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REVOLUTIONIZING AGRICULTURE: THE DIGITAL TRANSFORMATION OF FARMING

TEC 31228:2024

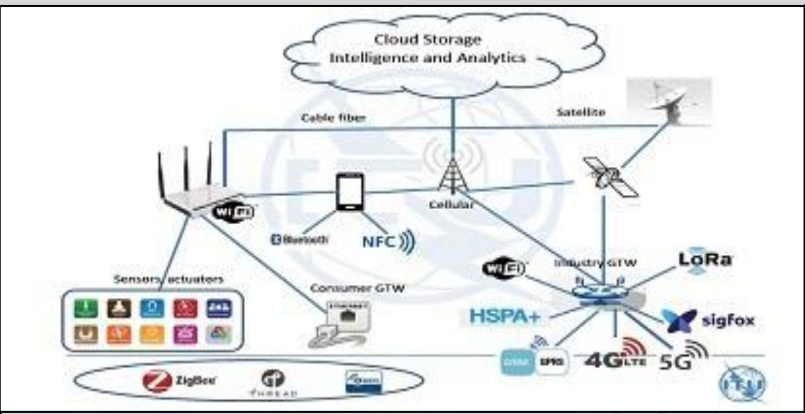
A JOINT TECHNICAL REPORT

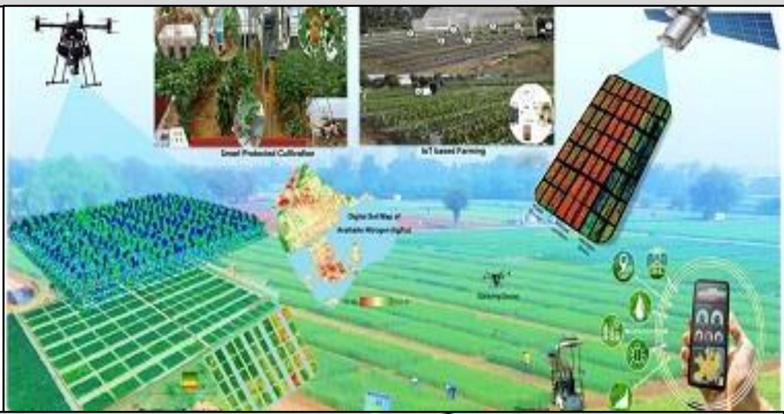
by

TELECOMMUNICATION ENGINEERNING CENTRE

&

INDIAN COUNCIL OF AGRICULTURAL RESEARCH





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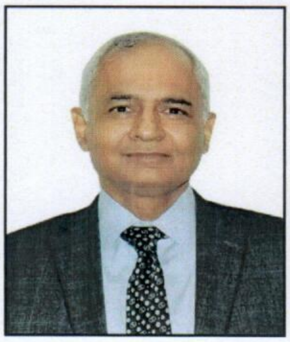

Message

I am delighted that Telecommunication Engineering Centre (TEC) and Indian Council of Agricultural Research (ICAR) have collaborated to prepare a Technical Report on ***Revolutionizing Agriculture: The Digital Transformation of Farming,*** which will be useful as a reference document for agricultural scientists, academia, startups and other related stakeholders.

The integration of smart technologies into agriculture has revolutionized traditional farming methods, harnessing the capabilities of cutting-edge technologies like the Internet of Things (IoT), Artificial Intelligence (AI)/Machine Learning (ML) and precision farming techniques. This paradigm shift holds immense potential to promote the adoption of sustainable agricultural practices, offering substantial opportunities to bolster productivity and profitability across the agricultural value chain.

The convergence of digital technologies and agriculture not only promises enhanced productivity and profitability but also addresses crucial challenges such as climate change, resource scarcity and the escalating demand for food. Digital agriculture will enable a comprehensive approach to sustainable food production.

In addition to discussing various cellular & non-cellular communication technologies and emerging technologies such as IoT and AI/ML, the report also highlights various ML algorithms commonly used in predicting crop traits, deep learning models for yield prediction, pest and diseases detection, weed detection, soil health management, crop quality management, smart irrigation and livestock management. Furthermore, it delves into the applications of big data analytics, hyperspectral data, blockchain, precision farming techniques and standards used in agriculture.

I extend my heartfelt appreciation to the Telecommunication Engineering Centre and the Indian Council of Agricultural Research for their diligent efforts in producing this report. I wish them continued success in their future endeavors.

New Delhi
12th March, 2024

(Neeraj Mittal)

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Message

I am genuinely pleased to learn about the Technical report on **"Revolutionizing Agriculture: The Digital Transformation of Farming"** which has been prepared after rigorous and collaborative efforts of Telecommunication Engineering Centre (TEC), Department of Telecommunication, Government of India and Indian Council of Agricultural Research (ICAR), Department of Agriculture Research and Education, Ministry of Agriculture and Farmers Welfare, Government of India. This monumental work represents a concerted effort among experts in this field, offering a comprehensive exploration of profound changes occurring in agriculture due to digital innovation.

In this report, we find a wealth of insights into the latest advancements in precision farming, data analytics, and technological integration, reshaping the agricultural landscape. This cover, from adoption of IoT devices to the implementation of AI algorithms. This report not only highlights the remarkable progress made in this field, but also addresses the challenges and opportunities that lie ahead. It serves as a roadmap for stakeholders across the agricultural sector, guiding decision-makers for harnessing the power of technology to drive sustainability, efficiency, and resilience in food production.

I whole heartedly extend my appreciation to the team from TEC and ICAR who have lent their expertise and dedication in bringing out with this report. I also congratulate them for organizing ITU/FAO Workshop on **"Cultivating Tomorrow Advancing digital agriculture through IoT and AI"** scheduled during March 18-19, 2024 at NASC Complex, ICAR New Delhi. As we celebrate this outcome, let us remain steadfast in our dedication to innovation and progress. Let us continue to pioneer solutions that empower farmers, strengthen communities, and safeguard our food systems. My best wishes for successfully organizing this event.

11th March, 2024
New Delhi

(Himanshu Pathak)

Telecommunication Standardization Bureau

Geneva, 12 March 2024

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Our planet is expected to host 9.7 billion people by 2050. Sustaining so many lives will demand significant technological progress. Advances in artificial intelligence (AI) and the Internet of Things (IoT) will form a key part of this progress.

ITU is committed to ensuring that the associated benefits are felt by everyone around the world. We share this commitment with the UN Food and Agricultural Organization. Together we support a focus group on AI and IoT for digital agriculture working towards new ITU standards.

New technologies are introducing compelling opportunities to improve the precision and sustainability of farming techniques and create very meaningful improvements to the quality of life enjoyed by millions of people around the world.

I am delighted that the Telecommunication Engineering Centre and Indian Council of Agricultural Research have prepared this Technical Report on Revolutionizing Agriculture: The Digital Transformation of Farming. Many of the contributors to this report are also contributors to our focus group.

This technical report focuses on how digital agriculture integrates various technologies in areas like precision farming, drones, and data analytics to optimize agricultural production.

The future of agriculture looks brighter every day. Let's ensure that we take full advantage of innovations for digital agriculture by building consensus on the necessary international standards.

Seizo Onoe
Director of the Telecommunication
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Message

I am happy to note that Telecommunication Engineering Centre (TEC) and Indian Council of Agricultural Research (ICAR) are jointly bringing out a Technical Report on ***Revolutionizing Agriculture: The Digital Transformation of Farming***.

Traditional farming methods are increasingly facing limitations in meeting the demands of a growing population amidst changing environmental conditions. Conventional agriculture often relies on intuition and historical practices rather than data-driven decision-making, leading to inefficiencies in resource utilization and productivity. Moreover, factors such as unpredictable weather patterns, soil degradation and water scarcity further exacerbate the challenges faced by farmers.

In response to these challenges, the concept of Digital Agriculture has emerged as a promising solution by leveraging cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI)/ Machine learning and precision farming techniques.

I am delighted to share that this technical report has elaborated the emerging technologies, standards and IoT use cases in smart agriculture. This document is good reference for agricultural scientists, academia, startups and other related stakeholders as it gives the meaningful insights of latest technologies being used in agricultural domain for improving the productivity amid growing demand for food.

I appreciate the efforts put in by Telecommunication Engineering Centre and Indian Council of Agricultural Research in bringing out this report. I also congratulate IoT division, TEC for all their hard work and best wishes for the future.

(Ajay Kumar Sahu)

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Foreword

TEC is the National Standardization Body (NSB) for telecommunication in India and the national enquiry point for WTO-TBT (Technical Barrier to Trade) for telecom sector. TEC has also been mandated to interact with various international standardization bodies like ITU, APT, ETSI, IEEE, oneM2M, 3GPP etc. for standardization works.

TEC takes up development of standards based on study, continuous participation/ submitting contributions in the meetings of standardization bodies and interaction with stakeholders. The oneM2M Release 2 and Release 3 specifications have been adopted as National Standards by TEC.

TEC has released twenty-two Technical Reports in IoT/M2M domain covering various verticals viz. Automotive, Power, Health, Safety & Surveillance, Smart Homes, Smart Cities, Smart village, Intelligent Transport System ,Smart Agriculture, in the horizontal layer – M2M Gateway & Architecture, Communication Technologies, EMF radiation from IoT/M2M devices, IoT Security etc. All the technical reports are available on TEC website (https://tec.gov.in/M2M-IoT-technical-reports). Important actionable points emerged from these reports are being used in the development of standards / policies; enabling the proliferation of IoT ecosystem in the country.

TEC is the nodal authority for Mandatory Testing and Certification of Telecommunication Equipment and ensures testing as per the Essential Requirements formulated for various telecom products viz, Smart Electricity meter, IoT Gateway, Tracking device etc.

IoT/ M2M , one of the most emerging technologies is transforming the way producers cultivate, harvest and distribute agricultural commodities. The use of technology in Indian agriculture, has accelerated agricultural and rural development by adopting innovative ways to improve the existing information and communication processes. By harnessing the power of technology, farmers can mitigate risks, improve productivity, and ensure food security for future generations while minimizing the environmental footprint of agricultural practices.

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Traditional agriculture has limited capability to meet the growing demands of a rapidly changing world, necessitating the adoption of more modern and sustainable farming approaches. Smart agriculture represents a transformative shift towards a more sustainable and efficient food production system. As digitization of agriculture continues to evolve with technologies like IoT, Artificial Intelligence, robotics, UAVs etc., it holds the potential to revolutionize the way we produce, distribute, and consume food, paving the way for a more resilient and sustainable future.

I am delighted to share that, Telecommunication Engineering Centre (TEC) and Indian Council of Agricultural Research (ICAR) have worked jointly to prepare a Technical Report on *'Revolutionizing Agriculture: The Digital Transformation of Farming'*. This Technical Report explores concepts of the emerging technologies being used in agriculture. It explains in brief various types of communication technologies, used in M2M/ IoT domain depending upon the coverage, power, specific use-case requirement etc. It also covers concepts of Artificial Intelligence (AI)/ Machine Learning (ML), Big data analytics, Blockchain, Digital twin and Metaverse; components of digital agriculture such as precision agriculture, agriculture robotics, Remote Sensing and Satellite, drones/ UAV; and their applications in agriculture. The report also has a compilation of various use cases on Digital Agriculture.

This technical report is expected to provide guidance to agricultural scientists, academia, startups and all concerned stakeholders.

I appreciate the efforts put in by officers of IoT division, TEC and ICAR in bringing out this report. I wish them success in all their future endeavors.

Saxena

(Ms. Tripti Saxena)

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Executive Summary

Agriculture, with its allied sectors, is the largest source of livelihoods in India. Agriculture employs more than 50% of the Indian workforce and contributes approx. 20% to the country's GDP. India ranks first in the production of milk, jute and pulses, and is placed second in producing wheat, rice, groundnut, vegetables, fruits, cotton and sugarcane. India is also among the leading producers of fish, livestock, poultry, spices and plantation crops[1]. However, due to small landholdings, farmers' incomes are definitely not sufficient.

The agricultural domain is also facing numerous challenges related to increase in productivity, climate change, crop health monitoring, and water management, as well as optimal use of fertilizers. To address these challenges, IoT technology and AI/ML is opening up new promising technological paths and pushing the future of agriculture to the next level. The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) can significantly revolutionize agricultural sector, offering a multitude of benefits that enhance efficiency, sustainability, and productivity. Precision agriculture can optimize various aspects of farming operations with use of IoT and AI-driven analytics. Real-time monitoring of soil conditions, crop health and weather forecast enables farmers to make informed decisions, enhancing crop yield with efficient utilization of resources. AI/ML can also be used in yield prediction, pest and diseases detection, weed detection, livestock management etc. Thus, Digital Technologies in agriculture can play important role in increasing the overall efficiency of the agricultural production processes as well as the entire value chain.

This Technical Report explores concept of the emerging technologies being used in agriculture. IoT/M2M communications has been explained in Section 1. Various types of communication technologies used in M2M/ IoT domain depending upon the coverage, power, specific use-case requirement etc. are covered in Section 2. Concepts of Artificial Intelligence (AI)/Machine Learning (ML), Big data analytics and Block chain have been elaborated in Section 3. Components of digital agriculture such as precision agriculture, agriculture robotics, Remote Sensing and Satellite, drones/ UAV, Cyber Agrophysical System, Digital Twin and Metaverse in agriculture have been explained in Section 4. Standardization activities in agriculture domain are mentioned in Section 5. TEC /DoT initiatives in M2M/ IoT domain are mentioned in Section 6. Recommendations are mentioned in Section 7. Few diverse Use Cases in Digital Agriculture are elaborated in Section 9 of this report.

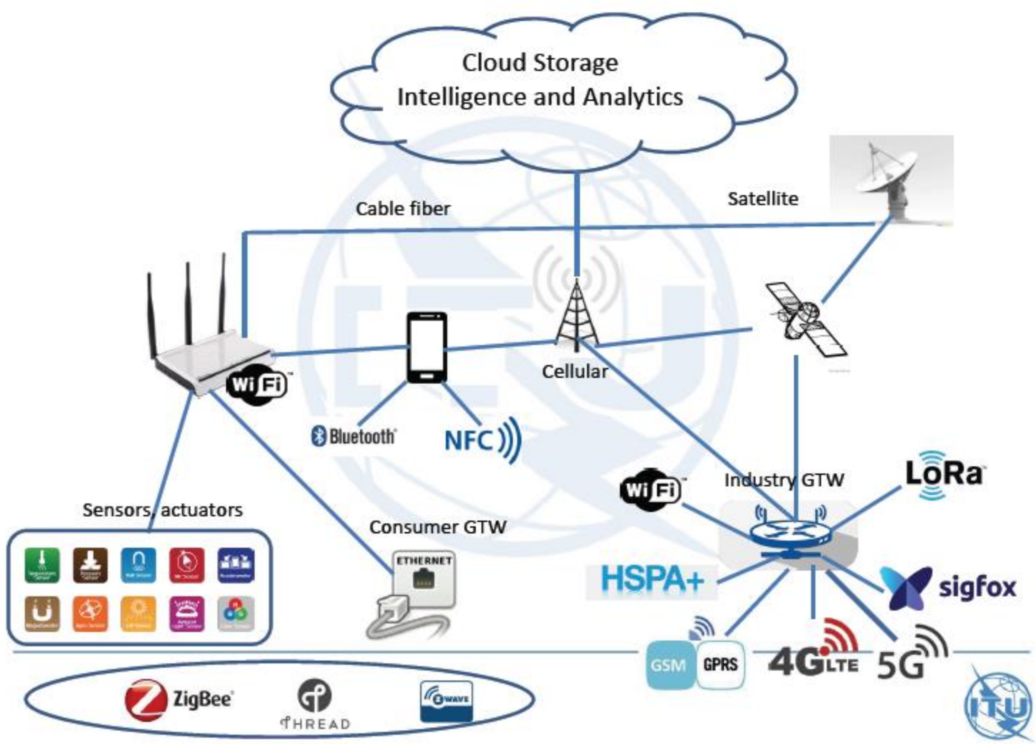
[1] https://www.fao.org/india/fao-in-india/india-at-a-glance/en/

1. Introduction to IoT and M2M

1.1. Internet of Things

The Internet of Things (IoT) is defined as the network of physical objects or things, embedded with sensors, software, and other technologies that connect and exchange data with various devices and systems over the internet or other communication networks. The primary goal of the Internet of Things is to enhance efficiency, automate processes and enable new applications and services by connecting the physical world to the digital world. An IoT system collects data from sensors installed in IoT devices and transfers that data through an IoT gateway for it to be analyzed by an application or back-end system to take informed decisions.

International Telecommunication Union (ITU) has defined IoT as “A global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies” [ITU-T Y.2060 (06/2012)].



（Source：Adapted from ITU）
Figure 1: IoT Architecture

IoT gets benefitted by a number of other technologies such as Machine-to-Machine (M2M) communication, Artificial Intelligence (AI), Machine Learning (ML), Big Data, Cloud/Edge Computing, Cellular & Non-cellular communication technologies. Research and development in these technologies will further help in creating smart infrastructure in various verticals and in turn improving the quality of life of citizens.

1.2. Machine to Machine (M2M) Communication

Machine-to-Machine (M2M) communication refers to the direct communication between devices or machines without human intervention. This type of communication enables devices to exchange information and perform actions based on the exchanged data. M2M communication can include industrial instrumentation, enabling a sensor or meter to communicate the information it records (such as temperature, inventory level, etc.) through a network (wireless, wired or hybrid) to application software that translates the captured event into meaningful information.

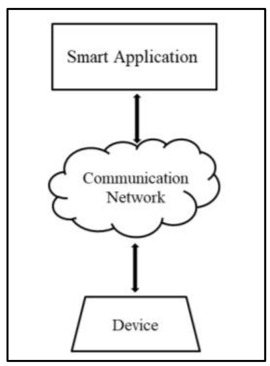


Figure 2: Machine to Machine (M2M) Communication

1.3. IoT Solutions in Various Verticals

IoT based solutions are being used in various verticals as summarized below:

1. **Agriculture:** Smart Irrigation, Weather Monitoring and Forecasting, Precision Agriculture, Remote Crop Monitoring, Remote Monitoring of Soil Health, Smart Warehousing, Smart Pest Control, Smart Greenhouse, Logistics and Distribution.
    a. **Aquaculture:** Precision Fishing, Water Quality Monitoring, Automated Feeding Systems, Environmental Conditions Monitoring, Disease Detection and Prevention.
    b. **Livestock Farming:** Animal Production, Animal Tracking and Geo-fencing, Livestock Remote Health Monitoring and early detection of illness.

c. **Sericulture:** Smart Silkworm Rearing, Automated Feeding Systems, Remote Monitoring.
d. **Viticulture:** Vineyard Monitoring, Crop Health Monitoring, Grape Quality Assessment, Smart Pest Management.

2. **Automotive/Intelligent Transport System:** Vehicle Tracking, Emergency Call System (e-call : 112 adopted in India), Cellular V2X Applications, Traffic Monitoring and Control, Navigation, Infotainment, Fleet Management, Asset Tracking and Logistics, Smart Parking, Connected Car, Advanced Driver Assistance Systems (ADAS).
3. **Education:** Tele-education, Attendance Tracking, Smart classrooms, Smart Libraries.
4. **Energy:** Renewal energy sources like Solar, Biomass connecting to Smart Micro Grid, Smart Distribution Network, Smart Metering, Smart Grid, Smart Street Lighting.
5. **Health Care:** Remote Diagnostics, Remote Monitoring of Patient, Medication Reminders, Tele-medicine, Wearable Health Devices, e-ICU based Applications, Remote Surgery, Smart Ambulances.
6. **Safety & Surveillance:** Commercial and Home Security Monitoring, Surveillance Applications, Video Analytics and Sending Alerts, Fire Alarm, Police/Medical Alert.
7. **Smart City:** Intelligent Transport System, Waste Management, Street Light Control System, Water Distribution and Management, Smart Parking, Intelligent Buildings, Safety & Security, Environmental Monitoring.
8. **Smart Home:** Security and Surveillance, Connected Appliances, Smart Lighting System, Home Automation.
9. **Smart Manufacturing (Industry 4.0):** Predictive Maintenance of Machines, Shop Floor Remote Monitoring and Control, Industry Automation, Digital Twins, Smart Inventory Management, Worker Safety.
10. **Utilities:** Smart Metering (Electricity /Water /Gas), Electric Line Monitoring, Gas /Oil /Water Pipeline Monitoring, Sewage Monitoring.

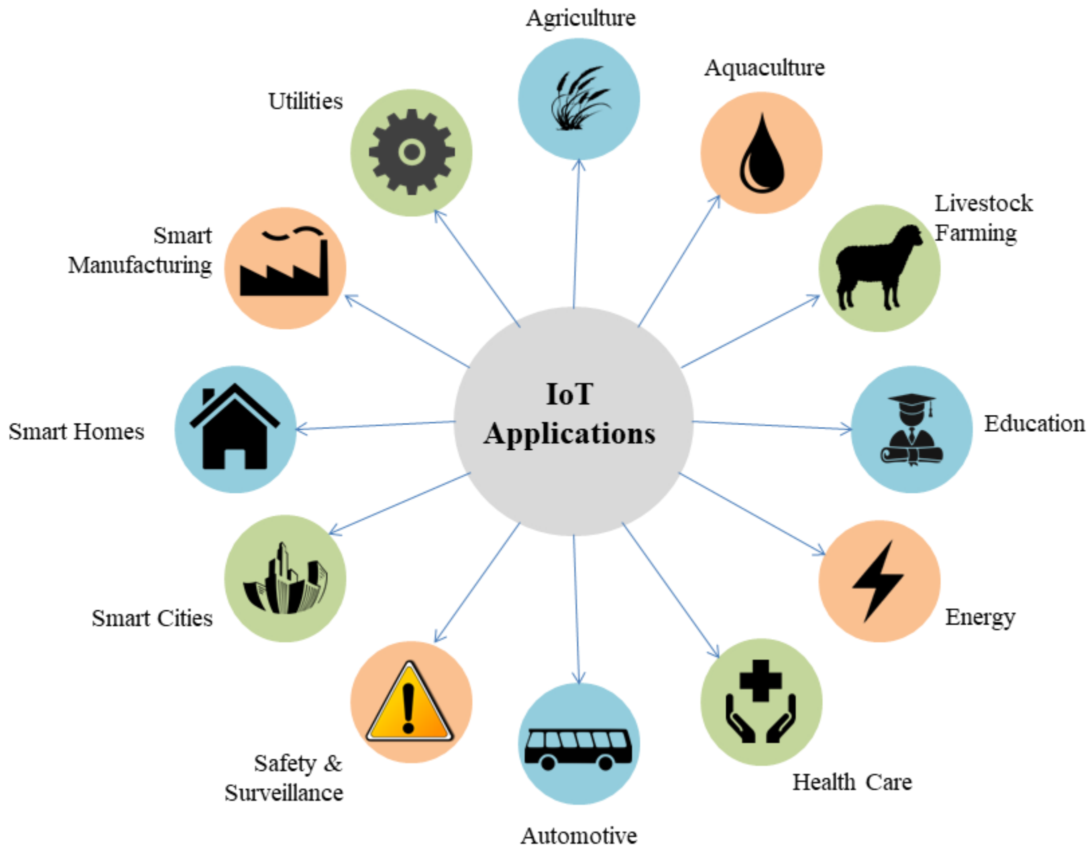


Figure 3: IoT Applications

2. Communication Technologies

Various types of communication technologies are used in M2M/ IoT domain depending upon the coverage, power, QoS, specific use-case requirement etc. These communication technologies may be categorized to work in Personal/ Neighborhood /Local /Wide Area Network i.e. PAN/ NAN/ LAN / WAN depending upon the coverage distance.

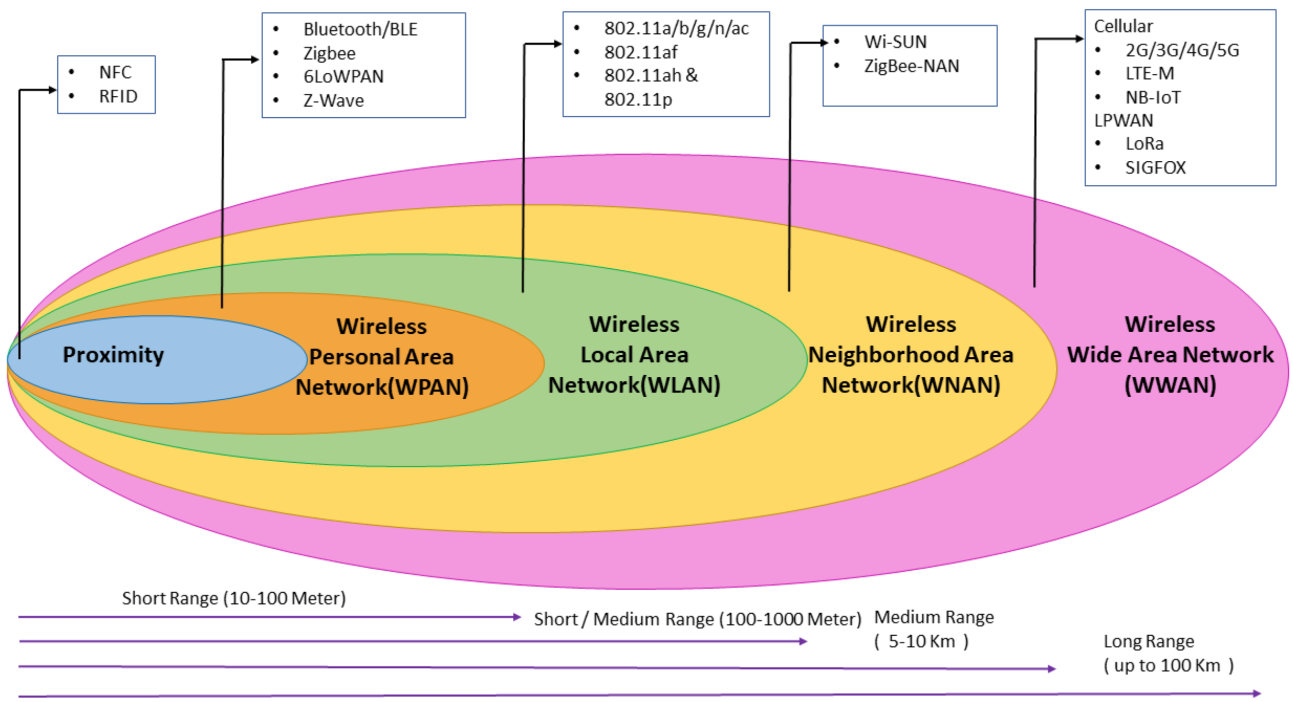


Figure 4: Communication Technologies in M2M/ IoT domain

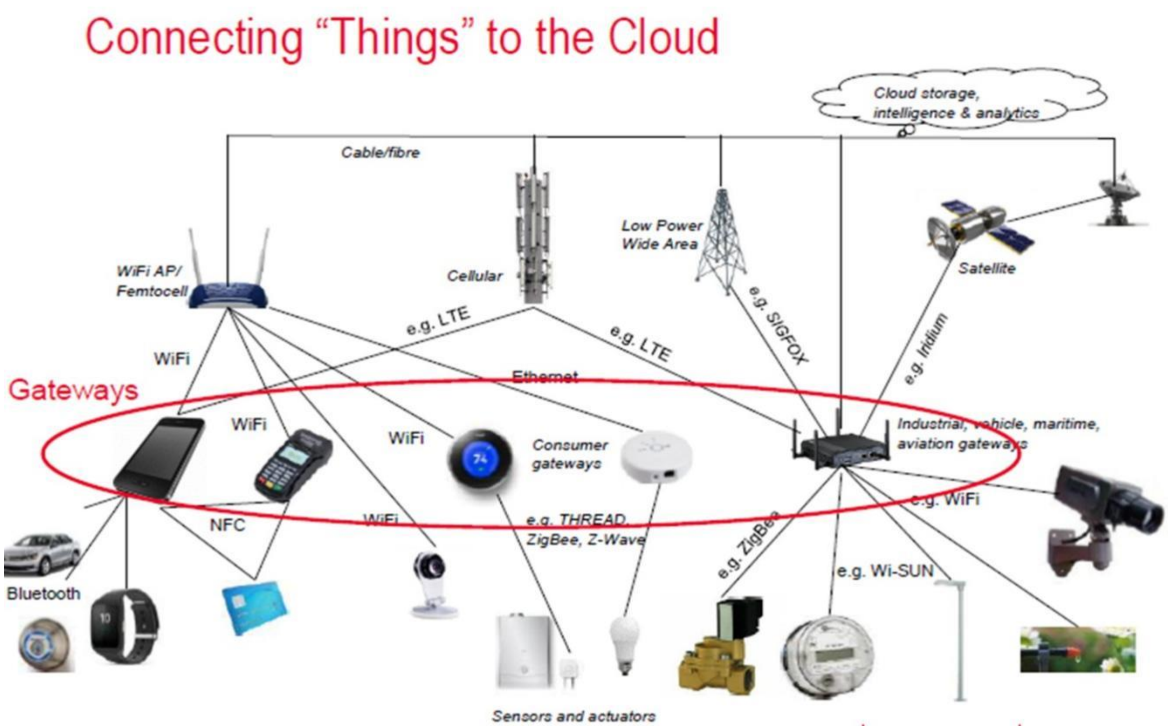
Communication technologies for M2M / IoT domain have been studied in TEC, resulting in two technical reports, released in 2017 and 2021.

Technical Report on ***Communication technologies in M2M/ IoT domain***[2] was released in 2017. This report covers Cellular Technologies **(**2G, 3G, 4G i**.**e**.** up to LTE 3GPP Release 14**)**, Low power wireless communication technologies **(**NFC, RFID, Bluetooth, ZigBee etc**.)**, Low power wide area network technologies **(**LPWAN **–** cellular**/** non-cellular**)**, Wi-Fi **[**IEEE 802**.**11 a, b, g, n, ac**]**, DSRC **(**802**.**11p**)**, wire line **(**PLC, DSL, FTTH**)** etc and the related use cases**.**

[2] https://tec.gov.in/pdf/M2M/Communication%20Technologies%20in%20IoT%20domain.pdf

Due to advancement in technology, further study was done and the Technical Report on ***Emerging Communication Technologies and Use cases in IoT domain***[3] was released in November 2021. This report covers 5G, Wi-Fi 6, Wi-Fi 6E, WiFi HaLow, Bluetooth Mesh and some important use cases such as Intelligent transport system (Connected vehicles, C-V2X etc.), Private Industrial Network (Smart factories, Industry 4.0), Smart homes etc.

Figure 5 below illustrates the connectivity of IoT devices with the headend system/ cloud directly or through IoT Gateway on various communication technologies.



(Source: Keysight technologies)

Figure 5: IoT Architecture

IoT devices typically utilize wireless communication technologies, although they may also be connected via wireline. Some of the examples of the IoT devices may include smart camera, smart watch, smart meters, tracking devices etc. IoT gateways may include POS machines, smart phones, Wi- Fi routers etc. Further, the data collected from IoT devices is transferred to the cloud either directly or through an IoT gateway for storage and analysis purpose, for taking informed decisions.

[3]https://tec.gov.in/pdf/M2M/Emerging%20Communication%20Technologies%20&%20Use%20Cases%20in%20IoT%20domain.pdf

2.1. Cellular Technologies

2.1.1. Evolution of Cellular Technologies

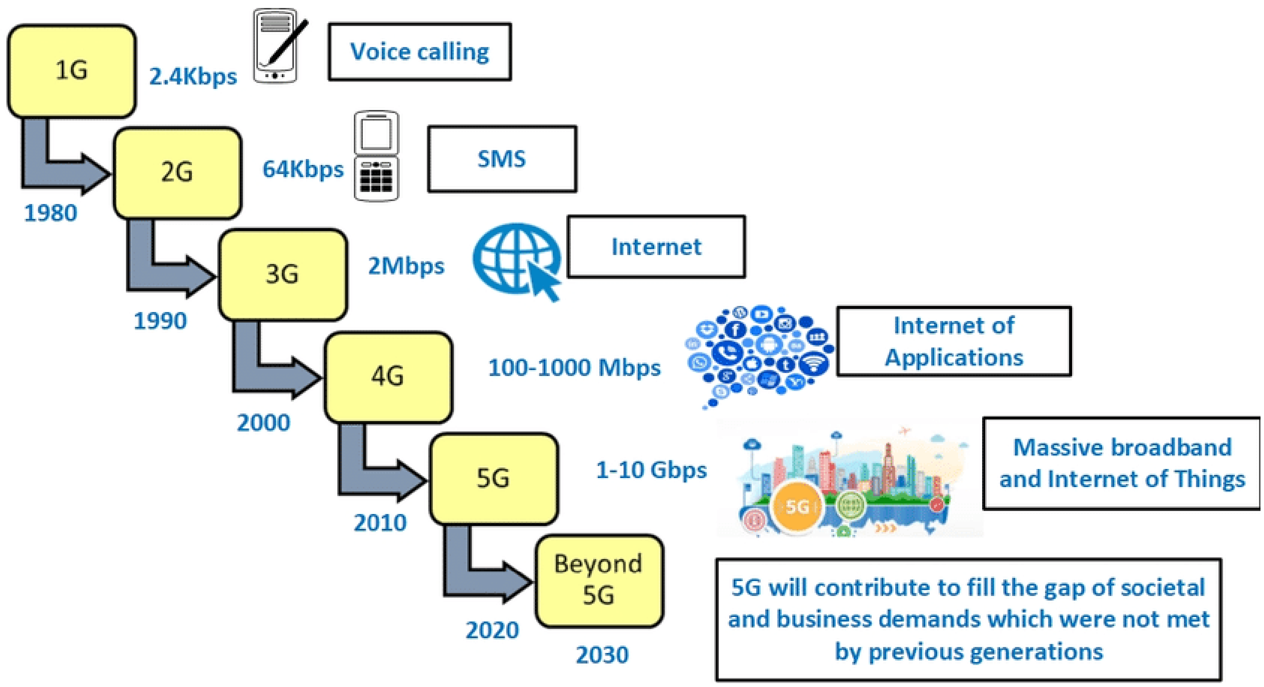


Figure 6: Evolution of Cellular Technologies[4]

The GSM standard originally described a digital, circuit-switched network optimized for full duplex voice telephony. This expanded over time to include data communications, first by circuit-switched transport, then by packet data transport via General Packet Radio Service (GPRS), and Enhanced Data Rates for GSM Evolution (EDGE). 2G networks developed as a replacement for first generation (1G) analog cellular networks. Subsequently, the 3rd Generation Partnership Project (3GPP) developed third-generation (3G) UMTS standards, followed by the fourth-generation (4G) LTE Advanced and the fifth-generation 5G standards.

The Universal Mobile Telecommunications System (UMTS) was a 3rd generation wireless telecommunication system. UMTS combined the properties of the circuit-switched voice network with the properties of the packet-switched data network and offered a multitude of new possibilities compared to the earlier systems. Some of the key features of UMTS (3G) were enhanced data transfer rates, wider bandwidth, supporting wide range of multimedia services. High-Speed Packet Access (HSPA) and HSPA+ were introduced in 3GPP Release 5 and 7 which significantly increased the data rate.

[4]https://www.researchgate.net/figure/Timeline-of-Mobile-communication-generations-27_fig2_349740908

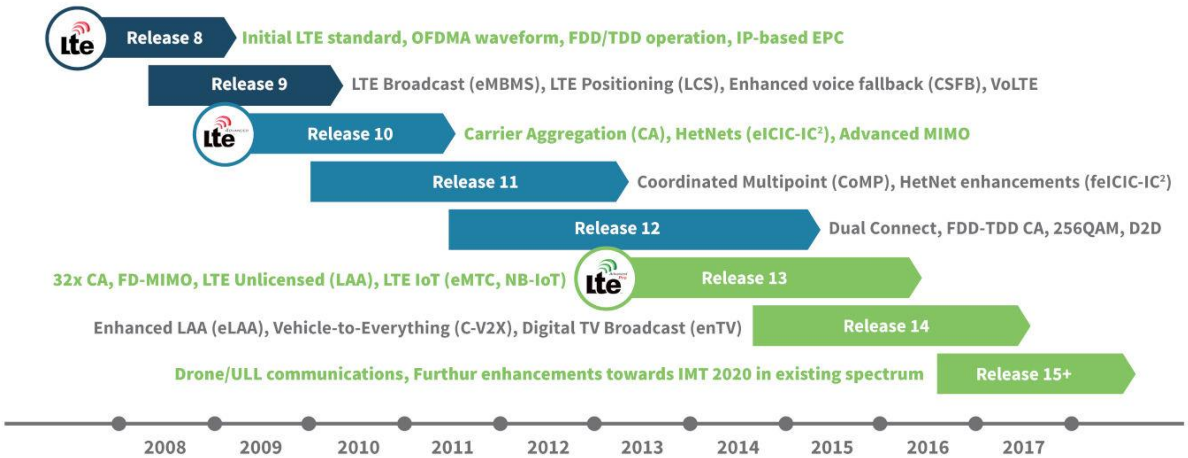
An overview of some key 3GPP releases is shown in Table 1:

Table 1: Summary of 3GPP Releases upto Release 15 and their main features

Release 99 • The basics of early 3G deployment **Release 4** • 1st step towards IP based operation • Also defines the low chip rate TDD mode (TD-SCDMA) **Release 5** • IMS – IP-based Multimedia Services • HSDPA – High Speed Download Packet Access **Release 6** • 2nd phase of IMS • High Speed Uplink **Release 7** • Enhanced uplink • Other Spectrum • Multiple Input Multiple Output (MIMO) antennas **Release 8** • Long Term Evolution (LTE) and System Architecture Evolution (SAE)	**Release 9** • Enhancement of Release 8 features • Refinement of LTE • Preliminary studies into LTE Advanced **Release 10** • LTE Advanced (IMT Advanced) **Release 11-12** • Improvement in LTE – A • Enhanced Small Cell Support • Improved Self Organizing Networks (SON) **Release 13** • Features like LTE – M and Narrowband IoT (NB-IoT) were introduced **Release 14** • Provided additional support to IoT • Mission Critical Services • Device to Device Communication **Release 15** • IMT 2020

2.1.2. 4G-LTE/ LTE-Advanced

LTE, originally introduced in 3GPP Release 8, was developed to provide faster mobile broadband access, offering a generational performance leap over 3G. The major change in LTE compared to previous systems was the adoption of an all-IP approach. LTE Advanced (3GPP release 10, 11, 12) evolved to optimize for better mobile broadband experience, enabling gigabit-class throughput with the introduction of advanced techniques, such as carrier aggregation and higher-order MIMO. Some applications of LTE in agriculture are Remote Monitoring, Data Collection and Analysis, Surveillance Systems, aerial surveys by using drones/ UAV’s etc.

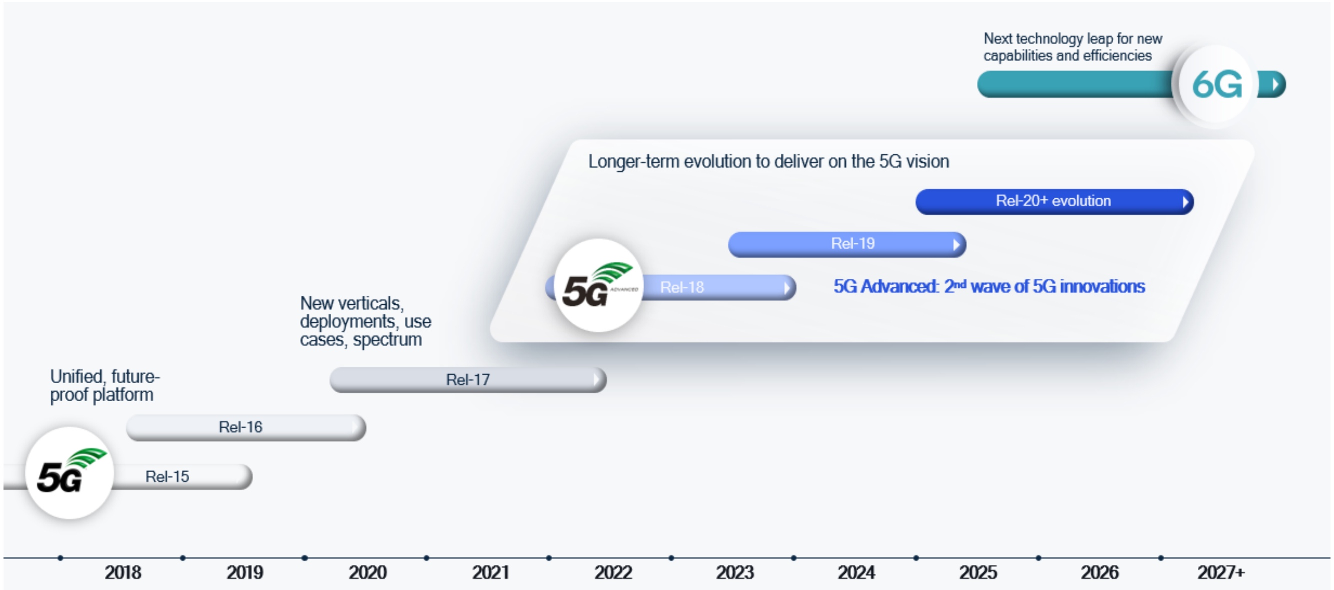


(Source: Qualcomm)
Figure 7: 4G LTE evolution by 3GPP Release

3GPP Release 13 introduced a suite of new narrowband technologies optimized for the IoT. LTE-M (eMTC) enables the broadest range of IoT capabilities and NB-IoT scales down further in cost and power for low-end IoT use cases. Low power consumption and long-range capabilities make NB-IoT well-suited for applications in remote agricultural areas, providing farmers with valuable data to make informed decisions and optimize their farming practices. Few applications of NB-IoT in agriculture are Soil Health Monitoring, Crop Health Monitoring, Livestock Tracking, Weather Stations, Smart Irrigation, Asset/ livestock Tracking, Precision Farming, Water Quality Monitoring, etc.

