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Research Article

Cloud-Based Analytics for Sustainable Agriculture: Leveraging AI to Bridge Farming and Rural Health Outcomes

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ARTICLE INFO **ABSTRACT**

The global population is projected to reach over 9.5 billion and possibly up to 10 billion by 2050. Its growing economy requires increases in sustainable food, fuel, feed, and fiber for global security. The agricultural sector faces grand challenges to meet these increased demands under the constraints of climate change and dwindling natural resources with limited arable land and fresh water. Combination of intensifying production and expanding crops has led to serious challenges such as worsening soil and water quality, greenhouse gas emissions, and crop productivity sustainability. Sustainability of agriculture under the strain of grand challenges depends on coalescing affordable and reliable sensors and IoT instrumentation, advanced computing power and algorithms in data processing and machine learning modeling, and secure internet connections with portable and user-friendly interfaces and user experiences. The rapid adoption of IoT data sensing technologies in agricultural settings brings new opportunities to help bridge farming practice and rural health outcomes at both behavioral and clinical levels. While sensing technologies are arguably more affordable, accessible, and versatile than ever, the sheer amount of data is overwhelming.

In agriculture, farm management systems and other platforms have been providing various forms of decision support for on-farm data collection and analysis. While increased data innovations, availability, and digitization are advantageous, they bring data inflation challenges and data-related issues to agricultural producers. Data generated from different disciplines can be highly heterogeneous. Datasets across disciplines may not share the same ontology, modality, or format. The growing amount of data diversity presents additional challenges. If left untamed, it may lead to underutilization of data information and opportunity, mistaken insights, and degraded trust. Agricultural data, such as remotely-sensed satellite, aerial, drone, weather station data, and on-site soil, elevation, land use, pest, and irrigation data, are often big and complex. The data types are highly structured and may contain both temporal and spatial dimensions. First, data is collected by various types of telemetry systems and machine-level devices. Then, data is exchanged and transmitted from cloud-based systems for data fusion and cross-scale information extraction. Standard data sharing protocols are needed to ensure the cross-compiling capability of data services and applications such as remote sensing data safety and security.

Keywords: Data Analytics, Cloud, Cyber-Physical Systems, Internet of Things, Sustainable Agriculture, Smart Farming, AI.

1. Introduction

Agriculture and human health are intimately linked. Agriculture provides food, fiber, and biofuel, affecting health through nutrition, food safety, price stability, and environmental impacts. Conversely, health status affects agriculture through decisions about farming practices and crop/animal portfolio. Health and agricultural systems are integrated with water and environmental systems. To achieve both improved agricultural productivity and health outcomes, explicit consideration of synergies and trade-offs is needed across the agrifood system. There is demand for a holistic African agri food health model for optimizing investments and policies toward improved outcomes across all four sectors. Despite high levels of investment, outcomes in Africa contrast sharply with those in wealthier regions. The growing availability of detailed and long-term datasets offers unprecedented opportunities to understand and improve health and agricultural outcomes. Important knowledge, however, is still missing on the interlinkages and spillovers between health and agricultural choices and outcomes in Africa.

While there has been extensive work modeling either the agrifood system or its relationship with health, to date, there is no modeling of the intertwined agricultural and health decision-making systems. More broadly, the agri-health models that do exist are interdisciplinary but often a simple aggregation of agriculture and health sub-models. This approach lacks attention to feedback loops, limit cycle behavior, and other emergent phenomena between health and agriculture. To bridge health and agricultural models and with the aim of better understanding agrifood choices, a multi-agent farming game model and an epidemiological state variable agent-based health choice model are integrated. The two components and their interactions are described, as well as key calibration and data requirements. The design of the application including the visualization tools for empirical use is also overviewed. Through a detailed description of the integrated modeling, this framework for linking agriculture and health systems and its application to long-term data in Latin America are put forth. It is hoped that this pioneering contribution will activate a more significant focus on the interconnections between agriculture and health in the world.

The mission is to deliver high-priority, on-demand information products and services to stakeholders for environmental and agricultural monitoring and management using cloud-based analytics, integrated in the USDA's Agricultural Research Service, U.S. Department of Agriculture High-Performance Computing and Analytics for Data-Intensive Research Efforts. Data from ground-based sensors and remote sensing satellites can be used to derive high-value information products related to weather, soil, plant, pest, and socio-economics, and integrated to support forecasting and long-range decision-making. Cloud analytics, combined with open access data and data sharing services, automated products, and interoperability of models, can extend the scientific data life cycles and increase the public benefits from investments in research and data.

