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# Development of intelligent systems for monitoring and management of agricultural enterprises

**Yaroslav Tupalo**
V.M. Hlushkov Institute of Cybernetics, Kyiv, Ukraine
ORCID 0000-0003-3563-898X

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**Abstract:** Modern agriculture faces a number of challenges, among which are the growing demand for food, the impact of climate change, limited natural resources and the need to ensure the environmental sustainability of production. In this context, the introduction of new technologies, in particular intelligent systems, becomes an important tool for improving the efficiency and competitiveness of agro-industrial enterprises. Intelligent Systems Based on Use artificial intelligence, machine learning, the Internet of Things (IoT) and big data are opening up new opportunities for monitoring and managing agricultural processes. The article presents the results of a study aimed at the development of intelligent systems that provide comprehensive monitoring of the state of fields and management of production processes at agricultural enterprises. The proposed system integrates data from various sources, such as sensors, drones, satellite images and other IoT devices, which allows you to create a detailed and up-to-date view of the state of crops, soils and climatic conditions. This, in turn, allows you to make prompt and sound management decisions that increase the productivity and efficiency of agricultural production. Particular attention is paid to the development of algorithms for processing big data and machine learning methods, which are used to analyze the data obtained and generate recommendations for optimizing the use of resources. This includes managing water resources, fertilizers, crop protection products, as well as predicting yields and identifying potential threats such as plant diseases or pests. The implementation of such systems allows not only to reduce resource costs, but also to minimize the environmental impact of agriculture by reducing the use of chemicals and water. Thus, the article makes a significant contribution to the development of intelligent technologies in agriculture, offering new approaches to the management and monitoring of agricultural enterprises. These approaches can form the basis for the development of future innovations in this area, contributing to improving the resilience and efficiency of agro-industrial production in response to modern challenges.

**Keywords:** PCA - Principal Component Method, IoT - Internet of Things, AI - Artificial Intelligence.

## 1. Introduction

In recent years, the development of information technology, in particular artificial intelligence (AI), has led to the creation of new approaches to the management of agricultural enterprises based on the use of big data and analytical methods. One well-known example is the use of the Climate FieldView platform [1], developed by Monsanto (now part of Bayer AG). This platform uses artificial intelligence and big data to analyze information [2] obtained from various sources such as satellites, drones and field sensors. It helps farmers make informed decisions about crop management, resource optimization, and yield prediction. Climate FieldView allows farmers to create field maps, monitor soil and plant health in real-time, and predict potential threats such as diseases or pests. The system analyzes large amounts of data and provides recommendations for optimizing irrigation, fertilizer application, and other agronomic measures. Through the use of this platform, farmers can significantly increase the productivity and profitability of their farms.

Traditional management methods in the agricultural sector, which are based on the experience and intuition of farmers, often have limitations in efficiency due to their lack of flexibility and dependence on subjective factors. Such methods typically involve routine practices that may not take into account current changes in environmental conditions, such as weather conditions, soil conditions, pests, and other factors that can significantly affect yields.

One of the main problems is the uneven yield in the fields, which can be caused by differences in soil composition, water availability, as well as the presence of plant diseases or pests. Traditional approaches often do not have the ability to adequately respond to these challenges due to the lack of timely and accurate information, which leads to uneven development of crops and, as a result, to a decrease in the overall productivity of the farm.

Another critical issue is the optimization of the use of resources such as water, fertilizers, and chemical plant protection products. Traditional methods involve the use of these resources on the basis of general recommendations, without taking into account the specific needs of individual areas of the field. This leads to overuse of resources in some areas and insufficient in others, which reduces the efficiency of their use and increases costs. In addition, this approach can have a negative impact on the environment, causing water pollution and soil degradation.

One of the most serious threats to crops is plant diseases and pests, which can spread quickly and cause significant damage. Traditional methods of detecting and combating these threats are often based on visual assessments, which may not be effective enough, especially in large areas. A delay in identifying the problem can lead to the loss of a significant portion of the crop.

In the context of the digital transformation of agriculture, there is a need to integrate the latest technologies that allow not only to collect and analyze large amounts of data, but also to respond quickly to changes in production conditions. Intelligent systems based on artificial intelligence, machine learning, and other digital technologies have the ability to significantly improve management processes in the agricultural sector.

Intelligent systems can provide real-time data analysis, taking into account a variety of factors, such as changes in weather conditions, soil conditions, humidity, the presence of diseases or pests, and provide recommendations for optimal actions. For example, such systems can offer precise dosing of fertilizers or pesticides for each area of the field, optimize the irrigation schedule, and anticipate possible risks such as drought or heavy rain.

