Shahid Bahonar University of Kerman
Agricultural Biotechnology Journal
Iranian Biotechnology Society
Print ISSN: 2228-6705 Online ISSN: 2228-6500

A big data-driven agricultural system for remote biosensing applications

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Abstract

Objective

This study explores two big data (BD)-driven agricultural models backed by the National Institute of Food and Agriculture (NIFA). It examines the benefits of thorough agricultural records, efficient phenotyping techniques, and teamwork in promoting agriculture, highlighting the role of technological advancements like sensors, robotics, machine learning (ML), big data analytics, remote sensing, and genomics in addressing global food and water security issues. The study's primary goals were to examine the advantages of maintaining accurate agricultural records for better breeding and agronomy, investigate strategies for efficient phenotyping and data collection in agricultural systems, then support interaction between plant breeders, agricultural scientists, and specialists in ML, remote biosensing (RBS), and BD, and to determine the financial requirements for the ongoing advancement of BD-driven agriculture models.

Materials and methods

The AVIRIS Indian Pines database was utilized in these tests. The Indian Pines database encompasses the farming industry. The dataset consists of 16 different groups. The studies used an Intel i5 laptop with a 2.4-GHz Central Processing Unit (CPU) (four cores) and 16 gigabytes of Memory.

Results

The integration of technology, including sensors, remote sensing, robots, and BD analytics, enhances high-throughput phenotyping and precision farming. Multidisciplinary cooperation accelerates crop breeding and management. Future financing is needed for predictive machine learning models and scalable phenotyping techniques.

Conclusions

BD analytics, remote sensing, and machine learning have the ability to transform agronomy and plant breeding, tackling issues related to food security. Sustained cooperation and sufficient infrastructure investment are essential for successful implementation, with specific funding required for the development of cutting-edge instruments and technologies that guarantee sustainable farming methods.

Keywords: Agricultural system, big data, biotechnology, remote sensing

Paper Type: Research Paper.

Citation: Biswas D, Tiwari A (2024) A big data-driven agricultural system for remote biosensing applications. *Agricultural Biotechnology Journal* 16 (4), 321-334.

Agricultural Biotechnology Journal 16 (4), 321-334. DOI: 10.22103/jab.2025.23995.1603

Received: September 25, 2024. Received in revised form: December 07, 2024.

Accepted: December 08, 2024. Published online: December 30, 2024.

Publisher: Faculty of Agriculture and Technology Institute of Plant Production, Shahid Bahonar University of Kerman-Iranian Biotechnology Society.

Introduction

The advancement of earth observation technology, particularly satellite remote sensing (RS), has resulted in vast amounts of RS information for study and diverse uses (Zhang & Zhang 2022). Over a thousand operational satellites are in orbit above the Earth, with a significant portion dedicated to RS. Satellites are outfitted with various sensors or tools according to their intended use. Multiple sensors are installed on board to gather diverse observational data from the Earth's surface, encompassing land, ocean, and environment. These satellites continuously capture photographs of the Earth's surface using their sensors, which have varying time and space resolutions. A vast amount of remotely captured photos is accessible in several countries and worldwide organizations, and this volume continues to increase perpetually, on a daily, hourly, and even second basis. Precision agriculture has transformed agricultural practices since the 1980s using advanced technology such as Global Positioning Systems (GPS) (Perez-Ruiz et al. 2021) and Remote Biosensing (RBS) (Chen et al. 2024). These advances have greatly enhanced the efficiency and accuracy of agricultural automation (Mamdapur et al. 2017). In the last three decades, Precision Farming (PF) has advanced from using satellite imaging to make regional decisions to employing satellite low-altitude data for field-scale site-specific therapy, allowing for more precise monitoring and management (Pržulj & Tunguz 2022). Data science and Big Data (BD) technologies (Bhat & Huang 2021) are being integrated into PF systems (Pandey et al 2021). This allows for the quick analysis of data to make informed decisions (Surendar et al. 2024). However, there is still ongoing study on effectively handling BD and transforming it into smaller, more specific datasets for precise agricultural operations.

