Use of Neuron Networks for Planning the Correct Selection of Plant Samples in Precision Agriculture Technologies

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Abstract

The article is devoted to the study of the use of neural networks to improve the selection of plant stands in precision agriculture technologies. The study takes into account the complex aspects of sample selection, such as the speed of image acquisition, the effectiveness of assessing the state of mineral nutrition and soil moisture, etc. The use of neural networks makes it possible to automate and increase the accuracy of selection, improving the quality of the analysis of plant stands, subject to compliance with soil sample evaluation technologies. The obtained results indicate the prospects of implementing this approach in modern agriculture.

Keywords [1]

neural network, precision agriculture, plant samples, image recognition, training, shooting with a UAV

1. Introduction

Modern real systems and processes to one degree or another have development in time, therefore, they are stochastic. This means that the characteristics that describe their functioning are probabilistic and are random variables. The values of these quantities, as a rule, are in a certain interval, which sometimes has clearly defined boundaries, and more often - the boundaries are indefinite, vague. For example, such boundaries are inherent in parameters that are predictive in nature. Moreover, the more distant in time the forecasting horizon, the less its accurate, i.e. accuracy of estimates of the boundaries of possible values of such parameters. Therefore, in such conditions, the use of fuzzy intervals is preferable. Declaring model parameters in the form of a fuzzy interval is a convenient form for formalizing imprecise values. It is psychologically easy to give a fuzzy interval estimation, and the carrier of a fuzzy interval is guaranteed to contain the value of the parameter under consideration.

Recently, fuzzy modeling has become one of the most active and promising areas of applied research in various fields [1-4]. In fuzzy modeling, to represent fuzzy sets, fuzzy values are most often used, which are the basis for constructing mathematical models using linguistic variables. Fuzzy Monte Carlo Simulation (FMCS) [5-9] is widely used in stochastic fuzzy models for modeling random variables. The main point of the FMCS considered in these works is the representation of parameters and variables only by triangular fuzzy numbers. However, in practice, the intervals of possible values of a random variable are often known. In this case, such parameters are given by trapezoidal fuzzy numbers. In article [10], a mechanism for fuzzy modeling of random variables by the Monte Carlo method based on the Gaussian

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membership function is proposed. This article is a development of these studies. It discloses a method for modeling random variables, the value intervals of which are given in a fuzzy linguistic form. In this case, both the Gaussian membership function and the beta distribution are used.

The conditions for agriculture are becoming more and more difficult, taking into account climate change, the disproportionate increase in the cost of fertilizers and political risks. Precision agriculture, also known as precision agriculture or precision agriculture, is an approach to agriculture that uses modern technologies such as satellite imagery, sensors, geographic information systems (GIS) and others to collect and analyze data about soil, plants and other factors of agriculture. The main goal of precision agriculture is to optimize the use of resources (productive soil, water, fertilizers, etc.) and maximize the yield while simultaneously reducing the negative impact on the environment. Implementation of the concept of precision agriculture requires solving many organizational and methodical issues and fundamentally improving the culture of production in the agricultural industry in general and in crop production in particular. Thus, it is necessary to ensure the accumulation and processing of large data sets, that is, to implement information technologies at a new level within the limits of not a separate field, but an economy or even an industry, as shown in D. Yuniarto et al (2020) in [1]. For Ukraine, it is necessary to increase the number of sensor equipment for monitoring by several orders of magnitude, for which it is advisable to develop universal languages for the description of sensor equipment such as Verilog, implemented in India by the group of J. Patidar et al (2019) in [2].

