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Applications of Internet of Things, Remote Sensing, and AI for Precision Agriculture and Its Adoption Status in Nepal

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Abstract. *Modern technologies combined with precision agriculture have made revolutionary advances in the field of agriculture. The Internet of Things (IoT), remote sensing, wireless sensor networks, machine learning, and smart farm management systems have brought agriculture into a new era. In this context, the purpose of this review is to summarize the most recent advanced tools and their potential directions for further research by synthesizing the recent literature. Sensors, robotics, global positioning systems (GPS), satellites, and aerial imaging drones have facilitated data-driven actions, programmed management, and real-time monitoring in agricultural systems. These tools, when combined with Artificial Intelligence (AI) and machine learning, enable real-time decision-making and smart farm management. Some advanced applications include computer-based image recognition in weed control robots, early pest and disease detection through image identification, irrigation based on field water, fertilizer application through soil nutrient mapping, livestock health tracking through behavioral biometrics, and yield prediction analytics to inform breeding and harvest planning. The emergence of "digital agriculture" paradigms, such as Agriculture 4.0, signifies the convergence of interconnected intelligent farm management systems. In Nepal's setting, the growing use of mobile apps and Information and Communication Technology (ICT)-enabled advice services provides smallholder farmers with crucial, location-specific information even in the absence of advanced technical infrastructure. Precision agriculture technologies have enormous promises to meet the country's food demand. However, data privacy, technical proficiency, and technology accessibility must be resolved simultaneously. The discussion of policies and collaborative tactics required to ensure precision agricultural technology empowers rather than displaces poor food producers. Seventy-three scholarly articles on the topics of IoT, AI and precision agriculture were reviewed to introduce relevant concepts, ideas and implementations to offer a framework for the application of novel technologies in the Nepali agricultural landscape.*
Keywords: *Precision Agriculture; IoT; AI; Agriculture 4.0.*

Type of the Paper: Regular Article.

1. Introduction

The evolution of human civilization is inherently based on agriculture. In light of increasing food demands, individuals are striving to augment food output through additional endeavors and innovative methods [1]. In the year 2022, when this narrative began to take shape, our planet supported an approximate population of 8 billion people. With global food production reaching a level of 5,000 kcal in energy per person per day, the prospect of providing wholesome, abundant,

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and diverse nourishment seemed attainable for most of our communities [2]. Projections indicate that as the global population reaches 9 billion by 2050, it is anticipated that food demand will rise by approximately 59 % to 98% [3]. The disparity exists in individual consumption, with wealthy nations having over 8,000 kcal daily and poor nations around 2,000 kcal. Concurrently, around 800 million individuals face undernourishment, including 250 million children under five who are malnourished, stunted, or excessively fed [2]. The primary global issue is ensuring food security for a swiftly growing global population [3]. With climate change remaining a central focus of scientific discourse, there's broad consensus on the necessity for agricultural systems to evolve. Intensive farming practices' extensive ecological and societal consequences are well-understood [4].

The swift expansion of the global population, the decrease in available agricultural land, the amplification of worldwide climate shifts, the degradation of water resources, the decrease in the labor pool, and energy scarcities have caused the agricultural sector to encounter substantial challenges and hindrances [5]. The foremost global issue at hand involves guaranteeing food stability for the swiftly expanding global population [3]. Over time, climate change results in a rise in the average annual temperature, accompanied by heightened severity and frequency of climatic extremes. Climate change will also induce changes in water distribution and availability. Additionally, effects such as advanced flowering periods, extended growing seasons, increased instances of crop failures, heightened pest infestations, and other changes will be observed [2]. Given that 52% of agricultural land is currently categorized as degraded, agricultural yield patterns will alter, and yields are more likely to decline than rise. Even today, global cultures struggle to provide everyone with enough nutritious food. The question of what will happen when a larger, wealthier population faces a rapidly changing climate remains a significant challenge [2]. To avert potential food scarcity in the coming times, it is imperative to adopt forward-looking and enhanced agricultural methods that can attain an optimal harvest by effectively managing crop inputs. These inputs encompass agrochemicals like insecticides and herbicides, which are employed or introduced during the process of agricultural production [6]. Aside from stability in production at sufficiently higher levels, it must be well understood that food security is not solely a function of production volume. Rather, it is a matter of availability, accessibility, affordability, distribution, and use [2]. Empirical methods establish direct connections between inputs and outputs solely through statistical approaches, being notably uncomplicated and necessitating more data collection to enhance the model's resilience. Conversely, mechanistic models focus on the relationships of cause and effect between inputs and outputs, while comprehensively considering the multitude of biophysical processes in operation [7]. One approach involves the integration of various technological innovations into agriculture. Alongside agrscientific advancements, it plays a critical role in the agricultural domain. The monitoring and decision-making capabilities of this domain are enhanced by technologies like satellite navigation, sensor networks, grid computing, ubiquitous computing, and context-aware computing [1]. To enhance agricultural output and minimize crop losses attributed to environmental challenges and other adverse influences, it is advisable to utilize agronomic monitoring devices within the Internet of Things systems and to undertake organized practices for planting, tending, and nurturing crops [8]. Given the global apprehensions, the agricultural sector has recently integrated solutions rooted in artificial intelligence (AI), leading to a substantial departure from conventional farming practices in the contemporary era. Within the domain of spraying technologies, the expansion of AI applications is notable, as they aim to advance the processes of learning and real-time monitoring of crop conditions [6]. Despite agriculture being a demanding and quickly evolving field today, there aren't many scholarly works that cover all the most recent technological advances and how they are being applied in industry. We mainly concentrate on the possible advantages of innovative agricultural technology, including the comments from development experts, smallholder farmers, and other relevant parties, which could offer helpful alternate perspectives. With the aid of this review paper, we intend to provide a comprehensive understanding of the emerging technologies like IoT, AI, and precision agriculture and their implementation methodologies in the agricultural industry, specifically in the context of developing economies like Nepal, allowing stakeholders to make informed decisions regarding their use and significance.

2. Materials and Methods

To conduct this review about technological progressions and their utilization in agriculture, a structured literature search approach was followed. Searches for relevant literature were conducted in widely recognized electronic databases—Google Scholar, PubMed, Scopus (Elsevier), Web of Science, Semantic Scholar, and Academia. In addition, information for the grey literature were extracted from websites of the International Rice Research Institute (IRRI), the Nepal Agricultural Research Council (NARC), and other organizations. Keywords such as "IoT", "AI", and "Precision Agriculture" were applied to identify and reference relevant literature. Publications directly pertaining to the keywords were included; studies which lacked implementation details and practical applications were excluded. In total, excess of 100 research and studies were retrieved, of which 27 were excluded during abstract screening. Seventy-three articles were retained for a thorough review. The selected studies were then classified into broad categories such as IoT and remote sensing applications and the use of artificial intelligence in agricultural applications, with a focus on their adoption status in Nepal. This search also includes several regional studies to extract insights about the applicability of AI and IoT technologies from economic regions like Nepal.