In conjunction with satellite positioning data, Agricultural RBS (ARBS) generates spatially diverse information and statistics for crop forecasting and PF operations using the Geographical Information System (GIS) (Weiss et al. 2020). ARBS information is in several formats, obtained from diverse sensors at varying intervals and scales. All agriculture remotely sensed information possesses the attributes of BD (Angin et al. 2020). The successful implementation of PF relies heavily on acquiring, processing, storing, analyzing, and visualizing large amounts of farming RBS information. With the latest advancements in information and technology for electronics and the help of satellite imagery BD, PF will evolve into a more sophisticated and innovative form known as intelligent farming. Moreover, data generation in agriculture and biotechnology has greatly increased in recent years due to the very rapid development of high-performance technologies (Mohammadabadi et al. 2024). These data are obtained from studying products, foods, and biological molecules to understand the role of different aspects of agriculture in determining the structure, function, and dynamics of living systems (Hamidi et al. 2017). Artificial neural networks have been proposed to alleviate limitation of traditional methods and can be used to handle nonlinear and complex data, even when the data is imprecise and noisy (Hamidi et al. 2017). Agricultural data can be too large and complex to handle through visual analysis or statistical correlations. This has encouraged the use of machine intelligence or artificial intelligence (Ghotbaldini et al. 2019). Thus, the main goal of this study was to examine the advantages of maintaining accurate agricultural records for better breeding and agronomy.

History: RBS technologies have been advanced to observe the Earth using various sensors and platforms. Sensors primarily serve the purpose of acquiring data, either in the form of broad-band multidimensional or narrow-band hyperspectral information, through photography or non-imaging techniques (Camgözlü & Kutlu 2023). Frameworks for satellite-based sensors are located in space, while platforms for monitoring piloted and uncrewed aircraft are in the air. Ground-based systems are used for field on-the-go and laboratory devices (Benelli et al. 2020). Objects on Earth perpetually emit, reflect, and assimilate electromagnetic radiation. RBS technologies distinguish objects by analyzing transmitted, reflected, and absorbed electromagnetic radiation variations. RBS operates within the electromagnetic bandwidth, utilizing the visible, infrared, and microwave frequencies. The combination of elements such as geospatial dispersion and data gathering frequency leads to the generation of RBS-based BD, characterized by its large volume and significant complexities.

The field of RBS has been advancing with new, advanced sensors that offer improved spatial, spectral, and temporal sensitivities. ARBS is a highly trained discipline that involves the acquisition of large volumes of complex pictures and spectral data. This data is then used to make informed decisions regarding agricultural growth. RBS is used in farming to monitor soil parameters and crop stress. This data is used to make informed decisions on fertilization, agriculture, and pest control to optimize crop yield. Common ARBS structures consist of visible sensors for analyzing plants, sensors for studying plant humidity, detectors for examining crop field exterior or crop cover temperatures, and microwave detectors for analyzing soil moisture (Ge et al. 2021). RBS is essential in PF practices for implementing site-specific agricultural field administration, considering the heterogeneity of soil, stress on crops, and the impact of therapies. Due to the swift advancement of RBS technology, particularly the utilization of novel sensors possessing more excellent laws, the quantity of RBS information will significantly escalate, accompanied by a heightened level of intricacy. A significant issue is identifying the most efficient methods for extracting valuable insights from large datasets to improve analysis, address inquiries, and resolve issues (Weiss et al. 2020). The focus areas in research include storage, quick processing, removing details, fusing details, and utilizing large amounts of RBS information.

ARBS-based BD shares the same characteristics as other types of RBS-based BD. ARBS is unique in its ability to strategically oversee and plan crop production locally, nationally, and worldwide (Veerasamy & Fredrik 2023). It provides precise control data for farming operations at the level of individual farms. ARBS has the potential to generate data with greater geographical and time resolution. Unmanned Aerial Vehicles (UAVs) have emerged as a distinct platform for agriculture RBS, offering the ability to capture multiple photographs of crops from a shallow height (Olson & Anderson 2021). The photos can be transformed into both a two-dimensional depiction and a three-dimensional rendering of the field. UAVs equipped with agricultural RBS contribute substantially to collecting large-scale ARBS information. UAV-based RBS is a unique form of aerial RBS that allows for surveillance of crop fields at extremely low altitudes. Extensive research is being conducted on the efficient and quick processing and utilization of data obtained from ARBS systems on UAVs.

