



Techniques For Making Agricultural Decisions Using Artificial Intelligence and Big Data Analytics

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ABSTRACT

Human needs are always difficult to balance with the output of agriculture. However, it is now even more difficult given the anticipated increase in the World's population, shifting dietary preferences, environmental concerns, economic effects, and sociopolitical difficulties. The fields of automation, agrochemicals, and plant and animal genetics have significantly shaped the field of agricultural science.

Technologies up to this point. Given the complexities of the future, new technologies, including paradigm shifts, must be utilized to advance agricultural research and enhance resource utilization efficiency. Current farming systems are designed to satisfy the needs of the coming ages. Big Data Analytics and Artificial Intelligence are two paradigms that have drawn the attention of thinking leaders. At the bottom of the Big Data ladder paradigm, agricultural research raises both concerns and offers several new opportunities. Precision agriculture and other agricultural issues are thought to be resolved by artificial intelligence (AI) tools. The data gathering and presentation techniques are state-of-the-art. Data collection and analytics sharing, as well as artificial intelligence plant breeding, were attempted. The agriculture area uses many applications for AI and CNNs many benefits for environmental protection.

Keywords: Multispectral data, big data analytics, artificial intelligence, and agronomy. An unpiloted aerial vehicle.

I INTRODUCTION:

Earth's current population is 8.22 million, but 2 2050 the population is projected to be 9.7 million. In the past, agricultural Science and technology had to find a solution to the food security issue to keep up with the growing number of people and Animals. The evolution of agriculture can be traced through three major shifts: the adoption of mechanical energy that took over tasks once performed by animals, the chemical revolution marked by the widespread use of fertilizers and pesticides, and the rise of genetic innovations that introduced high-yield crop varieties and improved livestock breed are widely acknowledged as the most important scientific interventions that have transformed agricultural production. These technologies could help with the world's food security problems to a large degree. However, given the serious risks to the environment, farm economics, and sustainability, the agriculture sector's expansion has slowed under the current paradigm. In addition to employing these technologies, agricultural scientists have predicted that natural resources management, which entails maximizing input requirements and environmental impact without sacrificing financial gains, will pave the way for a better than Earth and mortal solicitations in the future. The period of resource exploitation appears to be a luxury, with significant consequences to human existence and Earth systems.

To better understand these systems and optimize them to suit our future needs for food, fuel, and fodder, humans began to recognize patterns in physical and environmental occurrences. Analyzing vast amounts of data with scientific inputs to aid in the management of agroecosystems is one new paradigm.

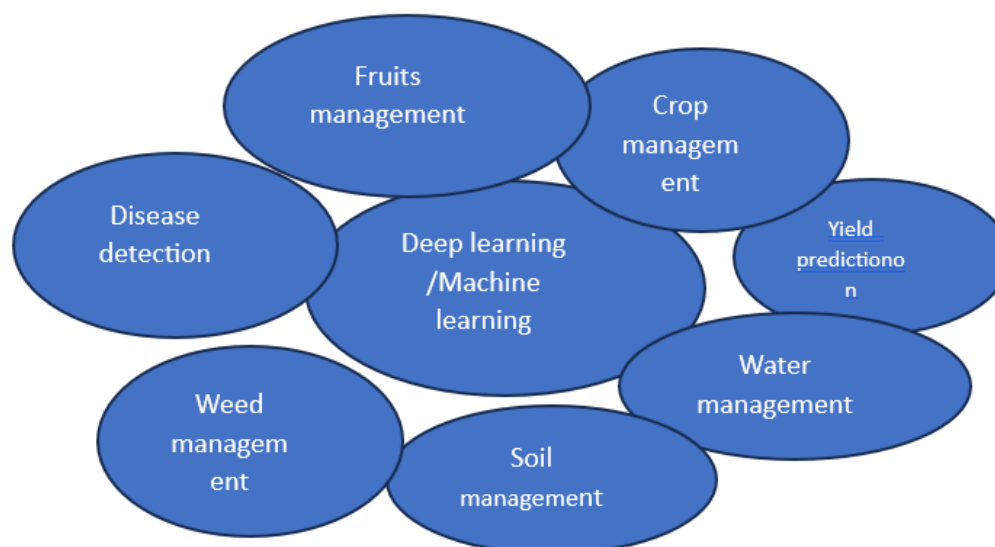


Fig. 1: Structure for the machine and deep learning algorithm

Machine and deep learning algorithms are used for crop disease classification, yield prediction soil mapping. Describe the data for the input data and key features used for the model.

