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An Overview of Digital Technologies in Agriculture and their Applications

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ABSTRACT: Sensors, drones, and precision farming software especially artificial intelligence and machine learning are rapidly being used in agriculture to increase efficiency, production, and sustainability. These technologies may be used to monitor and improve various aspects of agricultural and livestock production, such as irrigation, fertilization, pest control, and animal health. Additionally, via the use of data analysis and predictive modelling, they may help with improved decision making. Digital technology may also assist to increase food safety and traceability while decreasing waste and resource consumption. Globally, the use of digital technology in agriculture has the potential to increase the economic viability of agricultural operations and contribute to the global food supply. However, poor digital literacy, infrastructure availability, internet connectivity, and low level of awareness among all the agriculture stake holders. Moreover, there are few papers which have given an overview of all the digital technology components. So, the present review paper has discussed the digital agricultural technology components available in agriculture sector.

Keywords: Artificial intelligence, digital technology, machine learning, software.

INTRODUCTION

"*If agriculture is to continue to feed the world, it needs to become more like manufacturing"- Geoffrey Carr, The Economist.*

Digital agriculture is the practise of employing digital tools to collect, store, analyse and share data along the agricultural value chain. According to the United Nations' Project Breakthrough, "digital agriculture" is the use of advanced technology in a unified framework to assist farmers and other industry participants in increasing crop yields.

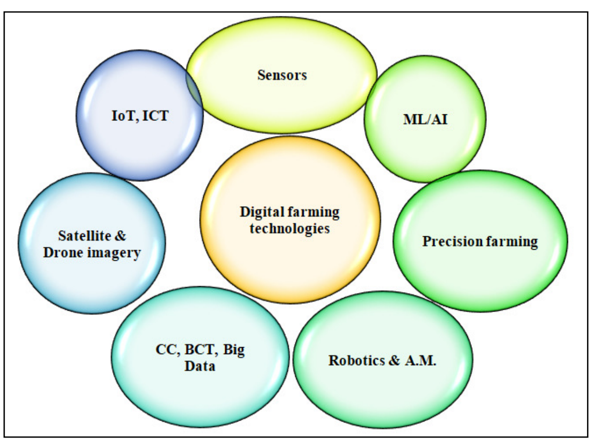

Fig. 1. Components of Digital farming technologies.

The use of digital farming technologies has the potential to dramatically enhance agricultural productivity, resource conservation, and profitability. Pictured in Fig. 1 are some of the many components that make up digital technology. These digital technology components were explained in detail in following sections

Robotics and autonomous guided machinery: Autonomously guided robots equipped with both local and global sensors can improve the productivity of farming operations. Two such examples are the X Machines X-100 field robot and the John Deere iTEC Pro, the latter of which uses the Global Navigation Satellite System to regulate its direction. Robots can be used for a variety of agricultural operations, such as crop scouting, irrigation, transplanting, pest and weed management, spraying, harvesting (Li *et al.,* 2011), trimming, milking, sorting, phenotyping, etc. (Jorgensen *et al.,* 2007). Although most of these are currently in prototype form, they have the potential to increase precision in farm operations if they are developed further and implemented on a larger scale. Recent advancements in Unmanned Ground Vehicles (UGVs) for weed control, field scouting, and harvesting were discussed by Shamshiri *et al*. (2018). They emphasized that field scouting robots can play a significant role in reducing production costs, increasing productivity and quality, and enabling individualized plant and animal care if they are properly integrated and implemented.


John Deere


iTEC Pro


Hortibot


Robotic Milking machine (DeLaval)


X 100 (X machines)


Apple picker (FFRobot)


VineRobot

Other applications of automation include automated planting, selection of quality seed, establishing protection from pets to avoid crop damage, automated processing etc. (*Edan et al*., 2009).


Automatic tray seeder machine


Automatic weather station


Automatic processing machine


Automatic sett treatment machine

Satellite and Drone imagery techniques

Remote Sensing Platforms: Satellite remote sensing became an integral part of the evolution of smart farming as field data became readily available from artificial satellites. Important sources of agricultural data include the European Sentinel 2 satellite system, the Indian Cartosat and INSAT satellites, the American Landsat satellites, and other satellite systems.

Recent advances in image processing techniques and new generations of satellites have enabled several agricultural applications, such as real-time crop monitoring, irrigation requirements, etc. (Steven and Clark 2013).