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

Proposed Big-based Agriculture Remote Biosensing Application: The RBS surveillance for PF, specifically Low-Altitude Remote Sensing (LARS) monitoring, has generated substantial data that needs to be processed and analyzed. This represents the emerging frontier of BD derived from ARBS. Information administration from satellites for PF was structured using file-based methods and kept distinct from processing and analytic tools. To effectively manage RBS information for PF, organizing, manipulating, and analyzing information spanning various dimensions of time, spatial setting, and spectral spectrum is necessary. This should be done within a single structure to share collected, processed, and analyzed information and goods at regional, national, and worldwide levels. Information can be inputted into the proposed architecture to fulfill the necessary criteria and seamlessly integrated into the data collection, processing, evaluation, and administration workflow, as depicted in Figure 1. Efficient utilization of photos in flow image coverage relies on effective grouping to minimize duplication and eliminate non-agricultural covering.

The ARBS Monitoring System (ARBSMS) was initially created by the RBS Applications Center inside the Ministry of Agriculture (MOA) of Chinese. The system tracks changes in the area of cultivated land, crop yield, manufacturing, growth, flooding, and other agricultural data for seven critical crops. The system delivers monitoring data to the MOA and other relevant agricultural management areas, generating over 100 reports annually.

The ARBSMS technology is a thorough operational agricultural tracking system in the RBS in MOA (Figure 2). The system comprises a database structure and six modules dedicated to tracking changes in crop acreage, estimating crop production, monitoring the growth of crops, tracking soil moisture, monitoring disasters, and providing information services. The seven crops indicated earlier are under surveillance. Additional crops are being gradually incorporated into this structure.

The system monitors crop development and soil moisture every ten days, estimates yields of crops every 30 days, predicts sowing region and production 25-30 days before harvesting, monitors the development of grass every 25 days, and estimates aquacultural space once every year. A combined technology is used to acquire agricultural information from numerous sources, including spacecraft, ground-based structures, and Wireless Sensor Networks (WSNs). This system coordinates the collection of remotely observed crop metrics. UAVs have been used to collect agricultural information at low elevations, in addition to ground-based technologies.

