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Review Article

Computer Vision—The Frontier of Modern Environmental Diagnostics: A Review

Anna Sergeyevna Olkova* and Evgeniya Vladimirovna Tovstik

Vyatka State University, 36 Moskovskaya St, Kirov, 610000, Russian Federation

ABSTRACT

Computer vision (CV), in combination with various sensors and image analysis algorithms, is a frontier direction in diagnosing the state of the environment and its biogenic and abiogenic objects. The work generalizes scientific achievements and identifies scientific and technical problems in this area of research based on the conceptual system of analysis on the time axis: from implemented achievements as part of the past and present to original new solutions—the future. Our work gives an idea of three areas of application of CV in diagnosing the state of the environment: phenotype recognition in digital images, monitoring of living and abiogenic objects, and development of new methods for identifying pollution and its consequences. The advantages of CV, which can be attributed to scientific achievements in this field of research, are shown: an increase in the volume of analyzed samples, simultaneous analysis of several parameters of the object of observation, and leveling of subjective evaluation factors. The main CV problems currently solved are the accuracy of diagnostics and changing quality of the survey, identification of the object of analysis with minimal operator participation, simultaneous monitoring of objects of different quality, and development of software and hardware systems with CV. A promising direction for the future is to combine the capabilities of CV and artificial intelligence. Thus, the review can be useful for specialists in environmental sciences and scientists working in interdisciplinary fields.

Keywords: Bioassay, computer vision, deep learning, environmental quality, monitoring, phenotype

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E-mail addresses:
morgan-abend@mail.ru (Anna Sergeyevna Olkova)
tovstik2006@inbox.ru (Evgeniya Vladimirovna Tovstik)
* Corresponding author

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INTRODUCTION

The scientific community supports an interdisciplinary strategy for assessing the quality of the environment since nature is a complex system of interrelated abiotic and biotic factors. One of the newest (frontline) directions in the biodiagnostics of natural and natural-technogenic systems is developing and implementing software and hardware systems using computer vision (CV). CV technologies are understood as a field of artificial intelligence associated with automatic and semi-automatic extraction of significant features from digital images obtained using automatic microscopes and cameras, drones, robotics, satellites and other equipment in order to detect, classify, segment, recognize objects of interest (Vaganov et al., 2021; Lurig et al., 2021).

At the initial stages of the development of the CV, it was engaged in solving such problems as reconstructing 3D scenes from 2D images, decomposition of images into their parts, recognizing and assigning labels to observed objects, deducing and describing relations among scene objects, matching stored descriptions to image representation (Fischler & Firschein, 2014). One of the first applications of CV in environmental research was the recognition of objects on satellite images of the Earth. Success in the work was achieved using the PASCAL VOC Challenge test (Everingham et al., 2010) and the Large Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al., 2015).

It should be noted that computer vision currently refers mainly to working with three-dimensional objects. At the same time, it, in some parts, exceeds the capabilities of biological vision. The term "machine vision" can also be met in the literature, which, for the most part, characterizes the ability of robotic machines to evaluate various visual parameters (linear dimensions, distance to an object) (Shapiro & Stockman, 2001). Machine learning is used to speed up and automate image analysis. At the same time, algorithms based on a new field of machine learning (deep learning) show more accurate performance compared to traditional approaches to tasks based on computer vision (Mochida et al., 2019). CV uses characteristics such as color, shape, and texture of the image to determine the content of an image (Weinstein, 2018).

Using computer vision to extract useful information from images and videos is becoming a key method for studying environmental objects. CV allows scientists to increase the volume of received and processed data and the number of measured parameters; it eliminates subjective assessments of biological macro- and micro-objects, reduces research costs, and makes it possible to develop new methods of diagnostics using IT. With the help of CV, it is possible to obtain biological and environmental data of a new generation with high speed, accuracy and reliability (Lopez-Marcano et al., 2020).

For example, digital holographic microscopy has become an alternative to conventional microscopy. Modern digital cameras have Charge-Coupled Device (CCD) or Complementary Metal Oxide Semiconductor (CMOS) sensors and digital image processing tools. Multiple angles of digital holographic tomography and tomographic phase microscopy have rapidly evolved to recover a full three-dimensional (3D) refractive index map of intracellular structures or to estimate micro samples' three-dimensional morphology and shape (Monaldi et al., 2015).

