IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 6, 2021, accepted January 11, 2022, date of publication January 14, 2022, date of current version January 24, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3143524

Artificial Neural Networks and Computer Vision's-Based Phytoindication Systems for Variable Rate Irrigation Improving

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ABSTRACT The article proposes a methodology for optimizing the process of irrigation of crops using a phytoindication system based on computer vision methods. We have proposed an algorithm and developed a system for obtaining a map of irrigation for maize in low latency mode. The system can be installed on a center pivot irrigation and consists of 8 IP cameras connected to a DVR connected to a laptop. The algorithm consists of three stages. Image preprocessing stage - applying an integrated excess green and excess red difference (ExGR) index. The classification stage is the application of the method that we choose depending on the system's operating conditions. At the final stage, a neural network trained using the Resilient Propagation method is used, which determines the rate of watering of plants in the current sector of the location of the sprinkler. The selected methods of pretreatment and classification made it possible to achieve an accuracy of plant identification up to 93%, growth stages - up to 92% (with unconsolidated maize sowing and good lighting). System performance up to 100 plants in one second, which exceeds the performance of similar systems. The neural network showed an accuracy of 92% on the training set and 87% on the test set. Dynamic analysis of spatial and temporal variability leads to an increase in productivity and efficiency of water use. In addition, given the ubiquitous distribution of agribusiness management systems, this approach is quite simple to implement in the farm's conditions.

INDEX TERMS Artificial neural networks, computer vision, image classification, irrigation, machine learning.

I. INTRODUCTION

According to statistics, agricultural production on a global scale over the past half-century has grown 2.5-3 times, and the growth of acreage was about 12%. In addition, according to UNESCO data, agriculture is undoubtedly the largest consumer of water, while 70% of the total freshwater intake is used for irrigation [1]. In water-stressed regions, irrigation is of fundamental importance, as irrigated agriculture accounts for 16% of the world's cultivated area, which produces 30% to 40% of the world's food [2]. At the same time, the area of irrigated land has more than doubled over fifty years and comprises on average more than 16% of all agricultural land, and the volume of water withdrawn for irrigation has almost doubled. FAO's projected 1-2% annual growth in global irrigated areas, as well as trends in climate change (temperature and precipitation), in the next 20 years could lead to a significant increase in water consumption (according to FAO estimates by 14%) and energy, which in turn puts forward the problem of saving water, energy and material and technical resources, protecting the natural environment [2]. Traditional methods of planning irrigation based on visual inspection lead to significant water losses and raise the issue of optimizing irrigation. All of this has contributed to the emergence of various methods of controlled irrigation such as sprinkler, drip, and furrow irrigation. The introduction of these methods allows to reduce water losses by 30–70% and contributes to the sustainable development of irrigated

The associate editor coordinating the review of this manuscript and approving it for publication was Huiyu Zhou.

agriculture [3]. Further development of optimization methods led to the emergence of the so-called precision irrigation, which allows you to estimate the amount of water, irrigation time, and maintains the exact water content in the soil, depending on the needs of the growth and development of crops. In this regard, technologies of precision farming have become widespread, which involve considering spatial and temporal variability and differentiating the use of resources [4], [5].

In this regard, a key problem of irrigation management arises - its optimization both from the point of view of irrigation technique and from the point of view of technology. Classical water resources management is based on the use of uniformly introduced resources across the field, considered as a single spatial unit and if the actual operating parameters of the sprinkler equipment coincide with the theoretical ones. However, on the one hand, sprinkler technology is a complex dynamic system, the operation of which is influenced by many stochastic factors. On the other hand, the object of the impact of technology - the field is a complex biological system with Spatio-temporal heterogeneity of the characteristics of soil, climate, plants, and, therefore, uneven need for irrigation [6], [7].

The operation of irrigation equipment plays an important role in irrigated agriculture. Optimizing irrigation equipment is an important strategy for conserving resources, increasing productivity, and improving production efficiency. Among the various systems, one can distinguish Center Pivot Irrigation Systems, which account for up to 23% of the total area irrigated by sprinkler irrigation systems [8]. And in Russia, for example, about 22% of the total irrigated area is irrigated with such systems.

A. PRECISION AGRICULTURE, DIGITALIZATION, AND ARTIFICIAL INTELLIGENCE

In connection with the role played by Center Pivot Irrigation systems (CPI), numerous studies are being carried out to improve the technical parameters of these systems: improving the uniformity of irrigation, modeling sprinklers, and lateral corner joints [9]–[11]. In addition, the Precision Agriculture methodology appears for such systems as well. Variable Rate Irrigation (VRI) considers Spatio-temporal variability by delivering a variable amount of water to a specific area following crop water requirements. At the same time, for sprinkler systems of circular action, VRI assumes either irrigation at a controlled speed (assumes a change in the irrigation rate in the direction of a moving sprinkler by changing the speed of its movement) or irrigation with a controlled zone (involves a change in the irrigation rate both along the side pipeline and in the direction of movement sprinkler) [12]. Many scientists have been involved in the development and improvement of VRI methods [12]–[14] since the creation of optimal VRI solutions is rather difficult and must consider a large number of factors. Some scientists considered the properties of water in the soil as a basis for monitoring, others - the state of plants. Thus, in the study [12], automatic control of the speed of movement is based on technologies for monitoring the electrical conductivity of the soil and altimetry, the moisture content in the soil, and vegetation indices obtained from satellite images. In [13], the interaction between spatially changing soil properties and the time-varying dynamics of water in crops is investigated. It is shown that modeling soil moisture depletion can be an effective planning tool in VRI. A decision support system for variable rate irrigation is presented in a study [14]. The system is based on the vegetation index (VI), obtained after processing multispectral images obtained by unmanned aerial vehicles. And the evapotranspiration model and the crop water stress index are derived from their established relationships with the vegetation index. Work [15] summarizes the advantages and disadvantages of the variable rate irrigation methodology. Until now, these methods need further development and improvement as further studies of space-time variability are needed to make these improvements.

