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Prospects of the introduction of digital technologies in agricultural activities

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Abstract. In the digitalization of agriculture activities, fundamental changes are taking place in the paradigm of agricultural production management, because as a result of the robotization of production and the automation of production management systems, strategic decisions are made by humans, and tactical decisions are made by machines based on the displayed information. This article will talk about the system used to digitize agricultural activities. This program's main function is covered and in what sequence the process takes place. The program was developed as a web application, the Backend of which was based on the Python programming language. In this case, an algorithm and program for achieving the final result are developed based on modular programming methods.

1 Introduction

Modular programming is a software design technique based on dividing the functionality of a program into independent, interchangeable methods/modules. In this case, each of the modules contains all the actions needed to perform only a part of the system functions. Modularity is based on building blocks, where each block builds on other blocks. Each block can be reliably tested, and multiple blocks can be combined to create a complete program. Therefore, thinking about the concept of modularity is like creating the entire architecture of an application.

A module is described as a part of a program that contains one or more subprograms. By combining one or more modules, we can have a common program. Modules are implemented in the program through interfaces. The introduction of modularity allows developers to reuse pre-written code in new applications. Modules are compiled and combined with compilers, where each module performs a business or routine operation within the program. According to the presidential decree, the Ministry of Agriculture of Uzbekistan together with the Ministry of Information Technologies and Communications of Uzbekistan will launch an electronic platform within two months to monitor the cultivation of agricultural crops, including cereals, and their development using drones.

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The State Research and Design Institute of lands will monitor the vegetative state of agricultural lands and crops using unmanned aerial vehicles.

The Jizzakh Organic cluster is among the first in agriculture to start using drones. Unmanned aerial vehicles from China FOXTECH Great Shark 330VTOL are used to create field maps, monitor crop growth, detect and diagnose diseases, as well as control pests.

In 2021, the first experimental work carried out by the specialist was successfully carried out on 10 hectares of grain fields, 4 hectares of vineyards and 5 hectares of arable land in the Kibray district of Tashkent region. A self-propelled drone is used in the surveillance work of the designated areas in mere 6 minutes.

As a result, measurements of soil moisture, and yield height showed error of 5-8% with more than 8-fold decrease of measurement time.

2 Literature review

Nowadays, on a global scale, the use of digital technologies in almost all areas of human activity is rapidly developing [1-5]. Agriculture is no exception. Therefore, in our country, in recent years, particular importance has been attached to developing the digital economy in this network.

According to the analysis, the agricultural producer has to adopt more than 40 different solutions during the season. Most of it is considered an object of digitization and directly affects production efficiency. The census shows that 33% of the crop is lost in planting, cultivation, storage and transportation. Under such conditions, "smart" or "smart agriculture" technologies, which ensure the rational use of existing land, water, material and technical and labor resources, are paramount.

The technical and technological base of the industry, on the other hand, largely determines the general development of the agro-industrial complex. This is manifested in the technological improvement of livestock and plant production, the increase of land productivity and the replacement of manual labor with mechanized activities. The lack of techniques limits farmers' capabilities and increases labor costs at the cost of products. Using existing technical means, effectively technology reduces its coverage period and speeds up the reproduction process while applying innovative technologies.

Technological transformation is digitising all production processes and automation, and management change is the introduction of new management methods. Practice shows that companies that use digital technologies and new production management methods make an average of 26% more profit than their competitors. On the contrary, those who use digital technologies without changing their management system will have 11% less profit, and companies that only switch to new management methods will increase their profit by only 9% [6]. Therefore, during the transition to digitalization of agricultural activities, it is necessary to introduce new technologies to production and change the management system [7].

In the digital economy, fundamental changes are taking place in the paradigm of agricultural production management because, as a result of the robotization of production and the automation of production management systems, humans make strategic decisions, and tactical decisions are made by machines based on the displayed information [8]. As a result, the communication time is reduced, the speed of business processes increases, and the accuracy and efficiency of the decision-making process increases [9].