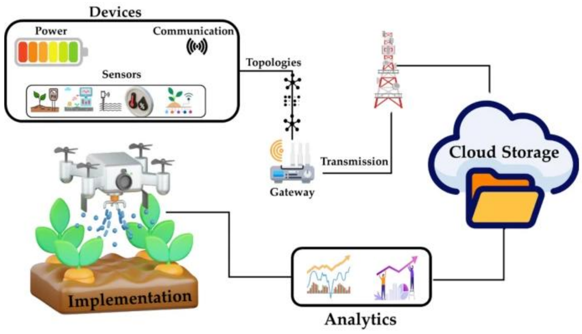

Fig : 1 Future of sustainable farming

1.1. Background And Significance

As the population continues to grow and climate change and dwindling natural resources pose ever-increasing hurdles, the demand for food, fuel, feed, and fiber is increasing tremendously . It has been recognized that food security and safety can be achieved only with sustainable agricultural practices. Sustainable agriculture aims to ensure food security and farmer profits, while conserving the natural resources and environment for future generations. Data innovation is in urgent need to secure and improve the productivity, sustainability, and resilience of our agricultural systems. The rise of various sensors and Internet of Things (IoT) instrumentation has made it practically possible to collect, integrate, and analyze data in real-time. This tremendous amount of data poses challenges to the storage and question answering systems of data management and makes current data management practices inefficient.

In the meantime, data generated from different disciplines are usually highly heterogeneous, which prevents effective data sharing and reuse. Currently, approaches employed to data archive with minor immersive on-farm data and end-user services are not true sense data systems. A new data management infrastructure is in urgent need to be designed according to the principles of Findable, Accessible, Interoperable, and Reusable. To overcome these challenges, we proposed a conceptual framework of Agriculture Data and Management Analytics consisting of three components: i) modular and extensible data acquisition and storage, ii) user-centric data management and knowledge generation, and iii) smart and scalable data analysis and analytics. The architecture is built based on the principles and is able to be intelligently integrated with the data systems over cloud systems.

Equ : 1 Crop Yield Prediction with Environmental Factors

$$Y = f(W, T, S, A)$$

Where:

- Y = Predicted crop yield
- W = Weather patterns (e.g., precipitation, temperature)
- T = Type of crops
- S = Soil health indicators (pH, moisture, nutrients)
- A = AI model output (e.g., from remote sensing + cloud-based analytics)

2. The Role of AI in Agriculture

In recent times, Artificial Intelligence (AI) techniques have been widely adopted in almost every field. AI has brought significant benefits to agrifood systems' sustainability, food security and reduction of food waste. Most of the intelligent technologies used in agriculture rely on controlled data capturing equipment like sensors and drones to observe environmental changes and leverage appropriate AI methods to make conversions smarter. This chapter discusses AI techniques for crop yield prediction, crop disease identification, crop growth monitoring, food waste reduction and smart fisheries.

In terms of the first challenge of data collection, satellite-based Remote Sensing (RS) data can be exploited for agriculture-related tasks at a coarse resolution within large areas. However, the problems induced by these costly methods include the limited image resolution, still resulting in down-sampled information and high hidden figure costs. In recent years, earth-observing satellites like Sentinel-2 and commercial satellites have provided high-resolution RS data and new, diverse data collections to match different requirements. However, such rich, complex RS data still needs manual exploration of relevant knowledge. Intensive-scale image searching and timely data processing also suffer as point clouds and images become bigger.

Equ : 2 Sustainability Index Score

$$SI = \frac{R_u + E_e + W_s}{3}$$

Where:

- SI = Sustainability Index
- R_u = Resource utilization efficiency (e.g., water, fertilizer)
- E_e = Energy efficiency in operations
- W_s = Waste reduction score (biodegradable use, runoff control)

3. Sustainable Agriculture Practices

Sustainable agriculture is an important part of agricultural production systems in the 21st century, and how to implement them sustainably is a core issue in agronomy, ecology, economy, and sociology. Sustainable agriculture is defined formally as a production system that can maintain its productivity and usefulness in the long term. The recent interest in sustainable agriculture resulted in some practical developments, including organic agriculture, agro-ecology, conservation tillage, integrated pest management, etc. Given the multiple dimensions and consequences of agriculture, food production systems should be assessed holistically. This means that all relevant environmental, social, and economic consequences of agricultural practices should be considered in the evaluation of sustainability.

