

**ARCHITECTING AN IoT DRIVEN MODEL FOR
WEATHER AND SOIL CONDITIONS BASED
PRECISION IRRIGATION**

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in

Electronics and Communication Engineering

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**LOVELY PROFESSIONAL UNIVERSITY, PUNJAB
2023**

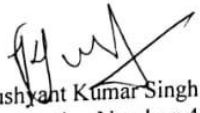
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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled "**Architecting an IoT based Model for Precision Irrigation based on weather and soil conditions**" submitted in fulfillment of the requirement for the reward of degree of Doctor of Philosophy (Ph.D.) in the Electronics and Communication Engineering, is a research work carried out by Dushyant Kumar Singh, 41800189, is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.


A handwritten signature in black ink, appearing to read 'Rajeev Sobti', is written above a horizontal line. A vertical line descends from the left end of this horizontal line, and a diagonal line extends from the intersection point towards the signature.

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ABSTRACT

Worldwide agriculture plays an important role in the sustainability of life. Agriculture activities includes the cultivation of crops and livestock management. In simple words, agriculture is the science of cultivating the soil, growing crops, and medicinal plants, and raising animals to sustain and enhance life. India is known as an agricultural country with more than 50% of the population dependent on agriculture for their survival, directly or indirectly. The contribution of agriculture to India's Gross Value Added is more than 17% and is continuously increasing. Out of the total of India's geographical area, about 43% is utilized for agriculture. On the world scale, India stands second in the production of farm-based products and is the largest producer of fruits and vegetables. In the modern urbanization era, agriculture is not only limited to rural areas but has found its way to cities. City farming or urban farming is the livestock growth or cultivation of growth in urban areas or around the urban centers and is occupying an important position in the development of smart cities. Urban agriculture is important and needed, as by 2050 it is expected that the world's 50% population will be accommodated in cities.

Fertilization, application of pesticides, insecticides, and irrigation are a few of the agricultural practices for the improvement of crop growth. By the end of 2050, the city's population is estimated to increase by 50%. With the rise of urbanization, growing population, and climate change agriculture are under stress to provide food security to ever rising population. For providing food security under new paradigms, new and advanced methods of agriculture with improved production and efficient utilization of agricultural resources such as fertilizers, pesticides, and most importantly irrigation water are required. Inefficient utilization of agricultural resources results not only in food security threats but also leads to environmental pollution such as water, soil pollution, food pollution, and depletion of natural resources, like ground water, at a faster rate.

In agriculture, irrigation occupies an essential position as it affects crop development or overall crop yield. Worldwide about 75% to 85% of the fresh water is used for irrigation only. India shares 4% of the world's fresh water resources and out of which,

80% of the water is utilized for irrigation purpose. Inclination towards groundwater irrigation in India is supported and accelerated by a few of the government policies such as free electricity in Punjab, and subsidy on solar pumps in Gujrat and Maharashtra. Because of such activities, India's ground water is falling by 2-3 inches/year, and by 2050 India is expected to face a severe water shortage.

For the efficient utilization of agricultural resources, monitoring, control, and application of required resources as and when required i.e site specific application at the required amount is important. One of the strategy developed to improve agriculture productivity and utilize resources efficiently is Precision Agriculture. Precision Agriculture deployed technology for observing, measuring, and responding to agricultural parameters and crop needs. Precision Agriculture provides exactly to crop what and when needed. Similarly, Precision Irrigation is an unconventional form of irrigation with need and site-specific water application and is helping farmers to have better yield and profit. Rapid technological developments such as the IoT, Information and Communication Technology (ICT), Wireless Sensor Networks (WSN), Low Power Wireless Area Network (LPWAN), Big Data, Cloud services for IoT, Artificial Intelligence (AI), Machine Learning, Long Range Wide Area Networking (LoRaWAN) has succored the Precision Irrigation. Further availability of low-cost sensing devices has a positive impact on Precision Irrigation system development. Many precision irrigation systems have been developed in various research literatures/patent.

The automated Precision Irrigation systems so developed in various researches ignores dominant factor affecting the irrigation planning. In terms of data collection on farmland much of the developed systems only gave importance to soil moisture for determining the need of irrigation. There are few literature articles taking into account the weather conditions such as air temperature and relative humidity for irrigation but almost all research ignores importance of wind conditions and soil temperature in irrigation planning. From technical perspective of data collection majority of the systems developed for soil moisture monitoring implemented only one sensor node which is suitable only for plants in pot or small area of farmland. But for monitoring the large farmland a scalable network of soil monitoring nodes is required. Information

and Communication Technology (ICT) plays an important role in reporting of the measured parameters to the user.

From the front of ICT, the major aspects to be considered are distance range, power consumption and scalability. The present implementations in various literatures mainly focusses on Zigbee technology which is scalable, comes under short distance range technology, upto 10 mtrs and has low power consumption. But for the transmission of soil parameters to the user or control unit, apart from low power consumption and scalability, long range is also desired for monitoring of large farmland. Although the Zigbee falls under scalable and low power technology but because of short distance range upto 10 meters it is not suitable for large fields. LPWAN technologies such as NB-IoT, LoRa offers the power efficient solution for long range communication.

A system is truly intelligent when the system can make decision of its own apart from transmitting the measured information and reporting to the user. In this machine learning plays an important role letting the machine to learn and make decisions. Exploitation of machine learning in precision irrigation is not much visible in most of the literature and implementations. Few of the research papers do attempt to utilize machine learning in irrigation but they fail to compare and provide the suitable machine learning algorithms for irrigation systems. But while monitoring the large farmland with huge dataset of weather and soil conditions, machine learning is a smart choice to make decision precisely for irrigation requirement.

The previous systems developed for precision irrigation majorly faces the challenges— (1) that they focus only on soil moisture but soil temperature and weather conditions do have important role in irrigation planning, (2) majority of the solutions developed are with shortrange communication technology, which is not suitable for monitoring the larger fields, (3) the solution present fails to create any WSN network for monitoring the larger fields but are focused on only single node implementations, (4) available literature on deployment of machine learning for irrigation system is minimal that too without any comparative study of machine learning algorithms on the selected dataset.

Encountering the various challenges in the present system, the thesis is attempting to automate the irrigation in agriculture by developing an enhanced Precision Irrigation

Decision Support System (PI-DSS) based on the agronomy and agrometeorology of farmland using LPWAN technology for monitoring larger fields and IoT for remote monitoring.

The first objective of the thesis is to collect the dataset for the soil conditions and transmit the same over long range LPWAN technology. Uptake of nutrients and the proper growth of the crop is not only affected by the soil moisture but soil temperature also plays an important role. So, soil moisture and soil temperature are the important parameters required to be observed for efficient irrigation planning and proper crop growth. Sensors used for soil moisture is VH400 which capacitive sensor and capable to measure the Volumetric Moisture Content (VMC) of soil. For soil temperature DS18B20 encapsulated in rust proof case is used. Both the sensors can be buried into the soil without any damage to them for longer period. The soil VMC sensor is an analog sensor while soil temperature is digital sensor communicating the temperature using 1 – wire serial protocol. The 8 -bit AVR microcontroller based open-source development board Arduino gets connected with the sensors. The Arduino gets connected with soil sensor through 10-bit inbuilt Analog to Digital Converter and soil temperature sensor is connected to digital pin of Arduino. The Arduino gets the digital temperature value and applies the calibration equation to the analog signal converted to digital value of moisture sensor. Being open source, Arduino allows the system development without any design cost (involve only hardware cost) and its hardware design can be modified as per requirement. Multiple such soil nodes with sensors and Arduino are required to monitor the farmland with a long-range communication technology to communicate the observed parameters.

For monitoring the soil condition efficiently, a WSN using LPWAN - LoRaWAN technology is required to be established. The developed system uses UART SX1278 433MHz LoRa module with a theoretical, as per data sheet, communication range of up to 8000 meters or 8 Kms. For the thesis work two such soil sensor nodes equipped are developed and deployed in farmland in Phagwara, Punjab for data collection. The criteria for selecting the LoRaWAN is its low power consumption, scalability and long range, practical tested for 1.00 – 1.50 Kms. The collected soil conditions from the both nodes are communicated to the weather station.

The second objective of the thesis is to develop a weather station whose role is in 4 ways – (1) to observe the weather conditions namely air temperature, relative humidity, wind speed and wind direction, (2) to collect the soil condition namely soil moisture level and soil temperature from soil sensor nodes, (3) to upload the observed soil and weather conditions to Thingspeak IoT cloud for remote monitoring and (4) to apply the machine learning model developed to the measured soil and weather conditions for making decision regarding irrigation. The weather station monitors the air temperature and humidity using digital sensor DHT22. It is the advance version of DH11 sensor with better accuracy for temperature and humidity measurement but sampling rate just half of that of DHT11, but that is sufficient as in agriculture sampling rate of 0.5Hz as supported by DHT22 is still very frequent. For wind conditions analog three cup type wind speed sensor voltage type (0-5V) and vane type wind direction sensor are used. The processing board selected for weather station is quad-core 64-bit Broadcom BCM2837 ARM Cortex-A53 SoC processor Cortex based Raspberry Pi board. The Raspberry Pi is the suitable choice in terms of its processing capability and board size as per the requirement. The other criteria for selection of Raspberry pi are that the weather station require to measure the weather condition and collect soil condition parameters from soil sensor nodes. It also applies the machine learning algorithm and develops Machine Learning model using observed agricultural parameters for irrigation decision making.

The weather station collects soil parameters via LPWAN – LoRaWAN communication technology and along with weather data uploads the information to Thingspeak IoT cloud. LPWAN along with IoT provides the capability to monitor the larger farmland from remote. Thingspeak cloud is freeware IoT cloud service upto 8 channels and provides the good graphical visualization of data. The cloud stores the data in .csv format, which can be downloaded for the analysis. The soil sensor nodes are programmed with Embedded C, which is customized version of system C programming. As the development board for weather station is Raspberry Pi, it is programmed using Python. The weather station and soil sensor nodes are deployed on farmland near the house at Phagwara with geographical locations as geographical coordinates latitude as 31.199325275018488 and longitude as 75.7736178548299 for

about 3 days in the month of December 2018. The system successfully monitors the soil and weather parameters and uploads them on IoT cloud. The dataset so obtained through the soil and weather monitoring is utilized for the leaning of the machine using machine learning techniques.