Even though digitization of agricultural activity has not yet reached a significant scale, it is gradually spreading to individual production operations, and preparations for it should begin now [10-13]. This is because the consequences of digitalization change not only production methods but also goals, tasks, and management methods [14-17].

Using digital technology-based surveillance systems to monitor real-time video footage of each crop field detects any movement on the ground and sends an immediate alert. It should be noted that improving the monitoring of supply chains of agricultural products, bringing new and safe crops to the market and ensuring competition are among urgent problems.

A well-managed tracking system can help reduce inventory shrinkage by providing greater control throughout supply chains. Many tracking systems rely on advanced sensors to gain more information about the delivery status of each product [18]. For example, sensors of IoT (Internet of Things) technologies play an essential role in solving the above problems. The effectiveness of such technologies in delivering agricultural products is shown to be 16 times more profitable than before.

3 Materials and methods

The developed system also consists of several blocks that can operate independently. The results obtained from each block's tasks are provided as input data for the next blocks. Each block can also function as an independent program created based on Python. Open-source software was used to write these programs. The functions of each block are listed below, block numbers are shown in Figure 1 [19].

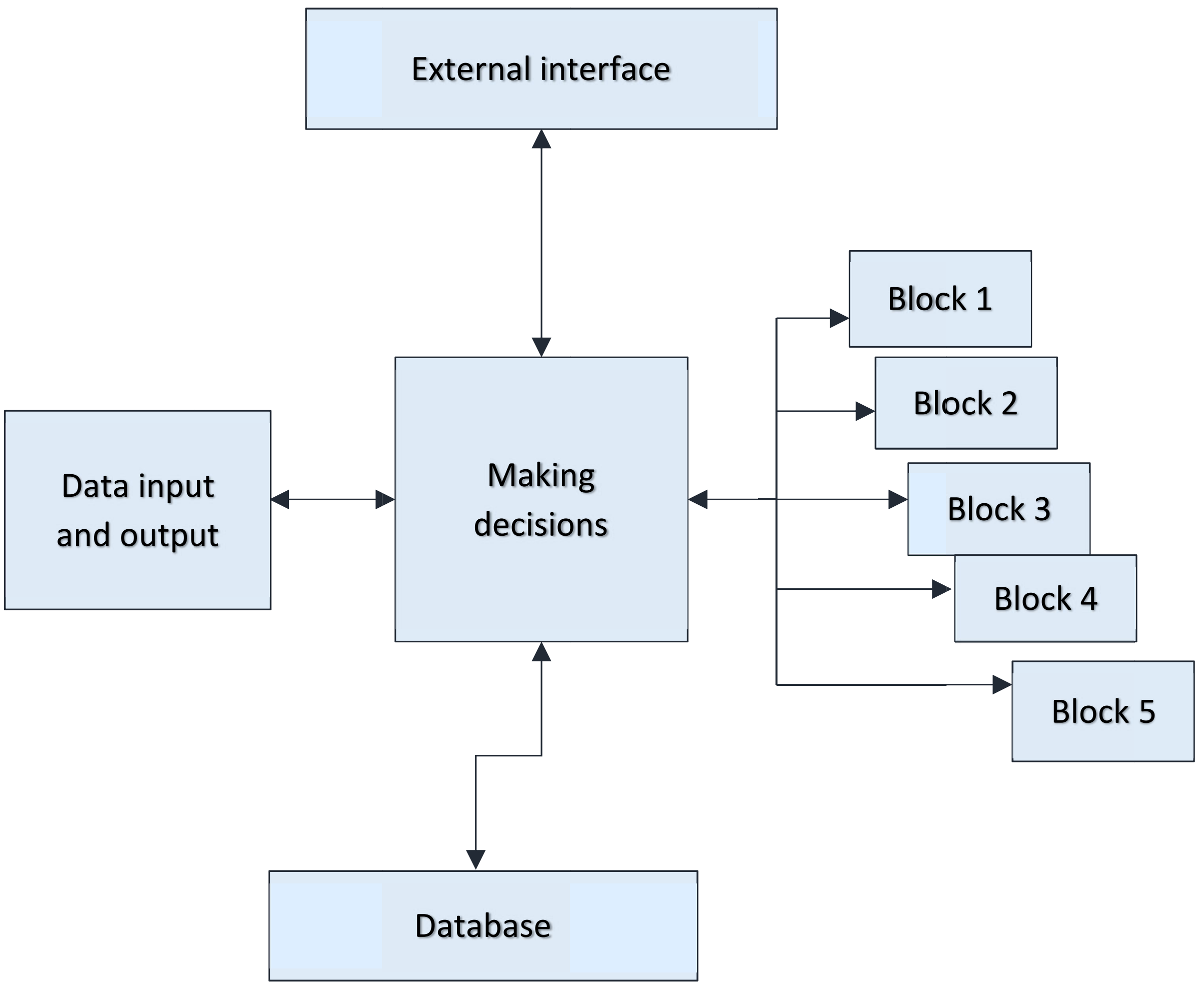

Fig. 1. A model of the developed system.

Block 1. *A program for creating a sequence of frames based on video material and extracting files of individual tempos.*

During the operation of the system, all operations (recognition operation, classification operation) are performed on photo frames. Therefore, first of all, the resulting video must be formed as a set of files consisting of a sequence of steps. The program used is developed based on the OpenCV library written in Python.

