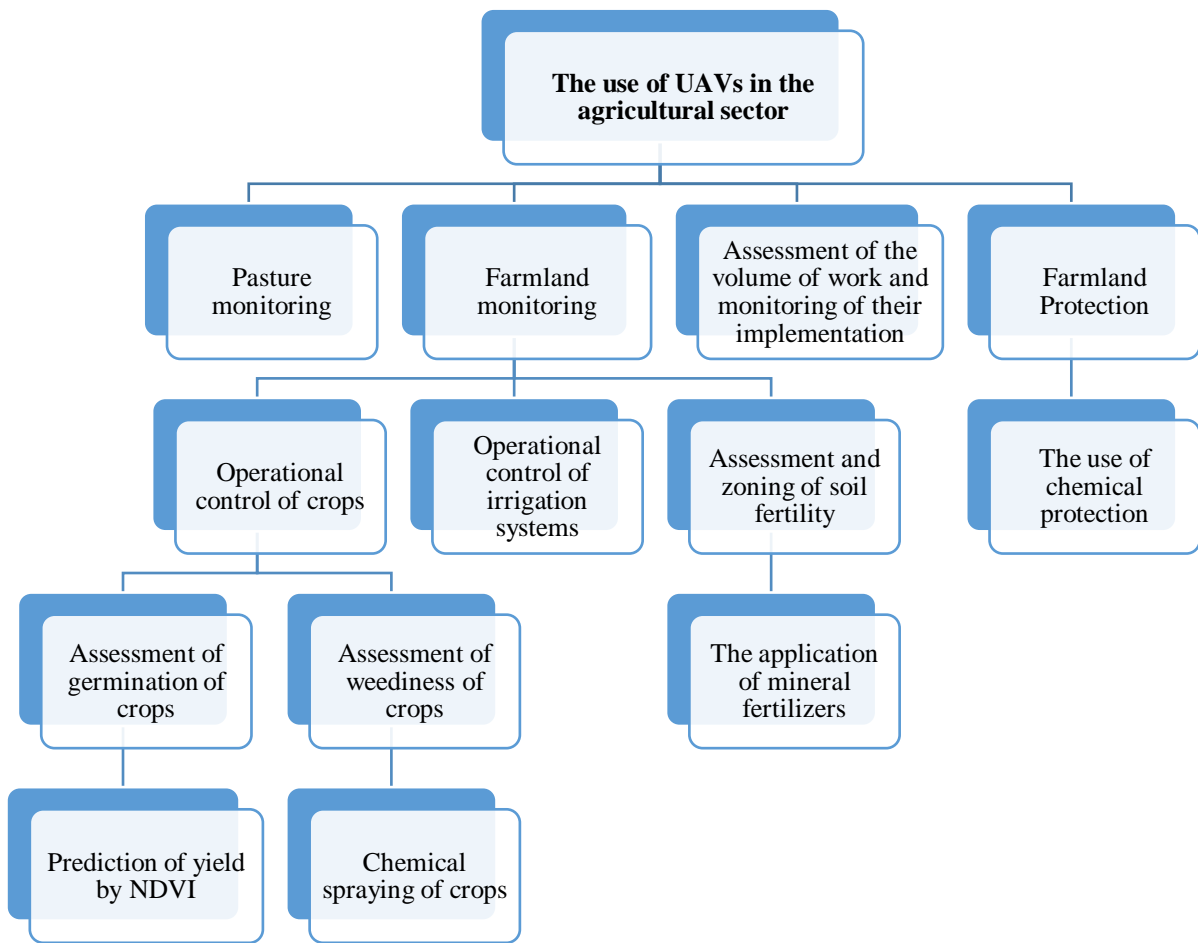
Figure 1. The use of UAVs in agricultural production.

Table 1 presents the possible functional features of the applied means of remote sensing of agricultural land.

For the automated search and selection of relevant information on the subject of assessing the level of productivity of agricultural crops, the most difficult problem was the automated assessment of the affiliation of quantitative and qualitative information to the subject area being studied [22].

Table 1. Analysis of the functional applicability of remote sensing of agricultural land.

Functional Features	Data Source			
	Satellite	quadrocopter	UAV aircraft-type	mobile technological units
Determination of uniformity of sowing	±	+	+	-
Soil assessment	+	+	+	+
Field weed detection	±	+	+	-
Determination of soil moisture	-	-	-	+
Area determination	+	+	+	-
Process control	±	+	+	±

Such a statement can be reduced to the problem of multidimensional classification, for which the graphic information received from mobile carriers is the initial one. In particular, to solve the problem of identifying crop heterogeneity affecting crop yields, an artificial neural network (ANN) was developed.