Digitalization is becoming one of such powerful tools for increasing the efficiency of both irrigation and agriculture in general. The current stage of development of precision farming and digital agriculture makes it possible to widely use such tools based on artificial intelligence, and the Internet of Things (IoT) is the basis for intelligent agriculture. Thus, [16] provides an overview of best practices in the implementation of sensor irrigation systems, along with the most used nodes and wireless technologies. In such systems, wireless sensor networks and all kinds of sensors (soil moisture, soil temperature, ambient temperature, etc.) are actively used. Optimization of irrigation is achieved in various ways, in [17] - by precise control of the water valve using neural network forecasting of soil water demand, and in [18], for example, by integrating an automated irrigation system with an irrigation decision support tool. In addition, all sorts of applications are created for data analysis and decision support at all stages of the agricultural cycle. SWAMP platform [19] for intelligent water management based on the Internet of Things for precision irrigation. The system for optimal irrigation of crops [20] is based on a wireless sensor network using nodal sensors in the field and data management via a smartphone and a web application. [21] presents a study on the integration between various tools to improve water efficiency in agriculture (field sensors and remote sensing). The systems considered in [22], [23] involve data monitoring, their preliminary processing, integration, synchronization, and storage with subsequent use for intelligent irrigation. Thus, the digitalization of agriculture makes it possible to make the transition from classical control systems to systems with artificial intelligence.

In recent years, many researchers in the development of the Precision Agriculture methodology in general and for irrigation management use such a tool as artificial neural networks. The range of applications of artificial neural networks in agriculture is very wide. Researchers are using these tools to model agricultural production, replacing classical mathematical models. They can be both part of precision farming systems and decision support. An overview of the application is presented in [24], [25] and includes forecasting in agriculture, intelligent monitoring of diseases and pests, and weed control. Artificial intelligence methods are also used to optimize storage and transportation processes. In addition, AI methods contribute to the improvement of the automation of various processes.

The introduction of artificial intelligence in agriculture is associated with the problems of the systematic collection of data from multiple sources of storage and analysis. Approaches to solving these problems are outlined in [26], [27] and represent pilot projects for the analysis of advanced control systems in various natural and climatic conditions. One of the key artificial intelligence techniques, such as machine learning, has significant potential for solving numerous problems. The work [28] provides an overview of the use of machine learning in agriculture, namely, the management of water resources, soil, and animal husbandry. Big data and machine learning (ML) open new possibilities for understanding agricultural processes using data, along with this, there are numerous problems of integrating these technologies that require research and solution [29]. Machine learning is an important decision support tool, for example in [30] it has found application in yield forecasting, including making decisions about crop types and cultivation technologies during the growing season. Artificial intelligence methods are gaining importance in agricultural robotics. A study of the similarities and differences between industrial and field robots is presented in [31], along with a suggestion of potential methods for use on farms.

B. ARTIFICIAL INTELLIGENCE IN IRRIGATED AGRICULTURE

In recent years, data-driven models have begun to play a key role in comparison with classical physical models. Methods of artificial intelligence, machine learning (ML), artificial neural networks show good predictive characteristics, more quickly and efficiently process large arrays of Spatio-temporal data. This is especially important for irrigation management due to the large Spatio-temporal variability of external conditions and, often, the need for continuous calibration in real-time. These methods have numerous applications for irrigation and water management. Some systems [32] are based on an intelligent algorithm that considers the received sensor data together with the parameters of the weather forecast (precipitation, air temperature, humidity, and UV radiation) for the near future. In others [17], [33], irrigation is optimized by precise control of the water valve, current sensors using neural networks forecasting soil water demand, or fuzzy inferences [34] by creating prescriptive maps to control the rotation speed of the central axis based on remote sensing. The combination of big data and machine learning technologies with remote sensing technologies leads to the creation of new methods and algorithms presented in [35]. And [36] presents the development of a combined intelligent agricultural machine that can automatically weed and irrigate at a variable rate on a cultivated field. Some approaches to the intellectualization of CPI control systems are considered in [37].

One of the directions is the creation of intelligent decision support systems. In [38], a comparative study of various algorithms and training methods (ANN, linear regression (LR), random forest regression (RFR) and auxiliary vector regression (SVR), k-nearest neighbor (kNN), and adaptive gain (AdaBoost) algorithms were carried out to determine the admissibility of the erroneousness of the experts' decisions. Such systems are also developed at the level of management of irrigation systems. The AWARD system [39] uses artificial neural network techniques to predict water level, a fuzzy logic control algorithm to estimate the sluice adjustment period, and hydraulic equations to adjust the sluice level. An example is DLiSA's intelligent irrigation system based on a deep learning neural network for predicting the volumetric moisture content in the soil, the period of irrigation, and the spatial distribution of water, considering the need for it [40]. In addition, models of artificial neural networks and machine learning are used to calculate important irrigation parameters, such as soil moisture [41], soil salinity [42], horizontal daily global solar irradiation predictive modeling [43], modeling the water-soil regime and transport of dissolved substances [44]. And, artificial neural networks, machine learning to use to develop strategies for irrigation management with given economic parameters to reduce water and energy consumption without compromising crop yields [45]–[47].

Yang *et al.* [48] proposed an integrated CNN model based on hyperspectral and RGB images taken at 5 stages of corn growth. Pang *et al.* [49] based on drone images using the combined convolutional neural network MaxArea Mask Scoring RCNN, areas of poor germination of corn were identified. The authors noted the high processing speed, however, does not allow the use of this system for real-time applications. Zhong *et al.* [50] recorded different stages of plant growth using a method based on a combination of time series with convolutional neural networks. Kuznetsova *et al.* [51], [52] use high-speed computer vision techniques YOLOv3 and YOLOv5 on a robotic crop picker.