First, the OpenCV Python library is installed. Because the frame rate or frame duration varies from video to video, you must enter this parameter to specify the number of frames to be extracted and stored per second. In the developed block, the value of this parameter is 10, which allows you to save only 10 frames of video per second, although the actual frame rate of the video is 24 frames per second. If the video is 30 minutes long, a total of 18,000 frames will be saved. For our system, this is a sufficient value to ensure sufficient reliability of the recognition process in subsequent blocks. As a result of the program, a folder is created in advance in which the footage is saved along with a time stamp in the file name.

Block 2. *Program for determining the level of mineralization on the surface of dry soil.*

In the developed system, an open program code was used based on the method of creating soil maps during the long-term analysis of the dry soil surface. This is an alternative method of using vegetation indices. Determination of the dry soil surface was carried out using the soil line spectral analysis technology. Computer code based on deep machine learning (neural networks) was used to automatically recognize minerals in each ground image. The data set "Land Cover Raster Data (2017)" was used as a data set for training the program. This dataset is a 6-inch resolution Class 8 land cover dataset from the 2017 Light Detection and Ranging (LiDAR) dataset, developed as part of the updated Urban Land Assessment and thus represents a "top-down" mapping perspective, eight land cover classes are mapped: (1) trees, (2) grass/shrub, (3) dry land, (4) water, (5) buildings, (6) roads, (7) other waterproofing materials and (8) railways.

Half of the dataset was used as the training set. The other half was used as a test piece. Each rate pixel is set to "1" when detecting soil minerals. A value of "0" is set in the absence of a mineral. The machine's accuracy in predicting the presence of minerals was 75%. Degradation detection is based on average long-term red and UV spectral responses. As an integral characteristic of average long-term values, the coefficient C_{mean} was calculated, which is the distance of the point with average long-term values of red and ultraviolet from the origin of the red and ultraviolet spectral plane. High average long-term values of spectral brightness served as an indicator of the spread of soil degradation. The soil test values of this coefficient made it possible to estimate the amount of organic matter in the plow horizon (R2 = 0.841) and the thickness of the humus horizon (R2 = 0.8599). A total of 30 soil plots on 100 hectares were analyzed in eight agricultural fields.