The need to introduce CV in biodiagnostics was due to several reasons. Macroscale observations over large areas, such as forests, mountain systems, seas and oceans, and large man-made zones, in the 20th century mainly used methods of route descriptions and selection of representative sites (Ashikhmina et al., 2011). The obtained information was extrapolated to the entire macro-object, so there were risks of missing valuable data about the study area or even making incorrect scientific conclusions. The appearance of space and aero photography made it possible to "take a look" at large-scale natural objects and phenomena. When studying abiotic macro objects, information on the dynamics of the hydrological regime of water bodies (Kantor & Ashikhmina, 2014; Mu et al., 2022) and geothermal activity (Moraga et al., 2022; Xiong et al., 2022) is valuable. New methods of wildlife census appeared (Li et al., 2022; Norouzzadeh et al., 2020; Roy et al., 2023). As a result, studies of biotic processes were enriched with new data on the migration routes of terrestrial and marine animals (Zhou et al., 2022). Biogeographic maps with plant boundaries and biodiversity data can now be updated automatically (Wägele et al., 2022).

Biodiagnostics of the environment according to the characteristics of the meso- and macrocosm is still carried out on a representative sample of observed biological objects. However, the cost and complexity of data collection often limit the breadth and scope of environmental research (Weinstein, 2018). The main scientific approaches traditionally established in environmental biodiagnostics take into account several fields of view when microscopy of the studied object (Karl & Proctor, 2007; Ruiz-Santaquiteria et al., 2020), creating a model group of organisms in ecotoxicological tests (Gad, 2016), trapping a part of the natural population for studying (Abou-Donia, 2015), collecting biosamples for laboratory analysis (Ashikhmina et al., 2011). In each of these areas, it is practically impossible to bring information about the working sample of organisms closer to the characteristics of the entire population in the study area or the population of organisms in laboratory culture. As a result, part of experimental organisms' individual variability and sensitivity to various factors remains unaccounted for. CV methods cannot completely solve this problem, but they significantly increase the sample size and reliability of the received information. In addition, a CV allows new parameters into diagnostics that are inaccessible for visual and other classical accounting.

The purpose of this review is to demonstrate the application of computer vision for biodiagnostics of the state of the environment and to highlight the latest achievements in this interdisciplinary field and unsolved problems.

MATERIALS AND METHODS

Scientific publications for review were selected in the international scientometric databases Web of Science, Scopus, ScienceDirect, and the Google Scholar search engine by thematic queries and subsequent filtering by year and type of publication. The criterion for selecting databases was the international coverage of authors and publications. At the same time, the principle of impartiality to publications was implemented: we did not filter magazines by rating. Keywords used were computer vision, environment, environmental quality, environmental pollution, deep learning, machine learning, artificial intelligence, monitoring, and phenotype. These keywords were used in different combinations according to the rules of the corresponding database.

The concept of the work was to consider the scientific foundations, the current state and the future of CV in the diagnosis of environmental quality on the time axis. We analyzed publications older than five years to include important original research and fundamental work in the CV field in the review. Among these works, preference was given to monographs and thematic books. In the books on diagnostics, we paid attention to the description of technical and methodological problems that are difficult to solve without a CV. The works published over the last five years (2019–2023) demonstrated the implemented technologies—these are already accomplished discoveries and achievements. The first criterion for using the works of 2019-2023 was the description in them of solutions to existing problems in the related field of “CV-biodiagnostics.” The second criterion is information about the implementation of the technology. These innovations informed us about the CV frontiers in the present time—generalization and analysis of unsolved problems we attributed to the future.

Studies were excluded if unrelated to digital phenotyping, biological objects and environmental resources monitoring, and environmental pollution research. We have not analyzed unpublished reports and conference materials not mentioned in Web of Science, Scopus, ScienceDirect.

In accordance with the concept, 70 sources covering current developments, experimental models and the introduction of computer vision-based software and hardware complexes in the diagnostics of natural and man-made systems were included in the review.

RESULTS

Directions for Using CV in the Environmental Diagnostics

Digital Phenotyping

Observations of the environment began with the formation of biological systematics and knowledge of the diversity of life forms. In the 20th century, a separate group of scientists consisted of specialists in the taxonomy of living organisms. Hardware and software systems based on CV can partially facilitate their work. As a rule, they are aimed at automatic, accurate and high-throughput measurements, including the analysis of external signs and factors influencing the development of biota (Mochida et al., 2019).