The use of intelligent systems also allows for the automation of field monitoring using sensors, drones and satellite technologies, which provides more accurate and timely data for decision-making. This allows not only to increase yields, but also to optimize costs, reduce risks and ensure the stability of agricultural production.

Thus, the introduction of intelligent systems in the management of agricultural enterprises becomes a necessary step to increase production efficiency, reduce losses and ensure sustainability in the face of the ever-increasing complexity of agricultural processes. This makes it possible not only to solve current problems, but also to prepare for future challenges in agriculture, creating a new level of management that meets the requirements of the modern world.

## 2. Object and subject of research

The object of research is complex intelligent monitoring and management systems that are used in modern agricultural enterprises. These systems are based on a combination of advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), big data (Big Data), and cloud computing. The main task of the object of research is to improve the efficiency and automation of processes in the agro-industrial complex. Intelligent systems provide the ability to collect and process and real-time data analysis from a variety of sources, including sensors, drones, satellites, as well as ground-based controls. In this way, they contribute to optimal decisions regarding resource management, agricultural planning, yield forecasting, and minimizing risks associated with weather conditions and other factors.

The subject of the research covers the analysis of methods for the development, implementation and adaptation of intelligent systems for monitoring and management in the agricultural sector. The focus of the study is the study of architectural solutions of such systems, their functionality and efficiency in the conditions of different types of agricultural enterprises. Particular attention is paid to the study of decision-making algorithms based on the collected data, their integration with other information systems of the enterprise, as well as cybersecurity and data protection issues. The subject of the study also includes an assessment of the economic feasibility of implementing such systems and their impact on the productivity of agricultural processes.

In addition, the study examines aspects of the adaptability of intelligent systems to the specific conditions of different regions, their ability to scale and integrate with other technologies, such as robotics and automated transport management systems. This provides a holistic picture of how smart systems can be effectively used to support sustainable agriculture, reduce production costs, and increase yields.

The purpose of the study is to develop, implement and optimize intelligent monitoring and management systems for agricultural enterprises in order to increase the efficiency of agricultural processes, reduce production costs, and ensure sustainable agricultural development.

## 3. The purpose and objectives of the research

Analysis of modern technologies and methods for monitoring and management in agriculture, including the Internet of Things, artificial intelligence, big data and cloud computing. Development of an intelligent system architecture for an agricultural enterprise, which includes the integration of various data sources such as sensors, drones, satellites, and ground controls. Development of algorithms for data analysis and processing in order to support real-time decision-making, including yield forecasting, resource management and planning of agronomic activities. Analysis of modern technologies and methods.

Modern agricultural enterprises are increasingly introducing innovative technologies to increase the efficiency and productivity of agricultural processes. This is due to the growing demands for sustainability, product quality improvement, and cost optimization. This section discusses key modern technologies and techniques that play an important role in the monitoring and management of agricultural processes.

The Internet of Things (IoT) is one of the leading technologies that allows you to combine various devices and sensors into a single data collection system. In the agricultural sector, IoT is used to continuously monitor environmental conditions such as temperature, soil moisture, light levels, as well as to monitor the condition of plants and animals. For example, thanks to IoT sensors, farmers can receive real-time information about the condition of the soil and crops, which allows them to apply fertilizers or irrigate on time. This reduces resource costs and helps increase yields.

Artificial intelligence (AI) and machine learning [3] are becoming an integral part of modern agriculture. These technologies are used to analyze large amounts of data from various sources, such as satellites, drones, and IoT sensors. Thanks to machine learning algorithms, it is possible to predict yields, detect plant diseases at an early stage, optimize resource use and plan agronomic measures. For example, deep learning algorithms [4] , [5] make it possible to classify field images to automatically determine the condition of crops and predict their development.

Big Data [6] plays a key role in modern agriculture. By collecting, storing and processing large amounts of data from various sources (sensors, satellites, markets), agricultural enterprises are able to more accurately predict changes in the market, assess risks and make informed decisions. Big Data allows you to create models that take into account numerous factors that affect yields, such as weather conditions, soil conditions, and economic trends.

Cloud computing provides flexibility and scalability in data storage and processing. In the agricultural sector, cloud platforms allow you to store and process large amounts of data received from various sources, as well as provide access to this data from anywhere in the world. This ensures responsiveness in decision-making and allows data from different businesses to be combined for benchmarking and sharing best practices.