2.1.3. 5G/ IMT 2020

5G is an emerging communication technology introduced in 3GPP Release 15. 5G Technology is evolving in various 3GPP releases as shown in figure 8 below-



(Source: Qualcomm)

Figure 8: 5G Technology evolution

Table 2: Summary of 5G related 3GPP Releases and their main features

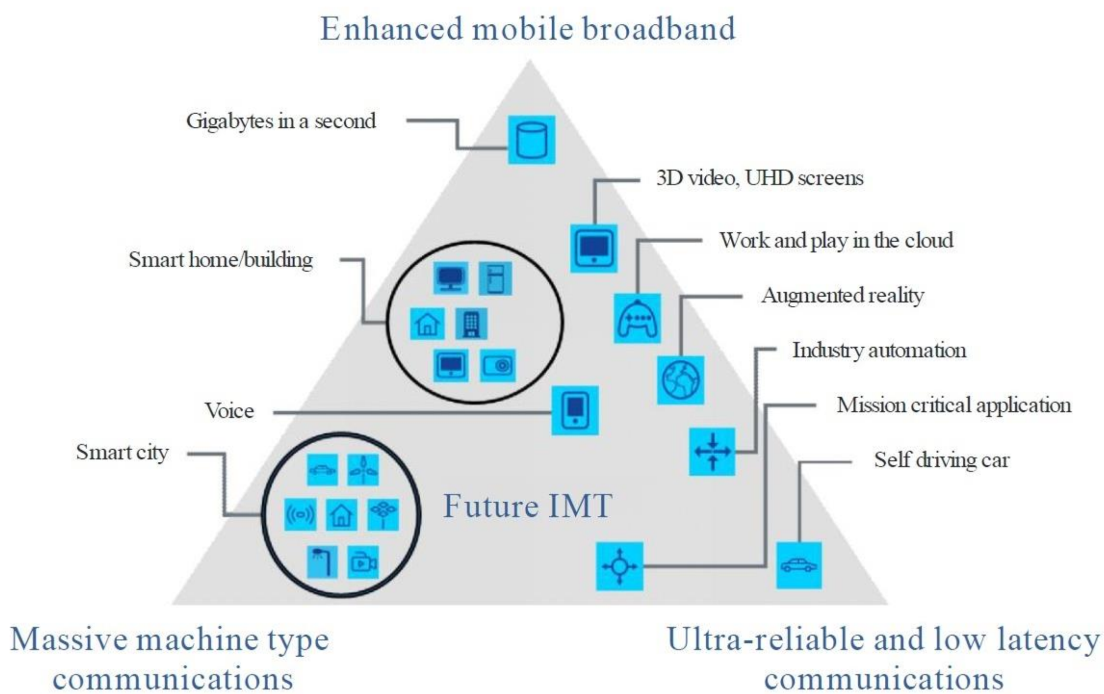
Rel 15 eMBB focus	Rel 16 industry expansion	Rel 17 continued expansion	Rel 18+ 5G Advanced
•5G NR foundation •Sub-7 and mmWave •Scalable & forward compatible •Basic URLLC support •mMTC via eMTC & NB-IoT	•Unlicensed spectrum (NR-U) •Enhanced URLLC •New functionalities: Sidelink (NR V2X), Positioning 5G broadcast •eMTC/NB-IoT with 5G core •Topology: IAB •eMBB enh: MIMO, device power, CA/DC, mobility	•mmWave extended to 71GHz •Lower complexity “NR-Light” (RedCap) •Non-terrestrial communication (satellites): NR NTN and NTN IoT •Improved IIoT, positioning, V2X •Enhanced IAB, RF repeaters	•Next set of 5G releases (i.e., 18, 19, 20, …) •Rel-18 scope decided in Dec ’21

5G provides faster speed, lower latency, and wider coverage. The requirements for 5G broadly cover three main usage scenarios as shown in in figure 9-

- Mobile IoT/ Massive IoT/ LPWAN: improved network coverage, long device operational life time and a high density of connections. This is also known as Massive MTC (mMTC).

- Critical communications: high performance, ultra-reliable, low latency for industrial IoT and mission critical applications. This is also known as Ultra Reliable Low Latency Communications (URLLC).

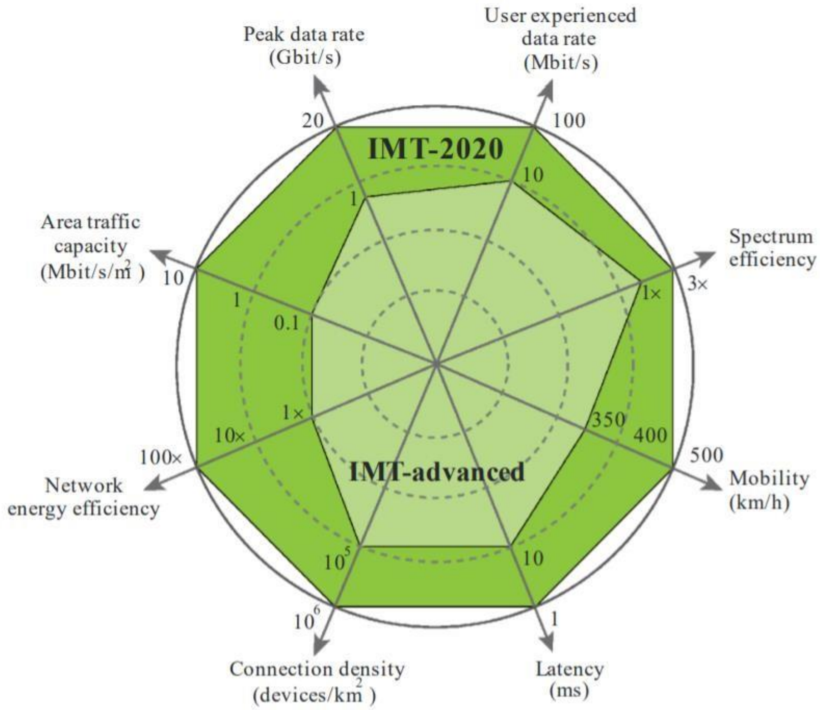
- Enhanced Mobile Broadband: Improved performance and a more seamless user experience accessing multimedia content for human-centric communications. This is also known as Enhanced Mobile Broadband (eMBB).



(Source: ITU-R Rec. M.2083)
Figure 9: 5G Usage Scenarios

5G technologies in precision agriculture will ensure greater profitability and efficient utilization of resources by use of automated tractors / harvesters, precision seeders, and automated weed & pest controllers. Drones with 5G technology may be used for efficient & precise spraying of fertilizers in fields, and also to scan and identify unwanted weeds through the use of AI. It will help farmers to better organize and allocate their time and attention towards areas that really need it. Massive MTC and uRLLC features of 5G may also be used for remote monitoring and maintenance of machines centrally and that data could be transmitted in real-time. 5G is the key in this area because if such systems function on other legacy networks such as 3G and 4G, then there may be delay in transmission and uploading of collected data on the server.

5G and beyond technologies are envisaged to expand on the IMT-Advanced performance requirements like Peak data rate, User experienced data rate, Spectrum efficiency, Mobility, Latency, Connection density, Network energy efficiency, and Area traffic capacity as depicted in Figure 10.



(Source: 3GPP)

Figure 10: Enhancement of key capabilities from IMT-Advanced to IMT-2020 (4G to 5G)

Each of the different usage scenarios utilizes the capabilities of IMT-2020 to realize the various use-cases. A summary of the IMT-2020 minimum technical performance requirements as described by ITU-R is provided in the table below:

Table 3: Summary of Minimum Technical Performance Requirements

Minimum Technical Performance Requirement	**Key Use-Case**	**Values**
Peak Data Rate	eMBB	DL:20 Gbps; UL:10 Gbps
Peak Spectral Efficiency	eMBB	DL:30 bps/Hz; UL:15 bps/Hz
User Experienced Data Rate	eMBB	DL:100 Mbps; UL:50 Mbps (Dense Urban)
Area Traffic Capacity	eMBB	DL:10 Mbps/M^2 (Indoor Hotspot)

User Plane Latency	eMBB, URLLC	4ms for eMBB and 1ms for URLLC
Control Plane Latency	eMBB, URLLC	20 ms for eMBB and URLLC
Connection Density	mMTC	10^6 devices/km^2
Energy Efficiency	eMBB	Capability to support high sleep ratio and long sleep duration to enable low energy consumption when there is no data
Reliability	URLLC	1-10^{-5} success probability of transmitting a layer 2 protocol data unit of 32 bytes within 1 ms in channel quality of coverage edge
Mobility	eMBB	Upto 500 km/h
Mobility Interruption Time	eMBB, URLLC	0 ms approx.
Bandwidth	eMBB	At least 100 MHz; Upto 1 GHz for operation in Higher frequency bands (e.g. above 6 GHz)

Some other key aspects of 5G/ IMT-2020 are detailed below-

Network Slicing: 5G introduces network slicing, allowing the network to be divided into multiple virtual networks to accommodate diverse use cases with varying requirements for latency, bandwidth, and reliability.

Massive MIMO (Multiple Input Multiple Output): Increased Antenna Arrays, 5G networks leverage massive MIMO technology, involving a large number of antennas at both base stations and user devices. This enhances data rates, spectral efficiency, and overall network capacity.

Network function virtualization (NFV): It is cloud-native architecture, allowing network components to be virtualized and deployed as software-defined functions.

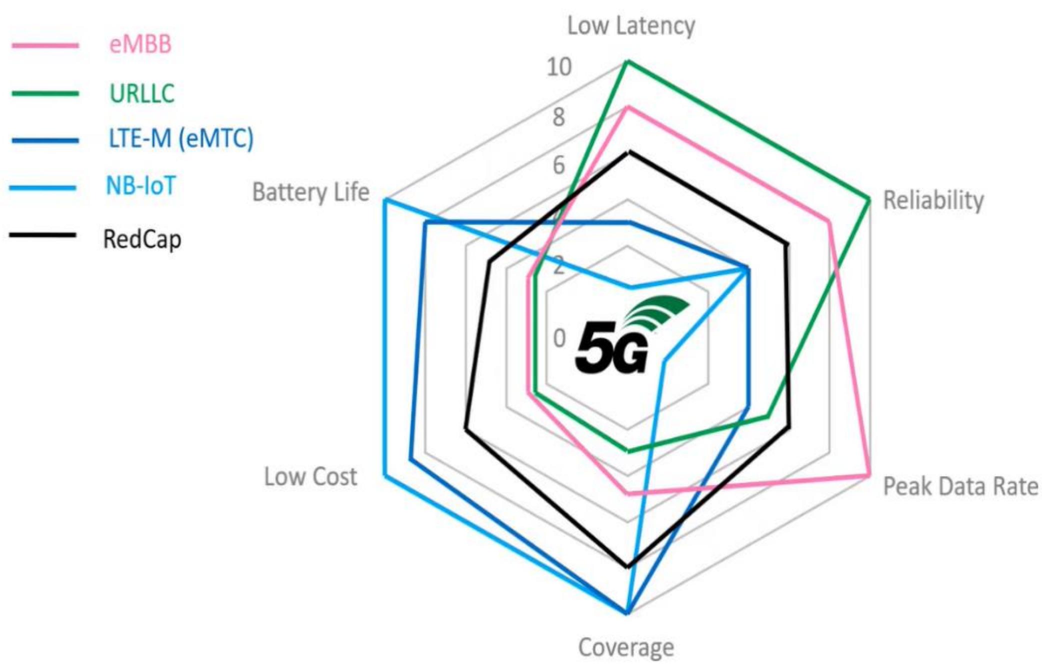
New Radio (NR): 5G NR specification defines how 5G NR edge devices (smart phones, embedded modules, routers, and gateways) and 5G NR network infrastructure (base stations, small cells, and other Radio Access Network equipment) wirelessly transmit data. 5G NR is the global standard for a unified, more capable 5G wireless air interface for radio communication. NR supports both non-standalone (NSA) and standalone (SA) deployment options. It is delivering significantly faster and more responsive mobile experiences.

RedCap (Reduced Capability) / NR Lite / NR light

3GPP Release 17 introduced 5G RedCap in 5G NR, also termed NR-Light, a new standard for devices known as reduced capability (RedCap) devices. 5G RedCap is the latest advancement in cellular technology within the IoT landscape, catering to a range of use cases thus adding a new dimension to IoT connectivity. It is designed to address the use cases in between the high speed Enhanced mobile broadband (eMBB), the ultra-reliable low latency communications (uRLLC) and the low throughput and battery efficient Massive Machine-Type Communication (mMTC) technologies. This innovation represents a bridge between the extremes in 5G technology.

For massive IoT services, narrowband IoT (NB-IoT) and enhanced machine type communication (eMTC)/LTE-M devices prioritize low power consumption and the lowest complexity for wide-area deployments (LPWA), while enhanced ultra-reliable, low-latency communication (eURLLC) devices deliver on the most stringent use case requirements in industry. But there exists an opportunity to address a broad range of mid-tier applications more efficiently, with capabilities between these extremes.

Different types of NR RedCap UEs / Devices may include video surveillance, Industrial Wireless Sensors i.e. CO2 sensors, Pressure sensors, Motion sensors, Fluid sensors, etc. It may also include Low-end Wearables.



(Source: https://www.3g4g.co.uk/Training/beginners0039.html)
Figure 11: 5G Spider Diagram combined with RedCap

2.2. Low Power Wide Area Network (LPWAN) Technologies

2.2.1. Cellular LPWAN Technologies

NB-IoT and LTE-M

3GPP introduced technologies such as NB-IoT and LTE-M to address requirements of IoT applications, with a specific emphasis on long-battery life, low complexity, including requirements on support of large number of devices, low device cost, and coverage in challenging locations.

There is a good compatible and complementary relationship between LTE-M and NB-IoT since both are based on the LTE platform. The primary difference is their operational bands. LTE-M operates at 1.4 MHz in- band with LTE, whereas NB-IoT can operate at 180 kHz in-band, in guard band, or in a standalone mode. This allows NB-IoT to repurpose GSM frequency structure as well. Retuning of the antenna and provisioning the frequencies in the eNodeB can support both technologies.

Major areas in which LTE-M and NB-IoT differ include bandwidth support, latency, power consumption and device cost. LTE-M has higher throughput with lower latency and battery use is optimized accordingly. The battery life of a LTE-M device can be lower than that of NB-IoT and power consumption is more at comparatively high data rates as opposed to NB-IoT which consumes less power at low data rates. LTE-M can also carry voice for applications such as residential security systems. LTE-M and NB-IoT both support the 5G connection density requirement of 1,000,000 connected devices per km^2 with a service delivery within 10 seconds.

In summary, LTE-M and NB-IoT meet the IMT-2020 and 3GPP 5G requirements for Massive IoT and support seamless coexistence between NR, LTE-M and NB-IoT. This makes LTE-M and NB-IoT today's most prominent and futureproof 5G Massive IoT technologies.

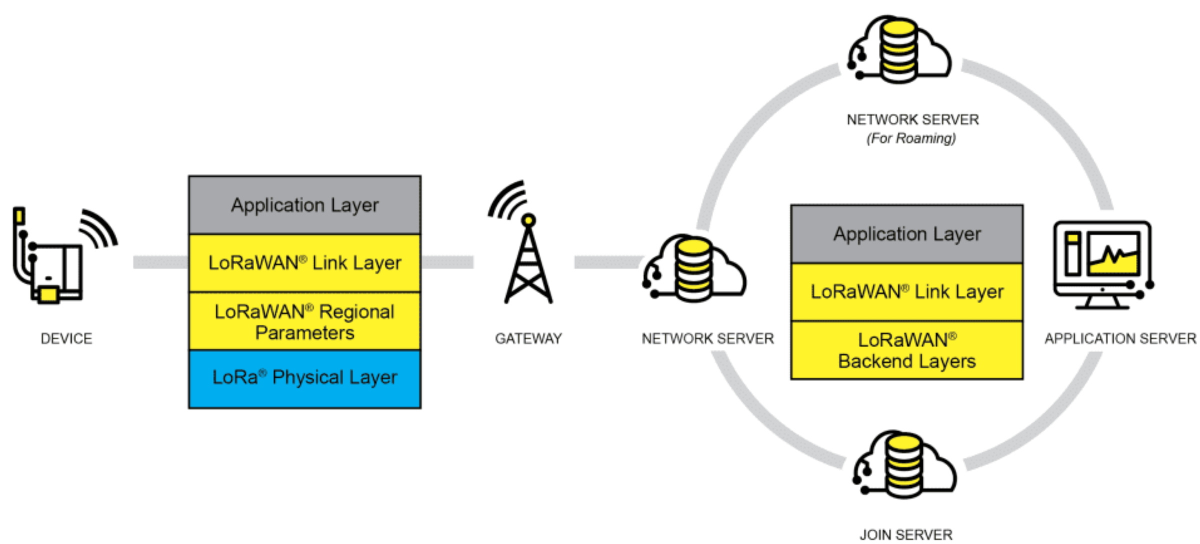
Some of the key applications of NB-IoT and LTE-M are in smart cities (smart street lighting, waste management, environmental monitoring, and smart parking). The low-power characteristics make them suitable for long-term deployment in urban infrastructure, Agriculture, Industrial IoT, Healthcare, Smart Metering, Environmental Monitoring etc. In precision agriculture, NB-IoT facilitates the deployment of sensors in remote agricultural areas for applications like soil monitoring, crop health assessment, and efficient water management, leading to improved yields and resource utilization.

2.2.2. Non-Cellular LPWAN Technologies

LoRaWAN

LoRaWAN, which stands for Long Range Wide Area Network, is a communication protocol designed for lowpower wide area networks (LPWANs) that offer long range and secure data transmission for M2M and IoT applications. LoRa is based on chirp spread spectrum modulation, which has low power characteristics like FSK modulation but can be used for long range communications. LoRa technology enables efficient, low-cost, and low-energy communication for devices that need to transmit small amounts of data over considerable distances. LoRa can be used to connect sensors, gateways, machines, devices, etc. wirelessly to the cloud.

LoRa Technologies operates in different frequency bands in different regions; in India it operates in the frequency band of 865 to 868 MHz. Its distinctive features include an impressive communication range, covering several kilometers in rural environments and reaching a few hundred meters in urban areas. LoRa devices are characterized by their low power consumption, ensuring extended battery life for connected devices, making it well-suited for applications in remote or challenging locations where frequent battery replacements are impractical.



(Source: LoRa-Alliance)
Figure 12: LoRaWAN Network Architecture

SigfoxoG Technology

SigfoxoG technology[5], a proprietary wireless communication technology, is a Low-Power Wide-Area (LPWA) networking protocol owned by UnaBiz. It is designed to connect sensors and devices securely at low-cost in the most energy efficient way to enable Massive IoT. Sigfox is a long range, low power, low data rate form of wireless communications that has been developed to provide wireless connectivity for devices like remote sensors, actuators and other M2M and IoT devices.

The main competitive advantage of the Sigfox technology is for the deployment with a large coverage with a limited number of base stations.

2.3. Low Power Short Range Technologies

2.3.1. Wi-Fi/ IEEE 802.11 Based Technologies

Wi-Fi is a family of wireless network protocols based on the IEEE 802.11 family of standards, which are commonly used for local area networking of devices and Internet access, allowing nearby digital devices to exchange data by radio waves. Wi-Fi is a trademark of the Wi-Fi Alliance. Wi-Fi most commonly uses the 2.4 GHz and 5 GHz radio bands; these bands are subdivided into multiple channels. Channels can be shared between networks, but within range only one transmitter can transmit on a channel at a time.

Wi-Fi compatible devices can connect to the Internet via a WLAN network and a wireless access point. Such an access point (or hotspot) has a range of about 20 meters indoors and a greater range outdoors. Hotspot coverage can be as small as a single room with walls that block radio waves, or as large as many square kilometers achieved by using multiple overlapping access points. Various IEEE 802.11 standards are mentioned in table below-

Table 4: Various IEEE 802.11 Standards

IEEE Standard	Frequency Bands	Max Speed
802.11a	5 GHz	54 Mbit/s
802.11b	2.4 GHz	11 Mbit/s
802.11g	2.4 GHz	54 Mbit/s

[5] https://www.sigfox.com/

802.11n	2.4 GHz and 5 GHz	600 Mbit/s
802.11ac	5 GHz	3.5 Gbit/s

Wi-Fi is an important communication protocol pertaining to M2M communication as in several scenarios Wi-Fi hotspots are potentially the gateways for most sensor nodes.

Wi-Fi 6

Wi-Fi 6, or IEEE 802.11ax, stands as the latest evolution in wireless technology, surpassing Wi-Fi 5 (802.11ac). This advanced standard introduces significant enhancements to wireless connectivity, delivering higher data rates through use of wider channels, advanced modulation techniques, and overall efficiency improvements. Operating in both the 2.4 GHz and 5 GHz frequency bands, Wi-Fi 6 ensures backward compatibility while providing a migration path for devices from 802.11n and 802.11ac.

IEEE802.11ax focuses on better efficiency, capacity and performance as compared to previous technologies of Wi-Fi family, thus providing 4x improvements in average throughput per user and better user experience even for dense indoor/outdoor deployments such as airports, railway stations, shopping malls, stadiums, homes, school campuses.

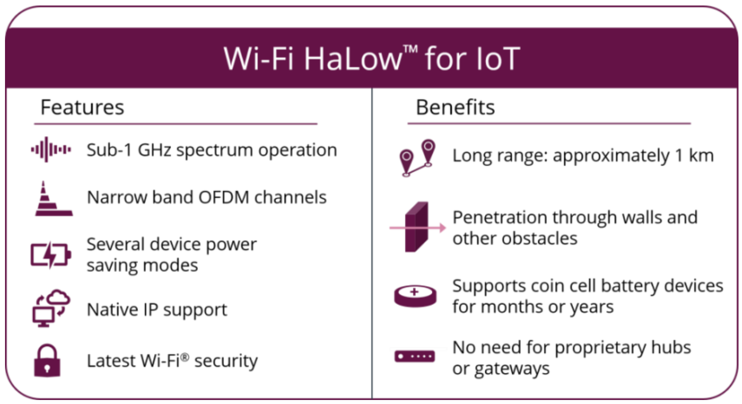
Key features include Orthogonal Frequency Division Multiple Access (OFDMA), dividing a channel into smaller sections to enable simultaneous communication with multiple devices, enhancing efficiency and reducing latency.

Several nations around the globe are making 6 GHz band available for unlicensed use. Wi-Fi 6E extends Wi-Fi 6 to the 6 GHz band. Wi-Fi 6 operation in the 6 GHz frequency band enables Wi-Fi to continue delivering positive experiences for the most bandwidth-intensive applications.

Wi-Fi HaLow

Wi-Fi HaLow, also known as 802.11ah, is a wireless communication standard developed by the Wi-Fi Alliance to address the specific requirements of the Internet of Things (IoT). Wi-Fi HaLow operates in the sub-1 GHz frequency band, providing longer range, lower power consumption, and better penetration through walls and other obstacles compared to traditional Wi-Fi standards. Wi-Fi HaLow achieves an extended range due to its operation in lower frequency bands, providing reliable connectivity over greater distances. Wi-Fi HaLow supports the Internet of Things (IoT) use cases in industrial, agricultural, smart building, smart homes, and digital health care and smart city environments. Wi-Fi HaLow extends Wi-Fi in to the 900 MHz band.

Many devices that support Wi-Fi HaLow operates in 2.4 and 5 GHz in addition to 900 MHz band, allowing devices to connect with Wi-Fi's ecosystem. Wi-Fi HaLow devices will support IP-based connectivity to natively connect to the cloud, which will become increasingly important in reaching the full potential of the Internet of Things (IoT). Dense device deployments will also benefit from Wi-Fi HaLow's ability to connect thousands of devices to a single access point. Some of the features and benefits of this technology are depicted in Figure 13 below:



(Source: Wi-Fi Alliance)
Figure 13: Features and benefits of Wi-Fi HaLow for IoT

2.3.2. Bluetooth Low Energy

Bluetooth Low Energy (BLE), also known as Bluetooth Smart, is a wireless communication technology designed for short-range communication with low power consumption. It is a part of the Bluetooth wireless communication standard and is specifically optimized for energy efficiency, making it well suited for a wide range of battery-powered devices and applications in the Internet of Things (IoT). BLE devices operate in the unlicensed 2.4 GHz ISM band. A frequency hopping transceiver is used to combat interference and fading.

Unlike the classical Bluetooth which uses 79: 1-MHz-wide channels, BLE uses 40: 2-MHz wide channels. Three of these channels, which are located between commonly used wireless local area network channels, are used for advertising and service discovery and are called advertising channels. The remaining 37 data channels are used to transfer the data.

2.3.3. Bluetooth Mesh

Bluetooth Mesh is a wireless communication standard that extends the capabilities of Bluetooth Low Energy (BLE) by introducing a mesh network topology. Unlike traditional Bluetooth connections, Bluetooth Mesh allows devices to form interconnected networks, facilitating communication from one device to another. This technology allows for the creation of large-scale networks where devices form an interconnected web, enabling them to communicate with each other seamlessly. Bluetooth Mesh is designed to enhance the range, coverage, and flexibility of communication in comparison to traditional Bluetooth connections as data can hop between devices, creating a self-healing and self-optimizing infrastructure. The reliability of communication is strengthened through multiple paths, ensuring that if one device fails or is out of range, the network finds alternative routes. It is ideally suited for control, monitoring, and automation systems where hundreds, or thousands of devices need to communicate with one another.

(Source: https://www.bluetooth.com)
Figure 14: Features of Bluetooth Mesh

2.3.4. Near Field Communication

Near Field Communication (NFC) is a short-range wireless communication technology that enables seamless and secure data exchange between devices in close proximity, typically within a few centimeters. Operating at the radio frequency of 13.56 MHz, NFC facilitates communication between devices by simply bringing them close together or tapping them. NFC is commonly integrated into smartphones, credit cards, and various electronic devices, making it a convenient and versatile technology for a range of applications. The data rate is 106 Kbit/s to 424 Kbit/s. NFC is an offshoot of radio-frequency identification (RFID) with the exception that NFC is designed for use by devices within close proximity to each other. NFC requires 4 cm or less to initiate the connection with the tag. There are two variants of NFC. One is the Transceiver and the other is Tag.

NFC operates in two modes: active and passive. Transceivers are active devices which need power to operate. An active NFC device, such as a smartphone, would not only be able to collect information from NFC tags, but it would also be able to exchange information with other compatible phones or devices and could even alter the information on the NFC tag if authorized to make such changes.

Tags are the passive devices and work on the principle of inductive coupling when the tag is brought near a transceiver. NFC allows transferring small amount of data between transceiver and tags. There are three mode of data transfer in NFC-

• **Peer to Peer communication**: Peer-to-peer mode enables two NFC-enabled devices to communicate with each other to exchange information and share files.

• **Card Emulation**: Card emulation mode enables NFC-enabled devices to act like smart cards, allowing users to perform transactions such as purchases, ticketing, and transit access control with just a touch.

• **Reader/ Writer**: Reader/ writer mode enables NFC-enabled devices to read information stored on inexpensive NFC tags embedded in smart posters and displays, providing a great marketing tool for companies. Examples include reading timetables, tapping for special offers, and updating frequent flyer points.

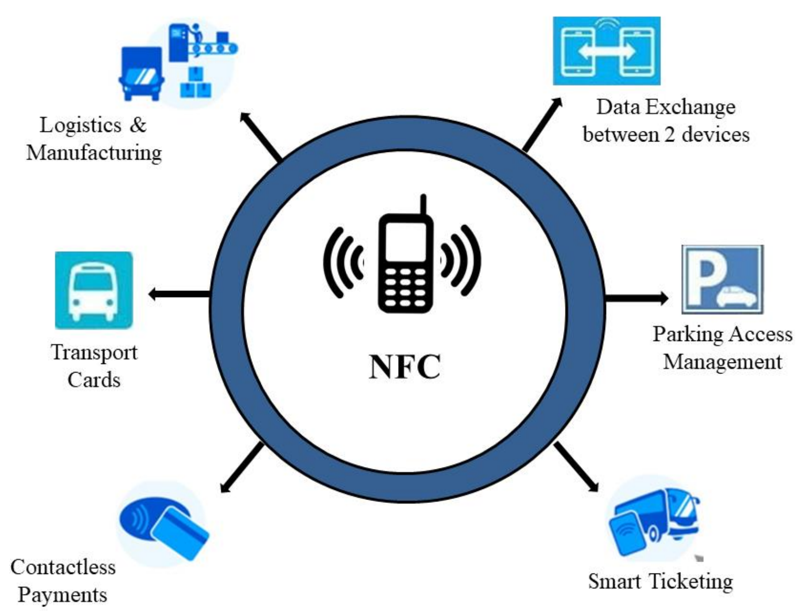


Figure 15: Applications of NFC

2.3.5. Radio Frequency Identification

Radio Frequency Identification (RFID) is a type of wireless communication that uses electromagnetic or electrostatic coupling in the radio frequency spectrum to uniquely identify an object, animal, or human.

A typically RFID system consists of tags (transmitters/ responders) and readers (transmitters/receivers). The tag is a microchip connected with an antenna, which can be attached to an object as the identifier of the object. The RFID reader communicates with the RFID tag using radio waves. The RFID tags come in various forms, including passive, active, and semi-passive, each designed for specific use cases.

Passive RFID Tags: These tags rely on the energy emitted by the RFID reader to transmit data. They are cost-effective and widely used in applications such as inventory management and access control.

Active RFID Tags: Active tags have their own power source, enabling them to transmit data over longer distances and in real-time. These are suitable for applications requiring continuous monitoring, like tracking the location of high-value assets.

Semi-Passive RFID Tags: Combining elements of both passive and active tags, semi-passive tags use their own power source for data transmission but rely on the RFID reader for energy to power other functionalities. This strikes a balance between extended range and power efficiency.

The functions of RFID system generally include three aspects: monitoring, tracking, and supervising. The most interesting and successful applications include supply chain management, production process control, and objects tracking management. Few RFID applications are shown in Figure 16 below-

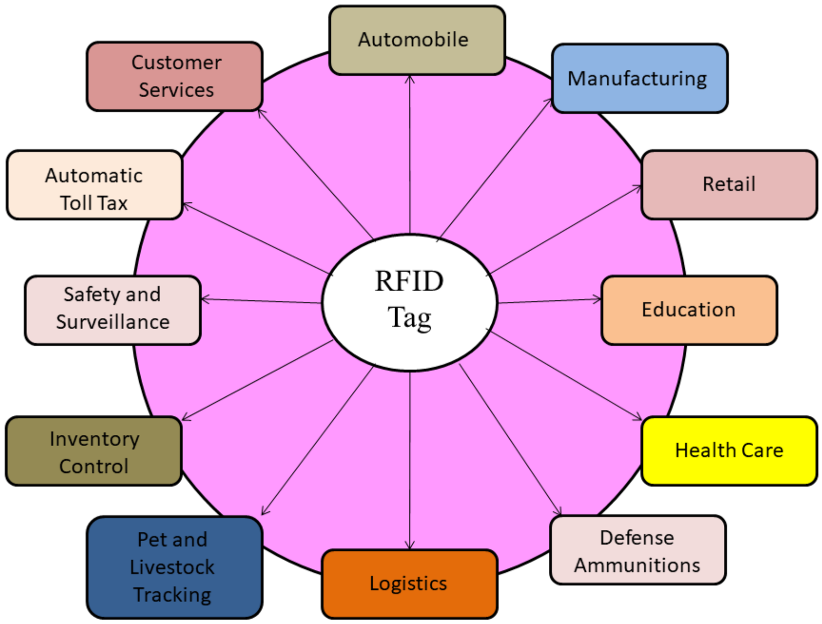


Figure 16: Applications of RFID

2.3.6. Z-Wave

Z-Wave stands out as a prominent wireless communication protocol specifically designed for home automation, facilitating seamless communication among various smart devices in an affordable and reliable manner. Operating under source crowdedness architecture, Z-Wave enables nodes or devices to communicate with each other, even when direct communication is not feasible. In this architecture, a node communicates with the nearest available node, creating a mesh network where messages are relayed until reaching the intended destination. The process of adding or removing nodes from the mesh network is standardized.

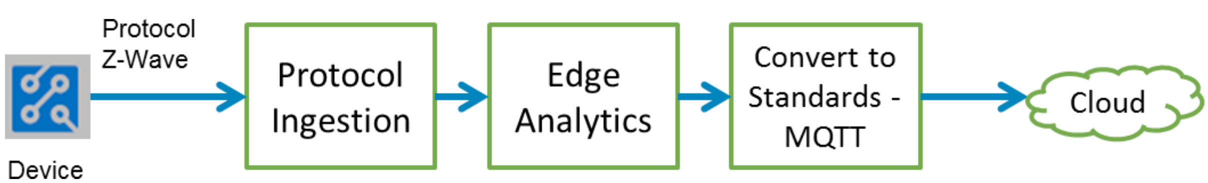


Figure 17: Z Wave Architecture

Each Z-Wave network has a unique ID, which is assigned to the Z-Wave Hub and to every device in the network. This ensures that the neighbor’s hub cannot control other’s devices when an extra level of security is needed, such as for door locks and other high security devices. Z-Wave has another level of security which uses AES128 encryption at the same level that major banks use to protect financial information. Z-Wave AES encryption is mandatory for hubs with the Z-Wave Plus support.

Z-Wave's frequency varies across countries, adhering to regulations specific to each region. For instance, in India, it operates in 865- 868 MHz.

2.3.7. ZigBee

ZigBee is a wireless mesh network standard characterized by its affordability and low-power features, primarily designed for the widespread deployment of devices with extended battery life in wireless control and monitoring applications. ZigBee devices have low latency, resulting reduction in average current consumption. ZigBee mostly operates in the ISM band i.e. 2.4 GHz worldwide including India.

As a globally recognized communication protocol, ZigBee is established by a significant task force operating under the IEEE 802.15 working group. It builds upon the physical layer and media access control defined in IEEE standard 802.15.4 for low-rate Wireless Personal Area Networks (WPANs). ZigBee supports various network topologies, such as star, mesh, and cluster tree configurations, ensuring adaptability to diverse application requirements. One of its key strengths lies in its commitment to low-power consumption, making it suitable for battery-powered devices and applications requiring intermittent data transmission.

2.3.8. 6LoWPAN

6LoWPAN stands for IPv6 over Low Power Wireless Personal Area Networks. It is a communication protocol designed to enable the transmission of IPv6 packets over low-power, low-rate wireless networks. It specifically targets devices with limited resources, such as low-power sensors, actuators, and other IoT devices. Rather than being an IoT application protocol technology like Bluetooth or ZigBee, 6LowPAN is a network protocol that defines encapsulation and header compression mechanisms. The standard has the freedom of frequency band and physical layer and can also be used across multiple communications platforms, including Ethernet, Wi-Fi, 802.15.4 and sub-1GHz ISM. A key attribute is the IPv6 (Internet Protocol version 6) stack, which has been a very important introduction in recent years to enable the IoT. IPv6 is the successor to IPv4 and offers approximately 2^{128} addresses (approximately3.4×10^{38}), enabling any embedded object or device to have its own unique IP address and connect to the

Internet. IPv6 provides a basic transport mechanism to produce complex control systems and to communicate with devices in a cost-effective manner via a low-power wireless network.

Designed to send IPv6 packets over IEEE802.15.4-based networks and implementing open IP standards including TCP, UDP, HTTP, COAP, MQTT, and web sockets, the standard offers end-to-end addressable nodes, allowing a router to connect the network to IP. 6LowPAN is a mesh network that is robust, scalable and self-healing. Mesh router devices can route data destined for other devices, while hosts are able to sleep for long period.

Salient characteristics of this technology are:

a. Small packet size
b. Low bandwidth (250/40/20kbps)
c. Topologies include star and mesh
d. Low power, typically battery operated
e. Relatively low cost
f. Networks are ad hoc & devices have limited accessibility and user interfaces

3. Artificial Intelligence (AI)/ Machine Learning (ML), Big Data Analytics and Blockchain

3.1. Artificial Intelligence (AI)

As per ITU, Artificial Intelligence is interdisciplinary field, usually regarded as a branch of computer science, dealing with models and systems for the performance of functions generally associated with human intelligence, such as reasoning and learning [ITU-T F.749.13].

Artificial Intelligence (AI) is characterized as machine intelligence designed to emulate human-like functioning. It serves as a cognitive engine, facilitating analysis and decision-making based on data acquired from various sources. AI processes this acquired information to derive meaningful insights. This collaborative approach is evident in everyday personal devices like fitness trackers, Google Home, Amazon Alexa etc. Examples of tasks that machines equipped with artificial intelligence can undertake include:

1. Speech recognition
2. Problem solving
3. Planning
4. Learning

The figure below illustrates the concept of Artificial Intelligence -

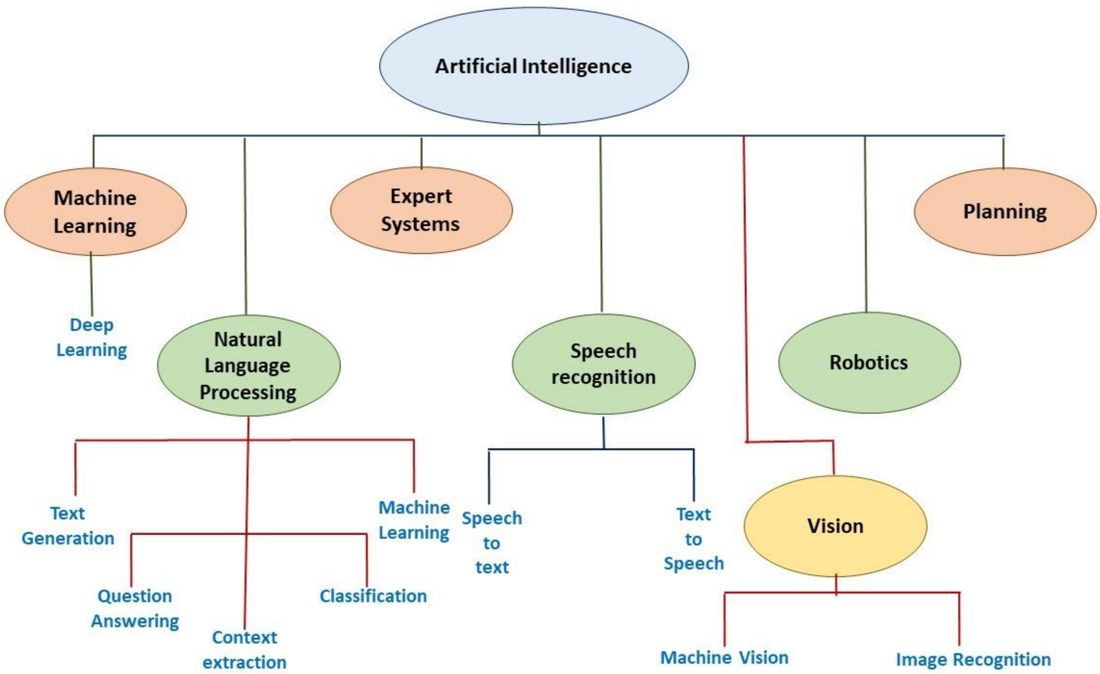


Figure 18: Artificial Intelligence

Developing an AI involves implementing appropriate algorithms, utilizing various forms of data such as documents, audio, video, or images. It entails training the system through the integration of algorithms with the provided data, necessitating iterative refinement until the training produces a satisfactory outcome. This entire sequence must be repeated multiple times to achieve optimal results.