The implementation of Internet of Things technologies is promising, the experience of which is shown in T. Wiangtong and P. Sirisuk (2018) in [3] and U. A. Bhat et al (2022) in [4]. Significant progress has been achieved primarily in closed soil technologies as shown in P. Patil et al (2022) in [5], but there the environmental impact is fundamentally less than in the open air. For the industrial scale of traditional fields, it is necessary to implement fundamentally more complex technologies that will involve not only obtaining experimental data, but also their filtering for unreliable results, which can be achieved in multi-agent systems described in M. Zaryouli et al (2020) in [6]. In Ukraine, Smart Farming technologies for plant nutrition are most often implemented according to the following algorithm: survey using UAVs, identification of characteristic areas, ground sampling and their subsequent laboratory analysis to create maps, in particular, of nitrogen nutrition. But the state of plants can be determined not only by the state of mineral nutrition, but also, in particular, by the state of moisture, and accordingly neglecting this indicator leads to big mistakes. The process of sampling is time-consuming and it is impractical to complicate it by determining soil moisture at different depths. Accordingly, the aim of the work is the development of methodical approaches to determine the optimal places for the selection of control samples of plants in conditions of different conditions of crop moisture.

2. Literature review

Sampling is advisable to be carried out using robots, since means of accurate positioning are necessary in any case, since visual positioning according to landmarks in the field is not always possible at all Winterhalter, W. et al (2020) in [7]. For the European market, which is characterized by fields with an area of several to several dozen hectares, it is possible to use special multispectral sensors capable of immediately issuing maps of the distribution of vegetation indices. Such sensors as Mapir Survey3W shown in Z. Zhang et al (2022) in [8] or Sentera Double 4K shown in N. u. Sabah et al (2022) in [9] are designed for small UAVs of the mini class and require constant radio communication with the operator, which is not always possible for the fields of Ukraine with an area of 60-100 hectares. Based on the experience of research inpatients N. Pasichnyk et al (2020) in [10], the order of 6 gradations and the corresponding number of repetitions are required to study the fertilizer application system. Therefore, the amount of ground work is considerable and the use of robots is quite appropriate. The expediency and effectiveness of such an unconventional tool was studied in the work of M. Edmonds and J. Yi (2021) in [11], where the problems and prospects of such solutions are shown.

In general, considerable attention has been paid to the use of robots in agricultural production. Thus, methods of route selection based on various optimality criteria have been developed in the works Y. R. Milijas et al. (2021) in [12], D. Drake et al. (2018) in [13] in the presence of obstacles, J. Pak et al (2022) in [14] and A.N. Voronin et al (2002) in [15] for minimum mileage. You can also use a tool such as fuzzy logic [16]. These tools can be effectively used in crop production, taking into account the topography of the area, the presence of known obstacles, and the energy efficiency of the devices. With regard to operational data, the work of N. Pasichnyk et al (2021) in [17] describes the experience of choosing the optimal route on the basis of data obtained from UAVs with the Slantrange complex. The work shows that with the Slantrange multispectral complex and the SlantView software, maps of the distribution of vegetation indices, on the basis of which the state of vegetation is determined, can be obtained for a field of 60-70 hectares within 1-2 hours. Calculations do not require cloud services and, accordingly, access to the Internet and, accordingly, are acceptable given the dynamics of state changes inherent in vegetation.

For the most common unmanned aerial vehicles with electric motors, which are easier to control due to the absence of electromagnetic interference generated by internal combustion engines, the issue of power supply is also well studied. These are the optimal routes in the conditions of limited storage batteries, described in the work of N. Pasichnyk, et al (2021) in [18], and alternative energy supply from solar galvanic cells, shown in R. S. Krishnan (2022) in [19]. That is, the main methodological issues regarding the selection of samples are not in the technical area regarding the possibility of selection or the organizational area regarding the availability of such places, but rather in the identification of optimal characteristic areas with different states of mineral nutrition.

The issue of remote moisture assessment is extremely important for crop production, and the review work by M. J. Pandian and D. Karthik (2022) in [20] describes the existing experience with UAVs, which primarily involves the use of thermal imagers. When taking samples, it is technically possible to measure soil moisture, but reliable consideration of the dynamics of changes in the state of moisture supply of plants, especially in drought conditions, has doubtful prospects. A possible variant of remote establishment of the state of plants is the assessment of the parameters of the distribution of indices on the site, shown in relation to the prolonged effect of herbicides in the work of N. Pasichnyk et al. (2021) in [21], Y. Cao et al. (2020), Y. Liu et al. (2012), G. Yan (2019), A. Coy (2016).