Unmanned aerial vehicles or drones are becoming increasingly popular in agriculture due to their ability to carry out high-precision monitoring of large areas. They are used for aerial photography, monitoring the condition of crops, identifying diseases and pests, as well as assessing the condition of soils. Drones can provide high-quality, high-resolution images, allowing for targeted actions, such as the application of crop protection products.

Satellite monitoring is an important tool for agriculture, allowing data on large areas with a high update rate. Satellite images are used to monitor the condition of crops, assess the chlorophyll content of plants, identify risk areas and predict yields. Satellite data can also be integrated with other information sources to create comprehensive models that aid in enterprise-level decision-making.

In modern agriculture, there is a growing need to create intelligent systems that can effectively integrate different technologies and data sources to improve productivity and sustainability. This section is devoted to the development of an intelligent monitoring and management system architecture for agricultural enterprises.

## 4. General requirements for system architecture

The architecture of an intelligent system must meet several key requirements. The system should consist of individual modules that can be easily upgraded or replaced without affecting other parts of the system. The system must be expandable to handle large amounts of data and new sources of information. The architecture should support the integration of various technologies and tools, such as IoT, AI, drones, and satellite data. The system must provide a high level of data protection and smooth operation in conditions of heavy use.

## 5. System Architecture Components

The development of an intelligent system architecture includes several key components. This component is responsible for collecting data from various sensors located in fields and greenhouses. Sensors can measure parameters such as temperature, soil moisture, light level, carbon dioxide concentration, and other indicators important for agricultural processes. The data collected by the sensors is transmitted to a server or to the cloud, where it is processed for further analysis. This module includes Big Data technologies for storing and analyzing data, as well as machine learning algorithms for interpreting and predicting data. The use of artificial intelligence allows you to create models to predict yields, detect anomalies, and optimize resources. This module integrates data from various sources (sensors, drones, satellites) to create complex analytical models. Based on the processed and analyzed data, the system generates recommendations for farmers or automatically makes decisions such as adjusting the irrigation regime, fertilizing or applying plant protection products. A user-friendly interface is developed to interact with the system, giving users access to reports, recommendations, and the ability to manage processes remotely. The interface can be implemented as a web application or a mobile application. To ensure an integrated approach, the system must be able to integrate with other enterprise information systems, such as resource management (ERP) systems, production planning systems, and others.

The components of the architecture must interact effectively with each other to ensure a continuous cycle of data collection, processing, analysis, and decision-making. Interaction is carried out through standardized data transfer protocols, which ensures the reliability and speed of information exchange.

Since intelligent systems work with large amounts of critical data, it is necessary to ensure a high level of data protection. The architecture of the system includes data encryption, user authentication, access control, and activity monitoring to prevent cyber threats.

After the development of the architecture of the intelligent system, it is necessary to test and validate it on real data from agricultural enterprises. This will allow you to evaluate the effectiveness of the system, identify possible problems and make the necessary adjustments.

## 6. Development of algorithms for data analysis and processing

In modern intelligent systems for monitoring and managing agricultural enterprises, data analysis and processing algorithms play an important role. These algorithms make it possible to convert large amounts of data collected from various sources into useful information on the basis of which management decisions are made. This section discusses the main approaches and methods used to develop such algorithms. Before starting the analysis, the data must go through a pre-processing stage, which includes several key steps. Data Cleanup: Removes noise, missing or incorrect values that may affect the accuracy of further analysis. Bringing data to uniform scales and formats to facilitate further processing and analysis. Combining data from different sources, such as sensors, drones, satellites, into a single database to simplify their analysis. These steps allow for improved data quality, which is critical to ensuring the accuracy and reliability of analytical algorithms. Big data analysis is a central element of today's intelligent systems, which are used to group data by similar features. In agriculture, clustering can be used to identify areas with similar conditions that require the same agronomic measures. Allows you to automatically define categories or classes of data based on training examples. This method is useful for identifying plant diseases or soil types. It is used to predict values based on the analysis of dependencies between variables. For example, it is possible to predict yields based on historical data on weather conditions and technological operations.

Machine learning algorithms [7] and artificial intelligence [8] , [9] are used to analyze complex data, including those coming from various sensors and satellites. They allow you to identify hidden patterns and make accurate predictions.

Neural networks [10]. These models allow you to build complex, multi-level relationships between data. In agricultural systems, they can be used to recognize images of fields and determine the condition of plants.

Randomized forest algorithms (Random Forest). They are used for classification and regression based on an ensemble of solutions, which allows you to increase the accuracy of predictions.