Analytics of big data: Big Data Analytics, especially relevant to agriculture or any data-intensive field:

1. Data collection: sources, drone satellite imagery, social media, machinery logs.
2. Data storage: use of a distributed system.
3. Data processing: cleaning, transforming, and integration.
4. Data analysis: techniques, clustering, regression, classification, prediction.
5. Decision support: crop selection, yield prediction.

To farmers. The vast, large-scale, and multi-resolution nature based on this data, which comes from a variety of sources, makes it impossible to manually analyze it on a basic computer with standard tools. Powerful, high-capacity supercomputers with sophisticated analytical methods are needed for such endeavors to analyze data. Agricultural productivity can be aided by big data analytics, high volume data analysis methodologies, and climate and weather informatics have been widely studied (Rakesh & Goswami, 2016; Himesh et al., 2018; Rakesh & Ramesh, 2019; Edwin et al., 2019, 2020; Ramesh et al., 2020). Fig. 2 Different agricultural or associated domains in which AI and big data are likely to be applied. Powerful, high-capacity supercomputers with sophisticated analytical Methods for Analyzing Big Data and AI are needed for such endeavors to analyze data.

Situation:

High demand: satellite imagery is essential for precision farming resource management.

Sentinel (ESA): Offers high-resolution optical radar data and excellent vegetation and soil, water monitoring. Traditional agriculture may become digital agriculture as a result of the adoption of mobile and sensor technologies. To improve efficiencies in crop input usage, productivity, as well as net economic returns in agricultural fields, both the public including private sectors are working. Improving input-use efficiency and crop performance by developing more precise agronomic practices, guided by historical agricultural data such as seed type, crop yield, weather patterns, soil properties, fertilizer usage, and pesticide application. Using IoT-enabled systems supported by data analytics, such an approach helps design Agricultural DSS solutions for real-time, evidence-based decision-making that enable precision agriculture to maximize economic returns and optimize input consumption (Henry and Keogh, 2016).

To determine the cause of declining rice yields, select high-performance varieties and resilient varieties, and determine the best time to plant each location in Colombia. Big data approaches were implemented to examine the effects the impact of climate variability on rice (*Oryza sativa* L.) yields (Delerce et al., 2016). It is anticipated that these focused treatments will boost rice yields by 1 to 3 tons per hectare. If pertinent climate history and crop yield datasets, crop output, and farm operation techniques are accessible, etc, such treatments could be implemented in various agroclimatic settings around the world. An automatic examination of images system known as the CIAT Pheno-i system served as a tool for creating at the CIAT to extract measures for the canopy and vegetation indices at a plot level.

For the various critical growth stages of cassava (*Manihot esculenta* Crantz), multiple linear regression models were developed and subsequently validated using observed field data.

NaLamKI, on cloud-based Software as a Service (SaaS) platform offering open interfaces, designed to support stakeholders across both upstream and downstream segments of the agricultural and industrial sectors, as well

as third-party service providers for specialized applications in use in crop production, is the result of the German Research Center for AI's initiative on sustainable application of AI in agriculture. Another project, Agri-Gaia, is creating an AI ecosystem depending on Gaia-X for the German meals and agriculture sector. It links consumers or developers of artificial intelligence algorithms, provides industry-specific AI building blocks, news, and optimizes continuously.

Through the integration of technology in agronomy and data sources, including forecast data, aerial photos, and other ground-based sensors, Agritask (agritask.com) comprehensive farming operation system that enables informed decision-making for agricultural companies. It analyzes the information, measures the dangers, and generates warnings, suggestions, and useful information. Agronomists haven't arrived in India to investigate artificial and depend on BD technologies, while the potential is to make use of these developments (Ramesh, 2019; Rao, 2018); for example for instance, the distribution of rainfall in India exhibits substantial spatiotemporal variability (Ramesh and Goswami, 2007, 2014).

Due to obstacles like low Internet penetration (Kshetri, 2014), bandwidth, etc.. The uptake of big data technologies remains slow in development. However, recent advancements like increased mobile phone penetration and mobile-broadband connections will also benefit data-driven smart agriculture in developing nations (Salami et al., 2015). Up until now, big data interventions have mostly concentrated on increasing the average farm productivity and efficiency of large-scale commercial agriculture in developed nations, which are largely driven by the private sector. In developing nations, however, they have concentrated on agri-market and supply-chain management, where public and private organizations may be the main forces behind these initiatives (Protopop and Shanoyan, 2016).