3. Results and Discussion

3.1. Precision Agriculture

Precision agriculture, in its broadest sense, refers to a farming operation that aims to provide management in the appropriate quantity, at the appropriate time and location. Instead of providing uniform management, it uses regulated inputs by dividing the croplands into management blocks or zones [9]. Precision agriculture offers the potential to boost yield per acre while simultaneously enhancing farm automation and environmental friendliness [6]. For farms to achieve maximum productivity, precision agriculture seeks to optimize and improve agricultural processes. To this end, it requires quick, accurate, distributed measurements to give growers a more thorough picture of the current conditions in their cultivation area and/or to coordinate automated machinery in a way that maximizes the use of water, energy, and pesticides for plant growth and control [10]. The terms 'digital farming' and 'precision agriculture' (PA) are commonly interchanged and pertain to employing advanced crop and environmental analytical instruments alongside vast data reservoirs. These tools support farmers in enacting suitable managerial methodologies at exact rates, moments, and sites to achieve economic and environmental aims in tandem [7].

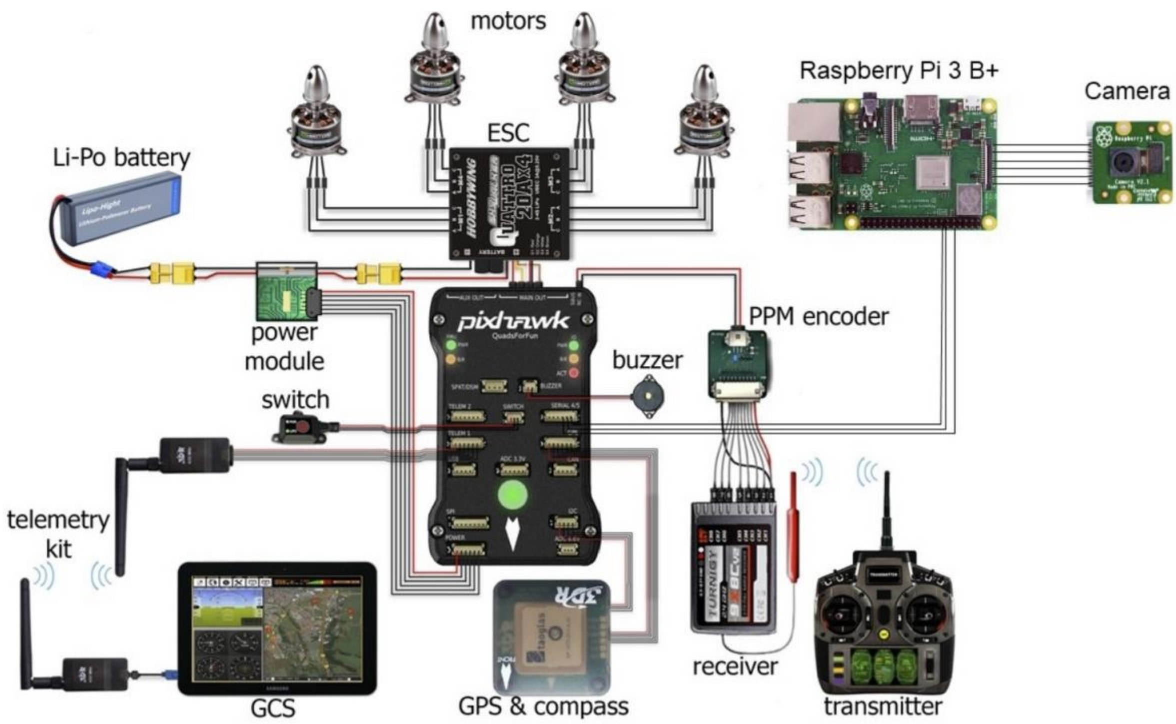

Fig. 1. Hardware for accurate landing of UAV using ground pattern recognition [11]

Precision agriculture has evolved from the mid-1980s, from the usage of the first GPS and yield maps to the most recent use of controlled traffic farming with RTK systems and UAVs (Unmanned Aerial Vehicles) loaded with GPS and cameras for crop reconnaissance [12]. In Fig.

1, hardware requirement for accurate landing of a UAV using ground pattern recognition has been demonstrated. In the literature, precision agriculture is referred to by several terminologies, including Variable Rate Treatment (VRT), Site-Specific Input Application (SSA), and Precision Farming (PF) [12]. On a worldwide scale, there has been a recent surge in enthusiasm for precision agriculture (PA) [13] as a potential strategy to tackle the substantial requirement for generating increased high-quality food and energy in a more ecologically viable manner, achieved through the optimization of external factors [7].

For increasing the effectiveness of using agricultural resources and ensuring sustainable agricultural development, precision agriculture is a contemporary approach to agricultural management and an operational technology system that utilizes mutation analysis and geographic information management [14]. Since inputs are reduced while yield is maintained or enhanced, this should have a positive influence on the environment and boost the farmers' income. Understanding the within-field spatial variation of edaphic variables and crop state is a requirement for precision agriculture [13]. Precision agriculture as a management tool comprises four components: geographical location (GPS), information collecting, decision assistance, and variable rate treatment. Yield mapping is a fifth component that allows farmers to track the actual outcomes from variable inputs [12]. There is a technical push for the deployment of specialized sensor networks that enable precise monitoring for commercial agriculture production optimization [15]. The fourth industrial revolution has been made possible by several core technologies, including agricultural robotics and automation. They are frequently seen as key tools for accomplishing the UN's Sustainable Development Goals (SDGs), which include ending hunger and poverty as well as safeguarding the environment and life on land [6]. Sensor network technologies are ushering in a new age of agricultural production operations. These devices are enhancing off-farming environment monitoring.

The results of this technology have given rise to data analytics in this agricultural setting, to help in the optimization of such agricultural operations' productivity and output [15]. Several precision farming technologies have arisen in recent years, including GPS systems, yield mapping, smart sensors, and auto-steering systems [12]. Nevertheless, until a short while ago, the application of satellite-derived information for precision agriculture was limited to the extensive surveillance and cartography of agricultural well-being due to the shortage of satellite data with both fine spatial (greater than 5 meters) and frequent temporal (daily) resolution [7]. The primary trend in precision agriculture right now is the use of robots and electric cars that are powered by renewable energy sources. They give the best tools and techniques to handle difficulties confronting the agricultural industry, such as population growth, growing fuel prices and their environmental impact, labor shortages, and climate change [6]. In modern agricultural settings, data acquired by sensor networks may be used to influence farming practices and, as a result, can be used for commercial purposes. Increased product yields and lower production costs and waste are two examples of such uses. As a result, statistical modeling faces new challenges in adapting modeling and optimization methods to these novel sensor network data outputs for use in agriculture [15]. These current developments and technology should help farmers enhance production, save fertilizers and labor time, and ultimately increase farm profitability while minimizing negative environmental impacts [12]. Optimizing growth conditions by a particular business objective, like yield maximization, is a major issue in precision agriculture commercial applications. To address this issue, a framework based on functional regression can be created for statistically modeling the output from sensor networks that provide multivariate time series data and connecting it to variations in the production process, such as crop yield [15].