Artificial Intelligence in IoT involves embedding AI technologies, such as machine learning, deep learning, and natural language processing, into IoT devices, sensors, and platforms to enable smart decision-making, learning, and autonomous actions. It represents the integration of AI capabilities into IoT devices and systems, enabling these devices to analyze data, make decisions, and perform tasks autonomously. It aims to enhance the intelligence and efficiency of IoT deployments by leveraging AI algorithms and techniques.

AI enhances IoT capabilities by enabling the analysis of vast amounts of real-time data generated by IoT devices, facilitating predictive maintenance, and identifying patterns or anomalies. Machine learning contributes to smart automation and behavioral analytics, allowing IoT devices to adapt and optimize processes based on user behavior. In terms of security, AI implements advanced measures such as anomaly detection, authentication, and authorization to safeguard IoT networks. Real-time decision-making benefits from edge computing, reducing latency in critical applications like autonomous vehicles. Natural Language Processing (NLP) and voice recognition enhance human-machine interactions, particularly in smart homes. The collaboration of AI and IoT finds applications in healthcare for remote monitoring and predictive analytics, smart agriculture for precision farming, and energy management for optimizing consumption. This synergy extends to smart cities, where AI-powered IoT devices contribute to traffic management and public services. Overall, the convergence of AI and IoT holds tremendous potential, ushering in a new era of intelligent, adaptive, and efficient systems.

3.2. Machine Learning （ML）

Machine learning is essentially the scientific approach enabling machines to interpret, process, and analyze data for addressing real-world issues. It is simply a subset of Artificial Intelligence (AI) that imparts machines with the capacity to autonomously learn and enhance their performance through experience, without explicit programming. In essence, machine learning involves empowering machines to think and solve problem. This discipline relies on vast amounts of both structured and unstructured data, ensuring that machine learning models deliver accurate results or predictions based on the acquired knowledge. Application of machine learning in agriculture allows more efficient and precise farming with less human manpower with high quality production. Machine learning is categorized into four types, namely:

a. **Supervised Learning:** A supervised learning algorithm gains knowledge from labelled training data, enabling it to make predictions for new, unseen data. For instance, supervised learning can be employed to predict crop yield or disease and pest detection based on training data. In this scenario, the input variables may include factors such as the geographic location, weather patterns, soil quality etc. locality and size of a house.

b. **Semi-supervised learning:** Semi-supervised learning is a machine learning paradigm that lies between supervised learning and unsupervised learning. In this approach, the model is trained on a dataset that contains both labelled and unlabelled examples. In semi-supervised learning, a portion of the training data is labelled, and the rest is unlabelled. The model is trained on both the labelled and unlabelled data to learn patterns and relationships. This can be especially useful when obtaining labelled data is expensive or time-consuming, as it allows the model to leverage the available labelled examples along with the potentially larger pool of unlabelled data. Semi-supervised learning methods aim to improve the performance of machine learning models by combining the benefits of supervised and unsupervised learning, making it a practical choice in scenarios where acquiring labelled data is a limiting factor.

c. **Unsupervised Learning:** Unsupervised learning entails training with unlabelled data, enabling the model to operate without explicit guidance. It can be applied to predict "Human Behaviour," where a learner equipped with advanced visual and speech recognition capabilities observes numerous television shows to learn about human behaviour. For instance, the learner could develop a model capable of detecting when people are smiling, correlating facial patterns with spoken words like "what are you smiling about.

d. **Reinforcement Learning:** Reinforcement Learning is a form of machine learning that enables software agents and machines to autonomously ascertain optimal behaviour to enhance system performance. This approach is prominently employed in sophisticated machine learning domains, including applications like Autonomous Machinery Control (Agriculture robot), Irrigation Optimization etc.

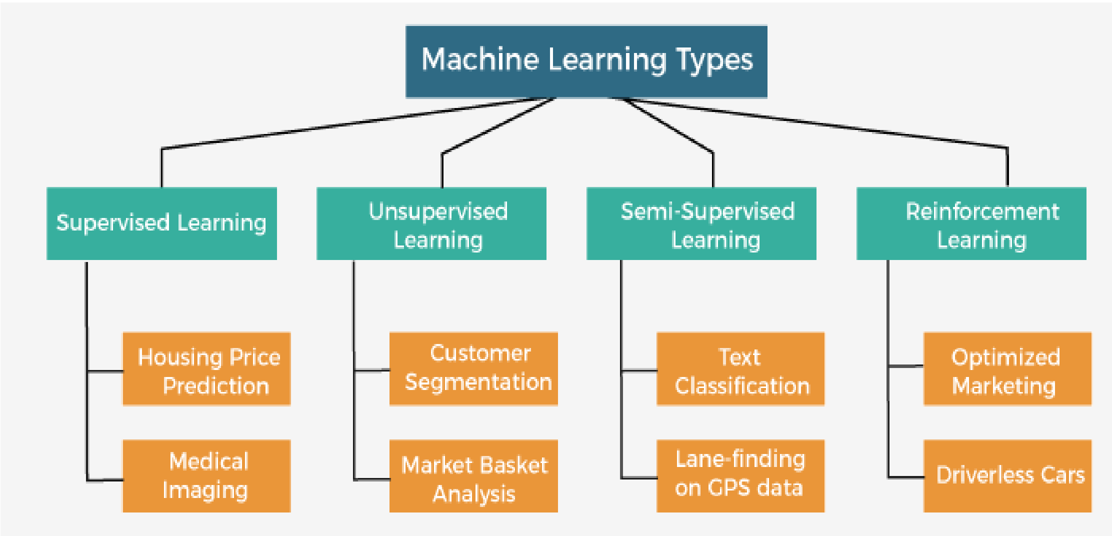


Figure 19 : Basic Block Diagram of Machine learning[6]

[6]https://www.newtechdojo.com/list-machine-learning-algorithms/

Some commonly used models in predicting crop traits are listed below-

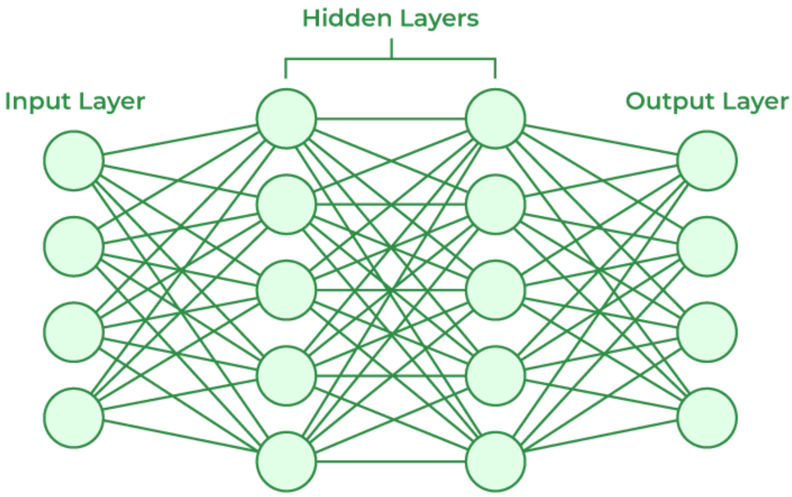
Table 5: List of some commonly used models in predicting crop traits

S. No.	Algorithm	Features
1.	Kernel ridge regression (KRR)	Kernel is introduced to RR. Uses squared error loss. Faster for medium-sized datasets. Matrix inversion
2.	Least squares linear regression (LSLR)	Model the relationship between a dependent variable and one or more independent variables. Does not consider the complexity of data.
3.	Neural network (NN)	Approach that uses a standard back-propagation algorithm applied to a set of input, hidden, and output layers. Predicts the results for unknown datasets. Requires labelled data for the training process. The training of the network takes time.
4.	Support vector regression (SVR)	Works on the concept of maximizing the margins. Generates a decision boundary with maximum separation. Proves helpful when multiple heterogeneous classes are available.
5.	Extreme learning machine (ELM)	Learning algorithm for single-layered feed-forward neural network. Fast learning. Computationally scalable. Independent from the tuning process. Evaluation speed is low.
6.	Bagging trees (BaTs)	General-purpose procedure for reducing the variance of a statistical learning method. Makes predictions on the tree’s out-of-bag observations. Multiple trees can be trained simultaneously. All the trees trained on different bootstrap samples are correlated.
7.	Boosting trees (BoTs)	Transforms weak decision trees (called weak learners) into strong learners. Tends to overfit. Better than random predictions. Good at handling tabular data with numerical features. Able to capture nonlinear interactions between the features and the target. Not designed to work with very sparse features.
8.	Random Forest	An ensemble approach uses decision trees. Creates multiple decision trees on different data samples and then predict the data from each subset. Finally the forest (group of random trees) is averaged.
9.	Gaussian Process regression (GPR)	Probabilistic (Bayesian) approach, An additional quantitative measurement of prediction accuracy in terms of uncertainty estimates, Use of kernels or covariance functions to reduce the processing time.

10.	Partial least square regression (PLSR)	Combines the benefits of principal component analysis and multivariate linear regression by reducing data dimensionality, transformation, and regression

3.2.2 Deep Learning/ Artificial Neural Networks

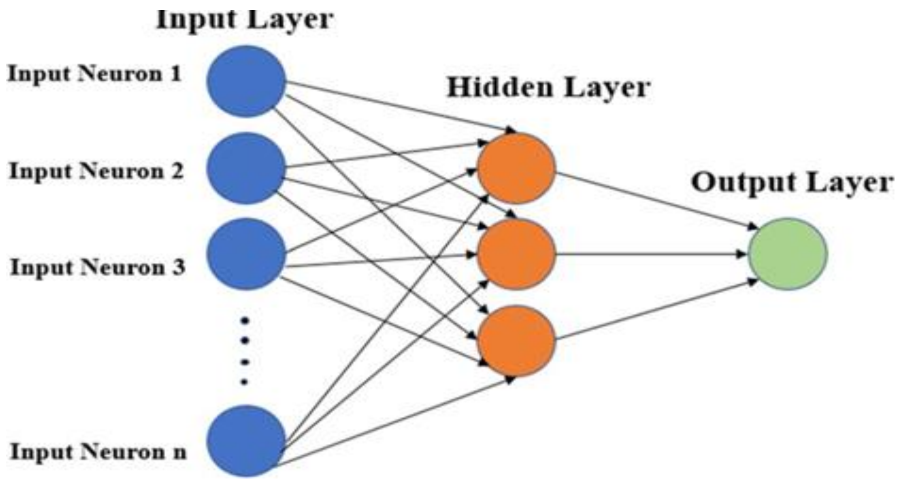
Deep Learning is the process of implementing neural networks on the high dimensional data to give insights and provide solutions. The use of Deep Learning in different fields of agriculture, including smart farming is seed analysis, water management, soil analysis, weed and pest detection, stress detection, plant disease detection and crop yield detection.



(Source:https://www.geeksforgeeks.org/artificial-neural-networks-and-its-applications/)
Figure 20: Artificial Neural Networks

Artificial Neural Networks consist of artificial neurons referred to as units, organized in layers that collectively form the entire neural network within a system. The number of units in a layer can vary significantly, ranging from a dozen to millions, depending on the complexity required for the neural network to discern hidden patterns in the dataset. Typically, an Artificial Neural Network includes an input layer, an output layer, and hidden layers. The input layer receives external data that the neural network aims to analyze or learn. Subsequently, this data traverses one or multiple hidden layers, where it undergoes transformations to become valuable input for the output layer. Ultimately, the output layer generates a response, presenting the output of the Artificial Neural Network in response to the provided input data.

In most neural networks, units are interconnected between layers, and each connection possesses weights that dictate the impact of one unit on another. As data moves from one unit to another, the neural network progressively learns more about the data, culminating in an output from the output layer.



(Source: Sahoo et al., 2023c)

Figure 21: Basic Architecture of Artificial Neural Network (ANN)

The structures and functions of human neurons form the foundation for artificial neural networks, commonly referred to as neural networks or neural nets. The initial layer in an artificial neural network is known as the input layer, responsible for receiving input from external sources and transmitting it to the subsequent layer, known as the hidden layer. Within the hidden layer, each neuron receives input from neurons in the preceding layer, computes the weighted sum, and transmits the result to the neurons in the subsequent layer. These connections involve weighted means, where the impacts of inputs from the preceding layer are fine-tuned by assigning varying weights to each input. These weights are adjusted during the training process to optimize model performance.

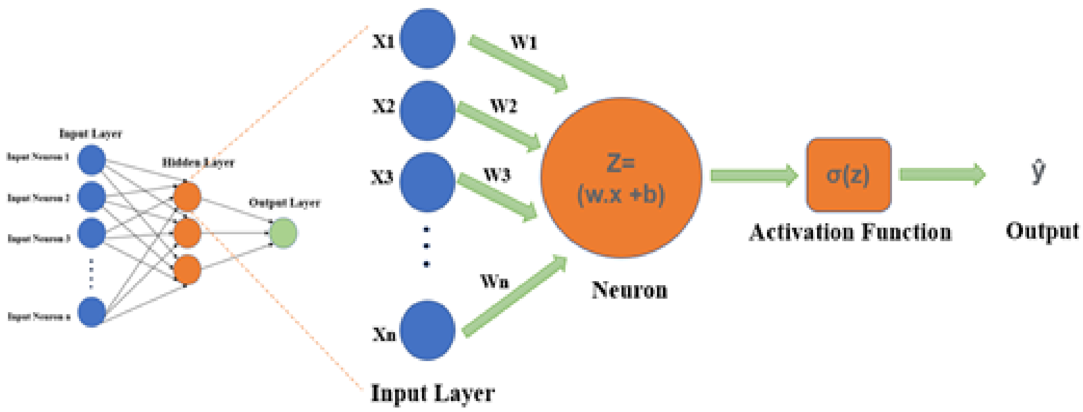


Figure 22: Single-layer perceptron

The major advantage of neural networks is their ability to predict and anticipate via parallel thinking. Artificial Neural Network can be taught instead of being extensively programmed. Figure below depicts relationship between AI, ML and Deep Learning/ Neural Network-

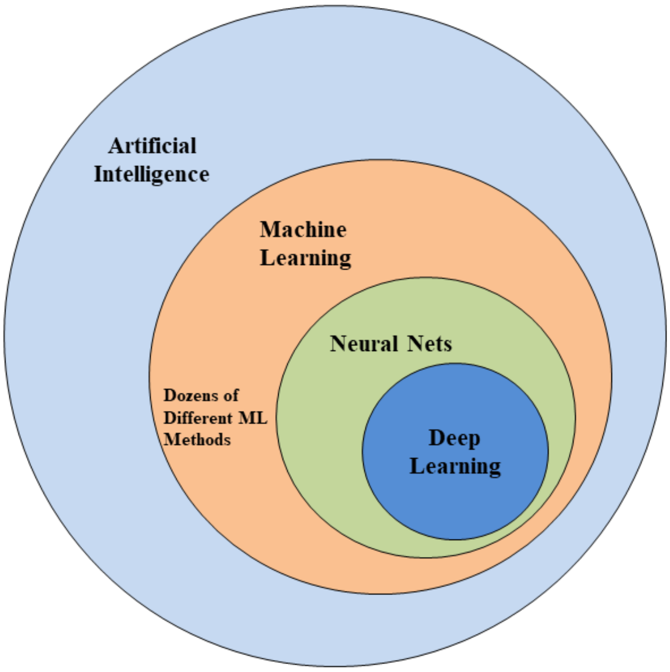
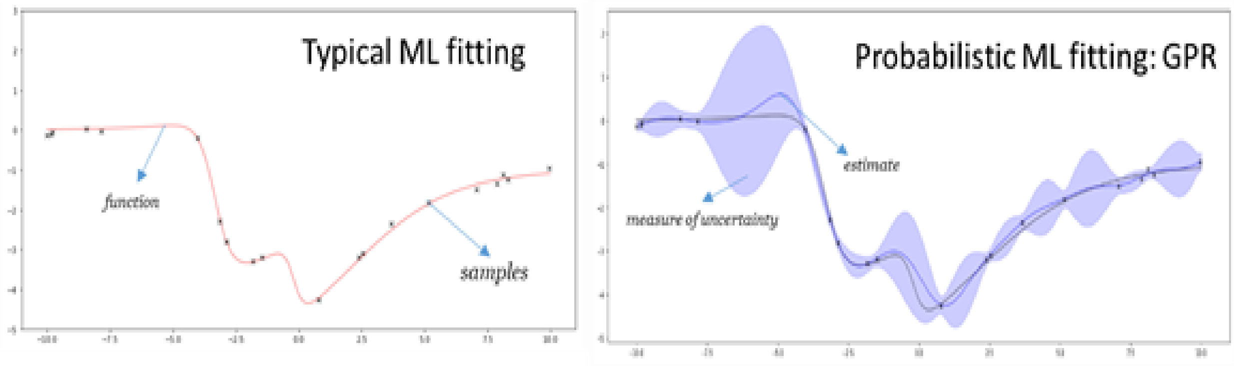


Figure 23: Relationship between AI, ML and Deep Learning

3.2.3. Hybrid ML approach using Gaussian Process Regression (GPR)

Gaussian Process Regression (GPR) provides a probabilistic (Bayesian) approach for learning generic regression problems with the help of kernels (Verrelst et al. 2013). On comparison with other ML models, the GPR shows two major advantages of (i) generating additional quantitative measurement of standard deviation and coefficient of variation (CV) along with prediction estimates, (ii) second is the use of kernels of co-variance functions to reduce the time taken during model training. Figure 24 gives a differentiation of GPR fitting with a typical ML fitting. The uncertainty can be noticed in regions where there are large gaps of missing data points. The squared exponential is the widely used kernel function for retrieving crop traits from multispectral and hyperspectral datasets. The best prediction performance for GPR models can be achieved by integrating with radiative transfer models. This hybrid modeling approach with the aid of dimensionality reduction and active learning techniques demonstrated accurate retrieval of multiple cropland traits using satellite and UAV-borne datasets (Sahoo et al. 2023b).



(Source:https://jessicastringham.net/2018/05/18/Gaussian-Processes/)
Figure 24: Regression with Gaussian Processes

The hybrid model combines the capabilities of Real Time (RT) modelling with the help of non-parametric regression models. The simulated spectral data from the RT modelling is used for training the GPR model. Several active learning methods were also used for reducing the training size of model, making it lighter to integrate with online platforms such as Google Earth Engine to generate accurate maps of multiple crop traits of larger areas (Sahoo et al. 2023b).

AI and IoT in Agriculture

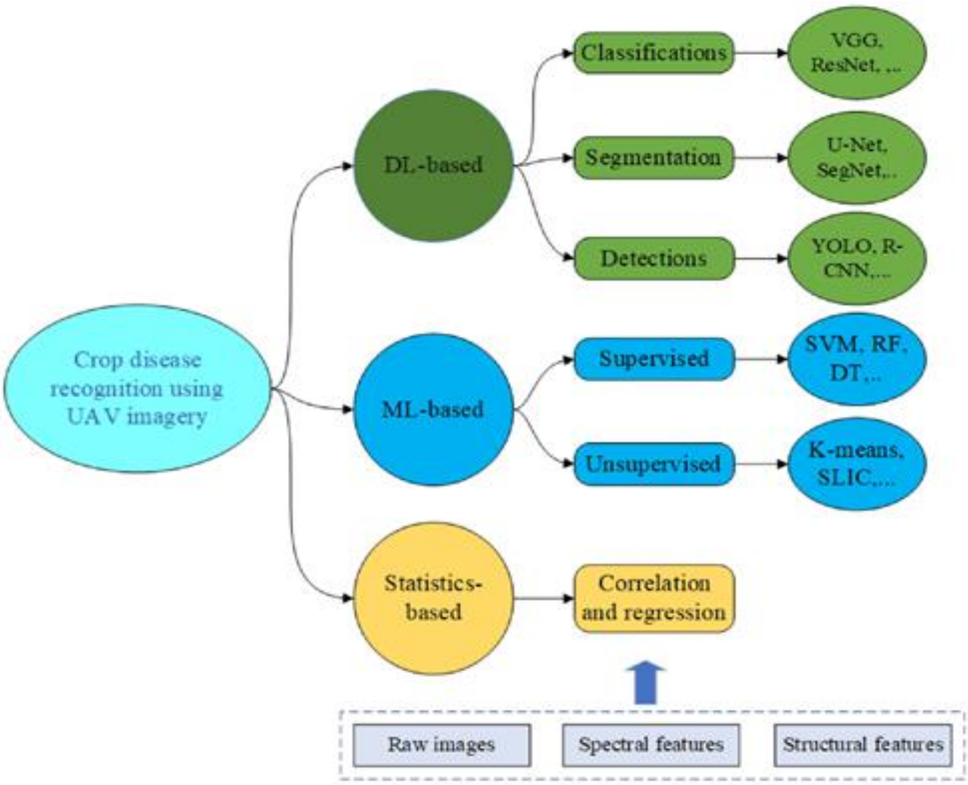
The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) has significantly revolutionized the agricultural sector, offering a multitude of benefits that enhance efficiency, sustainability, and productivity. One key advantage lies in precision agriculture, where AI-driven analytics and IoT devices collaborate to optimize various aspects of farming operations. Real-time monitoring of soil conditions, crop health, and weather patterns enables farmers to make informed decisions, enhancing crop yield and resource utilization.

Applications of AI/ ML in Agriculture

Some of the AI/ ML based applications in agriculture sector are-

• **Yield prediction:** Several machine learning models were used to support crop yield estimation using remote sensing data. As per a Systematic Literature Review (SLR) conducted by van Klompenburg et al. in 2020, the most applied ML algorithm is Artificial Neural Networks and the deep learning model is Convolutional Neural Networks (CNN). The outperformance of other ML models like Bayesian regularization BP (back propagation) neural network, Support Vector Regression (SVR), Extreme Learning Regression (ELR), Random Forest Regression (RFR), and Partial Least Squares Regression (PLSR) were also observed for estimating the crop yield using UAV and satellite remote sensing data (Kumar et al. 2023; Maimaitijiang et al. 2021; Xu et al. 2021). Vegetation indices like Red edge, canopy chlorophyll content index, red edge chlorophyll index, chlorophyll absorption ratio index, green normalized difference vegetation index, green spectral band, and chlorophyll vegetation index were among the most suitable variables in predicting crop yield using ML models. Timely prediction of multi-stage crop yield with ML models using a limited number of training data is vital in crop management.

• **Pest and diseases detection**: Early detection of crop disease is vital to prevent possible losses on crop yield. The accurate estimation of crop disease requires modern data analysis techniques such as machine learning and deep learning. The Figure shows the important deep learning and machine learning techniques applied to UAV data for identifying crop diseases. MLR models successfully identify Maize Dwarf Mosaic Virus and wheat Powdery Mildew Disease from Hyperspectral Measurements (Khan et al. 2021; Luo et al. 2021), Kiwifruit Decline Syndrome from UAV multispectral data (Savian et al. 2020), etc. Some of the major deep learning and machine learning models for crop disease identification using UAV datasets are shown in Figure 25. These studies facilitate smart farming allowing farmers to accurately identify the infected crops. This facilitates reduced application of pesticides and chemicals while preserving good crop quality.

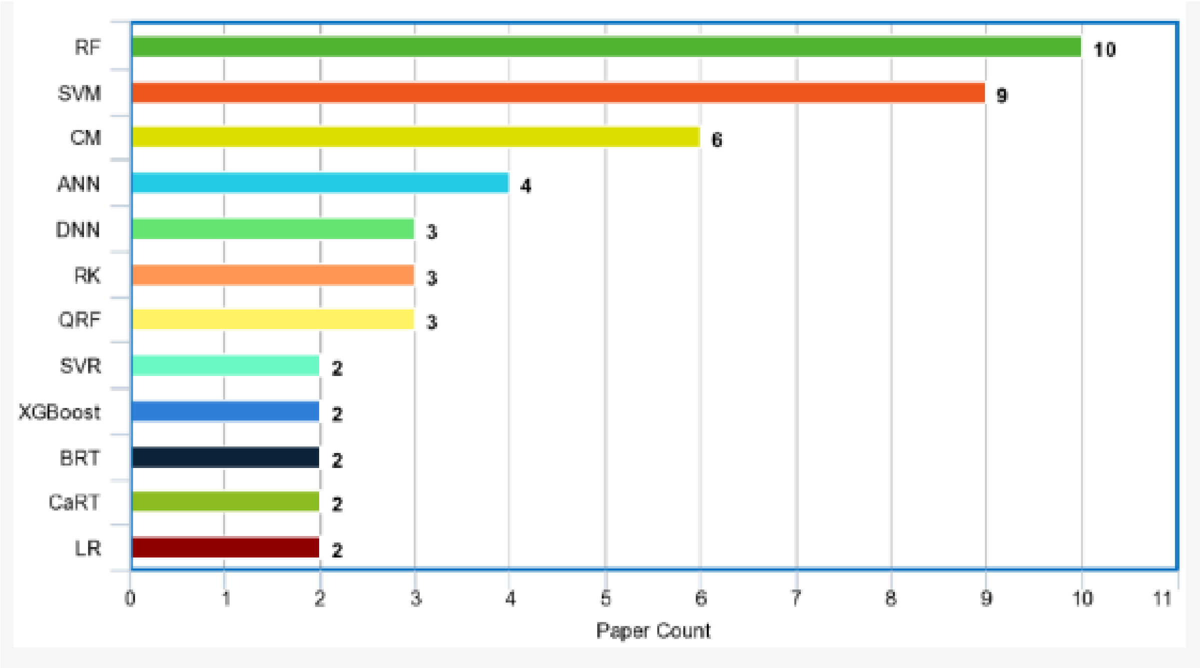


(Source: Shahi et al. 2023)

Figure 25: DL and ML based crop disease assessment techniques

• **Weed detection**: Weeds are considered as a harmful agricultural pest for the crops, which affects their yield and productivity. The ML/DL techniques demonstrated a superior performance in the early identification of weeds in agricultural farms. The RGB images often taken using drones, robots, and digital cameras are processed using DL/ML algorithms for identifying the weeds. In the case of ML, SVM showed better performance with a highest accuracy of 99% compared to other ML algorithms in identifying weeds. The CNN with its variants also showed superior performance with the highest accuracy of 99%(Murad et al., 2023). The lowest performance was shown by VGGNet.

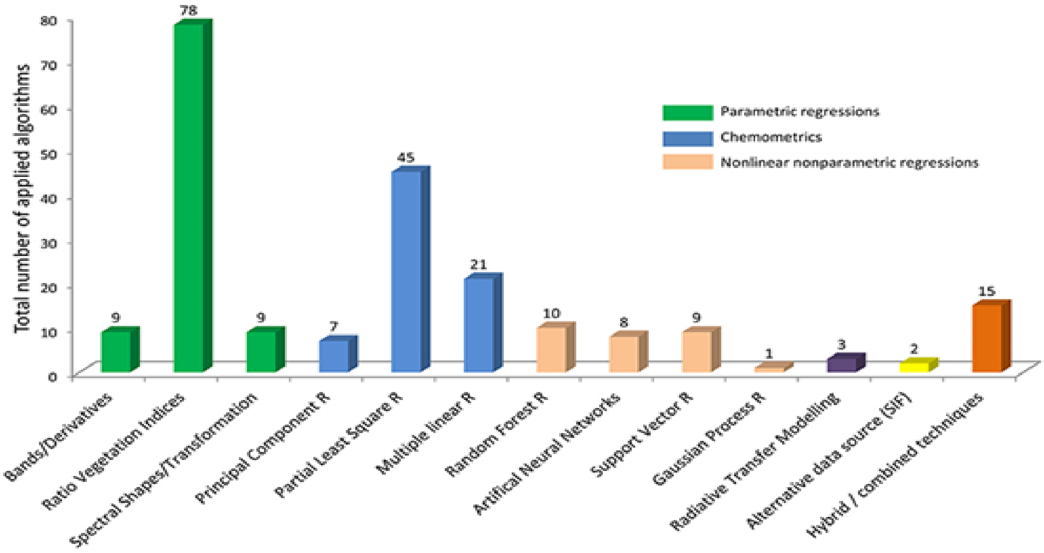
• **Soil health management**: Digital soil mapping and smart prediction of soil nutrients are important for maintaining healthy soil to achieve sustainable food production. Now ML has become an intelligent prediction system for soil nutrients. On a comparative review of different MLs, it was observed that random forest (RF) and deep learning outperformed other conventional ML models for predicting soil nutrients (Folorunso et al., 2023). The graphical representation of top machine learning models in soil nutrient predictions are shown in Figure 26.



(Source: Folorunso et al., 2023)

Figure 26: Graphical representation of the top 12 ML models used for soil predictions

• **Crop quality management**: Sensing technologies and ML models play a vital role in managing the quality of the crops by assessing N and chlorophyll status in plants. In contrast from last decades where the simple parametric regression algorithms with narrowband vegetation indices was used, an increasing trend was observed in machine learning and its hybrid version by integrating radiative transfer models as shown in Figure 27 (Berger et al., 2020). Moreover, the role of leaf protein content in estimating N status using the SWIR spectral region of hyperspectral data was also explored using hybrid physical-based models (Verrelst et al., 2021). Major crop traits such as leaf area index (LAI), leaf chlorophyll content (LCC), and canopy chlorophyll content (CCC) are also important for monitoring the crop quality. Recent trend in using hybrid models, mainly coupling the radiative transfer model with Gaussian process regression demonstrated a fast and accurate retrieval of these parameters (Sahoo et al., 2023b). The reported regression models for crop N estimation is shown in Figure 27.



(Source: Berger et al., 2020)
Figure 27: Estimation of N content using different methods

• **Smart irrigation**: A layer of machine learning-based irrigation architecture was proposed by (Abioye et al., 2022), where data from multiple sources like UAV and satellite-captured data, soil and weather information was stored in cloud server integrated with a ML model to make, predictions, decisions, and recommendations on scheduling smart irrigations. To achieve precise and smart management of irrigation practices in fields, (Sayari et al., 2021) recommend the use of machine learning models such as supervised learning, unsupervised learning, reinforcement learning, and federated learning models.

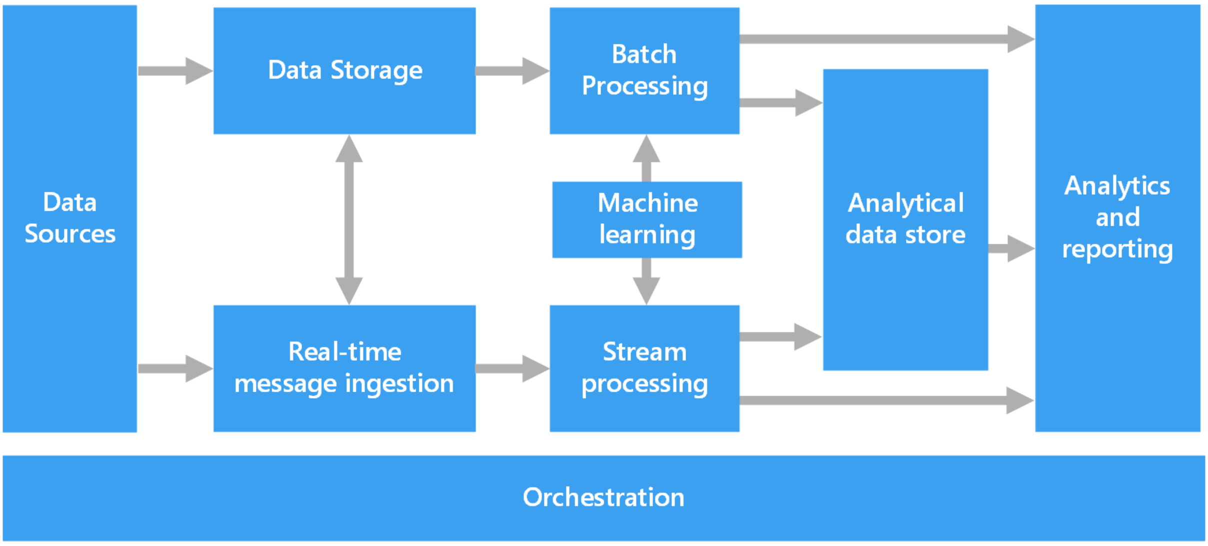
• **Livestock Management**: Livestock management involves critical disease detection, vaccination, production management, tracking, and health monitoring. Based on a comprehensive review conducted by (Hossain et al., 2022), the most used ML models for cattle identification were support vector machine (SVM), k-nearest neighbor (KNN), and artificial neural network (ANN). Based on evaluation metrics, SVM, KNN, ANN, and quadratic discriminant analysis (QDA) shows highest accuracy of more than 99% in cattle identification. The cattle identification with more than 99% accuracy was also achieved using DL models like ResNet, Inception, DenseNet, and the neural architecture search network (NasNet).

3.3. Big Data Analytics

Big data analytics is the use of advanced analytical techniques against very large and diverse datasets containing structured, semi-structured, and unstructured data of varying sizes from terabytes to zettabytes from different sources. With the analysis of big data, analysts, researchers, and business users are enabled to make better and faster decisions by using previously unused data. For this purpose, advanced analytical techniques such as text analytics, machine learning, predictive analytics, data mining, statistics, and natural language processing can be used. Big data has prominent applications in agriculture. For this reason, it is also called big data-driven farming. Big data supports better quality and more informed decisions.

Big Data is often defined in following terms-

- **Volume** - the amount of data generated, stored and analysed. The amount of data stored determines the level of insight that can be obtained from that data.
- **Variety** - type and nature of data. Historically data was structured and from a single source - in which case it would fit readily into 'columns' and 'rows'. Increasingly data is sourced from a variety of sources with many different formats
- **Velocity** - the speed at which data is generated and processed. Where historically data could reasonably be expected to be uploaded via a daily 'batch' process now data is measured in thousands or even millions of transactions per minute.
- **Veracity**- Addresses the quality and reliability of the data.
- **Value**- Focuses on extracting meaningful insights and value from the data. The value of big data usually comes from insight discovery and pattern recognition.

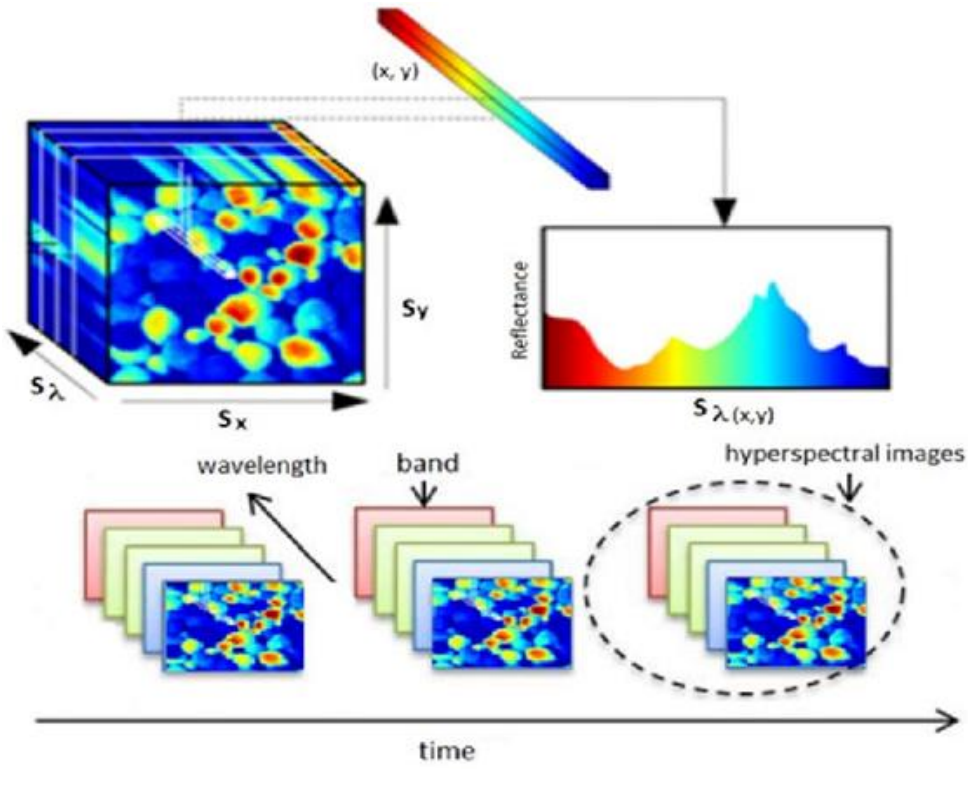


(Source: Microsoft Azure)
Figure 28: Big Data Architecture

3.3.1. Big Data and Machine Learning for Hyperspectral Data

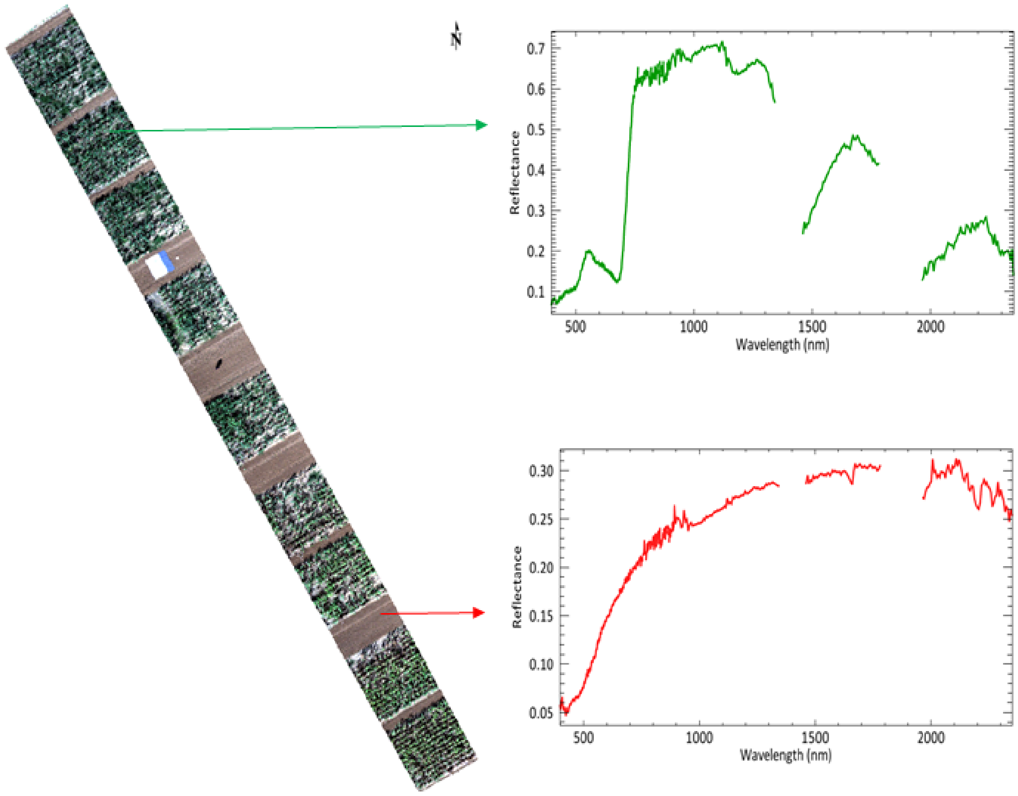
Unlike destructive techniques, hyperspectral imaging combined with ML regression models provides a non-destructive, non-invasive, near-real-time, efficient, and robust method for the estimation of crop biophysical and biochemical traits. This technology proved to be promising for plant phenotyping that incorporates indoor (controlled environment) and outdoor (field-scale) phenotyping. A hyperspectral big data constitutes a large number of narrow continuous spectral bands throughout the visible, near-infrared, and mid-infrared portions of the electromagnetic spectrum. The very high spectral resolution of these hyperspectral data facilitates in finer discrimination of target materials using the spectral response from each narrow band. A 3-D representation of hyperspectral data is shown in Figure 29. In the 3-D cube, the X and Y denote the spatial data while the spectral bands are denoted by Z-axis.