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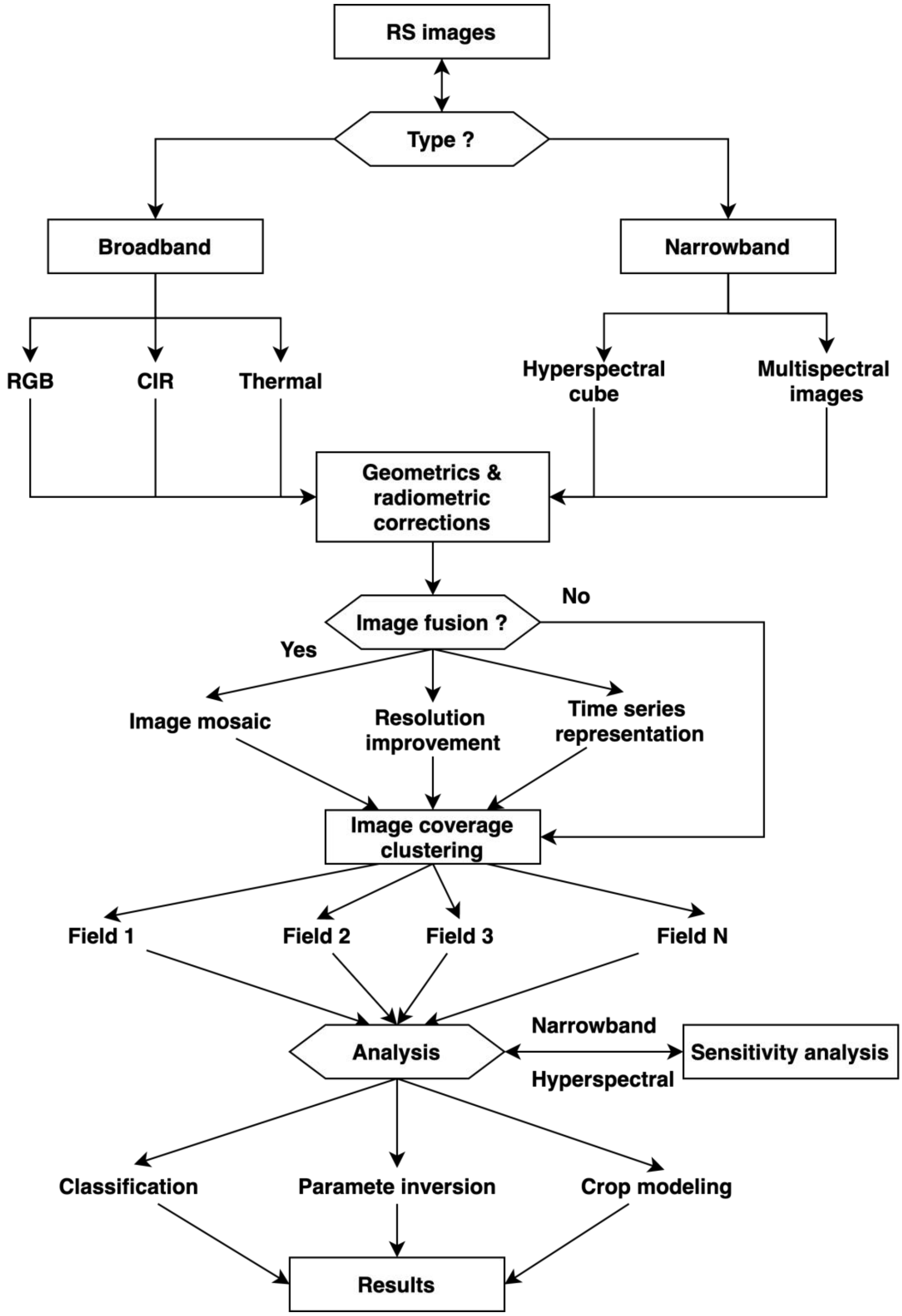

