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AI-Powered Agricultural Equipment: Enhancing Precision Farming Through Big Data and Cloud Computing

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Abstract
Precision agriculture is becoming more important because it can improve farm yields and efficiency by using new technologies. These innovations are based on the collection of big data and outputs from agricultural equipment at the farm level. Agricultural equipment includes machines that help farmers with farming tasks, such as tractors, harvesters, and seeders. For example, GPS units mounted on tractors can collect georeferenced data every second while working in fields, such as field location and speed. Agricultural machinery systems are used to accomplish a certain farming task in a certain area within a predefined period of time. Big data obtained from agricultural machines are in the shape of time series inputs and provide a spatial-temporal understanding of farming areas. An increasing amount of research and advanced pilot projects are developing agriculture data analysis and sharing services, which will create business opportunities for information service providers and research on service method improvement. Business-oriented services are intended to be delivered by manufacturers or their partners. Farmers usually have the need or will to adopt machinery but tend not to be able to afford the dear price. The services to be provided are better suited for cooperative sharing. The business model will fit with domain horizontal partnerships, information cooperation and data open, for which analysis results should be retained within data providers. Thus cross-domain common efforts are required.
Outcomes of precision farming could be improved quality of crop production, reduced cost of production, and increased total yield. In addition, characteristics of modern agricultural development such as land increasing, multi-functional farm and one family managing many farms should also be taken into account. The results on the needs of precision farming indicated that simple decision farming, monitoring crop environments such as herbicidal status, temperature and moisture fields, and machine tracking. In addition, professional services, such as variable fertilization prescriptions and process recommendation, should also be developed. The future services from big data-acquiring agricultural machinery systems towards professional grower were also discussed. Cloud computing, high-speed internet, and social media have provided a carrier for data sharing across disciplines. Closed user group applications on precision farming were developed in cooperation with a tractor manufacturer. Precision agriculture has been made possible with the development of satellite imaging, GPS, GIS, and other related technologies which can measure field variability and therefore prescribe site-specific management as a means to enhance crop yield and reduce production cost.

Keywords: Agriculture 4.0, Agricultural IoT, Intelligent Transport System for Precision Agriculture, Smart Agriculture, Big Data and Agriculture, Industry 4.0, Cloud Computing, and Machine Learning and Agriculture.

1. Introduction

The agriculture industry is one of the main sectors driving economic growth all over the world. The population of countries is expanding rapidly, which results in huge demand for food. It has been projected that the worldwide food demand will double every 30 years and, consequently, the agriculture field should produce more food. However, the agriculture field has different challenges in this process, some of which arise from the traditional farming system. Addressing these challenges has become a prominent research topic, especially with the rapid advancement of information and communication technologies. Since accuracy is crucial for growing crops, to obtain a high volume of crops with great quality, farmers are being encouraged to opt for data-driven farming systems. The farming system that employs Information Technology (IT) driven by big data for monitoring and managing agricultural activities is called precision farming or site-specific crop management.

Precision agriculture is an innovative management system based on computer, information, and other technologies which are meant to access crop growth environments with the purpose of obtaining corresponded yield-information in big-data and cloud-computing, and to clarify the quantized rule of future crop growth. In recent decades, precision agriculture has been focused mainly on agronomic variables related to soil, weather, and pest management for controlling time and space functionalities of field operations. Precision agriculture has been further developed to include sensors, satellite images, and climate inputs to yield better crop management than conventional farming practices. Meanwhile, crop growth modeling to the field-operation level has provided a better awareness of crop growth processes, such as soil usage and irrigation management. However, collecting spatial variability from satellite images is difficult, though it is inexpensive and easy to deploy. Thus, a cloud-enabled platform for machine learning-driven decision support is proposed utilizing sensed images with gridding in a specific collected area with rainfall information.

The input information is based on gridding, such as soil moisture, sunshine hours, soil water holding capacity, gridding rainfall information, temperature-related indices, and moisture indices for rice and corn field classification. The inputs and features are built based on a drone sensor for machine learning. To help farmers avoid excessive fertilization, improve fertilization efficacy, and reduce fertilizer loss, a fertilizing band is categorized as (i) excessive fertilizing band (EF), (ii) removing fertilizing band (MF), and (iii) fertilizing band (F). In addition, the development of a cloud-enabled crop recommendation platform is proposed utilizing analysis outputs of fertilizing bands with climate and soil features. This platform is accessible for farmers and aids in crop type recommendation and mixed-cropping type recommendation during sowing seasons.

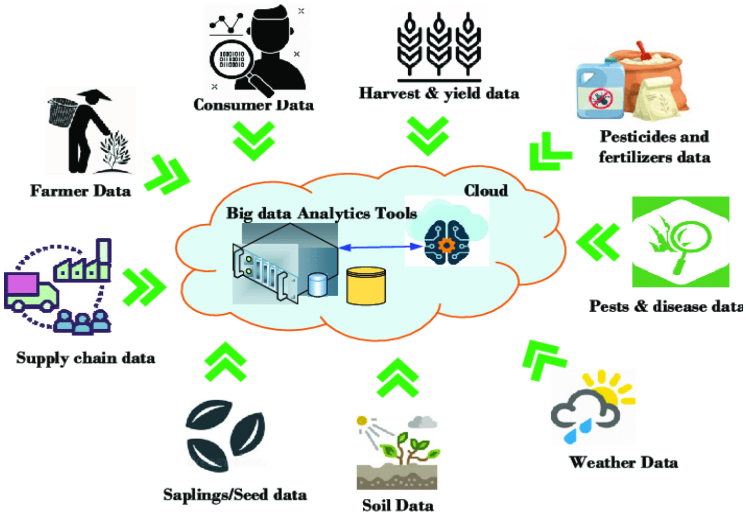

Fig 1: Precision Farming Big Data and Cloud Computing

1.1. Background and Significance

Food security is one of the key issues facing humanity in the 21st century. The global population is expected to exceed 9 billion by 2050, making it necessary to produce 70% more food. The problem is further complicated by climate change, as the number of extreme weather events increases, directly affecting agricultural production and food supply. Agriculture is the world's most important consumer of freshwater, accounting for about 70% of freshwater withdrawals. In addition, around one-third of all food produced annually—approximately 1.3 billion tons—is wasted. These problems underline the need for advanced agricultural technologies that increase crop production while significantly reducing water and chemical inputs.

The wide adoption of computer hardware, mobile devices, big data, and cloud computing in recent years has created many new opportunities to solve these problems by connecting agricultural stakeholders such as suppliers, farms, and market traders using the Internet and sharing data among them. Smart Agriculture uses IoT, drones, big data, cloud computing, and AI on massive amounts of data collected to deliver options or recommendations normally made by experts to decision-makers, such as farmers, agricultural suppliers, and customers. This technology allows agriculture to be more productive, efficient, and environmentally friendly.