Furthermore, an entirely electric and digital system needs to always be present in the agricultural field to integrate Industry 4.0 technologies like 4G/5G connections, artificial intelligence, blockchains, and the Internet of Things (IoT). Agriculture 5.0 and smart farming require solar-powered electric vehicles and robotic platforms as essential components [6]. Precision agriculture's use cases in Nepal have been an area of interest in recent literature. One of the challenges of implementing smart agricultural techniques in precision agriculture in the Nepali agricultural landscape is the scope of agricultural practices. Most of the farmers in Nepal are smallholders who are not the primary market of the companies offering precision agricultural technologies. These issues have been identified, and an IoT-based platform with a cost-effective solution for offseason grafting of citrus fruits inside a polyhouse for real-time regulation and climate monitoring has been proposed [16].

3.2. Role of Technological Intervention in Agriculture

The imperative to uphold the nation's sustainable way of life and enhance food security underscores the importance of advanced technologies that elevate productivity while minimizing food wastage [3]. Nanotechnology has the potential to open avenues for generating top-tier meals in greatly improved and practical formats, along with augmenting the bioavailability of nutrients [3]. During the span of two decades from 2000 to 2019, there has been exponential growth in research focused on the utilization of Remote Sensing (RS) in the agricultural domain [7]. Remote sensing techniques, such as unmanned aerial vehicles (UAVs) and satellite-based imagery, on the other hand, offer excellent potential for monitoring the water stress level of crops cost-effectively [17]. In recent decades, the creation and rapid growth of drones and unmanned aerial vehicles (UAVs) have ushered in a new era of remote sensing, delivering data with unparalleled geographical, spectral, and temporal precision [13]. The utilization of RS and GPS technology can be employed for tracking crop dynamics, which encompasses factors like crop yield and spatial variations [18]. It allows farmers to collect, visualize, and evaluate the well-being of both crops and soil throughout various production stages using an economical and feasible approach. It has the potential to serve as an early alert mechanism for potential issues and offer opportunities for swift issue resolution. Leveraging advancements in GPS, equipment, hardware, software, cloud computing, and IoTs, the implementation of RS technologies has become feasible on a significantly reduced scale compared to traditional field-level applications. This trend is underscored by the notable development of a diverse array of high spatial and temporal resolution satellite sensors launched into Earth's orbits since 1999 [7]. The distinctive features of sensors and their platforms, including satellite orbit positions, the alignment and orientation of Unmanned Aerial Systems (UASs), and sensor specifications, play a decisive role in defining the type of remote sensing information that holds the greatest value in aiding agricultural decision-making [7]. Extensive research has been dedicated to crop remote spectral sensing, revealing its pivotal role in sophisticated agricultural monitoring. Remote spectrum sensing in agriculture typically relates to the imagery acquired from an aerial perspective above a field, where the incoming electromagnetic radiation is primarily sunlight [19]. Several investigations have established a robust correlation between the vegetation indices obtained through remote sensing methodologies and both crop yield and biomass. Examining crop yield on a regional level utilizing lower-resolution satellite imagery can offer enhanced insights into crop canopy conditions and yield projections. Consequently, this enables informed assessments of product import and export within the region [18]. Globally, farmers are directing their attention towards embracing novel concepts and technology to amplify crop production using intensified and extended agricultural practices. Ongoing endeavors are being reinforced by the integration of nano-enhancers and precision farming techniques [3]. Emerging in this domain are refined precision spraying methods that seamlessly blend the flourishing realms of robotics, computer vision, and artificial intelligence. This harmonious integration empowers spraying technologies to discern and differentiate between crops and weeds, ensuring the precise application of chemicals at the designated plant sites [6]. As an illustration, consider the case of the Mediterranean fruit fly (Ceratitis capitata) and the Mexican fruit fly (Anastrepha ludens), both renowned as highly destructive pests causing billions of dollars in agricultural losses. These pests have been effectively managed through the application of the sterile insect technique, which has been integrated into area-wide management programs in specific regions around the world [20]. The achievement of SIT relies on the irradiation process, where technicians must determine the right duration by inspecting pupae, exposing their eyes, and matching eye color to a chart. This can be time-consuming and prone to human error due to technician skills, experience, biases in color interpretation, fatigue, sick days, and visual challenges, all impacting accuracy [20]. To address these challenges, Artificial Intelligence (AI) emerges as a solution. Mexico's Secretary of Agriculture, in partnership with artificial intelligence specialists from Universidad Veracruzana, has collaborated to create algorithm-based techniques capable of precisely assessing the age of a pupa using a standard mobile device to capture digital images [20]. An agriculture system reliant on knowledge augmentation boosts productivity, elevates quality, widens services, and decreases costs, benefiting both small- and large-scale farmers. It offers an understanding of a range of agricultural challenges, including weather prediction, crop and livestock health issues, irrigation management, and the balance of supply and demand for agricultural resources. These challenges are subsequently addressed and resolved through the provided insights [5]. In summary, controlled environment agriculture is increasingly feasible, with innovations in lighting, ventilation, robotics, and irrigation enabling the cultivation of high-value specialty crops beyond traditional fields. While fully regulated systems may be inaccessible for underdeveloped nations, semi-controlled systems offer practical alternatives [21].

3.3. Evolution of Wireless Sensor Networks and IoT

The initiation of remote sensing technology in agriculture traces back to 1972, marked by the launch of the Landsat Multispectral Scanner System (MSS) satellite [7]. In recent times, wireless technology has swiftly evolved. Emerging wireless technologies span from the basic IrDA, utilizing infrared light for short-range, point-to-point communication, to wireless personal area networks (WPAN) like Bluetooth and ZigBee, designed for short-range, point-to-multi-point communication. This spectrum extends to mid-range, multi-hop wireless local area networks (WLAN) and finally encompasses long-distance cellular phone systems such as GSM/GPRS and CDMA [22]. Modern agriculture management heavily depends on a variety of sensing technologies to provide accurate data about crops, soil, climate, and environmental factors. Virtually any sensing technique holds relevance within the agricultural and food sectors [19]. A wireless sensor network is an assembly made up of RF transceivers, sensors, microcontrollers, and power supplies. Wireless sensor networks have been developed to tackle challenges or enable functionalities beyond conventional technologies with attributes like self-organization, self-configuration, self-diagnostics, and self-repair capabilities. Upon their availability, these technologies will open doors to a myriad of innovative applications previously deemed unattainable [22]. Technological progress has substantially reduced sensor sizes, enabling their application across various aspects of human life. The significance of sensor technology has led to extensive research into numerous issues concerning sensors and their corresponding networks [1]. Coined by the British futurist Kevin Ashton in 1999, the term 'Internet of Things' (IoT) originated [10]. It functions as a system of objects that employs software intelligence, sensors, and ubiquitous Internet connectivity to accurately ascertain elements [23]. The IoT has emerged as a significant trend in upcoming technologies, with the potential to reshape various industries. It offers enhanced connectivity for end devices, systems, and services, leading to broader advantages across the entire business landscape [24]. It constitutes a fundamental element of the upcoming Internet. It blends worldwide information, internet-linked items, and entities. The primary emphasis is on automating procedures by reducing human involvement. It acquires information through sensors, evaluates this information using controllers, and accomplishes automation operations through actuators [23]. Given the extensive recognition of the IoT for its vast capabilities across various aspects of contemporary living, sensors, wireless networks, and software applications have evolved into essential and invaluable elements of modern agricultural systems [25].