The third objective of the thesis is to apply the machine learning algorithms to the observed dataset uploaded on IoT Thingspeak cloud for soil and weather conditions and create a machine learning model for the developed system. The machine learning algorithms are applied to the obtained dataset using Python programming with scikit-learn Python package for machine learning. Other packages required for the machine learning implementation are NumPy for mathematical operations and Matplotlib for information visualization in Python.

For the selection of the best machine learning model, the dataset is applied to six different machine learning algorithms considering both linear and nonlinear algorithms. The linear algorithms considered are Logistic Regression (LR), Linear Discriminant Analysis (LDA) and nonlinear algorithms applied are K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), Gaussian Naive Bayes (NB), Support Vector Machines (SVM). The dataset is divided into the training (80%) and validation data (20%). Once the machine learning algorithms are applied to the dataset, the accuracy of prediction is calculated using accuracy score which is obtained by dividing the number of correct predictions by the total prediction number. Bases on the accuracy score of the top three algorithms with efficiency of prediction are LDA (91.25%), CART (85.00%) and NB (85.00). SVM gave the least efficiency of 63.75%. Based on the accuracy score, the LDA machine learning algorithms provide the best prediction accuracy of 91.25% for the agricultural dataset. Once the system is learned, the random use cases are applied to the model to test the system. Three different use cases are applied to the system and the system took the right decision for the irrigation actuation.

The fourth and the last objective is to validate the development system by comparing it with the automated irrigation automation system designs already available. The system is compared with the designs published in literature, as patent and the developed weather station is also compared with the commercially available weather stations.

The developed system is able to address the main challenges in the previously developed system for automated irrigation being able to monitor the open-ended large farmland, able to create scalable WSN network of soil sensor nodes to monitor farmland precisely, using LoRaWAN technology for long-range reporting of soil parameters, deploying Machine Learning techniques for decision making and using IoT for data logging with remote monitoring. The soil sensor nodes are tested in urban area and able to communicate upto 1.5 Kms. The soil and weather data collected are applied to Machine Learning algorithms and was 91.25% efficient in irrigating planning. The developed weather station is compared for cost and features such as IoT implementation and use of Machine Learning with commercially available weather stations, the developed system is much cost efficient with ease of accessibility of information and Machine Learning.

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Chapter 1 INTRODUCTION

"Words can be like X-rays if you use them properly--they'll go through anything. You read and you're pierced"

Aldous Huxley, Brave New World

IoT has revolutionized the conventional communication system and has added new dimensions to communication which is Machine to Machine (M2M) communication and is achieved by adding intelligence to things and making them smart. IoT collaborating with Wireless Sensor Networks (WSN) technology offers a good solution for remote monitoring and control in various application areas such as water distribution systems, electric meter monitoring, health monitoring, and many more [1, 2, 3, 4, 5, 6, 7, 8, 9, 10].

Agriculture makes use of land for growing crops and breeding of animals in a artificially created ecosystem to provide food, medicinal herbs, and other products to support and enhance life. India is mainly an agricultural-based economy and as per the *Krishi Report 2017-2018 and Krishi Report 2021-2022* by Agriculture, Cooperation & Farmers Welfare, Ministry of Agriculture & Farmers Welfare (Government of India) departments, about 54.6% of the overall Indian population is involved in agriculture or allied activities and contribution of agriculture in India's Gross Value Added (GVA) was 17.4% of the country's total Gross Value Added (GVA) from all sectors in 2016-2017 (at current prices). The GVA contribution has increase from 17.4% to 18.8% as reported in *Krishi Report 2021-2022*. [11, 12].

The chapter is organised such that it defines firstly the Precision agriculture (PA), then it proposes a model for PA consisting of Agronomy, Agrometeorology and IoT, and then the chapter concentrates on Research Gap, Problem statement and Research objective. All the literature is presented keeping in mind the final research objective. Each section of the chapter is connected with the research objectives.

1.1 PRECISION AGRICULTURE

The International Society of Precision Agriculture has defined the Precision Agriculture as

“Precision agriculture is a management strategy that gathers, processes, and analyzes temporal, spatial, and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability, and sustainability of agricultural production.”

Precision Agriculture deploys technology for the spatial and temporal variability linked with various aspects of agricultural production. Precision agriculture aims to improve crop performance and reduce the effect on the environment [13]. Precision Agriculture exploits technologies such as sensors, information systems, and advanced machines to enhance agricultural production by considering the variabilities and uncertainties of the agriculture system. The main aspect of Precision Agriculture is to adopt the production inputs to a specific agriculture site or animal. This increases the efficient utilization of resources, and aids in improving food supply sustainability and quality of agricultural production [14].

IoT and Wireless Sensor Networks (WSN) are the major driving technologies in Precision Agriculture.

1. Precision Agriculture deploys determined sensors and software to make sure that the crop receives exactly what is needed to optimize both agriculture productivity and sustainability.
2. Precision Agriculture includes information collection about soil, crop, and weather from field sensors for a better understanding of farmland.
3. Precision Agriculture also utilizes images from satellites or other platforms for extracting important information about farmland that can help make future decisions.

IoT and WSN have the potential to modify agricultural practices from static and manual to dynamic and smart, leading to enhanced productivity with minimum human efforts [15].

1.2 AGRI – METERO – NOMY

In agriculture, soil management, water management, and weather monitoring are very important as it affects the overall yield, yield quality, irrigation water management, soil quality, etc. While using technology for irrigation, major challenges faced are scalability, power efficiency, and communication range. The proposed work is to develop a scalable, and long-range irrigation system based on wind speed and direction, humidity, air temperature, soil temperature, and soil moisture. *Agri – metero- nomy* is used to signify the role of agronomy and agrometeorology in precision irrigation. *Agri – metero- nomy* is the amalgamation of the two terms in agriculture namely *Agrometeorology* and *Agronomy*. *Agrometeorology* study and make use of weather information in enhancing the overall agricultural productivity whereas *Agronomy* deals with crop and soil study. Internet is taken from the well-known technological revolution i.e *Internet of Things*. The objective of introducing the *Internet of Agri – metero- nomy*, tri – section relationship of the Internet, Agrometeorology and Agronomy as shown in the Venn diagram in Figure 1.1, the field of study is to contribute towards the remote monitoring of weather and climatic conditions, soil conditions, monitoring of crops concerning weather and soil conditions and monitoring of live stocks for achieving the three primary objectives of Precision Agriculture (PA) namely profitability, sustainability and protection to the environment.

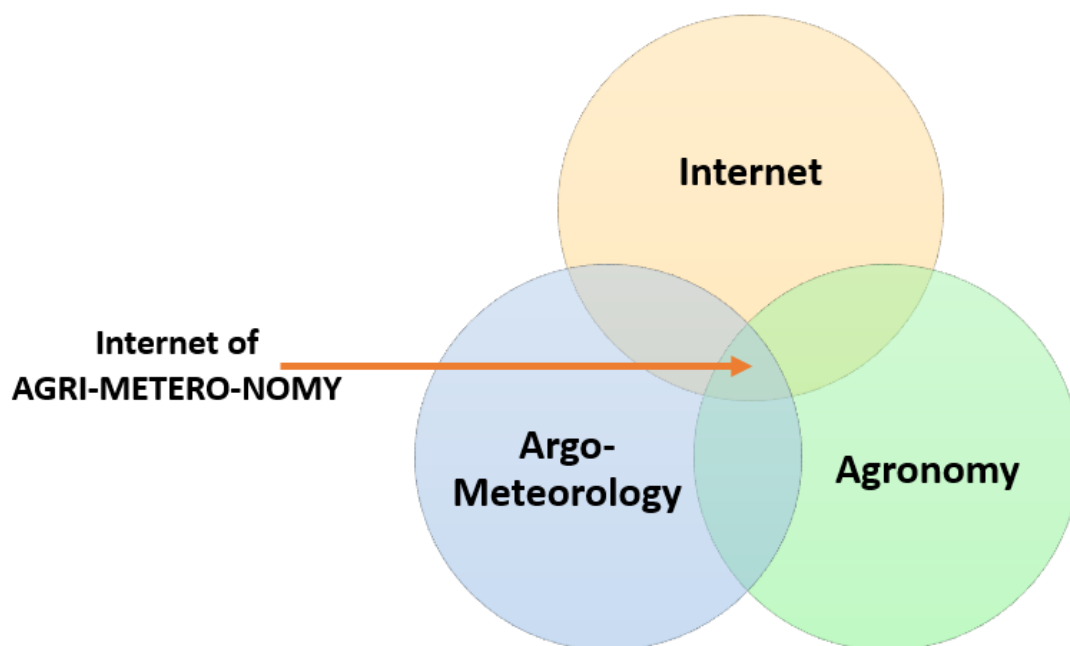


Figure 1.1 Internet of Argi-metero-nomy

1.3 BACKGROUND AND CURRENT STATUS

India is an agriculture-rich country with 56.4% as per *Krishi Report 2017-2018 and Krishi Report 2021-2022* of population surviving on Agriculture directly or indirectly. In 2016 – 2017 agriculture sector's contribution to the country's Gross Value Added (GVA) was 17.4% which rose to 18.8 in 2021-2022. Table 1.1 presents the stats of Gross Value Added (GVA) from 2013 – 2014 to 2021 - 2022. As per the statistics of the year 2015 – 2016, out of the total 328.7 million hectares of the geographical area of the country net sown is 140.1 million hectares (43% of the country's overall geographical area) and the gross cropped area is 198.4 million hectares. India shares 2nd position in the production of farming-based products and is the world's largest producer of fruits and vegetables, spices, milk, and certain crops like jute. India is also the second-largest producer of wheat and rice [11, 12, 16].