Figure 1. Workflow of the proposed research

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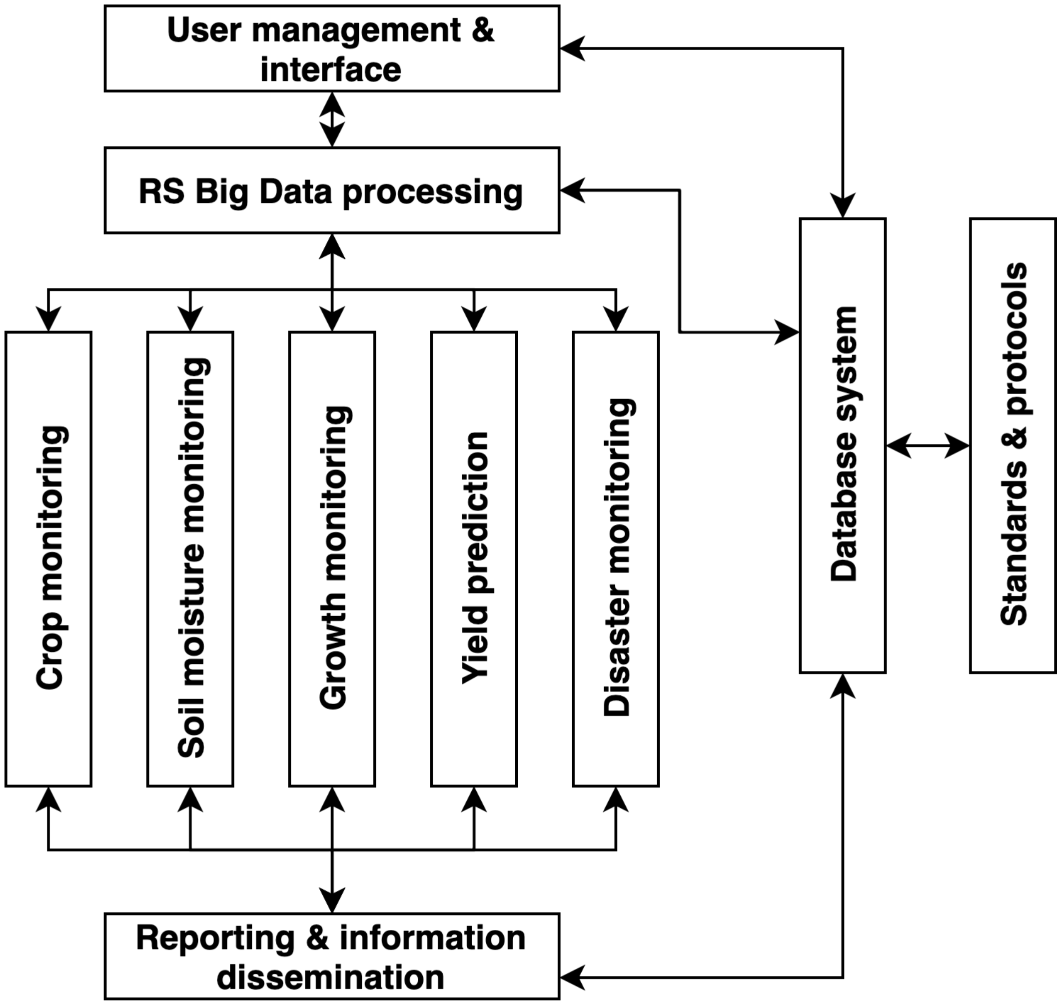

Figure 2. The architecture of the proposed RS application

The ARBSMS system has successfully conducted a series of ARBS surveillance analyses. RBS information assessed the regions of rice, wheat, and maize growing. High-resolution satellite photography, such as RapidEye imaging, was employed. The change in land area was identified using medium-resolution imagery analysis. The development patterns of wheat, corn, soybeans, and grain were analyzed using high-resolution data. This analysis combined ground observations, agronomic designs, and low-resolution satellite photos. The growth of rice was observed by analyzing images. The estimation of crop yields was achieved by integrating RBS research with crop growth designs, agriculture meteorological designs, and yielding trend forecasts and analyzed pictures using RBS information to track and analyze losses caused by severe drought, flooding, snow, and wildfires. A study of RBS information was undertaken to manage pests when cultivating crops. A study was conducted to track grass development and production using RBS technology.

Materials and methods

This section provides a detailed discussion of the experimental execution and evaluation of the ARBS application. It includes information on the datasets utilized, the computing setup, and the outcomes and comments.

Experiments: The initial collection of tests showcases the effectiveness and efficiency of the proposed system. The subsequent group of experiments showcases the acceleration in computing times achieved by implementing ARBS on parallel computing designs, namely multicore systems. The tests aim to showcase the effectiveness of the conquer-and-divide strategy for ARBS on concurrent designs, utilizing the binary tree and its row-based re-merging methods.

Data: The AVIRIS Indian Pines database was utilized in these tests. The Indian Pines database encompasses the farming industry. The Indian Oaks testing site in Northwestern Indiana was gathered using the AVIRIS sensors. The dataset consists of 16 different groups. It is in the form of a cube with dimensions of 150 × 150 × 225. The spatial resolution of the data is 25 meters, and the spectral range spans from 0.1 to 2.5 micrometers.

Computational setup: The studies used an Intel i5 laptop with a 2.4-GHz Central Processing Unit (CPU) (four cores) and 16 gigabytes of Memory.