3.4. Application of IoT in Agriculture

Incorporating IoT applications into agriculture can completely transform the sector by improving its efficiency, sustainability, and adaptability to changing conditions [26]. The concept of the IoT model suggests that it creates a technological environment where numerous tangible items, termed "things," like sensors, common devices, and machinery augmented by computational ability and network connectivity, will have the capacity to participate. They can function as individual entities or as a collaborative network of varied devices [10]. Agriculture is the main beneficiary of IoT as it offers effective and low-cost data-collecting options [23]. The agricultural sector harnesses various IoT applications, encompassing crop water management, pest control, precision farming, ensuring food safety, minimizing fertilizer and pesticide usage, optimizing soil health through intelligent adjustments, overseeing crop condition and post-harvest integrity, enhancing machinery productivity, real-time monitoring of livestock welfare, and tracking equipment status throughout the processing chain [27].

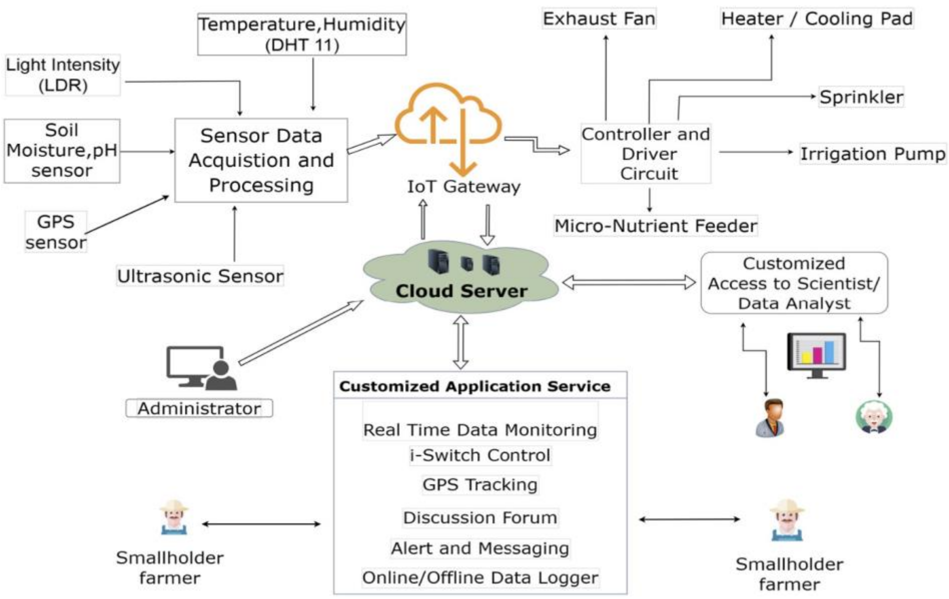

Fig. 2. Custom IoT framework for smart agriculture [16]

Cutting-edge IoT technology has addressed these challenges comprehensively, presenting remedies to enhance efficiency and reduce expenses [24]. In today's IoT smart agriculture development trend, more intelligent mobile agricultural robots are being deployed to monitor and gather crop data in the field condition [8]. By investigating many obstacles and challenges in farming, IoT has brought about a big shift in the agricultural environment [24]. An example of a custom IoT framework for smart agriculture is shown in Fig. 2. Modern IoT devices are frequently capable of conducting some amount of computation, and in some systems, a portion of the computation is handled on-premises by local servers [28]. IoT generates substantial data known as big data, marked by high volume, varying speed, and diverse types. Assessing IoT systems and their core attributes is crucial for optimal use. In agriculture IoT, sensors gather extensive environmental data, enhancing sustainability via dataset-based modeling [23]. Drawing from collected data, robust analytical instruments can furnish insights into the optimal agricultural practices essential for achieving ideal production levels and quality standards. When this data analysis is combined with information from alternate origins, it has the potential to anticipate potential risks, offer multifaceted understandings and explanations regarding occurrences, and furnish suggestions for appropriate courses of action [25]. As Tzounis et al. [10] state, IoT is built on three layers: perception (sensing), network (data transport), and application (data storage and manipulation). Jaliyagoda et al. [21] say the physical or perception layer, the network layer, the middleware layer, the service layer, and the application layer are the five key levels of agricultural IoT. The responsibility for various tasks like data collection, transfer, storage, processing, display, and related applications lies within these layers. At the bottom-most level of the system is the physical layer, which focuses mainly on data collection. This layer comprises sensor nodes, actuators, and one or more sink nodes that function as data assemblage points [21]. Initiatives involving wireless sensor networks facilitate the collection of data from sensors, transmitting it to central servers [24]. At the core of IoT's operation are embedded sensors, which have progressively shrunk in size, resulting in micro-scale sensors that can now be inconspicuously incorporated into distinctive locations [29]. Deployed throughout wireless networks, sensor nodes gauge various physical data in different monitoring zones to accomplish tasks. Crop growth is affected by factors like light, soil moisture, humidity, temperature, pH, and fertilizer use. Within the realm of agriculture, Internet of Things (IoT) technology employs sensors to amass extensive data regarding agricultural surroundings. This data is subsequently employed to recognize, scrutinize, and address patterns formulated from extensive datasets, to enhance the sustainability of agricultural output. IoT presents cost-efficient and efficient avenues for gathering data. Vital aspects such as weather patterns, water availability, soil health, and pesticide employment play significant roles. Consequently, the utilization of IoT has the potential to yield advantageous outcomes for the agricultural sector [23]. Employing technology and sensors to establish a structured operational system cannot just supplant such labor but also enhance efficiency within the realm of agriculture [8]. Multiple sensors for parameters such as humidity, light, and temperature can be found in each sensor node, along with a microprocessor, and include a wired/wireless connectivity module to enable data transfer [21]. The intricacy of the algorithms required for real-time processing of scattered data is too high to be performed directly on a low-power Wireless Sensor Network (WSN) node. Nevertheless, for the IoT, where all devices are interconnected, it becomes feasible to shift the processing burden to the cloud or distribute it among numerous interconnected devices [10]. The information extracted from data collected by sensors relates to various environmental situations, allowing thorough monitoring of the system. Nonetheless, assessing crops involves more than just environmental and production elements. An assortment of factors, encompassing field management, soil quality, crop surveillance, protection against unwanted intrusions, wildlife risks, and thefts, exert a substantial influence on agricultural yield [24]. Numerous countries and global entities have introduced a range of regulations and guidelines about IoT applications in the agricultural sector. However, despite the substantial progress achieved in the field of IoT within agriculture, a comprehensive examination focused on the context of IoT's role in agriculture is essential to fully comprehend the current state of research and its standing [30]. End users have multiple avenues to access IoT systems, either through online means via the internet or offline through local networks. The method of access varies based on the platform and software in use, potentially offering users a diverse array of user interfaces. These interfaces enable users to monitor and manage their surroundings according to their preferences [28]. These devices based on the Internet of Things (IoT) help reduce human intervention, energy usage, and expenses within the agricultural sector. Additionally, applications related to agriculture that utilize IoT have been implemented for tasks like pest management, weather observation, fertilizer control, and greenhouse oversight [23]. A fresh iteration of WSNs referred to as Wireless Sensor and Actuator Networks (WSAN) has surfaced, offering combined functionalities for sensing and control purposes [31]. Actuators are employed to react to input and regulate conditions, whereas sensors are utilized to collect information concerning physical and environmental attributes [1]. Subsequently, these signals are examined and adapted for wireless conveyance through the network to the sink node or core station, which functions as the central unit responsible for processing and managing within the WSN [25]. WSNs are commonly utilized in diverse functions associated with overseeing and regulating environmental conditions in storage and logistics setups. RFID technology is acknowledged as the primary and fundamental instance of interconnected "Objects." These RFID tags house information in the structure of the Electronic Product Code (EPC), and RFID readers initiate, read, and manage an extensive assortment of these tags. Both RFID and NFC technologies are pivotal within the agricultural domain, affording the capacity for object recognition, monitoring, and information preservation via either powered or unpowered (lacking internal power supply) tags [10]. Varied wireless technologies, specifically wireless sensors and sensor networks, possess extensive possibilities for advancement and implementation. Beginning with military and environmental surveillance, M2M technology has the eventual potential to infiltrate all dimensions of our existence [22]. Up to this day, various remote sensing systems – handheld and aerial (airplanes, satellites) - are in use, offering data collection at differing spatial, temporal, and spectral resolutions. The ideal resolution for precision agriculture varies based on factors like management goals, crop growth stages, field size, and farm equipment capabilities to adjust inputs (seeds, water, fertilizers, pesticides, etc.) [7].