According to Himesh et al. (2018), big data analytics may be crucial to comprehending and reducing the risks associated with climate change in the agriculture industry.

There are issues in the fields of AI and big data analytics. The hype around AI has been recognized (Gordon, 2021). Current AI advancements can be built around limited data sets, and while big data analytics have useful uses in consumer internet companies, this is not the case in other areas like industries, health, or agriculture. The recent failure of AI in COVID analytics (Heaven, 2021) has demonstrated that algorithms must be developed in the future using improved techniques and quality-ground observations.

In the Big Data era, the appropriate methods of data analysis are changing and call for statistical expertise (Stigler, 2018) (<https://www.thehindu.com>).

Since AI applications in the agriculture industry are still in their infancy, suitable approaches should be developed to steer clear of previous errors made in AI applications and produce accurate and reasonably priced AI technologies.

Big Data Analytics's Structure in Agriculture: Expertise and involvement from a wide range of disciplines, including agronomists, climate scientists, digital designers, and researchers studying human-computer interaction, are necessary for big data analytics in agriculture (Jeske et al., 2020). Three primary characteristics of big data are volume, velocity, and variety. Since the size of data is increasing quickly due to IoT and sensors, the volume dimension of Big Data is not always about size; rather, it is about the size of data sets that are larger than what can be processed by traditional database systems. It can range in size from several terabytes to petabytes.

The velocity feature, which is essentially the pace at which data is processed, describes the ability to gather, analyze, comprehend, and interpret data in real time. According to Steve (2014), the variety feature is new and fascinating, but to put it simply, it relates to the variety of data types (text, numbers, images, etc.). Advocates of big data promise a degree of accuracy, data processing, storage, and analysis that was previously unattainable owing to technological constraints (Datafloq, 2015). Interest in the potential large-scale applications of Big Data in agriculture, ranging from productivity to risk management, has been sparked by the quick expansion of mobile-broadband connections, the availability of high-resolution agricultural data, and reasonably priced computer power (Woodard, 2016).

Rainfall variability accounts for 80% of agricultural production variability in rainfed farming, and big data analytics can significantly benefit the farming community by lowering the risks associated with biotic and abiotic stresses in addition to traditional weather forecasts and climate projections.

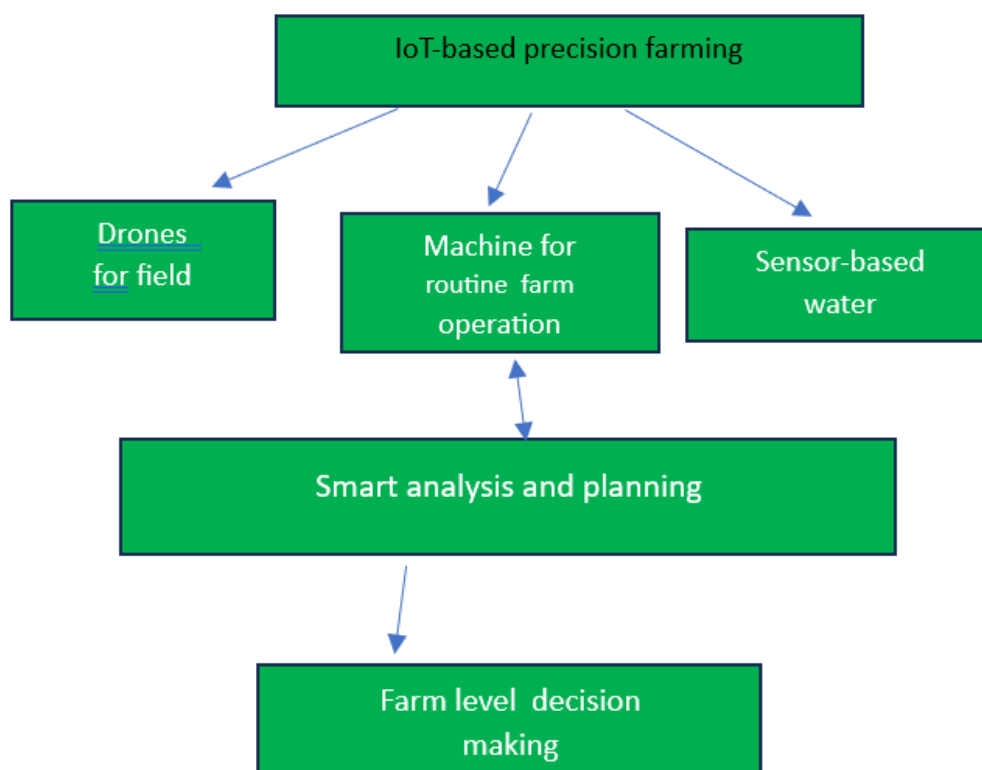
Data collection: Obtaining high-quality, up-to-date, and varied data (weather, soils, and crops) is essential for applying AI to agriculture. The several ways to obtain the information are: Field data collection: Traditionally, researchers and field staff gather data from farmers' fields and research studies. These enormous data sets are accessible through several organizations, most of which are public. Such information is also provided via sample surveys conducted under various state and private sector programs. These data sets, however, may or may not be structured, and some may or may not be in the public domain.