2. The Role of AI in Agriculture

AI is an emerging technology that simulates human learning so that machines can respond intelligently based on conditions. AI is a significant technology that supports big data analytics, a foundational technology for precision farming used to make precise decisions. AI provides computational intelligence enabling machines to learn and respond to a varying situation and achieve specific objectives. In the agriculture domain, AI is currently being applied in precision farming applications, which help farmers analyze the crop in a timely manner. As farmers conduct their campaigns, solutions for AI-driven precision farming incorporate real-time analysis of big data produced at high velocity by IoT sensors and UAV onboard the farms. This big data is transferred into the cloud where AI infers its meaning. In precision farming, the data from the IoT sensors gets analyzed to predict crop yield, weather conditions, disaster occurrences, etc. This information helps to meet the demand for agricultural food production across the globe.

Cloud computing is an emerging strategy for data storage and processing, providing ubiquitous access to global computing resources. This storage and processing are highly valuable in precision farming as massive amounts of big data are generated continuously by the on-field IoT sensors, which have to be processed in real-time to make timely and accurate decisions. AI enhances cloud computing by mining existing data to improve agricultural productivity, sustainability, and efficiency in the farm industry. Moreover, AI is empowered and enhanced by big data analytics to improve predictive modeling by finding hidden patterns among existing data. Cloud computing is nudging a paradigm shift in farm data management and processing to improve efficiency and reduce initial acquisition investment. In precision farming, ML is a major subfield of AI and is involved in preparing an ML powered crop recommendation platform for smart farmers to determine what crop to harvest based on environmental parameters. ML is a method of data analysis that automates analytical model building. It is a branch of AI based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention. ML mimics human problem-solving abilities to conduct predictive analysis. It is an important decision-making instrument in precision farming and is applicable to the whole growing and harvesting cycle.

2.1. AI-Driven Supply Chain Optimization and Market Forecasting in Agriculture

The agricultural supply chain is a multi-tiered model that includes all of the processes from farm to customer outlets. The sources of raw and semi-finished products are numerous and ungovernable in this model, and they can be produced by numerous equally unmanageable suppliers and/or regions, spread over large geographical areas. There are numerous methods for delivering/moving products. Some options might be applicable for other sources and delivery methods . As a result, product delivery and maintenance is a non-trivial problem that necessitates a big math-model-based optimization effort executed periodically before each season. Agriculture is currently highly productive due to the invaluable work being done in this area. Even if crop yields are immediately available, forecasting future production is required for all the closely intertwined sectors of the agri-food supply chain. Demand, area coverage with respect to climate change, and crop yield forecasting all have a sizable role in agriculture. Regardless of their location, farms must contend with many surrounding factors that can have an impact on their farming business and agricultural yield. Farms are not the only input consumers in the agricultural market. Agriculture has the significant benefit of being able to support supply chain development in other connected sectors to some extent, due to numerous processes that lead to product loss or many economic and supply chain forecast processes concerning planted crop production ratios.

From a business perspective, precision agronomy entails the precision application of both inputs and practices. This precision approach is based on a comprehensive understanding of crop and soil growth conditions. Big data analysis and AI machine learning have become complimentary tools in agricultural technology over the last two decades. Precision agriculture has a bright future thanks to AI's modeling capabilities and big data's storage and processing capabilities. Besides the economic potential, health, food safety, and environmental issues are also closely related to precision agriculture. AI agriculture has the potential to raise global output and productivity through ecological production systems while lowering input use and post-harvest waste. AI and big data backed precision agriculture approaches can improve crop selection, current status prognosis, and the incorporation of seed, fertilizer, pesticide, and farming device applications as advisory tools during farming cycles given the availability of massive amounts of geolocalized spatial-temporal data.

Equ 1: Crop Yield Prediction Model (Regression-Based).

$$Y = \beta_0 + \beta_1 T + \beta_2 H + \beta_3 M + \beta_4 N + \epsilon$$

Y = Predicted crop yield (e.g., kg/hectare)

T = Average temperature

H = Humidity

M = Soil moisture content

N = Nutrient level

β_i = Model coefficients learned from big data

ϵ = Prediction error

2.2. Precision Farming and Crop Monitoring Using AI

With the rapid growth of IoT-enabled agriculture technologies, the amount of data generated at the farm level is growing exponentially. This expansion of data, coupled with the scarcity of qualified talent, has made the data analysis task very challenging but also very important for farmers to make decisions based on the latest available information. AI is currently revolutionizing the world, including agriculture, where algorithms and computational intelligence are playing a major role in making precise decisions based on underlying conditions. As a key pillar of precision farming, from soil to harvest, AI is currently involved in many precision farming applications where farmers can act on time for cultivation decisions. However, energetics and knowledgeable farm management in agriculture have strong impacts on productivity and sustainability. With the advent of IoT-based smart devices for near real-time data collection, data analytical techniques have been introduced to leverage the maximum amount of data while exploiting cloud infrastructure. However, smart farming and specifically data analytics and deep learning services are relatively new concepts. IoT sensors embedded in soil, plants, livestock, greenhouses, machinery and other configured agriculture hardware produce millions of data points daily, which are transferred to the cloud. Analysing these data point-in-data poor environments are crucial. The rapid coverage of the Internet globally has allowed cloud computing and data storage to flourish. Cloud provides the necessary storage and computing that many farmers cannot afford. This kind of big data, which is generally unstructured raw data of any kind, does not provide useful information on its own. For actionable insights from data, big data analytics based on AI algorithms are required. AI-driven data automation technologies are rapidly being developed to enable farmers to automate repetitive data processing tasks. AI now provides both applications and technologies for the agriculture sector and precision farming. AI algorithms are being applied to ML with various data sources like weather data, farm sensor data and more data on land characteristics, crop genetics and prices to predict crop yield and related weather conditions, allowing timely adjustments in long-term agricultural food production.

3. Big Data in Precision Farming

The main aspects of precision farming and how big data, cloud computing and farming equipment powered by AI may enhance the productivity of modern agriculture are introduced. The use of big data and its importance to precision farming technologies have also been highlighted. An overview of the relevant machine learning algorithms and cloud computing solutions for precision farming applications that the proposed platform may adopt is then presented. The advanced version aimed at designing the machine learning platform for precision farming services utilizing the cloud just formulating recommendations based on artificial intelligence development is aimed at the work referring to the HRM based cloud computing architecture and objective of the solution.