Despite a large amount of research, there are still many open problems in the field of optimal irrigation management using CPI systems. The variable rate irrigation approach has undoubtedly proven to be effective. However, an analysis of the current state of research on VRI optimization by CPI systems allows us to identify the main problem points:

- The complexity of collecting the required data set, the lack of time series data on the state of a particular field, and crop yields in this field, considering the temporal climatic variability.
- Difficulty in choosing appropriate data analysis methods to find a compromise between the two paradigms for monitoring spatial variability - water properties in soil and plant health.

- Difficulty in applying more accurate methods of intellectual analysis in dynamics during the entire agricultural season.
- Difficulty in the technical implementation of the proposed solutions, for example, expensive sensors, sensors, and other equipment.

With current advances in proximal and non-invasive sensing technologies, IOTs can provide a wealth of information about soil, crops, and related environmental properties, and artificial intelligence techniques to analyze all this data are contributing to new approaches to improve the situation. The use of computer vision systems for condition monitoring seems to be quite interesting due to the relatively inexpensive implementation and the possibility of using more accurate methods of intellectual analysis. Optimal variable rate irrigation management requires a combination of both computer vision systems and additional climate and remote sensing data to detect Spatio-temporal dynamic variability in crop water requirements.

The purpose of this study is to develop a methodology for optimizing irrigation by creating dynamic maps of irrigation prescriptions. It is based on the implementation of regular monitoring of the state of crops and the environment through phytoindication, as well as forecasting the dynamic variability of the state of water availability to improve irrigation. The proposed solutions offer a combination of neural network approaches, from the use of multilayer artificial neural networks to pattern recognition and convolution neural networks.

The algorithm of the proposed approach is as follows:

At the first step, the Phyto monitoring of the state of the agricultural crop and the environment is carried out based on computer vision using convolution neural networks.

At the second step, a dynamic variable forecast is constructed based on the time series of data of average daily air temperature (T), amount of precipitation (R), Air humidity (AH), Wind speed (WS), and Normalized Difference Water Index (NDWI) -ability of water availability based on multilayer artificial neural networks.

As a result, we obtain dynamic maps of irrigation prescriptions based on the classification procedure of the results of the first two neural networks.

II. MATERIALS AND METHODS

A. MATERIALS

The study was conducted in the Saratov region of the Russian Federation. Russia has significant soil and water resources, but the largest part of its land used for agricultural production is in areas of risky agriculture with insufficient or excessive modes of natural moisture. Only 2% of the land in the Russian Federation is in optimal moisture conditions. The main share of agricultural products (in value terms) is produced in the arid zone, where more than 78% of arable land is concentrated. The land reclamation fund of the Russian Federation amounted to an area of 9.45 million hectares of which 75% was used, including 4.67 million hectares of irrigated land, of which 82% was used and 4.78 million hectares of drained land, of which 68% were used [46].

The Volga region is one of the largest regions of Russia, where land reclamation is developed. The Saratov Region occupies about 10% of the total area of the Volga Federal District. The Volga Federal District is in third place among the federal districts in terms of reclaimed lands and the leader in terms of the percentage of irrigated lands in good condition. Among all regions, the Saratov region ranks first in the district in terms of the area of reclaimed land - 19%. The main climatic parameters of the irrigated zone of the Saratov region are presented in Table 1.

TABLE 1. The main climatic parameters of the study area.

Parameter	Value
Winter temperatures, °C	–10…–15
Summer temperatures, °C	21,6…22,6
Sums of effective temperature sums, °C	2400…3100
Frost-free period, days	130…170
The period of active vegetation of crops, days	165…180
The depth of soil freezing, cm	100…145
Average annual rainfall, mm	310…500
Spring moisture reserves in a meter layer of soils, m^3/ha	600…1700

The sums of air humidity deficits in the warm season increase from north to south from 1800 to 2200 millibars. On the contrary, the sums of active temperatures decrease in the same direction from 3500 to 3000 °C. The zonal soils of the left-bank regions (the main irrigation zone) of the Saratov region are classified as southern chernozems, chestnut of various subtypes (dark-chestnut, light-chestnut, and chestnut proper), as well as brown semi-desert in the extreme southeast of the left bank. In terms of the content of organic matter, the soils of the Left Bank are rather poor: it varies within 3.0 …5.0% in southern chernozems, 2.5 …4.0% in dark chestnut soils; 1.5 …3.0% for light chestnut and chestnut.

In the natural and climatic zone of the Saratov region, there is significant spatial variability of natural conditions, primarily soil, geomorphological, hydrogeological. Analysis of the data of the geoinformation system for monitoring irrigated lands showed that within the framework of the site of one farm, they can be located on 133 contours of 29 soil differences. Moreover, individual irrigated fields were located on several soil differences - from 2 to 5.

The quantitative and qualitative composition of irrigation techniques plays an important role both in the condition of irrigated lands and in increasing the efficiency of agricultural production on irrigated lands. In Russia about 22% of CPI systems are used; in the melioration complex of the Saratov region, these systems are the main ones.

To collect data, experimental studies were carried out in the Engelsky district of the Saratov region of Russia (experimental farm ≪Povolgy≫ of the Saratov State Agrarian University). The irrigated area is equipped with the Center Pivot Irrigation (CPI) system ≪Cascade≫. It is equipped with GPS trackers, cameras and real-time data is displayed in the ≪Agrosignal≫ digital platform for agribusiness management (Figure 1). In addition, the ≪Agrosignal≫ system allows collecting data on weather, soil condition, and basic agrotechnical information about crops, equipment operation based on weather station sensors, remote sensing, etc. In this study, the following data were used:

FIGURE 1. The ≪Agrosignal≫ system window.