Block 3. *The program for determining the type and disease of plants.*

In the development of this block, a search-based recognition method based on the classification of nearest neighbor plants was used in the deep embedding space of machine learning to automatically identify plant types and positions based on images. This method is based on Resall@k, a model trained with surrogate loss in image acquisition. This method has been proven to be more efficient than modern image classification approaches based on convolutional neural networks (CNN) and vision transformers (ViT). The PlantCLEF 2017, ExpertLifeCLEF 2018, and iNaturalist 2018 datasets, the largest publicly available plant recognition and status datasets, were used to train and evaluate this block. is a set.

The PlantCLEF 2017 dataset contains more than 1.15 million images collected by querying the Encyclopedia of Life via the Bing and Google search engines. The dataset covers 10,000 plant species, mainly from North America and Europe, making it the largest dataset to identify plant species by number of classes. The test set contains 25,170 images (17,868 observations).

The ExpertLifeCLEF 2018 training dataset differs from the PlantCLEF 2017 dataset only in the test set. The test set contains 6,892 images (2,072 observations) covering species mainly from Western Europe and North America. In addition, some endangered species, as well as cultural and ornamental plant species have been added. iNaturalist is a public science platform that allows citizens and experts to upload, annotate, and categorize worldviews. iNaturalist has extensive geographic and taxonomic coverage of over 343,000 species with approximately 97 million observations. iNaturalist 2018 - The iNaturalist Challenge 2018 dataset contains 2,917 plant species, 118,800 training and 8,751 validation images. In addition, full taxonomic information is provided for all images.

Block 4. *Program for determination of soil moisture level.*

Identifying different pixels with similar points in the images collected in the database is a reliable way to get an accurate picture of the soil moisture status in a given area. In this context, an artificial intelligence-based self-organizing map (SOM) method is used to classify the same pixels using parameters extracted from images. As a cluster indicator, the central pixels of the clusters are selected, one from each cluster. Then neural networks consisting of three layers, input, hidden, and output, are trained using a time series of extracted satellite images of the central pixels of the clusters. The proposed methodology and obtained results can be used to provide a cost-effective way of determining soil moisture status in the region by reducing monitoring costs.

To predict soil moisture based on this algorithm, it is necessary to combine relevant information about soil moisture conditions in different pixels of the area and define sample pixels. Therefore, SOM, as an ANN-based clustering approach, is a general machine-learning method for image recognition that can establish relationships between groups of unlabeled data without considering natural phenomena. One of the simple characteristics of SOM in the developed system is that it can divide images into different regions based on the same features. The operation of this block consists of two stages. In step 1, a two-step SOM was used to classify pixels into close color classes. Usually, such two-stage SOM clustering is proposed to understand homogeneous regions and estimate the number of clusters considering the topology of the plane. The Euclidean distance criterion is then used to determine the dominant (central) pixel of each cluster. The dominant pixel was determined to obtain the best sample representing the entire cluster structure. In this way, land areas are divided into clusters, and moisture level is determined according to the entered criteria.

Block 5. *A program for determining the size and location of land area.*

This block works based on the data of the above blocks and the GPS data of the drone movement. The main task of this block is to receive the data of the marked areas, add them, determine their location, and create a grid map. A grid map, also known as a raster map, is usually drawn based on image data. If the grid is treated as a matrix and the value of each point in the matrix represents the gray value of the corresponding image element, the image can be sampled and the corresponding digital matrix can be used to abstract the geographic information [20]. Unlike the abstract representations of a metric map, topological map, and semantic map, the accuracy of a grid map for depicting an actual path can be controlled by the size of the grid cell.

4 Results

To determine the relationship between the modules of the system developed based on modular programming, to ensure the exchange of information between the modules, and to solve the problems of integration of the system blocks, the system was divided into functional levels and interconnecting interfaces were developed for each level [21]. The generalized model of the developed web application-based system is presented in Figure 2.