Such data sets may be difficult to get for Big Data analysis. Among the main issues encountered while attempting Big Data analysis are data quality, the lack of data-sharing protocols, privacy protection, and incentives for data sharing.

Historical data collections are frequently fragmentary, difficult to extract, and not geo-referenced. Data scientists must therefore come up with ways to extract, format, and prepare the data sets for study. Although this task seems challenging, it is essential, even if it is just performed for typical circumstances, because it may aid in validating models created using other data-acquisition techniques.

Sensors: Several kinds of sensors can be installed on farm machinery, including field-installed, hand-held, and tractor-mounted devices. These technologies include Wireless Sensor Networks (WSN), Internet of Things (IoT), and laser-field leveling (Pal et al., 2020) (Sadowski and Spachos, 2020).

The emergence of cloud computing, sensors, IoT, and IT is facilitating the creation of new smart devices that can produce real-time field data.



Farmers in the southern Indian state of Karnataka have been given access to digital tools like e-Kisaan tablets, which are packed with information on IT-enabled agriculture, education, and health. The tablet catalyzes for farmers to exchange best practices and promote more in-depth communication. There are numerous examples of this type in various nations (Himesh et al., 2018). The perception layer (data-aware acquisition), transport layer (data transmission), and application layer make up the new and developing trend of facility agriculture based on IoT technologies in contemporary data-driven smart farming. Data analysis, early warning, automated control, and scientific decision-making are primarily the responsibility of the application layer. RFIDS, sensors (light, temperature, humidity, CO₂, plant growth), wireless data transfer via GPRS, intelligent information processing, and cloud computing make up Facility Agriculture. Fig. 3 depicts a typical facility for agriculture (Zhou et al., 2012).

The most recent development in precision agriculture is the use of small, needle-like sensors that are implanted into plants. Researchers extract real-time data using microneedles, a medical technology, to make farming more sustainable and hyper-efficient (Bryce, 2021). These polymer-based sensors, created by Bukhamsin et al. (2021), could be a potent addition to the precision-agriculture toolkit since they are implanted into plants. A little electrical current can be passed through needles in plants to measure bio-impedance, which provides information on the health of the plant based on how it reacts to the current's flow. This is given that a plant's responses vary based on several elements, such as light, nutrients, and water availability. Silicon molds immersed in chloroform could prevent long-term harm to plant skin. Several industries have made extensive use of remote sensing to record terrain features Identification of crops, calculation of crop acreage, planting, and harvesting date recognition, pest and an infestation of illness identification, Crop condition evaluation, stress identification, soil moisture measurement, and irrigation control and monitoring, Remote sensing is widely used to study land use shifts and assess land degradation risks and other applications are among the agricultural fields where remote sensing can be employed. By combining these statistics with past data, farmers will be able to manage their crops more scientifically, increasing production and optimizing resource consumption.