Table 1.1 Net Contribution of Agriculture and allied sector to Country's GVA [11, 12]

Items	Years					
	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	2021-222

Agriculture and Allied Sectors GVA (Rs. In Crore)	2518662	2829826	3016277	3394033	3616523	3945411
% to total GVA	18.0	18.3	17.6	18.4	20.2	18.8

Irrigation plays an important role in India's agricultural sector and 68.4 million hectares of agricultural land in India are dependent on irrigation. As per *Krishi Report 2021-2022*, the gross irrigated area over gross cropped area is about 52.03%. India shares about 17% of the total world population and only 4% of the world's freshwater resources, out of which 80% is used for agriculture. About 39 million hectares of land in India is irrigated by groundwater 22 million hectares by canals, and the rest still depends on the monsoon for irrigation. Nearby 40% of the global irrigation water requirement is fulfilled from groundwater and in India, around 39 million hectares of land is irrigated by groundwater which amounts to more than 50% of the total irrigated area because many of the states (Punjab) offer free electricity and subsidy (Gujrat and Maharashtra) on solar pumps for pumping groundwater. Some of the states having a high dependency on groundwater for irrigation are Punjab (79%), Uttar Pradesh (80%), and Uttarakhand (67%) [11, 12, 16].

In India, irrigation practices are not efficient and mainly the flood irrigating method is used due to which not only irrigating water is wasted but soil tends to become saline or soil nutrients are washed away with water. The survey done by the Tata Institute of Social Science shows that the groundwater table is falling at the rate of 2 – 3 meters per year, which is an alarming situation and need to be addressed immediately. As in India, 80% of the available freshwater is used for irrigation, using the precision irrigation technologies like a sprinkler system or drip irrigation method will help in proper irrigation water resource management. The government of India is also providing subsidies on such systems to improve water usage efficiency. The government of India and the Indian Council of Agricultural Research (ICAR) is continuously working on the initiative of doubling the farmer's income by 2020 and irrigation management can be one of the areas to be worked on [11, 12, 16, 17, 12].

Owing to the scarcity of water, fast rate of groundwater depletion and inefficient irrigation practices being followed in India, by 2050 India is going to face severe water constraints. In this regard, efficient monitoring and control of irrigation are required in which technological infringement is necessary, even though the same is supported by the government of India. Through the research, it has been proved that up to 90% of water savings can be achieved with proper irrigation monitoring and control [17, 16, 18, 19, 20, 21, 22, 23, 24, 25].

Precision agriculture is the use of technology to the agricultural sector with the aim of boosting agricultural product production by offering a better means of monitoring and managing agricultural activities. It includes monitoring of livestock, plants growth, soil conditions, and meteorological conditions. Irrigation water plays an important role in soil management, crop health, and crop yield, and also it is proper planning to improve irrigation efficiency is an important part of Precision Agriculture. Looking into the dependency of agriculture on irrigation in India and the depletion of water resources at a faster rate, proper irrigation planning in Precision Agriculture shares a very important position and is the need of today.

For proper irrigation planning in Precision Agriculture, Real-Time monitoring of soil, weather, and crop monitoring are required which needs relevant sensing and communication technology for sensing and reporting the soil, weather, and crop information. Table 1.2 gives the available sensors for soil monitoring, Table 1.3 gives the available sensors for plant monitoring and Table 1.4 gives the available sensors for weather monitoring systems [26].

Technology with the IoT has revolutionized the way of communication for agricultural applications. IoT along with Wireless Sensor Networks (WSN) is presenting a feasible and globally acceptable solution, with ease of internet availability to everyone, for monitoring and control in Precision Agriculture. Figure 1.2 and Figure 1.3 below mention the various communication technologies and IoT platforms suitable for agriculture.

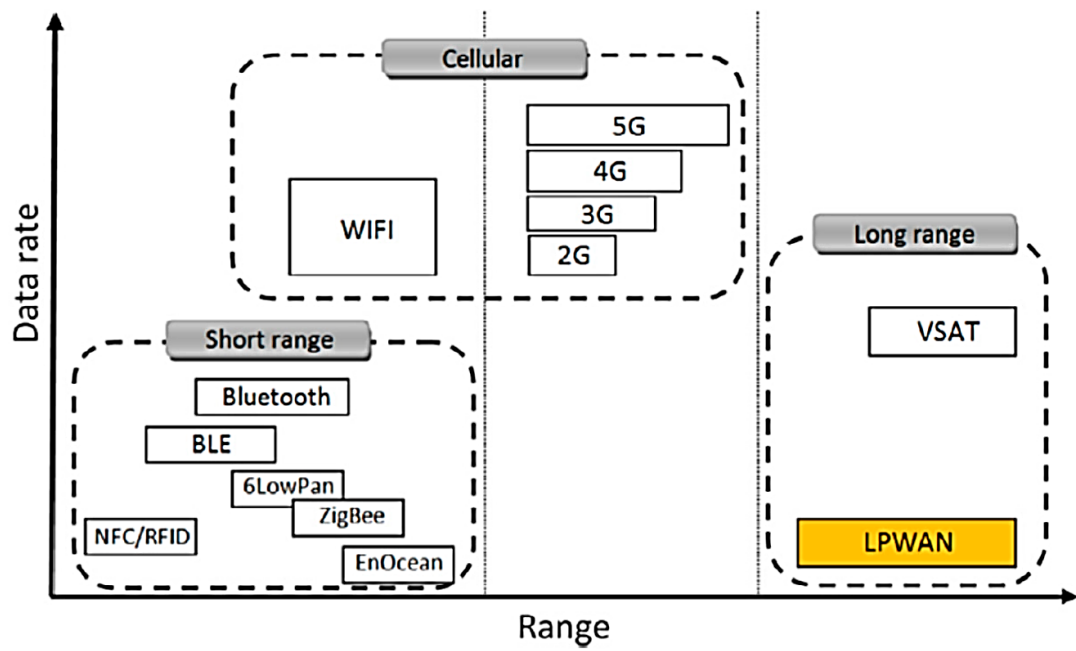


Figure 1.2 Comparison of data rate and communication range in communication networks [17]

Table 1.2 Soil Monitoring Sensors [27]

S.No	Sensors	Temperature	Moisture	Dielectric permittivity	Rain/Water flow	Water level	Conductivity	Salinity	Reference
1	Hydra probe II-soil sensor	✓	✓	✓	✓	✓	✓	✓	www.stevenswater.com
2	Pogo portable-soil sensor	✓	✓	✓	✓	X	✓	X	www.stevenswater.com
3	MP40-soil moisture sensor	✓	✓	✓	X	✓	X	X	www.ictinternational.com.au
4	ECH2O-soil moisture sensor	✓	✓	✓	X	X	X	X	www.ictinternational.com.au
5	EC sensor (EC250)	✓	✓	X	✓	X	X	X	www.stevenswater.com/catalog/products/water_quality_sensors/manual
6	ECRN - 100 high-REC rain gauge	X	X	X	✓	X	X	X	http://www.decagon.com
7	Tipping bucket rain gage	X	X	X	✓	X	X	X	www.stevenswater.com
8	BetaTherm 100K6A1B thermistor-temperature Sensor	✓	X	X	X	X	X	X	http://www.campbellsci.com/107-1

Table 1.3 Plant Monitoring Sensors [27]

S.No	Sensors	Photosynthesis	Moisture	Hydrogen	Wetness	CO ₂	Temperature	References
1	237 leaf wetness sensors	–	✓	–	✓	–	✓	http://www.campbellsci.com
2	LW100, leaf wetness sensor	–	✓	–	✓	–	✓	http://www.globalw.com/LW100B.pdf
3	SenseH2™ hydrogen sensor	–	–	✓	✓	✓	✓	http://www.NTMSSENSORS.com
4	Leaf wetness sensor	–	✓	–	–	–	–	http://www.decagon.com
5	YSI 6025 chlorophyll sensor	✓	–	–	–	–	–	http://www.ysi.com/ysi_6025.pdf
6	Field scout CM1000TM	✓	–	–	–	–	–	http://www.specmeters.com/pdf/2950FS.pdf
7	TT4 multi-sensor thermocouple	–	✓	–	–	–	✓	www.ictinternational.com.au/thermocouple.htm

Table 1.4 Weather Monitoring Sensors [27]

S.No	Sensors	Temperature	Humidity	Atmospheric pressure	Wind speed	Wind direction	Reference
1	Met station one-MSO	✓	✓	✓	✓	✓	www.stevenswater.com
2	XFAM-115 KPASR	✓	✓	✓	X	X	http://www.pewatron.com/100-31-102-006-EH-0110.pdf
3	SHT75 (Humidity and temperature sensor)	✓	✓	✓	X	X	http://www.sensirion.com/humidity
4	CI-340-hand held photosynthesis	✓	✓	X	X	X	http://www.solfranc.com/CI-340_handheld_photosynthesis_solfranc_ENG.pdf
5	BetaTherm 100K6A1B thermistor-temperature Sensor	✓	X	X	X	X	http://www.campbellsci.com/107-1