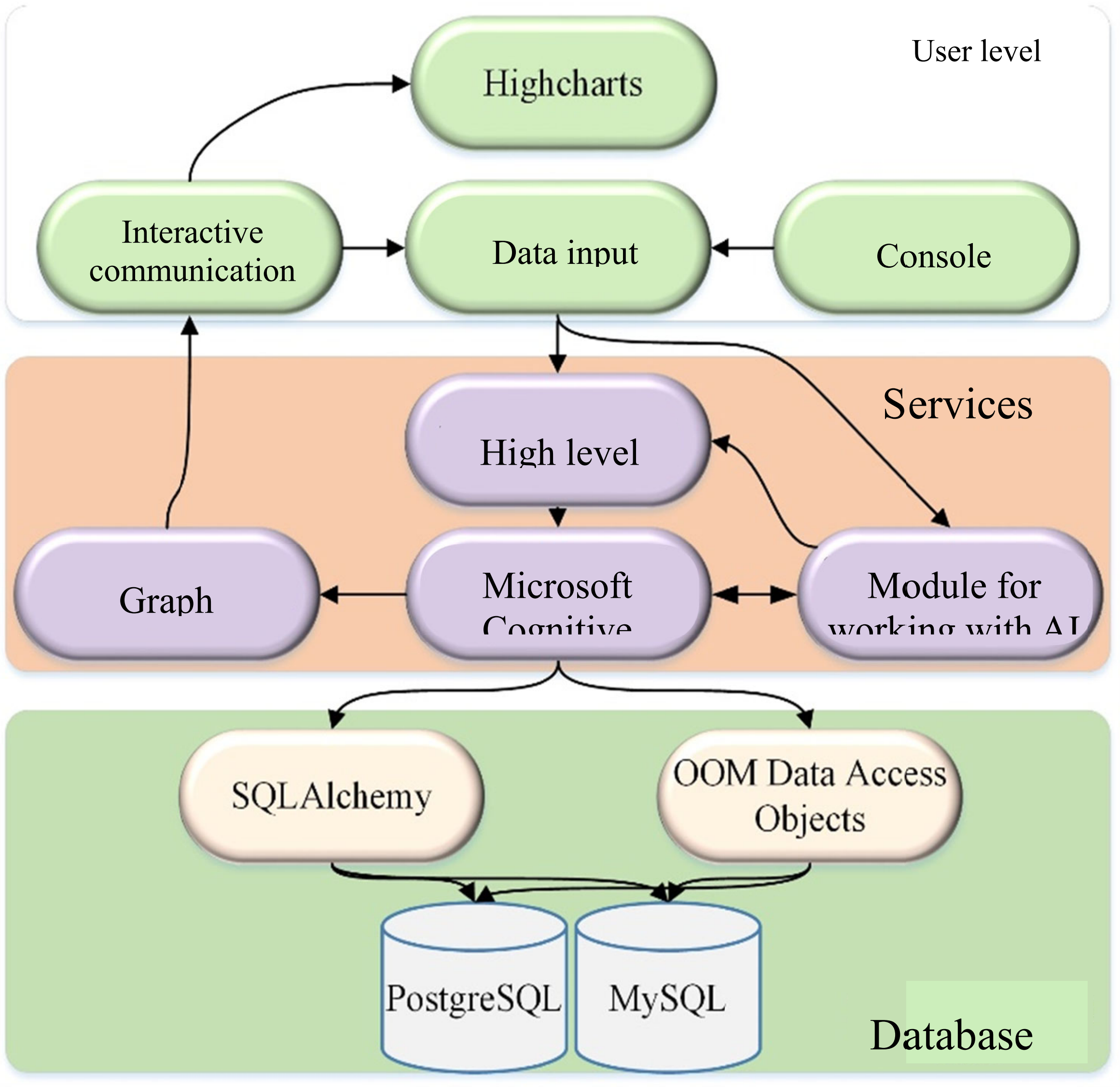

Fig. 2. Developed system architecture.