Results and discussion

Figure 3 displays the accuracy of ARBS in performing binary tree row-based conquering and re-merging procedures. The precision is measured using three distinct classifications (Support Vector Machine (SVM), K-Nearest Neighbours (k-NN), and Ensemble Trees (ET)) on the Indian Pines database. This classifier was selected based on the representativeness of many available categorization methodologies. Alternative classification, such as Random Forest (RF), Bayesian classification, and Logistic Regression (LR), can be employed to categorize. The RF is an Ensemble ML (EML) classifier. Additional instances of EML methodologies include bagging, increasing, and stacking. The tests utilized adaptable boosted trees as the ensemble tree technique. The SVM employed the Gaussian kernel, whereas the k-NN algorithm utilized several k equal to 10.

The classifications underwent training utilizing various samples, ranging from 10 to 50 for every category. The SVM achieved the highest efficiency among the classifications. The research mainly emphasizes reducing complexity using the conquer-and-divide ARBS technique. The research needs to explore enhanced classifications extensively to improve recognition accuracy.

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

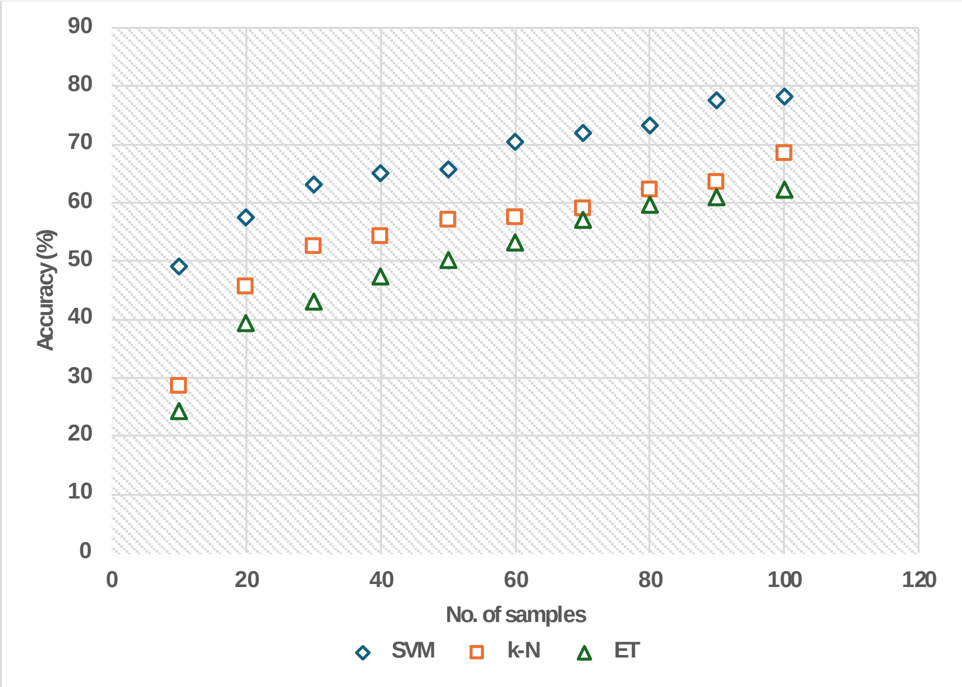

Figure 3. Accuracy analysis of different methods

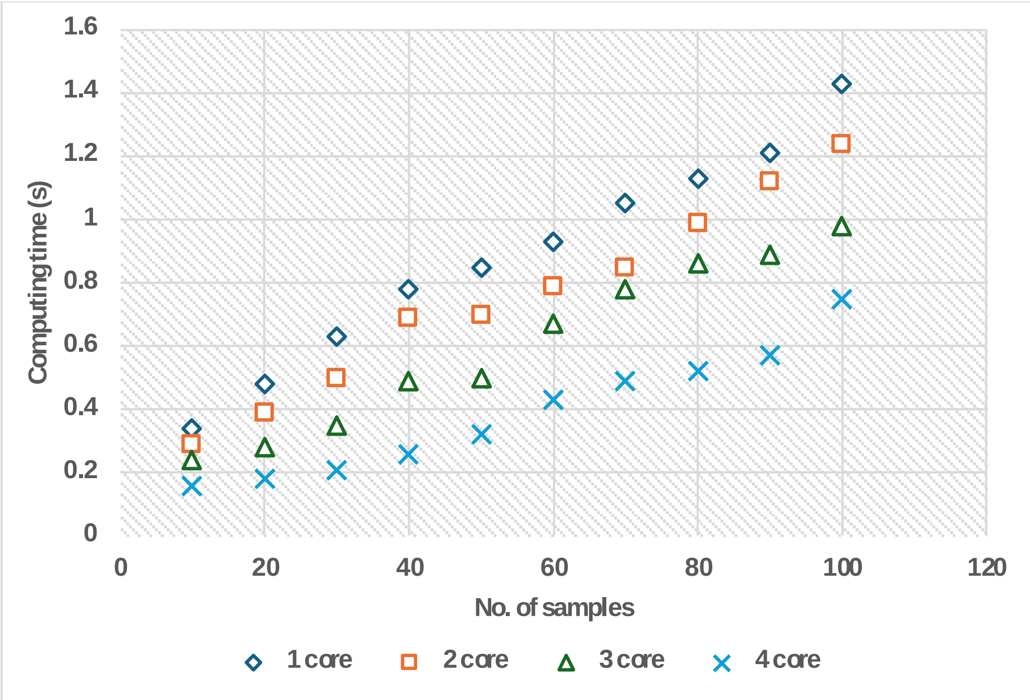

Figure 4. Computing time analysis

The ARBS offers the benefit of a conquer-and-divide technique, which enhances the execution rate on parallel computing units. A further inquiry was conducted to examine the processing time of the ARBS method on multicore systems for various datasets. Figure 4 compares the processing times for multiple samples per category on single-core to four-core systems when executing the Indian Pines database. Utilizing the four-core dividing and re-merging design increased 1.35 times for the Indian Pines database, showcasing the suggested methodologies' efficacy. A more excellent acceleration is anticipated for computational systems with more computing units, such as Graphical Processing Unit (GPU) and highly parallel computers.