Precision farming or precision agriculture is aimed at providing real-time information about the farms and livestock to the farmers, which allow the farmers to take precise and timely decisions that lead to higher harvest with less wastage of scarce resources like water, fertilizers, and energy . A coalition of three main technologies – Artificial Intelligence (AI), agriculture robotics, and Internet of Things (IoTs) makes up precision farming. A variety of IoT sensors are used to gather the environmental parameters related to the farms and livestock including soil fertilizer level, water requirement, soil nutrient level, and health of the animals. The data gathered by the various sensors are sent to the cloud or remote servers through wired or wireless communication media. Various data analytic methods are utilized in the cloud for reasoning useful meanings and interpretations of the gathered data, based on which, the agriculture robotics then make precise and accurate decisions. The collected data after being analyzed and refined might provide useful insights to the farmers on various aspects like condition of crops, plant and animal diseases, weather condition, forecasting and prediction of future conditions, and prediction of crop yield. Presently, in many parts of the world, precision farming solutions are heavily relied upon to increase productivity and maximize the crop yield. Along with the increase in harvested crop yields, the total market value for precision agriculture solutions has now almost doubled with respect to that in 2016.

In recent years, many respective startup companies have been established that offer various commercial precision agricultural services namely, both hardware and software solutions. On a high-level view, in precision farming, autonomous robots may perform a wide range of tasks and they can replace human laborers while performing most of the agricultural tasks which may include land preparation, seeding, planting, and harvesting.

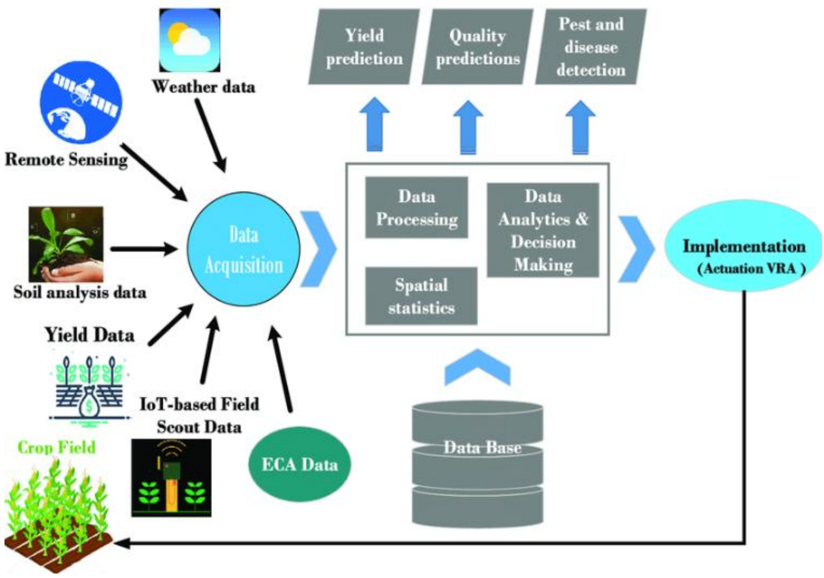

Fig 2: Big data-based precision agriculture.

3.1. Data Collection Techniques

The data acquisition and analysis of smart agricultural machinery are key technologies in an IT-based smart agricultural system. detailed data gathering techniques, such as displaying with near field communication, data transmission using Wi-Fi, and data storage on a cloud platform. Data can be sent to farmers through SMS or an APP on smartphones, and remedy plans can be automatically generated and shown. To create a smart agricultural information system, sensor-based appearance recognition rice pest detection systems are also designed. To create an intelligent agricultural ecosystem that integrates seed supply, seedling supply, quantitative fertilization, and smart control, a smart seedling supply system for vegetable seedlings based on a seriation supply chain is constructed.

The key technologies in precision agriculture include Global Positioning System (GPS) and Geographic Information System (GIS) technology, remote sensing technology, monitoring technology with remote control, communication technology, and automatic and mechanized machinery technology. The significant internal and external factors that affect precision agriculture adoption for farmers in Johor, Malaysia, are studied. This research employs the technology acceptance model and the theory of planned behavior. Farmers with a higher level of innovativeness more positively perceived the usefulness and ease of use of precision agriculture. An adoption model of precision agriculture for farmers in Johor, Malaysia, based on qualitative methods, systematically identifies a two-tier adoption model with the top tier of primary enablers or inhibitors occurring on one level.

The IoT big data cloud service platform in precision agriculture should have standards and interfaces to connect several devices, and design Data Collection Systems (DCS) that are simple, low cost, and easy to assemble. The system-on-chip architecture of DCSs combined GPS, pressure, temperature, humidity, light, soil moisture, and soil conductivity sensor nodes with a low power and low-cost wireless communication method to collect accurate farming information/usages with low energy consumption. Analysis of precision farming for the changing paradigm of agriculture from high input agriculture to precision agriculture based on ICT and DCS is carried out.

3.2. Data Analysis Methods

Data analyzing is the main component of Crop Recommendation platform construction. Data preprocessing is involved here to clean the transfer data out of noise and missing values. After that, four crop recommendation algorithms (KNN, SVR, Decision Tree, and Random Forest) which convert environmental values to suitable crops through a learning process are implemented and evaluated with an accuracy metric. The implementation of each AI method is not confined to the programming language but carried out with the state of the art JavaScript. Cloud computing, more specifically the cloud platform, is introduced to build a front end web application to monitor weather values and possible crops given environmental input values.

With the current growth and evolution of agriculture from ancient civilization to modern and smart farms. The crop yield prediction and accurate weather forecasting from ground sensors are one of the larger concerns and challenges every farmer faces daily. Precision farming still employs outdated techniques without the use of Information and communication technology (ICT), which needs to be corrected. In this paper, machine learning algorithms are implemented to predict the yield of crops based on climate parameters like rainfall, temperature, humidity, and sunshine hours. In agriculture, the study dramatizes crop yield, weather forecasting with IoT sensors, and how machine learning algorithms predict crop yield and plant weeds. Based on the analysis of climate and historical dataset agriculture crop prediction is based on the choice of regression algorithm deemed fit to determine the crop best suited for the given region. Random forest regression gives the best result with lower MSE and MAE, leading its practical implementation in crop yield prediction. For the comparative analysis of weather parameters, crops grown on the specific land, and associated yield information filter are selected. The developed system provides a robust and accurate solution for key factors affecting crop yield estimation and potential yield increase.

4. Cloud Computing Infrastructure

Cloud computing is one of the main technologies of the latest generation. It uses the concept of virtualization to optimize the usage of computing resources and provides its customers with services via web interfaces. In the agricultural society, cloud computing is the basis for the establishment of a crop intelligence system which is capable of serving the agricultural producers with high quality products. Building a crop intelligence system from scratch is an extremely complex operation and usually takes a long time to complete. Thanks to cloud computing development, crop intelligence as a service is feasible today. Designing the data warehouse and data management policies, the crop intelligence as a service in the form of a cloud service can be expanded to a continental level which is capable of serving the collaboration of agricultural producers on a multi-continent scale. This work focuses on the design and implementation of a prototype data warehouse for a European continent level agricultural big data warehouse on the cloud computing infrastructure.