As can be seen from this model, the development of the system requires the distribution of common functions based on a multi-level architecture. In this case, the implementation of each block based on single artificial intelligence components makes it possible to simplify the system architecture and speed up the implementation of the system. The architecture of the system is presented in Figure 2.

The system consists of three functional levels, and each lower level integrates with the upper level based on the connecting interface [22].

The first level of the system is the user interface, which consists of data entry, an interactive user communication module, graphics rendering, and a Python console. Because the presentation of graphs is the main module of the system for providing information to the user, this module Highcharts library was built. Highcharts is one of the richest and most popular JavaScript libraries for creating charts and graphs with support for SVG (VML) services in HTML5 [23].

The second layer of the system is the service layer, which consists of artificial intelligence modules and related elements. The "Microsoft Cognitive Toolkit" software solution was used as an artificial intelligence module. The Microsoft Cognitive Toolkit is an open-source module based on deep learning that can be integrated into a web application through a high-level API to build neural networks. It delivers knowledge to the web application through API optimizers [24].

The third level of the system is the database level, and we conditionally include the functions of working with databases at this level. The SQLAlchemy module was mainly used in this step, but other alternative tools can be used. SQLAlchemy is a collection of Python SQL tools and object-relational mapping tools that allow you to take advantage of the full power and flexibility of SQL [25].

First, the program of block 1 will work on the file, and as a result, a file consisting of a collection of many images will be formed. After that, the loop starts, and the actions are performed on each image in the file. Initially, NDVI is based on speed [26].

NDVI (Normalized Difference Vegetation Index) - Normalized relative vegetation index - a simple quantitative indicator of the amount of photosynthetically active biomass (usually called the vegetation index). One of the most common and widely used indices used in the quantitative assessment of vegetation cover [27].
It is calculated according to the following formula:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

NIR - the area reflected in the near-infrared spectrum; RED - the area reflected in the red spectrum.

An NDVI value greater than 0.2 means that there is a crop in the area. In this case, the area is marked as cropland E or dryland Q.

5 Discussion

If there are no plants on the ground, this image is transferred to the 2nd block program. As a result of the block, the area is marked as mineralized land M or not M_ and binarized to determine moisture. After the binarization process, the 4th block program is started and the moisture level of the soil in the image is determined. An image with a moisture content above 30 percent is marked as irrigated land SY, otherwise, it is given a SY_ marker [28].

On the other hand, binarization and filtering operations are carried out on the images where areas with vegetation are detected. They increase the accuracy of identifying the type of plant in the image. After that, the 3rd block program will be launched. The quality of the result of this program determines the type of plant and determines whether it is infected or not. In addition, it is determined whether the illness was caused by the impact of insects or another disease. According to the results of the program, healthy plants are marked as SO', H affected by insects, and K affected by disease [29].

All marked images are transferred to block 5 and collected. In this block, the map is formed and saved as a file. As the final result of the system, the total area of all the marked areas and the percentage indicators based on their ratio to the total land is presented in the form of a diagram.

An additional feature of this system is the provision of a GPS map, in which information about each area is presented with markers, and it is possible to mention, for example, the identification of the types of planted and grown plants. They can be provided upon further request [30-38].