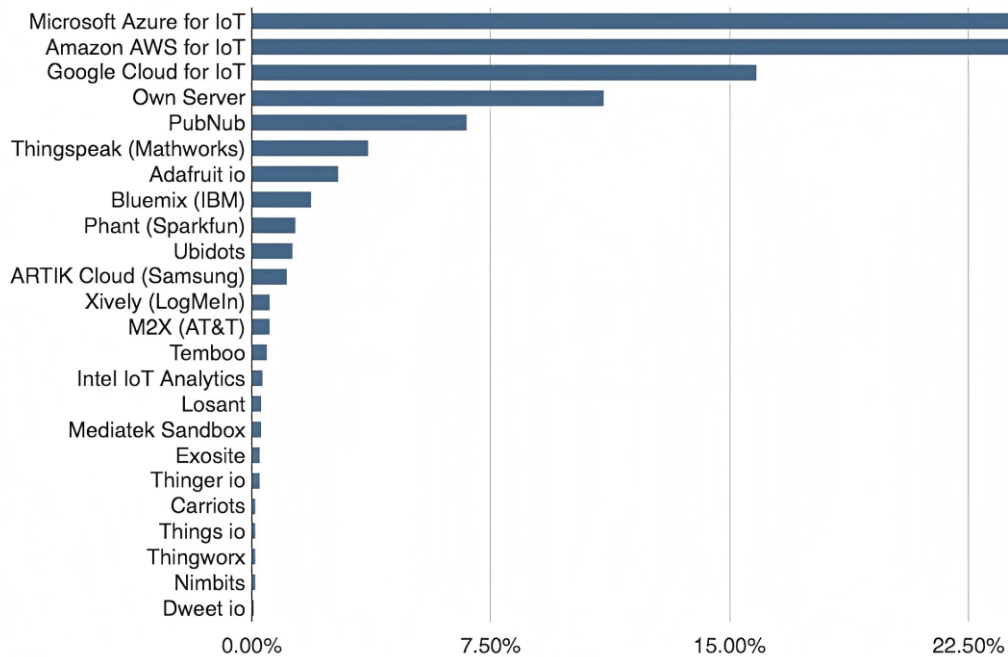


Figure 1.3 Top IoT Platforms [17]

respectively. Much of the work has been done in irrigation automation by developing Zigbee, Bluetooth, GPRS, and the latest LoRa-based irrigation systems. Most of the solutions provided for the irrigation aspect of Precision Agriculture mainly take into account soil moisture only and are based on the low range, up to 100m, wireless protocols like Bluetooth and Zigbee. The work presented in [17] provides a long-range monitoring system for agriculture but uses the LoRa module at 868 MHz frequency which falls under licensed frequency, which will increase system cost and involve a IoT of paperwork to get the license, band in India, and measures only soil moisture. Until now no work has been reported on LoRa at 433MHz module for agricultural application, which is under an unlicensed frequency band in India. Other than adding more agricultural parameters and improving the range of communication for IoT solutions for Precision Agriculture, the IoT face many other challenges like power management, scalability, availability, mobility, storage, and recording data, reliability, security, etc [26, 17, 27, 28, 25, 29, 30].

Looking into the challenges and available technologies for the IoT in Precision Agriculture, the present work is proposed. The proposed work aims to target a few of the challenges and provides the most suitable solution for irrigation monitoring to

improve irrigation water efficiency, agricultural yield production, and quality. Although the present thesis work is proposed for application in agriculture the same has scope for deployment in industrial applications etc medical and wellbeing monitoring, home automation, etc.

1.4 RESEARCH GAP

Finding the research gap enables the research scholar to focus on those research issues that are either still challenging or left unnoticed. IoT with wireless Sensor Networks (WSN) offers a solution to agricultural monitoring but still has many the addressed areas such as

1. **Scalability and reliability:** Adding new devices to the present infrastructure is scalability and correctly receiving the data packets at a high success rate from the sensor node is reliability. By 2025 about 75 billion devices are expected to be connected, in agriculture compromising the reliability of data reception can cause agricultural disaster. Hence scalable and reliable solutions to agriculture IoT are required [26, 31].
2. **Power efficient solution:** Wireless sensor node for agricultural IoT operated on battery. Improving the power efficiency of sensor nodes in agriculture IoT along with identifying the appropriate alternate energy harvesting techniques to ensure the longer life of sensor nodes and consecutively uninterrupted IoT based agricultural monitoring is an important area for researchers to explore [26, 31, 32, 33, 18, 19, 20, 21, 22, 34].
3. **Communication Range:** In agricultural IoT, wireless sensor technology suffers from short communication range like Bluetooth can reach up to 10m and Bluetooth Low Energy technology/ ZigBee can reach up to 100m. Solution to large coverage range of wireless sensor node in agricultural IoT is required to be explored with new emerging technologies [26, 31, 32, 33, 18, 19, 20, 21, 22, 35].
4. **Interoperability:** IoT network consists of the integration of a large number of wired and wireless heterogeneous devices/sensors. Communicating with these

devices is a difficult task and thus poses a challenge in Precision Agriculture [26, 31].

5. **Real Time:** Most crops are sensitive to various environmental parameters like temperature, rainfall, and humidity and even in greenhouse occurrence of fire may lead to agricultural disaster. Thus, real-time monitoring reporting within the specified time frame to agricultural parameters is required and is yet another important research area in Precision Agriculture [26, 36].
6. **Design for the worst:** Agriculture IoT suffers from robust wireless sensor design and mobility. Firstly, wireless sensor nodes deployed in open agricultural fields are exposed to harsh weather conditions like rain, strong sun radiations, extremely high or low humidity, heat, cold environment, etc. Secondly, most of the monitoring application is based on the mobile interface. Hence robust sensor design to tolerate weather extremes and connectivity of agriculture IoT wireless sensor with the mobile interface is also important to research questions [37].
7. **Storage and recording data:** A large amount of data is required to be recorded in agriculture due to a large number of wireless sensor nodes with numerous sensors attached to each node. Therefore, an adequate solution for the storage and recording of large data is required [26].
8. **Crop Irrigation Prediction:** Prediction of irrigating requirements for the crop based on the agrometeorological and agronomy dataset.

A comparison of the important research work on irrigation automation based on selected few challenges are tabulated in Table 1.5. From Table 1.5, it can be concluded that various implementations left many of the issues unaddressed. The present work provides a solution for precision irrigation based on soil and weather conditions. In addition, the present work also focuses on the scalability and long-range technical aspect of irrigation systems. This is much required, as ignoring the scalability and long-range technical aspect of irrigation systems result in control over irrigation for smaller agricultural fields.

1.5 MOTIVATION

Technology in today's era is changing at a very faster pace and these developments leading to technological advancements for the benefit of society always motivate researchers and scientists to set new benchmarks. Searching for feasible, affordable, and acceptable solutions with the help of available latest technologies and as per the need and requirements of the agriculture sector, is much required in Precision Agriculture.

As per the report [16], inefficient usage of irrigation water due to ill irrigation practices will result in scarcity of water in India by 2050. The technical solution for improving agriculture practices is expected to contribute toward the three major goals of Precision Agriculture:

- **Profitability:** Profitability to the farmer is to minimize expenses and maximize income. Overuse of fertilizers, pesticides, and inefficient use of irrigation water not only adds to the expenses but also affects agriculture production and its quality.
- **Sustainability:** Sustainable agriculture aims to fulfill the present needs of society for agricultural products without compromising future requirements. Inefficient use of agricultural resources like irrigation water, fertilizers, and pesticides not only has economical background but also affect soil properties. Continuation with the same inefficient agriculture practices may lead to permanent damage to land and agricultural water resources may exhaust completely in the future, as forecasted by the report [16].
- **Protection to environment:** Many of the agriculture practices like stubble burning, overuse of fertilizers, and pesticides are contributing towards air, soil and water pollution. In this regard also, inefficient flood irrigation practices being followed in India may lead to water scarcity. As per a report [16], water scarcity will have severe effects on the environment such as an increase in soil salinity, degradation, and loss of flood lands and wetlands.

Table 1.5 Comparison of Research in Irrigation Automation for Precision Agriculture

S.No.	Challenges	Irrigation automation based on IoT, cloud, and free hardware in 2019 [17]	Irrigation Automation in Greenhouse with Zigbee in 2016 and 2009 [23, 24]	Irrigation Automation using Bluetooth in 2016 and 2014 [25, 29]
1	Scalability	✓	✓	✗
2	Communication Range	✓	✗	✗
3	Agrometeorology	✗	✗	✗
4	Agronomy (Soil Temperature)	✗	✗	✗
5	Irrigation Prediction	✗	✗	✗

Irrigation water usage efficiency along with agriculture productivity can be increased with proper monitoring and timely control of field irrigation. Consideration of additional factors including only soil moisture such as air temperature and humidity, soil temperature supports in efficient irrigation planning by providing need based water to plants and helps in reducing

crop disease development due to soil moisture and temperature. The urge for efficient utilization of agriculture resources and improving the yield and its quality is the main motivation behind the proposed work to provide a feasible, acceptable and economical technological solution by using recent technologies for Precision Agriculture.

1.6 PROBLEM STATEMENT

To sustain life on earth water is an essential resource and its efficient utilization is very important. Irrigation uses 75% to 85% of fresh water available on earth. Thus, there is much need for efficient irrigation strategies. Though there is much evidence in published literature for the automated irrigation systems using Zigbee, BLE, Bluetooth, and NFC majorly focusing on soil moisture observation and very few considering weather conditions too. Technologically the disadvantages of the present research on automated irrigation systems are (1) short range up to 100 meters only, (2) high power consumption, (3) low scalability, (4) limited usage of intelligent decision-making techniques such as Machine Learning, (5) observing mainly soil moisture for irrigation scheduling, ignoring factors such as weather conditions, soil temperature. The ignored parameters of farmland play an important role not only in proper irrigation planning but also in improving overall crop yield. The present work focuses to address the challenges in the research for automated irrigation systems and develops a IoT based *Precision Irrigation – Decision Support System (PI – DSS)* for need based irrigating of farmland.

1.7 OBJECTIVES OF STUDY

The objective of the work is defined as the overall purpose of the study or what is expected to be achieved from the proposed work. The objectives for the proposed thesis work are:

1. To collect the data set of soil environment like moisture and temperature using smart sensors for IoT based irrigation system.
2. To design and implement IoT based weather station for analysis and processing of data set.
3. To predict the scheduling of IoT based irrigation system using machine learning algorithms.
4. Comparative analysis and Evaluation of IoT based irrigation system.