- Climatic data - wind speed and direction, air temperature, relative air humidity, temperature and humidity of foliage and soil, atmospheric pressure, amount of precipitation.

- Indices - Normalized Difference Water Index (NDWI).

-CPI information - speed.

An example of a date-set of climatic data for a month (June 2020) is given in Table 2. The Normalized Difference Water Index (NDWI) provides information on both the spatial distribution of water stress on vegetation and its temporal development. The example of an image of the NDWI index for the experimental site is shown in Figure 2.

The second component of our system is based on biological methods for diagnosing anthropogenic changes - this is both the state of the agricultural crop itself and the state of the environment. The active use of these methods is associated with the quick reaction of organisms to any deviations in the environment from the norm. In our study, these are the parameters of the soil condition in the irrigated area. Control is necessary for almost all-important parameters of the state of the soil. These include the provision of soil with moisture, mechanical composition, type of oxidation-reduction regime, etc. We use an approach based on determining the qualitative properties of the soil using indicator plants. It is based [53] considering the species diversity of macrophytes and their indicator significance. Phytoindicators are called plants, plant communities, or their features that indicate some specific properties of the environment. Phytoindication is one of the practical uses of various traits and properties of individual plants or plant communities and their complexes to obtain qualitative and sometimes quantitative characteristics of the environment. With the help of plants, it is possible to identify individual characteristics of soils: their texture, moisture, acidity, salinity, nutrient supply. Figure 3 shows plant bioindicators used in our study.

TABLE 2. Data-set: climatic data.

T Average daily air temperature, °C	R The amount of precipitat ion, mm	AH Air humidity, %	WS Wind speed, m/c
16,63	0	75	3,16
16,84	0	66,52	5,63
14,08	0	67,17	4,2
12,94	0	83,26	4,22
15,92	0,1	84	3,09
17,12	0	82,41	1,38
18,5	0	75,27	1,48
18,25	0	72,95	1,77
18,75	0	76,91	2,46
19,08	0	71,45	2,98
19,42	0	71,95	1,58
20,35	0	77,09	2
20,79	0	74,77	3,19
18,86	3,38	88,14	2,53
20,75	0	76,68	3,02
21,9	0,66	78,18	4,53
21,1	0	74,55	5,15
17,64	0	69,68	5,09
18,42	0	65,9	3,28
21,56	0	63,55	2,03
23,08	0,87	67	1,9
24,83	0	61,91	2,21
25,37	0	52,82	2,65
25,37	0	63,41	3,23
25,25	0	62,52	2,81
25,22	0	66,14	2,4
25,61	0	62,14	3,01
26,57	0	65	2,22
24,64	0	72,71	3,32
22,1	1,01	79	2,57

B. CALCULATION OF THE VEGETATION INDEX

For better localization of plants in the image, we use the vegetation index. This increases the contrast between vegetation and soil. Three bands of the spectrum are used as color sources: red (R), green (G), and blue (B). Since the encoding of each band is carried out in the range from 0 to 255, we normalize the image using (1):

$$r = \frac{R}{R+G+B}; \quad g = \frac{G}{R+G+B}; \\ b = \frac{B}{R+G+B}; \quad r+g+b = 1 \tag{1}$$

Considering the peculiarities of the object of study of video filming, we are interested in the index of excess green (ExG) (1) and excess red (ExR) (2). Based on these indices, the

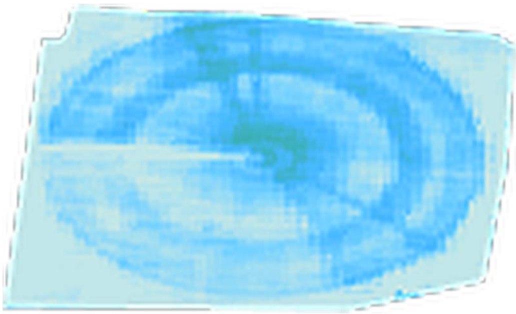

FIGURE 2. NDWI index snapshot.

FIGURE 3. Plants—bioindicators and the main crop: 1) Cirsium arvense, 2) chamomile, 3) wormwood, 4) main crop—corn.

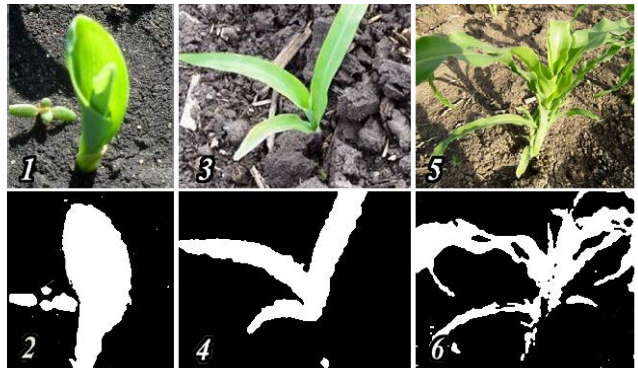

FIGURE 4. Images of corn plants at different stages of growth: 1), 3), and 5) color image and 2), 4), and 6) image binarized using the ExGR index.

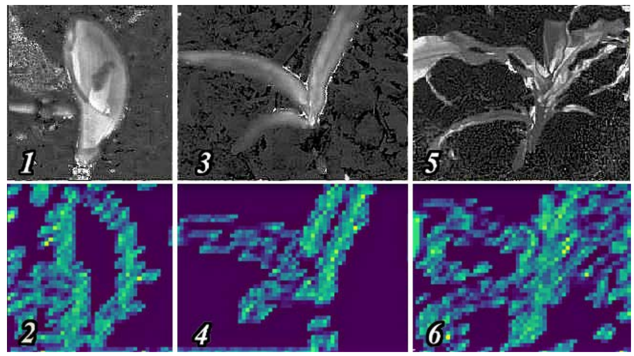

FIGURE 5. Images of corn plants at different stages of growth: 1), 3), and 5) in grayscale, obtained using the ExGR index and 2), 4), and 6) obtained by the HOG method.