The data warehouse of the crop intelligence platform is a distributed cloud service for the storage, migration, governance, backup & recovery, and data quality control of agricultural big data. Based on the extraction, transformation and loading (ETL) process, the data warehouse employs OLAP queries processed in cloud database systems to extract data sources from agricultural big data, data sources, and determining data management policies. The data warehouse then transforms the datasets into an OLAP structure and loads the transformed datasets into a big data analysis tool. The only experimental evaluation can be conducted on a limited dataset that cannot represent the requirements and constraints of the actual system. The reliability and scalability of a data warehouse are also challenges in terms of service provision. Firstly, there is no single cloud service provider that covers the entire European continent. Optimally allocating and replicating the datasets on the cloud databases for fast access by data consumers on a multi-continent level is also complicated. Secondly, the data warehouse processes many ETL and OLAP concurrent tasks at the same time. Hence, limitations in fields of network throughput, I/O bandwidth, and computational power must be considered.

4.1. Cloud Storage Solutions

Big data analytics, as a cross-disciplinary area which involves statistics, mathematics, databases, distributed storage & computing, cloud computing and knowledge engineering, is a key technology in precision agriculture. Open-source frameworks and libraries from big data technology stacks such as Hadoop, Spark and Storm have been adopted for big agricultural data storage, scaling out data-centered computation, streaming analytics and interactive analytics. They will accelerate the equitable use of abundant agriculture data and increase new knowledge discovery and farm productivity through its distributed storage, speed, and scalability. Cloud-computing as a service-oriented technology can enable cost-efficient on-demand storage, computation and persistence of precision farming big data. Massive volume of data can be rendered in a distributed manner, stored/cached in cluster-based file systems/storage with high access throughput and redundancy, and processed with low processing latency, thus can improve the discoverability, accessibility and usability of precision farming data.

Equ 2: Real-Time Fertilizer Optimization.

$$F_i^* = \arg\min_{F_i} \left(C(F_i) + \lambda \cdot L(F_i, S_i) \right)$$

F_i = Fertilizer amount applied to grid cell i

$C(F_i)$ = Cost function (e.g., cost of fertilizer)

$L(F_i, S_i)$ = Loss function measuring crop underperformance based on soil data S_i

λ = Weighting factor between cost and performance

Solved using AI models in cloud infrastructure

4.2. Cloud Computing Models

The term "cloud computing" refers to a new technology that allows users to manage or store data and various applications online, which is rented from a commercial cloud service provider or a hybrid private cloud. Cloud computing systems can be classified according to the service and deployment models. Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS) are just a few examples of the services that cloud computing can provide. On the other hand, cloud deployment models can be categorized as public clouds, private clouds, hybrid clouds, and community clouds. In this section, various models of overview cloud computing are summarized.

A public cloud is a highly capable external cloud environment that delivers applications and cloud services to various users. Hardware, software, and any resources are owned publicly, which allows consumers to share them. As a result, the initial capital investment and on-going maintenance are reduced, and also provide scalable systems with virtually limitless storage with access to network servers. The public cloud infrastructure is owned, managed, and operated by third-party cloud service providers who deliver mechanisms for services based on multiple tenants. In this model, the data is stored in the third-party facility and consumers only pay for the service they use. However, with the public cloud, users have less control over the back-end infrastructure, and there is a higher risk of a data breach when open to the public. Furthermore, cloud providers will not have customized solutions as there are many consumers renting the same infrastructure. As commercial cloud services are shared among many users, computing resources are shared in public clouds, and it becomes difficult for data privacy preservation.

A private cloud is a dedicated cloud environment for one organization. The goal is to enhance utilization and profits by deploying high-capacity systems to consolidate and run various applications in multiple operating systems with improved flexibility. Co-location of machinery and/or applications in a facility can be achieved in terms of databases and workloads. Ownership may also apply to a third-party organization, but the services will be delivered to the organizations as a single client. Sometimes, a private cloud may extend to include partner ecosystems or to allow sharing with select, trusted external entities. Security and compliance policies are often stricter within the organization and are easier to comply with when data does not leave the facility.A private cloud offers a dedicated environment tailored for a single organization, aiming to maximize efficiency and profitability by consolidating applications across multiple operating systems using high-capacity systems. While ownership may lie with a third party, the infrastructure ensures secure, compliant service delivery, potentially extending to trusted partners within a tightly controlled ecosystem.

5. AI Algorithms for Crop Management

Crop management plays an important role in the field of agriculture since it ensures a better harvest yield with premium crop quality. This is achieved by making sure that actions such as irrigation or spraying required for crop management are performed only when it is necessary. This decision-making process is done using rules specified by agricultural experts. AI provides computational intelligence such that the machines can learn, understand, and respond according to varying situations. Since the beginning of this century, the use of AI has exploded, and now it is involved in a lot of applications across many industries. AI is currently involved in many precision farming applications, allowing farmers to act in a timely manner. With the help of IoT sensors and UAVs, agriculture is being digitized, producing millions of data points in a single day. All of these data are captured for future analysis, accumulating a large volume of data. In precision farming, the data captured from IoT sensors is used to predict crop yield and many other related conditions with the help of AI algorithms. As such, it is essential to embrace these precision farming solutions.

In this paper, the involvement of AI in precision farming through the development of an AI-powered cloud-enabled crop recommendation platform is focused on. AI or computational intelligence has improved a lot over the past decade and has migrated from being a mere theoretical concept to being a commercially successful technology. It removes the fabrication difficulties in creating human-written codes, which are cumbersome for difficult tasks. The purpose of this paper is to demonstrate how ML, a subset of AI, is involved in precision farming through the development of an ML-powered crop recommendation platform. The application trained the data using three different tree-based learners and a dense neural network to classify the crops that can be cultivated based on the user-specified value of basic agronomy factors. ML allows generalization without needing to be explicitly programmed, and it mimics human thought and problem-solving ability. It is an essential discipline of AI that facilitates the computer's ability to learn automatically from data and preexisting knowledge.

Fig 3:AI Algorithms for Crop Management.

5.1. Machine Learning Techniques

AI, or artificial intelligence, has emerged as a principal technology of the 21st century and is a cornerstone for the growth of many of the technologies in use today. It is a computational intelligence, allowing things to think for themselves and learn over time, thereby responding differently to the same situation. AI is currently being used in a variety of industries to make precise decisions. Several disciplines fall under the category of artificial intelligence of which some of them are widely known are machine learning (ML), deep learning (DL), natural language processing, computer vision, fuzzy logic, expert systems, and swarm intelligence . Currently, AI is widely used in precision farming applications, in which the farmers need to act in a timely manner. IoT sensors and UAVs produce millions and millions of data points on a daily basis, creating big data. This big data, produced on a daily basis, is transferred in, through limited bandwidth, to the cloud and AI makes an inference of the meaning of the data, produced by IoT sensors. In precision farming, the IoT sensors predict the crop yield, weather conditions over a period of 14 days ahead, to devise a contingency plan against the disaster. This AI in precision agriculture is mainly focused on these four tasks, which are crop prediction, weather prediction, pest/disease prediction, and soil prediction. ML, in broad terms, is to give a computer the ability to learn how to do something without explicit programming. It is the science of making predictions, computationally mimicking human issue solving. This act is an important part of a broader goal of making machines and devices that can cope with mutability and uncertainty without complete characterization of the environment in which they operate. Its use in precision farming is mainly in developing an ML-powered crop recommendation platform for farmers. The work presented here focuses on developing a cloud-enabled crop recommendation platform, with multi model aggregation and performance analysis of the ML algorithms on the chosen dataset and crop. Therefore, the results of this work carry practical implications and to help address the need to feed the ever-growing population.