1.8 METHODOLOGY

Methodology in research sets the procedure and methods to be carried out for doing something. It is defined as a systematic and theoretical analysis of the methods applied to an area of research. The proposed work aims to design and develop a scalable Long – Range irrigation system. Based on the literature following methods and procedure has been identified.

1. **Wireless communication protocols and IoT – Cloud:** Numerous Low Power Wireless Communication Networks (LPWAN) communication protocols like Bluetooth, BLE, Zigbee, NB-IoT, LoRa, and SigFox under licensed and unlicensed categories are available. Similarly, there are an almost infinite number of IoT cloud services like Amazon Web Services IoT Platform, Microsoft Azure IoT Hub, IBM Watson IoT Platform, Google Cloud Platform, Oracle, Salesforce, Bosch, Cisco IoT Cloud Connect, General Electrics Predix, ThingSpeak, Blynk, Cayenne – myDevices and many more are available with free or paid services. For Long Range and cost-effective implementation LoRaWAN (sub – GHz long-range unlicensed communication) and Thingspeak as a wireless communication method and IoT – Cloud is selected respectively. The proposed solution makes use of Thingspeak IoT platform for receiving, storing and monitoring information from soil and weather sensors. Thingspeak IoT cloud is selected because of its low infrastructure requirements, its ability to provide data in excel format and also display the data graphically which makes monitoring easy, and also provides mathematical analysis tools i.e. MATLAB thereby enabling the researchers to perform information processing.

2. **IoT enabled Weather Station:** Weather station in the proposed work serves three-fold requirements namely the weather station provides localized weather information, acts as a server node for the proposed work, and connects the proposed model to the IoT cloud. Firstly, it serves as the central node for collecting the data from soil smart sensor nodes and secondly it measures the weather parameters. Thirdly, the weather station provides the collected weather and soil conditions to the IoT cloud.
3. **Server-Client model with wireless sensor nodes:** The weather station acts as a server node, in addition, to providing weather information and connectivity to the IoT cloud. Client nodes are wireless sensor devices consisting of sensors for sensing and measuring the soil details of soil like soil temperature, and soil moisture content. The soil sensor node is connected to the weather station via long range communication protocol called LoRa. Each node on the network is identified with its unique address.
4. **Storage and Recording data:** As weather station uploads all the received and measured data to the IoT cloud. IoT cloud can store huge amounts of agriculture data even with a freely available subscription for cloud service. Still, if more storage space is desired for a certain application, as per requirement users can opt for paid IoT cloud.

The proposed model for precision agriculture is a 4 – level monitoring system as shown in Figure 3.2.

1.9 THESIS OUTLINE

Chapter 1: The chapter defines the Precision Agriculture and discusses the background for the proposed work along with the present status. Various technological development in precision irrigation and challenges are enumerated. The chapter also identifies the research gap in the previously developed automated precision irrigation systems.

Chapter 2: In this chapter detailed literature study is provided. The study is presented in various sections focussing on IoT, WSN, LPWAN, LoRaWAN, Machine Learning in agriculture and importance of agrometeorology and agronomy in PI.

This chapter also discusses urban farming's importance and need for PI in urban farming are elaborated. Machine Learning is used in many agricultural practices. The chapter enumerates the various machine learning techniques and algorithms for agriculture. The various agricultural practices in which Machine Learning is exploited are also provided in the chapter.

Chapter 3: This chapter deals with the development of the proposed automated irrigation system. The chapter discusses the development of the individual blocks of the proposed PI system. The chapter also compares the developed irrigation system with the previous PI irrigation systems.

Chapter 4: This chapter focuses on the results of the development system. The tested communication range, accuracy in weather monitoring, and relation between various agricultural parameters and ML results are presented in the chapter.

Chapter 5: Conclusion and future enhancements are listed.

1.10 CONCLUSION

This chapter initially introduces the basic concept of IoT, and Precision Agriculture and also presents the revolution in communication with IoT. The importance of Precision Agriculture and the need for Precision Irrigation are presented. Agriculture utilized 75% - 85% of the freshwater resources for irrigation only. Various sensors, communication technologies, and IoT cloud services utilized in agriculture are summarized. After discussing the background, importance, and need of Precision Agriculture and Precision Irrigation, the chapter focuses on the research gap, and motivation of the present work, and provides the objectives and methodology for the proposed work. At the end organization of the thesis is given.

Chapter 2 LITERATURE STUDY

“Our review of the Literature says this appears to be bigger than in the past”

Bob Dietz

A literature survey is the most important part of any research and if we say it is the backbone of any literature or project work would not be wrong. A literature survey or literature review is the review of scholarly papers, articles, books or thesis that already exists on the topic of interest. Literature review contributes to or helps the researcher in terms of the current status of research, theoretical and methodological approaches being already explored, and wasting the researcher’s own time on problems or problem-solving approaches which already exist for the topic under study. Literature review contributes towards the framing of the problem statement, research objectives, finding the research gap, and selection of appropriate methodology for problem-solving.

For the proposed work more than 250 scholarly articles were initially identified and out of those 219 were considered for the literature review and articles were thoroughly studied. The summary of the selected scholarly articles is presented in the consecutive parts of the chapter. The literature review presented is divided into seven sections as

1. First section discusses in detail the concept of the IoT and its scope in near future.
2. The Second section discusses the Wireless Sensor network and available technologies.
3. The Third section presents the role of Low Power Wide Area Networks (LPWAN) in agriculture IoT.
4. The Fourth section introduces the latest Long-Range Wide Area Network (LoRaWAN) and its applicability in agriculture IoT.
5. The fifth section of the chapter deals with some important agrometeorological and agronomy parameters and their effect on crop health.
6. The sixth section discusses the importance of urban agriculture and need of PI in urban agriculture.

7. Section seven and eight deals with the machine learning and Machine Learning algorithms
8. Section last section of the chapter discusses about the utilization of Machine Learning algorithms in agriculture for decision making.

2.1 INTERNET of THINGS

The IoT has revolutionized the way of communication. The conventional way of communication was either human to human communication or communication between human and machine but with IoT a new form of communication has risen has i.e., machine to machine (M2M) communication offering a great future to the internet. The first ever application based on IoT was demonstrated in 1982 in the form of modified coke machine enabling it to providing information about the drinks contained and their temperature remotely. In 1991, ubiquitous computing concept to IoT was given by Mark Weiser. Thereafter in 1999, Bill Joy introduces with the concept of Device-to-Device communication and the terminology “IoT” was coined by Kevin Ashton in the same year [2].

IoT stands for the Internet of Things, which is also known as a self-configuring wireless network of objects. It enables the remote sensing and control of commonly used electronically embedded objects across a network. As more objects are connected to the internet, it becomes a dynamic, self-configuring global network [4]. Three paradigms—internet-oriented (middleware), things-oriented (sensors), and semantic-oriented(knowledge)—have been used to frame the Internet of Things in paper [6]. The deployment of numerous distributed devices with embedded identification is how the IoT extends into the physical world [1]. IoT introduces the idea of connecting digital and physical entities using appropriate information and communication technologies, opening up new possibilities.

The idea behind an IoT device is to transfer the critical data between uniquely identified real-world objects that are outfitted with cutting-edge hardware like Wireless Sensor Networks (WSN) and Radio-Frequency Identification (RFID) and the data received is processed for decision-making [2]. By integrating electronics into everyday objects and creating "smart" goods out of them, the IoT aims to link physical items to digital

infrastructure. In this usage, the term "IoT" may refer to 1) a global network connecting intelligent things using improved internet technology, II) gathering the technologies needed to make the notion a reality, and III) opening up new market and business opportunities through diverse applications and services that make use of the technology [1].

In the near future, the IoT will make it feasible for common objects to be outfitted with microcontrollers, transceivers for communication, and the necessary protocol enabling them to connect with both each other and the users. Because of this, the internet will become more omnipresent and immersive. It is difficult to find a solution that can meet the needs of all potential applications due to the heterogeneous application fields of IoT, such as consumer electronics, healthcare, industrial automation, smart homes, public administration, mobile healthcare, smart grids, and intelligent energy management. This can result in the spread of unique or occasionally incompatible solutions for the actual deployment of IoT systems. Apart from presenting the new opportunities IoT also faces many challenges, mainly security issues, IoT architecture standardization, and opens new research area [3, 7, 8, 9, 10].

IoT in agriculture is mainly adopted for monitoring, controlling and tracking. The various applications of IoT agriculture along with their contribution ratio is depicted in Figure 2.1 [38].

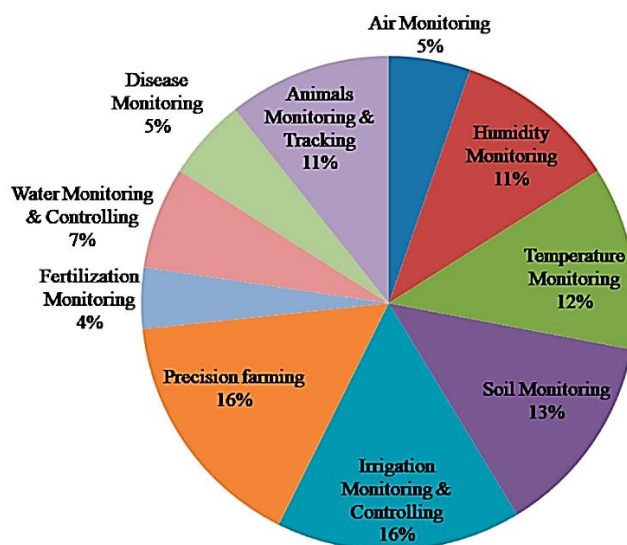


Figure 2.1 IoT in agriculture [38]

2.2 WIRELESS SENSOR NETWORKS

Wireless sensor networks (WSN) are used in many applications like military, agriculture, sports, medicine and industry. One of the emerging application areas of Wireless sensor networks (WSN) is precision agriculture. Precision agriculture aims towards the strategies using the wireless or wired information technology for crops and livestock management to improve the productivity and quality. Precision Agriculture consists of five stages namely – data collection, diagnosis, data analysis, precise field operation and finally evaluation. Precision Agriculture also contributes towards the improvement in field management which includes availability of nutrients to crops, wastage of pesticides used to control weeds, pests and diseases. Wireless sensor networks are deployed in Precision Agriculture for weather monitoring, soil nutrient availability to forecasts crop health and agriculture product quality [26, 39].