It has become widely acknowledged that a farming system can only be called sustainable if there is a long-term positive trend in all its relevant elements, in the face of environmental, economic, and social factors controlling its functioning. However, the divergence of the short-term objectives and long-term values, as well as the site-specific nature of these sustainability problems increases the importance of investigating contextualized balances on diverse scales and applying deliberative approaches in problem framing and (re)assessment. Therefore, the use of interdisciplinary knowledge, modeling, and stakeholder input is needed in the development of site-specific measures of sustainability.

Machine learning and deep learning applications could support consumers and producers in addressing some challenges of agro-food systems. These applications can help to achieve sustainable farming by mitigating risks of pest and diseases, reduce environmental impacts, lower production costs, enable targeted actions, support farmers' decision-making, improve collaboration, prevent food waste, enhance prediction models for financial and weather conditions, and eventually improve yield and food quality. Overall, machine learning and deep learning based agro-food technologies are being diffused only in a few specific sectors and higher investments in R&D are needed, especially in less affluent regions.

Equ : 3 Farmer Health Risk Assessment

$$HR = \alpha P + \beta E + \gamma N$$

Where:

- HR = Health risk score for rural workers
- P = Pesticide exposure levels
- E = Environmental hazard exposure (e.g., dust, smoke)
- N = Nutritional intake from local crops
- α, β, γ = Weights learned via AI model

3.1. Crop Yield Prediction

In agriculture, yield prediction systems have been widely used to provide insights to farmers about potential crop productivity, food security, policy assessment, yield gap analysis, and resource usage. Agricultural yield depends on a complex combination of biophysical, managerial, socio-economical, climatic, and technological inputs, along with the interplay of numerous processes that are still not completely understood. Current efforts in the field are focused on data-driven approaches. The first study assessed the efficiency of winter wheat yield predictions in Ukraine using different methods. The first was based on data from GlobCover maps with 70 types of land cover and land use, which were aggregated according to WSN site numbers used to delineate the initial datasets. This map was extrapolated through linear regression models to produce 1 km2 crop yield data for grid cells where the Ukraine was cultivated with wheat. This provides essential information on the spatial structure of winter wheat yield predictions. An empirical model based on meteorological observations selected using the forward stepwise method was evaluated for its prediction success. This method exploits the fact that cumulative precipitation, extended over an appropriate time scale prior to harvest, is one of the most important explanatory variables in the prediction of crop yield in general. WOFOST is a widely used crop growth simulation model that simulates biophysical processes and the interaction with external climatic forces that determine the potential growth of a crop. The different yield estimation methods were evaluated in a 2–3 months period that precedes the harvest, where adequate data are available for prediction. The second study proposed a combined approach using satellite and climate data to predict wheat production in Australia. Data from sea surface temperatures, Niño3.4 indexes, rainfall, and European Centre for Medium–Range Weather Forecasts 45 years reproduced data were used along with a combination of different traditional and machine learning approaches. Results comparing traditional methods and machine learning approaches are presented. The study shows that combining climate and satellite data to predict wheat production in Australia can achieve much higher performance compared with state-of-the-art systems. The third study focused on a multi-task learning algorithm for predicting yield in cotton fields from MODIS NDVI images using historical production reports. This work exploits the spatial and temporal features that can be learned from NDVI images to model variations in soil, climate, tillage, and irrigation conditions. Moreover, it also proposes a combination of a model that learns to predict yield jointly for all fields with per-field models. The fourth study applied transfer learning to predict soybean yield for Argentina and Brazil using a trained model on the latter and then augmented with Argentine data. The results were promising, with a noticeable increase in prediction accuracy for Argentina and minor improvements for Brazil.