3. Materials and Methods

3.1. Methodology of the experiment

Research was conducted on production fields in 2019-2020 in Boryspil district of Kyiv region with coordinates 50º16' N, 30º58'E 50.0347. The Slantrane 3p system mounted on the base of the DJI Matrice 600 Pro UAV was used for spectral research. Data on separate spectral channels and vegetation indices calculated by the Slantview program were considered. The maximum detail (GSD 0.04 m/pixel) was obtained from the image window of the Slantview software (available variants of the NDVI index - Green, Red and RedEdge). Monochrome images were used when studying the results of individual spectral channels (window of images), which were stored in bmp format to ensure completeness of information (Fig. 1).

4. Results and discussion.

4.1. Assessment of the nature of the distribution.

To approximate the experimental data, the amplitude version of the modified Gaussian function (hereinafter GaussAmp) was adopted, without a shift along the ordinate axis. The choice of the Amplitude version of Gaussian peak function is due to the fact that, compared to the classical Gaussian function, it better describes the peak values and it is easier to adapt it to the variable size of the experimental area, which is important for the industrial implementation of solutions (1):

$$N = A \times exp^{\frac{-(X-xc)^2}{2w^2}} , \quad (1)$$

where: N is the number of measurements (in our case, the number of pixels); X is the intensity of the color component, A is the amplitude; xc – average value; w is the standard deviation (corresponds to the value of A/2).