The various wireless communication protocols which are suitable and can be exploited for Precision Agriculture are Zigbee, Bluetooth, WiFi, GPRS/3G/4G technology, Long Range Radio (LoRa) protocol, Sigfox. The Zigbee protocol is identified as one of the important members amongst various protocols for Precision Agriculture wireless sensor networks. Zigbee is a short-range communication protocol and provides communication range up to 100m and as minimum as 30m for indoor applications. Zigbee has been used in many applications including water quality management, irrigation automation, greenhouse monitoring and livestock monitoring. Bluetooth is another protocol for wireless communication used for the short-range communication ranging up to 10m and with new version of Bluetooth i.e., BLE range has been extended up to 100m. Bluetooth technology in Precision Agriculture has been deployed in monitoring weather, soil moisture, temperature and sprinkler positioning integrated with Global Positioning System (GPS). WiFi is yet another protocol used in Precision Agriculture to collect agriculture data such as soil moisture, soil temperature, air temperature and humidity, sunlight intensity, Carbon Dioxide (CO₂). The agricultural system using WiFi system stores the agricultural information so obtained in a gateway before it is being transmitted to server system. Global Packet Radio Service (GPRS) is GSM – based data packet service and with Wireless Sensor Networks (WSN) is utilized for automatic crop irrigation system. Using GPRS. A drip irrigation prototype was

developed and evaluated for soil moisture measurement. For transmitting soil, plant and weather information, GPRS was equipped with different wireless sensor nodes. WSN – GPRS forms a gateway between for transmitting the information from Wireless Sensor Networks (WSN) to central data management facility for extended analysis of received information with the help of mobile phones, tablets or computers.

SigFox was used to develop geo location system to localize animals in mountain pastures during summer and is used for low data rate applications. SigFox was used in system developed to locate cattle and enhance their productivity. Next and the latest contender in Wireless Sensor Networks (WSN) is LoRa alliance established in 2015. The LoRaWAN technology is a low power, wide area IoT communication protocol. LoRa network basically comprises of 3 – element namely LoRa end devices, LoRa gateway and LoRa network service. LoRa end devices communicates with LoRa gateway which make use of LoRa with LoRaWAN. The received raw LoRaWAN data packets are transferred to LoRa network server by LoRa gateway. In many applications the LoRa protocol has been utilised, few to be mentioned are monitoring of soil moisture, soil temperature, air temperature, air humidity and light intensity inside greenhouse using variety of sensors and embedded systems platforms. By setting side by side the various WSN protocols for IoT in agriculture, as demonstrated in Figure 2.2, also, LoRa has been found as one of the most power efficient technological solutions for long distant communication. It has been reported that by the making use of Wireless Sensor Network in irrigation monitoring systems the water saving of 90% using Zigbee [23], 33% of water saving using Zigbee [24], 50% of water saving using Bluetooth [25], 90% of water saving using Bluetooth [29] is achieved in comparison to conventional irrigation practices [40, 41, 28, 42, 43, 44, 45, 46, 47, 48] [23] [24] [25, 27, 30].

In automatic irrigation system major challenges are long distance and lack of communication networks. New perspectives have emerged in the field of irrigation automation. With urban lawn irrigation programming and evapotranspiration data from weather station, one of the proposed works of automatic irrigation system succeeded in saving 48% of water as compared to previous irrigation practices. As per the coverage range of different communication networks are classified as short-range networks,

cellular networks and long-range networks. The data rate and range of communication networks is given in 1.2 [17].

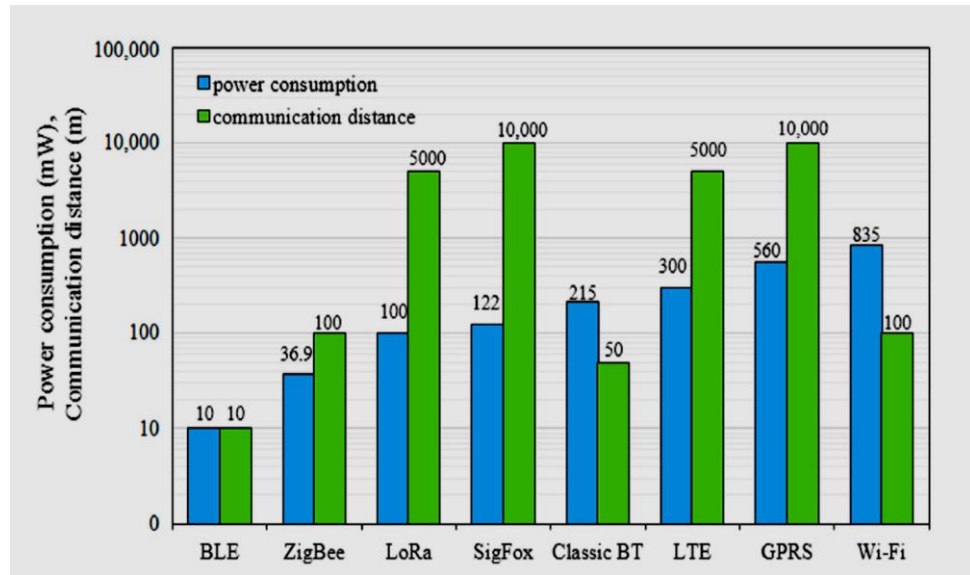


Figure 2.2 Comparing Available Wireless Technologies for their Power Consumption and Communication Range [26]

The recently developed Low Power Wide Area Network (LPWAN) has proposed two models for technical development i.e. first using existing facilities to provide coverage for the devices compatible with telecommunication technology and secondly by developing the collaborative networks for global integration of IoT applications with the help of low-cost tools. SigFox transmission speed is about 100bps and allows 140 uplink and 4 downlink messages per day. It permits 12 bytes of payload for upload and 8 bytes of payload for download. With no special requirement for deployment and with high coverage in many countries, SigFox is suitable for wide range of agriculture projects. LoRaWAN has significant edge over the other long – range protocols/technologies in terms of cost, as no cost is involved with the use of radio space as it operated in unlicensed range of radio frequency, and symmetry in communication but the availability of LoRaWAN network in agriculture area is very low. Narrow Band (NB) – IoT used restricted frequencies as require license for use. NB - IoT provides higher transmission speed, in comparison to other LPWAN technologies, but impose service cost per use, range is reduced and availability of devices in very limited. WiFi, Bluetooth, Zigbee and LoRa are the most suitable

wireless communication protocols for local network. Table 2.1 compares the various characteristics of local network communication technologies.

Table 2.1 Characteristics of Local Network Communication Technologies [17, 19]

Parameter	Wi-Fi	Bluetooth	Zigbee	Lora
Standard	IEEE802.11 a,b,g,n	802.15.1	802.15.4	802.15.4g
Frequency	2,4 GHz	2,4 GHz	868/915 MHz, 2,4 GHz	433/868/915 MHz
Data rate	2–54 Mbps	1–24 Mbps	20–250 kbps	0.3–50 kbps
Transmission Range	20–100 m	8–10 m	10–20 m	>500 m
Topology	Star	Star	Tree, star, mesh	Star
Energy consumption	High	Medium	Low	Very Low
Cost	Low	Low	Low	Low

Based on IoT and cloud computing, literature has revealed three possible approaches for monitoring and performance evaluation. Firstly, specific programming model for specific problem but it requires high programming efforts. Secondly, customized client based commercial solution adapted to customer’s need in terms of data measurement and uploading to the cloud. This solution has drawback being closed to the user. The last approach to address the technological challenge is to use or deploy the generic commercial IoT platforms where the user can adapt the application as per their specific needs. Figure 1.3 present the most common IoT platforms along with their distribution in the market [18, 49, 50, 51, 52, 53, 54, 55, 56, 16, 23].

In papers [17, 28], IoT cloud computing and free hardware-based solution for monitoring and operating irrigation networks was proposed. The proposed solution uses Long Range Wireless Sensor Network (LoRaWAN) for local area network and SigFox for uploading the information to IoT platform/cloud. The proposed method only includes a soil moisture sensor despite citing the significance of air temperature and humidity, wind speed, precipitation, and irradiance in the planning of irrigation. The proposed solution uses ThingSpeak IoT platform for receiving information from field sensors and record the information in its database. ThingSpeak IoT cloud is chosen for its low infrastructure requirements, its ability of displaying the data graphically and also

providing mathematical analysis tool i.e. MATLAB thus enabling it to perform information processing.

Internet of things as the name depicts is the association of things to Internet via Wireless Sensor Network (WSN), Radio Frequency Identification (RFID), Near Field Communication (NFC), Long Term Evolution (LTE) and many other smart communication technologies. In mid-80's communication was mainly confined to either voice over telephone or through letters. But with the passage of time and technological developments, internet came into existence and provided all new way of communication. But today the concept of IoT has left internet far behind. The concept of IoT was introduced at Massachusetts Institute of Technology (MIT) Auto – ID Labs in in 1990. The first IoT application was Trojan Room Coffee Pot developed in 1999 and first IoT controlled device developed was a toaster that could be turned off and on over the internet.