The high-resolution hyperspectral imagery of outdoor (field-scale) fields can be acquired using sensors attached to UAVs or drones. The UAV-borne hyperspectral data of the experimental fields in the ICAR-IARI research farm is shown in Figure 30. These high-resolution hyperspectral big data combined with various in-field biophysical and biochemical variables have opened opportunities to remotely measure these cropland traits. Further, this made the beginning of various data processing and analysis techniques using machine learning algorithms. The ML models readily explore the nonlinear relationship between the spectral reflectance values and target crop traits such as leaf area index, canopy content, chlorophyll content, dry biomass, etc. High accuracy in the retrieval of cropland traits from hyperspectral data includes majorly four ways, (i) parametric regression, (ii) nonparametric regression, (iii) inversion of RTMs, and (iv) hybrid or combined methods. Stepwise multiple linear regression (SMLR), partial least squares regression (PLSR), decision trees, artificial neural networks (ANNs), support vector regression (SVR), genetic algorithms, and Gaussian process regression (GPR) are some of the standard machine learning techniques used for crop variable estimation. The hyperspectral imagery having a large number of contiguous bands may lead to data redundancy and results in suboptimal performance in the ML models. To reduce redundancy and computational time, a suitable dimensionality reduction strategy is to be applied to hyperspectral data (Sahoo et al. 2023).



(Source: Ang and Jasmine 2021)

Figure 29: 3D cube representation for Big hyperspectral data



(Source: ICAR-NePPA)
Figure 30: Hyperspectral data of the experimental fields in ICAR-IARI research farm captured using UAV

3.4. Distributed Ledger Technology/ Blockchain:

Distributed Ledger Technology (DLT) is a decentralized and distributed database architecture that allows multiple participants to share and synchronize a digital ledger across a network of computers. The term is often used interchangeably with blockchain technology. DLT operates on a network of computers (nodes) that are geographically distributed. Each node has a copy of the ledger, and there is no central authority controlling the entire system. Once data is recorded in the ledger, it is typically challenging to alter or delete. Immutability ensures the integrity of the historical records, providing transparency and trust.

Opportunities for DTL/ Blockchain Technology in Agriculture Sector:

A DTL/Blockchain technology has several applications in agriculture that aim to enhance transparency, efficiency, and trust within the supply chain. Here are some ways DLT is used in agriculture:

Supply Chain Traceability:

DLT allows for the creation of an immutable and transparent record of the journey of agricultural products from farm to table. Each stage of production, including planting, harvesting, processing, and transportation, can be recorded on the blockchain. This enhances traceability and helps consumers verify the authenticity and origin of the products.

Smart Contracts for Agreements:
Smart contracts on blockchain platforms enable the automation and execution of agreements between different stakeholders in the agriculture supply chain. For instance, contracts between farmers and buyers, specifying terms for the sale of crops, can be automatically executed based on predefined conditions.

Digital Representation of Assets:
Blockchain enables the tokenization of agricultural assets, representing ownership of physical assets like land, machinery, or even specific crops. This can streamline transactions involving these assets and make them more accessible for investment.

Preventing Counterfeiting:
Blockchain can be used to combat food adulteration by preventing the counterfeiting of products. By recording each step of the supply chain on an immutable ledger, consumers can trust the authenticity of the food they purchase.

4. Digital Agriculture

Digital agriculture encompasses a wide range of technologies and practices aimed at enhancing various aspects of agricultural production. These include precision farming, data-driven decision-making, smart irrigation systems, crop monitoring using drones and satellites, automated machinery, and predictive analytics. By collecting, analyzing, and interpreting vast amounts of data, farmers can gain valuable insights into soil health, crop growth, weather patterns, pest infestations, and market trends, enabling them to make informed decisions and optimize resource allocation.

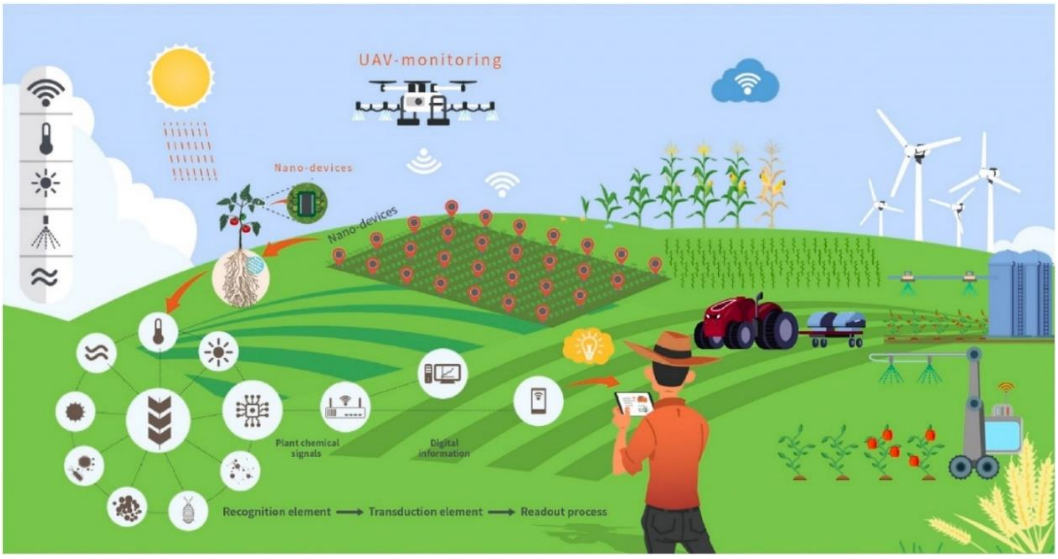
The digitalization of agriculture involves integrating cutting-edge digital technology into the farm production system, including artificial intelligence (AI), blockchain, remote sensing and GIS technology, use of drones and robots, sensors and communication networks.

4.1. Precision Agriculture

Food and Agriculture Organization (FAO) has defined Precision Agriculture as "a management strategy that gathers processes and analyses temporal, spatial and individual data to support improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production. Precision agriculture includes precision livestock farming (PLF) and equivalent approaches in aquaculture and agroforestry".

Precision agriculture often employs technologies to automate agricultural operations, improving their diagnosis, decision-making or performing. The goal of precision agriculture is to define a decision support system for whole farm management with the goal of optimizing returns on inputs while preserving resources.

Figure below depicts important components of Precision Agriculture-



(Source: ScienceDirect[7])
Figure 31: Precision Agriculture System

[7] https://www.sciencedirect.com/science/article/pii/S0981942823007556

The Wireless Sensor Networks (WSN) are widely used in agriculture monitoring to improve the quality and productivity of farming. Sensors are used to gather different types of data (i.e., humidity, carbon dioxide level, and temperature) in real-time scenarios. The Sensor Network consists of small, typically battery powered wireless devices.

The data is collected at sensor and then relayed from sensor to the network. Further, data analytics is being used to create intelligence which enable farmers and agricultural stakeholders to gain valuable insights, make informed decisions, and optimize farming practices.

Table 6: Sensors used in various agriculture applications

Smartphone Sensor(s)	**Purpose**	**Common Agriculture Usage**
Soil Moisture Sensor	Measure the amount of moisture present in the soil	Integrated into the soil at various depths, these sensors provide real-time data, enabling farmers to optimize water usage and prevent waterlogging or drought stress in crops.
Soil Temperature Sensor	Monitor the temperature of the soil to determine optimal planting times, seed germination conditions and microbial activity.	Placed at different depths within the soil profile, these sensors transmit temperature data, helping farmers make informed decisions regarding crop selection, planting schedules, and pest management strategies based on temperature thresholds.
Soil Nitrate Sensor	Measure the concentration of nitrate ions in the soil, guiding fertilization practices	These sensors provide real-time nitrate level readings, allowing farmers to adjust fertilizer applications precisely, minimize nutrient leaching and optimize crop yield.
Humidity Sensor	Monitor air humidity levels to prevent fungal diseases, optimize photosynthesis, and maintain favorable microclimates	These sensors transmit humidity data, enabling farmers to regulate irrigation, ventilation, and heating systems for optimal crop health and yield.
Dissolved Oxygen Sensor	Measure the concentration of oxygen dissolved in water to maintain suitable	Deployed in aquaculture ponds or tanks, these sensors transmit dissolved

	conditions (Mainly used in Aquaculture)	oxygen levels, allowing aquafarmers to adjust aeration, feeding rates, and stocking densities
pH Sensor	Monitor the acidity or alkalinity of soil or water to regulate nutrient availability, microbial activity, and overall crop health.	Positioned in soil or irrigation systems, pH sensors provide continuous pH measurements, empowering farmers to adjust soil amendments or water treatment strategies, select appropriate crops, and prevent nutrient imbalances
Image Sensor(Camera)	Takes pictures of any object	Disease detection, chlorophyll status, Fruit ripeness, Leaf area index (LAI), Harvest readiness, Soil erosion and other analysis
Global Positioning System(GPS)	Measuring the latitude and longitude of device, location.	Local information is attached to generate alerts. Mostly used for machine driving &control, and tracking, land management and Crop mapping.
Inertial Sensor	Uses accelerometer and gyro sensor to determine the object altitude in relation to the inertial system	Precise distance of plant, leaf or any other object is measured from camera
Barometer	Measure air pressure as an altimeter. Mostly used in correcting altitude measurements by the GPS	Measures the elevation height in hilly agriculture
Gyroscope	Senses the angular velocity to track the object rotation or twist	Equipment movement, Canopy structure measurement
Accelerometer	Measures acceleration forces that used to observe the tilting motion and orientation of the object	Precise movement or rotation of the camera during use. Detect workers or machine activities
Microphone	Detect usual / unusual sound and convert to electrical signals	Machine maintenance , Bug detection to make audio queries

Precision agriculture relies on GNSS/NavIC/GPS technology to provide accurate and real-time location data for farming equipment, allowing farmers to navigate their fields precisely. This helps optimize the use of resources such as water, fertilizers, and pesticides.

Satellite technology is becoming an invaluable tool in modern agriculture, providing a bird's-eye view of large agricultural landscapes. Remote sensing satellites capture data in various spectra, offering insights into crop health, land use, and environmental conditions. Drones also have many applications for agricultural field surveillance and remote diagnostics of agronomic conditions such as plant and crop diseases, water resources and soil quality.

Thus, Integration of remote sensing, satellite imagery and drone technology in agriculture is transforming traditional farming practices into data-driven, precision-based systems.

Benefits of Precision Agriculture:

Resource Efficiency: Precision agriculture optimizes the use of resources, reducing waste, environmental impact and also results in cost savings for farmers. This includes precise application of fertilizers and pesticides, targeted irrigation, and efficient use of fuel for farming equipment.

Increased Productivity: By leveraging data-driven insights and automation, farmers can enhance their decision-making processes. This leads to increased productivity, improved crop quality, and higher yields per acre.

Data-Driven Decision-Making: The data collected through precision agriculture tools empowers farmers to make informed decisions. Access to real-time information enhances the ability to respond quickly to changing conditions and optimize farming strategies.

Enhanced Sustainability: By minimizing the use of fertilizers, pesticides, and water through targeted application, precision agriculture reduces environmental impact and promotes sustainable farming practices. Precision management of inputs helps preserve soil health, minimize erosion and conserve natural resources.

4.2. Agricultural Robots

Agricultural robots often referred to as agri-robots, can play a crucial role in reshaping traditional farming practices. These sophisticated machines are designed to automate various tasks in agriculture, ranging from planting and harvesting to monitoring and maintenance. The use of robots increases productivity, safety, efficiency, quality, and consistency of products. Robots can be much more accurate and precise than humans.

Figure 32: Agricultural Robots

Types of Agricultural Robots:

Autonomous Tractors and Machinery: Autonomous tractors equipped with GPS, sensors, and navigation systems can perform tasks such as plowing, seeding, and harvesting with precision. Smart machinery and implements, including planters, sprayers, and harvesters, are designed to operate autonomously or with minimal human intervention, increasing efficiency and reducing labor costs.

Unmanned Aerial Vehicles (UAVs) and Drones: UAVs and drones equipped with cameras, sensors, and imaging technologies provide aerial surveillance and monitoring of crops, livestock, and fields. Drones can assess crop health, detect diseases, identify pest infestations, and monitor environmental conditions, enabling early intervention and decision-making.

Robotic Harvesters and Pickers: Robotic harvesters are capable of selectively picking fruits, vegetables, and crops with precision, reducing damage and minimizing harvest time. Vision systems, robotic arms, and grippers enable robots to identify and harvest ripe produce while leaving unripe or damaged crops untouched.

Weed Control Robots: Weed control robots use various methods such as mechanical weeding, thermal treatment, and precision herbicide application to manage weeds in fields. These robots can navigate rows of crops, identify weeds, and selectively apply treatments, reducing the need for herbicides and manual labor.

Soil Monitoring and Cultivation Robots: Soil monitoring robots equipped with sensors and probes assess soil moisture, nutrient levels, pH, and compaction, providing valuable data for precision agriculture. Cultivation robots, including robotic tillers and weeders, perform soil preparation and cultivation tasks with accuracy, promoting optimal crop growth and yield.

Benefits of Agricultural Robots:

Labor Savings: Agricultural robots automate repetitive and physically demanding tasks, reducing the reliance on manual labor and alleviating labor shortages in the agriculture sector. By freeing up human resources, farmers can focus on more strategic and value-added activities, such as crop management and decision-making.

Increased Efficiency: Robotic systems operate with precision and consistency, minimizing errors and improving operational efficiency in various agricultural tasks. Autonomous navigation and real-time data analysis enable robots to optimize resource utilization, reduce input wastage, and maximize yields.

Improved Crop Quality: Robotic harvesting and picking ensure gentle handling of produce, minimizing damage and preserving quality throughout the harvesting process. Selective harvesting and sorting capabilities enable robots to identify and harvest ripe crops, resulting in higher-quality yields and reduced post-harvest losses.

Enhanced Sustainability: Agricultural robots promote sustainable farming practices by reducing the use of chemicals, water, and energy through targeted and precise application. By minimizing soil compaction and erosion, robots help preserve soil health and fertility, contributing to long-term environmental sustainability

Applications of Agricultural Robots:

- Precision Planting
- Harvesting Robots
- Autonomous Tractors
- Monitoring and Sensing Robots
- Robotic Dairy Farming

4.3. Remote Sensing and Satellite Imagery in Agriculture

Remote sensing involves the collection of information about objects or areas without direct physical contact. In agriculture, it can play a pivotal role in monitoring and managing crops, soil, and environmental conditions. Satellites are a crucial platform for remote sensing applications. In agriculture, satellite imagery can provide a comprehensive view of large agricultural landscapes.

Remote sensing and satellite imagery are integral components of precision agriculture, which can offer valuable insights for farmers and agricultural stakeholders. These technologies may contribute to data-driven decision-making, optimized resource usage, and enhanced overall farm management.

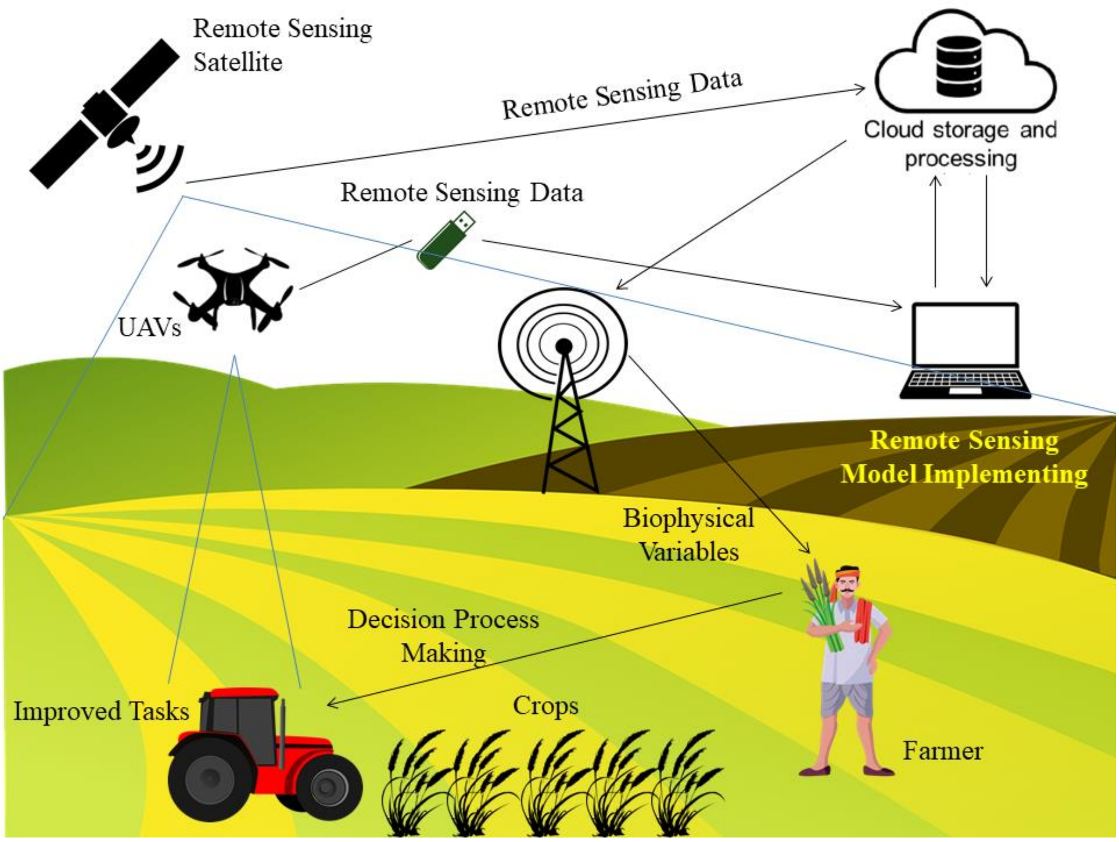


Figure 33: Remote Sensing in Agriculture

Applications of Remote Sensing and Satellite Imagery in Agriculture:

- Crop Monitoring and Health Assessment
- Yield Prediction
- Soil Moisture Monitoring
- Drought Monitoring and Prediction
- Land and Crop Mapping

Benefits of Remote Sensing and Satellite Imagery in Agriculture:

- Data-Driven Decision-Making
- Resource Optimization
- Early Problem Detection
- Increased Productivity
- Sustainability

4.4. Drones and Unmanned Aerial Vehicles (UAVs) in Agriculture

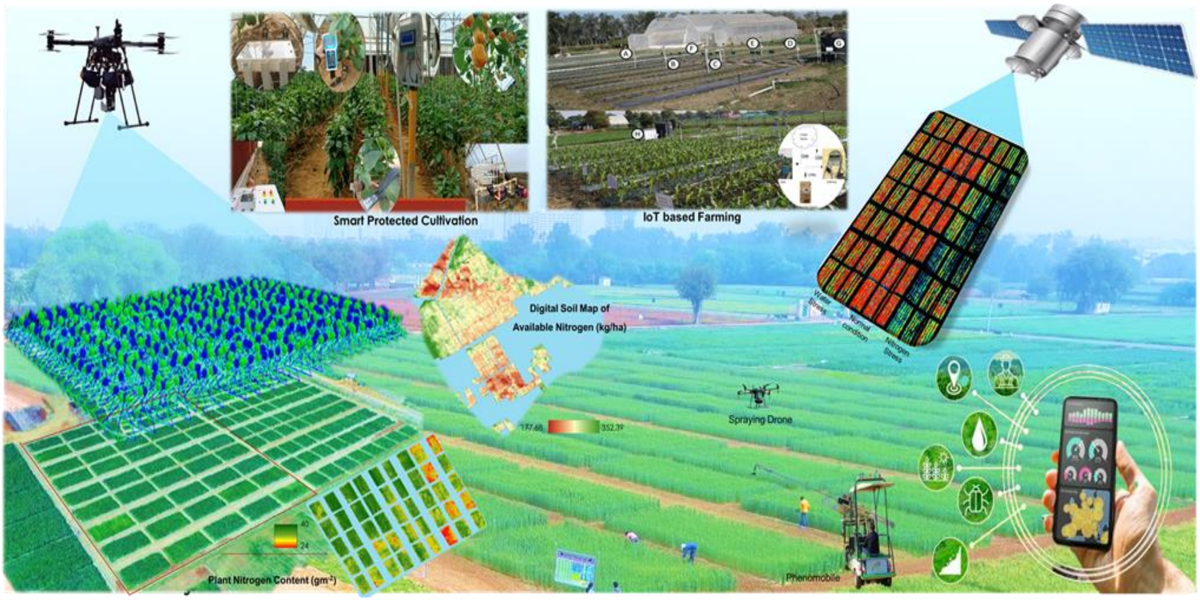
Drones, also known as Unmanned Aerial Vehicles (UAVs), are becoming valuable tools in modern agriculture, revolutionizing the way farmers can monitor, manage, and optimize their crops. These aerial vehicles equipped with cameras and sensors provide a bird's-eye view of fields, collecting valuable data for analysis and decision-making.

(Source: NePPA, IARI, ICAR)

Figure 34: Spraying Drones in Agriculture

(Source: NePPA, IARI, ICAR)

Figure 35: Imaging Drones in Agriculture



(Source: NePPA, IARI, ICAR)

Figure 36: Smart Farming in Agriculture 4.0

Applications of Drones and UAVs in Agriculture:

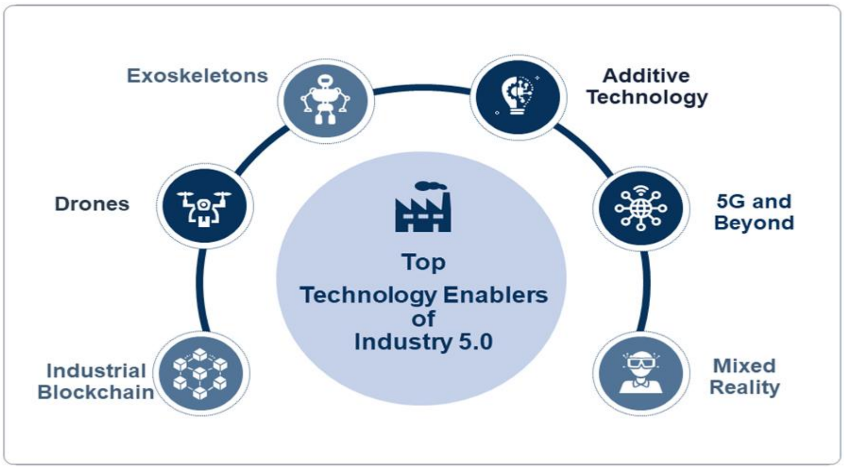
- Crop Monitoring and Health Assessment
- Precision Agriculture
- Field Mapping and Surveying
- Crop Scouting and Surveillance
- Planting and Seeding
- Irrigation Management
- Livestock Monitoring
- Post-Harvest Assessment
- Precision Spraying of pesticides

Benefits of Drones and UAVs in Agriculture:

- Efficiency and Speed
- Precision and Accuracy
- Cost-Effective Monitoring
- Enhanced Crop Management
- Accessibility in Challenging Terrain
- Environmental Sustainability

4.5. Agriculture as Industry 5.0

A revolution and concept going way beyond the traditional manufacturing with emphasis on integration of humans and machines to collaborate more effectively is referred to as Industry 5.0 (Fraga et al. 2021). It marks a noticeable change from Industry 4.0 that focused majorly on automation, data exchange and adoption of smart technology in the field of agriculture (Skobelev & Borovik, 2017). The additions in Industry 5.0 enables the farmers to leverage data analytics, sensors, and IoT devices to make more informed decisions about planting, irrigation, fertilization, and pest control. Instead of replacing humans with machines, Industry 5.0 in agriculture emphasizes collaboration between the farmers and technology. The labor intensive tasks are performed by the advanced instruments while the decision making and control stands in the hands of the stakeholders (Rane, 2023; Adel, 2022). This technology goes beyond the hard coding and enables the customizations and personalization based on the user specific needs and environmental conditions. Here, integration with blockchain technology is used to create transparent and traceable supply chains, ensuring food safety and quality while reducing waste and inefficiencies (Akundi et al. 2024). Going beyond the technology, it also works forward towards enhancing the skills and training of the farmers to keep them well updated of the changing technologies and to help them stay competitive in a rapidly evolving agricultural landscape (Mourtzis et al. 2022). The technology also aims to promote the sustainable and resilient agricultural practices. By combining traditional wisdom with cutting-edge technology, farmers can adopt regenerative farming methods that enhance soil health, biodiversity, and ecosystem resilience while mitigating the effects of climate change. It holds immense potential to reshape agricultural landscape, helping us to march into a future where human creativity seamlessly merges with cutting-edge technology, unlocking the full capabilities of Industry 5.0 (Figure 37) and setting up grounds for Society 5.0 (Aggarwal et al. 2024, Paschek et al. 2024).



(Source: https://www.frost.com/frost-perspectives/industry-5-0-bringing-empowered-humans-back-to-the-shop-floor/)

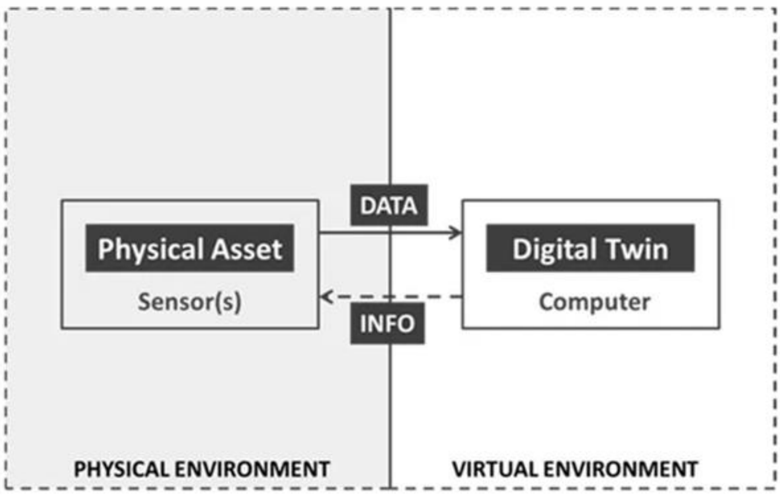
Figure 37: Technology enablers of Industry 5.0

4.6. Cyber Agrophysical System (CAPS)

Cyber Agro-Physical System (CAPS) is Cyber Physical System in agriculture, in which computation/ information processing and physical processes are tightly integrated and non-separable from the behavioural point of view; where functionality and salient system characteristics are emerging through the interaction of physical and computational objects and computers, networks, devices and their environments in which they are embedded have interacting physical properties, consume resources and contribute to the overall system behaviour. Such agricultural systems and approaches constitute the paradigm of intelligent agriculture, based on quality, efficiency and sustainability requirements. The implementation of such a system could be made by degrees, stepwise increasingly both the production diversity and the automation level, thus ensuring a lean transition from a monoculture specialized agricultural enterprise towards a flexible, diversified, adaptive improved version and making agriculture as Industry 4.0 /5.0 with good agricultural practice and new way of connectivity of digital and physical world.

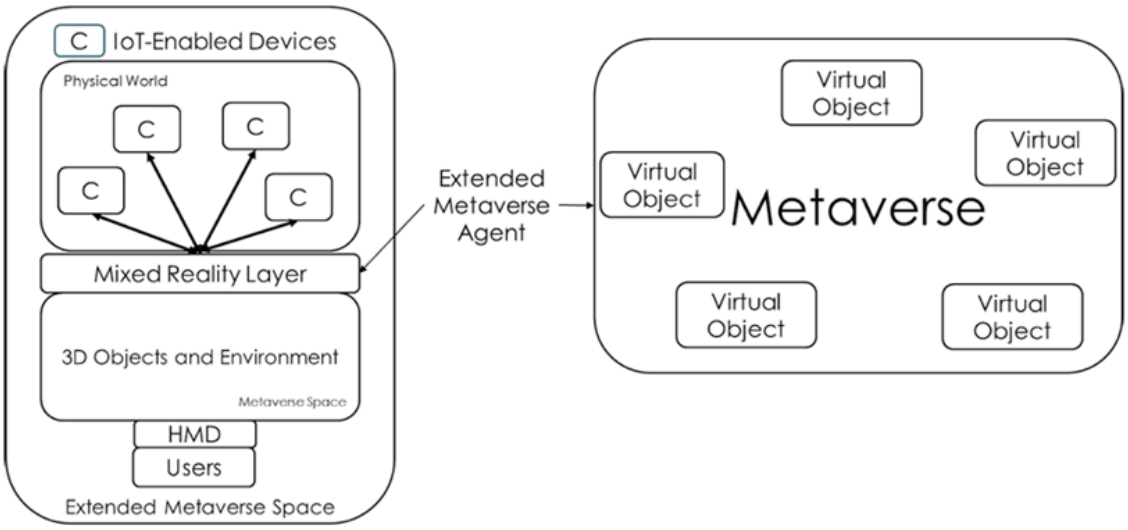
4.7. Digital Twin and Metaverse

The transformation of agriculture sector is moving to accomplish the demands of efficient and sustainable production. In this attempt, a digital twin is another step forward to modern smart farming. It is a digital replica of a real-world entity that is kept updated with constant inflow of data and simulates not just the physical and biological state but also the behaviour of the real-world entity based on input data (Neethirajan and Kemp, 2021) (Figure 38). It helps in predicting, optimizing, and improving decision making. Integration of Digital Twin (DT) and Generative Artificial Intelligence (AI) has emerged as promising technology in agricultural sector (Du et al.2023). By leveraging immersive virtual environments and AI-driven technologies, stakeholders in the agricultural sector may enhance productivity, sustainability, and resilience in farming practices while fostering global connectivity and knowledge exchange (Nie et al.2022).



(Source: Neethirajan and Kemp, 2021)
Figure 38: The relationship between digital twin and the physical asset

AI can be integrated with metaverse to enhance the agricultural education and facilitate virtual collaboration among stakeholders (Figure 39). Virtual training scenarios can simulate real-world field conditions and challenges, allowing farmers to gain practical skills. AI algorithms can power virtual marketplaces within the agricultural metaverse, where farmers can buy and sell agricultural products, equipment, and services. AI-driven collaborative platforms in the agricultural metaverse can facilitate virtual collaboration among researchers, agronomists, and agricultural experts from around the world.



(Source: Rekimoto and Nagao (1995))

Figure 39: The framework of the extended metaverse agent, integrating the metaverse of virtual objects with XR/IoT environments

5. Standardisation Activities in Agriculture Domain

Significant Standardization work has already been done in the area of agriculture-

5.1. Standardization Activities in ITU

ITU−T SG−20 has been working to create standards on *IoT and its applications on Smart cities and communities* since 2015. ITU−T SG−20 has also created a Focus Group on "*Artificial Intelligence (AI) and Internet of Things (IoT) for Digital Agriculture (FG-AI4A)*" on 21 October 2021 in collaboration with FAO to examine key concepts, and relevant gaps in current standardization landscape related to agriculture, and the best practices and barriers related to the use of AI and IoT-based technologies within this domain (more details available on https://www.itu.int/en/ITU-T/focusgroups/ai4a/Pages/default.aspx). A large number of recommendations have been released in the IoT domain, some of the important standards are-

Table 7: ITU Standards related to Agriculture

Sl. No.	**Standards**	**Title**
1	ITU-T Y.4000/Y.2060	Overview of the Internet of things.
2	ITU-T Y.4450/Y.2238	Overview of Smart Farming based on networks
3	ITU-T Y.4218	IoT and ICT requirements for deployment of smart services in rural communities
4	ITU-T Y.4466	Framework of IoT-based Smart Greenhouse
5	ITU-T Y.4482	Requirements and framework for smart livestock farming based on the Internet of things
6	ITU-T Y. 4107	Requirements for water quality assessment services using ubiquitous sensor networks
7	ITU-T Y.2245 (09/2020)	Service model of the agriculture information based convergence service
8	ITU-T L.1504 (2016)	ICT and adaptation of agriculture to the effects of climate change
9	ITU-T Y.4495	Requirements and a reference model of data for smart greenhouse service

5.2. Standardization Activities in ISO

Standardization roadmap on smart farming was developed by the International Standardization Organisation (ISO) Strategic Advisory Group (SAG) on Smart Farming. Nine thematic areas were examined in relation to the UN Sustainable Development Goals (SDGs): crop production, livestock, urban farming, terminology and semantics, social aspects, supply chains, original equipment manufacturers, climate adaptation, environment and data. ISO standards for agriculture cover all aspects of farming, from irrigation and global positioning systems (GPS) to agricultural machinery, animal welfare and sustainable farm management[8].

Some of the important standards released by ISO related to agriculture sector are mentioned below-

Table 8: ISO Standards related to Agriculture

Sl. No.	Standards	Title
1	ISO 15003	Agricultural engineering – Electrical and electronic equipment – Testing resistance to environmental conditions
2	ISO 24631	Radio frequency identification of animals
3	ISO 11783	Tractors and machinery for agriculture and forestry
4	ISO 22005	Traceability in the feed and food chain – General principles and basic requirements for system design and implementation
5	ISO 20966	Automatic milking installations – Requirements and testing
6	ISO 4002	Equipment for sowing and planting
7	ISO 11783	Serial control and communications data network for agricultural tractors

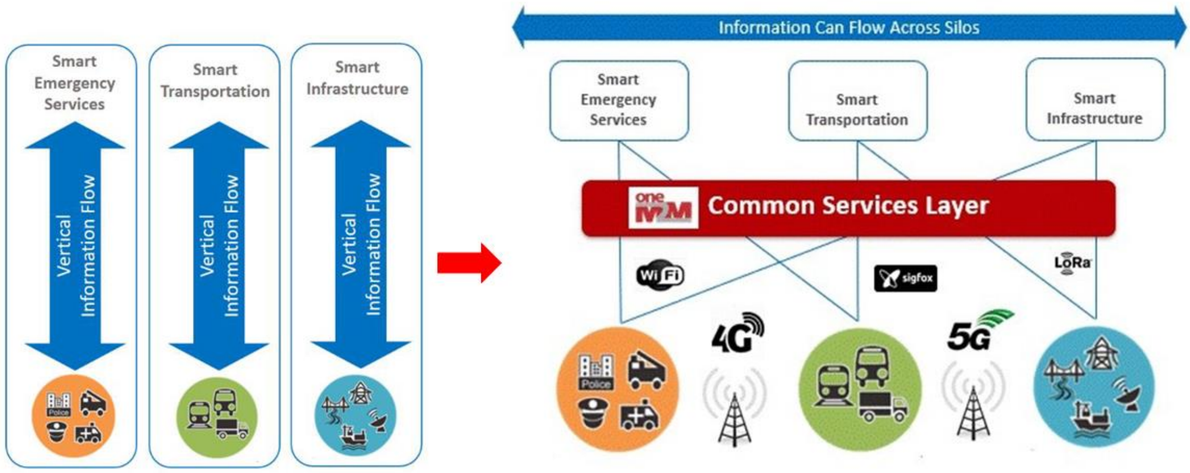
5.3. oneM2M Standards

oneM2M is the global standards initiative that covers requirements, architecture, API specifications, security solutions and interoperability for Machine-to-Machine and IoT technologies. oneM2M was formed in 2012 and consists of eight of the world's preeminent Standards Development Organizations (SDOs): ETSI (Europe), TSDSI (India), TTC (Japan), ARIB (Japan), ATIS (USA), TIA (USA), TTA (Korea), CCSA (China).

From India, TSDSI is the member of oneM2M. oneM2M has released first set of specifications in Jan 2015, 2nd in March 2016, 3rd in Dec 2018. The oneM2M Release 2 and Release 3 specifications have been adopted as National Standards by TEC, DoT in 2020 and 2022 respectively. The important benefits of implementing oneM2M standards based solution includes interoperability of device & application; authentication & authorization of devices; and Data security & Privacy. The details of these National Standards are available on TEC website (https://www.tec.gov.in/onem2m).

[8]https://www.iso.org/news/supporting-agrifood-systems

A common service layer has been depicted in the figure below:



(Source: https://www.onem2m.org/)
Figure 40: oneM2M Architecture

Deployment of IoT Applications using oneM2M Standards based Common Service Layer

The oneM2M compliant field domain application on the Gateways would send the data to the oneM2M based Common Service Platform. The data consuming applications for the various domains hosted on the cloud would be collecting the data from the Common Service Layer Platform received from the respective sensors in a secured manner for visualization, analysis or for taking some actions. This architecture ensures that only authorized and authenticated devices and applications are able to communicate. It also makes it possible to share the data among divergent applications without the need for additional layer of software.

The Common Service Layer mentioned here is a horizontal layer of functions commonly needed across different market segments / not segment-specific. This is similar to generic versus use case-specific computer/OS in early times of computers. It would enable the industry to develop standard based applications which would reduce the development, test and deployment lifecycles.

By deploying the Standards Compliant Common Service Layer Platform, M2M Service Providers can offer wide range of services developed by the industry. It can also play a pivotal role in the Smart City Projects by easing the development efforts of the application providers offering solutions for smart city project.

Major benefits of oneM2M Standards

Following are the major benefits of oneM2M Standards:

1. The development of new innovative applications would be much easier due to well defined standards. This would be immensely beneficial even for smaller organisations/start-ups.
2. Interoperability of devices and applications would become possible due to standardized interfaces.
3. Only authenticated and authorized devices would be able to communicate.
4. Information and statistics regarding the loT devices and applications would be available.
5. Resource utilization can be monitored by the authorities.
6. Regulations, KYC can be enforced.
7. Data Security and Privacy concerns are addressed.
8. Data sharing would be feasible in a standardized way among divergent applications.
9. Integration of innovative applications across domains would be much easier.
10. Device Management becomes easy.
11. Certification would become feasible (with standardized test suites) for-
    a. Devices: Ecosystem of Certified products
    b. Applications: Sharing of data, interworking, Security
    c. Services: Compliance

C-DOT Common Service Platform (CCSP):

C-DOT Common Service Platform (CCSP) for IoT/ M2M Communication is based on oneM2M specifications. CCSP (IoT platform) allows any IoT application to discover and interact with any IoT device.

6. DoT/ TEC Initiatives in M2M/ IoT Domain

DoT/ TEC has taken several initiatives to facilitate organized and sustainable growth in M2M/IoT domain. Few important initiatives are given below-

1. National M2M Roadmap was released in 2015 (https://dot.gov.in/sites/default/files/National%20Telecom%20M2M%20Roadmap.pdf). Through this document "National Telecom M2M Roadmap", Government has made efforts to put together various standards, policy and regulatory requirements and approach for the industry on how to look forward for M2M. This document focuses on communication aspects of M2M with emphasis on Interoperable standards, policies and regulations to suit Indian conditions across sectors, across the country.

2. National Digital Communication Policy (NDCP) was released in 2018 (https://dot.gov.in/sites/default/files/Final%20NDCP-2018_0.pdf). It covers many points related to IoT, Artificial Intelligence and 5G including ' Developing market for IoT/ M2M connectivity services in sectors including Agriculture, Smart Cities, Intelligent Transport Networks, Multimodal Logistics, Smart Electricity Meter, Consumer Durables etc. incorporating international best practices'.

3. Guidelines for KYC of M2M SIMs & Instructions for embedded-SIMs (e-SIMs) were issued in 2018 (https://dot.gov.in/sites/default/files/M2M%20Guidelines.PDF?download=1). It describes the Instructions for implementing restrictive feature for SIMs used only for Machine-to-Machine (M2M) communication services (M2M SIMs) and related Know Your Customer (KYC) instructions for issuing M2M SIM to entity/organization providing M2M Communication services under bulk category and instructions for Embedded- SIMs (e-SIMs).

4. The 13-digit numbering plan for SIM based IoT/ M2M devices has been implemented w.e.f 1st October 2018.

5. The oneM2M Release 2 and Release 3 specifications have been adopted as National Standards by TEC, DoT in 2020 and 2022 respectively. The important benefits of implementing oneM2M standards based solution includes interoperability of device & application; authentication & authorization of devices; and Data security & Privacy. Details of these National Standards are available on TEC website (https://www.tec.gov.in/onem2m).

6. DoT has issued following advisory guidelines to all M2M/IoT stakeholders for securing consumer IoT 2023: (https://dot.gov.in/circulars/advisory-guidelines-m2miot-stakeholders-securing-consumer-iot)
   - No universal default passwords
   - Implement a means to manage reports of vulnerabilities
   - Keep software updated

7. National Trust Center (NTC) for M2M/IoT Devices and Applications is being implemented on pilot basis by C-DoT, based on the TEC Technical Report *'Framework of National Trust Centre for M2M/IoT Devices and Applications'*, which will help in managing the vulnerability related issues reported by IoT platforms to NTC portal, through device manufacturers / researchers. The main requirement is to address the security challenges in the deployment of IoT/M2M Devices and Applications that can pose threats to the custodians and users, its own operation and also potentially harm the networks that it connects to. It shall serve the purpose of managing/ addressing the vulnerability related issues of IoT devices reported by IoT/ Smart city platforms working in the network.