A wide range of automated taxon accounting systems has been developed. Thus, plant phenotyping occurs based on their images, including in conjunction with the results of molecular genetic analysis of DNA (Stefen et al., 2022). At the same time, information processing can include the capture of both plant organs, including underground and aboveground, and the entire plant, including its three-dimensional phenotype (Li et al., 2020). High-throughput 3-D phenotyping according to the geometric parameters of tree crowns is implemented using two main technologies: mobile ground laser scanning based on light detection and ranging sensors (LiDAR) and digital aerial photogrammetry using images from unmanned aerial vehicles (UAVs) (Torres-Sanchez et al., 2023).

Recognition and search for botanical micro- and macroobjects using CV allows for obtaining fundamentally new phenotypic data for species classification and taxonomy and understanding plant processes and speciation (Vaganov et al., 2021). The solution to such problems is based on the interpretation of the plant surface's chromatic features, contour features, and textural features (Alam et al., 2022). Deep learning or transfer learning is the common approach for most of the studies (Hussein et al., 2021). Such technologies already make it possible to create digital herbariums.

Achievements in computer vision and deep learning make it possible to determine variations in phenotypic traits, behavior and interactions of insects and other invertebrates. Such non-invasive research methods make it possible to determine the abundance, biomass, and diversity of insects within the framework of the global problem of reducing their biodiversity (Høye et al., 2021), assess the foraging of honeybees (Ratnayake et al., 2021).

Phenotyping is especially difficult in the field of quantitative accounting of microorganisms. Microorganism image analysis technologies have progressed significantly from classical image processing and traditional machine learning to modern deep learning and potential visual transformation methods (Ma et al., 2023). Thus, when recognizing colonies of microorganisms on agar nutrient media, deep learning algorithms are applied that use geometric features, for example, the edge detection of colonies in a liquid nutrient medium—the watershed boundary between the globule formed by microorganisms and the liquid. Methods for identifying and enumerating microbial colonies on diagnostic culture media are usually based on various image enhancement methods: gray level contrast and image conversion to a three-channel (RGB) color model (Zhang et al., 2022; Boukouvalas et al., 2019).

A more advanced approach is deep learning technologies using Convolutional Neural Networks. The classification model created on its basis, in particular, of three types of stained bacteria, *Bacillus coagulans, Staphylococcus aureus* and *Clostridium perfringens*, allows achieving training and testing accuracy of 96.75% and 81.35%, respectively (Rani et al, 2022).

The transition from algorithms and laboratory setups to devices for mass use is already beginning. Thus, the automated multiwell station Automated Open-Hardware Multiwell Imaging Station is proposed, which combines a microscope, a digital camera and a low-power single-board computer, which is capable of automatically collecting samples using 3D-printed pumps and capturing images with optical magnification up to 50 times (Gervasi et al., 2022).

Thus, the biological taxonomy of micro- and macroorganisms, which previously required a huge investment of time and material resources and highly qualified specialists, is now equipped with software and hardware systems with CV and elements of artificial intelligence.

CV helps to combine the study of the characteristics of biological species with the monitoring of biogenic and abiogenic objects.

Monitoring of Biological Objects and Environmental Resources

The second vector of using CV is monitoring living objects in the environment and their non-living components, which are valuable resources. It is known that monitoring—long-term and systematic observations—is the leading approach to studying the dynamics of ecosystems, which occurs under the influence of jointly acting natural and anthropogenic factors. It should be noted that monitoring is often associated with a large set of data, which creates difficulties in their interpretation. Software and hardware systems with CV can autofocus on biological objects of interest, capturing and analyzing images or videos, including those containing multiple objects of observation. Applying these technologies to systematic observations of populations and communities of organisms is an advance in ecological monitoring.