Conclusions: The primary results of the BD-Driven Agriculture system were (i) the production of a white paper containing recommendations for NIFA and other funding and (ii) the facilitation of connections between researchers from different fields and the MOA, Security, Energies, and other agencies of the government to talk about the adoption of innovations and the creation of possibilities for the study of agriculture. To foster innovation, it is necessary to develop new funding sources. The BD-based ARBS model has identified six essential suggestions for establishing a thriving phenotyping society:

1. The success of complex systems initiatives necessitates a more extended setup period than conventional research studies. Funding sources should consider implementing phased financing arrangements that include phases and gradual rises in money. This approach would provide effective teams with the necessary continuity to create significant impacts.

2. Scientists require a central location for data to store, contrast, and repurpose information. This resource has the potential to assist academics in preserving data and reusing it by offering the services of a fresh group of data analyzers.

3. It is crucial to provide the community with the means to utilize proven and low-risk phenotyping methodologies and technology to achieve desired breeding or ARBS results.

4. Increased funding is necessary for offering training to undergraduates and postdoctoral investigators in various fields, along with the required resources and tools for the upcoming generation of farming investigators proficient in computer technology and agricultural machinery.

5. Groups can target particular difficulties to expedite phenotyping attempts. This approach enables the comparison of methods and facilitates coordination of activities on a program basis.

6. Cooperation will improve by creating uniform and comparable data and software. The inclusion should encompass processes for uniform gathering of data and testing, benchmark datasets of the highest quality for method evaluation, and widely accepted formats for data interchange to ensure compatibility. Collaborating with institutions like the National Institute of Standards and Technologies (NIST) would prove advantageous.

Acknowledgement: The author declares that no funds, grants, or other support were received during the preparation of this manuscript.

Conflict of Interest: There is no conflict of Interest.