8. Additional 1 MHz spectrum has been reserved in unlicensed ISM band leading to 865-868 MHz (https://dot.gov.in/spectrummanagement/use-low-power-equipment-frequency-band-865-868-mhz-short-range-devicesexemption).

9. DoT has issued guidelines for registration of M2M service providers (M2MSPs) and WPAN/WLAN connectivity providers. Few salient points are mentioned below-

    a. IoT/M2M Services are offered through a connected network of objects/devices, with unique identifiers, in which Machine to Machine (M2M) communication is possible with predefined back end platform(s) either directly or through some gateway. IoT/M2M services may include use cases in fleet management, supply chain management, agriculture automation, smart utilities including power, water, gas etc. M2M Service Provider (M2MSP) provides M2M services to third parties using telecom resources.

    b. DoT vide office memorandum No. 4-10/2015-NT dated 08.02.2022 has mandated registration of M2M Service Providers(M2MSP) & WPAN/WLAN Connectivity Provider for IoT/ M2M Services on Saral Sanchar portal of DoT (https://dot.gov.in/latestupdates/guidelines-registration-process-m2m-service-providers-m2msp-and-wpanwlan-connectivity).

    c. WPAN/WLAN Connectivity Provider uses WPAN/WLAN technologies for providing M2M connectivity for commercial purposes, operating in unlicensed spectrum. Further, any organization which intends to use WPAN/WLAN for M2M connectivity for captive, non- commercial use, shall also be covered under this definition.

    d. M2M Service Provider (M2MSP) is an Indian company, registered under the Indian Companies Act, 2013 or LLP Act, 2008 or a partnership firm which provides M2M services to third parties using telecom resources. Provided that (a) such third parties utilising M2M services from registered M2MSP in connection with its products or as part of its offerings to its end customers as a product or service, and (b) any organization which intends to provide M2M services for its own use (captive use) and not for commercial purpose, shall also be covered under this definition. The scope of the registration also covers all types of business entities such as company, Government Departments/Organizations, Partnership Firms, LLPs, Institutions, Undertakings, Proprietorship Firms, Societies and Trusts vide Addendum to the guidelines for registration of M2M Service Providers (M2M SPs) & WPAN/WLAN Connectivity Providers for M2M Services, issued on 01.01.2024 https://dot.gov.in/sites/default/files/Addendum%20to%20M2M%20SP%20guidelines.pdf?download=1)

e. New license authorization for UL(M2M) and UL-VNO(M2M) under UL and UL-VNO is required for entities providing services exclusively through the LPWAN or equivalent technologies using unlicensed band or obtain licensed spectrum to provide M2M services exclusively.

f. M2M SPs and WPAN/WLAN connectivity providers are required to mandatorily connect to licensed telecom operators network for backhaul connectivity.

10. TEC is the nodal authority for Mandatory Testing and Certification of Telecommunication Equipment (MTCTE). Every telecom equipment must undergo mandatory testing and certification in respect of parameters as determined by the telegraph authority from time to time prior to sale, import of use in India. The testing of telecom products to be carried out by TEC accredited testing labs as per the Essential Requirements (ER) prepared for corresponding device under MTCTE regime. IoT devices hardware will be tested as per Essential Requirements (ERs) under MTCTE having testing specifications related to EMC, Safety, communication interfaces, IP, SAR and Security. IoT/M2M devices such as IoT gateway, tracking device, environment end point monitoring device have been covered under mandatory testing and certification w.e.f. 01.01.2024. Smart Electricity meters will fall under mandatory testing and certification w.e.f. 01.04.2024. Security specifications i.e ITSARs (Indian Telecom Security Assurance Requirements) which are also the part of ERs, are being prepared by NCCS (National Centre for Communication Security), Bengaluru.

11. TEC released standard on *Fairness Assessment and Rating of Artificial Intelligence Systems* in 2022. This Standard enumerates detailed procedures for accessing and rating artificial intelligence systems for fairness. Artificial intelligence is increasingly being used in all domains including telecommunication and related ICT for making decisions that may affect our day-to-day lives. Any unintended bias in the AI systems could have grave consequences. This standard provides a systemic approach to certifying fairness for AI systems. (https://www.tec.gov.in/pdf/SDs/TEC%20Draft%20Standard%20for%20fairness%20assessment%20and%20rating%20of%20AI%20systems%20final%202022_12_27.pdf)

12. TEC Technical Reports in M2M/ IoT domain

TEC has released Twenty-two Technical Reports covering various verticals such as Power, Automotive （Intelligent transport system）, Remote Health Management, Safety & Surveillance, Smart homes, Smart cities, Smart Village & Agriculture etc., and also in the horizontal layer (requirements common to all the verticals) such as M2M Gateway & Architecture, Communication Technologies, EMF Exposure from IoT devices and Security aspects in M2M/ IoT domain. All the Technical Reports are available on TEC website[9].

Out of these, one Technical Report on "IoT/ ICT Enablement in Smart Village and Agriculture"[10], was released in March 2021. This technical report focuses on diverse issues related to IoT/ ICT infrastructure and also in the verticals such as agriculture, animal husbandry, fisheries, healthcare, education, water management etc. in rural areas; resolving these issues by creating telecom infrastructure for providing smart solutions using IoT/ ICT and the related use cases.

[9]https://www.tec.gov.in/M2M-IoT-technical-reports
[10] https://tec.gov.in/pdf/M2M/IoT_ICT%20enablement%20in%20Smart%20Village%20&%20Agriculture.pdf

7. Recommendations

7.1. Registration of M2M service providers (M2MSPs) and WPAN/WLAN connectivity providers with DoT

DoT vide office memorandum No. 4-10/2015-NT dated 08.02.2022 has mandated registration of M2M Service Providers(M2MSP) & WPAN/WLAN Connectivity Provider for IoT/ M2M Services on Saral Sanchar portal of DoT. Therefore, it is recommended to ensure that IoT/ M2M based solutions being implemented/ used/ planned in various sectors including agriculture sector are provided by DoT registered M2M SPs and WPAN/WLAN connectivity providers. This is to address concerns like interface issues with TSP, KYC, Security and encryption. All M2M service providers utilizing telecom facilities from authorized TSPs should have M2MSP registration.

Further, as per directions contained in DoT letter No. 4-63/2023-NT dated 05.02.2024, all Telecom Licensees (TSPs) shall henceforth not provide telecom resources for M2M Services/connectivity including M2M SIMs, to unregistered M2M Service Providers and WPAN/WLAN Connectivity Providers for M2M Services. For existing entities, the DoT Registration Number shall be obtained and recorded by 31.03.2024, and for new entities, telecom resources shall be provided only after mandatorily obtaining the Registration Number.

7.2. Standards

It is recommended that oneM2M based IoT platforms may be used for IoT applications in various sectors including the agriculture sector. The oneM2M Release 2 and Release 3 specifications have been adopted as National Standards by TEC, DoT. The important benefits of implementing oneM2M standards based solution includes interoperability of device & application; authentication & authorization of devices; and Data security & Privacy.

7.3. Mandatory Testing and Certification of Telecommunication Equipment

It is recommended to ensure that IoT/ M2M telecom products / equipment being used in various sectors including agriculture sector should be tested and certified as per the Essential requirement (ER) prepared for corresponding device under MTCTE regime.

Security specifications, prepared in ITSAR (Indian Telecom Security Assurance Requirements) for IoT devices are also the part of ERs.

7.4. Guidelines for securing consumer IoT

Following broad guidelines may be ensured by all M2M/IoT stakeholders for securing IoT ecosystem-

- No universal default passwords
- Implement a means to manage reports of vulnerabilities
- Keep software updated

8. Abbreviations

ADAS	Advanced Driver Assistance Systems
AES	Advanced Encryption Standard
AI	Artificial Intelligence
ANN	Artificial Neural Network
BaTs	Bagging Trees
BLE	Bluetooth Low Energy
BoTs	Boosting Trees
CAPS	Cyber Agrophysical System
CBAM	Convolutional Block Attention Mechanism
CCC	Canopy Chlorophyll Content
CIFRI	Centre Inland Fisheries Research Institute
CoAP	Constrained Application Protocol
CM	Clinical Mastitis
CNN	Convolutional Neural Network
CWSI	Crop Water Stress Index
DL	Deep Learning
DO	Dissolved Oxygen
DoT	Department of Telecommunications
DT	Digital Twins
EBD	Euclidean Distance Based Diversity
ELISA	Enzyme Linked Immunosorbent Assay
ELMs	Extreme Learning Machine
eMBB	Enhanced Mobile Broadband
EMF	Electromagnetic Field
FAO	Food and Agricultural Organisation
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GPR	Gaussian Process Regression
GPRS	Global Packet Radio Service
GR	Generic Requirement
HSPA	High Speed Packet Access
HTTP	Hypertext Transfer Protocol

IAB	Integrated Access Backhaul
IARI	Indian Agricultural Research Institute
ICAR	Indian Council of Agricultural Research
ICT	Information and Communication Technology
IEEE	Institute of Electrical and Electrical Engineering
IMT	International Mobile Telecommunication
IoT	Internet of Things
IIoT	Industrial Internet of Things
IR	Interface Requirement
IRT	Infrared Thermography
ISM	Industrial, Scientific and Medical
ISO	International Organization for Standardization
ITU	International Telecommunication Union
KYC	Know Your Customer
LAI	Leaf Area Index
LAN	Local Area Network
LCC	Leaf Chlorophyll Content
LIDAR	Light Detection and Ranging
LLP	Limited Liability Partnership
LPWAN	Low Power Wide Area Network
LoRa	Long Range
LSP	Low Set Point
LTE	Long-Term Evolution
MAE	Mean Absolute Error
MBPS	Mega Bit Per Second
M2M	Machine to Machine
M2MSP	Machine to Machine Service Provider
ML	Machine Learning
MLRA	Multiple Linear Regression Analysis
MQTT	Message Queuing Telemetry Transport
MTCTE	Mandatory Testing and Certification of Telecom Equipment
NasNet	Neural Architecture Search Network
NavIC	Navigation With Indian Constellation

NB-IOT	Narrowband-Internet of Things
NDCP	National Digital Communication Policy
NDRI	National Diary Research Institute
NePPA	Network Programme on Precision Agriculture
NFC	Near Field Communication
NFV	Network Function Virtualization
NLP	Natural Language Processing
NPV	Net Present Value
NR	New Radio
NRMSE	Normalized Root Mean Square Error
NST	Non- Standalone
NTC	National Trust Center
OFDMA	Orthogonal Frequency Division Multiple Access
PAN	Personal Area Network
PCA	Principal Component Analysis
PCR	Polymerase Chain Reaction
PLF	Precision Livestock Farming
PLSR	Partial Least Squares Regressions
QDA	Quadratic Discriminant Analysis
QoS	Quality of service
RedCap	Reduced Capability
RFID	Radio Frequency Identification
RFR	Random Forest Regression
RMSE	Root Mean Square Deviation
RRMSE	Relative Root Mean Square Error
RSAL	Residual Active Learning
SAE	System Architecture Evolution
SAG	Strategic Advisory Group
SDGs	Sustainable Development Goals
SIM	Subscriber Identity Module
SLR	Systematic Literature Review
SMLR	Stepwise Multiple Linear Regression
SON	Self Organizing Networks

SVR	Support Vector Regression
SWM	Single Wire Multi-switch
TCP	Transmission Control Protocol
TD-SCDMA	Time Division Synchronous Code Division Multiple Access
TEC	Telecommunication Engineering Centre
TRAI	Telecom Regulatory Authority of India
UAVs	Unmanned Aerial Vehicles
UDP	User Data-gram Protocol
UGVs	Unmanned Underground Vehicle
UL VNO	Unified License Virtual Network Operator
UMTS	Universal Mobile Telecommunication System
UN	United Nations
URLLC	Ultra Reliable Low Latency Communication
USST	Under Skin Surface Temperature
WAN	Wide Area Network
WLAN	Wide Local Area Network
WPAN	Wide Personal Area Network
WSN	Wireless Sensor Network
XR	Extended Reality

9. Use Cases in Digital Agriculture

9.1. Use Case: Applications of AI and IoT in Cashewnuts farming

Source: 1. Dr. Manojkumar Rajagopal, VIT Chennai, India
2. Dr. Bala Murugan MS, VIT Chennai, India

1. Introduction

Cashew nuts are one of the most important nuts in the world. The cultivation of cashew is primarily carried out in eight states of India. It is estimated that India produces about 6.74 lakh tonnes of raw cashew nuts every year with an area under cashew of 9.53 lakh ha (2010-11). In terms of production and exports, India ranks third behind Vietnam and Nigeria. The country is the second largest consumer of cashews and also the biggest processor. Currently, around 23% of the world's cashew production comes from India.Cashew is a major source of livelihood for many small and marginal farmers in India, especially in coastal areas. Approximately two million people are involved in cashew cultivation, processing, and marketing directly or indirectly of which over 70% of the cashew area is cultivated by small and marginal farmers, and cashew plays an important role in their development.

However, little is known about how farmers may increase cashew production in line with climate-friendly farming practices as the cashew sector is vulnerable to adverse effects of climate change, ultimately lowering the production.

2. Description (Background)

Current crop management practices rely on labour-based systems. However, to increase the production digital technologies are being integrated into smart farming solutions in some countries worldwide. For instance, TechnoServe is implementing the CajùLab project in Benin, in partnership with Wehubit, to promote farmers' adoption of climate-smart agricultural practices using emerging technological solutions, including drones and machine learning. However, in the Indian scenario the adaption of digital farming practices are yet to be shaped in the agriculture industry especially in the cashew farming.

The cashew tree is endangered by many fungal and algal diseases, which result in significant yield losses. In particular, powdery mildew, damping off, anthracnose, and inflorescence blight are considered significant in a few cashew-growing regions. In order to take timely countermeasures against plant diseases and infections, it is imperative to monitor them regularly. In addition to anthracnose, a few insect pests also infest cashew at specific times and cause damage. Certain pests may not pose a problem in some regions, but they could pose a problem in others. To prevent economic loss, separate spraying of pesticides may be necessary during certain periods.

In order to manage the crop efficiently and continually, a drone fitted with a camera will be used to take pictures aerially. These pictures will be transmitted to the data processing system as part of the Intelligent Crop Monitoring and Warning System. A platform built on the Internet of Things and Artificial Intelligence, processes these images. These images can help to determine the stage of infestation, the crops affected; how to prevent the spread of the disease, and what type & quantity of pesticides to use. These UAVs can also protect crops from animal and human predators. The purpose of agricultural drones is to optimize agricultural operations, increase crop production, and monitor crop growth. Farmers can monitor their fields using sensors and digital imaging. Crop yields and agricultural efficiency can be improved by collecting information using agricultural drones and also by using the soil monitoring devices to monitor the soil parameters such as pH, Temperature, humidity and sol nutrients etc.

Part B

3. Architectural considerations

a. Data management

Resnet-based deep learning model has been used to design the training model of this project for real-time and large-scale processing. The main idea behind this model is to speed up the analysis of a huge amount of data by overlapping executions (multi-tasking) in order to make the most of the learning relationships between the data flows. In addition, the sliding window technique has been used in the learning process.

b. System architecture

A robust drone-based deep learning approach is proposed to overcome the limitations of existing approaches, as shown in Figure-1. A more specific improvement has been made to efficient RestNetV by adding dense layers at the end of the architecture. The customized EfficientNetV2-B4 calculates the deep key points and classifies them in their related classes by utilizing an end-to-end training architecture. To evaluate the performance of a drone system, a standard dataset along with samples captured using a drone are used, which is complicated by the fact that there is a variety of image samples with diverse conditions under which the images are captured. Average precision, recall, and accuracy values of 99.63, 99.93, and 99.99%, respectively have been achieved.

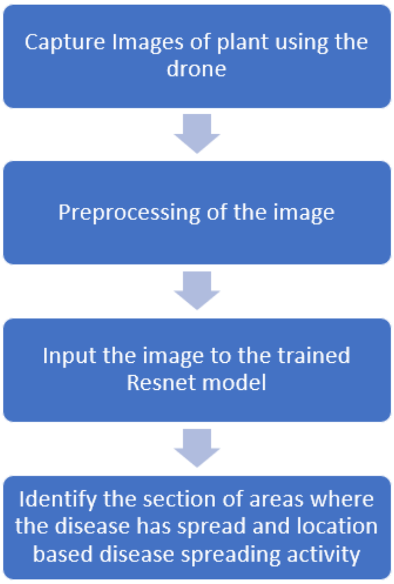


Figure 1- AI model process Disease identification

In order to achieve environmentally sustainable agriculture, sensor networks are designed to collect, store, and monitor data efficiently. Additionally, this model of architecture deployment should be affordable so that low-income farmers can adopt it into their farming practices. So this system is built using a low-cost LoRa-based communication protocol to aggregate the sensor data from the field to the cloud as shown in figure -2. These sensor nodes are deployed in the field, to measure physical parameters, such as the temperature of the field, the intensity of the light's source, the pH of the rainwater, atmospheric humidity and soil moisture. These sensor nodes are placed according to the range of the base station. The data thus collected are transmitted to the gateway using LoRa protocol. The microcontroller of this system is designed using STM32 controller.

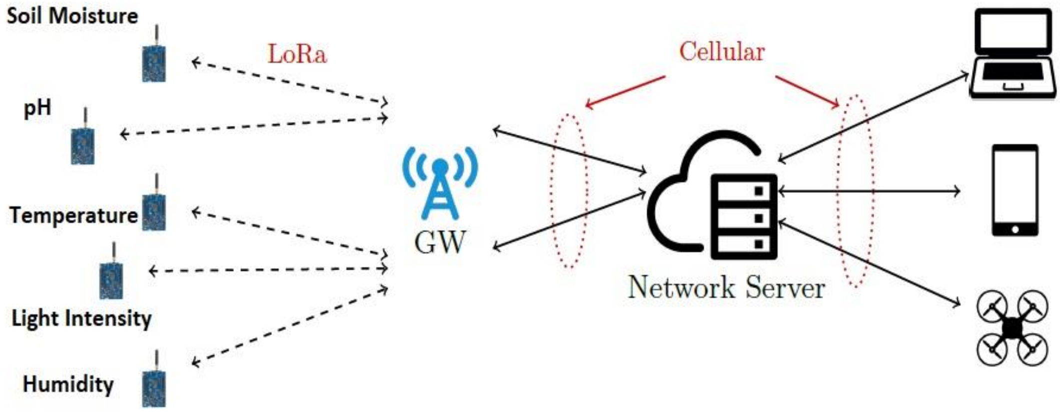


Figure 2. LoRa Network Architecture in Cashew crop management

c. Communication infrastructure

(i) (a) drone with cellular connectivity 4G/ 5G (or) 5.8 GHz RF Transmitter on the UAV and receiver on the control station, for control and live transmission of images.

(b) 2.4 GHz Wi-Fi for communication with the controller and Memory card to store images.

(ii) Wired connectivity from camera units to local hub and 2.4 GHz Wi-Fi for communication between hub and main server.

- *Interfaces, protocols for communications*
- (i) (a) 5G modem (or) RF Interface (b) Wi-Fi NIC
- (ii) Wi-Fi NIC

d. Deployment considerations

Images from the cashew field were taken using smart phone and sent to cloud server using 4G. Since the number of images was considerably high, the latency of the system was significant. The delay performance could be improved, if the smart phones are replaced by drones and transmit the images using 5G. Alternatively, fixed low-cost camera units, connected through cables to a local hub, could send the pictures to cloud server through 5G modem.

e. Regulatory considerations

Country specific regulatory norms may be followed while deploying the use case. [In India Cellular network is deployed across the country and same may be used for drone applications]

4. Results of the use case (outcomes)

The Plant Disease Detection System is modelled to allow farmers to quickly and easily identify the diseases the plants might be suffering from. The fundamental structure of this module is illustrated in the Figure 3. This work employs the Mohanty [5] dataset of Epidemiology lab, EPFL, Geneva for training and validating the plant disease identification. With modified Resnet model deployed on the cloud for the purpose building a smart disease prediction.

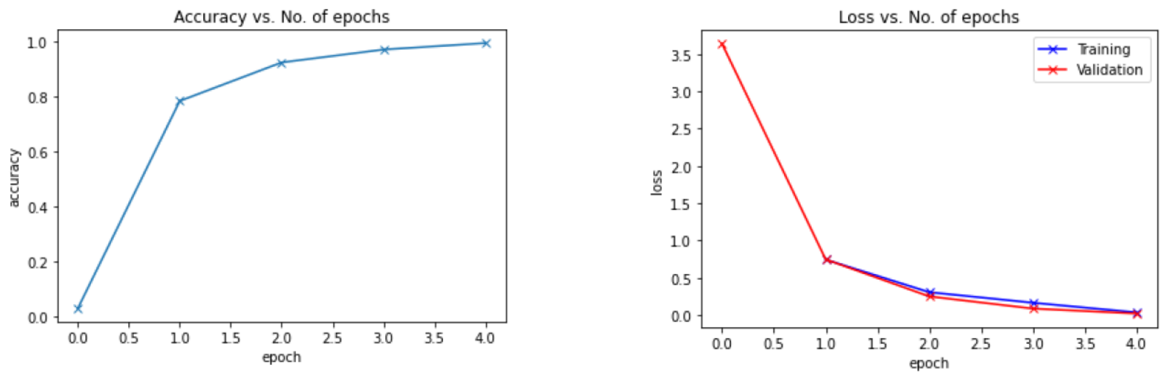


Figure 3- Accuracy vs epoch of Resnet Model for test dataset and Loss vs epoch of Resnet Model for test dataset [6]

This system comprises of two major components:

1. Creating the CNN model: The first step is to create a Machine Learning model. This work is carried out using a Convolutional Neural Network (or CNN) model.

a. A comprehensive study of Deep neural networks models for plan disease identification
b. Improvising the Resnet model for the dataset by deploying a "One cycle Learning Rate Policy" instead of traditional fixed learning rate
c. The hyper parameters are further optimized for weight decaying and gradient clipping to suit to the training the plant disease identification.

2. Using the model to predict: The next step is to use the created model to identify the diseases in the leaves. This step would be carried out in real-time. The model is trained on a Nvidia GPU for faster processing purposes. This model is trained using Resnet architecture for feature extraction. The model is trained for 65,89,734 params. These

features are used to train class specific intermediate convolutional neural layer. This system achieved 99.35% accuracy for the dataset. The Edge computing based disease identification was tested in the agricultural field to identify the healthy and disease affected leaves and the model was able to predict the healthy leaves in realtime.

Figure 4- Die back or Pink disease and Anthracnose disease in Cashew farming [2]

Figure 5- An Image of high yielding seedling progeny of cashew in proper farming practice [3]

The healthy leaves and disease affected leaves are shown as in fig. 6 and fig.7.

Fig. 6. Healthy cashew leaves

Fig. 7. Disease affected leaves

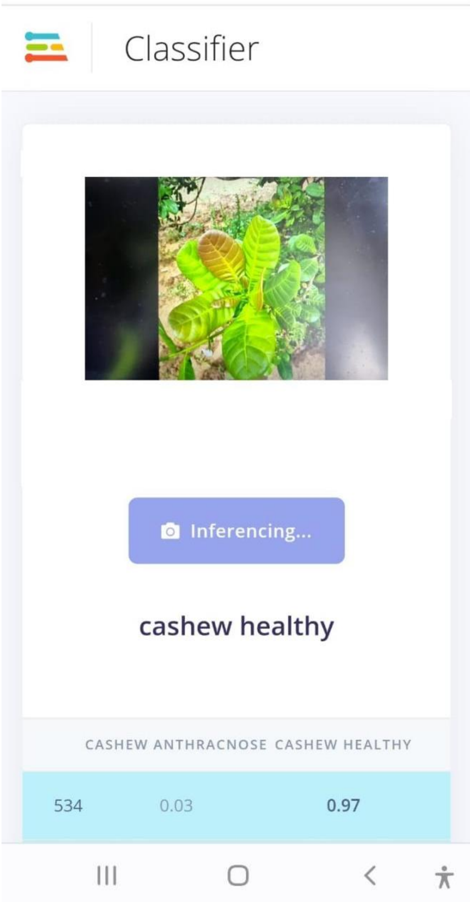


Fig. 8 Edge computing result of identifying a healthy cashew leaf

The detailed dataset for the processing is provided here for reference - https://1drv.ms/u/s!AneykNbf8_Tbodkec2mIwruwUnQoSA?e=MsHjZG

Figure 9- Drone for Crop management in cashew farms

5. Lessons learned (particular to implementations of use case)

We have identified the following plant's location by Tamil Nadu Agricultural University (TNAU) and Council of Scientific and Industrial Research (CSIR). It is located in the district of Cuddalore, Tamil Nadu, India, in the village of Vridhachalam. Die back and Anthracnose disease are the most commonly identified diseases in these plants, as shown in Figure-4. We are working on identifying and training a Deep learning model to identify Anthracnose.

Agricultural drones allow farmers to see their fields from the air. This bird's eye view can reveal many problems, such as watering problems, soil changes, and pest and fungal infestations. A multispectral image shows a near-infrared view and a visible spectrum view. This combination shows farmers the difference between healthy and unhealthy plants that are not always clearly visible to the naked eye. These views are therefore helpful in assessing plant growth and production. In addition, drones can measure plants regularly according to the farmer's wishes. Weekly, daily, or hourly images can show crop changes over time and highlight potential 'problems'. After these problem areas are identified, farmers can try to improve crop management and production.

6. Available standards

1. [ITU-T Y.2060] Recommendation ITU-T Y.2060 (2012), - Overview of the Internet of things.
2. [ITU-T Y.2060] Recommendation ITU-T Y.2238 (2015), - Overview of Smart Farming based on networks.

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8. Appendix

Appendix 1: Actor / Business role

The IoT ecosystem is composed of a variety of business players. It is possible for each business player to play more than one role. The figure shows the identified IoT business roles.

S No	Actor	Business role
1.	Acquisition of Images from cashew tree	The dataset is collected from rural areas of interest, which includes total (10017 images). Out of the total images collected, 5007 images are images without disease affected and the rest 5010 are affected by this anthracnose disease. 33 images.
2.	Pre-Processing	Includes filtering, color conversion and detail enhancement of image
3.	Classification of Cashew crop leaves disease	Resnet model based on deep learning algorithm is built for classification and identification of disease.

Appendix 2: Actor role

Actor name	Actor type	Role description
Drone	Device	Captures images of paddy leaves
Deep Learning algorithm	Software	The model is trained by a dataset and prepared to identify the disease.

Appendix 3: Communications technologies

Scenario	Communication network	Technologies
Field to cloud	LPWAN	- LoRaWAN
Drone to cloud	LAN/ WAN	- 4G/ WiFi

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9.2. Use cases: IoT based Farmland Surveillance System with Disease Detection in Paddy Crops

Source: 1. Dr. Vydeki D, VIT Chennai, India
2. Dr. Jagannath M, VIT Chennai, India
3. Dr. S Ramesh, School of Engineering, SIMTS Chennai, India

Part A

1. Introduction

The survival of human beings is dependent on the proper productivity of agriculture. The paddy plant is considered as a major planting crop in improving the economical level of our country. It is a known fact that a number of diseases could reduce the yield level of the paddy crop. The main culprits behind this disease's prevalence on the paddy crop include bacteria, fungus, viruses, and some dangerous insects. The illnesses that damage rice crops in their early stages have an impact on the entire stage of crop cultivation. Farmers have been performing manual disease detection since the beginning of agriculture. To manually identify crop diseases, naked eye inspection is frequently used. This outdated method typically results in mistakes and requires a great deal of effort to classify the diseases. One of the newer methods for identifying and categorising the various types of diseases is image processing, which solves the problems with manual disease identification. The identification and classification of plant illnesses, the differentiation of specific weeds, and disease forecasting are only a few of the problems that image processing technique addresses in crop management.

The objective of the use case is to provide an alternative solution to naked-eye observation of disease in paddy crops. This use case employs an image processing technique for identifying and classifying the different types of diseases using machine learning.

2. Description (Background)

- *Materials and methods*

The dataset that consists of paddy leaf images would be trained using neural network, to detect leaf diseases specific to rice crop. The images captured through image sensing units from the farm land could be transferred to cloud server for testing. In this use case, a total of 650 images were captured and labelled for applying to AI model. Out of the available data set, 555 images contained pictures of paddy leaves with disease. (Refer Appendix-1)

- *Country specifics*

Eastern India's main cereal crop and staple diet is rice, and for the majority of farmers, it is their only source of income. The majority of India's rural areas rely heavily on agriculture. The methods used to cultivate rice depend heavily on the factors that affect crop growth, such as the type of soil, the availability of water, and the monsoon season. Ecosystems that need to be preserved and improved receive benefits from rice growing that are both concrete and intangible. India is the only country in the world with such a variety of rice ecosystems. India has developed many types of ecosystems due to the country's extensive farming. Wet, dry, and semidry systems are the main types of rice ecosystems practised in southern part of India i.e. in Tamil Nadu, Kerala, and Karnataka states. In the northern part of India i.e. in the states namely Punjab, Haryana, Uttar Pradesh, Jammu & Kashmir, Andhra Pradesh, Tamil Nadu, Sikkim, Karnataka, Himachal Pradesh, and Gujarat, rice is farmed under irrigation (wet) conditions.

- *Process flow diagram*

The flow diagram shown in Fig. 1 indicates the process steps used for Blast disease recognition using K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN) classifier algorithms.

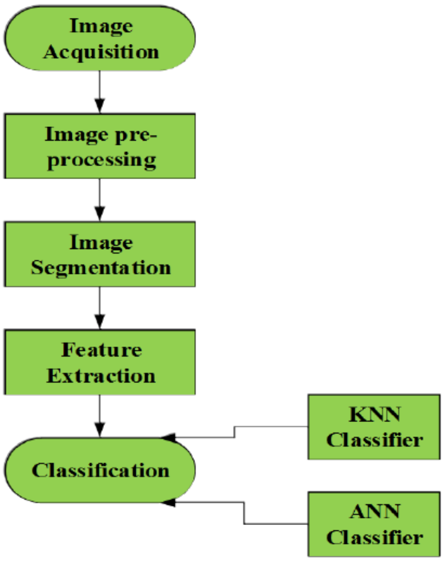

Fig. 1. Flow Diagram of Proposed Method.

The digital camera is used to take a 512× 512 pixel image of a rice leaf as part of the image acquisition process. To improve accuracy, the pixel size of images is lowered to 256 × 256 pixels. For use in a subsequent operation, the scaled colour image is converted into a grayscale image. During the pre-processing stage of an image, the HSV image is separated from the RGB image. Fig. 2 (a) and (b) depict the normal and blast-affected pictures that were employed in the processing processes. After pre-processing paddy leaf images, image segmentation is done using k-means clustering with a range of k values. The sample output of the k-Means clustering applied to images impacted by blast disease is shown in Fig. 3.

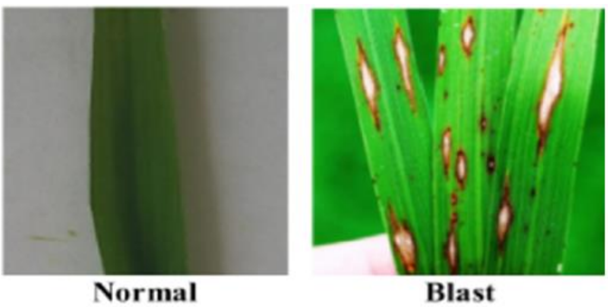

Fig. 2. (a) Normal image (b) Blast affected image.

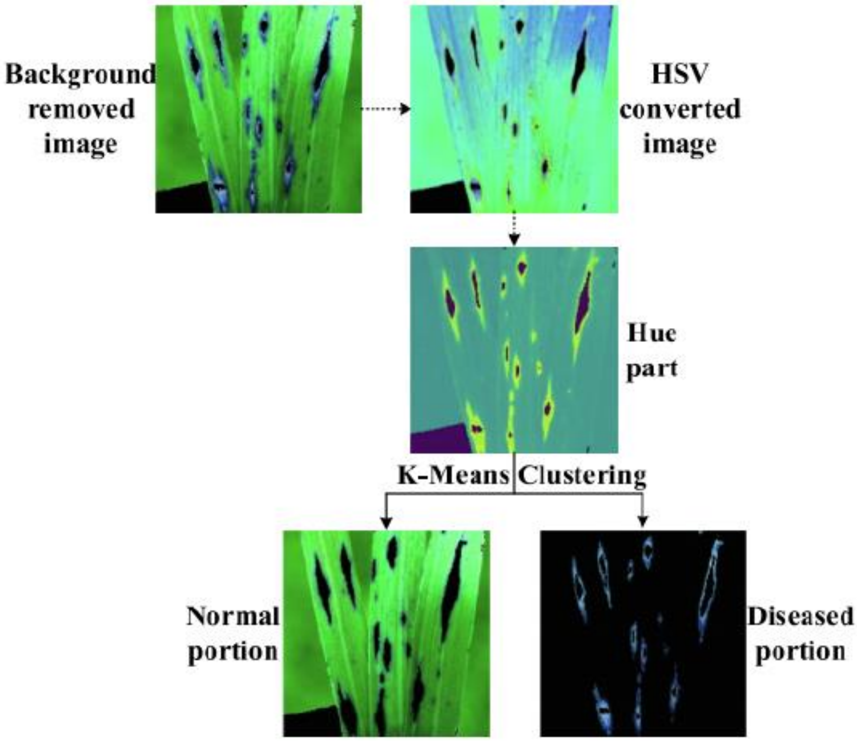

Fig. 3. K-means clustering image.

- *Outcomes/ results of use case high level*

The outcome of the use case indicates the status of the paddy crop with respect to leaf diseases. Bacterial blight, blast, sheath rot and brown spot are the disease types are detected using the deep learning algorithm.

Part B

3. Architectural considerations

a. *Data management*

The presented use case heavily depends on the image acquisition in order to predict the various leaf diseases in rice crop. Hence, the proper deployment of image collecting nodes and its transmission are critical to the success of the system. There are two possible choices for the deployment of image acquisition:

(i) Periodically (once in 2 days) fly drones over the farmland and capture geo-tagged images. Adding intelligence to image acquisition such as, taking a close-up shot of the leaves which have developed suspicious spots, would improve the prediction accuracy. The images captured by drone cameras could be sent to a main server for further processing.
(ii) Drones could be connected to local hubs through Wi-Fi for transmitting the images to the hub, which will be further transmitted to Cloud server.

b. System architecture

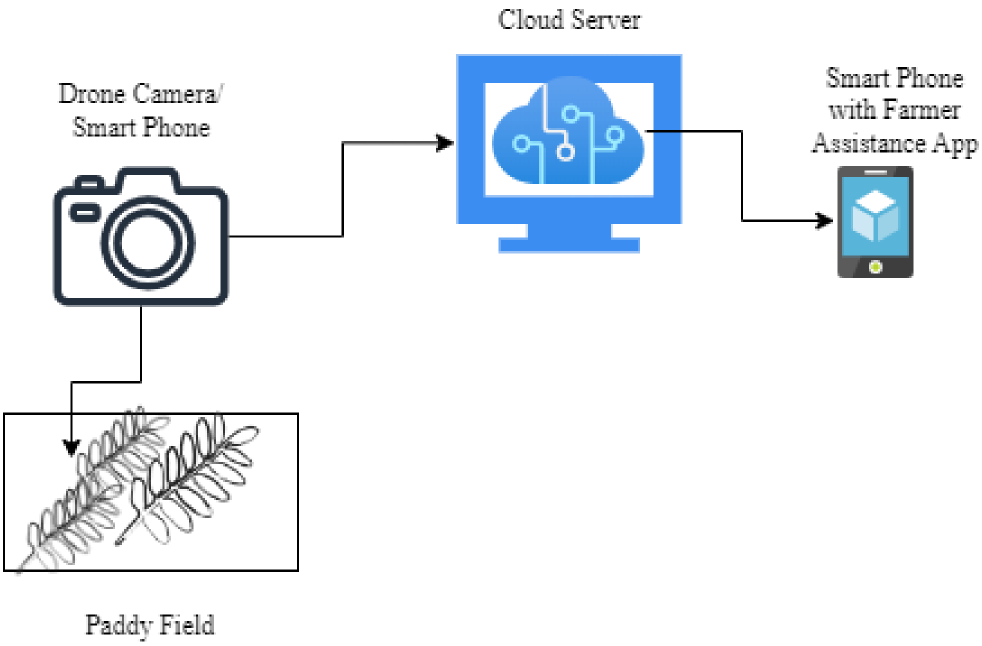

Fig.4 Leaf-disease Detection System Architecture

As shown in Fig.4, the image sensing unit (camera) available in a smart phone or drone would capture the images of leaves in the paddy field. These images are transmitted to cloud server that runs the AI algorithm to detect any of the four leaf diseases occur and communicates the outcome to the mobile app on the farmer's smart phone.

- *Definition and description of sub-systems*

The use case was tested in a rural place of Tamilnadu, called 'Paimpozhil', located in Tenkasi district. Pictures of the agricultural farm land was captured on a regular basis and the data thus collected was processed at a cloud server. The neural network based optimization algorithm, which was trained on the various data sets, detected the presence of leaf diseases such as blast, blight etc. The outcome of the algorithm could be received through a mobile app.

c. *Communication infrastructure*

(a) Drone/ Smart Phone with cellular connectivity such as LTE/ 5G for control and live transmission of images to the cloud server.
(b) 2.4 GHz/ 5.8 GHz might also be used for Wi-Fi communication between drone and the local hub, which would later transmit the images over cellular/ wireline network.

- *Interfaces, protocols for communications*
- (a) LTE/5G connectivity (modem) (b) Wi-Fi NIC

d. Deployment considerations

Images from the paddy field were taken using smart phone and sent to cloud server using 4G. Since the number of images was considerably high, the latency of the system was significant. The delay performance could be improved, if the smart phones are replaced by drones and transmit the images using 5G. Alternatively, smart phones/ drones may transmit to local hubs and further to cloud.

e. Regulatory considerations

Country-specific regulation related to drones.

4. Results of the use case (outcomes)

- *Performance and evaluation criteria*

The performance of the presented use case is evaluated by generating the confusion matrix for the applied AI algorithm.

- *Qualitative and quantitative comparison of before and after implementation of the use case, the comparison can be illustrated by graphs, tables, figures, etc.,*

Based on the identification of blast-affected images among the normal images, the training phase accuracy of K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN) classification algorithms is demonstrated. Among the normal images, 99% of the blast-affected images are detected by ANN classifier. However, the KNN classifier only offers 90% accuracy. In the training phase, the detection accuracy for normal images is 99% for ANN and 90% for KNN, respectively. The efficiency of both ANN and KNN classifiers during testing, where KNN and ANN's accuracy for detecting typical images is 63% and 88%, respectively. While KNN only achieves 79% accuracy in the detection of paddy leaf images impacted by blasts, ANN achieves 90% accuracy in this area. The results are summarised in Fig.5 and Table 1.

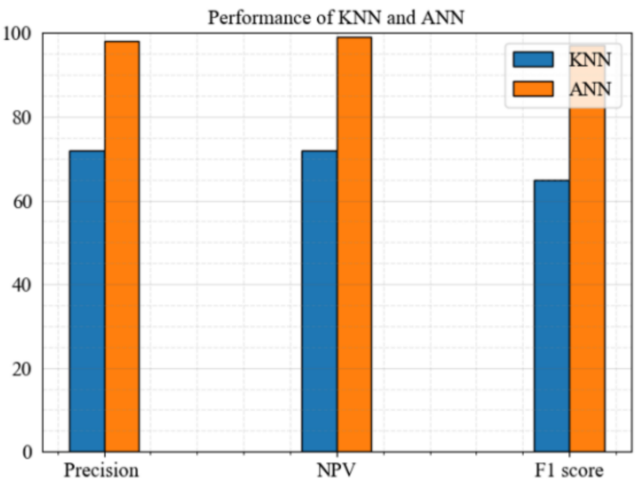

Fig.5 Performance of KNN and ANN

Table 1

S.No.	Performance Measure	KNN (%)	ANN (%)
1	Accuracy	70	90
2	Recall	65	88
3	Specificity	78	90
4	Precision	72	98
5	NPV	72	99
6	F1 Score	65	97

5. Lessons learned (particular to implementations of use case)

Pictures are taken through smart phone and uploaded to cloud server manually, which is a time-consuming process. However, during the implementation phase, drones will be used.