Monitoring animals, including protected species, their behavior, and the number of individuals in herds is extremely important for biodiversity conservation and managing invasive species. Combining remote sensing with unmanned aerial vehicles with CV technologies solves these problems in this study. Five animal species: (1) African elephant (*Loxodonta Africana*), (2) giraffe (*Giraffa camelopardalis*), (3) white rhinoceros (*Ceratotherium simum*), (4) wildebeest (*Connochaetes taurinus*), and (5) zebra (*Equus quaggas*) have shown that a new image analysis based on point pattern analysis allows picking up a drone from the height of 15 m to the height of 130 m, which increases the image capture area (Petso et al., 2021). The combination of computer vision camera traps, sensors, machine learning applied to satellite images, and GPS collar data can detect, track and localize animals in vast hunting areas (Dorfling et al., 2022). It will make it possible to combat the poaching of elephants and rhinos and then apply technology to protect other animals.

An invaluable tool for the high-throughput collection of species activity data is automated trackers, which are improved on the basis of CV and deep learning technologies. As a result, scientists provide software and hardware systems, including a portable motion activity monitor and a mobile activity detector. The monitored biological processes can include circadian rhythms, eclosion and diapause timing, and pollination. (Sondhi et al., 2022). Similar approaches are implemented by Bjerge et al. (2021). The authors developed an automatic moth trap with multiple light sources and a camera to attract and observe live insects at dusk and night. A computer vision algorithm based on a deep analysis of the captured images allows tracking and counting the number of insects and identifying their species.

CV makes it possible to observe populations of micro- and macro-organisms in the water column, which again was not possible with traditional methods. For example, CV technologies monitor ichthyofauna diversity in natural habitats (Ditria et al., 2021; Sheehan et al., 2020). Daily and seasonal monitoring of the vertical migration of cyanobacteria, which significantly affects water quality, has also become feasible with a CV-based instrument (Li et al., 2022). With the advent of high-speed digital cameras that feature large enough electronic sensors with small enough pixels, a time series of thousands of single holograms per second yielded some observations. They showed 3-D structures of the spatial distribution of marine plankton without further manual refocusing (Moreno et al., 2020).

A big threat to marine ecosystems and human health in recent years has been red tides caused by the reproduction of algae of the group of dinoflagellates. Their monitoring recognition and classification system based on CV was developed, which includes image segmentation, artificial feature extraction and classification based on a machine learning algorithm. Image segmentation allows for detecting the single algae's boundaries and getting its bounding rectangular areas as the sub-image from the original images, even if several objects stick together (Yang et al., 2020).

Monitoring plants and their communities on a micro- and macroscale has research and economic functions. The review (Keefe et al., 2022) reveals the advantages of monitoring forest resources using CV: mapping forest plantations with the possibility to take into account each seedling, optimizing logging routes, and introducing machine navigation, automation and robotics into the work of forestry. It was shown that CV provides an excellent opportunity to diagnose and monitor plant diseases (Xia et al., 2022; Patil et al., 2021). Thus, some algorithms allow registering plant damage by powdery mildew by visualizing *Erysiphe necator* hyphae directly on leaves without their preliminary sowing on a diagnostic nutrient medium (Bierman et al., 2019).

Monitoring invasive alien plants is relevant for preventing and controlling the biodiversity of agricultural and natural ecosystems. Using satellite images and expert processing is possible (Tovstik et al., 2019). More advanced are images taken with intelligent UAVs (Qian et al., 2020). UAVs in a complex with "deep learning" are ideal for collecting, processing and extracting complex data obtained in real situations (Dudukcu et al., 2023). However, there is a problem with the high cost of global navigation satellite systems of the survey level (GNSSs). Yuan et al. (2022) proposed a novel approach for registering UAV-LiDAR data of level agricultural fields utilizing a colored iterative closest point algorithm, GNSS location, and inertial measurement unit orientation information from the UAV.

Thus, a fait accompli in monitoring the environment and its processes can be considered the need to use photo and video materials obtained using CV technologies. Innovative technologies with laboratory and single prototypes can be called hardware and software complexes with systems for navigation, information transmission, and primary processing. The future of monitoring research lies in improving the share of artificial intelligence in such products.

Studying Environmental Pollution

Thirdly, CV is very promising for assessing environmental pollution, especially in terms of neurobehavioral analysis of biological objects as their response to chemical impacts. Sensorimotor and cognitive-behavioral bioassays have enriched world science. For example, in the toxicological assessment of water by *Artemia franciscana* responses, the software detects organisms and analyzes their trajectory using image processing algorithms (Henry et al., 2019). For each specimen of *Daphnia magna*—a classic test organism—the following parameters are determined: swimming speed, height of the test object in the chamber, current and total distance traveled, size of the test object and its orientation in space, complexity of the movement trajectory (fractal dimension of the trajectory) (Nikitin et al., 2018).