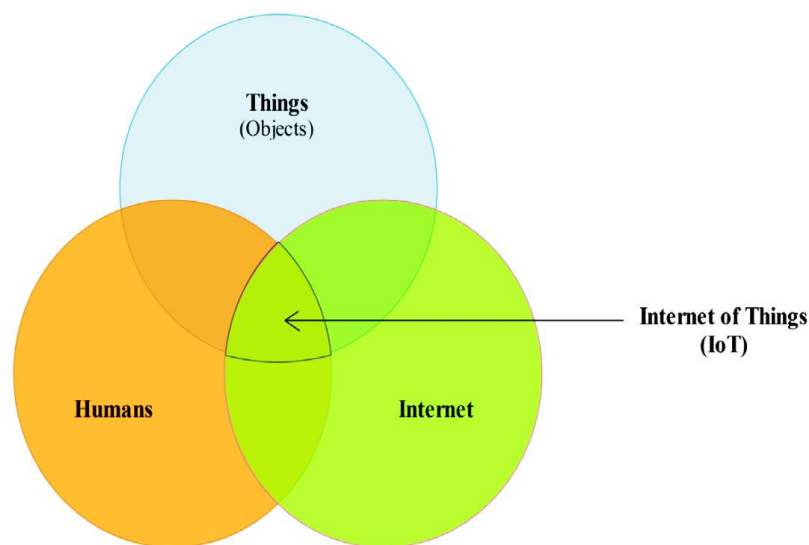


Figure 2.3 IoT Tri-sectional relationship

Various organizations have defined the term IoT and according to ITU – T IoT is “Global Infrastructure for information Society enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving, interoperable information and communication technologies”. Figure 2.3 depicts that IoT basically a tri – sections relationship among the three aspects of IoT i.e Human, Internet and Things [31, 40, 41, 42, 43].

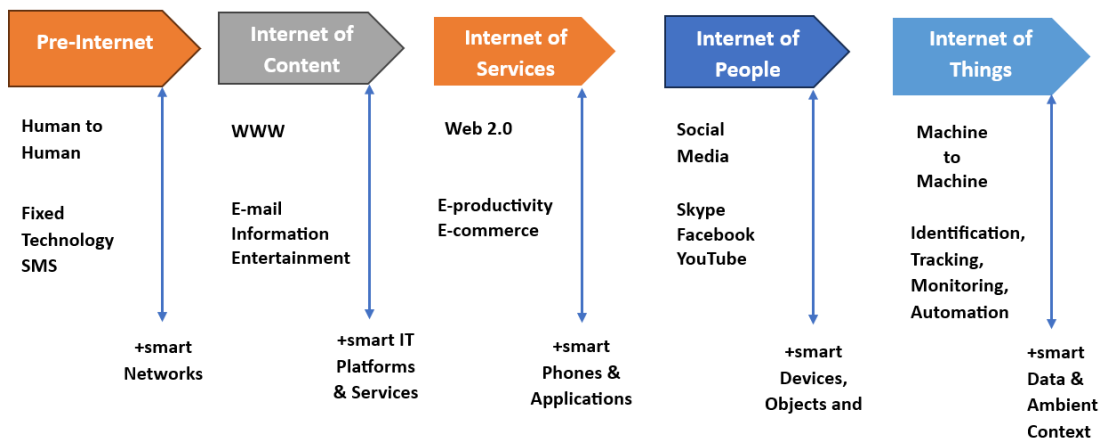


Figure 2.4 Transformation from Pre-Internet to IoT [31]

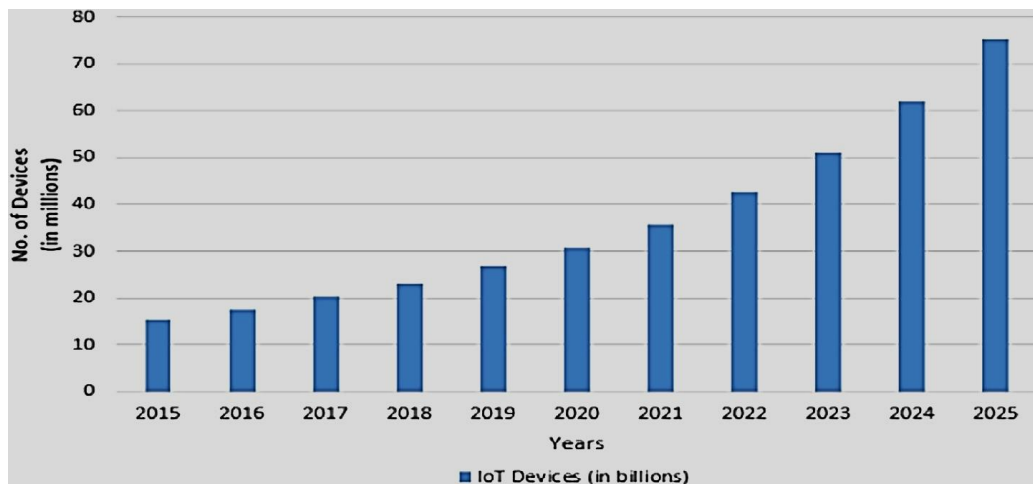


Figure 2.5 Projection of IoT devices being associated via Internet (2015–2025) [31]

The Transformation from pre – internet to Internet and finally to the present IoT is depicted in Figure 2.4. Till date there are about 5 billion devices connected through IoT which is expected to grow up to 75 billion devices by 2025, trend being depicted in Figure 2.5. It has also been projected that IoT is going to share a value that would surpass \$300 billion by 2020 [31, 40, 41, 42, 43].

The various existing communication technologies for Internet of Things are Radio Frequency Identification (RFID), IEEE 802(RFID), Long Term Evolution (LTE), Zensys wave(Z – wave), Long Range (LoRa), Ultra – Wide Band (UWB), Near – Field communication (NFC), Machine to Machine (M2M), IPv6 Low Power Wireless

Personal Area Network (6LoWPAN) and shown in Figure 2.6. . Table 2.2 compares the frequency of operation and distance covered by various technologies used in IoT applications [31, 32, 33, 18, 19, 20, 21, 34].

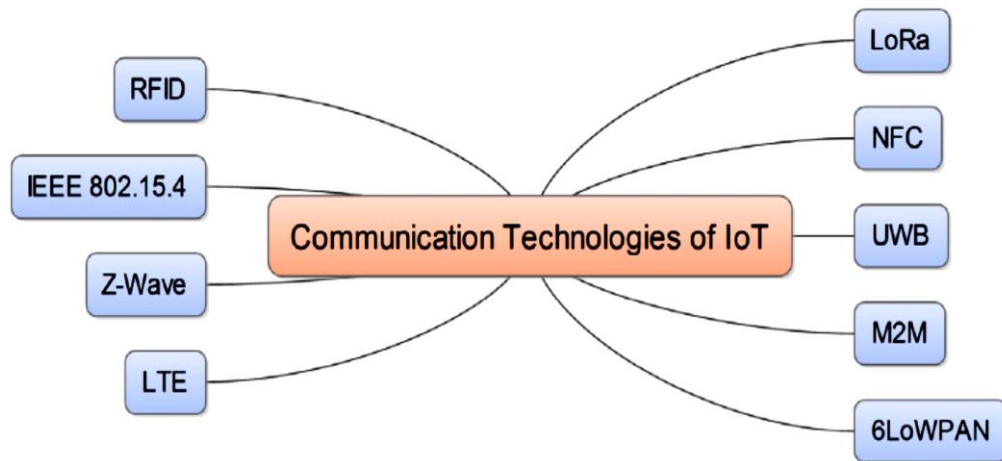


Figure 2.6 Different Communication Technologies for IoT [31]

IoT has potential towards its adaption due to its great impact on social, environmental and economic area. Smart Homes/Buildings, Smart Grid, Medical and Healthcare, Industrial Processing, Agriculture and Breeding and Independent, Public Safety and Environmental Monitoring are some of the applications which has adopted the concept of IoT. Figure 2.7 gives the various applications areas of IoT [31].

Precision Agriculture uses Information Technology for field management to optimize health and productivity of crops by ensuring that the soil and crop receive exactly what they require. The main objective of Precision Agriculture is to achieve profitability, sustainability and protection of the environment. Sometimes Precision Agriculture is also termed as Satellite Farming and Site-Specific Crop management [31].

Table 2.2 Frequencies and Distance Covered by Various IoT technologies [31]

Technology	Standard	Year of discovery	Downlink/Uplink	Range (in metres)	Operating frequency (in MHz)
RFID	Wireless	1973	100 kbps	2	0.125–5876
IEEE 802.15.4	6LoWPAN	2003	250 Kbps	30	826 & 915
Z-Wave	Wireless	2013	100 kbit/s	30	868.42 & 908.42
LTE	3GPP, LTE and 4G	1991	100 Mbps	35	400–1900
LoRa	Wireless	2012	0.3 37.5 (kb/s)	3000–5000	169, 433 & 868 (Europe) & 915 (North America)
NFC	ISO 18092	2004	106, 212 or 424 Kbits	< 0.2	13.56
UBW	IEEE 802.15.3	2002	11–55Mbps	10–30	2400
M2M	ready to accept any communication protocol	1973	50–150 Mbps	5–20	1–20
6LoWPAN	Wireless	2006	250 Kbps	30	915

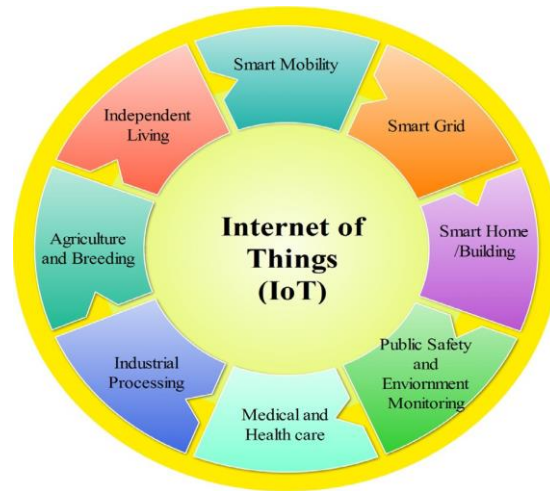


Figure 2.7 IoT applications areas [31]

2.3 LOW POWER WIDE AREA NETWORK (LPWAN)

In – spite of the rise that IoT using Wireless Sensor Networks (WSN) has achieved in the last few years, it suffers from many of the conceptual and fundamental limitation because of its management and performance.