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مجله بیوتکنولوژی کشاورزی
شاپا چاپی: ۶۷۰۵-۲۲۲۸ شاپا الکترونیکی: ۶۵۰۰-۲۲۲۸
دانشگاه شهید باهنر کرمان
انجمن بیوتکنولوژی ایران

یک سیستم کشاورزی مبتنی بر داده‌های بزرگ برای کاربردهای سنجش زیستی از راه دور

دبرقی بیسواس

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تاریخ دریافت: ۱۴۰۳/۰۷/۰۴ تاریخ دریافت فایل اصلاح شده نهایی: ۱۴۰۳/۰۹/۱۷ تاریخ پذیرش: ۱۴۰۳/۰۹/۱۸

چکیده

هدف: این مطالعه به بررسی دو مدل کشاورزی مبتنی بر داده‌های بزرگ (BD) می‌پردازد که توسط موسسه ملی غذا و کشاورزی (NIFA) پشتیبانی می‌شوند. مزایای سوابق کشاورزی کامل، تکنیک‌های فنوتیپ کارآمد و کار گروهی در ترویج کشاورزی را بررسی می‌کند و نقش پیشرفت‌های تکنولوژیکی مانند حسگرها، روباتیک، یادگیری ماشینی (ML)، تجزیه و تحلیل داده‌های بزرگ، سنجش از دور، و ژنومیکس را در پرداختن به غذا، مواد غذایی جهانی و مسائل امنیتی آب برجسته می‌کند. اهداف اولیه این مطالعه بررسی مزایای حفظ سوابق کشاورزی دقیق برای اصلاح نژاد و زراعت بهتر، بررسی استراتژی‌هایی برای فنوتیپ‌سازی کارآمد و جمع‌آوری داده‌ها در سیستم‌های کشاورزی، سپس حمایت از تعامل بین اصلاح‌کنندگان گیاه، دانشمندان کشاورزی، و متخصصان ML، سنجش زیستی از راه دور (RBS) و BD، و برای تعیین الزامات مالی برای پیشرفت مداوم کشاورزی مبتنی بر مدل‌های BD بود.

مواد و روش‌ها: پایگاه داده AVIRIS Indian Pines در این آزمایش‌ها مورد استفاده قرار گرفت. پایگاه داده Indian Pines صنعت کشاورزی را در بر می‌گیرد. مجموعه داده از ۱۶ گروه مختلف تشکیل شده است. در این مطالعات از یک لپ‌تاپ Intel i5 با واحد پردازش مرکزی (CPU) 2.4 گیگاهرتز (چهار هسته) و ۱۶ گیگابایت حافظه استفاده شد.

نتایج: ادغام فناوری، از جمله حسگرها، سنجش از راه دور، ربات ها و تجزیه و تحلیل BD، فنوتیپ سازی با توان بالا و کشاورزی دقیق را افزایش می‌دهد. همکاری چند رشته‌ای پرورش و مدیریت محصول را تسریع می‌کند. تامین مالی آینده برای مدل‌های یادگیری ماشینی پیش‌بینی‌کننده و تکنیک‌های فنوتیپ مقیاس‌پذیر مورد نیاز است.

نتیجه‌گیری: تجزیه و تحلیل BD، سنجش از دور، و یادگیری ماشینی توانایی تغییر زراعت و اصلاح نباتات را دارند و مسائل مربوط به امنیت غذایی را حل می‌کنند. همکاری پایدار و سرمایه گذاری زیرساختی کافی برای اجرای موفقیت آمیز ضروری است. به بودجه خاصی که برای توسعه ابزارها و فن آوری‌های پیشرفته که روش‌های کشاورزی پایدار را تضمین می‌کنند، مورد نیاز است.

واژه‌های کلیدی: بیوتکنولوژی، سنجش از دور، سیستم کشاورزی، داده‌های بزرگ

نوع مقاله: پژوهشی.

استناد: بیسواس دبرقی، تیواری آنکیتا (۱۴۰۳) یک سیستم کشاورزی مبتنی بر داده‌های بزرگ برای کاربردهای سنجش زیستی از راه دور. *مجله بیوتکنولوژی کشاورزی*، ۱۶(۴)، ۳۲۱-۳۳۴.

Publisher: Faculty of Agriculture and Technology Institute of Plant Production, Shahid Bahonar University of Kerman-Iranian Biotechnology Society.