5.2. Predictive Analytics

Agriculture is a multifaceted topic that includes farming, horticulture, plantation, and aquaculture. Farmers provide services in crop production and animal husbandry, developing value-added products such as honey and wool. New farming styles gained momentum in the late 20th century with the advent of increasing population, food scarcity, and environmental degradation. These styles are sustainable agriculture, green farming, organic farming, and precision farming. The term precision farming describes an extensive agricultural management system based on data gathered in grids over farm fields. This spatial variability influences crop production and supply. Many data points in precision agriculture can help analyze and predict everything that happens in agricultural systems. Machine Learning (ML) is increasingly being applied to these data points to enhance agricultural systems.

AI is a major technology comprehensively utilized in agriculture. Advanced data processing, procurement, modeling, tracking, and influencing decisions are all part and parcel of agriculture. Achieving precision needs to make a precise decision or interference based on some underlying condition. AI is the art of designing machines that perceive, comprehend, and act in that way. AI provides a computational intelligence such that machines learn, understand, and respond to a varying situation in a complex, undefined, fast-changing environment. AI and its heterogeneous aspects are currently applied in a myriad of views of human life. AI has applications in image processing systems for deciding the face of a person, analysis of voices and responding to them through voice recognition systems, medical diagnosis, stock selection, and decision-making systems. AI serves as friendly virtual assistants, capable of managing various chores ranging from setting reminders to giving alarms, sending messages, running applications, laying queries for information, tracking stock prices, and even speaking with humans. Being the key pillar of precision farming, AI is currently involved in many applications in irrigation management, disease diagnosis, crop yield and weather prediction, pest monitoring, and precision herbicide spraying.

6. Smart Irrigation Systems

The best method to effectively control crop irrigation is to utilize smart irrigation systems. In recent years, agricultural operations around the world have adopted smart irrigation systems using the Internet of Things (IoT) technology. The current technologies of smart irrigation using affordable sensor nodes are evaluated and discussed, and the potential for controls using the IoT technologies is explored. Currently, agricultural irrigation systems in the countryside of the Philippines use manual control for their irrigation systems. Farmers have to travel long distances, which could take an entire day, just to check whether the irrigation canals have water. They manually control the ventilation fans in a greenhouse or shade house, causing inconsistencies and water waste. Furthermore, the productivity of rice farming is affected by the low agricultural wage rates . In testing current technologies of smart water irrigation, affordable-priced soil moisture sensors, moisture sensors, and weather stations are used, which are suitable options for deployment in rural areas. These sensors could send real-time valuable data about the landscape of the crop, supply information for better irrigation, and warn about extreme weather. Automated irrigation systems are mainly protocols and control strategies that are mainly used for water delivery in harvesting networks. Basic programming methods provide irrigation monitoring, controlling, and automation. The smart irrigation systems should abide by the general requirements for automated irrigation controls applicable to types boards, weather-based irrigation, and soil moisture-based irrigation. In tropical countries, automation rules are based mainly on weather conditions, which are a significant factor affecting evapo-transpiration. Automatic irrigation systems can still be tried to be developed using soil moisture sensor convergence with the expected prediction of large-scale flooding and drought conditions. It can lead to a better economic return on resources, curbing water wastage, and a direct impact on changing crop growth conditions by adapting irrigation schedules to weather changes. High-accuracy predicting models can aid the development of irrigation systems more suited to real-world application scenarios. Soil moisture controllers, climate condition controllers, weather forecasting, and allocation controllers are vital to building a comprehensive smart irrigation system after careful mathematical modeling.

6.1. Sensor Technologies

The most significant technological advancement that Precision Agriculture (PA) has received is the development of machine-to-machine communications, which allows sensors, actuators, and systems to transmit data without human intervention over long protocols. Thanks to low-cost sensor, positioning, and other meteorological devices, the possibility has arisen to implement wireless networks of small sensors and remote reach grids. As a result, operators and managers have access to a huge quantity of process data and the knowledge of the real-time state of their crops, soil microenvironments, and atmospheric variables. With the rise of the Internet of Things (IoT), this process has increased significantly. However, many issues delay wider participation by farmers: incompatible communication standards in use by sensors and meteorological stations, difficulties in obtaining wireless communications in certain conditions, and the need for programming skills to create computing applications. The aim of this research is to develop a platform that overcomes these issues while integrating easy-to-use programming tools. To do this, the fusion of machine-to-machine communication protocols with human-to-machine protocols through Web Services is chosen. This low-cost platform operates with sensors, actuators, image processing systems, and a regional weather station, and it is designed to be flexible and scalable. A web application allows access to the platform and process data.

As the world population keeps increasing, the demand of agricultural production goes with it. To meet the ever growing demand of food during next decades, more and more advanced technologies are required in the agricultural domain. Precision Agriculture (PA) concepts are promising and technologies, especially Wireless Sensor Networks (WSNs) and Ubiquitous Computing, are resulting key factors of an evolving agri-food industry. Harvesting quality crops with reduced impacts on the environment is becoming a must today. However, many barriers are still delaying sipheness of successful PA projects. PA is a multi-technical approach. Its application in farming focuses on improving productivity. The techniques move from general settings to particular ones, i.e., from the field scale down to m2 and m3, or crop supporting zone (CSZ) level, from a single product to a basket of products or a field block crop sequence, from uniform treatments to differential ones.

6.2. Automated Water Management

Water is one of the important natural resources for irrigation in agriculture. Agricultural irrigation is a task that must be performed frequently on large farms. Currently, irrigation has to be performed manually with many difficulties. Outsiders do not notice the availability of weather data at a distance. So there may be leftover irrigation costing unnecessary. On the other hand, this data is an indicator for improving the irrigation plan. Heavy irrigation causes the loss of soil nutrients which are necessary for plant growth. Therefore, it is preferred to control the irrigation based on soil moisture data. Removing the problems mentioned above, a pilot study of agricultural irrigation using unmanned aerial vehicles (UAVs) based IoT cloud systems is proposed.