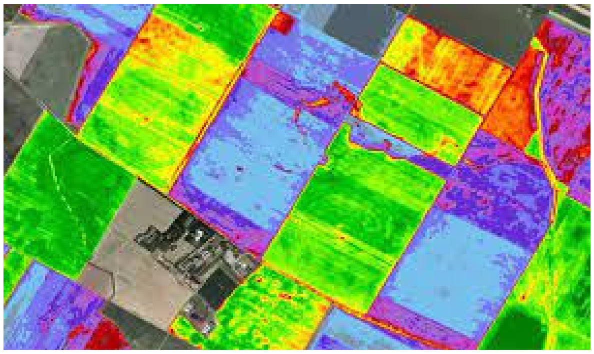

Fig. 2. Picture representing processed satellite image.

Aircraft Systems: Unmanned aerial vehicles have helped improve the poor spatial and temporal resolutions of satellite systems. The uses for UAVs are diverse and include crop monitoring, spraying chemicals, and even phenotyping them (Yao *et al.,* 2019). However, drones can't fly in strong gusts and can't carry as many sensors as they could because of their limited payload capacity. In addition, it is typically challenging to perform the post-processing of data and the image mosaicking. With active sensors, environmental factors like bright sunshine or dim lighting are no longer a problem, and with real-time processing, machine learning algorithms may be used in real-world applications like spraying herbicides after detection (Lameski *et al*., 2018).

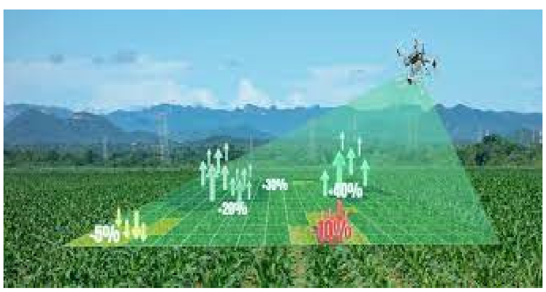

Fig. 3. Picture representing processed drone image.

Embodied digital technologies utilize one or more technological methods to increase efficiency in handling materials, labour, etc. Technologies such as global positioning satellites (GPS), geographic information systems (GIS), sensors, decision support systems, and precision agriculture equipment all fall within this category. For agricultural purposes, precision farming employs both proximal sensing (such as soil nitrate sensors) and distant sensing (e.g., satellite imaging). Whereas, precision irrigation uses sensors and other technologies to optimize the amount of water applied to crops. Machine learning and other techniques are utilized to analyze data gathered from sensors and other sources to make decisions about farming practices. Geographic Information System (GIS)-based Decision Support Systems are commonly used for this purpose, and they may incorporate data from crop simulation models to ascertain the optimal level of input to be applied to a given portion of a field for maximum yield. Soil type, nutrient level, soil moisture, pH, fertility, weed and pest intensity maps, and other fundamental maps are all part of a GIS system (Yousefi and Razdari 2015). These maps and data are then used in combination with other decision-making aids to apply the prescribed dosages of fertilizers or pesticides. To enable the site-specific application of inputs, agricultural machinery (including the sowing machine, the fertilizer or liquid manure spreader, or the pesticide sprayer) must be designed so that the amount applied may be changed within the field; this method is known as Variable Rate Technology (VRT) as stated by Guan *et al.* (2015). When implementing variable rate technology in the field, GPS gives a precise location-based positioning solution. Spray booms, spinning disc applicators controlled by electronic control units, and global positioning systems (GPS) have all been put to use in patch spraying (Miller *et al.,* 1998). Apart from these, infrared spectrometer, soil inductance metre, and leaf chlorophyll metre are a few instruments that have become increasingly popular in recent years (Sudduth *et al*., 1997). In order to help farmers, these systems employ various methods, including data analytics, to make recommendations on how their operations could be improved. Moreover, the whole information can be used for determining the impact that changes in other agronomic elements have had on a harvest by crop yield estimation. Mapping, interpreting, and correlating yield with the spatial and temporal variability of other agronomic variables are all useful in shaping the crop management approach for the upcoming season.