ExGR index (3) is created.

$$ExG = 2g - r - b \tag{2}$$

$$ExR = 1.4r - b \tag{3}$$

$$ExGR = ExG - ExR \tag{4}$$

The ExGR index results (Figure 4) in an image in which pixels range from positive (plant) to negative (soil and residues) values. This allows segmentation without the need for additional processing tools such as Otsu, Niblack, etc.

C. USING A DESCRIPTOR

The HOG method assumes that the type of distribution of image intensity gradients makes it possible to accurately determine the presence and shape of objects present on it.

The image is split into cells. Histograms hi of the directed gradients of the interior points are calculated in the cells. They are combined into one bar chart $\mathrm{h} = \mathrm{f}(\mathrm{h}_1, \ldots, \mathrm{h}_\mathrm{k})$, after which it is normalized in brightness. The normalization factor can be obtained in several ways, but they show approximately the same results. We will use the following:

$$h_L = \frac{h}{\sqrt{\|h\|_2^2 + \varepsilon^2}} \tag{5}$$

where $\|h\|_2$ – used norm, ε – some small constant.

When calculating the gradients, the image is convolved with the kernels $[-1, 0, 1]$ and $[-1, 0, 1]^\mathrm{T}$, as a result of which two matrices D_x and D_y of derivatives along the x and y axes are formed, respectively. These matrices are used to calculate the angles and magnitudes of the gradients at each point in the image.

Figure 5 (2, 4, 6) shows the result of applying the HOG method to an image processed using vegetation index 5 (1, 3, 5). For clarity, only the magnitude of the gradient is shown (the brighter the pixel, the larger the gradient).

The scale-invariant feature transform (SIFT) descriptor is used to extract feature points from the image, which are later used in classifiers. The key point in finding them is building a pyramid of Gaussians and the difference of Gaussians. Gaussian - image blurred with a Gaussian filter:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y), \tag{6}$$

with coordinates (x, y) and blur radius σ; $G(x, y, \sigma)$ – Gaussian kernel; $I(x, y)$– the value of the original image; $*$ - convolution operation.

The difference of Gaussians is an image obtained by pixel-by-pixel subtraction of the Gaussian of the original image from a Gaussian with a different blur radius $(k\sigma)$:

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \tag{7}$$

A pyramid of Gaussians and Gaussian differences is constructed. When moving from one level of the pyramid to another, the dimensions of the images are halved.

After building the pyramids, the singular points are determined, which are the local extrema of the difference of the Gaussians. False key points are discarded, and for the remaining ones, their orientation is calculated. The magnitude of the gradient m and the direction of the gradient θ is determined from the (8)-(9):

$$m(x,y) = ((L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2)^{1/2} \quad (8)$$

$$\theta(x,y) = tan^{-1}\left(\frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)}\right) \quad (9)$$

In the SIFT method, the descriptor is a vector. Take a 4×4 square area centered at the singular point, rotate following the direction of the singular point. Each element of the area indicates the magnitude of the gradient in eight directions.

D. IMAGE CLASSIFICATION USING BOVW

BOVW is used to improve the performance of descriptors. This approach considers the blocks as key parts of the plant, and each block's HOG represents the local information of the corresponding part. Next, we cluster the HOG of all the blocks in the training set into homogeneous groups using K-means, and the centers will be the mean value of the blocks' HOG within the cluster. (We then group the HOGs of all the blocks in the training set into homogeneous groups using K-means, and the centers will be the average of the HOGs of the blocks in the cluster.) These centers will play the role of Visual-Words in BOVW (Figure 6).

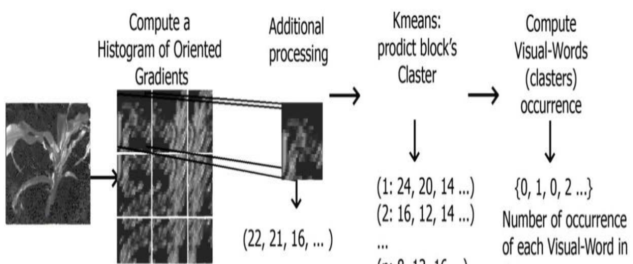

FIGURE 6. **Steps to create a Visual-Words.**

III. EXPERIMENTS AND RESULTS

A. INSTALLATION

8 IP cameras were installed on the irrigation system, connected to an 8-channel video recorder, constantly filming plants. For more efficient video recording, the cameras were not evenly fixed to the irrigation system. The first camera was installed at a remote point of the irrigation system. The removal of the rest was determined by (10):

$$r_i = K * \sqrt{(2i - 1)/2} \quad (10)$$

where i is the ordinal number of the chamber, starting from the axis of rotation of the irrigation system, r_i is the distance to it. The K coefficient is obtained by substituting the number of chambers involved and the distance from the axis of rotation to the most distant point of the irrigation system into this formula. In our case, with a radius of the irrigation system equal to 370 meters, the coefficient is 95.5 meters.

We used camcorders with a fixed focal length of 3.6 mm, matrix size 1/2.8, which allowed us to take pictures with a viewing angle of up to 96 degrees. The protection class of the camera is ip67. The protection class was fundamentally important because the cells were constantly exposed to streams of water. The large viewing angle of the video camera allows you to track the same plant from different angles while moving it. This allows you to collect much more information on each object under study, and therefore more accurately determine its state and phase of development.