The role of UAV is to collect the environmental data. The cloud handles the inference to compute the water amount for each farm region related to its soil moisture and farm region. Based on visualization of the farming cloud data, the regions needing water are mapped. Using the application mobile and on/off controls of electronically controlled pumps, water is sent to the regions needing water. These data are also sustainable for improving the irrigation plan. The proposed algorithm is the first step for agricultural automation via UAVs. Soil-moisture based on remote-controlling water management tasks is also a closed system based on decision. The control system proposed may arrange with aerial and ground-sampled sensors. In addition, UAVs can be implemented in other fields rather than the agriculture area as fire tickets monitoring. Different studies provide systems to control the irrigation automatically but not recommended to agriculture general public users at this time. There still does not exist any ground-sampled moisture based irrigation control system worldwide.The uncertainty measures (i.e., SU and MEE) can be computed via two fully-connected neural networks (one for each measure). Consequently, uncertainty-aware precision farming can be achieved using a modular online system (i.e., data acquisition modules, uncertainty estimation modules, visualization modules, etc.). In the data acquisition stage, the environmental parameters can be measured periodically by PMEE sensors, and collected or transmitted by a gateway. Measured data can be processed, and suitability measures as well as sampling sizes can be computed via ELM or analytical solutions.

Equ 3: Drone Flight Path Optimization for Crop Monitoring.

$$\min_{\vec{P}} \sum_{i=1}^{n-1} d(P_i, P_{i+1}) + \alpha \cdot T_{\text{process}}(\vec{P})$$

$\vec{P} = [P_1, P_2, \ldots, P_n]$ = Sequence of GPS points (flight path)

$d(P_i, P_{i+1})$ = Distance between monitoring points

T_{process} = Time to process sensor data (in cloud)

α = Trade-off factor for efficiency vs. data throughput

7. Precision Planting Technologies

The optimization of sowing depth can be turned into a binary classification problem, and SVM classifiers can be used separately. Three SVM classifiers can be built and combined to classify crops into six classes (though they should be chosen in accordance with their assistance in securing maximum profit). Sowing depth optimization can be achieved via class-wise probabilities of the six classes as p(y2|x2), p(y3|x2), . . . , p(y7|x2), where x2 represents soil and environmental data. Each of the p(y2|x2), . . . , p(y7|x2) is continuous in the closed range of [0, 1]; and the summation is always equal to one. The optimization of the sowing depth can be expressed as using the covariance matrix to capture behavioural aspects with respect to uncertainty:

C= Cov(P(y|x)) (1)

where P(y|x) = (p(y2|x) . . . p(y7|x)) in one case; and where Cov is the covariance of the p(y|x). A genetic algorithm can be used to determine the approximate location of min (C) for each crop. Then the selection probability should be assigned using the softmax function, and the sampling number should be drawn. After generating new samples, the population size should be selected as equal to N; and their fitness must be computed according to their uncertainty.

Particularly, the fitness should be converted into a selection probability using the softmax function. Then the next generation should be generated from the parents using a random operation of crossover and mutation. The training process commonly defaults after the number of user-defined generations is met. The network regimes (including the number of hidden nodes and the transfer function) as well as initial weights can be generated and evaluated using the genetic algorithm to ensure an optimal network regime. Hence knowing optimal initial weights can be used in ELM for further finetuning of network regime and weights.

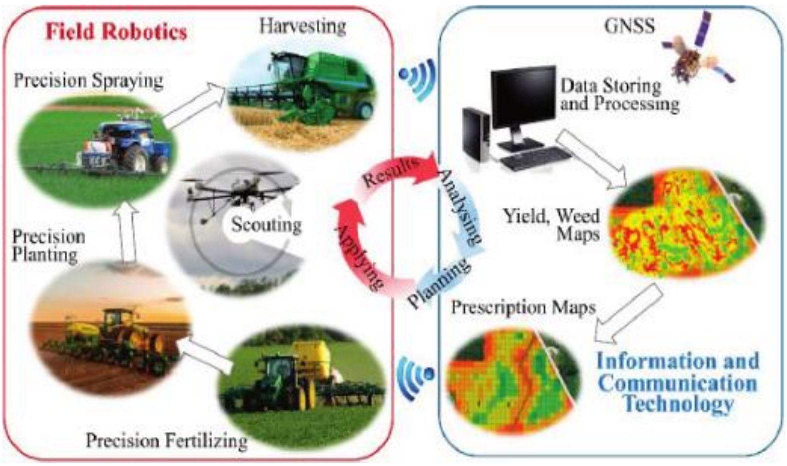

Fig 4: Precision agriculture basic technologies.

7.1. Seed Placement Algorithms

In a time in which food production has to grow to feed a rising population, modern technologies help to improve the management of farming. In particular, the development of non-linear biosensors for soil and crop state detection, combined with evolution in global position systems, allows for an increase of yields while minimizing the use of inputs. However, this information needs to be treated before it can be used to establish guidelines for management, adaptive to the current state, which crop requires the development of sophisticated models. Moreover, to be useful for the farmers, the data collected and the advice given have to be delivered in near real-time, which requires the use of cloud infrastructures for the data storage and management. As a step toward this goal, seed placement algorithm has been designed and validated on a larger public data set formed from agricultural colonies of different crops at different growing stages and locations with different weather patterns. The use of a Bayesian approach has allowed to create a service easily usable by any schools or company, independent of their budget and data available.

Current developments in drones are instrumental for the big data revolution farming is currently facing. However, this revolution is still missing in education, universities not providing the means for students to learn the necessary skills to create cloud infrastructure. Although introductory courses exist, they use techniques relying on outdated paradigms. Far too cumbersome implementations still rely on programming languages, while a wide range of powerful tools ready to use by simply following a few clicks in a web browser are now available. For instance, any school should rely on cloud infrastructure, bringing email, online storage, document edition, data analysis and archiving, and even web page creation services. Universities could provide their students with an analysis-ready data set, and with the know-how to leverage on it by simply logging on their workstation to go beyond teaching data treatment implementation.

7.2. Soil Health Monitoring

Soil nutrients (pH, Nitrogen, Potassium, and Phosphorus) directly affect crop yield, plant growth, and harvest quality. Providing timely fertilizer and water according to soil health is crucial to achieve long-term and stable soil fertility. At present, a multitude of professional fertilizer measuring devices are available in the market, while inexpensive agricultural-grade soil nutrient monitoring devices and NAND flash based data storage methods are lacking. To bridge the gap, this work presents a soil nutrient information monitoring mechanism which consists of a soil nutrient monitoring platform, a client mobile application, and an analytical reporting cloud platform. After soil information is collected by the digital soil nutrimeter, the soil data can be uploaded to the cloud through Wi-Fi/4G MQTT protocol and visualized in dashboard format. More importantly, a polynomial regression model to predict soil nutrients was constructed using several models, including linear, ridge, lasso, and support vector regression. Also, measures for oversampling imbalance data and sensitivity analysis of variables are provided.