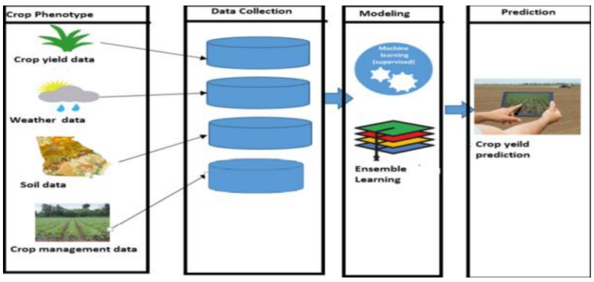

Fig : 2 Crop yield prediction

4. Impact of Agriculture on Rural Health

In the 21st century, agriculture remains fundamental to economic growth, poverty alleviation, improvement in rural livelihood, and environmental sustainability. Three-quarters of the world's poor live in rural areas, particularly in Asia and Africa, and depend on agriculture as their primary source of livelihood. Ninety percent of the world's billion impoverished and malnourished people live in low-income rural areas; seventy percent of the population in lower-middle-income countries live in rural areas. Apart from being the mainstay of their livelihood, agriculture is the dominant sector driving their economic growth, employment, and income. Agriculture can foster economic growth and job creation, particularly in Africa, where many countries are failing to create jobs at a rate equal to population growth. This report provides an overview of the impact of

health issues on farm-level productivity and decision-making, and the impact of agriculture on health. Findings are based on a review of relevant studies of agricultural regions throughout the developing world.
Agriculture underpins the health of rural households. It provides income that makes households resilient to health shocks; it provides food to meet their nutrient and energy needs; it provides medicinal plants for treating ailments. Agriculture provides a source of employment for people affected by illness in the farm household. Where there is housing security, agriculture increases the value of assets and provides collateral for credit. But agricultural systems can also have negative effects on health. Agricultural development may lead to environmental change with adverse health impacts. Mechanization of agriculture can increase the incidence of non-communicable diseases, such as respiratory illnesses and occupational injuries among farm workers. Growth in agriculture has been associated with an increase in the burden of food safety, nutrition, and vector-borne disease. Soil degradation can contribute to adverse health outcomes through decreased productivity, increased labor input, and decreased ability to adapt to climate change.

5. Data Collection Techniques in Agriculture

In recent years, precision agriculture that uses modern information and communication technologies is becoming very popular. Raw and semi-processed agricultural data are usually collected through various sources such as the Internet of Things (IoT), sensors, satellites, weather stations, robots, and farm equipment. Agricultural datasets are very large, complex, unstructured, heterogeneous, non-standardized, and inconsistent. Hence, agricultural data mining is considered a Big Data application in terms of volume, variety, velocity, and veracity. It is a key foundation to establishing a crop intelligence platform, enabling resource-efficient agronomy decision-making and recommendations.
There are various sources of data for agriculture. A crop dataset is a compilation of raw data for an area covered during a period. A processed crop dataset is a collection of data for a specific area at a specific time based on raw data. Crop data collection is a necessary step in studying and monitoring crop development or change. Cloud-based agricultural surveillance services give agronomists a chance to analyze farming and rural health datasets comprehensively. By utilizing machine learning algorithms such as CNN, RNN, and Random Forest, they can compare the differences in farming actions and levels, the distinctions in the generation of crop yield impacts, and the fluctuations in the lifestyle of animal husbandry and aquaculture, so the corresponding movements can be taken timely.