3.5. Sensors and Biosensors in Agriculture

As a possible answer to various environmental and socio-demographic concerns, different data-driven technology advances are emerging in the agricultural machinery business [32]. In agriculture, digitalization is a rapidly growing trend. Digital agriculture, sometimes also referred to as "Smart Farming," is characterized by the utilization of data-driven and precise technology to assist farmers in making site-specific and real-time decision [33]. The upkeep and operation of agro-based sectors like greenhouses, floriculture, and horticulture, among others, is now easier than ever because of recent advances in information and computer technology and wireless sensor networks. Despite having a long history that goes back thousands of years, advancement has been accelerated by the adoption of various new systems, methods, technologies, and approaches across time. It employs more than one-third of the workforce worldwide [5].

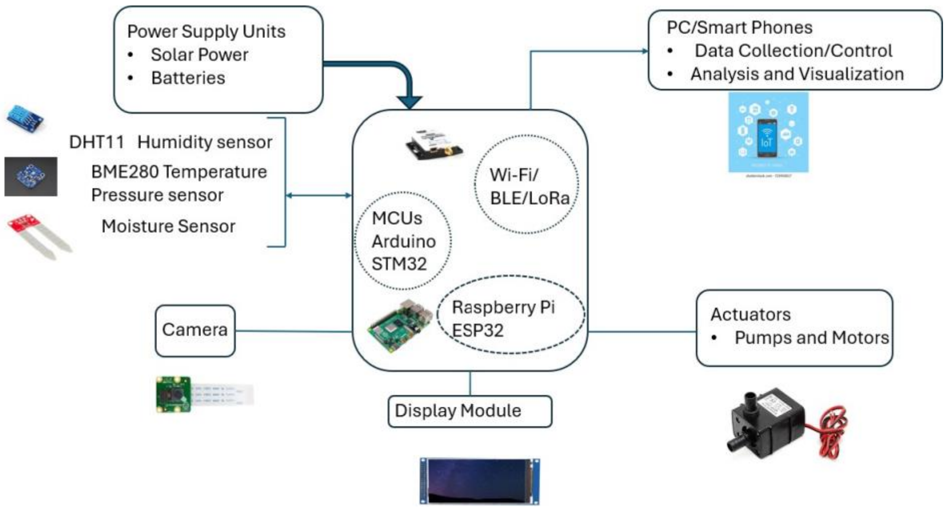

Fig. 3. IoT architecture for smart farming applications

3.6. Application of IoT in Agriculture

The hierarchically nested soil variation that occurs in space has a significant impact on the spatial patterning of soil biota, which varies from the micro-scale (mm) to the regional scale (km) [34]. At many different scales, species distribution models (SDM) provide helpful insights into the mechanisms underlying these spatial patterns. By employing a thorough selection of predictors and appropriate information, these models assist in explaining or forecasting the geographical distribution of species and their abundance [34]. TensorFlow, Google's open- source AI library, is currently being utilized in Africa to monitor agricultural disease, as AI's capacity to recognize disease from photos beats that of humans [35]. This technology is being used by a start-up in Kenya to recognize species and diseases in crop leaves using a model made up of convolutional neural networks that have been taught to test each step of the process, achieving 94% accuracy after 10 epochs, a figure that can be enhanced to more than 99% after refinement [35]. A key factor in raising agricultural output is information gathering using sensors and communication technology. Agriculture is increasingly more networked and decision-making, and the input-intensive agricultural culture has changed to a knowledge-intensive one [5]. Biosensors are currently gaining traction across all industries, from farming to dining, as one of the new and innovative trends and streams in agriculture [36]. A biosensor is defined as a small, portable analytical equipment that includes a biological or biomimicking component that is either directly coupled to or incorporated into a transducer system [37]. The biosensor definition provided by the International Union of Pure and Applied Chemistry (IUPAC) defines it as a device that uses signals such as electrical, thermal, or optical indications to identify chemical molecules. These signals are often produced by unique biochemical reactions that are aided by immune systems, tissues, organelles, or entire cells [38]. It is a completely consolidated device for material sensing and differentiation [36]. Biosensors have provided a fresh avenue for the whole agricultural community viz. farmers, scientists, and final consumers to dive into the world of precision and smart agriculture. A biosensor consists of two essential components: (1) a biomolecular recognition element (referred to as a bio-probe), responsible for identifying and interacting with the target pathogen, and (2) a transducer that generates a detectable signal because of the interaction between the bio-probe and the target analyte [19]. Frequently utilized bio-recognition systems include antibody-antigen inter-actions, enzyme-coenzyme-substrate reactions, and nucleic acids-complementary sequence binding. Furthermore, bio-recognition elements such as microorganisms, plant cells, animal cells, and tissues can also be utilized [36]. Biosensors hold vast potential in agriculture and food processing, encompassing various applications, each with distinct demands regarding analyte concentration, precision of output, sample volume, assay duration, biosensor readiness for reuse, and system cleaning prerequisites [37]. Environmentally harmful effects are becoming increasingly out of step with the slowly rising body of knowledge. Today, yield prediction is an important area of research since it serves as a point of comparison for farming operations during structuring, agrotechnological enforcement, and pre-harvest procedures [39]. The main ways that sensors are used in agriculture are in agricultural monitoring, crop data collection, and intelligent route planning. In addition to replacing this type of work, the use of IoT and sensors to create a systematic system of work can increase the effectiveness of the agricultural sector [8]. Fig. 3 depicts a typical IoT architecture employed in smart farming applications. It is possible to estimate yield using simple statistical techniques or decision-making tools that are currently in use when farm and field data are combined with pre-existing databases. It also validates the potential for the use of machine learning [39]. Utilizing the particularity and sensitivity of natural systems in compact, affordable devices like biosensor technology provides are a potent replacement for traditional analytical methods [37]. Biosensor development has gone through several phases. Initially distinct in previous generations, the transducers and the biocatalysts later became so intimately interwoven that eliminating one would impair the other's performance. There is no longer a requirement for a mediator in current biosensors. These biosensors instantly diminish the enzyme on the electrode surface [36]. In Fig. 4, a snippet of code written in the C programming language to interface a Tiva C Series T4MC123GH microcontroller with a DHT11 temperature and humidity sensor is shown.