Many physicochemical and biotic characteristics of water testify to its quality. These properties can also be determined using a CV. For example, a system for estimating water viscosity was created, making it possible to automatically judge water quality in real time. Its applied aspect is to ensure the health and safety of growing royal goldfish in small aquaculture (Ma & Wei, 2021). A simple detection and counting method for *Escherichia coli* in the water samples, including a combination of DNAzyme sensors, microfluidics, and computer vision strategies, was developed (Rauf et al., 2022). Attempts were made to assess climate change according to the biotic responses of butterflies through digital image processing (Wilson et al., 2021).

In ecotoxicological research, monitoring Earthworm behavior in the soil using deep learning is of particular value. Quantification of their activity is based on neural network model predictions made based on image sequences taken during exposure to an environmental factor or xenobiotic (Djerdj et al., 2020).

CV technologies provide rapid screening of contamination. For example, a digital image of an analyte drop is decomposed into three color components: red, green and blue. The concentration of colored substances is related to these color characteristics. The software processes the color signal to construct calibration curves and further chemical analysis (Fashi et al., 2020). This technology, with modifications, formed the basis of an Android application that determines the copper content in water, food and soil. An electromembrane extraction device with red-red-green-blue analysis based on a QR code has a detection limit and a quantitative determination limit of 0.1 µg/ml. Intra- and inter-assay relative standard deviations ranged between 2.0% and 2.3% and 3.1%–3.7 %, respectively (Zaroudi et al., 2023).

Combining the latest CV technologies (deep reinforcement learning, neural networks, and object recognition algorithms such as the dragonfly algorithm) makes it possible to observe and sort waste in real time (Al Duhaiyyim et al., 2022). With the help of independent machine learning models, it is possible to control water pollution sources by forming algae, floating impurities and changing the color of water bodies (Sharma et al., 2021). As a result, CV technologies, remote sensing and artificial intelligence technologies became one of the most sought-after strategies for automating environmental monitoring in terms of environmental pollution, especially in the face of global climate change problems (Yang et al., 2022).

DISCUSSION

Scientific Problems of CV in Environmental Diagnostics

Despite the many advantages of digital methods of environmental research, scientists have to solve a number of problems. A typical computer vision and signal processing workflow may include image pre-processing and segmentation—separating the "foreground" from the "background" to obtain a "binary mask," measuring a parameter of interest (Lürig et al., 2021). At the same time, it is known that variability of such video file parameters as resolution, frame rate, file container types, codecs, and compression levels can be a source of experimental errors in behavioral analysis (Henry et al., 2019). These are the most common problems when using CV in environmental diagnostics. It is also possible to single out the scientific problems inherent in the scientific and practical areas discussed in this paper.

For digital phenotyping of living objects, it is extremely important to solve the problem of simultaneously tracking several significant parameters (Arya et al., 2022). A variation of this task is the acquiring and processing of volumetric (3D) images of living moving objects. Observation of unmarked animals in their natural habitat (in uncontrolled conditions) on video is reported to be difficult due to occlusion in the 3D environment (Ratnayake et al., 2021). However, the work of Kuswantori et al. (2022) shows progress toward fish digitization: accuracy increased to 72.65% with the landmarking technique, then increased to 76.64% with the subclassing technique, and finally increased to 77.42% by adding scale data.

The problems of biodiversity monitoring include problems resulting from a complex data structure, imperfection of statistical models, and communication of algorithms for different objects of study. Johnston et al. (2022) propose potential solutions to these problems: collecting additional data or metadata, analytically combining different data sets, and developing or refining statistical models. It should be noted that the quality of digital images of terrestrial (land) objects is still higher than that of underwater objects and the hydrosphere. Object crowding and occlusion reduce the latter's quality, as well as the difficulty of obtaining large-scale data (Salman et al., 2020; Zhang et al., 2022).

The solution to these problems should be at the intersection of the efforts of biologists, ecologists and IT specialists. Some works devoted to CV for environmental research contain ideas that will be fully demanded and implemented in the future.