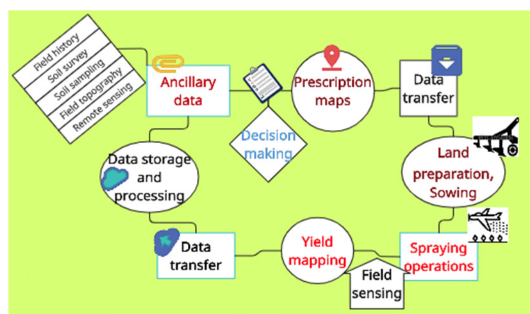

Fig. 4. Source: Redrawn from Meena *et al.* (2019); *Advances in agronomy.*

Precision livestock farming is made possible by attaching sensors to cattle or to the barn apparatus used in livestock production. For instance, the barn's temperature or animal movement patterns can be managed automatically with the help of sensors and machinery (Jungbluth *et al.,* 2017). Modern advancements in precision farming equipment: Precision farming methods can now be used in crop and livestock production due to drones and other cutting-edge technologies.

Big data analytics. As the quantity of data available to managers in the field grows, creation of an automated method to extract operational information from the data is crucial. There are several potential ways where big data analytics could improve agricultural practice, including the implementation of precision agricultural-based techniques at the field level, the development of an efficient food supply chain, and the mechanization of the entire operation to maximize profits (Tsiolias *et al*., 2015). The use of big data analytics to mine enormous climate datasets has raised awareness of the differences between traditional big data and mining techniques and strategies specific to mining climate data (Rani, 2017).

Fig. 5. Five dimensions of Big data.

The challenges of gathering, storing, and processing massive data from many sources is a serious impediment for new breeding facilities. The original plant breeding data translated to the format suitable for computational analysis using machine learning [ML] is depicted in Figure. Hadoop, MapReduce, Hive, NoSQL/NewSQL databases, data integration techniques, in memory methodologies, and cloud technologies are just a few examples of the big data technologies, services, and tools that have arisen to tackle the problems provided by the massive amount of online, social media, IoT, and Machine-to-Machine data. Since the cloud takes care of its own servers and databases, academics can put their attention where it belongs: on analyzing and mining data. Problems with big data and cloud implementations include network reliance, latency issues, and reduced command over security and compliance (Chan, 2018; Xu *et al*., 2022).

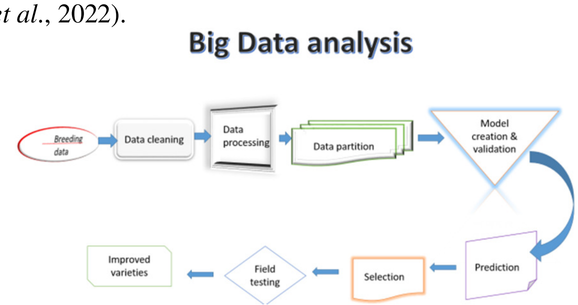

Fig. 6. Original breeding data translated to suitable format for computational analysis using machine learning.

Internet of Things in Agriculture is a cutting-edge approach that offers trustworthy and efficient solutions for the modernization of numerous industries. IoT-based solutions are being developed to allow for the autonomous management and monitoring of farming systems with the least amount of human intervention. The advancement of wireless sensor networks has made it possible to collect information from sensors and transmit it to the main servers (Ojha *et al.,* 2015). The collected information is then wirelessly transferred to a central hub for analysis and application to farm management. This data has uses in irrigation management, crop forecasting, livestock health monitoring, and disease identification. Sensors and gadgets connected to the Internet of Things can be set up in agricultural settings, including greenhouses, fields, and barns, to monitor environmental conditions in real time. Farmers can utilize machine learning algorithms to forecast crop production by collecting data on environmental conditions such as temperature, humidity, soil moisture, and air quality. Optimizing planting and harvesting schedules and selecting appropriate crops for various locations would be possible. With the use of the Internet of Things (IoT), farmers may boost their profits by enhancing the efficiency, productivity, and longevity of their operations. Water scarcity, cost management, and productivity issues are just some of the problems that agriculturalists and technologists hope to address via the Internet of Things (Kamienski *et al.,* 2019).

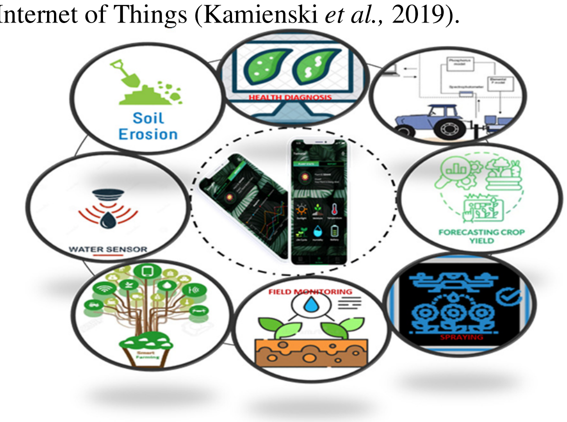

Fig 7. IoT in agriculture.