Genetic algorithms. They are used to optimize processes by imitating the evolutionary principles of natural selection. They can be useful for solving problems related to resource planning and production process management. Today's intelligent systems increasingly require real-time data processing. This is especially true for monitoring the condition of crops, water management or monitoring the implementation of agronomic measures. For such tasks, specialized algorithms are used [11]:

Stream-based data processing algorithms. They allow you to quickly analyze incoming data in real-time and respond to changes instantly.

Time series analysis. It is used to predict the future states of the system based on current and historical data. This approach is useful for predicting weather changes or analyzing production processes.

For the effective operation of the intelligent system, it is important to ensure the integration of data analysis and processing algorithms with enterprise management systems. This allows you to automate the decision-making process and optimize the implementation of agronomic operations. The integration also provides feedback, allowing algorithms to be adapted based on the results of their performance.

After the algorithms are developed, it is necessary to test and validate them on real data. This allows you to assess the accuracy and reliability of the algorithms, as well as identify possible errors or shortcomings that need to be corrected. Testing is done on different datasets to ensure that the algorithms are versatile and adaptable to different conditions.

Linear regression is used to predict key agricultural indicators, such as yield [12] or plant health status [13], based on various factors. To create the predictive model, historical data was used, where the dependent variable is the yield, and the independent variables are various environmental parameters (temperature, humidity, light level, etc.).

The linear regression model is as follows:

$$\mathrm{y} = \beta_0 + \sum_{i=0}^{n} \beta_i x_i + \epsilon \tag{1}$$

Where are the regression coefficients, is the random error. This allows you to identify the impact of various factors on yields and use this knowledge to improve management decisions. $\beta_0, \beta_1 \ldots \beta_n \epsilon$

As mentioned, linear regression can be used to predict yields based on agrometeorological data such as rainfall, average temperature, length of daylight, soil moisture content, and other factors. This allows farmers to better plan their resource use and expected income. Linear regression can be used to analyze the impact of different types of fertilizers and crop protection products on yield or product quality. For example, it is possible to assess how effective a certain type of fertilizer is in increasing yields or improving the quality of a product, taking into account other factors. Based on historical data on soil moisture, precipitation, and temperature conditions, a model can be created that predicts the need for irrigation for certain crops at different stages of their growth. This helps to avoid over- or under-watering, which can save resources and improve yields. Linear regression can be used to model the impact of long-term climate change on crop productivity. For example, it is possible to estimate how changes in average annual temperature or changes in precipitation patterns will affect yields in the future. Using historical data on agricultural prices and other economic factors such as supply and demand, models can be created to predict product prices. This can help farmers and businesses better plan their operations and make economically sound decisions. Linear regression can be used to assess plant health based on sensor data (e.g., spectral data) or drone imagery. These models can predict the development of diseases or stressful conditions for plants, which allows timely intervention and minimization of losses. Linear regression models can help optimize the use of resources such as fertilizers, water, seeds, and labor to minimize costs and maximize production efficiency. Based on past data and current conditions, recommendations for optimal resource allocation can be developed. Linear regression can be used to assess the impact of new technologies, such as automated control systems or new tillage methods, on plant productivity and efficiency. This allows for a scientifically grounded assessment of the feasibility of introducing innovations. Linear regression can be applied to model the impact of genetic factors on yield or disease resistance, which can aid in the selection of the most productive plant varieties for specific conditions.

Thus, linear regression is a powerful tool that can help in various aspects of agricultural enterprise management, providing science-based solutions and improving the efficiency of their operations.

The principal component method (PCA) is used to reduce the dimensionality of data [14] from sensors collecting information in agricultural fields. Initial multidimensional data is converted into several main components, which allows you to save as much information as possible while reducing computational complexity. PCA allows you to reduce the data matrix to a few main components that explain the variation of the data as much as possible $X$ [15]:

$$Var(a^T X) \rightarrow max \tag{2}$$

Where is the vector of weighting coefficients.$a$

This not only simplifies data processing, but also improves data visualization, which contributes to a more accurate analysis of the state of agricultural facilities.