6. Available standards

- ICT or Agricultural
- Available international standards

7. Links for supporting material (website, articles, etc.,)

https//:doi.org/10.1016/j.inpa.2019.09.002

Rice-Blast Disease Monitoring Using Mobile App | Ramesh | International Journal of Engineering & Technology)sciencepubco.com(

IEEE Xplore Full-Text PDF:

8. Appendix

Appendix 1: Actor / Business role

S No	Actor	Business role
1.	Acquisition of images of paddy crops	The dataset is collected from rural areas of interest, which includes total (650 images). Out of the total images collected 95 were normal paddy leaves, 150 with brown spot, 125 with bacterial blight, 110 with sheath rot and 170 with blast disease infected leaves. 70% of the total images were used for training the AI model, 20% for testing and 10% for validation purposes.
2.	Pre-processing	Includes filtering, color conversion and detail enhancement of image
3.	Segmentation	The diseased and the non- diseased part of the images are extracted with the help of k-means clustering

4.	Feature Extraction	Feature extraction enhances the accuracy of the classification process. Both colour and texture features are extracted in this phase, which, the standard deviation and the mean value are utilized in the colour features. The gray-level co-occurrence matrix parameters such as contrast, energy, correlation and homogeneity are involved in the texture features.
5.	Classification of Paddy Leaf Diseases Using Optimized Deep Neural NetworkWith Jaya Algorithm	Paddy leaf diseases are recognized and classified with the help of Optimized Deep Neural Network with Jaya Algorithm. Four diseases such as, bacterial blight, blast, brown spot and the sheath rot of the paddy crop are considered for the proposed type of classifier.

Appendix 2: Actor role

Actor name	Actor type	Role description
Camera	Device	Capture images of paddy leaves
AI based detection algorithm	System	Using a trained data set, attempts to detect the presence of any leaf disease in the test image
Smart Phone	Device	Receives the result regarding the status of leaf disease from the system

Appendix 3: Communications technologies

Scenario	Communication network	Technologies
Smart phone to Cloud server	WAN	4G/ 5G
Cloud server to Mobile phone of the farmer	WAN	4G/ 5G

9.3. Use Case: Retrieval of Wheat Crop Traits from UAV-Borne Hyperspectral Image using hybrid machine learning models

Source: Rabi N. Sahoo, Shalini Gakhar, R. G. Rejith, Rajeev Ranjan, Tarun Kondraju,Amrita Anand, Mahesh C. Meena, Joydeep Mukherjee, Anchal Daass and Viswanathan Chinnusamy. ICAR-Indian Agricultural Research Institute, New Delhi, India

Part A

1. Introduction

The advent of high-spatial-resolution hyperspectral imagery from unmanned aerial vehicles (UAVs) made a breakthrough in the detailed retrieval of crop traits for precision crop-growth monitoring systems. Here, a hybrid approach of radiative transfer modelling combined with a machine learning (ML) algorithm is proposed for the retrieval of the leaf area index (LAI) and canopy chlorophyll content (CCC) of wheat cropland at the experimental farms of ICAR-Indian Agricultural Research Institute (IARI), New Delhi, India. A hyperspectral image captured from a UAV platform with spatial resolution of 4 cm and 269 spectral bands ranging from 400 to 1000 nm was processed for the retrieval of the LAI and CCC of wheat cropland. The radiative transfer model PROSAIL was used for simulating spectral data, and eight machine learning algorithms were evaluated for hybrid model development. The ML Gaussian process regression (GPR) algorithm was selected for the retrieval of crop traits due to its superior accuracy and lower associated uncertainty. Simulated spectra were sampled for training GPR models for LAI and CCC retrieval using dimensionality reduction and active learning techniques. LAI and CCC biophysical maps were generated from pre-processed hyperspectral data using trained GPR models and validated against in situ measurements, yielding R^2 values of 0.889 and 0.656, suggesting high retrieval accuracy. The normalized root mean square error (NRMSE) values reported for LAI and CCC retrieval are 8.579% and 14.842%, respectively. The study concludes with the development of optimized GPR models tailored for UAV-borne hyperspectral data for the near-real-time retrieval of wheat traits. This workflow can be upscaled to farmers' fields, facilitating efficient crop monitoring and management.

2. Description (Background)

- *Materials and methods*

The block diagram of the methodology used for the proposed approach is shown in Figure 1. The main steps involved in the workflow are (i) field experimentation, UAV image acquisition, and pre-processing; (ii) PROSAIL simulations and model evaluation; (iii) Gaussian process regression (GPR); (iv) dimensionality reduction using principal component analysis (PCA); and (v) active learning methods and field verification. Each step is explained in detail in the subsequent sections.

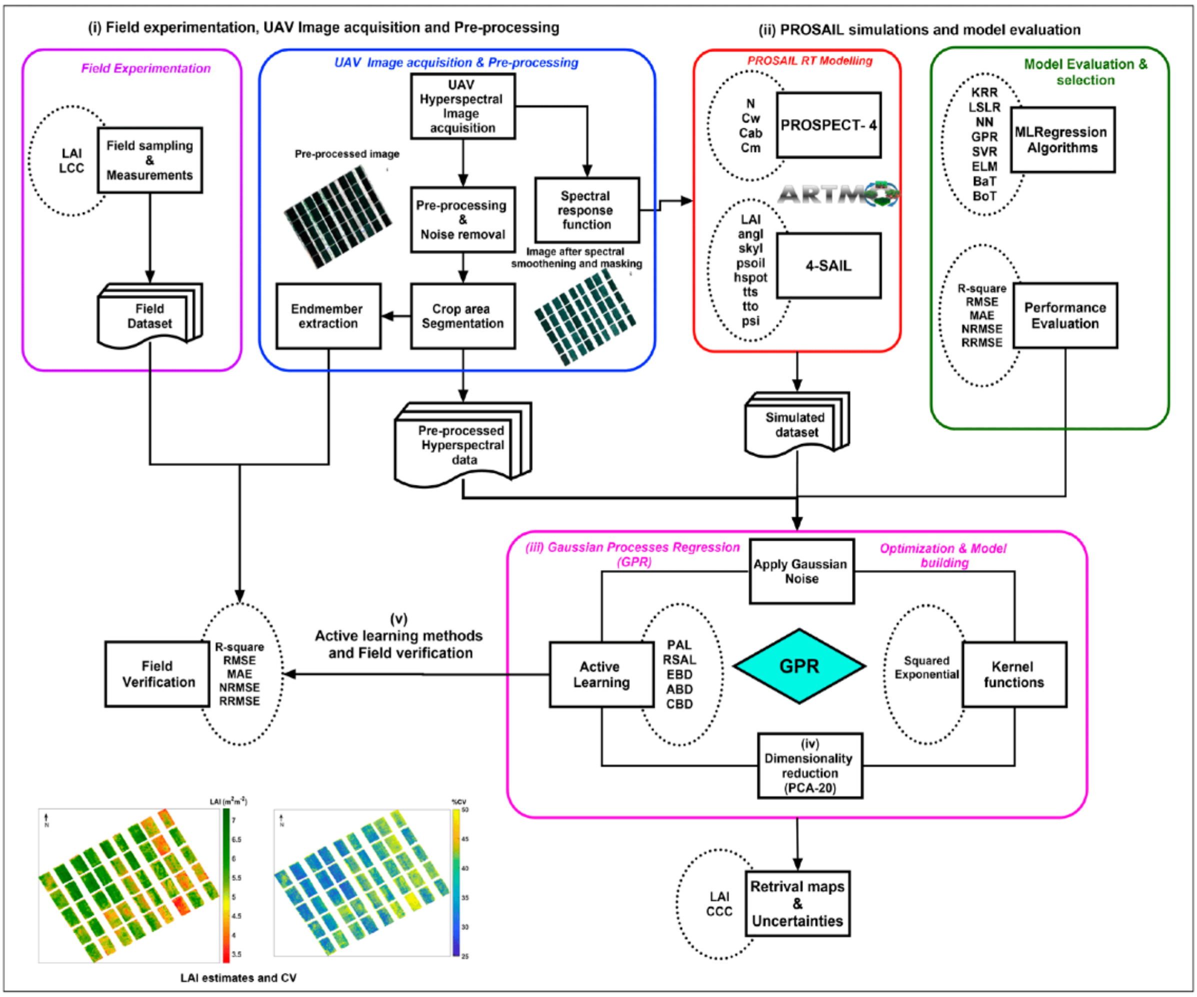

Figure 1. Block diagram of the methodology used for the study.

This study targeted an experimental wheat field of the HD 3059 variety located at the research farm of Indian Council of Agricultural Research-Indian Agricultural Research Institute (ICAR-IARI) (28°38′28.314″N latitude and 77°9′3.106″E longitude) 228 m above mean sea level. The wheat field consisted of three replications of fifteen plots (7.2 × 13 m size each), maintained at five graded nitrogen levels (0, 50, 100, 150, and 200 kg N ha−1), and three irrigation treatments (soil moisture sensor-based treatment (I1); crop water stress index (CWSI)-based treatment (I2); and conventional treatment (I3)). The study area map showing the location of experimental plots and wheat fields is shown in Figure 2. The experiment was carried out during the winter season of 2021–2022, with the crop being sown on 13 December 2021, and harvested on 15 April 2022. LCC was estimated using the dimethyl sulfoxide (DMSO) method, and LAI was measured using a LAI-2000 plant canopy analyser (Li-Cor, Inc., Lincoln, NE, USA). Three measurements were taken from each plot, and their average was used for the analysis. Finally, CCC was obtained by multiplying LCC with LAI (LAI × LCC).

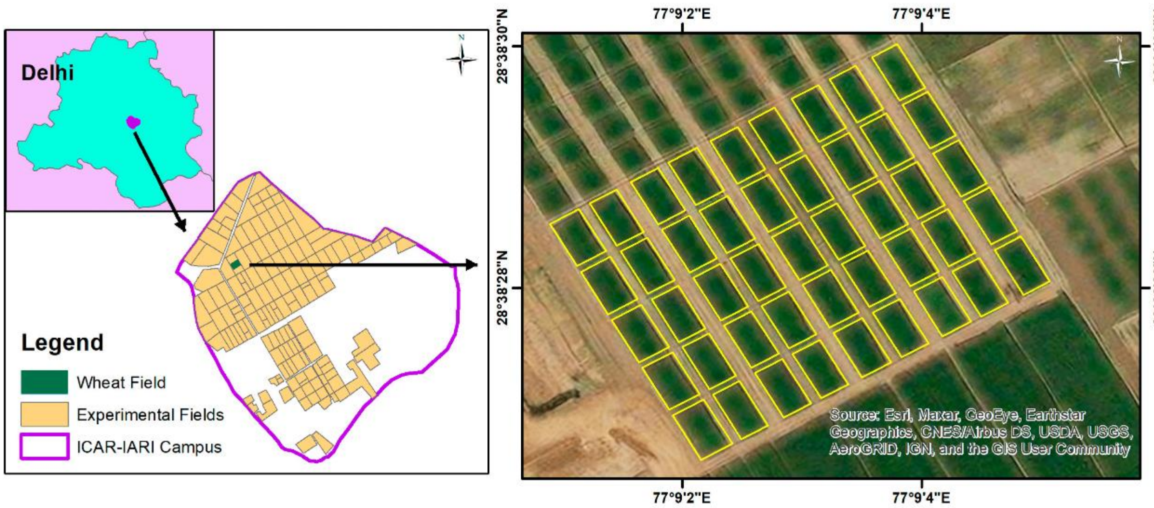

Figure 2. Location map of study area showing the experimental wheat fields at the research farm of ICAR-IARI, New Delhi.

The experimental plots were overflown by a Headwall Nano-Hyperspec hyperspectral camera (Headwall Photonics Inc., Bolton, MA, USA) mounted on a UAV hexacopter on 17 March 2022. The hyperspectral image composed of 269 bands in the range of 400–1000 nm with a spectral interval of 2.2 nm and spatial resolution of 4 cm was captured at a flight height of 21 m. UgCS Mission planning software was used for planning the mission route. Headwall SpectralView (v3.1.4) software (Headwall Photonics, Bolton, MA, USA) and ENVI (version 5.6.3) were employed for processing the acquired hypercube. After image acquisition, the pre-processing steps of radiance correction, reflectance conversion, orthorectification, and image mosaicking were accomplished using the aforesaid software.

The scale of the use case type: Experimental field, may be upscaled to farmers' field

Model Evaluation and Selection of GPR

Eight multivariate models were evaluated for estimating LAI and CCC using PCA as a dimensionality reduction method with 20 components. The theoretical results showing the goodness-of-fit statistics calculated for each regression model are tabulated in Table 3. Validated against simulated data, GPR outperformed all other models in predicting the LAI by showing the highest R2 value of 0.996, and KRR was found suitable for predicting the CCC with an R2 value of 0.9997. The MAE values reported for LAI and CCC are 0.019 and 0.016, whereas the RMSE values are 0.143 and 0.024, respectively. In the case of NRMSE, the lowest values for estimating LAI and CCC are 1.946% and 0.433%, respectively. As evident from Table 3, based on NRMSE and R2 values, the model performance sequence for LAI is GPR > KRR > NN > LS > ELM > BaTs > BoTs > SVR and that for CCC is KRR > GPR > NN > LS > ELM > SVR > BaTs > BoTs. Both GPR and KRR produced more accurate and robust results in estimating various crop traits. Since GPR possesses the unique characteristic of delivering uncertainties associated with mean estimates, the GPR algorithm was selected for further training optimization applicable to UAV ultrahigh-spatial-resolution hyperspectral imagery for estimating crop traits.

Table 3. Accuracy assessment of MLRA models for retrieving LAI and CCC.

S. No.	MLRA	MAE	RMSE	RRMSE (%)	NRMSE (%)	R^2
LAI						
1.	GPR	0.019	0.143	3.796	1.946	0.996
2.	KRR	0.114	0.153	4.065	2.084	0.995
3.	NN	0.129	0.232	6.150	3.153	0.988
4.	LS	0.189	0.247	6.545	3.355	0.987
5.	ELM	0.189	0.321	8.499	4.357	0.978
6.	BaT	0.218	0.357	9.469	4.854	0.976
7.	BoT	0.303	0.413	10.933	5.604	0.963
8.	SVR	0.334	0.449	11.892	6.096	0.957
CCC						
1.	KRR	0.016	0.024	1.562	0.433	0.9997
2.	GPR	0.031	0.043	2.756	0.746	0.999
3.	NN	0.031	0.050	3.262	0.904	0.999
4.	LS	0.038	0.050	3.292	0.912	0.999
5.	ELM	0.042	0.063	4.115	1.140	0.998
6.	SVR	0.075	0.093	6.099	1.690	0.995
7.	BaT	0.068	0.109	7.105	1.969	0.995
8.	BoT	0.139	0.176	11.521	3.192	0.98

Performance of AL Techniques

Figure 3 represents the comparative results of various AL techniques for retrieving LAI and CCC. Smooth convergence can be noticed, which implies the usage of NRMSE over other statistical measures, such as R2. The usage of NRMSE over R2 for selecting the optimal AL was proposed in many earlier works. The addition of a new sample at each iteration of the AL technique causes a stable decrease in RMSE and an increase in R2 when validating with the field dataset. Optimal GPR model performance was achieved by a set of a few samples, i.e., 97 and 119 for LAI and CCC, respectively. On adding new samples, the NRMSE of RSAL decreases from 80.76 to 16.84 for LAI. In the case of CCC, the NRMSE of EBD shows a steady decrease from 21.6 to 19.42 for CCC. RSAL outperformed other AL techniques for LAI, while

EBD showed the highest performance for CCC. The convergence observed at a low sampling size may be attributed to the low number of training data points used (n = 45).

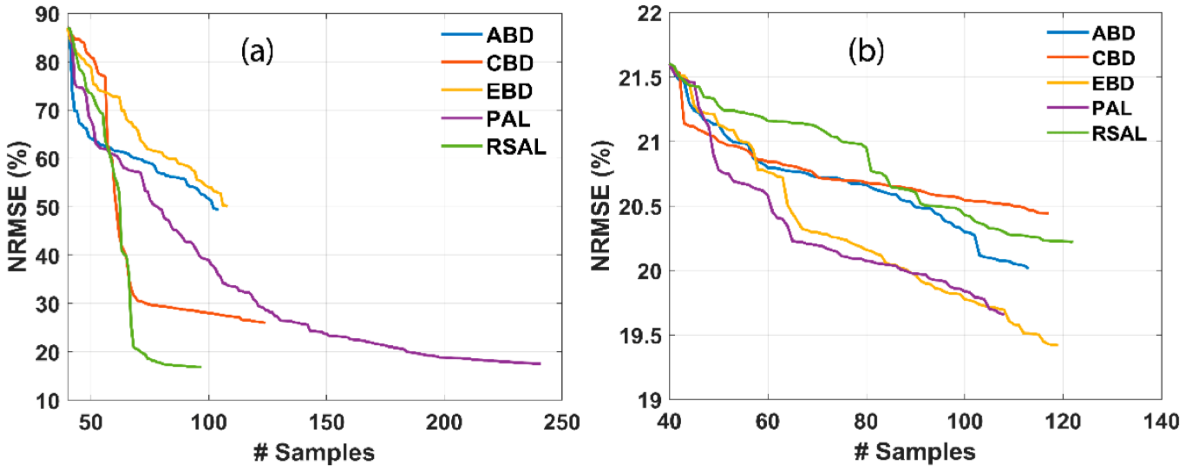

Figure 3. NRMSE (%) for several trait estimations using different AL methods. (a) LAI and (b) CCC. # samples denote the number of samples.

Retrieval of LAI and CCC

The final GPR models were applied to pre-processed UAV hyperspectral imagery to obtain estimates and the accompanying uncertainties. The LAI and CCC retrieval maps and their associated coefficient of variation (CV) are shown in Figure 5. The in situ measurements for LAI and CCC range from 3.46 to 7.27 m2 m−2 and 1.03 to 3.76 g m−2, respectively. On inspecting the retrieval maps, it is understood that they are strictly following the ranges of in situ measurements. The experimental plots with low values of LAI and CCC are clearly visible with red-coloured pixels, which indicate a strong pixel-wise variation of the retrieved values. For both the LAI and CCC maps produced, the maximum and minimum values appear on the same plots, which suggests that the retrieved maps are realistic and represent the best spatial variability. Even though the GPR models were trained with non-vegetation spectra added to the training with trait values set to zero, they were finally applied to a soil-masked pre-processed UAV image. Notably, no zero or close-to-zero values were obtained in the final estimated maps, which indicates the absence of non-vegetated regions, proving the advantage of including them during model training.

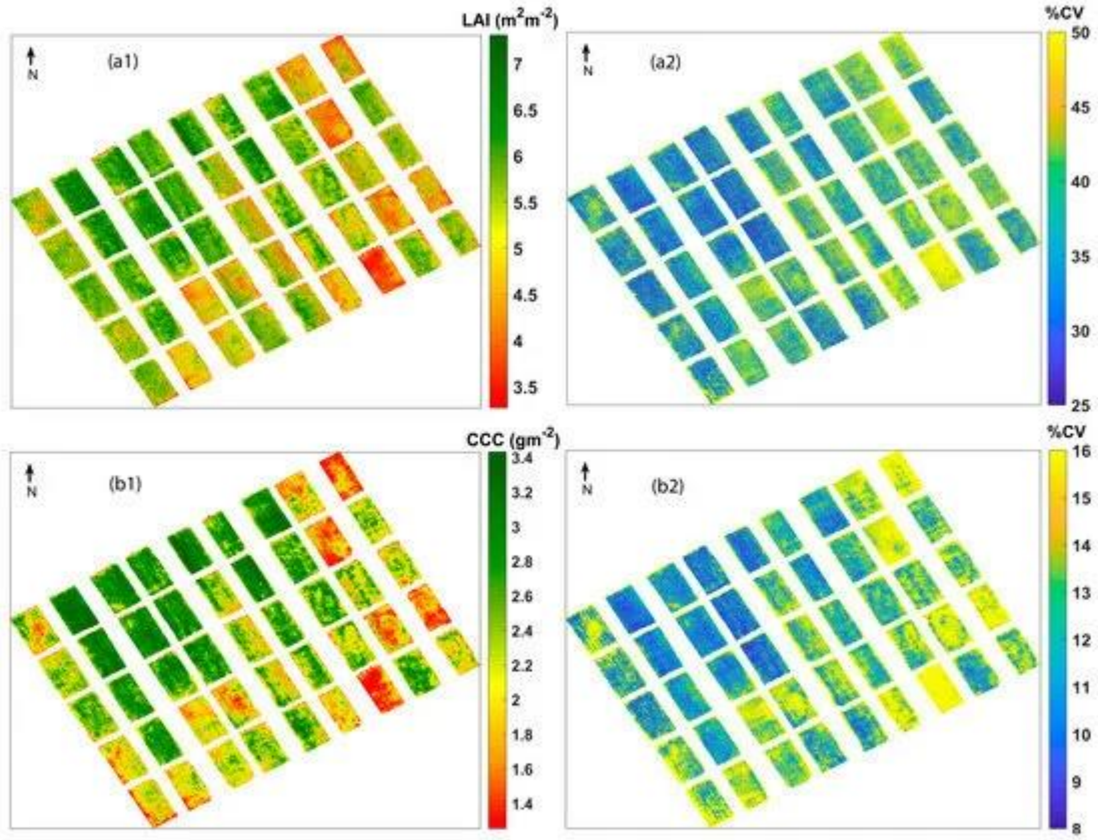

Figure 4. Mean estimates and coefficient of variation (CV) of (a1,a2) LAI and (b1,b2) CCC.

Part B

3. Architectural considerations

a. Data management

The experimental plots were overflown by a Headwall Nano-Hyperspec hyperspectral camera (Headwall Photonics Inc., Bolton, MA, USA) mounted on a UAV hexacopter on 17 March 2022. The hyperspectral image composed of 269 bands in the range of 400–1000 nm with a spectral interval of 2.2 nm and spatial resolution of 4 cm was captured at a flight height of 21 m.

- *Image distance:* A 21m distance between the camera on mounted drone and the crop was maintained. Images were captured from a top-view of the crop.
- *Image quality:* The image quality was very high for retrieval of the crop health traits accurately.
- *Image consistency:* The images were taken consistently across the entire crop area, ensuring that the images are representative of the whole crop and not just certain areas.
- *Camera settings:* Camera settings, such as aperture, and shutter speed, were optimized to capture high-quality images in different lighting conditions.
- *Crop variability:* The wheat field consisted of three replications of fifteen plots (7.2 × 13 m size each), maintained at five graded nitrogen levels (0, 50, 100, 150, and 200 kg N ha−1), and three irrigation treatments (soil moisture sensor-based treatment (I1); crop water stress index (CWSI)-based treatment (I2); and conventional treatment (I3)).

b. Communication infrastructure

(a) Smart Phone / Drone with cellular connectivity such as LTE/ 5G for capturing the images and transmitting them to cloud/ server.
(b) Wi-Fi communication (2.4 GHz/ 5GHz band) may also be used for transmitting the images from the drone/ smart phone to local hub/ IoT Gateway, which will further transmit the images over cellular/ wireline network to the cloud/ server.

Interfaces, protocols for communications
(a) LTE/5G connectivity (modem) (b) Wi-Fi NIC

c. Deployment considerations (technical considerations e.g., 4G vs 5G)

Images from the field were taken using drone and sent to cloud server using LAN/ WAN infrastructure. For better performance at farm fields, high speed wireless communication network such as 4G/ 5G is needed. Alternatively, smart phones/ drones may transmit to local hubs and further to cloud. Upscaling of communication infrastructure will further help in replacing the smartphone images with drone images and retraining the model for the same.

d. Regulatory considerations

Country-specific regulation related to drones.

4. Results of the use case (outcomes)

- *Performance and evaluation criteria (including KPIs).*

The low NRMSE values of 8.6% and 14.8% obtained for the GPR models during field verification suggest good retrieval accuracy and lower uncertainties for mapping LAI and CCC. Altogether, the proposed workflow offers the benefits of using a powerful (kernel-based) and generic hybrid approach for retrieving wheat crop biophysical variables from UAV datasets using ARTMO, a freely available software package. The developed workflow was successfully applied at the field level and can be upscaled for the quantitative and real-time mapping of vegetation products from farmers' fields using UAV technology.

Both LAI and CCC estimations show superior results with RMSE and MAE values less than 1. The RMSE values obtained for GPR models for LAI and CCC retrieval are 0.624 and 0.559, respectively. Further, the MAE values for LAI and CCC are 0.481 and 0.423, with R2 values of 0.889 and 0.656, respectively. The most important statistical parameters, NRMSE values, reported for LAI and CCC retrieval are 8.579% and 14.842%, respectively.

Another remarkable observation is the improvement in NRMSE thanks to the addition of non-vegetation spectra to the AL-optimized dataset and upon re-training. The NRMSE value for LAI was improved from 16.8 to 8.6%, and the CCC was lowered from 19.4 to 14.8%. Five bare-soil or non-vegetation spectra (10% of in situ measurements) were added to the AL-optimized dataset before the validation of crop traits.

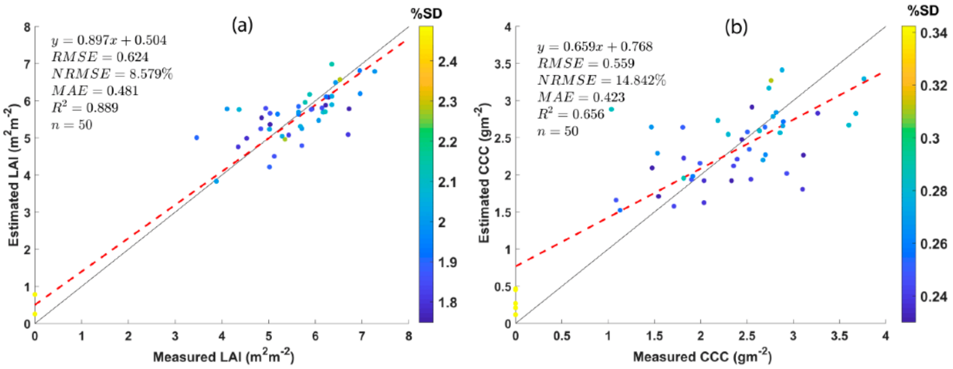

Figure 5: Scatter plots displaying the GPR model results against the in situ measurements along with goodness-of-fit statistics. (a) LAI and (b) CCC.

5. Lessons learned

We introduced an integrated hybrid workflow for estimating wheat crop biophysical variables from unmanned aerial vehicle (UAV) hyperspectral imagery in the spectral range of 400–1000 nm. To develop hybrid models, the Gaussian process regression (GPR) machine learning regression algorithm was applied to PROSAIL simulations. Theoretical validation using eight regression models revealed the superiority of GPR. Suitable dimensionality reduction and active learning techniques were combined to mitigate the problems of redundancy and suboptimal model training. Two active learning (AL) techniques, i.e., residual active learning (RSAL) and Euclidean distance-based diversity (EBD), were selected for the GPR modelling of leaf area index (LAI) and canopy chlorophyll content (CCC).

In brief, significant contributions of the proposed study is that a clear distinction of in situ values could be observed among plots and within plots, facilitating the use of these results for efficient farm nutrient management practices. Since these variables are clear indicators of plant stress, the retrieved within-field variability maps can be coupled with applied nutrient information to make decisions to improve crop health and yield.

6. Available standards

- ICT or Agricultural
- Available international standards

7. Links for supporting material (website, articles, etc.,)

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8. Appendix

Appendix 1: Actor / Business Role

S No	Actor	Business role
1.	Field Experimentation and UAV Image Acquisition	We collected images of an experimental wheat field of the HD 3059 variety located at the research farm of Indian Council of Agricultural Research-Indian Agricultural Research Institute (ICAR-IARI) (28°38'28.314"N latitude and 77°9'3.106"E longitude) 228 m above mean sea level. The wheat field consisted of three replications of fifteen plots (7.2 × 13 m size each), maintained at five graded

		nitrogen levels (0, 50, 100, 150, and 200 kg N ha−1), and three irrigation treatments (soil moisture sensor-based treatment (I1); crop water stress index (CWSI)-based treatment (I2); and conventional treatment (I3))
2.	Pre-processing	Includes resizing, normalization, noise reduction
3.	Augmentation	Flipping, Rotation, Zooming, Brightness adjustments
4.	PROSAIL Simulations and Model Evaluation	The simulated dataset from PROSAIL RTM was used for retrieving wheat biophysical traits. PROSAIL is a combined RTM of the PROSPECT-4 leaf reflectance model and the 4-SAIL canopy reflectance model
5.	Gaussian Process Regression (GPR)	First, it provides an additional quantitative measurement of prediction accuracy in terms of uncertainty estimates (σ). A lower σ indicates a better prediction for crop traits. The second advantage is the use of kernels or covariance functions to reduce the processing time. The best prediction performance was achieved with hybrid models developed by integrating GPR with RT models with the aid of dimensionality reduction and active learning techniques
6.	Dimensionality Reduction Using Principal Component Analysis (PCA)	Because the acquired hyperspectral imagery consists of 269 bands, such a large number of contiguous bands may easily lead to suboptimal performance in the ML models due to spectral redundancy (Hughes phenomenon). To reduce redundancy and computational time while optimizing accuracy, a suitable dimensionality reduction strategy is to be applied. The MLRA toolbox in ARTMO provides eleven dimensionality reduction techniques for retrieving the most significant statistical variables. According to the analysis of all of them as a trade-off between accuracy and runtime in various settings, the PCA with 20 components is the most recommended one for retrieving multiple crop traits from hyperspectral datasets using GPR
7.	Active Learning Methods and Field Verification	In RT modelling, a large, simulated dataset introduces redundancy and even makes it impossible to develop hybrid regression models for retrieving specific crop traits. In order to reduce the sample size without altering the model’s predictive performance, noisy and reluctant samples may be removed by adopting an effective sample selection criterion. In solving regression problems related to the prediction of crop traits using Earth observation data products, two types of active learning (AL) methods are widely used, i.e., uncertainty and diversity methods

Appendix 2: Actor role

Actor name	Actor type	Role description
Headwall Nano-Hyperspec hyperspectral camera	Device	Capture images of Wheat crop
UAV hexacopter	Device	Carry payload
AI-based detection algorithm	System	Using a trained data set for retrieval of crop traits

9.4. Use Case: Infrared Thermography and IoT Integration for Early Detection of Mastitis in Dairy Cattle: A Smart Approach to Animal Health Management

Source: Dr. T. K. Mohanty, Dr. Mukesh Bhakat, Dr. Gayathri S. Lal, ICAR-National Dairy Research Institute, Karnal, India and Dr. Rajeev Ranjan Kumar, Dr. K. K. Chaturvedi, Mr. Sanjeev Kumar, ICAR-Indian Agricultural Statistics Research Institute, New Delhi, India

Part A

1. Introduction

Mastitis, a prevalent and economically burdensome production disease in dairy animals, poses significant challenges to the global dairy industry. With estimated global losses reaching 20–30 billion US dollars (Blum, 2021) and approximately INR 7165.51 crores in India (Bansal and Gupta, 2009), its impact extends beyond financial losses. Mastitis affects the quantity and quality of milk produced and jeopardizes the overall udder health of dairy animals. Poor sanitation and hygiene practices contribute significantly to the flare-up of mastitic pathogens, including *Escherichia coli*, *Staphylococcus aureus*, and *Streptococcus uberis* (Sinha et al., 2014). The incidence and prevalence of mastitis cases are rising, paralleling the increasing milk productivity of dairy animals globally. Krishnamoorthy et al. (2021) reported a worldwide prevalence of 42% for subclinical mastitis (SCM) and 15% for clinical mastitis (CM), and in India, these figures were even higher at 45% for SCM and 18% for CM.

The commonly used mastitis detection methods involve somatic cell count estimation and the California Mastitis Test (CMT). While advanced diagnostic techniques such as polymerase chain reaction (PCR) and enzyme-linked immunosorbent assay (ELISA) exist, they are costly and require specialized infrastructure and skilled technicians. In this context, a rapid, noninvasive cow-side diagnostic tool is essential for assessing udder health, and infrared thermography (IRT) emerges as a promising solution. Infrared thermography, developed initially for military and medical purposes, utilizes the principle that every object above absolute zero emits infrared radiation. This technology, characterized by its simplicity, effectiveness, on-site applicability, and noninvasiveness, has the potential to revolutionize mastitis detection in dairy animals. The ability of IRT to capture and convert infrared radiation into thermal images allows for the visualization of temperature variations on the udder's surface. IRT is a simple, effective, on-site, and noninvasive tool that uses surface body temperature to generate images without causing radiation exposure.

Maximum IR temperature and its change are preferred in scientific study purposes rather than average and minimum IRT of the external body surface as maximum IRT is better associated with differences during lactation variables, behavioral responses of emotions, and metabolism (Byrne et al., 2019, Uddin et al., 2019 and Uddin et al., 2020). Assessment of infectious diseases (Menesatti et al., 2004) and estimation of welfare status among farm animals (Stewart et al., 2005, 2007) using IRT is practical (Kníˇzkova et al., 2007). A minute change in the udder skin surface temperature can be assessed using sensitive IR cameras. Thus, IRT is effective as a convenient portable tool in livestock management. Researchers have used IRT to assess the udder skin surface temperature (USST) changes in healthy and mastitis-affected quarters of dairy animals and its analysis of thermograms (Sathiyabarathi et al., 2018). The studies were primarily conducted under the induced model of mastitis infection or simple assessment of healthy and mastitis-affected quarters. The current project is centered on acquiring thermal images within the animal environment to assess their Intramammary Infection (IMI) status. Subsequently, the IMI status is evaluated through the California Mastitis Test (CMT) and Somatic Cell Count (SCC) methods. The thermal images, captured after the diagnostic confirmation of the animal's status, serve as the foundation for developing an algorithmic database.

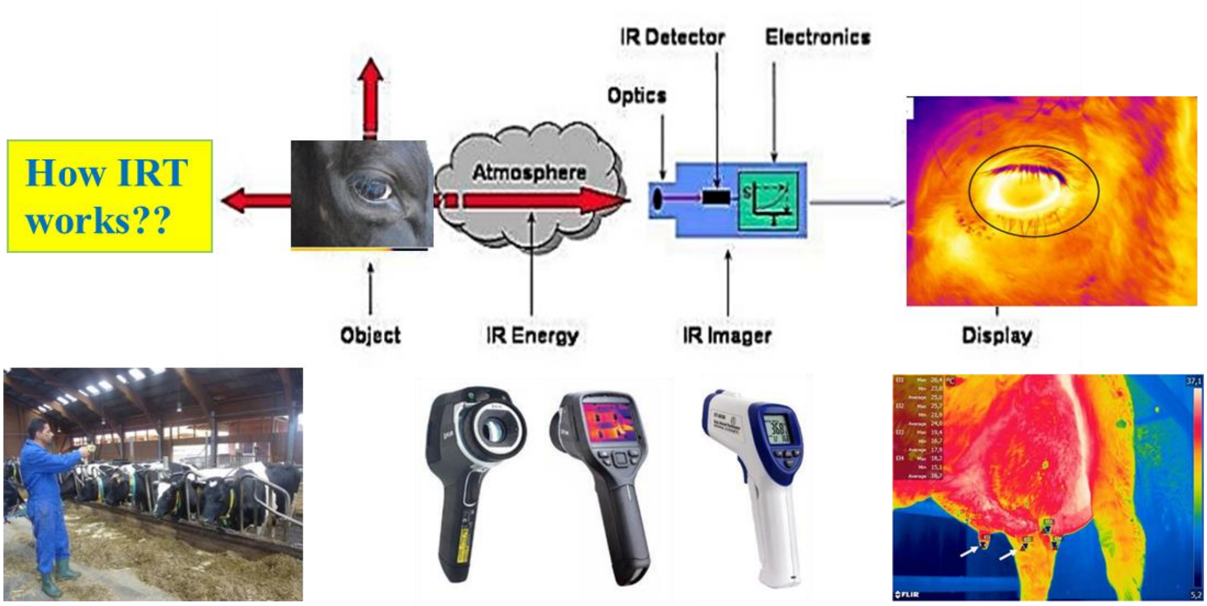


Figure 1: Infrared Thermography

The primary objective of this project is to revolutionize mastitis management in dairy farming through the utilization of Infrared Thermography (IRT). We aim to conduct diagnostic assessments using IRT, enhancing the accuracy of mastitis detection. Simultaneously, the project focuses on developing algorithms (DL-CNN) to automatically predict intramammary infection (IMI) status, streamlining the identification process in a farm setting. Beyond diagnostics, our ultimate goal is to implement precision farming techniques, providing actionable insights for proactive decision-making and optimizing overall health management practices.

The major actors are ICAR- National Dairy Research Institute (ICAR-NDRI), Karnal, Haryana and ICAR-IASRI, New Delhi. Notably, the project strives to democratize access to this technology by ensuring its practicality at the farmer level. We aim to make IRT and the developed algorithms user-friendly, empowering farmers with an accessible tool for early mastitis detection and improved health management in their dairy animals. By bridging the gap between advanced technology and on-the-ground farming practices, we aspire to directly benefit farmers, contributing to sustainable and efficient dairy farming practices in the evolving landscape of agriculture. Furthermore, this project envisions encouraging start-ups to focus on artificial intelligence and mastitis detection database management. By leveraging the insights and data generated from our diagnostic assessments and algorithmic predictions, we aim to create opportunities for innovative ventures. Encouraging entrepreneurship in this domain fosters technological advancements and opens avenues for the growth of a specialized industry dedicated to improving dairy health through cutting-edge technologies. Through such initiatives, we aim to contribute to the broader ecosystem of agricultural technology and promote sustainable practices in dairy farming.

2. Description (Background)

- Mastitis in Dairy Animals:
  - Definition: Mastitis is a prevalent and economically burdensome production disease in dairy animals.
  - Significance: Global economic impact estimated at 20–30 billion US dollars.
  - Impact in India: Approximately INR 7165.51 crores in losses.
- Causes and Pathogens:
  - Factors: Poor sanitation and hygiene practices contribute significantly.
  - Common Pathogens: *Escherichia coli, Staphylococcus aureus, Streptococcus uberis.*
- Prevalence and Incidence Rates:
  - Worldwide: Subclinical mastitis (SCM) prevalence of 42%, clinical mastitis (CM) prevalence of 15%.
  - India: SCM prevalence of 45%, CM prevalence of 18%.

The comprehensive technology involves optimizing thermal image acquisition for lactating cows, refining camera calibration in milking parlors, and establishing animal preparation protocols. We utilize a high image resolution (384 × 288) digital IR with a temperature range of −20 ◦C to +650 ◦C. Additionally, we will install IR cameras/gadgets to automatically capture thermograms of the lactating cows at the milking parlor of LRC, ICAR-NDRI, Karnal, Haryana, India. The scope of image capture will expand to diverse environmental conditions, incorporating lighting and animal behavior considerations. Continuous refinement of thermogram analysis software will integrate advanced algorithms for precise temperature variation detection, and robust quality control measures will be implemented for image clarity. In-depth statistical analysis will explore udder and teat skin surface temperature patterns. Collaboration with experts and validation from veterinary professionals will ensure scientific rigour. The plan includes technology transfer and adoption strategies, emphasizing continuous improvement and staying abreast of technological advancements. Additionally, the project envisions integrating applied artificial intelligence and the Internet of Things (IoT) specifically for mastitis detection. This includes exploring methods for automatically capturing IR images in the farm setup, allowing for online automatic updates to the database. Small farmers can utilize mobile devices equipped with IoT gadgets for Infrared Thermography (IRT), capturing images in their farms or homes. These images will seamlessly feed into the database, enabling automatic detection of mastitis status in dairy animals by image processing algorithm, thereby enhancing accessibility and usability of the technology for farmers at all scales.

The study was conducted at the Livestock Research Centre (LRC), ICAR-National Dairy Research Institute, Karnal, Haryana. Karnal is located at latitude 290 43" N and longitude 770 2" E, with an elevation (attitude) of 250 m above sea level. The region has a sub-tropical climate; hence, the minimum and the maximum temperatures often range from 4 ◦C (winter) to 45 ◦C (summer). The annual rainfall of Karnal is around 70 cm with a vapour pressure of 7 to 25 mmHg. Seasons were classified as winter (December to March), summer (April to June), rainy (July–August) and autumn (September to November). The dry and wet bulb thermometer readings will be recorded regularly at the respective milking parlour of each breed. The temperature-humidity index was calculated using "THI= 0.72(Tdb + Twb) + 40.6, where Tdb = Dry bulb temperature in ◦C and Twb= Wet bulb temperature in ◦C" (McDowell, 1972).