Cloud computing is the transmission of computer services such as storage, processing, networking, analytics, and intelligence through the Internet (the cloud), as opposed to local servers or personal devices. By enabling farmers to access and analyze data on their crops and livestock from anywhere with an Internet connection, cloud computing is helping to increase efficiency, production, and sustainability in the agriculture business. Cloud computing's ability to store and handle massive volumes of data is a major boon to the agricultural sector. Temperature, humidity, soil moisture, and air quality are some of the variables that can be monitored continually by sensors and equipment put in fields, greenhouses, and barns. This information can be wirelessly sent to a centralized hub, uploaded to the cloud, and then stored and analyzed utilizing extensive cloud-based computer resources (Patil *et al*., 2012). Because data is stored and processed on the cloud, farmers can access the information from remote areas too if there's an Internet connection, eliminating the need for costly servers. Using analytics and intelligence tools to obtain insights from data is another perk of cloud computing in agriculture. Machine learning algorithms can help farmers improve farm management by analyzing data like crop yields, soil moisture, and animal health. By utilizing cloud computing, farmers have access to numerous useful apps and programmes that can aid in planning, budgeting, and forecasting. By responding to farmer questions and updating the cloud service database with the most recent agricultural research relevant to their area of expertise, the agriculture expert shares their specialized knowledge with other professionals. (Gill *et al.,* 2017). Users may therefore keep an eye on any data pertinent to their domain and receive feedback without going to the agriculture assistance centre. In general, cloud computing is a game-changer in the agricultural sector because it gives farmers unprecedented convenience and mobility in gathering and analyzing data. Farmers may boost their bottom lines by using cloud computing to boost efficiency, production, and longevity (Hori *et al*., 2010).

Information and Communication Technologies are one of the key elements of smart farming. These technologies have the possibility of being implemented at many phases along the value chain for agricultural products, including production, processing, distribution, and marketing. It can be used in combination with sensors, Internet of Things (IoTs) to monitor and control various aspects of farming operations. Apart from these, information and communications technology (ICT) can also be utilized to increase communication and collaboration among farmers, agribusinesses, and other players in the agriculture value chain. For instance, information on market prices, weather conditions, and other crucial parameters that can effect farming operations can be communicated using mobile apps and social media platforms. The utilization of ICTs provides farmers with a better understanding of the numerous facets of agricultural operations and enables them to maintain ideal circumstances with minimal effort and high returns, resulting in agro businesses that are more effective, highly productive, economically viable, and successful. India has established a number of e-agriculture platforms to help farmers sell their goods to consumers. The two-most renowned of these are the National Agriculture Market (e-NAM) and the National Agriculture Cooperative Marketing Federation of India (NAFED). These market places rely on digital technologies to ease communication between customers and merchants. Krishi Shala, the Crop Insurance Mobile Application (CIMA), and Kisan Suvidha are the mobile apps that were developed to give farmers access to crucial data like weather forecasts and market prices. Whereas, the PLANTIX app provides information on prevailing pests and diseases in the locality. The use of such apps can also help farmers sell their goods to consumers. ICT can aid farmers in optimizing their operations and adjusting to shifting market conditions by facilitating more precise and data-driven decision making (Saidu *et al.,* 2017).

Block Chain Technology (BCT) could change the agriculture industry by making transactions and supply chain management more secure and open. The following are examples of how blockchain technology could be used in agricultural sector: Firstly, food safety, Blockchain technology can be used to track where food comes from, where it's been, and how good it is. A product's safety, authenticity, and quality can all be improved by this method, and any other problems that arise can be tracked back to the original source. In spite of this, Blockchain technology has the potential to streamline the agriculture industry's complicated network of distributors and retailers (Kamilaris *et al.,* 2019). By creating a secure and visible ledger of transactions, blockchain can aid in ensuring that products are delivered on time and that all stakeholders in the supply chain are paid properly. Moreover, the management of contracts and agreements between farmers, agribusinesses, and other agricultural stakeholders is another application of blockchain technology. Blockchain technology can increase transaction efficiency and reduce the likelihood of disputes by providing a transparent and immutable record of these contracts (Sylvester, 2019). Additionally, blockchain technology can be utilized to keep track of policies and claims in a way that is both trustworthy and auditable. Effective and timely delivery of insurance to farmers is facilitated by this. Overall, blockchain technology has the potential to make transactions and supply chain management in the agriculture sector much more transparent, efficient, and safe thus increases trustworthiness among anonymous individuals (Borah *et al*., 2020). Block chain's capacity for decentralized, immutable record keeping has the potential to boost confidence in the industry while simultaneously decreasing the likelihood of fraud and other problems. This also contributes to resolving the difficulty of tracing items in the extensive supply chain caused by the agri-food system's complexity. As a result, the technology offers answers to problems with food quality and safety, which are of great interest to customers, the government, etc.