A PCA can help identify the most important factors that affect crop performance, such as soil type, climatic conditions, how the land is cultivated, and fertilizer use. Based on these results, it is possible to optimize agronomic measures by focusing on the key factors that most affect yields. When analyzing the quality of agricultural products (such as grains, vegetables or fruits), a large number of indicators such as protein content, moisture, texture, color, etc., can be collected. PCA helps to reduce the number of variables by focusing on the most important factors that determine product quality. With PCA, it is possible to analyze data obtained from sensors or laboratory studies of the soil to highlight the main factors that affect fertility or the availability of essential nutrients. This can help with planning fertilization or choosing the optimal crops for planting. PCA can be used to analyze data relating to different types of stress for plants, such as drought, disease, or pests. The method helps to identify the most important factors influencing plant stress, allowing farmers to make decisions about protective measures. The PCA can be useful for classifying different plant varieties or soil types based on a large number of traits. This can help in breeding or choosing the most suitable varieties for specific growing conditions. In precision agriculture, where satellite or drone imagery is used to monitor fields, PCA can be applied to reduce the dimensionality of image data by highlighting critical components for further analysis. This allows you to process data more efficiently and identify anomalies or risk areas in the fields. In agricultural research, experiments with many variables are often carried out. PCA helps to highlight the main factors that influence the results of experiments, which makes it easier to interpret the data and focus on the most important aspects. Using data from a variety of sources (meteorological data, soil data, plant genetic characteristics, etc.), PCA can help create a model for yield prediction by focusing on the main factors that have the greatest impact. PCA can be used to analyze risks in an agricultural business, helping to highlight key risk factors such as market price fluctuations, weather patterns, or changes in demand. This allows you to better manage risk and make more informed decisions. The PCA can help assess the impact of different agricultural practices on environmental sustainability, such as biodiversity, water quality, or greenhouse gas emissions. This can help in the implementation of more environmentally friendly practices.

The principal component method is a powerful tool for analyzing multivariate data, which helps to identify the most important factors in various aspects of management and optimization of agricultural enterprises.

The k-means clustering method [16] is used to segment fields or crops based on similar characteristics such as moisture levels, soil fertility, etc. This allows for a differentiated approach to managing different segments, which increases overall efficiency. The clustering algorithm includes the following steps: initialization: selection of the k of the initial centroids, assign each object to the nearest centroid, compute new centroids as the average of all features in each cluster.

The total distance between the objects and the corresponding centroids is minimized:

$$\sum_{i=1}^{k} \sum_{x_j \epsilon C_i} \left\| x_j - \mu_i \right\|^2 \tag{3}$$

Where are clusters, are centroids.$C_i \mu_i$

This approach allows you to identify problem areas in the fields that require special attention and optimize the use of resources.

K-averages can be used to cluster plots of land according to soil parameters such as pH, moisture, organic matter content, and other chemical properties. This allows you to identify areas with similar conditions and develop appropriate treatment or fertilization strategies. Clustering fields by yield indicators can help identify areas with different productivity. This can be useful for optimizing the use of resources such as fertilizers, water, or crop protection products. The k-means method can be used to cluster crops according to their characteristics, such as growth rate, ripening time, or disease resistance. This allows you to plan sowing and crop management. This method can be applied to cluster regions by climatic conditions, such as rainfall, temperature, or humidity. This can help with yield prediction and agronomic planning. In animal husbandry, k-means can be used to cluster data on animal behavior (movement, activity, eating habits) to identify abnormalities that may indicate illness or other problems.

## 8. Conclusions

The article explores the possibilities of introducing intelligent systems for monitoring and management of agricultural enterprises. The implementation of such systems, which use modern technologies of artificial intelligence, machine learning and data analysis, can significantly increase management efficiency, optimize the use of resources and increase productivity. Particular attention was paid to the development of algorithms for processing big data and machine learning methods, which provide analysis of the data obtained and generation of recommendations for optimization of agricultural production. The implementation of these intelligent systems allows not only to reduce costs, but also to minimize the environmental impact, which is extremely important in the face of modern challenges related to climate change and growing requirements for environmental sustainability. Within the framework of the study, such methods as k-means clustering, principal component method (PCA) and linear regression were considered and practically applied. K-means clustering allowed for the segmentation of fields and crops based on similar characteristics such as moisture levels, soil fertility, and other parameters, which helped to optimize the approach to managing different segments of the field and improve overall resource efficiency. The principal component method (PCA) was used to reduce the dimensionality of the data, which made it possible to preserve as much information as possible while reducing computational complexity. This has contributed to a more accurate analysis and visualization of data used for monitoring and decision-making in agriculture. Linear regression was used to model and predict key agricultural indicators, such as yield or plant health, based on various factors, including agrometeorological data. This allowed farmers to better plan resource use and expected income, as well as assess the impact of different types of fertilizers and crop protection products on yield or product quality. Thus, the proposed intelligent system, which uses these algorithms, not only increases the efficiency of management of agricultural enterprises, but also ensures long-term sustainability and competitiveness in the face of global changes. The use of modern data processing algorithms is key to the further development of the agricultural sector, which can significantly improve management decisions and optimize production processes.

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