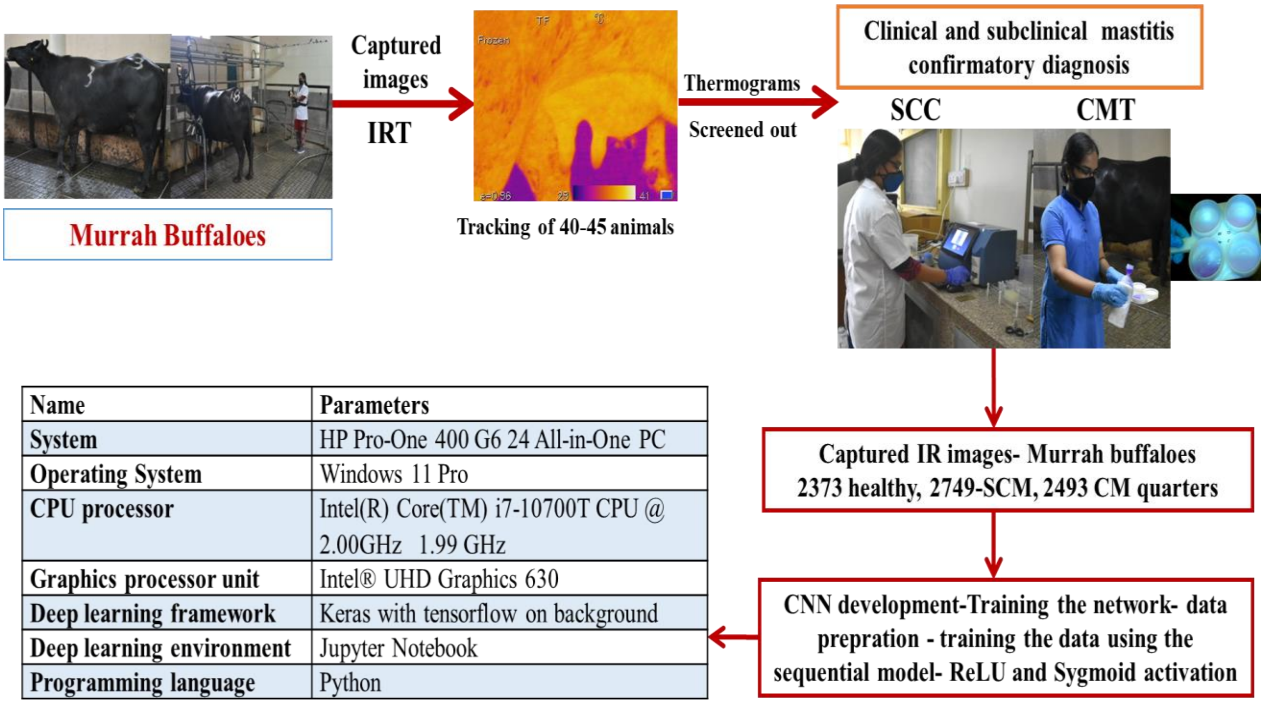
The month-wise analysis of the udder thermograms (USST) of experimental Sahiwal cows revealed a significant difference ($p < 0.01$) between the mean values of USST of SCM and CM-affected quarters compared to healthy quarters. During January, the mean values of USST showed an increase of 1.82 and 3.11 ◦C among SCM and CM-affected quarters compared to healthy quarters, respectively. Similarly, during February, March, April, May, June, July, August, September, October, November, and December, the mean values of USST showed an increase of 1.37 and 2.35 ◦C, 0.96 and 2.09 ◦C, 0.79 and 1.66 ◦C, 1.21 and 2.21 ◦C, 0.76 and 1.34 ◦C, 1.04 and 1.78 ◦C, 0.73 and 1.49 ◦C, 1.71 and 2.70 ◦C, 1.01 and 2.06 ◦C, 1.27 and 2.47 ◦C¸1.81 and 2.76 ◦C, among SCM and CM affected quarters compared to healthy quarters, respectively. Compared to healthy quarters, the highest increment in USST was observed during January in the SCM and CM-affected quarters. The lowest increment in temperature was observed during August for SCM compared to healthy quarters and June for CM compared to healthy quarters. Within the USST of healthy quarters of Sahiwal cows, the mean values were significant ($p < 0.01$) between the months except for October–November and August–April, and their mean values were comparable among themselves but showed a significant difference ($p < 0.01$) from the mean values of other months. In the case of USST of SCM quarters, the mean values differed significantly ($p < 0.01$) during different months except for February–March, April–May, and September–October and their mean values were comparable but showed significant differences ($p < 0.01$) with other months of SCM quarters. Similarly, the mean values of the udder thermograms of the CM quarters of Sahiwal cows showed significant differences ($p < 0.01$) among the different months and were comparable between February–March, August–April, May–June, and September–October but showed a significant difference ($p < 0.01$) between other months. A similar pattern was observed in the teat skin surface temperature of the Sahiwal cows. Similarly, seasonal assessments of mastitis using thermal image analysis were carried out in Tharparkar, Gir, HFCB, and Murrah buffalo cows.

The developed DL-CNN model had training and validation accuracy of (normal vs. clinical) to the tune of 0.96 and 0.98, respectively, and the sequential model (normal *vs.* subclinical) to the tune of 0.98 and 0.95. The testing accuracy for the DL-CNN sequential models was 0.96 in Murrah buffaloes. Similarly, the training and validation accuracy of the sequential model (normal *vs.* clinical) via the augmented dataset in Sahiwal cows reflected a performance to the tune of 0.994 and 0.938, respectively and the sequential model (normal *vs.* subclinical) to the tune of 0.941 and 0.751. The testing accuracy for the DL-CNN sequential model (normal *vs.* clinical) was 0.93, and the sequential model (normal *vs.* subclinical) was 0.77.

Objective/Purpose

- To enhance sub-clinical mastitis detection accuracy, utilize Infrared Thermography (IRT).
- Develop deep learning convolutional neural network (DL-CNN) algorithms to predict intramammary infection (IMI) status automatically and accurately.
- Implement precision farming techniques to provide actionable insights for proactive decision-making and optimize overall health management practices.

  The schematic representation of the mastitis assessment and further algorithm development in Murrah buffalo is depicted below:



Name	Parameters
System	HP Pro-One 400 G6 24 All-in-One PC
Operating System	Windows 11 Pro
CPU processor	Intel(R) Core(TM) i7-10700T CPU @ 2.00GHz 1.99 GHz
Graphics processor unit	Intel® UHD Graphics 630
Deep learning framework	Keras with tensorflow on background
Deep learning environment	Jupyter Notebook
Programming language	Python

Figure 2: Mastitis Assessment

Part B

3. Architectural considerations

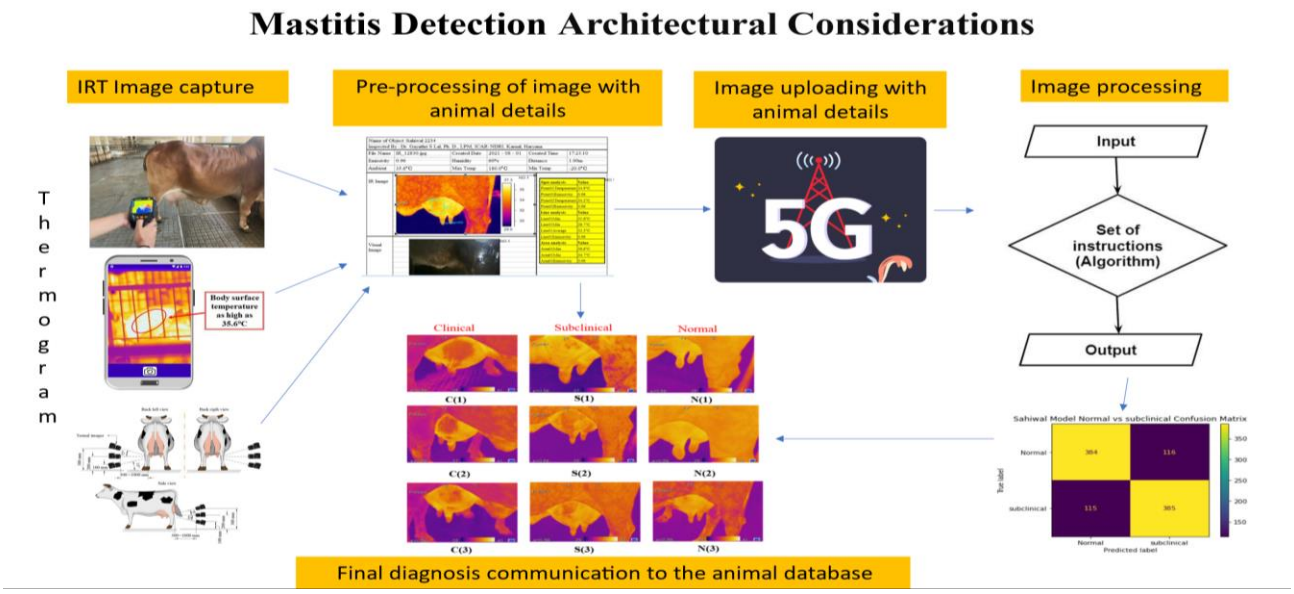
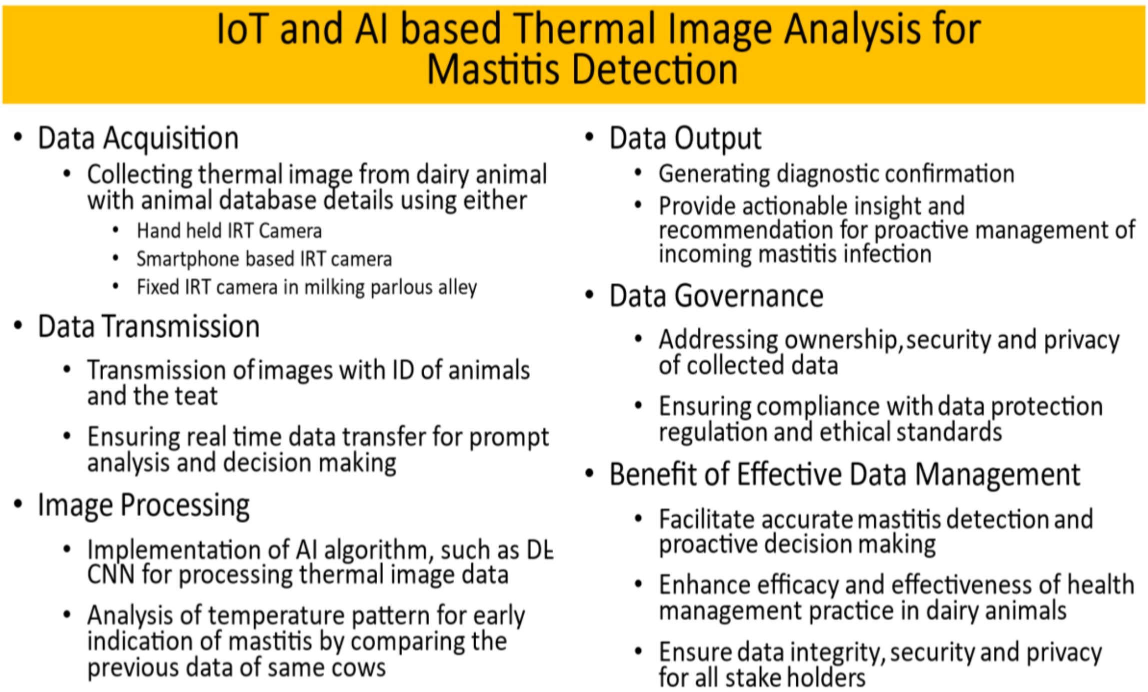


Figure 3: Mastitis Detection Architecture

a. Data management



b. System architecture

Description: The mastitis detection system comprises of interconnected data acquisition, processing, and management subsystems.

Sub-Systems:

- Animal Database system: History and performance recording with smartphone-based access
- Infrared Thermography (IRT) Sensors: Capture temperature variations on the udder's surface.
- IoT Subsystem: Facilitates data transmission, real-time monitoring, and remote access.
- AI Subsystem (DL-CNN): Analyzes IRT data for mastitis detection using deep learning algorithms.
- Data Management System: Stores, processes, and manages collected data for decision support.

c. **Communication Infrastructure:**

Interfaces and Protocols:

IoT Connectivity: For image and video and data communication
Benefits: Enables real-time monitoring, data analysis, and remote access for stakeholders.

d. **Deployment Considerations:**

Technical Considerations:- Evaluate network speed, coverage, and latency requirements for efficient data transmission. Compatibility with existing infrastructure and future scalability.

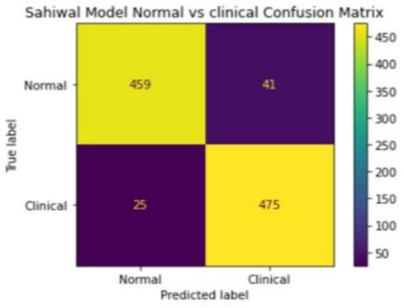
e. **Regulatory Considerations:**

- Compliance with Data Protection Regulations:
- Ensure adherence to privacy laws (e.g., GDPR) and industry standards for data security.
- Implement measures for data encryption, access control, and secure storage.

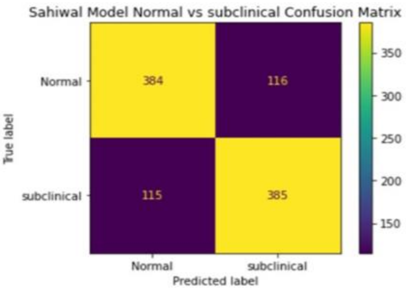
4. Results of the use case (outcomes)

Sahiwal Cows

Confusion matrix- Sequential DL-CNN model



(a) Sequential (Normal *vs* Clinical)



(b) Sequential (Normal *vs* Subclinical)

Diagnostic certainty of mastitis in the proposed sequential models (Augmented dataset)

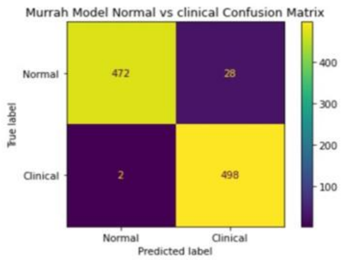
Model	Training Accuracy	Validation Accuracy
Sequential (Normal vs Clinical)	0.9940	0.9380
Sequential (Normal vs Subclinical)	0.9410	0.7510

	Normal *vs.* Clinical	Normal *vs.* Subclinical
Testing accuracy	0.9340	0.7690
Loss	0.0211	0.1533
Precision	0.9205	0.7684
Recall	0.9500	0.7700
F1_score	0.9350	0.7692

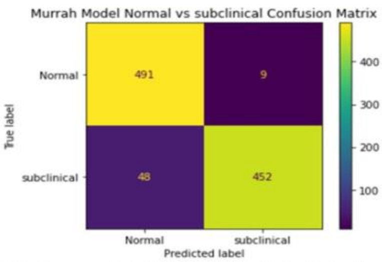
Figure 4: Results on Sahiwal Cows

Murrah Buffaloes

Confusion matrix- Sequential DL-CNN model



(a) Sequential (Normal *vs* Clinical)



(b) Sequential (Normal *vs* Subclinical)

Diagnostic certainty of mastitis in the proposed sequential models (Augmented dataset)

Model	Training Accuracy	Validation Accuracy
Sequential (Normal vs Clinical)	0.9990	0.9880
Sequential (Normal vs Subclinical)	0.9910	0.9780

	Normal *vs.* Clinical	Normal *vs.* Subclinical
Testing accuracy	0.9700	0.9430
Loss	0.0091	0.0291
Precision	0.9467	0.9804
Recall	0.9960	0.9040
F1_score	0.9707	0.9406

Figure 5: Results on Murrah Buffaloes

Qualitative and quantitative comparison

This non-invasive subclinical and mastitis detection is > 90 % accuracy compared to the conventional method of diagnosis by CMT and SCC count. For sub-clinical mastitis diagnosis, SCC analysis requires costly equipment and consumables. The testing consumable cost for each cow is Rs.200. It can not be done on the cow side and requires an expert to run the machine.

5. Lessons learned

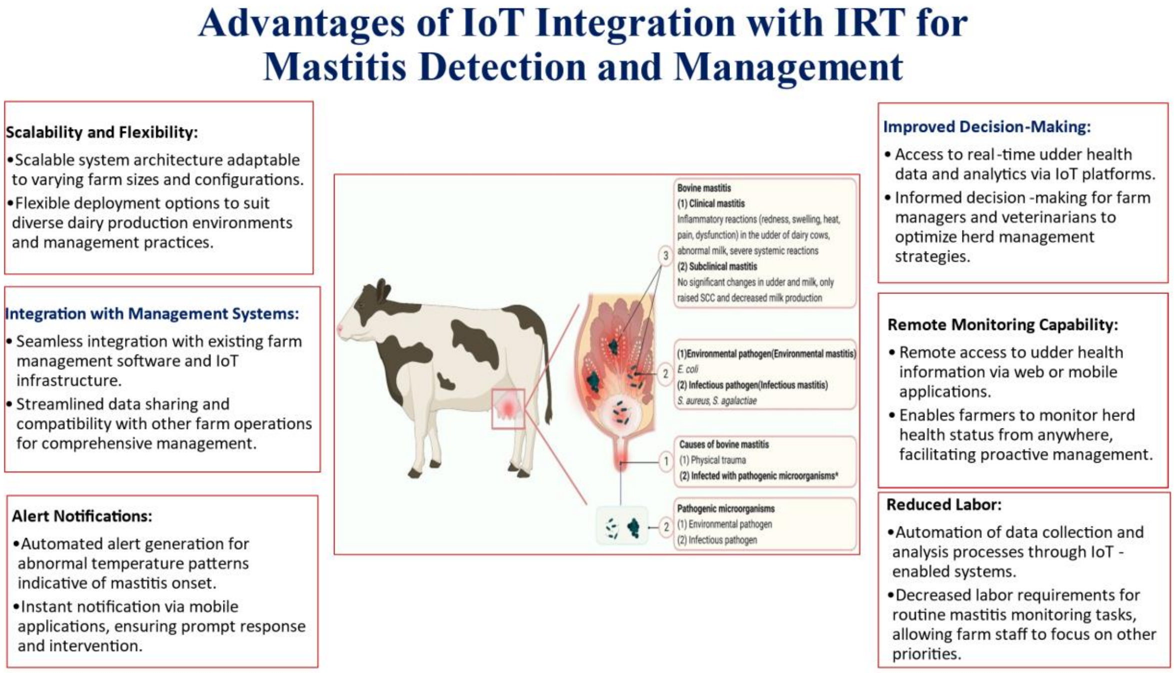


Figure 5: Advantages of IoT integration with IRT for Mastitis Detection and Management

6. Available standards

ICT Standards:

ITU-T Recommendations: Relevant standards for IoT connectivity, data transmission, and security protocols.

Available International Standards:

- OIE (World Organisation for Animal Health) Standards:

  https://www.woah.org/en/what-we-do/standards/codes-and-manuals/
- OIE Terrestrial Animal Health Code.
- OIE Provides guidelines for controlling and preventing animal diseases, including mastitis, to ensure international trade and animal health.

7. Conclusion

In the future, deploying and upgrading the integration of Infrared Thermography (IRT) and the Internet of Things (IoT) for mastitis detection in dairy cattle will involve advancements in sensor technologies, IoT infrastructure, data analytics, and integration with management systems. Efforts will focus on enhancing remote monitoring, automation and ensuring cost-effectiveness and accessibility for farmers. Continued research and validation will refine these systems, ensuring their effectiveness and reliability under various farm conditions. This holistic approach aims to improve the dairy industry's animal health, welfare, and productivity.

8. Links for supporting material

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- Byrne, D.T., Berry, D.P., Esmonde, H., McGovern, F., Creighton, P., McHugh, N., 2019. Infrared thermography as a tool to detect hoof lesions in sheep. Transl. Anim. Sci. 3, 577-588. doi: 10.1093/tas/txy132
- Gayathri, S.L. Bhakat, M., and Mohanty, T.K. (2023). Short milking tube thermogram analysis: an indicator of mastitis in Murrah buffaloes. *Tropical Animal Health and Production* 56: https://doi.org/10.1007/s11250-023-03853-4 (NAAS Score: 7.70)
- Gayathri, S.L. Bhakat, M., and Mohanty, T.K. (2023). Short-milking-tube thermograms: An alternative to udder thermograms for mastitis detection in Sahiwal cows. *Research in Veterinary Science,* 165:105056, https://doi.org/10.1016/j.rvsc.2023.105056 (NAAS Score: 8.40)
- Gayathri, S.L. Bhakat, M., and Mohanty, T.K.(2024). Seasonal assessment of mastitis using thermogram analysis in Sahiwal cows. *Research in Veterinary Science,* 166: 105083, https://doi.org/10.1016/j.rvsc.2023.105083 (NAAS Score: 8.40).
- Knížková, I., Kunc, P., Gürdil, G.A.K., Pınar, Y., Selvi, K.Ç., 2007. Applications of infrared thermography in animal production. J. Fac. Agric. Kyushu Univ. 22, 329-336. Microsoft Word - 2007 22 3 329-336.doc (dergipark.org.tr)
- Krishnamoorthy, P., Goudar, A.L., Suresh, K.P., Roy, P., 2021. Global and countrywide prevalence of subclinical and clinical mastitis in dairy cattle and buffaloes by systematic review and meta-analysis. *Res. Vet. Sci.* 136, 561-586. DOI: 10.1016/j.rvsc.2021.04.021
- Menesatti, P., Iacurto, M., D'Andrea, S., Pincu, M., Saltalamacchia, F., 2004. Infrared thermography for monitoring animal welfare. Inf. Agrar. 60, 49-53.
- Sathiyabarathi, M., Jeyakumar, S., Manimaran, A., Heartwin, Pushpadass, A., Kumaresan, A., Lathwal, S.S., Sivaram, M., Das, D.N., Ramesha, K.P., Jayaprakash, G., 2018. Infrared thermography to monitor body and udder skin surface temperature differences in relation to subclinical and clinical mastitis condition in Karan Fries (*Bos taurus* × *Bos indicus*) crossbred cows. *Indian J. Anim. Sci.* 88(6), 694-699. DOI: 10.56093/ijans.v88i6.80887
- Sinha, M. K., Thombare, N. N., Mondal, B., 2014. Subclinical mastitis in dairy animals: incidence, economics, and predisposing factors. Sci. World J., 523984, 1- 4.

- Stewart, M., Webster, J.R., Schaefer, A.L., Cook, N.J., Scott, S.L., 2005. Infrared thermography as a non-invasive tool to study animal welfare. Anim. Welf. 14, 319-325.
- Uddin, J., McNeill, D.M., Lisle, A.T., Phillips, C.J.C., 2020. A sampling strategy for the determination of the infrared temperature of relevant external body surfaces of dairy cows. *Int. J. Biometeorol*. 64, 1583-1592. DOI: 10.1007/s00484-020-01939-4
- Uddin, J., Phillips, C.J.C., Goma, A.A., McNeill, D.M., 2019. Relationships between infrared temperature and laterality. *Appl. Anim. Behav. Sci*. 220, 104855-71. https://doi.org/10.1016/j.applanim.2019.104855

9. Appendix

Appendix 1: Actor / Business Role

S No	Actor	Business role
1.	Veterinary Service Provider	Animal Database Management Provider
2.	Dairy Farmers Participation	Imageprocessing Service provider
3.	IoT infrastructure	Database management and IoT management company

Appendix 2: Actor role

Actor name	Actor type	Role description
Veterinary Service Provider	Veterinarian	Advising/treating based on diagnosis for mastitis management and treatment
Infrared Thermal Device	Owned by the farmer or Veterinarian or veterinary field worker	Sourcing the device
Image Capturing by the farmer or by the veterinary field worker	Veterinary Field worker or farmer	Database management and uploading the thermogram with details about the animals
IoT Infrastructure Management Company	Engineers	Database management in clouds
Image processing	Algorithm optimization and validity	Analysis of the Image and sending the prediction

Appendix 3: Communications technologies

Scenario	Communication network	Technologies
Online IR image capturing before milking or after milking by IR Camera	WAN and LAN, 4G and 5G network	Mobile Technology Or through the IPV6 network
Database and running of algorithms in the cloud	Computer server	IoT infrastructure

9.5. Use case: IoT based Dissolved Oxygen (DO) Monitoring and Management System in Cultured Fisheries

Source: Dr. Basant Kumar Das, ICAR-Central Inland Fisheries Research Institute (CIFRI) Kolkata, India

Part A

1. Introduction

Fish and shellfish culture especially in inland fisheries have gained momentum due to ever-increasing demand of those substances. Growth and survival of those aqua products like fish and shellfish are very much dependent on the ambient environment. Among different water parameters, role of dissolved oxygen and toxic gases like ammonia is well known. Fisherman/ fish farmer used to take suitable remedial measures to lessen the stresses caused by those parameters from their congenial range. In this scenario, aerators or water lifting pumps are used to operate to increase the oxygen level in the water.

In recent years, advancement in automation technology resulted in development of technologies that can improve the water quality of the fish farm, thus leading to increase fish production. Moreover, aquaculture and sensor-based water quality monitoring system have exponentially grown in the world but, combination of both domains still remains at its early stage. Generally, sensors are particularly vital in systems where water is recirculated and where stocking levels are high, but they are generally expensive, low limits of detection, high maintenance requirements. Many a cases, fisherman takes experience-driven management steps, rather than data driven which often not properly timed. Hence, an integrated automated system is necessary which will simultaneously identify the real issue and initiate appropriate management steps in real time to address the problem. The technology can complement in attaining SDG14 goals for sustainably manage and protect the ecosystem in life below water.

2. **Description (Background)**

- *Materials and methods*

The DO monitoring system helps to sense DO level present in water by using a DO sensor and switch a connected aerator on and off in case of any stress situation. The control box consists of microcontroller, signal conditioner and other small electronic components which converts the signal to numeric DO value and displays on local display device as well as uploads the data to the cloud sever which is dedicated for the system. The cloud server stores and displays the data on website which is accessible on PC or mobile device. On the same time the system controls the aerator to manage the stress situation. A set point of DO is set in the system according to which the connected aerator is turned on or off. When DO level goes below threshold level, the system signals the aerator to start its operation. Once DO level reaches to the desirable level, again signal goes to the aerator to stop its operation.

- Country specifics (Including geographical location)

In the recent past, Indian fisheries has witnessed a paradigm shift from marine dominated fisheries to inland fisheries, with the latter emerging as a major contributor of fish production in India. Within inland fisheries, a shift from capture to culture-based fisheries has paved the way for sustained blue economy. But, in capture fisheries, the development in terms of its production potential is yet to be realized. In this context, the advance technology of ICT, automation and sensors can play a major role in achieving this production potential. The present IoT based automated DO monitoring system is suitable for any cultured fisheries system specially in fish farming states of India like UP, Bihar, Chhattisgarh, Jharkhand, WB, Odisha, AP, Telangana etc. to improve the water quality for the fish survival.

-Process flow diagram

The process flow diagram indicates the process involved in the DO monitoring system for managing the DO level in the waterbody. DO sensor is placed in the water tank or waterbody. The sensor is connected to the controller box. In the controller box, the DO data is analyzed, processed and converted into computer understandable language. Then the system sends the data to the cloud server which is kept dedicated for the system via. Internet. The Internet connected through Wi-Fi. On the same time the system controls the aerator whenever there is a drop of dissolve oxygen in the water.

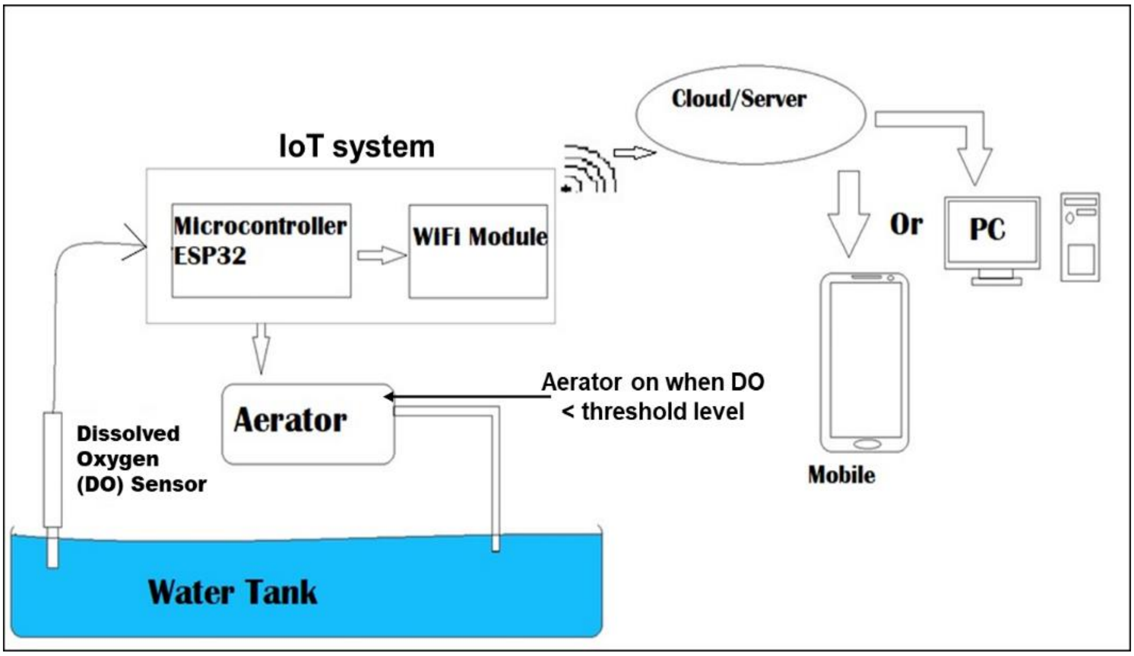

Fig 1 Process flow diagram of the system

-Outcomes/ results of use case

Automated DO management system will help to take automated decision that will immediately respond to improve the environment by controlling DO level in the waterbody and hence will prevent further deterioration of ambient water condition. It also generates real-time water parameter status report in the cloud-based application for monitoring purpose which is accessed via internet from any desktop or mobile (Table 2). The temporal variation of the DO level of the pond system is plotted in Fig 2.

Table 2: DO reading data with status ON/OFF in excel sheet

Date	Time	DO level	Temperature	Aerator Status (On/Off)
01/02/2024	00:00:41	5.10	27.56	OFF
01/02/2024	00:01:11	5.09	27.56	OFF
01/02/2024	00:01:41	4.90	27.56	ON
01/02/2024	00:02:11	4.93	27.56	ON
01/02/2024	00:02:41	4.97	27.56	ON
01/02/2024	00:03:11	4.99	27.5	ON
01/02/2024	00:03:41	5.51	27.5	OFF
01/02/2024	00:02:46	5.45	27.56	OFF

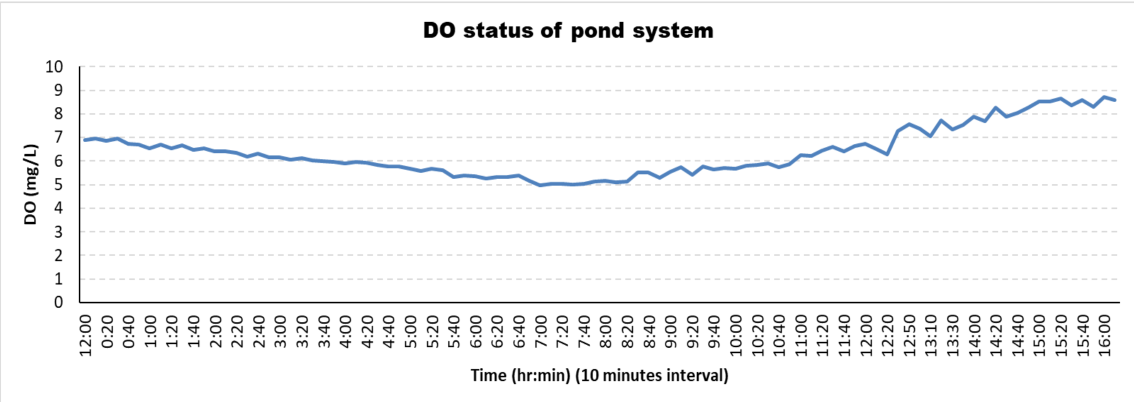

Fig 2: Temporal variation of DO status of the pond system

Part B

3. Architectural considerations

a. Data management

The sensor embedded with the IoT system captures DO level and temperature of the nearby water area preferably in 10-minute interval. The huge continuous data are transferred and stored in the cloud system. The data can be viewed from any location via developed web interface and downloaded in excel format for any further research. Web-interface was developed using ThingSpeak IoT analytic platform service.

b . System architecture

The architecture of the DO system is described in the Fig. 3. The system is made up of a microcontroller, an internet connectivity source for connecting to the internet and it attached with a DO sensor which is installed in the waterbody. The devise is capable of detecting the DO sensor and convert it into digital form. The converted DO reading is transmitted over the internet and store in the cloud space. A web interface was developed using ThingSpeak IoT analytic platform service to display the real time DO reading of the waterbody with an interval of 10 minute. The date wise DO status of the waterbody can be downloaded in Excel format. Farm owner/end user can access the real-time DO level and temperature of the waterbody via internet from any location. The continuous date wise DO and temperature data are stored in the excel file for further analysis. The power supply to the system can be battery-powered, standard electricity supply and/or solar battery powered.

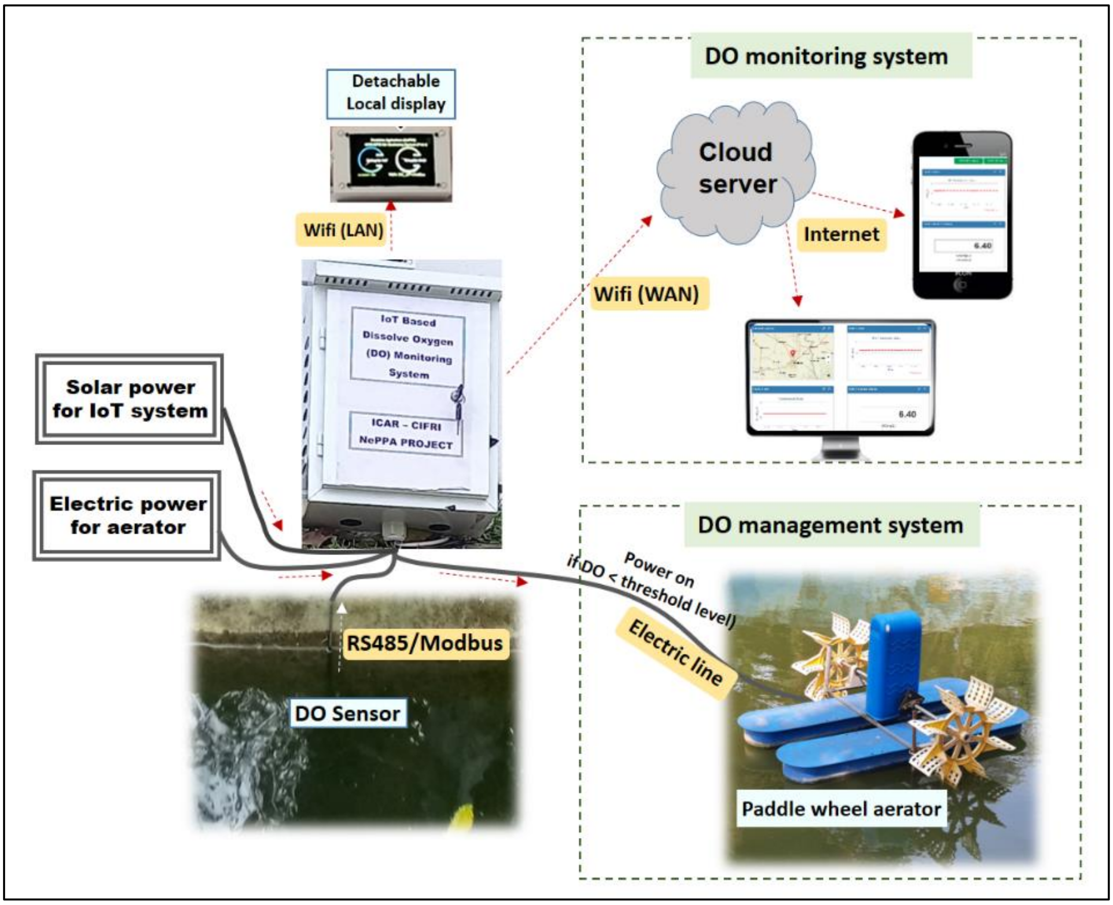

Figure 3: System workflow of DO monitoring system

- Dissolve Oxygen sensor is an optical dissolve sensor which detects dissolve oxygen optically.
- Controller box is the brain of the system. It acquires the signal from the sensor, processes it and then feeds it to the microcontroller where the signal is converted into DO data. After the conversion it is used to control the aerator by comparing it with the set-point set during the programming. On the same time the microcontroller uploads the DO value to the cloud server.
- Aerator supplies air bubbles to increase DO value in water, by receiving the signal from the microcontroller via the relay.
- Local display screen is used to display the DO and temperature data for real-time monitoring.
- Mobile phone or any PC is used to view the DO value live or previous stored data connected via internet.
- Cloud server stores the long-term data and displays real-time DO and temperature status of the waterbody through web-interface.

c. Communication Infrastructure

The controller is connected to the internet via Wi-Fi network. The data are transferred to the cloud via internet. Wi-Fi connection with 3G/4G/5G is used for connecting the gateway to the cloud server platform. The connection network is highlighted in the Fig 4.

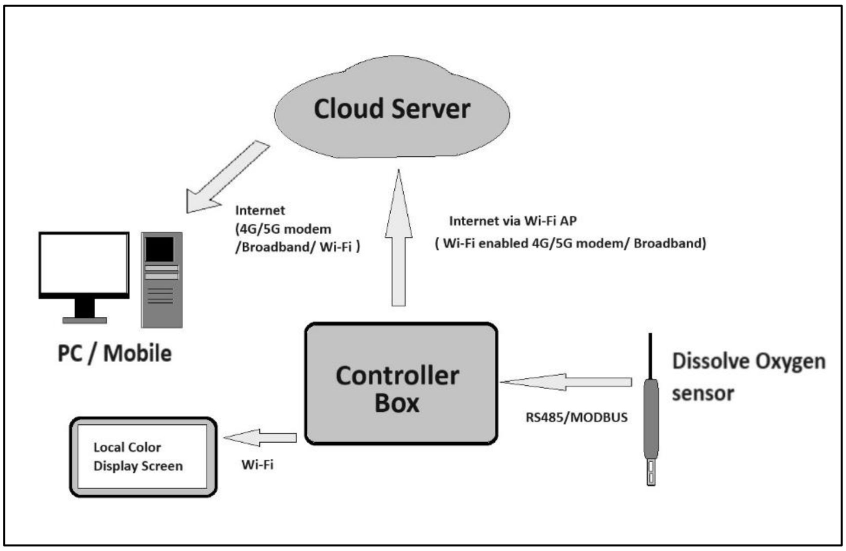

Figure 4: Connection network used in the DO monitoring system

- *Interfaces, protocols for communications*

  (a) LTE/5G connectivity (modem) (b) Wi-Fi (LAN) for local display and Wi-Fi (WAN) for transferring data to the cloud server.

d. Deployment consideration

The IoT system is able to operate with electric power or solar power. The system is suitable for commercial fish farming system where cultured fish sps are sensitive to the DO level of the water, where stocking level is high. The system is deployed at aquarium and pond system (Fig. 5).