```c
/* wait for two pulses before reading pulse stream */
    while (PE1 == 0x02);
    while (PE1 == 0);
    while (PE1 == 0x02);

            /* start reading data */
            for(d = 0; d < 5; d++){        // 5 bytes of data
            for (i = 0; i < 8; i++){   // reading each bits
                    do { timer1A_delayus(1); }
      while (PE1 == 0);
                    pulseWidth = 0;

                        do{
                                pulseWidth++;
                                timer1A_delayus(1);
                        } while (PE1 == 0x02);

                        data[d] = data[d] | (( pulseWidth > LOW_PULSE) << (7-i));
            }
      }

      for (j= 0; j < 4; j++){
            checkSum += data[j];
      }

      humid = data[0];
      temp = data[2];
```

Fig. 4. C Code to interface a microcontroller with DHT11 to read humidity and temperature data

3.7. Machine Learning and Its Application in Agriculture

Machine learning (ML) describes a system's ability to learn from a data set and get better over time instead of being specifically programmed. ML is a kind of artificial intelligence that enables machines to gain knowledge through experience [40]. It possesses the ability to manage a variety of factors and variables in perpetuity of space and time [39]. Crop prediction can be done using a variety of algorithms designed for machine learning, including mathematical and statistical methods [41]. Big databases developed with the use of precise management devices and data-gathering skills can be primarily utilized for information on weather, technology, or soil, along with traits of multiple species of plants [39]. Currently, machine learning models are being created to handle the varied and complex types of data found in practical uses [42]. Machine learning algorithms are categorized broadly into two types [40], which are presented in Table 1.

Table 1. Comparison of Supervised and Unsupervised MLAs

Supervised MLAs	Unsupervised MLAs
It involves using a predefined collection of data with clear labels to teach a model how to anticipate the desired outcome for new, unseen data [40].	It refers to feeding a program a significantly large volume of data, which will then autonomously uncover patterns and correlations within the data [41].
It creates a function that connects inputs to the intended outcomes [43].	Algorithms autonomously uncover data patterns. It grasps key data features, using them to classify new data [44].
In the supervised model, the categories are pre-established and formed as a finite collection through human definition. In practice, this results in specific data segments being assigned to these labels [45].	In unsupervised, there are no categories, and the primary task involves spontaneously creating these labels [45]
It frequently employs methods for both grouping and regression tasks [40].	Its primary function revolves around data clustering and diminishing feature count [44].
Some examples are Naïve Bayes, Artificial Neural Networks, Decision Trees, Bayesian Networks, Support Vector Machines, Random Forest, and so on [43].	Examples include K-means clustering, principal component analysis, K-nearest neighbor, self- organizing map, hierarchical clustering, and so on [41].

Machine Learning has found diverse applications within the agricultural domain revolutionizing the way farming operations are conducted and optimizing productivity. The data on prices and arrivals enhance farmers' negotiation stance and foster rivalry among traders. With price information, farmers can adeptly shift between neighboring markets, securing favorable prices for their goods. This information aids in strategic marketing decisions and should lessen irregular price fluctuations by facilitating widespread temporal and spatial exploitation [46]. The infusion of technology has converted agriculture into a sustainable enterprise. This conserves the farmer's funds and eradicates the intermediary who purchases from farmers at minimal rates and sells to final customers at elevated prices. Contemporary uses of computational intelligence methods furnish answers to location-targeted decision-formulating challenges within agricultural systems [42]. The inherent statistical properties of these algorithms can result in a notable yield enhancement. A considerable precision metric is sought after, given that the repercussions of its absence would be substantial, encompassing seed wastage, time loss, and a sharp decline in productivity. An array of diverse predictors can be employed for suggestions, including temperature, soil characteristics, humidity, and so on [47]. Some notable applications of machine learning algorithms in agriculture include:

1. Disease detection and diagnosis: Plantix, a mobile app, employs Machine learning to diagnose crop diseases based on images of plant leaves. Farmers can take photos of their crops and receive instant diagnoses, along with recommendations for treatment [27]. PDDApp, an app that provides users with the facility to submit images and textual explanations of afflicted plants via the online platform, receive a diagnosis for the ailment, explore disease explanations and collections of affected plants, validate the accurate identification of the specified disease, and the effectiveness of the recommended treatment [48].
2. Pest Management: The "Rice Doctor" by IRRI is an app designed to aid in identifying insect pests and diseases, empowering farmers to promptly enhance their pest management strategies. Machine learning algorithms can be trained to recognize symptoms of plant diseases based on images of leaves or other plant parts. This helps in early disease detection, allowing farmers to take timely action to prevent the spread of diseases and minimize crop losses.
3. Yield projection: Machine learning models can analyze historical data on soil quality, weather, agricultural productivity, and other topics. These models can precisely forecast agricultural yields by spotting trends and correlations, empowering farmers to decide wisely when to sow, harvest, and distribute resources [49]. Utilizing cloud-connected IOT technology enhances effectiveness across various factors such as soil conditions, water levels, fertilization, and pest control. This approach ensures precise acquisition of weather data, minimizing crop harm, providing timely outcomes, enhancing crop quality, diminishing labor expenses, and boosting agricultural yields [50].
4. Automated Harvesting: Robotics startup Agrobot has developed robots equipped with cameras and sensors that use machine learning to identify ripe fruits and vegetables. These robots can autonomously harvest crops, reducing labor costs and minimizing damage to produce [51]. A crop can be produced in a farm plot more effectively with the use of cloud-based agriculture, which can also evaluate and archive information for later use [50].
5. Pest Monitoring: Utilizing image processing via Raspberry Pi, the robot assesses plant health by observing the color of various plant parts. Subsequently, the LCD showcases the plant's condition based on this analysis [27].
6. Weed control: Blue River Technology, now part of John Deere, has developed a machine learning-powered device called "See & Spray." It uses computer vision to distinguish between crops and weeds, targeting only the weeds with herbicide, thus reducing chemical usage [29].
7. Market Insights: Gro Intelligence is a platform that employs machine learning to analyze vast amounts of agricultural data, including weather patterns, trade data, and supply chain information. This data-driven approach provides farmers and traders with insights into market trends and global supply-demand dynamics [26].

8. Livestock Monitoring: CowAlert, Cowlar, a smart collar for dairy cows, employs machine learning to track the animals' behavior and health. By analyzing data such as activity levels and rumination patterns, farmers can identify when a cow is in distress or heat, allowing for timely intervention [52].

9. Soil Fertility Management: CropX offers a soil sensor system that uses machine learning to analyze soil data, including moisture and temperature levels. By interpreting this data, farmers receive recommendations for irrigation and fertilization schedules tailored to their specific fields [30].

10. Aquaculture Monitoring: XpertSea employs machine learning to analyze images of aquatic organisms in fish farms. This technology helps aquaculturists monitor the health and growth of their fish, optimizing feeding schedules and ensuring optimal conditions [53].

11. Climate-Resilient Farming: IBM's Hello Tractor is a freely available mobile platform that empowers farmers to acquire tractor services whenever they require them. Innovations of this kind will offer the means for agriculturists who lack the means to purchase such machinery to more promptly and economically respond to the unpredictability engendered by shifts in climate conditions [35]. These examples illustrate the practical and diverse applications of machine learning in agriculture, enhancing efficiency, sustainability, and profitability across various aspects of farming and agribusiness.

Various machine learning techniques have been used in studies like anomaly detection and accurate yield estimation in Nepal. Wheat yield in Nepal is estimated using Sentinel-3 SLTR, soil, and topographic data, and the performance of Gradient Boosting Machine (GBM) and XGBoost models are compared [54]. Paddy productivity in Nepal's Kanchanpur district was studied using data collected from an expert-designed questionnaire and four machine learning models were compared where Decision Tree (SimpleCart) algorithm achieved the highest accuracy at 80.19% [55]. Random Forest models were used in the study of Nepal's Eastern Indo-Gangetic Plains to optimize nutrient management and predict yield variability in cereal crops [56]. These tools improve nutrient management and productivity by offering scalable solutions for smallholder farmers. Likewise, the Random Forest classifier was used to detect land use and land cover (LULC) changes in Nepal's Chure region of Sarlahi district. This study identified a 16% increase in forest cover, improved agricultural land use, and high classification accuracy for sustainable land management [57].

3.8. ICT and Agriculture in Nepal

Combining information and communication technologies (ICT) not only makes farmers more inventive but also enhances their capabilities, leading to a reduction in risks and uncertainties associated with agriculture. This technological empowerment provides farmers with tools and resources to navigate challenges effectively. In this context, mobile applications emerge as valuable assets, playing a pivotal role in the transfer of technology. These applications offer a cost-effective means of providing farmers with essential information and addressing field-specific problems. Through the utilization of mobile technology, farmers can access innovative solutions, fostering a more resilient and efficient agricultural sector [58]. As a nation heavily reliant on agriculture, Nepal needs to prioritize the improvement of its agro-advisory services to foster agricultural development. The conventional approaches to extending advisory services have proven to be inadequate. In light of this, the adoption of Information and Communication Technology (ICT) for agro-advisory services presents itself as a promising and practical alternative [59]. Through the use of Information and Communication Technology (ICT), farmers have access to market information, aiding them in making informed decisions and addressing technical challenges. In Nepal, the integration of ICT has positively impacted agricultural development, particularly benefiting marginal farmers. Mass communication tools such as television have effectively reached and educated farmers, facilitating the transfer of technology [60]. Additionally, the widespread adoption of mobile phones in Nepal, with over 41.1 million users in September 2019, and a 79% internet penetration rate, has created opportunities for enhanced connectivity. Nepal aims to connect 90% of its population to broadband services by the end of 2020, potentially bridging the gap between extension agencies and farmers if the increased internet accessibility is utilized effectively [61].

In Nepal, Information and Communication Technology (ICT) initiatives in agro-advisory services encompass various approaches. These include telecommunication initiatives such as farmer call centers, media initiatives like Krishi Samachar, and agricultural programs on television and FM radios disseminating information on current issues and agricultural technologies. Additionally, printed media such as Krishi Diary, bimonthly magazines, booklets, and pamphlets, including features like Krishak Pana in national magazines like Kantipur, contribute to agricultural awareness. Furthermore, internet-based initiatives like Smart Krishi, IBA Krishi, mobile applications, and other online portals from the Department of Agriculture (DoA) and the Agricultural Information and Communication Center (AICC) play a crucial role in providing agriculture-related information [62]. The most famous application, among others is Smart Krishi which is also used in India. The primary objective of Smart Krishi is to uphold the essence of farming, unite diverse regions, and foster agricultural advancement. It motivates young individuals to engage in agriculture, focusing notably on organic and lucrative farming practices. This initiative considers the well-being and prosperity of both humanity and nature, fostering a harmonious coexistence [27]. We have presented some of the mobile applications used in Nepal in Table 2.