For the formation of training, verification and testing samples, color images obtained using quadrocopters of the DGI Phontom 4 Pro type were used. Examples of images of uniform and not uniform crops of plant development are shown in Figure 2.

a   b

Figure 2. Typical images used for training ANN.

The classification problem was solved in the following formulation. For an arbitrary color image fed to the ANN input, determine the class to which it belongs: areas of fields with uniform development of plants (Figure 2a) or areas with defects (weediness of crops, uneven sowing, damage to plants by pests and diseases, etc. .). Due to the limited amount of available samples for training ANNs, generators were used to generate datasets by augmentation.

The learning outcomes of the developed composite neural network are presented in Figure 3.

The complexity of solving the classification problems in the described formulation is related to the need to pre-process the initial information supplied to the input of the ANN, as well as the justification of the architecture and hyperparameters of the developed ANN or their ensemble. The difference in options a) and b) in Figure 3 is due to the stochastic selection of the initial sets of weight coefficients of the ANN neurons, and we also distinguish between training and test samples of the analyzed images. In addition, the implementation of in-depth training of the designed ANN requires very extensive samples of pre-marked data for various variants of crop heterogeneity. Moreover, according to well-known recommendations, both the simplest fully connected ANNs and recurrent networks do not provide the required classification quality indicators, even with significant training samples.
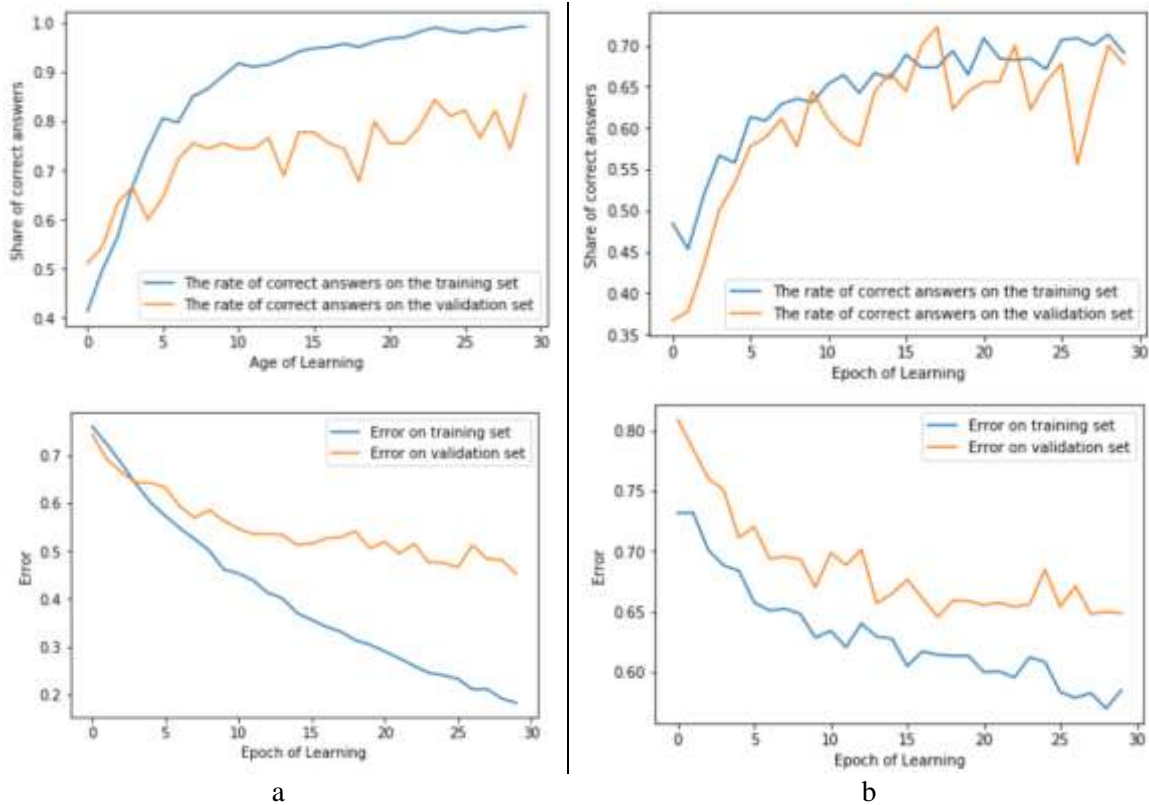
Figure 3. Diagram of training developed by ANN in identifying crop heterogeneity.

The developed software package for forecasting and operational management of agricultural production provides for accounting and retrospective information on the yields of the respective crops. This information in the form of multi-year time series provides for the solution of the regression problem. To solve this problem, a separate fragment of the ANN is used at the input of which structured numerical data are supplied.