The Internet of Things (IoT) has brought a revolution for smart agriculture. As soil condition offers fundamental information for crop growth, sensing soil properties for diagnostic assessment is essential in smart agriculture and precision farming. The current development trends in soil measuring devices mostly focus on small embedded sensors at the individual soil property level designed for low-power consumption and low-cost portable devices for one-dimensional soil nutrient ground truth verification. Besides, smartphone-based meteorological, dielectric spectrometric, and colorimetric devices are being investigated. Development in the semiconductors and MEMS has enabled the implementation of relatively inexpensive multi-sensor soil information depth characterization probes on microcontrollers with commercial RF modules and long-range LPWAN communication. Nonetheless, few studies detail soil information diagnostic assessment at the IoT level.

8. Yield Prediction Models

The development of predictive models is the third focus area in the approach to exploiting the potential of satellite imagery and deep learning in agriculture. The objective of the research on yield prediction models is to develop a model that, based on the predictive variables identified in the previous step, can estimate and possibly predict agricultural yields. Non-profit organizations, governmental agencies, companies, and other stakeholders are interested in such models at a country and continent scale. Nevertheless, the methods presented in this research can also be applied at a local scale, supporting farmers in their decisions and actions.

The work takes advantage of the ease with which large geolocation data sets can be processed by deep learning algorithms using parallel processing on GPU boards to calculate predicted yields for the entire planet. The first model used an extremely deep residual neural network trained on indexes of the visible, near-infrared, and infrared electromagnetic spectrum and weather and soil data were employed to make predictions that were close to the annual yield information for five countries. The database set up also contains training yields for 242 crops worldwide.

Using common data usually available to farmers, the use of high-resolution models enables the analysis of agricultural land productivity in the short, medium, and long terms. Scenarios can be run to analyze productivity in the event of maximum and minimum crop prices, among other information, providing data to be included in decision systems. In turn, these decision systems can analyze parameters such as proposed crop rotation, productivity by crop and location, and suggested inputs and cultural practices.

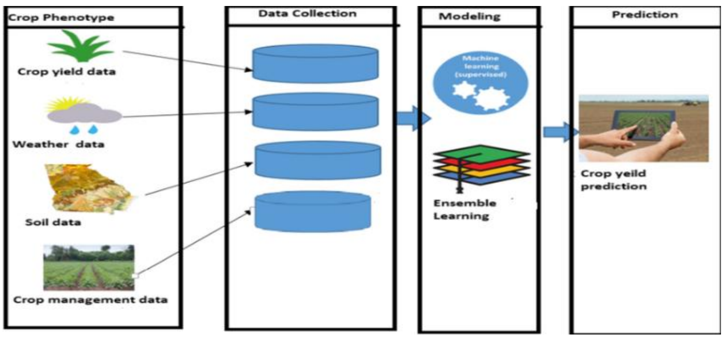

Fig 5: Crop yield prediction.

8.1. Statistical Approaches

Big data acquisition systems based on smart agricultural machinery systems have become an indispensable learning tool for precision farming. Precision agriculture collects, processes, and analyzes massive amounts of data in a water, pasture, or crop farming system. Precision farming can use customs sensors, farm machinery information, through UAV visual information, with high ground accuracy mass information acquisition. By incorporating the statistical approach, farmers can choose desired statistics when acquiring crop status. It allows improvement in systematic scientific farming technology in practical environments, thereby addressing the gradually growing challenge of global food scarcity.

Before big data acquisition using smart agriculture, the data acquisition scalability and transferability over time should be enhanced. This research presents an automatic technology and innovation roadmap overview for transferring smart farming

systems from a production-centered paradigm to a diagnosis-centered paradigm. It proposes a novel and open architecture, in which the role of each entity in smart agriculture is elucidated based on their cognitive capability.
The methodology is unique in that its components of the new technology and innovation roadmap are elicited from over 100 usable information sources, whereas the intelligent agriculture suppliers' perspective is presented in the design of the new smart agriculture architecture. Moreover, short- and long-term goals for newly identified and future roles are presented to provide insightful implications to the relevant stakeholders about the ways to improve intelligent agriculture intellect at different levels in terms of predicted timeline. It is significant that impacts of the smart farming transition roadmap on the supply-side stakeholders, such as farming machinery manufacturers and equipment leasing companies in smart agriculture, are discussed.

8.2. AI-Based Forecasting

AI-based forecasting is an effective approach applied to accurately predict and forecast crop-related outcomes based on historic data and other parameters. Further classification can be made between regression modeling and forecasting, regression modeling used to predict quantities and forecasting used to predict values based on time series data. Recent advancements in big data technology landscape leverage cloud-enabled, scalable, fault-tolerant and low-cost batch and real-time processing engines and frameworks, which lead to an exponential increase of aggregated data in raw and semi-structured formats. This manifested the event of Big Data Victoria and two paradigms of cloud computing and collaborative user-generated content, which in turn calls for the need of cloud-enabled big data management and analytics to adequately make sense of big geo-spatiotemporal and social data intelligently, timely, efficiently and interactively, promote the scientific and effective management of geographic space and related entities, and support the growing demand of location-based services in the public and commercial domains.
Analytic approaches to cloud-enabled big data management typically consist of three major components: 1) big data ingest and storage, including data cleansing, data integration and data warehouse; 2) big data processing and analytics in the batch or real-time processing mode, including data-oriented techniques and approaches such as privacy preservation, machine learning-driven and pressing analysis engines; and 3) big data visualization and interaction, including data representation and visualization, visual query languages and system architectures and platforms. This paper's contributions include the proposal of cloud-enabled spatiotemporal data processing and analytics with a focus on scalable and distributing data mining, a framework and system architecture integrating geo distributed big data management, analytics and visualization techniques into a web-based interactive platform, and a case study of a cloud-enabled spatiotemporal big data platform for precision agriculture analytics.

9. Challenges in Implementation

A few hurdles need to be overcome before agricultural machinery systems (AMS) can be widely adopted. To begin with, farmers must be trained on the new operation methods. The development of techniques and algorithms supporting real-time data gathering and big data analytics in the segment of farmer training. Analytics methods must be developed to properly visualize big data of AMS. Moreover, missing values exist in big data and new algorithms to forecast missing values efficiently are needed. Farmers often want basic knowledge to understand the models developed along with the data. The productized machine learning models, uncertainty and risk will be explained to the farmer using parameter databases, risk statistics as software functions.
Second, AMSs must be compatible with the equipment of diverse manufacturers. There is a need for practical standardization at the level of protocols, database structure and formats of the data files, and termination methods of the database transferring efforts with the assistance of policy-makers and agricultural sectors such as fertilizer manufacturers, agriculture colleges, banks and insurance companies.
Third, protect farm data. Common questions and concerns among the farmers include: Who owns my data? What can the agricultural technology company do with my data? Who can use my data? If my data is stolen, how will it affect me? Government refers to that critical parts of the agriculture sector ownership of data must be internal (in the sector) while non-essential parts of the food chain should remain outside national boundaries. The ownership of the farm data must be determined and commercial conflicts and risks encapsulated. In many countries, 3rd parties use analyzed farm data based on government regulations to advise farmers about the fertilizer application. The governance zero rights of farmer data owners will be considered worldwide.
Finally, appliances. The agricultural equipment manufacturers need to develop easy-to-use AMSs with off-the-shelf components. As computer-processed sensor data may infiltrate and be absorbed into the management process, the in-depth independence of appliances would likely be disrupted. Farmers also want to tailor AMS to their specific needs, but achieving them becomes harder as they need more sophisticated electronic apparatus and computer algorithms.