Table 2. Some of the mobile applications famous in Nepal

S.N.	Application Name	Features	References
1	Smart Krishi	Agricultural practices package, farming updates, written materials and e-books, weather information, online queries to experts	[58]
2	Krishi Guru	Agricultural guidance, meteorological updates, comprehensive practices, farming news, expert consultations, agricultural text messages	[60]
3	NARC Krishi	Agricultural methodologies	[61]
4	Bakhra Gyan	Web application compiling extensive veterinary data on goat farming in Nepal; offers a platform for farmers to access authentic information and facilitates communication between farmers and experts	[63]
5	Krishi Kapurkot	Crop cultivation guidelines, written materials, notifications, meteorological updates	[61]
6	Mobile Krishi	Agricultural updates, weather information	[61]

With the expansion of internet infrastructure and readily available smartphones, Nepali farmers are exploring new avenues using IoT to monitor crops, gather data and use it to optimize farm practices. Authors examined the impact of sensors and IoT solutions currently used by different farmers across Nepal and discussed the correlation between weather data of the Kathmandu valley during November to January and the data collected through IoT-based solutions using apps and data visualization techniques [64]. To aid agriculture decision-making with regional parameters and diverse geography, an Internet of Things-based Distributed Agricultural Decision Support System (ID-ADSS) is proposed [65]. The feasibility of the proposed framework is demonstrated using a LoraWAN-based infrastructure with a dataset of soil characteristics like texture, pH, mottles, etc. An IoT-based system with sensor nodes consisting of an assortment of environmental monitoring sensors like LM35(temperature), DHT11(humidity), VH400(soil moisture) and Arduino and Node MCU for interfacing sensors and transmitting data has been implemented in white button mushroom farming—a widely cultivated crop across Nepal [66]. A consumer-grade red-green-blue (RGB) camera-mounted drone was used in a study of height of the wheat plants with above-ground biomass and crop yield [67]. This type of study with readily available setup for crops monitoring is paramount in analyzing and mapping the crops for smallholder farmers in Nepal to effectively treat areas of disease-affected/underdeveloped plants. A digital camera mounted on a UAV was used to analyze the soil erosion control of traditional rain-fed agricultural terraces in the middle mountain region of Nepal [68].

3.9. Agriculture 4.0

The evolution of industries' competitiveness in the recent industrial revolution, marked by the digital transformation of manufacturing referred to as Industry 4.0, is propelled by a suite of emerging and groundbreaking technologies [69]. The rise of digitization paved the way for the integration of Industry 4.0 principles into agriculture, leading to the emergence of Agriculture 4.0. Aligned with the principles of Industry 4.0 initiated by the German Government in 2011, Agriculture 4.0 aims to establish a highly adaptable production framework for digital and customized goods and services. This framework is characterized by real-time interactions among individuals, products, and devices throughout the production process [70]. These innovative technologies are reshaping the agricultural land- scape, giving rise to a distinctive and forward-looking area of research. Consequently, digital agriculture, or Agriculture 4.0, encompasses the integration of contemporary technologies, including the Internet of Things, extensive data analysis, cloud computing, advanced robotics, and artificial intelligence, within the production processes of agribusiness [71]. The emergence of the fourth industrial revolution became apparent in the early 2010s, integrating advancements from Industry 4.0, sensors, robotics, and artificial intelligence, particularly machine learning techniques, for advanced data analysis. In tandem with the connections linking mobile devices and various platforms, Agriculture 4.0 produces and oversees a substantial volume of data, forming the foundation for informed decision-making [70]. Beyond directly applying state-of-the-art technologies, the main challenge confronting agriculture.

4.0 in its pursuit of sustainable development lies in its capacity to deliver dynamically integrated PF systems that (a) perform advanced and cost-effective automated agricultural tasks, such as cultivation and irrigation, (b) establish safer and more efficient working environments benefiting both the surroundings and involved parties (including farmers, agricultural engineers, policymakers, development cooperation experts, etc.), and (c) foster enhanced collaborations among all stakeholders, enabling them to make informed decisions even in areas traditionally beyond their spheres of expertise [72]. A prevailing belief suggests that Agriculture 4.0 holds the promise of substantial worldwide improvements, including increased productivity and efficiency in agricultural and food systems, improved aspects such as quantity, quality, and availability of agricultural products, adaptation to challenges posed by climate change, reduction of food loss and wastage, judicious use of natural resources in an ecologically sustainable manner, and, consequently, mitigating environmental repercussions in the years to come [70]. Many research initiatives emphasize the potential offered by Agriculture 4.0, such as improvements in strategic management and regulation achieved by intelligently utilizing data gathered through advanced technologies incorporated into tractors, mobile ground robots, UAVs and satellites, and promoting sustainable development [73]. With the capacity to improve the scale, efficiency, and effectiveness of agricultural production, digital technologies are positioned as innovative strategic solutions to promote agricultural growth. The United Nations Food and Agriculture Organization (FAO) identifies this transformative role as the "Digital Agricultural Revolution", while other sources term it Agriculture 4.0 [70].

4. Conclusion

The agricultural and food sector has undergone an intense transformation driven by technological advancements such as precision agriculture, the Internet of Things (IoT), machine learning algorithms, and Agriculture 4.0. Given the growing need for food, climate change, and finite resources, these developments present answers to these major problems. The main advancements are IoT systems for automated farm management, machine learning for yield prediction and disease diagnosis, and sensors for real-time monitoring. These technologies can boost output and encourage sustainable farming methods. However, adoption trends across the regions vary. Developing nations such as Nepal have been emphasizing the use of ICT to enhance agricultural extension services. This review sheds light in the current state of application of innovative ICT-enabled technology in the Nepali agricultural landscape. As agriculture develops, it is imperative to guarantee that technical innovations are available and advantageous in a variety of socioeconomic settings. Recommendations for future development include prioritizing user-friendly, cost-effective technologies for small-scale farmers; developing tailored solutions for diverse agricultural environments; investing in digital literacy programs; encouraging public-private partnerships; integrating traditional farming knowledge with modern technologies; and establishing robust data privacy measures. If these issues are resolved wisely, the agricultural technology revolution can benefit farmers at all operating scales by tackling these issues and resulting in more productive, efficient, and environmentally friendly farming systems globally.

Abbreviations

IoT	Internet of Things
GPS	Global Positioning Systems
ICT	Information and Communication Technology
kCal	Kilo Calories
AI	Artificial Intelligence
PA	Precision Agriculture
UAV	Unmanned Arial Vehicle
VRT	Variable Rate Treatment
IRRI	International Rice Research Institute
NARC	Nepal Agricultural Research Council
SSA	Site-Specific Input Application
PF	Precision Farming
SDG	Sustainable Development Goals
UAS	Unmanned Arial Systems
WPAN	Wireless Local Area Network
WSN	Wireless Sensor Network
EPC	Electronic Product Code
SDM	Species Distribution Models
IUPAC	International Union of Pure and Applied Chemistry
MLA	Machine Learning Algorithms
LCD	Liquid Crysal Display
GBM	Gradient Boosting Machine

LULC	Land use and Land Cover
DoA	Department of Agriculture
AICC	Agricultural Information and Communication Center
ID-ADSS	Internet of Things-based Distributed Agricultural Decision Support System

Data Availability Statement

Data will be made available on request.

CRediT Authorship Contribution Statement

Aarju Aryal: Conceptualization, Resources, Writing-original draft. **Yogesh Sapkota**: Resources, Visualization, Writing – review and editing. **Bishal Lamichhane**: Writing – review and editing. **Jiban Shrestha**: Supervision, Writing – review and editing.

Declaration of Competing Interest

The authors of this manuscript declare no conflict of interest or competing interest.

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