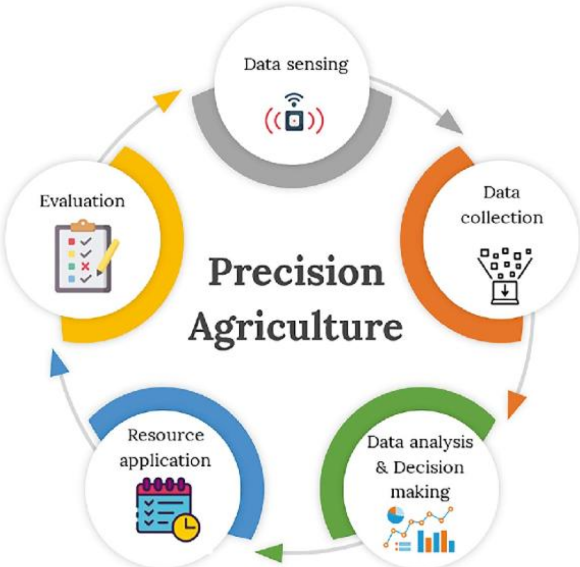

Fig : 3 Data Collection Techniques in Agriculture

5.1. Soil Health Monitoring

Soil is an important resource for human survival, and unique soil ecosystem scientists have defined soil health as an integrated expression of numerous soil functions. Understanding soil health analysis methods can help cultivate sustainable farming systems, combat environmental risks, and enhance food security. The ongoing agronomic revolution is based on innovative agricultural practices to ensure timely, enough, safe and healthy food for mankind. Recent advances of Internet of Things (IoT), machine learning, and deep learning are expected to accelerate the growth and adaptation of precision agricultural technologies. To help farmers identify potential soil health issues well in advance, an IoT-based soil health monitoring system was designed and developed using a range of state-of-the-art technologies, including soil moisture sensors, chemical sensors, microprocessors, cloud platforms, and deep reinforcement learning algorithms. When a specific soil health index (i.e., accurately and timely determined soil moisture and soil temperature) was exceeded, the intelligent

monitoring system was designed to send relevant notifications to farmers' smartphones via a mobile phone application.
A parallel computing framework was developed to analyze the physical parameters captured by sensors. Monitoring and inference tasks were systematically categorized, and 26 algorithms were implemented to address them at different nodes, including humidity, light, moisture, temperature, pressure, and traveling distance monitoring, and tree growth prediction. Data communication and mining strategies were implemented to reduce the amount of transmission and improve accuracy. Software agents were used for task encapsulation, service discovery, fault tolerance, and user interaction. The above-mentioned components were integrated into a prototype platform that can be deployed in real environments. Field experiments validated the performance of the proposed system, demonstrating its capability of multi-sensor distributed perception and efficient data processing and maintenance.

6. Cloud Computing Infrastructure

Sustainable and resilient rural development and growth of smart and inclusive communities have become global priorities because they are of developmental significance to developing countries and emerging economies, particularly those in Africa. The goal is not just to reduce poverty and inequality but also to include new tools and techniques towards stimulating the growth of digital economies in agriculture, finance, health, education, and business. The COVID-19 pandemic recently highlighted this. Policy guidance is available about emerging capabilities in AI to develop context-specific applications, with open-source code bases to build, train, and test the models. AI-driven solutions to agricultural problems constitute the primary focus. An analytical sub-area is focused on, examining the state-of-the-art of the more advanced capabilities in AI and machine learning (ML) techniques for crop, field, and pest classification using Earth observation (EO) data or seasonal monitoring using time series EO imagery. AI models and approaches for predicting weather, yield, soil moisture, and water availability using EO data, self-developed meteorological data, and soil property maps are elucidated. Policy recommendations are available on how these capabilities could be harnessed for rural and agriculture sector advancement in Africa, notably by countries in the southern tier.
Cloud computing stores and manages data in an Infrastructure-as-a-Service (IaaS) model for high-level processing and analysis of agronomic risk factors. However, cloud technology facilitates more than the mere delivery of on-demand computing power to researchers. Completely heterogeneous big data challenges the cloud infrastructure on which KDD systems depend on interacting streams of condition and measurement data. Moreover, commensurate choices of data acquisition frequency and precision do not assure correct representation of data integration. Appropriate choices of the many data abstraction techniques which differentiate data representation without corrupting information content form a major challenge. The evidential uncertainty in outcome decisions arising from uncertain data have their own challenges. Historically, large data were handled using parallelism over a local processor meta-structure and this approach remains an ongoing research endeavour. Alternative solutions to the 'big-data' computing problem have emerged in the form of massive cloud infrastructures. In contrast, fog computing proposes delivery of data-centric services at the network edge, within close proximity to users to meet larger needs for bandwidth, latency and availability.

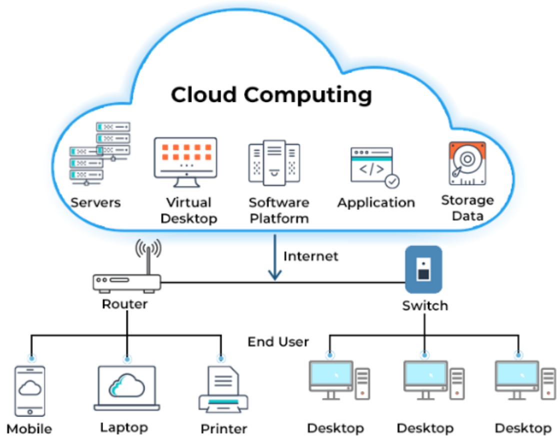

Fig : 4 Cloud Computing Infrastructure

7. AI Algorithms for Data Analysis

Agriculture has a critical role to play in the economies of developing countries, as it directly supports the livelihoods of over a billion smallholder farmers. Agricultural productivity and income determine individual and collective welfare. However, over the last several decades, productivity in agriculture has remained stagnant. Information and communication technology has been applied in agriculture for capacity building and knowledge transfer. An analysis of the challenges and existing approaches in applying ICT in agriculture prompted the choice of cloud-based analytics as the key approach to effectively tackle these challenges. Solutions using this approach have been deployed in early feasibility studies, providing at-scale yields of benefits to farmers during the cropping season.