We abandoned cameras with a viewing angle greater than 100 degrees because we must perform additional preprocessing methods to correct aberrations that significantly distort the image. In addition, the greater the angle at which the plant is located to the vertical, the more overlap of parts of nearby growing plants on it, and this leads to serious errors in classification. Considering the height of the cameras above the ground (in our case, 1 meter, we came to the optimal sliding window with a size of $1 * 1$ m.

Now about the shooting speed. The IP cameras used operate at a frequency of 30 Fpx. There is no point in processing all these frames. This would make our computer vision system extremely slow. The number of processed frames per second depends on the speed of movement of the irrigation unit and is determined from the following considerations: each plant that falls into the sliding window must be processed at least 2 times. For a linear speed of 0.5 m / s, the point farthest from the bore axis, from the outermost video camera, 1 image should be processed in 1 second. If you take images from all 8 cameras (the closer the camera is to the axis of rotation, the fewer shots you need to take per second), you need to process no more than 5 shots per second. If the number of weeds is not significant and the rotation speed of the extreme point does not exceed 1 m/s, the computer vision system works in real-time.

When setting up the video system, special attention had to be paid to protecting the camera lenses from water droplets and fogging. If we use a cone-shaped casing from direct moisture penetration.

B. IMAGE PROCESSING TECHNIQUES

Initially, the vegetation index was calculated from the photograph, which was used to obtain a grayscale and binary image. For further image processing, we tested three high-performance methods: SIFT-SVM, HOG-BOVW-BPNN, and binarization by the ExGR - CNN index. For comparison, the outdated HOG-CNN method was tested along with them. The first two methods were applied to grayscale images, and the third to a binary image. All algorithms used in the work are implemented using the OpenCV Python library.

The classification was made according to the following criteria: corn Figure 4, weed from the list of indicators Figure 3, weed. When corn is identified, the stage of growth is determined. To train the methods, a dataset was used, of 1500 corn plants at different stages of development. The dataset was marked by agricultural scientists working on the farm. In addition, a dataset with indicator plants was used (from 500 to 800 for each variety). The results of the methods are shown in Tables 3 and 4.

TABLE 3. Results of the work of methods for the determination of indicator plants and corn plants.

Pre-processing methods and descriptors	Used classifiers	Result (%)			
		Corn	Chamomile	Worm wood	Cirsium arvense
SIFT	SVM	71-86	73-87	70-84	71-87
HOG	CNN	66-74	68-76	65-75	66-73
HOG – BOVW	BPNN	84-91	86-91	84-88	83-90
Binarization by ExGR Index	CNN	81-92	87-93	83-90	84-92

TABLE 4. The results of methods for determining the stage of growth of corn.

Pre-processing methods and descriptors	Used classifiers	Result (%)			
		2 leaf	3-5 leaf	6-8 leaf	9 leaf
SIFT	SVM	86-90	83-90	78-87	75-84
HOG	CNN	70-80	69-80	65-77	60-70
HOG – BOVW	BPNN	87-92	90-91	81-88	77-86
Vegetation index binarization	CNN	90-92	85-92	79-89	75-87

It can be seen from the results obtained that the classical HOG - CNN method is significantly inferior to any of the three selected.

SIFT-SVM is not inferior to the other two in terms of processing speed, but the results of its work are slightly worse than the other two. We were unable to choose the best among the two remaining methods. Even though in the CNN method we used 3 x 3 convolutional kernels (this greatly accelerated it), the HOG-BOVW-BPNN method is 20% faster, but its classification results are slightly lower in sunny conditions. In cloudy weather, the results are reduced for both methods, but the HOG-BOVW-BPNN method is more stable in reducing the illumination level [54]. We assume that it makes sense to use both methods depending on the conditions.

The results of these methods (tables 3 and 4) significantly exceed the results presented in works on computer vision in recent years [48]–[50]. This is merit not only of modern methods of computer vision but also of successful shooting conditions. The sprinkler removes dust from plant leaves and the ExGR imaging method works most efficiently.

C. DYNAMIC MAPS OF IRRIGATION PRESCRIPTIONS

A schematic representation of the key algorithm is shown in Table 5:

TABLE 5. Algorithm.

	Steps	Objectives	Results
1	Computer vision's-based monitoring	Assessment of the current state of crops and soil	Map of deviation of the real development of corn plants from the norm and location of indicator plants
2	ANN forecasting the dynamic variability of water availability	Assessment of the dynamic variability in water availability at the site based on the available climatic data	Water availability variability map
3	Comparative analysis of deviations	Optimization of irrigation	Dynamic maps of irrigation prescription

In the previous works of the authors, a program [55] was developed for determining the optimal parameters of humidification in the calculated soil layer for the main crops, including corn, for a given region. This system also considers the phases of growth and development of the crop, the type, and the granulometric composition of the soil. Climate data is one of the main parameters, both in classical models such as AQUACROP and in models using artificial neural networks to predict crop water demand and water availability. In the developed system, a multilayer neural network model with input, hidden, and output layers were used. For training, the Resilient Propagation method was used, which has proven itself well in this kind of problem.

Our work considers several criteria when creating an irrigation map. In addition to the standard ones, such as humidity, temperature, etc. we consider the current state of the crop itself relative to the planned one and the presence of indicator plants. The neural network we use (Figure 7) was trained using a sample labeled by agronomists based on many years of research on the dependence of the state of the crop on the moisture deficit for a given climatic zone. For each specific case from the sample, they compared the irrigation correction factor. The HOG descriptor in the monitoring system was not chosen by chance in our work. One of the main advantages over other descriptors is that it is very resistant to lighting changes. Its performance changes slightly in the conditions in which shooting is usually done.