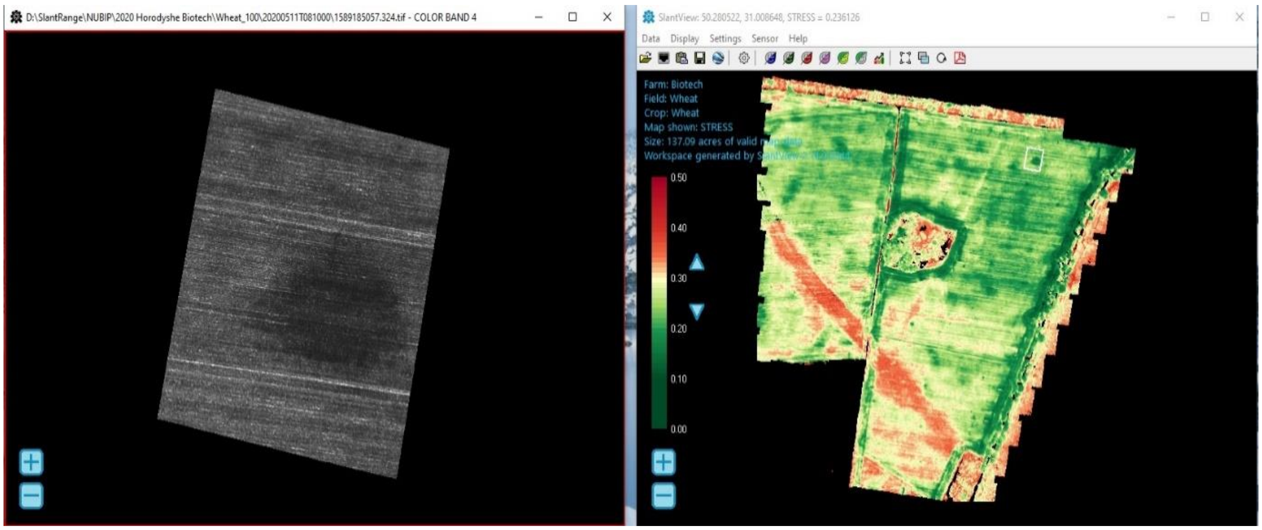


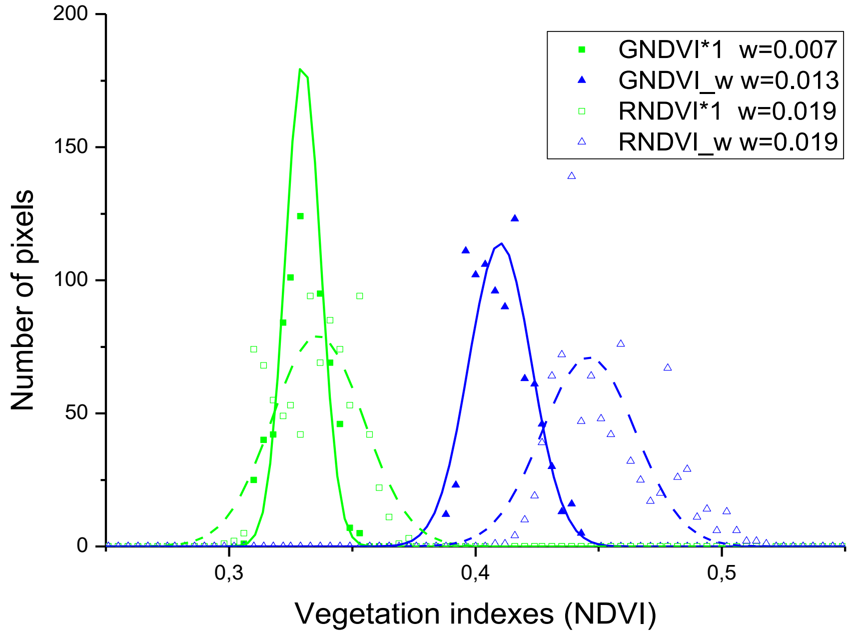
Figure 1. A picture in the IR spectrum of a field with a lowland (left) and a Stress map in the SlantView software (right).

The results obtained by separate spectral channels are shown in Table 1, where 1 is a normal wheat plot, and water is an area with improved water supply due to the accumulation of water in the lowlands.

Table 1
Results of approximation of experimental data using

	Green		Red		RedEDGE		NIR	
	1	water	1	water	1	water	1	water
xc	98	88	89	79	65,3	65	42	48,5
w	22	23	22,2	18,6	15	15,7	10,7	11,3
A	107	105	101	121	153	149	217	202

For individual spectral channels, the use of a perspective parameter - the standard deviation, shown in N. Pasichnyk et al (2021) in [20], to identify the best state of wet provision turned out to be ineffective. The difference in this parameter was recorded only in the red channel. With regard to the average value, the difference was recorded in the Red Green and NIR channels, while in the visible range the areas in the lowlands are darker, and the opposite is true for the infrared channel. This is probably explained by the difference in the dimensions of the plants, which was also recorded visually during ground observations. Therefore, a convincing identification of uneven moisture, based on the values and indicators of the distribution, could not be found, and the issue requires additional study. It is likely that identification by source channels is possible, but its practical implementation in relation to the needs of sampling raises certain doubts based on the required time for calculations. Available serial Slantrange software and hardware provides rapid acquisition of distribution maps within an hour, but does not include a vegetation index calculator. Data can be calculated on other software, but it takes time. According to the available experience, when using the alternative Agisoft software installed on the graphics station (Core_i5-9400F_2.90GHz_16.0GB_ 250SSD_2T_GeForce GTX1050Ti), more than 5 hours were spent. Given the amount of raw data of 9 GB and the bandwidth of the mobile Internet, the time to build the maps is too long for production use. Accordingly, it is expedient to use the possibility of the Slantrange complex and its standard vegetation indices, since for them the calculations with the Slantview proprietary software for a field of 60 hectares took 40-50 minutes. The Slantview program interface provides access to standard vegetation indices, such as various variations of the most common NDVI index, as well as several proprietary indices such as Stress, Veg.fraction, etc., whose calculation formulas are not disclosed. The GreenNDVI and RedNDVI indices were selected for research. The results are presented in fig. 2.