Cloud-based analytics is a cloud-hosted computing architecture that can be used for high-performance computing and analysis of huge datasets via the internet. Combining high-performance computing with the cloud transcends the limits of conventional computing and improves the speed, accuracy, and adoption of AI-enabled analytics. Means have been devised to understand the farming process and find the health outcomes of the crops and livestock. These means include agent-based simulation methods, AI-powered analytics, and social and natural language processing. Crop growth, livestock management, farm economics, and farmers' interactions with both physical and virtual agents have been simulated, based on estimates from agronomic and economic models. There are two ways that AI enables cloud-based analytics: without AI-enabled analytics and with AI-enabled analytics. AI models and simulations have been proposed and under development. Data collected by the farmers using recurring digital instruments and devices or by administrative institutions and their virtual agents using internet-enabled sensors and scanning instruments can be utilized by the analytics process. The intelligence process includes pre-processing of data, interpreting data, and expediting modelling and simulation processes, and uses AI models that can classify and justify health outcomes based on the findings of physical observation.

Local and national technocrats can use cloud-based platforms to access data that targets farmers without administrative involvement. In this modality, the data extracted from the farmers are aggregated and stored in cloud databases, which are accessible using analytics services across varying capabilities. The AI models can leverage a growing ensemble of crowd-sourced data from farmers. In the case of social agents funded by national administrations, outcomes from cloud-based modelling and simulation can be used to produce machinable actionable insights in natural languages. Based on the modelling and simulation outputs, unstructured observations can be classified, and grammatically structured responses can be formulated using Natural Language Processing models.

Fig : 5 AI Data Analysis Techniques

8. Case Studies of Successful Implementations

The implementation of cloud-based deep learning and machine learning techniques in agriculture has the potential to increase yield, save costs, and minimize the adverse effects of excessive fertilizer application. Machine learning techniques can be used to recommend crops for a farm's soil characteristics. The data requirements for such solutions are easily obtainable, and the presented methods are low-cost and low-maintenance, contributing to making agriculture more sustainable. Urban gardening is on the rise in recent years. There is a growing need to produce fresh and healthy foods closer to consumers for improving a healthy living in cities, which are believed to be the future trend. To address this concern, precision gardening using precision agriculture technologies for urban agriculture can be considered for smart city solutions. A fog computing-assisted Internet-of-Things framework for healthcare precision gardening in urban agriculture, consisting of various sensors to monitor environmental conditions in a rooftop garden. Smartphones as user's IoT devices using a mobile web-based platform can send modification commands to actuators for controlling environmental conditions. The proposed two-layer fog computing architecture can intelligently process data and forward the processed results to cloud servers for more in-depth analysis.

8.1. Case Study 1: Precision Farming

Precision farming, aimed at optimizing the efficiency of agricultural production and ensuring global food security in a sustainable manner, has emerged as a new generation form of agriculture. It integrates advanced hardware and cloud-based analytics with AI and deep learning for intelligent analysis to help farmers manage their crops in real time. There is a suite of physical devices such as cameras and robots for data collection, hardware infrastructure such as servers and clouds for efficient data storage analytics and model training, and advanced algorithms for automated data analytics and recommendation. The physical devices are usually deployed on the edge and the data is streamed over the cloud, where deep learning models are trained. The trained models predict the condition of individual plants and generate data processing orchestration graphs to compute recommendations for farmers in a real-time fashion. On the receipt of the recommendations, the edge devices invoke actuators to execute the actions such as broadcasting alerts to individual farmers or triggering robots to perform on-farm actions, which complete the data processing pipeline. The physical devices are used in a fully automatic or semi-automatic manner, depending on their characteristics, the algorithms running on them, and their interaction with farmers. The data processing orchestration graph is also auto-generated by the Change-point Detection (CPD) framework. With significant improvement in crop yield and food production, a growing range of practical systems are being deployed in farms on a daily basis. The deployed solutions can be categorized into the following five groups with different characteristics and utilities: remote sensing; precision spraying; precision harvesting; animal intelligent service; and information dissemination.