9.1. Cost Barriers

Cost barriers are traditionally linked to the high investment needs of the agricultural sector. Large investments in agricultural equipment, subsidies for heavy machines, advanced GPS systems, and other costly technological advancements hinder the development of precision agriculture. Although strata scaling systems are available, current sensors, tools, and equipment for precision farming are still economically unrealistic. Low-cost timely information systems including weather prediction, pest detection, disease prediction, irrigation scheduling, and variable rate application technologies are still a luxury for most farmers. Precision farming solutions are significantly transforming agriculture; however, the cost of technology needed to support these solutions is another barrier.

Many precision products are still prohibitively priced to develop widespread adoption or coverage. New terminals, controllers, or in-cab displays should be fitted to old tractors which economically discourages farmers to invest in sector expansion rate technologies. Although the software prices are more competitive, along with payment choices that include monthly agreements and month-long free trials, farmers still prefer to utilize fundamental products from crop consultants, extension agents, or friends for getting less than full capacity-priced applications. With a focus on productivity as a measure of farm scale, club degrees, income, and crop sale prices, small farms are disregarded by technology suppliers. Although large-scale producers are able to reap the most exacting benefits of precision agriculture, investments before the upsurge in commodity prices degraded coverage for technologies aside from guidance systems.

9.2. Data Privacy Concerns

The audience of this article includes all participants in precision agriculture, from equipment manufacturers /processors/developers to entrepreneurs, and farmers. As a result of collaborative networking optimal usage of Big Data is promised among actors of the value chain. Technical, political, and legal actions must lead to an improved data infrastructure. Mutual trust with accompanying confidentiality measurement protocols is needed. Farmers and cooperatives urgently need data contracts. Public authorities need to regulate Big Data in farming markets. Legal standards/boundaries on profiling/monitoring, appropriate efficacy thresholds, and liabilities of Artificial Intelligence are most needed in that respect. Therefore, unsolicited information is promised from diverse international perspectives to the target groups of accuracy/four-eyes principle on prediction accuracy.

The Big Data employees/service providers are requested to report to client farmers/cooperatives about the information on decisions about other competitors or data anonymization and protection. They need to report on feedback schemes on the optimal algorithms and other intentions in the collector's data sales platform for the acquisition of external data. Policymakers should check that farmers/cooperatives agree to the accumulation of their data of national and European importance as well as data anonymization and protection. Data without an ethical voice of elaboration should be recognized as low-quality. It is concluded that there is an urgent necessity for privacy regulations for the unprotected trade of recopied data/narrow AI in a data-as-a-service/fast-close-system.

The rapid advancements in the field of AI fostered the role of AI in many applications of the eco-society. Newest trends on that include GP-composition trees supporting better explanation of farm optimums, causal inference characterization of the previously unobserved phenomena of how to vary the settings for improving precision recipes, robust off-policy evaluation owing to the inherent uncertainty of precision agriculture, and artificial multi-modal digital twins of AI-containerized next-gen flexible autonomous Big Data systems.

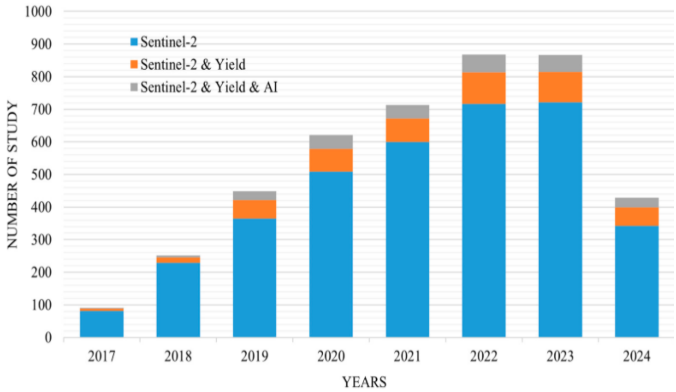

Fig 6: Artificial Intelligence Techniques in Crop Yield Estimation

10. Conclusion

AI is being incorporated into numerous machines used in agriculture, including tractors, sprayers, spreading machines, or drones. These machines can improve the efficiency of farm operations, and reliability of the product application. Improved efficiency also means reduced fuel consumption, elevated productivity of farm machinery, and reduced product costs. AI can optimize crop management by analyzing large datasets of agricultural systems, leading to better yield forecasting, detection of limiting environmental factors, assessment of soil health, and establishment of superior growing/harvesting strategies. Many fruit growers have implemented multispectral cameras to evaluate moisture stress and nutrient needs of trees. Integrated with AI analysis, this information can be transformed into computer-generated maps, allowing sprayers to accurately apply the right amount of product only where needed. AI combined with robotics is also expected to enhance the productivity of harvesters. Vision systems are being developed that enable robots to pick fruit, flowers, and vegetables. These systems can be used at night and on cloudy days, meaning improved yield reliability.

Additionally, machine learning and AI can be incorporated to augment field data with remotely gathered data. These AI-driven systems can detect changes in vegetation and infer plant health, moisture levels, levels of anxiety in cattle, etc. AI can also assist in monitoring, forecasting, and detecting the occurrence/design of pests and diseases. Advanced data gathering can also feed into crop market analysis, enabling better strategic crop choices. AI can improve data processing of existing precision farming hardware and software with benefits in speed, minimization of human errors, better robustness, and environmental exploitation. Providing affordably priced software for farmers may be an entry point for more complex technology use either downstream or upstream.

10.1. Future Trends

Since the advent of agriculture, farmers have relied on traditional farming practices. The traditional farming method is insufficient for the increasing demand for food due to the rise in global population. Precision farming, also known as precision agriculture, ensures improved productivity by tracking field variability in crops and animals. This type of farming is implemented by using AI tools on agriculture robotics and IoT technologies. Precision farming is a farm management strategy that focuses on observing, measuring, and responding to inter and intra-field variability in crops. The implementation of precision farming is tedious, as farmers have to set up hardware and software in the field and know how to operate it properly. However, with the rapid growth of Artificial Intelligence, the potential applications of AI in agriculture are becoming ever more important. Although farmers do not understand the working of AI tools in detail, they can still use them. Conclusively, these advanced AI tools can replace a complicated setup of hardware and software on the farm and ensure that precision farming is a far more available technology. The proposed platform can be uploaded on a cloud service with a subscription model for farmers and agricultural consultants. Again, farmers with an advanced mobile phone can subscribe to the platform application and access all the required tools through the mobile phone itself.

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