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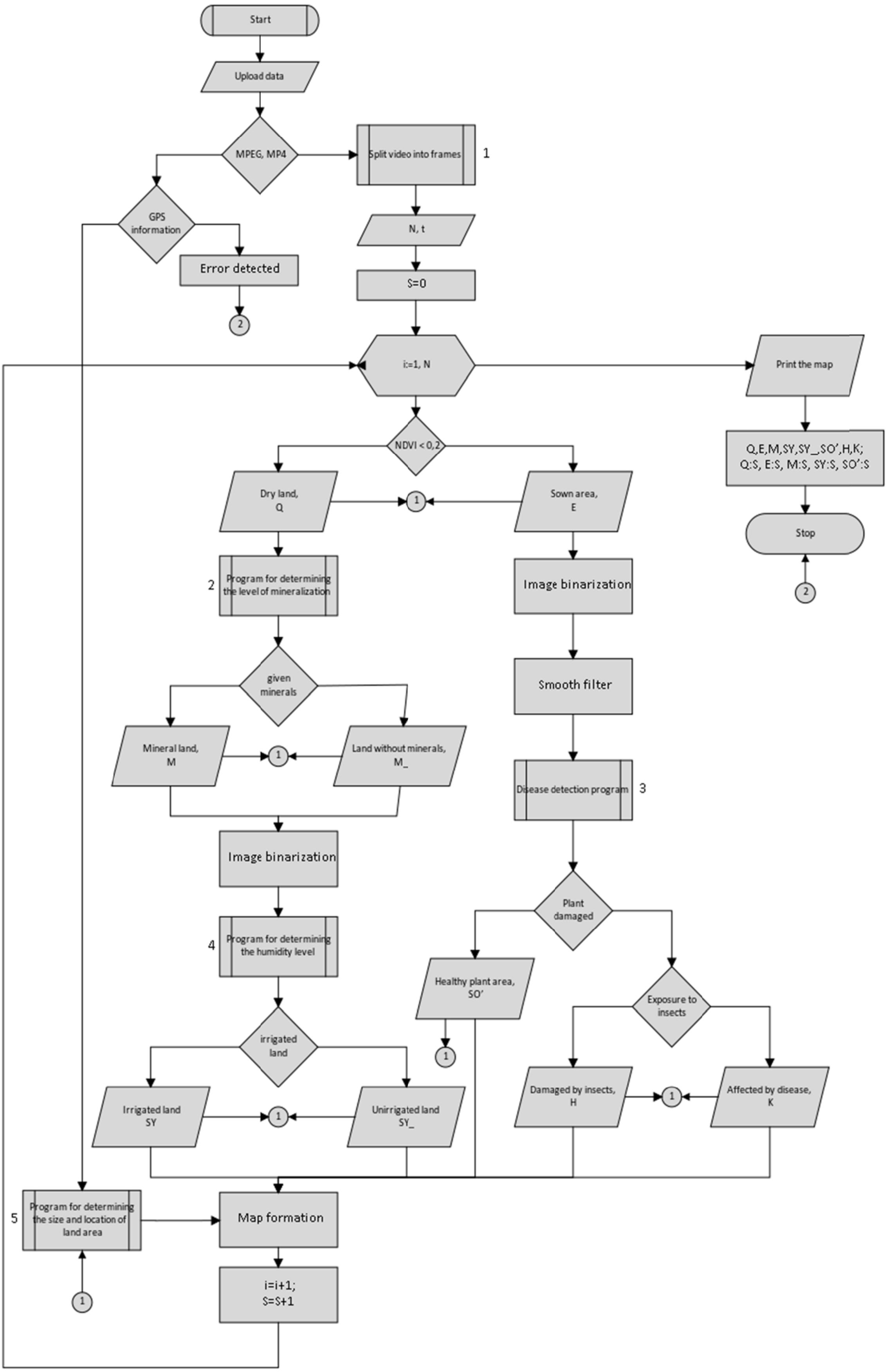

Fig. 3. A generalized algorithm of system operation.

6 Conclusions

In conclusion, it should be said that the created platform provides accurate information for remote monitoring of land areas for farms operating in the Tashkent region, and for making management decisions through drone videos. It also allows for remote monitoring of all processes of growing agricultural products planted on land, as well as the formation of the necessary database for farm managers and early forecasting of productivity indicators.

Implementation of the proposed digital platform model will significantly accelerate the process of digital transformation of agricultural production, which will ultimately lead to increased competition among small and medium-sized agricultural producers in domestic and international markets.

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