Based on the results obtained using the HOG - BOVW - BPNN method and binarization according to the ExGR - CNN index, the growth stages of plants caught in the camera lens are determined. These data are compared with the planned indicators for the given area. Figure 7 (a) presents the results of the deviation in development from the planned indicators for 10-15 days of growth (6 plant's leaf). Figure 7 (a) shows the center of the reference scale. Each new division differs from the previous one by 1 day of vegetation. The scale is not limited to five values and extends both in one direction and in the other direction. The yellow area is normal, the red area indicates a lag in plant development from the norm, and the green areas are ahead.

Our model also considers the distribution of indicator plants over figure 7 (b). The yellow area corresponds to an area with an undetected predominance of plants that prefer moist soils and dry-loving ones. In terms of numbers, this is either a complete absence of both types of plants or, the overweight of one of the types is no more than two times. This corresponds to a value of 3 on the scale figure 7 (b). Other values are determined according to the principle:

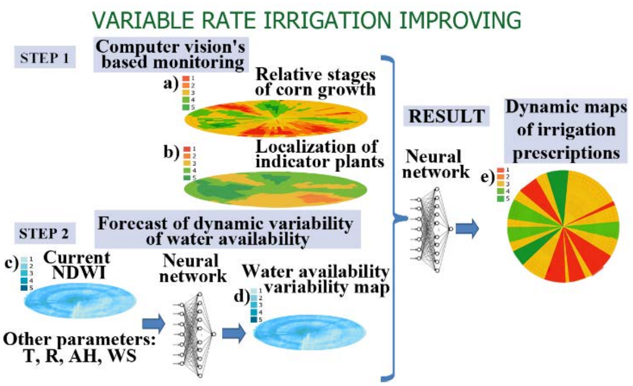

FIGURE 7. The process of obtaining a map of irrigation of crops for corn: a) map of deviation of the real development of corn plants from the norm; b) a map of the location of indicator plants; c) current NDWI; d) water availability variability map; e) maps of irrigation of crops for corn.

4 - prevalence of moisture-loving over dry-loving in the range from 2 to 4 times;

5 - prevalence of moisture-loving over dry-loving in the range from 4 to 8 times;

etc.

Similarly, zones with a predominance of dry-loving plants are determined.

Another element that we will consider when planning the irrigation of the field is NDWI figure 7 (c). We receive the current value of this indicator once every 10 days. To establish the correct irrigation regime, we created a neural network that, using previous NDWI results and weather reports, predicts the dynamic variability of water availability for some time ahead.

All parameters supplied to the neural network are presented in numerical values:

- NDWI color gradations are set according to the standard. They are converted into numerical values in the range from 0 to 1, where 0 is white (lack of moisture in the soil), 1 is dark blue (wetland). Intermediate values are calculated according to the shades of blue.
- Cloudiness is determined by discrete values from its absence - 0, to complete obscurity of the sun's clouds - 3.
- Air humidity - relative humidity ranging from 0 to 100%
- Temperature is measured in degrees Celsius.
- Wind speed is measured in meters per second.

When training the neural network, we used NDWI data in size (100 images), data from weather stations for the period of the NDWI study. The neural network was trained using the Resilient Propagation method [56].

At the final stage of obtaining a map of watering corn, data from steps 1 and 2 are passed through the second neural network, which determines the lack of moisture in the soil. This neural network was trained using the Resilient Propagation method [55] Based on the dataset obtained in the experimental farm ≪Povolgy≫ of the Saratov State Agrarian University in 2020 and previously marked by agronomical scientists.

The result of the network is a map of the field, divided into sections, indicating the amount of water required to irrigate 1 square meter of this section of the field.

Considering the peculiarities of the sprinkler system, the whole field was divided into sectors figure 7 (e). The parameters of each sector were determined based on the parameters of the sections of which it consists of. On this map, the yellow area is the base area. It determines the average amount of moisture required for a given field. The red area means that this sector requires more moisture than average, the green area requires less moisture relative to the norm.

The distribution of percentages of the total area under the influence of the prescription in each irrigation plan with a dynamic prescription for 6 irrigation actions is shown in Figure 8.

Computer vision's-based monitoring allows for a dynamic assessment of the actual state of culture and depending on the stage of development. Along with the forecast of water availability, this makes it possible to overestimate the irrigation rate.

So, for example, for irrigation actions 5-6, which corresponded to August-September, zones were identified where the culture reached late stages of growth and, as a result, a decrease in the amount of irrigation is possible, in contrast to standard prescriptions, as can be seen in Figure 8.

We carried out a comparative analysis of water consumption when implementing a standard irrigation strategy and a variable irrigation strategy based on dynamic prescription maps. Let us introduce the notation:

P^i – standard irrigation rate corresponding to the i-th irrigation action.

S – the area of irrigation plot, S_j – part of the area of the irrigation plot under the influence of the prescription j.

$$S = \sum_{j=1}^{5} S_j \tag{11}$$

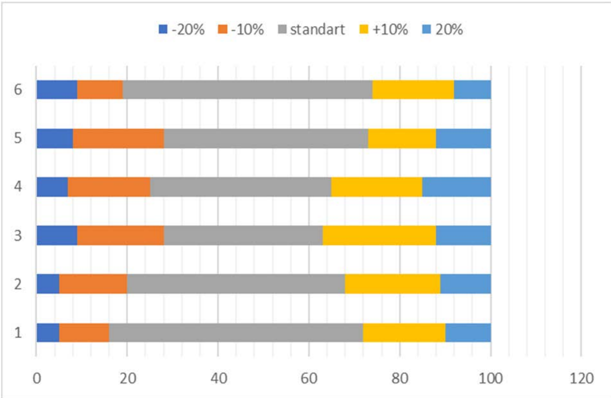

FIGURE 8. Distribution of percentages of the total area under the influence of the dynamic prescription.