Artificial intelligence in Agriculture. The premise upon which AI rests is that human intelligence can be described in such a way that it can be easily imitated by a machine and used to perform a wide range of tasks, from the simplest to the most complex. Artificial intelligence that can learn, reason, and perceive would be useful for accomplishing these goals.

"We're at beginning of a golden age of AI. Recent advancements have already led to invention that previously lived in the realm of science fiction – and we have only scratched the surface of what's possible" – JEFF BEZOS, Amazon CEO.

Examples include vision-recognition systems on autonomous vehicles, and recommendation engines that suggest things you might enjoy based on what you've bought in the past. Artificial intelligence is having a profound effect across all sectors of business. Every industry is looking for sophisticated machines to automate certain processes. The agricultural industry is one of the world's oldest and most important economic sectors. The agricultural industry is worth approximately $5 trillion worldwide. While still employing conventional methods, farmers are increasingly turning to artificial intelligence for help with a variety of issues (Kumar *et al.,* 2021). Managing difficulties related to agricultural production, irrigation, soil moisture sensing, crop monitoring, weeding, crop protection, and crop establishment are some of the ways in which AI-based technology is improving productivity in agriculture. AI-based image recognition app PLANTIX is the best application which aid in plant protection. Despite this, farming robots are developed to provide high-value AI solutions for the chosen sector. There is a crisis in the agricultural sector as a result of the increasing world population, but AI can bring essential solutions. Introduction of AI-based technologies has allowed farmers to raise productivity while decreasing inputs, boost product quality, and shorten the time it takes to bring their goods to market (Eli, 2019).

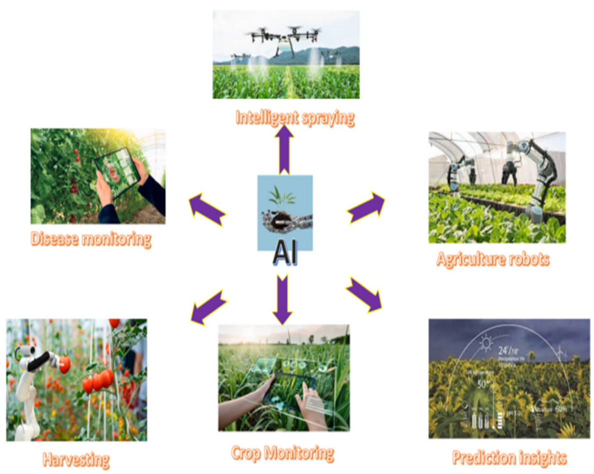

Fig. 8. Picture representing applications of Artificial intelligence in agriculture.

Machine Learning in Crop Genomics. Genome assembly, iterative inference of gene regulatory networks, and the identification of true SNPs in polyploid plants are some of the genomics research applications of machine learning. In order to facilitate the processing of plant data, Ma *et al.* (2014) provided a comprehensive set of open-source R tools and associated machine learning methods (Ma *et al.,* 2014). It was also stated that the adoption of ML can help polyploid genome assemblies with complicated genomic redundancy.

Discovery of agricultural features relies on a solid understanding of plant gene function and structure, both of which are facilitated by a complete genome assembly and annotation (Fig. 8).