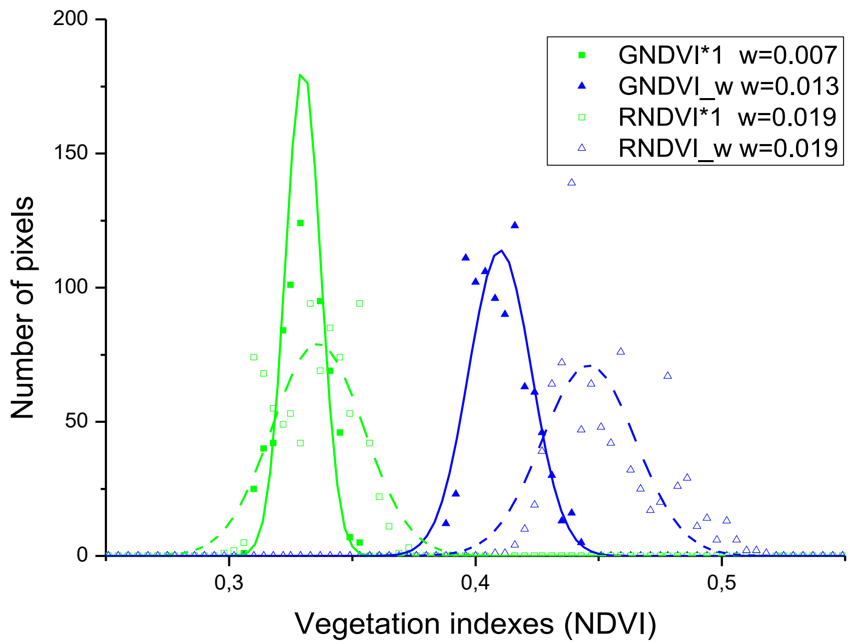


Figure 3. Dependence of the number of pixels on the value of the vegetation index GNDVI and RNDVI: where _1 is a normal state, _w is an increased state of water supply

Based on the results of the conducted research, it can be stated that the characteristics of the Gaussian distribution for the pixels of the NDVI vegetation index distribution map are significantly different from those obtained directly from the spectral channels. Thus, for NDVI indices, the standard deviation of the distribution in normal plants was equal to or even smaller than in those with a better moisture regime, in contrast to the results obtained directly based on the use of spectral channels. At the same time, the coefficient of determination for the distribution of NDVI indices was 0.85-0.95, which is significantly less than the distribution based on the results of using green and red spectral channels, where this indicator was 0.98 and higher. The red spectral channel and its derivatives in the form of indices turned out to be the most promising for identifying increased wet provision.

That is, as before the consideration of individual spectral channels or their combination in vegetation indices turned out to be insufficient for confident identification of correct samples for laboratory analysis.

A possible solution was proposed to use neural networks to analyze the distribution of areas in the field, since puddles are mostly circular in shape, which can be recognized in the field. In this case, there are no restrictions on the nomenclature of available indexes that can be used for analysis.

4.2. Neural networks.

Convolutional Neural Networks (CNNs) are a powerful class of deep neural networks specially designed for processing grid-structured data such as images and videos. Convolutional neural networks are based on two main concepts: convolutions and pooling. Mathematically, convolution for 2D data can be defined as follows:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i-m, j-n) * K(m,n), \qquad (2)$$

where I is the input data, K is the kernel (filter), S is the output data.