Sentinel missions, Landsat, and MODIS stand for Moderate Resolution Imaging Spectroradiometer most widely used satellite imagery remote sensing programs. The following data are provided by these satellites: a portion of Intercepted These include variables like FPAR (Photosynthetically Active Radiation), LAI (Leaf Area Index), NPP (Net Primary Productivity), LST (Land Surface Temperature), and LULC (Land Use/Land Cover), Vegetation Indices NDVI and EVI indicators and Evapotranspiration. To overcome heterogeneity and cloud-

cover issues, methods are being developed to improve their accuracy. When compared to Analysis of field data suggests that these methods can provide results that are reasonably accurate for agricultural planning, even though they may not benefit a single farmer (Ramesh et al., 2020). A program initiated by the Indian Agricultural Research Institute in delhi, CREAMS, the Consortium for Research on Agroecosystem Monitoring and Modeling from Space, specializes in using satellite technologies to study agroecosystems has been developing the ability to use agro-meteorology, agro-models, and remote sensing to asses qualitative and quantitative fatcors evaluation for agricultural systems at the field and regional levels in India, as outlined on the CREAMS website. According to recent research, using remote-sensing imagery, we can estimate carbon content emissions and biomass, offering a practical substitute for destructive protocols that require little ground truthing to show the carbon source-sink dynamics (According to Enghart et al. (2012) Although the majority of robotics and sensing technologies are still in the development stage in labs and spin-off businesses, they have the potential to address issues in agriculture (King, 2017). According to FAO estimates, pests and illnesses cause 20–40% of worldwide crop yields to be lost annually. Robots and drones, for example, could assist farmers in using fewer agrichemicals by accurately identifying bugs as well as applying insecticides. Drone spectral can be utilized to control nitrogen application at precise sites in crop fields and estimate chlorophyll. Rench agricultural technology business Airinov, a company featured on Devex (www.devex.com), specializes in agricultural drone technologies. It offered this service, which contributed to a reduction of almost 30 kg N/ha.

By facilitating the cultivation of various crops, soil mapping with such technology reduces monocropping, which is the cause of the recurring return of pests and diseases.

Uses for the drone in agricultural areas and benefits :

1. Crop monitoring
2. Soil and Field Analysis
3. Planting (Seed Dropping)
4. Spraying Pesticides/Fertilizers
5. Irrigation Monitoring

APPLICATION FOR AI TECHNIQUES AND OUTCOMES

- . Machine learning is used for weather data in crop yield prediction to improve the yield prediction of data.
- . Convolutional Neural Networks (CNNs) for image acquisition are highly accurate, real-time analysis of crops.
- . Irrigation optimization reduces water waste and improves the yield.
- . Soil fertility analysis collected from the field and testing for the lab, and benefits for precision fertilization.

A conceptual diagram There are several ways in which this technology can benefit farmers: ram of the process for imparting knowledge to farmers using modeling and data



There are several ways in which this technology can benefit farmers:

- Selection of crops and crop types
- The timing of planting or sowing
- weed identification and accurate weed control
- nutrient needs and accurate fertilizer application
- Identifying pests and illnesses and applying pesticides precisely

Using natural resources economically and increasing input-use efficiency

Adjusting agronomic practices in the middle of the season

Reducing pollutants in the air, water, and soil • Gaining access to market intelligence • Bargaining for better prices

Obtaining credit from financial institutions

While there may be several benefits to utilizing AI and big data technologies, it's crucial to recognize and address the many problems that come with doing so. Here, a few key points are emphasized.

1. Methodologies ought to be consistent depending on the experience in other industries, as the program of AI and agriculture's big data technologies is still in its infancy.
2. To support policy, public entities would focus on developing technologies and algorithms for the agricultural environment.
3. Private companies will create business models to reach individual farmers with service platforms built on AI and Big Data analytics.
4. Cooperation between social scientists, computer specialists, IT workers, and agricultural scientists is crucial.
5. The government should make data accessible to the general public so that Big Data-based solutions can be developed.
6. Procedures for gathering high-quality data and retrieving publicly accessible data.
7. Information about farmers is protected in terms of privacy, and farmers are paid appropriately for contributing their data.
8. To resolve conflicts, a data regulatory body must be set up; data exchange must be open and verifiable.
9. The government must set up a vast network of resource mapping facilities and weather stations.
10. Even in rural locations, mobile networks must be made available, and internet connectivity must be provided at nodal points.
11. Crop insurance and financial assistance systems must be integrated with digital technologies.
12. It is necessary to set up digital marketing for agricultural products.

CONCLUSIONS

The future paradigm of agronomic research and farm recommendations will heavily rely on BD and AI. To combine and improve bd and artificial intelligence and establish intelligent farming, agronomists must broaden the scope of their study to include new advances.

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