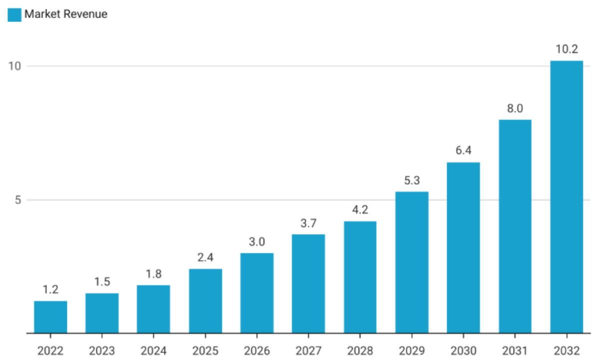

Fig : 6 AI in Agriculture Statistics

9. Conclusion

This article reviewed the analytics phase of a framework to explore machine learning and cloud services for agricultural cost-sensitive scenarios. Key specifications of the machine-learning data processing cost-optimization problem were discussed. For example, a new multimillion-dollar fine-tuned deep learning model using cloud-based big data capabilities reduces agricultural markup costs, but is found to increase annual costs associated with prediction backtesting and retraining. These costs were approximated in six flexible ways suited for agribusiness and cloud-based processor scale. Based on these cost approximations, a greedy algorithm heuristic framework for adding and retraining a ground-up model to a telegraphic model was created. This framework was able to offset perceived increases in prediction costs associated with a deep learning model desired for solutions to complex decision making. These theoretical developments are integrated into an analytics approach for agricultural ML applications, which could in turn foster adoption of such capabilities in sustainable, data-driven agriculture practices.
Tractability conditions for which the cost optimization problem is guaranteed to asymptote were shown, as well as for which ground-up models need not be a part of the solution. An experimental framework that builds on big data and cloud machine learning engine products for yet-to-be-analyzed agribusiness situations was also introduced. In developing the infrastructure for experimentation on a real agribusiness application, profound interactions between machine learning analysis and cloud services discovery were found. Feedback during development led the analyst to innovation that may not have been possible without existing cloud-oriented infrastructure. As cloud storage and analysis capabilities are becoming mainstream, new synergies between machine learning and cloud application development capabilities will increasingly foster data drives for agricultural analytics and product offerings. This will be driven in part by the resurgence of entrepreneurship due to the attractiveness of open-source scientific and computing tools.

9.1.Future Trends

Emerging technologies can provide creative solutions to tackle a wide range of issues in farming practices, enhancing productivity while minimizing environmental impacts. Therefore, incorporating big data and artificial intelligence knowledge in farming practices can optimize the yield of agricultural products while maintaining rural health and thereby having a positive effect on rural economies. Cloud-based solutions can transform large datasets into actionable insights through user-friendly interfaces for farmers, local governments, cooperatives, farm equipment manufacturers, etc. Thereby creating just-in-time information delivery systems instead of the classic one-way channels, which rarely became actionable insights (particularly for crop-monitoring). In parallel, cloud-like services and edge services can enable sustainable farming practices such as optimal irrigation scheduling, pesticide application, and planting distance.
Simple local solutions running on the tractor or drone can provide immediate outputs to farmers after data acquisition. The impacts of local climate and/or airborne diseases can be quantified using remote sensing information on cloud services outside the edge services. Bridges between in-farm sensors, UAVs, and cloud services should be constructed. It is challenging for the joint use of multispectral satellite imagery and drone-acquired data, as with traditional in-sensor preprocessing applications. On-demand and/or small-budget cloud

deployments could solve that problem. In this agricultural cloud-based product, capabilities and knowledge tightly interconnected with the type of business role can be reached at low costs in exchange for storing data online. Comprehensive risk management, including the risks of the growing season and yield losses may be designed for crops with a large dataset in contrast for small datasets. Farmer variance may be connected with local cooperatives, which might have access to larger datasets in addition to model training purposes. Cloud and fog edge end servers may provide different services whose selective usage would benefit both the farmers and farm equipment manufacturers.

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