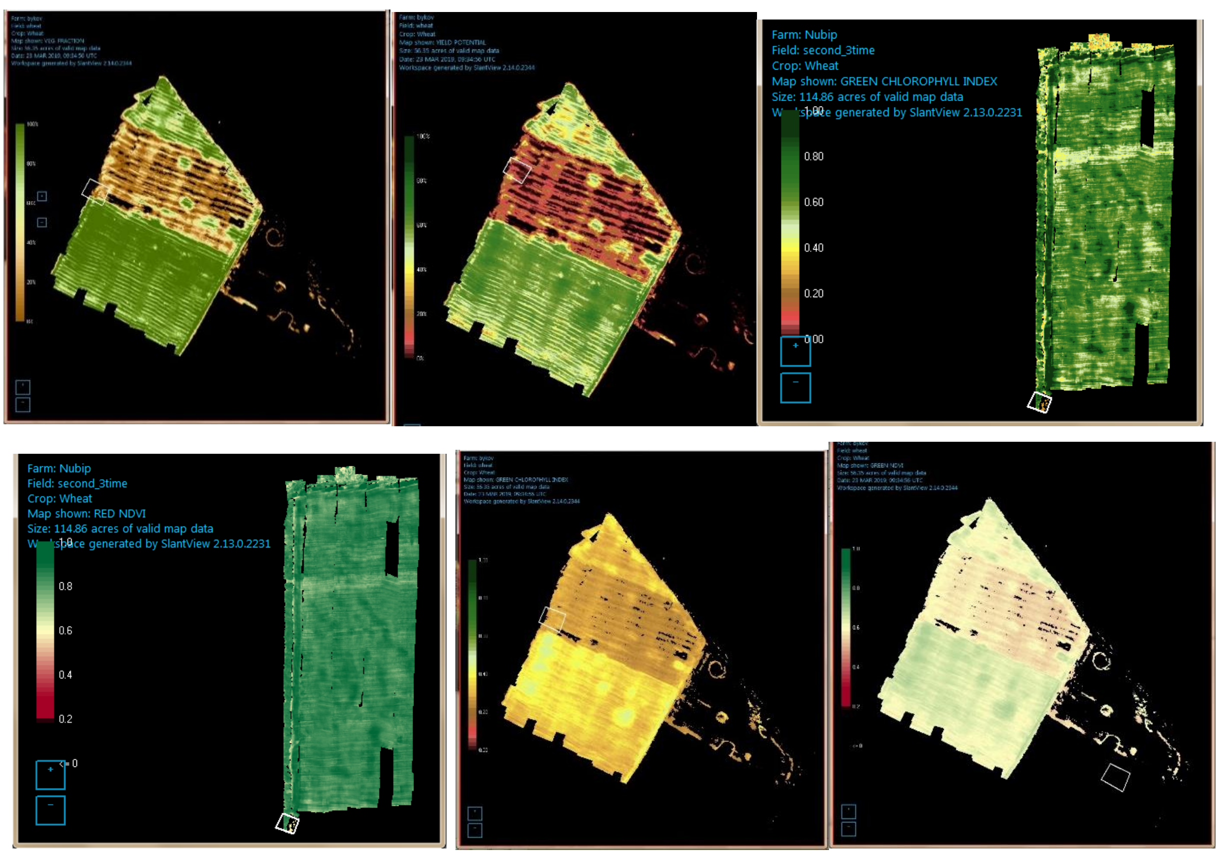


Figure 4. The data set (pictured by a UAV) for training a neural network

To achieve greater instability to various displacements in images, convolutional neural networks often use stride and padding operations. Print defines the step at which the filter moves over the input data, while padding adds extra pixels around the input data to help preserve dimensionality after convolution. Convolutional neural networks are often combined with fully connected layers to perform classification, regression, and other tasks. The results of the convolutional layers are concatenated and fed to the input of the fully connected layer. Convolutional neural networks have shown significant achievements in many areas where it is important to analyze large volumes of visual data. Their success is due not only to the power of the model, but also to the ability to learn abstract levels of representation of the hierarchical structure of input data, which makes them an indispensable tool for many tasks of analyzing and processing objects in large data sets, which allows considering this tool in the question of determining the optimal sampling point soil samples. Error backpropagation is based on gradient descent, where the loss gradient (a function that measures the difference between predicted and actual results) is calculated with respect to the network weights and parameters. This gradient shows how the weights and parameters should be changed to reduce the error. After calculating the gradient, the network applies an optimization algorithm (eg, stochastic gradient descent) to make corrective changes to the weights and parameters. This process is repeated for many data packages (mini-batches) during several training epochs. An important component of training convolutional neural networks is the use of a loss function, which measures the amount of error between predicted and actual results.