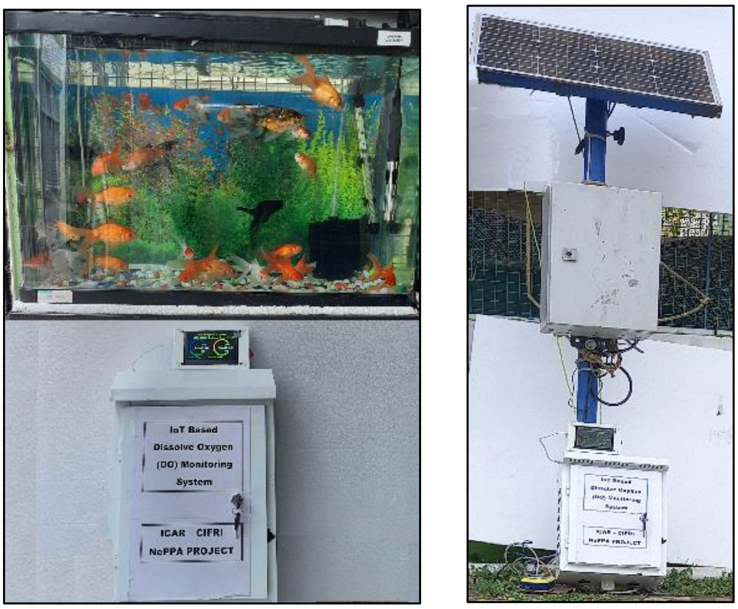

Fig 5 IoT system deployed in the aquarium and pond system

4. Results of the use case (outcomes)

- Performance and evaluation criteria

Maintaining optimal levels of dissolved oxygen in fisheries and ponds is crucial for favorable fish production. The system is able to manage the DO level in real time which not only promote the fish health but also reduce the mortality due to DO deficiency. High stocking density in proportion to the volume of water results in the shortage of DO for the biomass in a pond. In this scenario, the developed system can maintain the DO level with its smart embedded technology without human intervention. Besides that, it can reduce the cost of energy consumptions of continuous aerator operation or required manpower to operate the aerator.

The developed system is deployed in different water areas like aquarium, ponds, fish tank etc. to test the working process of the system as well as the DO readings from the sensor. The system generated DO readings were validated with lab tested results. The system was also tested for the aerator functioning when DO level goes below the threshold level. All the results were satisfactory (Table 1).

In this first attempt, the system is developed for real-time DO monitoring and management of the waterbody. With this process, the continuous DO and temperature with 10 minutes' interval data are recorded and stored in the cloud server.

DO concentration in water is a critical water quality parameter because of its direct effect on the feed consumption and metabolism of aquatic animals as well as indirect influence on the water quality. Therefore, long-term DO and temperature data will be used for simulating the spatio-temporal change scenario of waterbody health status for aquatic animals. Furthermore, machine learning (ML) techniques will be applied on long-term DO and temperature data for simulating the interactions of DO and other associated parameters with stocking density, fish biomass, thereby planning the fish stocking density based on the waterbody carrying capacity.

Table 1: Comparison of DO reading of different system

SL	Location	**Average DO reading**	
		IoT based DO system	LAB Test (chemical method)
1.	Bucket Water	6.86	7.00
2.	Pond	7.26	7.20
3.	Hatchery	3.30	3.60
4.	Pond1	3.90	3.50
5.	Pond2	7.23	7.31

-Qualitative and quantitative comparison of before and after implementation of the use case

The comparison can be illustrated by graphs, tables, figures, etc.,

The product is tested in different scenarios for validating its functioning. The real time before and after implementation comparison can be done after implementing in the commercial fish farm.

5. Lessons learned

- The initial cost for DO sensor is high.
- Continuous internet is required to upload the data in the cloud system, otherwise remote monitoring may be hampered.
- Continuous power is required for functioning of the system.

6. Links for supporting material (website, articles, etc.)

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7. Appendix

Appendix 1: Actor / Business role

S No	Actor	Business role
1	Fish farm	Farm where fishes are grown. The developed DO system is deployed.
2	IoT based DO monitoring system	It reads the DO data from the sensor, transferred the data to the cloud, signals the aerator for start functioning when needed. The system can monitor and control the DO level in real-time with acceptable range. This helps to maintain the good water quality and promote fish growth.

Appendix 2: Actor role

Actor name	Actor type	Role description
DO sensor	Device	It senses the DO and temperature of the water area
IoT system (Micro-controller)	Device	It is the main processor system, reads the DO data from the sensor, transferred the data to the cloud, signals the aerator for start functioning when needed.
Aerator	Device	Its task is to oxygenate the water column, or portions of the water column, thereby preventing the occurrence of low-DO conditions.
Internet connection	Device	The IoT system is connected via Wi-Fi for uploading data in the cloud system
Cloud system	Device	All the water quality data are stored in the cloud system for monitoring and other research purpose.
Web-Interface	Device	A web-interface was developed to display the real-time water quality data and provide access to download the data in excel format.
Power supply system	Device	The power supply system can be electric or solar powered for operating the aerator as well as the IoT system.

Appendix 3: Communications technologies

Scenario	Communication network	Technologies
Connection scenario (sender to receiver)	Network type (WAN, MAN , LAN, PAN)	-Mobile Technology (GSM, 2G, 3G, LTE, WiFi, (CDMA), -Fixed line broadband. Networks should have Ipv6 or dual stack (IPv4 and IPv6) capability.
DO Monitoring System to Cloud Platform (Thingspeak) (Internet access)	Wi-Fi Client mode (DO system) to any Wi-Fi enable Access point (AP) with internet. **wireless local-area network (WLAN)**	Currently use Fixed line broadband with Wi-Fi Enable access point (AP). Possible any Wi-Fi Enabled 2G, 3G,4G,5G Dongle/Router

		(dual stack (IPv4 and IPv6) capability)
DO Monitoring System to Local Display (without internet data view)	Wireless local area network (WLAN)	2.4GHz Wi-Fi AP mode in DO System
Cloud platform to Mobile or Computer system	WAN	4G/5G modem/ Broadband/ WiFi

9.6. Use case: Development of AI/IoT Based Intelligent Irrigation System for Field Crops

Source: Dr. C D Singh, Dr. Mukesh Kumar, Dr. Yogesh Rajwade, ICAR-Central Institute of Agricultural Engineering, Bhopal, India

Part A

1. Introduction

Most of the irrigation control systems used today are imported from abroad. These systems have relatively perfect functions but are too expensive. So their applications are only confined within some agricultural demonstrative fields and difficult to be widely popularized. Therefore, to develop an intelligent agricultural irrigation remote control system suitable for the Indian agricultural irrigation with convenience and low cost has become the focus of attention. To supply right quantity of water at the right time of day by automating farm irrigation.

Final goal of the project is to develop an intelligent micro irrigation system which has capabilities to monitor soil moisture and send signal when they need water (soil moisture content is less than defined threshold value) and check the Weather Prediction, and if the forecast is for fair weather, turn on the irrigation system and if the forecast is for rain, do nothing as per moisture condition in the field. Avoiding irrigation at the inexact time of day, reduce runoff from overwatering saturated soils. Save labor, time and precise application of irrigation water to the field. Human error elimination in adjusting available soil moisture levels.

The objective of the use case is to develop and evaluate AI/IoT based intelligent irrigation system for field crops.

2. Description (Background)

The system's central hypothesis is to apply the right amount of water at the right time to fulfill the water requirement of the crop. For achieving this condition, the intelligent irrigation system consist of a soil moisture sensors and temperature sensor installed at the effective root zone of a specific crop in undisturbed soil. It also consists a micro irrigation system, irrigation pump and electric solenoid valve in farmland fields using WSN, supported by communication technologies such as ZigBee/LoRa.

AI/IoT-based intelligent irrigation system – automate the collection of environmental, soil, and irrigation data; automatically correlate such data and filter-out invalid data from the perspective of assessing crop performance; and compute crop forecasts and personalized crop/irrigation recommendations for any particular field. After installing the sensors, set a lower set point (LSP) and a higher set point (HSP). When the available soil moisture content is below the LSP, the sensor sends signals to the controller to start the irrigation system to deliver water up to the field capacity (HSP). At the same time, it sends the text message to the user's mobile about the ON and OFF of the pump.

Once the soil has reached HSP, the sensors send a signal to the microcontroller. The microcontroller stops the pump, and at the same time, text messages sent to the user. The detail of the solenoid valve and pump operation is sent to the user's mobile in text SMS. The controller hourly saves the soil moisture content in the memory card over the entire crop period, so one can quickly get information about the entire crop period's field condition. The controller has the capacity and facility to store the data of soil moisture content in the field for two years, and it can be increased.

-Materials and methods

An AI-based irrigation system with sensors placed throughout crop field utilizes IoT protocol (MQTT) to collect real-time data on soil moisture levels, weather prediction from weather website. By integrating AI algorithms with IoT devices, users can optimize water usage to increase crop water productivity and reduce costs. These sensors continuously transmit data to the cloud server, the information are analyzed that help us make informed decisions about when and how much water should be applied to crops. Specifically, written algorithm can process data on weather forecasts on rain, and sensor readings to generate precise irrigation schedules suitable to the specific needs of crop and field. This optimization helps prevent overwatering or underwatering, leading to improved water efficiency and reduced water wastages.

To make decision making more robust the local weather information supported by AI/ML models would be incorporated in addition to weather prediction done from weather website. A deep learning model will be used that can learn from historical data and real-time local weather data to accurately predict real-time ET0/soil moisture for a specific geographical area for real-time irrigation.

Overall, the combination of AI and IoT technologies in irrigation systems may offer farmers greater control, efficiency, and sustainability in managing water resources while maximizing agricultural productivity.

This process flow diagram outlines the basic steps involved in implementing an AI and IoT-enabled irrigation system, from data collection and analysis to decision-making, control, monitoring, and optimization. It highlights the integration of technology and data-driven insights to enhance water management practices and agricultural productivity.

The economy of India is heavily dependent on agriculture, which also feeds a sizable population. To ensure that inputs are applied precisely, emerging technologies like artificial intelligence (AI) and the Internet of Things (IoT) are being used. Because of the country's diverse topography, which ranges from dry to fertile plains, effective water management is crucial to boosting agricultural output and guaranteeing food security. Water shortage and resource misuse are major issues in northern regions like Punjab and Haryana, where intensive farming techniques are prevalent. These issues can be resolved with AI-based irrigation systems that make use of IoT technologies. Farmers may obtain real-time field information by implementing sensor-based and Internet of Things technologies in the field to monitor soil moisture levels, weather patterns, and other factors. These are particularly useful in areas where the distribution of rainfall is affected by irregular monsoon patterns.

With the use of data analysis, artificial intelligence algorithms can create irrigation plans that are optimally tailored to the soil's characteristics and other variables. Farmers who live in areas with limited water supplies can increase crop yields while conserving water by using this precision irrigation technique. Furthermore, AI-enabled skills could aid in recognising and resolving a number of problems. This is especially helpful in the northern states, where smallholder farmers may not have access to new technologies yet largely depend on agriculture for their livelihoods.

In general, Indian farmers in a variety of geographical settings are empowered by the integration of AI and IoT in irrigation systems to make well-informed decisions, maximise water use, and sustainably enhance agricultural results, all of which support the nation's food security and economic growth.

In India, the use of AI and IoT-enabled irrigation systems can vary from small-scale installations on a single farm to extensive rollouts across whole agricultural districts. Using a local network or cloud-based platform, individual farmers, especially in southern India, may implement AI and IoT technologies on a small scale to optimise water usage and increase agricultural yields on their fields. In western states, agricultural groups or cooperatives may put in place medium-sized irrigation systems with AI and IoT capabilities that service several farms or areas of land. In order to gather data on crops, weather, and soil moisture, these implementations entail extending a network of Internet of Things (IoT) sensors over a wider region. Data is then analysed using AI algorithms to forecast and optimise resource management and irrigation scheduling. Large-scale installations of AI- and IoT-enabled irrigation systems across vast agricultural regions may be the result of government-led projects or collaborations with the private sector in states in central and northern India. These programmes seek to significantly increase agricultural output, modernise irrigation infrastructure, and improve water efficiency.

In general, many criteria including the scale of the agricultural operation, the degree of technology adoption, and the accessibility of resources and infrastructure influence how AI and IoT-enabled irrigation systems are used in India. These technologies have the power to completely change the way water resources are handled, resulting in more resilient and sustainable farming methods, whether applied to individual farms or to large agricultural landscapes.

- *Process flow diagram*

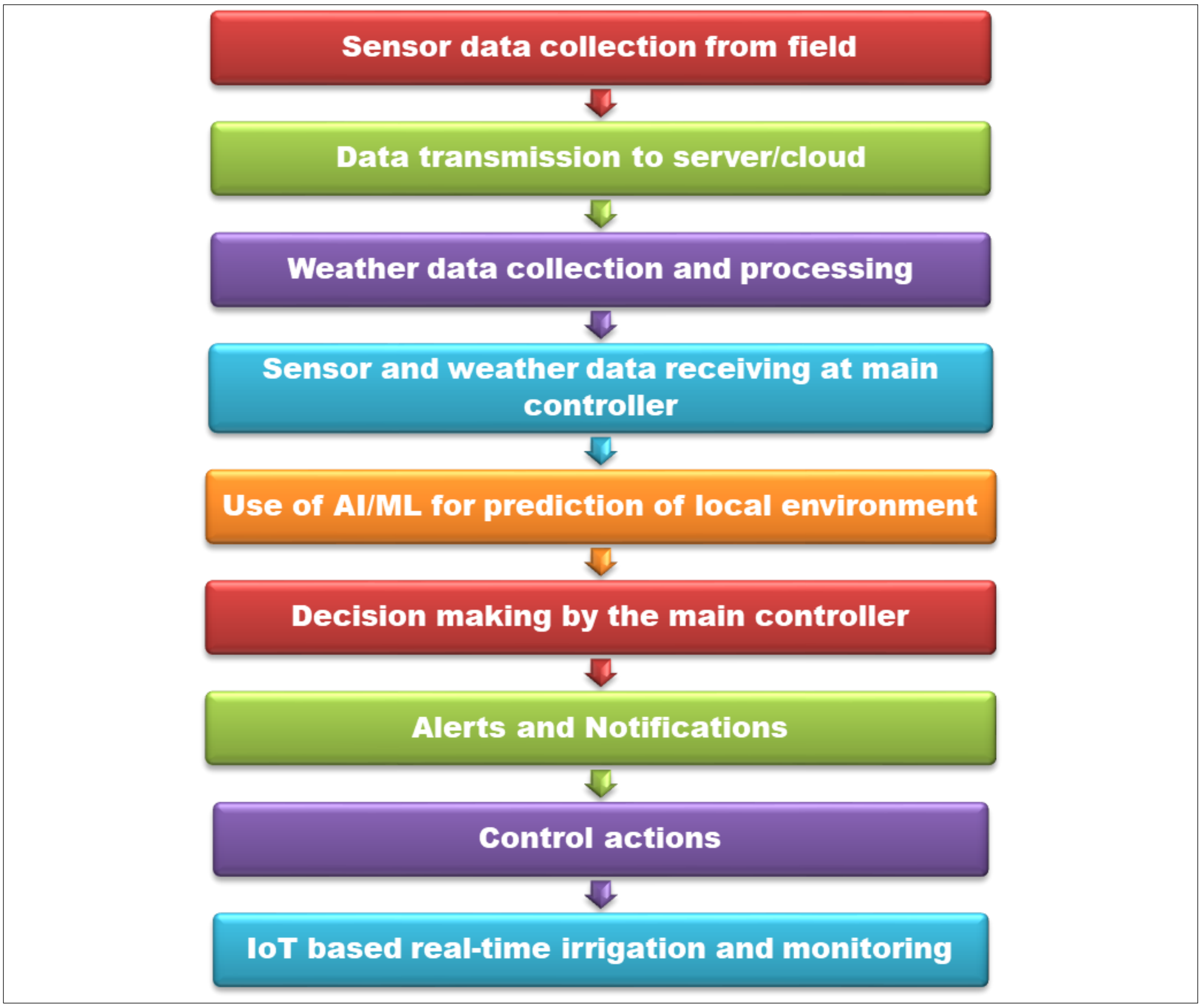

Fig. 1: Flow diagram for the proposed framework

- *Outcomes/ results of use case*

The outcome of the use case indicates the optimized irrigation scheduling based on soil moisture deficit as well as weather prediction to minimize water input and energy savings. Implementing AI and IoT-enabled irrigation systems in India comes with several lessons and challenges:

- One of the primary challenges is ensuring widespread adoption of AI and IoT technologies among farmers, especially in rural areas. Limited awareness, access to technology, and technical expertise may hinder adoption rates. Providing training and support to farmers is essential to overcome this barrier.
- In rural areas, inadequate infrastructure, including electricity and internet connectivity, can pose significant challenges for deploying IoT devices and accessing cloud-based AI services.

- The cost of implementing AI and IoT systems can be prohibitive for smallholder farmers with limited financial resources. Finding cost-effective solutions and exploring financing options, such as subsidies or grants, can help make these technologies more accessible.
- Ensuring the proper functioning of IoT sensors and AI systems requires regular maintenance and technical support. Building local capacity for troubleshooting and repairs, as well as establishing service agreements with suppliers can help minimize downtime and maximize system reliability.

Part B

3. Architectural considerations

a. Data management

NOTE - Topics that could be addressed here include data acquisition, transmission, processing, output, and governance (including ownership, security, privacy, etc.). - To be refined (inspiration can also be taken from the relevant details of the ITU-T FG-DPM template presented).

b. System architecture

The system's central hypothesis is to apply the right amount of water at the right time to fulfill the water requirement of the crop. For achieving this condition, the intelligent irrigation system consist of a soil moisture sensors and temperature sensor installed at the effective root zone of a specific crop in undisturbed soil. It also consists a micro irrigation system, irrigation pump and electric solenoid valve in farmland fields using WSN, supported by communication technologies such as ZigBee, GPRS and Internet. System architecture diagram is given in Fig.1

Definition and description of sub systems (Including AI and IOT subsystems) given in Fig. 2

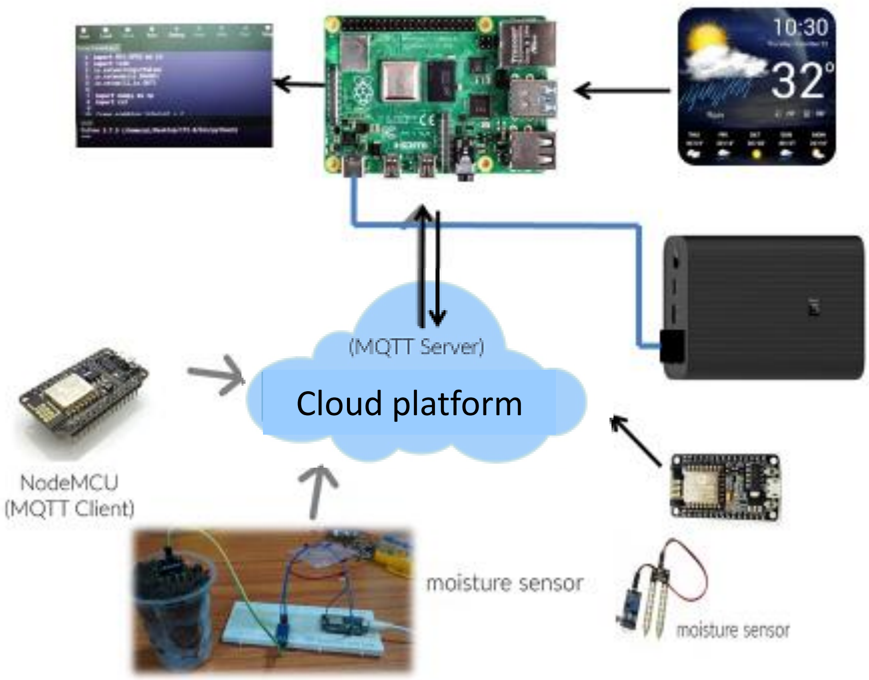

Figure 1: System Architecture

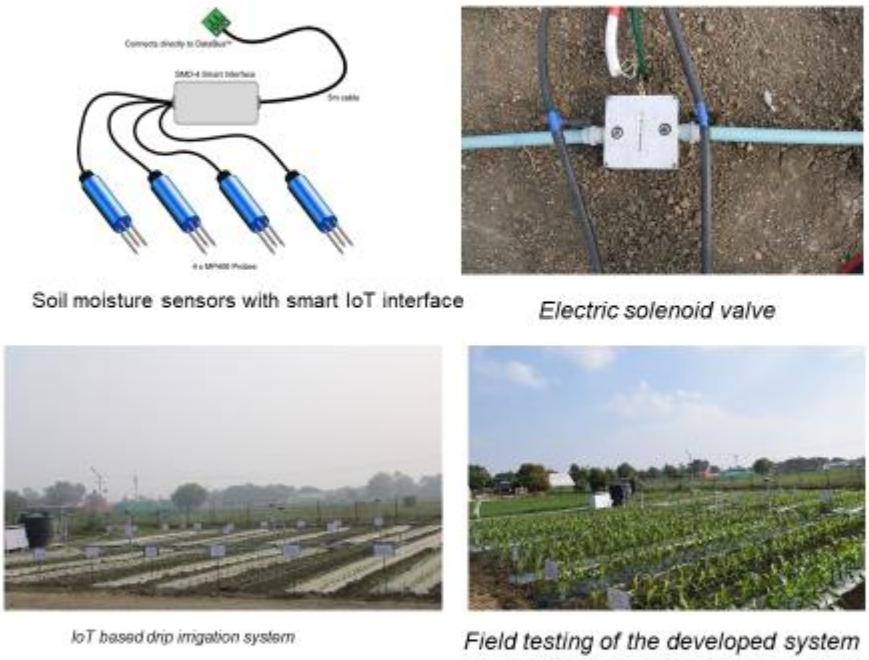

Fig. 2: Field layout and components of IoT based drip irrigation system

The IoT devices were tested to determine whether it could use sensors to collect environmental data and transfer them to an IoT platform. A local Wi-Fi network was connected to the data-gathering device for testing purposes. The ThingSpeak IoT platform was used to view the field data collected by the sensors. For numerous data entries, the system was operated for several hours. The environmental parameter data obtained by the sensors were effectively communicated to the web application, according to the observations. Things peak's visual depiction of data provides an enriched interpretation of the relationship between environmental surroundings and time, as illustrated in. While the temperature falls with time, the humidity rises. By assessing these trends over time, agricultural operators may make better judgements about their crops based on the surrounding conditions, resulting in improved precision irrigation techniques. As a result, the ThingSpeak platform was tested to evaluate whether it could capture and show in an accessible way the environmental parameter data stored on the cloud platform. The application successfully revealed the precise information of the document. The data acquisition module was then put to the test for waterproofing. This was done to ensure that the equipment could be used in open-field or outdoor situations. There were no leakages when the device was initially run beneath the water from the tap. Two areas were extensively evaluated and validated, namely monitoring system tests and control system tests. The environmental variables acquired by the data acquisition device, including soil moisture, soil temperature, relative humidity and temperature measurements, were associated with analyses from stand-alone, off-the-shelf sensors for the monitoring system test.

c. Communication infrastructure

An algorithm has been developed to predict soil moisture based on data from field sensors. According to the sensor readings, soil moisture levels changed in the test field over time. Sensor readings increased when irrigation or relevant rainfall events occurred, indicating increased soil moisture levels. Soil moisture remained within allowable limits in IoT-based drip irrigation treatment 100% FC, with an average of 38%. It took an average of 2 days for the next irrigation event to occur in this treatment. Irrigation at 100% FC represented 50% MAD before the next scheduled irrigation event. The IoT devices were directly connected to the IoT analytics platform (ThingSpeak) web service to access and analyze live cloud data like soil moisture values, soil temperature, relative humidity, and temperature at various times. Sensors were placed 15 cm below the soil surface and maintained at a constant depth throughout the growing season. At a depth of 15 cm, soil moisture sensors were used to determine how much irrigation should be applied. As soon as the soil moisture content reached ≤ 33.1%, a notification was sent, and the solenoid valves were opened remotely, triggering the irrigation pump automatically. When ≥ 43.5% soil moisture was measured in the sensors, a notification was sent, and the irrigating pump and solenoid valve was turned off.

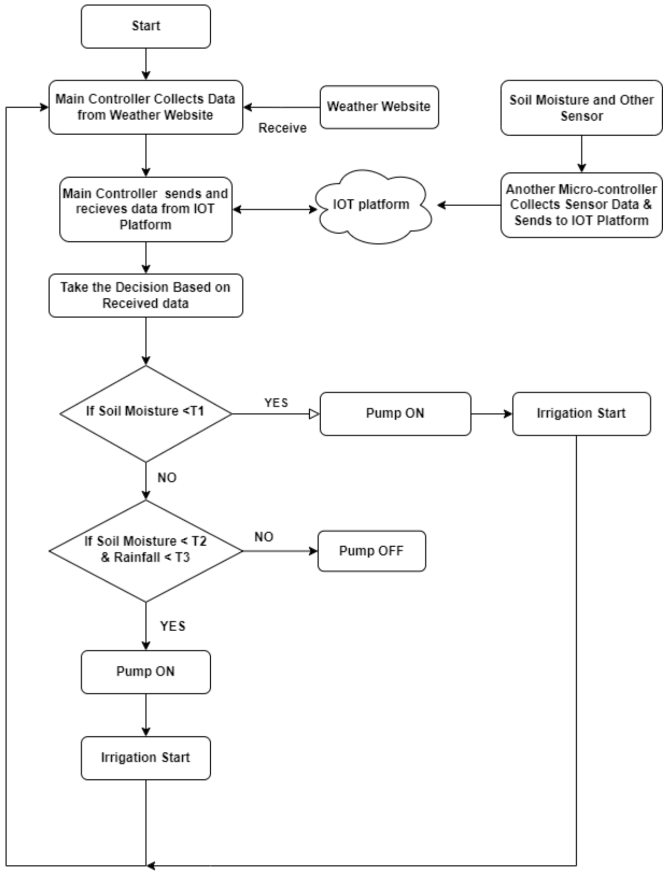

Fig. 3 Decision flow chart for AI/IoT based irrigation system

(a) Smart Phone with cellular connectivity such as LTE/ 5G for capturing the soil moisture data and transmitting them to cloud/ server.
(b) Wi-Fi communication (2.4 GHz/ 5GHz band) may also be used for transmitting the data from the smart phone to local hub/ IoT Gateway, which will further transmit the data over cellular/ wireline network to the cloud/ server.

-Interfaces, protocols for communications

(a) LTE/5G connectivity (modem) (b) Wi-Fi NIC

4. Results of the use case (outcomes)

The present IoT-based irrigation system comprises soil moisture sensors that can acquire field data in real-time and act according to that. The AI/IoT based precision irrigation system can give an optimal solution for autonomous agricultural operations for precision, economics, reduced human struggle, and environment protection. The moisture sensor sends the signal to the ESP 32's configured Wi-Fi module, which triggers the water pump and irrigates the field using the smartphone or computer application if the moisture level falls below the pre-defined value and prediction of occurrence of rainfall is low. The measured variables were continuously recorded automatically and sent to the ThinkSpeak cloud based server. The developed data acquisition unit was switched ON and staked in the agriculture field

During the growing season of the sweet corn crops the water depths applied (mm) in IoT-based and ETc-based drip irrigation was compared at 10-day intervals. The first row of Table 1 shows 20 mm of irrigation applied immediately after planting to bring the soil to its capacity. Drip irrigation with 100% ETC had the highest amount of water applied, followed by drip irrigation with 100% FC and 80% FC with IoT. In total, 443.7 mm, 393.6 mm, and 356.2 mm of irrigation were applied by groundwater (as blue water) under 100 % ETc-based drip irrigation, 100% FC IoT-based drip irrigation, and 80% FC IoT-based drip irrigation, respectively. During the growing season, irrigation water applied to the ETc-based treatments increased exponentially with ET_O. Compared to ETC 100% drip irrigation, IoT-based drip irrigation 100% FC and 80% FC used 12.7% and 24.5% less irrigation water, respectively.

Days after planting	**ET_C-based drip irrigation**	**IoT-based drip irrigation**	
	100% ET_C	**100% FC**	**80% FC**
0	20	20	20
10	17.2	13.7	12.33
20	26.4	22.2	19.98
30	37.7	32.5	29.25
40	43.9	39.9	35.91
50	51.8	44.7	40.23
60	53.1	47.3	42.57
70	57.7	56.7	51.03
80	64.2	53.9	48.51
98	71.7	62.7	56.43
Total (mm)	**443.7**	**393.6**	**356.24**
Water saved (%)	**0**	**12.72**	**24.55**

Table 1: Amount of water applied (mm) under different irrigation treatments.

5. Lessons learned

Customizing irrigation systems to the specific requirements of different crops, soil types, and microclimates within a region maximizes the system's effectiveness and acceptance among farmers. Providing training and technical support to farmers and system operators enhances their understanding of the technology and empowers them to utilize it effectively, ensuring long-term sustainability. Emphasizing the importance of accurate and reliable data collection, including sensor calibration and maintenance, mitigates errors and enhances the system's performance app which can be used by any user.

6. Appendix

Appendix 1: Actor / Business Role

S No	Actor	Business role
1.	Acquisition of soil moisture content and weather data	We collected soil moisture data from soil moisture sensor and connected to IoT cloud platform for storage. The weather data was retrieved weather website by web scrapping.
2.	Pre-processing	The soil moisture characteristic curve was prepared threshold values were designed based on lower set point (LSP) and higher set point (HSP)
3.	Actuation of the system	Based on soil moisture threshold and prediction of rainfall, the system shall actuate pump for irrigation.

Appendix 2: Actor role

Actor name	Actor type	Role description
Soil moisture sensor	Device	Measure soil moisture (v/v)
AI-based decision algorithm	System	Using real time values of soil moisture and weather (rainfall) prediction, the
Smart display	Device	Shows realtime

Appendix 3: Communications technologies

Scenario	Communication network	Technologies
Connection scenario (sender to receiver) Wireless, ZigBee and Internet	Network type (WAN, MAN, LAN, PAN) ZigBee, GPRS and Internet	-Mobile Technology (GSM, 2G, 3G, LTE, WiFi, -Fixed line broadband. Networks should have Ipv6 or dual stack (IPv4 and IPv6) capability.

9.7. Use case: SmartKheti

Source: Neeraj Dhawan (Managing Director) INVAS Technologies, Gurugram, Haryana, India

Introduction : The agricultural sector plays a pivotal role in India's economy, making it imperative to extend the advantages of technological advancements to the farming community. Leveraging cutting-edge IoT and AI technology, the aim is to provide farmers with the essential infrastructure and tools necessary for optimizing resource utilization, employing data analytics, and accessing value-added services to enhance their agricultural practices.

To achieve this, the implementation of 'oneM2M,' the Indian National Standard for IoT/ M2M, alongside other communication technologies, has been considered to offer cost-effective connectivity and services to farmers. The approach entails establishing a oneM2M-based platform, using LoRa technology for collecting and transmitting data from sensors to the field node (gateway) and Cellular/ internet connectivity, for transmitting data from field node to oneM2M compliant C-DOT's CCSP (C-DOT Common Service Platform) server. The data collected by the servers through the gateways is analysed using AI/ ML algorithms are used to get actionable inputs for the farmers and Govt agencies.

The data is collected and processed for following purposes:

1. Real-time monitoring of critical parameters such as soil moisture, temperature, and soil nutrient levels.
2. Remote control of farming equipment through a mobile application.
3. Provision of expert guidance and valuable insights to enhance crop yield per hectare.
4. Dissemination of the latest technical information, weather updates, and education onmodern equipment like drones, along with online equipment rental services.
5. Access to online market information, high-quality seeds, pesticides, and fertilizers.
6. Facilitation of data sharing with relevant government authorities to monitor farming activities and make accurate yield predictions for holistic planning.

Keeping in view the affordability of farmers with low income, the intent was to design, develop and produce a low cost solution after studying the day to day requirements of the farmers and discussions with the farmers during various ‘Kisan Mela’. This solution will have a significant positive impact on the agriculture sector by enhancing productivity and sustainability of the farmers. Moreover, the deployment of oneM2M based solution aligns with the Government's overarching goal of creating a standardised and secured IoT/ M2M ecosystem.

Figure 1: Process flow diagram

The primary objective of the product is to prove a cost-effective IoT infrastructure/solution utilizing oneM2M compliant C-DOT's CCSP (C-DOT Common Service Platform) for offering services to farmers to provide them with real time monitoring of soil humidity and temperature to improve the health of crops and prevent the spread of various diseases such as viruses, plant fungus, and at the same time provide a high level monitoring of the farm yield to the government authorities to enable them plan better. This initiative aims to optimize resource allocation, thereby benefiting both farmers and the agriculture sector as a whole. According to estimates from the Indian Agricultural Research Institute (IARI), the implementation of this solution is expected to result in a 30% reduction in water wastage and a 50% decrease in the requirement for manual labour.

The benefits of technological advancements can be passed on to the weak section of society by using such simple low cost product. The life of farmers is very tough and as they can't take leave or work from home, this product enables them to automate the key activities of their day to day working. People living in the metro cities can buy on line what they need for daily consumption, the same facilities can be extended to villages and especially farmers.
The youth in the villages are moving to cities and there is a big shortage of man power in villages, this application will create job opportunities in the villages by creating jobs such as seeds, pesticides, fertilisers deliveries, drone operators farming equipment operators and other commercial activities in the villages.

1. IoT technology when used in farming sector will save on the resources and increase the farm yield.
2. Farmers will be well informed about their crops and prepare soil for the next crop.
3. Farmers will be more educated about the possible plant diseases to take preventive measures with the advice from experts based on the geographical location and farming conditions

4. Farmers will easily be able to buy/rent fertilisers, pesticides and other farming equipment's on line.
5. Technological advancements in latest type of sensors and ensuring system security.
6. AI enabled data analytics make it possible to analyse the large data gathered and take actionable insights and decide for better results.

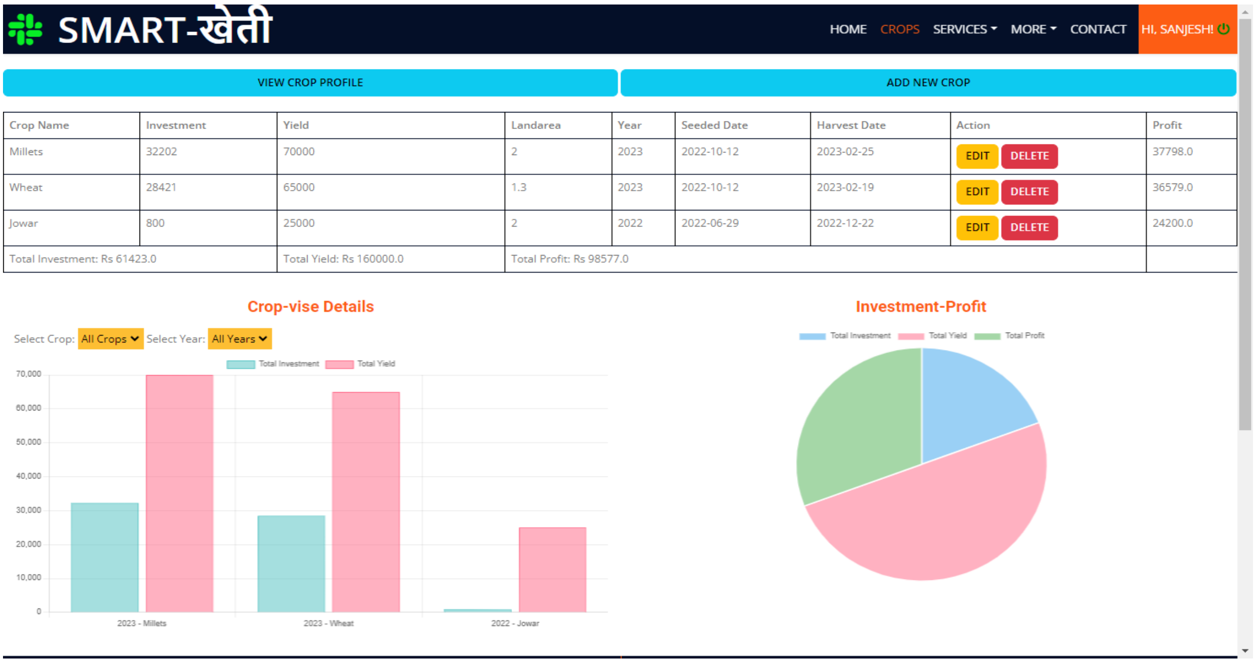

Figure 2 : Outcome

The solution comes with the advantages of using oneM2M standards such as interoperability and security etc. , . The solution can be expanded by adding more types of sensors and other devices compliant to oneM2M in future.

Value-added services : One of the important facilities in the solution is to provide farmers with various services through the mobile app or website. Some of the important services are mentioned below :-

Figure 3 : SmartKheti Services

Drone as a Service: By using this service a farmers can hire a drone as per their requirement. They can choose the application of drone (spraying of fertilizers of pesticides etc.) add the date and area of their field on which they want to use the drone facility. Available time slots for the said dates will be shown on screen. Farmer can choose their time slot and book the drone facility. Drone Operator along with drone can be availed to get the work done in a faster manner, less exposure to harmful fumes and improve productivity.

Machine as a Service: Farmers can also rent tractors, harvesters and other expensive farming machines for their farming activities

Fertilizers/ Pesticides/ Seeds : Farmers can be educated on the best fertilizer / Pesticides/ Seeds suitable for the soil profile of their farm, they can buy these items online. Any subsidies provided by the Govt, will be available for the online procurement and also the location of the nearest stores providing such items will also be available. Using this facility farmer can quickly purchase required fertilizers/pesticides/seeds at reasonable and subsidized price.

Market Places: The Application/Website also provides information on about various markets and e-NAM portal to the farmers. They can go through different options available to select the best possible rate they can get for their crops from the market and also find nearby mandis.

Crop – Insurance: This feature helps the farmers to take benefit of Govt sponsored crop insurance schemes. Farmers will get details on the crop insurance and also get connected with the insurance company. They have to give detail of the crop to the insurance company and avail the insurance benefit.

Your Products: Under this Tab, farmers can add the information on the produce available with them such as quality and quantity of the produce and availability date. This information will be displayed to nearby Anaj Mandi’s so that buyers can proactively contact the farmer for purchasing the produce.

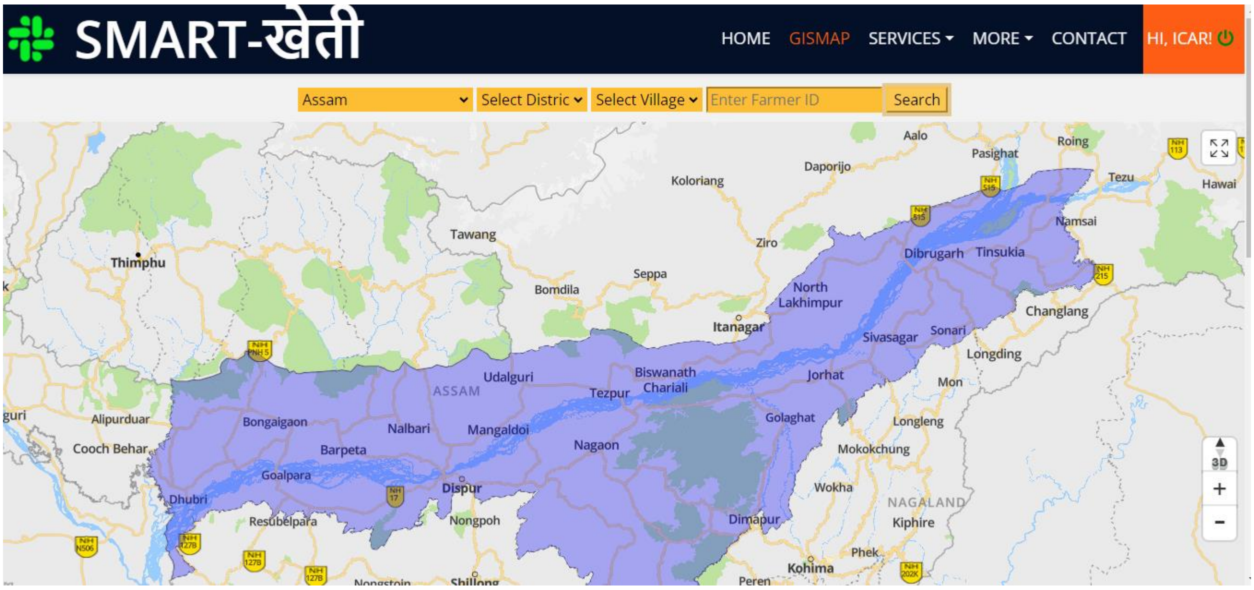

Figure 3 : SmartKheti App Display

Conclusion : This product will improve the quality of life of the farmers on the day to day bases, there will be improvement in the farm yield, save the water, make the crops safer against Viruses and other diseases, save the labour cost and keep the Government authorities fully informed about the expected farm produce on district level. Thus a big impact on the farming sector as a whole.

After attending a number of Kisan Mela’s, interactions with the farmers and discussions with State Government authorities like Karnataka, Kerala, Tamil Nādu, Jharkhand, Odisha etc., it was observed that a small farmer cannot afford an expensive tool so a low cost tool has been developed that is easy to operate. Smartkheti provides all these features.

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