In this regard, for the design of the specialized part of the ANN, the LSTM architecture was adopted, the structure of the basic element of which is shown in Figure 4a.
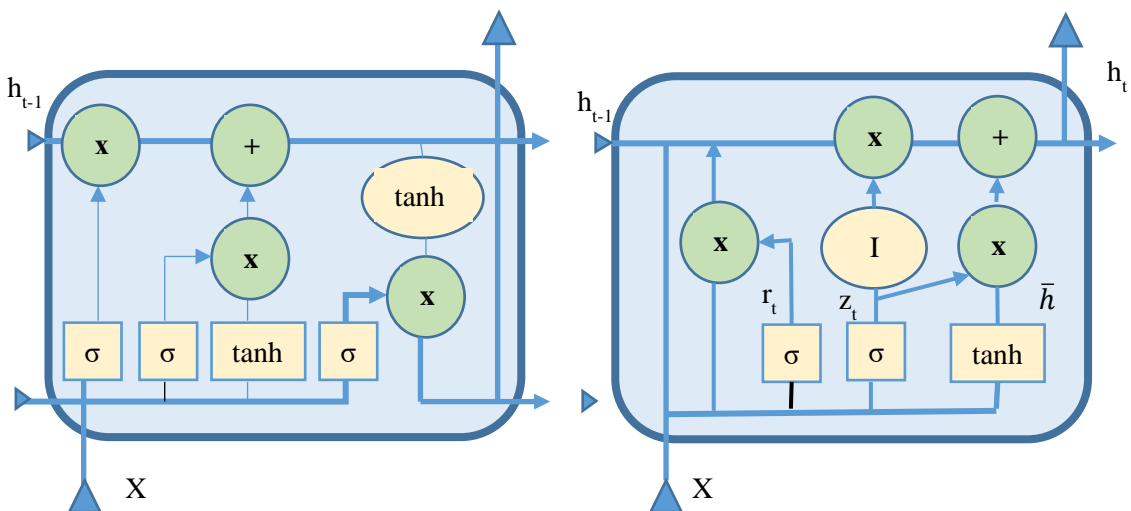

Figure 4. Scheme of a single element of the hidden layer LSTM configuration.

Each of the cells of the intermediate layer contains three types of interconnected filters (input, intermediate and output), several neurons with heterogeneous activation functions (sigmoidal and hyperbolic tangent), as well as controlled adders providing switching of the transmitted signals.

With all the advantages of such an ANN architecture, it is the possibility of training for complex temporal data combinations; its training takes a very long time, which, depending on the volumes of training and test samples, as well as the configuration and speed of the computers used, can be measured for hours and days.

To eliminate the noted drawbacks, a modified version [17] of a recursive ANN with memory can be used, the scheme of which is shown in Figure 4b.

Such a structure has actually three inputs and outputs, the mathematical interaction algorithm of which is described by the system of equations (1) - (4).

$$z_t = \sigma\big(W_z \cdot \big[h_{t-1,} \ x_t\big]\big) \tag{1}$$

$$\tau_t = \sigma\big(W_\tau \cdot \big[h_{t-1,} \ x_t\big]\big) \tag{2}$$

$$\tilde{h}_t = \tanh\big(W \cdot \big[\tau_t * h_{t-1,} \ x_t\big]\big) \tag{3}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t, \tag{4}$$

where x_t - the input signal of each cell in the layer;
h_t and h_{t-1} - intermediate signals transmitted between identical cell elements of the hidden ANN layer;
σ - is the sigmoid function of neuron activation;
tanh is the activation function of a neuron in the form of a hyperbolic tangent.

Learning a recursive ANN of such an architecture takes several times less time than the previously described LSTM, which is especially important when selecting hyperparameters and methods for preprocessing input data in deep machine learning. After choosing the optimal architecture, building and compiling the ANN in the Google Colaboratory environment [17], it is planned to conduct numerical studies of the effectiveness of the developed ANN.

4. Conclusions

The study allowed us to formulate the following conclusions:
1. The considered approaches to assessing the productivity of crops based on UAVs and developed tools, in particular, computer-based artificial intelligence tools using ANNs, allow the use of significant amounts of heterogeneous information from their statistical databases online.
2. The use of neural networks of the LSTM architecture and its modifications allows us to solve the problem of constructing regression for the automated detection of defective areas of agricultural fields.
3. Remote assessment of the state and the identification of short-term trends in the dynamics of changes in the optical indicators of crop development, allows to identify developmental defects using ANN methods of deep machine learning.

The results obtained were used to build and computerize neural network models that describe the patterns of relationships between the optical and spectral characteristics of agrocenoses and crop yields in agricultural production.

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