Prospects for CV Technologies in Biodiagnostics

The most promising works have multiple interdisciplinary connections. Wägele et al. (2022) give the foundations for combining CV technologies and "computer hearing," supplementing biodiversity data through decoding animal sounds. It also discusses the need to develop a database of barcodes of the DNA of organisms to collect even more complete and reliable information on biodiversity.

The prospects for CV are inextricably connected with improving artificial intelligence algorithms. Liu et al. (2022) note a significant scientific leap in developing neuromorphic patterns that simulate the functionality of the big brain. For deeper image processing by CV systems, a qualitative transition from two-dimensional neural networks to three-dimensional hierarchical neural networks, a biobrain characteristic, is required.

Figure 1 shows the development path of CV technologies in environmental diagnostics in the areas discussed in the review. From an idea, a prototype, or a pilot model to ordinary

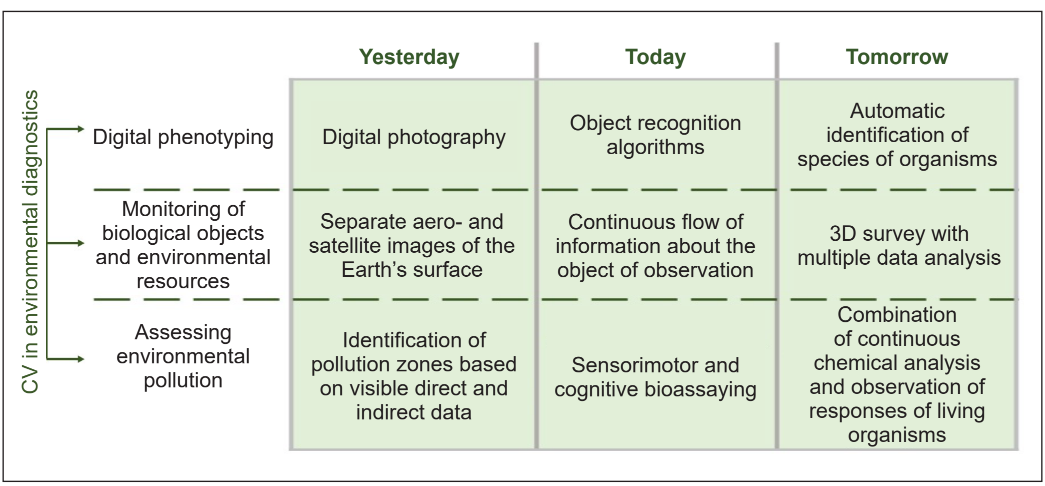

Figure 1. Vector concept of CV technology development in environmental diagnostics

equipment, technologies are gradually bringing ecological research to a new scientific stage, distinguished by the transition from a point study of environmental objects to systems of total monitoring of their significant parameters.

CONCLUSION

Thus, the scientific problems in the development of computer vision always come from practical problems that are solved with the help of such technologies.

The development and implementation of computer vision in environmental diagnostics is certainly a promising scientific direction, where the efforts of biologists, ecologists and IT specialists are needed. In the 20th century, the acquisition of satellite and aerial photographs was considered a breakthrough in visual environmental data. In the 21st century, digital processing of photo and video data will be applied to all objects in the micro and macro world.

Thanks to CV, 3-D herbariums, libraries of viruses and bacteria, non-invasive methods for determining species, and diagnostics of individual and population parameters of biological objects have become scientific achievements in phenotypization. Innovations in 3-D phenotyping, supplemented by other technologies, proved to be in demand in monitoring agricultural land, tracking moving objects, and monitoring processes in the water column. Environmental pollution assessment based on the CV family of technologies becomes rapid without losing analysis quality. At the same time, biotesting with short-circuit testing acquires consistency due to the variety of organisms' responses and the complexity of information processing.

Based on these scientific and technological achievements, databases of biological information will be created, new methods for studying biogenic and abiogenic objects, and algorithms for monitoring and managing environmental quality will be created. These achievements are important in solving global environmental problems of reducing species diversity and pollution.

The presented mini-review summarizes and structures the available information on using CV in environmental diagnostics and also suggests thinking about the future of environmental science methods and the role of scientists and artificial intelligence devices in bioecological and geoecological research.

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