Then the irrigation amount with standard irrigation, corresponding to the i-th irrigation action.

$$IA^i_{st} = SP^i \tag{12}$$

Irrigation amount with dynamic prescription, corresponding to the i-th irrigation action.

$$IA^i_D = \sum_{j=1}^{5} S_j(k^i_j P^i), \tag{13}$$

where k^i_j – irrigation correction factor for S_j, corresponding to the i-th irrigation action, $k^i_j = \{0, 8; 0, 9; 1; 1, 1; 1, 2\}$.

Irrigation correction factor k^i_j is a numerical expression of the dynamic prescription map obtained as a result of the third step of the algorithm. Further development of the method involves an increase in the set of k^i_j values, which will lead to an improvement in the efficiency of irrigation water use and productivity.

The decrease in the amount of irrigation water (in%) because of the implementation of a variable irrigation strategy instead of the standard one can be calculated because of maps of dynamic prescriptions, the number of irrigation measures, and the established correction factors based on (11) - (13).

The data of experimental studies of the volume of irrigation with standard irrigation and the volume of irrigation with dynamic irrigation for the purpose show an increase in this indicator in each irrigation action from 0.3% to 1.8%, which gives an increase in total for all irrigations of 7.4%. At the same time, the efficiency of the use of irrigation water, which links the yield of crops per unit of water used, increases due to an increase in yield by 8.9%.

IV. DISCUSSION

The irrigation technique plays an important role both in the condition of irrigated land and in improving the efficiency of agricultural production on irrigated land. In Russia, as well as on a global scale, about 22 -23% of CPI systems are used. One method for irrigation management is VRI, but the high implementation and management costs limit its application. On the one hand, the recently appeared agribusiness management systems such as "Agrosignal" allow collecting huge amounts of data, and on the other hand, even the simplest analogs of CPI systems have control panels with speed control modules, which makes it possible to implement inexpensive irrigation control systems ... For this, it is necessary to develop maps of irrigation prescriptions that consider the spatial-temporal variability of the irrigation site. The purpose of this study was to develop neural network methods for determining dynamic maps of irrigation prescriptions for automatic speed control using 1) phytoindication based on computer vision of the states of crops; 2) phytoindication based on computer vision of the state of the soil by plants - indicators; 3) intellectual analysis of data from monitoring systems of environmental conditions, the water indices, as well as the knowledge base of the optimal parameters of irrigation of crops in the region.

The question of defining irrigation zones is fundamental in this kind of research [13], [14]. From a formal point of view, the difference in approaches depends on the sets of available data, methods, and tools for their analysis. In [12], three main areas are indicated: measurements of soil electrical conductivity, monitoring of vegetation indices based on satellite images, and data on yield. The study [12], was based on mapping the NDVI at a certain time for different purposes. From the point of view of methods, artificial intelligence methods were used to calculate important parameters of irrigation, such as soil moisture and salinity, modeling the water-soil regime and the transfer of solutes [41]–[44]. However, all these approaches have drawbacks and require further research. There is an acute issue of the need to create maps of prescriptions in dynamics since the state of plants and the environment has a high dynamic of changes. The so-called dynamic spatial-temporal adaptation is needed. And the accuracy of such adaptation can be achieved only by using a combination of artificial intelligence methods.

In our study, to determine dynamic maps of irrigation prescriptions for automatic speed control, we used the methods of artificial neural networks, data mining, and phytoindication based on computer vision of the state of crops and the state of the soil by plants - indicators. Our model is field-tested in 2020. The key factors in assessing the impact of an irrigation strategy are crop yields and the amount of irrigation water used. An 8.9% increase in corn yields was recorded compared to a plot using conventional irrigation. In addition, the data indicate an improvement in the efficiency of irrigation water use. The limitation of this study is the impossibility of assessing the productivity of each site through the yield map, which will be done in the future.

Phytoindications based on computer vision of the state of the soil by plants - indicators can be an additional simple and cheap tool for analyzing the state of the soil in contrast to the rather expensive and not always available to farmers methods of chemical analysis. This study demonstrates the possibility of widespread use of artificial intelligence methods, contrary to the opinion about the complexity and high cost of such solutions. Further research will focus on scaling the results for different farms and climatic conditions with a full assessment of economic efficiency.

V. CONCLUSION

Climate change has direct implications for the availability of water, which requires the development of strategies to optimize its use. Conventional irrigation systems are based on the application of a uniform flow across the field, considered as a single spatial unit. However, fields can often have spatial heterogeneity in soil characteristics, relief, microclimate, and crop development. Improving the efficiency of water use is one of the main tasks facing the heads of farms today. A large area of crops with a pivot irrigation system both in Russia and in the world requires a differentiated response to irrigation management. The study is focused on the development of neural network methods (from multilayer artificial neural networks to pattern recognition and convolutional neural networks) to optimize irrigation by creating dynamic maps of irrigation prescriptions using 1) regular monitoring of the state of crops and the environment through phytoindication; 3) predicting the dynamic variability of the state of water supply, as well as a knowledge base on the optimal parameters of irrigation of crops in the region. Since agribusiness management systems, such as the "Agrosignal" system we use, are now often used by farmers, the use of complex methods of artificial intelligence is becoming more accessible. The results of the implementation showed a positive trend in decreasing spatial variability and increasing corn yields in this field. Sensor information, remote sensing, and neural network techniques have proven to be effective in defining dynamic control zones and are attractive due to the ease with which they can be implemented at the field scale. This relatively simple approach is quite inexpensive for the farmer and can be implemented on a large scale, which represents an important and sustainable contribution to improving water use efficiency in agriculture, especially in the current scenario of global warming and decreasing available water for agriculture.

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