Non-ML-based assembly strategies that use a linear method to assemble repeated sequence sections have trouble assembling extremely duplicated genomes. To go around this limitation, an ML strategy was employed to detect assembly errors and generate a high-quality assembly of bread wheat (*Triticum aestivum*) (Brenchley *et al.,* 2012). The RNA-seq mapping programme "Portcullis" employs ML to distinguish between natural and artificial splicing junctions, to annotate the bread wheat genome (Mapleson *et al.,* 2017). The field of inferring the relationships between regulatory elements and genes is one that shows a lot of promise. This can be used to find possible improvements for agricultural production. There are drawbacks to constructing a regulatory network in silico only on the basis of gene co-expression levels, as the resulting connections between genes may not accurately reflect common gene regulation (Hecker *et al.,* 2009). Therefore, there has been a rise in interest in a method for interactive inference of gene regulatory networks that is based on machine learning. This method has the potential to combine different regulatory signals from different databases. 2014's (Ma *et al.,* 2014) Data on 42 factor binding, conserved sequences, gene expression, and the transcriptional regulatory network of Drosophila melanogaster, which contains and over genes, can be exploited (Marbach *et al*., 2012). The most common type of variation in plants is SNPs (Flint-Garcia *et al*., 2003; Rafalski, 2002). But there are still challenges in the search for SNPs in polyploid plants (Buggs *et al.,* 2012). Korani *et al.* (2018) developed an ML-based analytical tool named that could be used to edges and tree models to filter erroneous SNPs. The accuracy of choosing real SNPs was further proved using SNP data from strawberry, cotton, and peanut, with above 98% 46. Additionally, neural networks Simulated variants have been used in laborious, error-prone scanning of genomic sequences to identify SNPs. To feed the estimated nine billion people that will live on the planet in 2050, agricultural production must grow by 70% 42. There isn't enough of anything to meet the escalating demand due to the expanding population. In order to maximise productivity, we must adopt a more strategic approach and improve our farming techniques. Overall, big data analytics can make use of machine learning approaches.

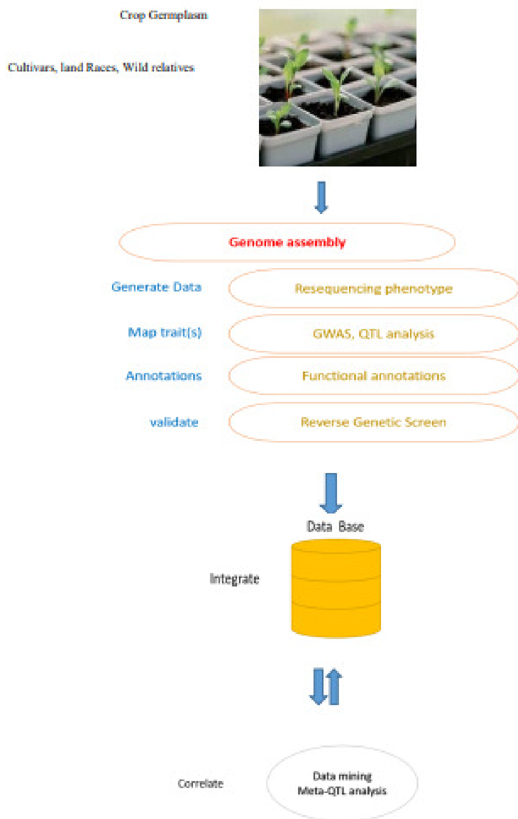

Fig. 9. Steps in data analysis of crop genomics by using machine learning.

CONCLUSIONS

To sum up, the use of digital farming technology has the potential to significantly enhance the efficiency, production, and sustainability of the agricultural sector. Farmers may better improve their practices and yields with the use of technologies like global positioning system (GPS) devices, sensors, data analytics, remote sensing, decision support systems, automation, and robots. In addition to lowering costs, these technologies may boost agricultural yields, making them a crucial resource for farmers everywhere. It's worth noting, however, that implementing digital farming technology isn't without its share of difficulties, including a potential need for new methods of education and support, as well as worries about personal data security and privacy. In sum, digital farming technologies have great promise as a means to combat the difficulties in the agricultural industry and provide a prosperous and environmentally friendly future for farmers.

FUTURE SCOPE

The future prospects of digital technologies in agriculture are very promising. Digital technologies such as drones, sensors and satellite images can help the farmers to monitor real time situations, applying of fertilizers, pesticides, and water more precisely. It reduces waste and increase yield. Use of big data analytics in agriculture, it will help the farmers to take more informed decisions about weather pattern, crop management and pest& disease control. IOTs and autorotation technologies useful to farmers by making task automation and monitor crop growth habits without human intervention. It will save the more time of experts and reduce resources uses.

Conflict of Interest. None.

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