In summary, training convolutional neural networks involves passing data through the network, calculating the error, calculating the gradient, and adjusting the weights and parameters to minimize the error during training. Training of a convolutional neural network in Python for recognizing circles (puddles) in images was carried out on the fields obtained as a result of UAV surveying (Fig. 4). For this, the TensorFlow library was used, which allows you to easily build and train neural networks. Part of the network training code is shown in Fig. 5. A convolutional architecture with three convolutional layers and pooling followed by a fully connected layer for classification was used.

```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Data loading and preparation
train_datagen = ImageDataGenerator(rescale=1.0/255.0) # Normalization of pixel values
train_generator = train_datagen.flow_from_directory(
    'path/to/training_data',
    target_size=(1270, 840),  # Image size
    batch_size=32,
    class_mode='binary')   #Binary classification

# building a convolutional neural network
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(1270, 840, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(1270, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(2540, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(2540, activation='relu'),
    Dense(1, activation='sigmoid')
])

# Compilation
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

Figure 5. Convolutional neural network learning code listing

To train the model on the task of binary classification, the binary loss function **binary_crossentropy** was used. The testing of the network was carried out in order to identify areas with increased moisture supply, which were located in the fields and had a shape close to circles and differed in color. The testing of the network was carried out in order to identify areas with increased moisture supply, which were located in the fields and had a shape close to circles and differed in color. Accuracy Metrics: The first and most important metric is accuracy. The created network showed high accuracy on the test data: 0.80375 (Fig. 6), i.e., with such accuracy, the areas with high moisture content and cannot be used for obtaining soil samples were determined on the images of the fields. ROC curve and AUC: The receiver operating characteristic (ROC) curve and the area under the ROC curve (AUC) help determine the relationship between the sensitivity and specificity of a model. In an ideal case, the ROC curve will rise up to the left.

Network Testing

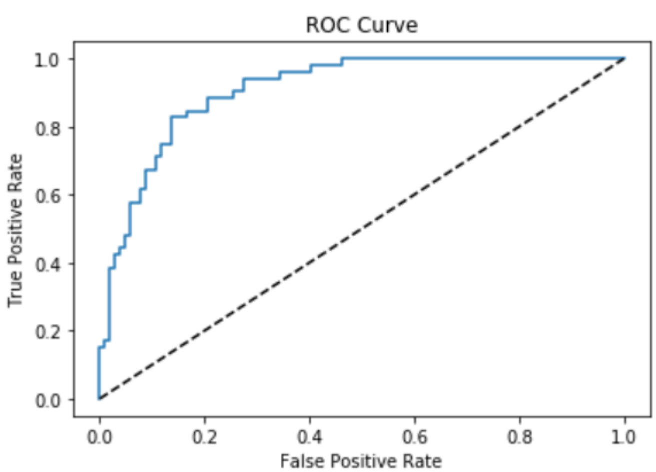
```
score = model.evaluate_generator(test_set, steps=100)

for idx, metric in enumerate(model.metrics_names):
    print("{}: {}".format(metric, score[idx]))
```

```
loss: 0.475635891854763
acc: 0.80375
```

Figure 6. Network test results

```
y_test_pred_probs = model.predict(X_test)
FPR, TPR, _ = roc_curve(y_test, y_test_pred_probs)
plt.plot(FPR, TPR)
plt.plot([0,1],[0,1],'--', color='black') #diagonal line
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
plt.clf()
```




```
<Figure size 432x288 with 0 Axes>
```

Figure 7. ROC curve of trained CNN

Fig. 7 shows the image of the curve, which allows us to establish the success of the network's training and its ability to recognize in the images areas that are not suitable for taking soil samples. Thus, the obtained distribution map was considered as an image, on which the objects defined as the remains of puddles were recognized using a neural network. Samples from these areas have different initial conditions and are limited in their suitability for mineral nutrition analysis.

5. Conclusions

1. The assessment of the nature of the distribution of both individual spectral channels and their combination in the form of vegetation indices turned out to be unprepared for the identification of uneven water supply of areas.

2. The red channel and its derivatives turned out to be the most promising in the direction of identifying the water supply of wheat.

3. The use of neural networks made it possible to identify probable areas with increased water supply on the maps of the distribution of vegetation indices in the field.

4. The duration of the identification using neural networks will not interfere with the sampling procedure, thanks to which such a procedure can be effectively implemented in agronomic practices.

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