Wireless Sensor Networks (WSN) save wiring costs and include, point to point and point to multipoint communications. Various communication protocols are Bluetooth, Zigbee (n short range) and cellular phone system (in long range). Bluetooth was used to transmit the soil moisture, weather information and for controlling the Programmable Logic Controller (PLC) based sprinkler system. Bluetooth uses radio waves to get connected with phones, computers and is a short-range communication protocol. Air temperature and humidity and radiation are the most important climatic condition in addition to soil moisture in greenhouse. The wireless irrigation system with Integrated Control Strategy (ICT) equipped with soil sensor, weather sensor, microcontroller, Programmable Logic Controller (PLC) and Bluetooth when applied to greenhouse showed that there was 90% saving (tested for two weeks) of electricity and water usage against the time-controlled irrigation practice. Yet another automated irrigation system also showed 90% of water saving (tested for 136 days) in comparison to traditional irrigation practices. of irrigation water resource. Proper planning before on field testing of automated system for Precision Agriculture plays an important role because factors

like hardware malfunction, time pressure, software bugs, misunderstanding the field under study, insufficient lab testing, in – effecting design in terms of robustness play very crucial role and neglecting them may result in failure of the project. The same happened with the project LOFAR – agro in which the designer overlooked certain important design parameters, as a result of which project failed [25, 29, 44, 45, 46, 47].

IoT needs technological solutions for low power, long range from several meters to several kilometers, low cost and less complex end devices. Low Power Wide Area Network (LPWAN) technologies are only solution to meet the needs of IoT. SigFox, NB – IoT or LoRa are some of the Low Power Wide Area Network (LPWAN) technologies. SigFox was planned to provide global coverage but currently available in only 45 countries, NB - IoT uses licensed spectrum, provides reliable solution and gives support to heavy traffic conditions and offers more reliability in comparison to sub – GHz technologies. LoRa is low power LPWAN and suitable for private network deployment. LoRa is being deployed in many applications such as agriculture monitoring, health and wellbeing monitoring, traffic monitoring, Wireless Sensor Networks (WSN), smart city applications, smart grids, Internet of Medical Things (IoMT) and tele – measurement. LoRa is reliable up to 2 Km with Packet Reception Ratio (PRR) as high as 95.5%. Mobility worsens the performance of LoRaWAN and packet loss reaches as high as 20% against 2% as measured for static far end LoRa node in indoor application. The range coverage being offered by LoRa is dependent on transmission parameter and weather conditions. In outdoor application LoRaWan can offer coverage up to 5 Km. In indoor applications LoRa coverage is sufficiently good and can offer communication up to 34000 m²with suitable transmission parameter settings. For outdoor applications packet loss was about 45% at a speed of 15 miles per hour up to a distance of 0.4 miles against only 2% for static end node. Strength, weakness, opportunities and threats i.e SWOT analysis of LoRa WAN are listed in the Table 2.4. LoRaWAN is a reliable solution for mobile applications with mobility at the rate of upto 25 Km/h but the communication deteriorates at speed exceeding 40 Km/h. **Error! Not a valid bookmark self-reference.** summarizes the various challenges/limitations observed in IoT [31, 66, 67, 28, 68, 69, 70, 71, 72, 73, 74, 75, 37, 76, 77, 35, 78, 79, 80, 81, 82].

Table 2.3 Challenges and Limitations of WSN in IoT

S. No	Challenge/Limitation	Short Description
1	Power management	In wireless Sensor nodes, RF communication components consumes more power than other components. Energy efficient algorithms, power efficient RF communication techniques and alternate energy sources such as solar can be utilized for addressing the challenge [26] [48, 44].
2	Communication Range	In agriculture applications most of the wireless technologies like Bluetooth, Zigbee, RFID, NFC, Z – Wave, UBW suffers from limitation of short range [26, 31, 32, 33, 34, 18, 19, 20, 21, 22].
3	Scalability	It is predicted that by 2020, about 50 billion devices will be connected via IoT. In agriculture applications also there is requirement of large-scale deployment of wireless sensor nodes. Hence, solution to scalable IoT platform always remains a challenging task [26, 31].
4	Availability	IoT realization of any application should provide anytime, anywhere access, service and control. IoT is not only providing the software application only, but importance of hardware part is equally significant and is associated with various communication protocols like Bluetooth, WiFi, 6LoWPAN, LoRaWAN etc. The entire setup should not be misunderstood as a different entity and this awareness of end user about the association of hardware and software will channelize the vision in more appropriate way [26, 31].
5	Mobility	Another challenge in smooth implementation of IoT is mobility. In this case connectivity to mobile interface or object under monitoring plays an important role and loss of connectivity with mobile interface or object under monitoring would be a failure of the system. [31].
6	Storage data	Large amount of data is recorded form agricultural observation. As agricultural application consists of many wireless sensor nodes and each node is equipped with number of sensors. Hence, IoT solution to agriculture application should be such that it can support large amount of storage and recording capacity [26].

7	Real Time	Wireless Sensor Networks (WSN) monitoring ecological conditions of agriculture need to be real time as most of the crops are vulnerable to the climatic condition [26, 36].
8	Reliability	Enhancing the reliability increases the success rate of IoT services. In agriculture different environmental parameters are also monitored which can also be used for pollution monitoring. Any of the important information is reported to agencies for further investigations and critical information needs to be dealt immediately. Therefore, failure of the system or threat from intrusion makes the reliability of the framework as major challenging factor in IoT task [26, 31].
9	Interoperability	Interoperability remains a challenge in IoT because handling a large number of heterogenous devices and establishing synchronization of different platforms is always a difficult task task [26, 31].
10	Security	Security and privacy of information in IoT holds special significance because information is transmitted over the Internet. Although lot of efforts are being put to make data transmission secure but many time shortcomings do occur task [26, 31, 48].

Table 2.4 . LoRaWAN SWOT Analyses [30]

Strength	Weakness
<ul style="list-style-type: none"> ➤ Large coverage offered in open environment ➤ Low power end nodes ➤ Low end nodes complexity ➤ Cheap end devices ➤ Opportunities for private network deployment ➤ Acceptable for monitoring applications 	<ul style="list-style-type: none"> ➤ Security issues ➤ Reply and DoS attacks possible ➤ Network security and Application security terminates at various points in the network ➤ Poor performance of ADR mechanism under heavy network load due to ➤ due to duty cycle offers low scalability in DL
Opportunities	Threats
<ul style="list-style-type: none"> ➤ Power usage can be decreased through modification of DL communication scheme ➤ Traffic synchronization under low-power conditions ➤ Possibilities for low-power traffic scheduling ➤ CSMA plans to prevent DL duty cycling 	<ul style="list-style-type: none"> ➤ Scalability problems in UL with high network traffic ➤ Interference from other technologies by modifying DL communication scheme ➤ Not-suitable for two-way communication

LoRaWAN has been designed to meet the real time requirements of application such as agriculture, leak detection and environment control [49]. IoT requires more sensors to be connected and it has already been predicted that 50 million devices are to be connected through IoT by 2020. For this Low Power Wireless Area Network (LPWAN) is the most feasible solution as they address the low power, long range, reliability, scalability requirement of IoT. There are many solutions available for LPWAN such as NB – IoT, LoRa, SigFox, LTE, EC – GSM.

Table 2.5 gives the summary of LPWAN technologies.

Table 2.6 and Table 2.7 present the results of comparative study for the various licensed and unlicensed LPWAN technologies respectively [50, 51, 52, 53].

Table 2.5 LPWAN Technologies Summary [51]

Feature	LoRaWAN	Sigfox	NB-IoT	LTE-M
Modulation	SS Chirp	GFSK/ DBPSK	UNB/GFSK/ BPSK	OFDMA
Data Rate	290bps - 50kbps	100bps 12/8bytes Max	100bps 12/8bytes Max	200kbps - 1Mbps
Battery lifetime	8 ~ 10 years	7 ~ 8 years	7 ~ 8 years	1 ~ 2 years
Power Efficiency	Very High	Very High	Very High	Medium
Range	2-5km urban 15km sub- urban 45km rural	3-10km urban - 30-50km rural	1.5km urban - 20-40km rural	35km - 2G 200km - 3G 200km - 4G
Interference Immunity	Very High	Low	Low	Medium
Scalability	Yes	Yes	Yes	Yes
Mobility/ Localization	Yes	No	Limited, No Loc	Only Mobility

Table 2.6 Licensed LPWAN Technologies [50]

Attribute	LTE-M (Rel. 13)	EC-GSM	NB-IoT
Frequency band	700-900 MHz	800-900 MHz	700-900 MHz
Data rate	375 kbps	70 kbps	20-65 kbps
Bandwidth	1.08 MHz	200 kHz	200 kHz
Range	<15 km	<15 km	<35 km
Mobility	Yes	Yes	No

Table 2.7 Unlicensed LPWAN Technologies [50]

Attribute	SIGFOX	LoRa
Frequency band	868, 902 MHz	SUB-GHz ISM
Data rate	0.1 kbps	0.3 kbps to 37.5 kbps
bandwidth	100 Hz	<500kHz
Range	Rural:30-50 km Urban:3-10 km	Rural:10-15 km Urban:3-5 km

2.4 LONG RANGE WIDE AREA NETWORKS (LORAWAN)

Scalability is the major requirement of IoT as it is growing at very fast pace with more and more devices being added daily. In 2016 research was done in order to measure scalability of LoRa and was found that LoRa can scale quite well but was not sufficient for smart city application. In another study held in 2016 it reveals that LoRa can serve several million devices. As per the latest study conducted in 2017, LoRa outperforms the ALOHA in terms of scalability. Table 2.8 enlisted the scalability of LoRa for various applications. The results show that LoRa had about 32% data packet loss while ALOHA shows loss of 90% data packets for 1000 devices per gateway [54, 55, 56, 57].

LoRa is a low power long range protocol of Internet of Things IoT but LoRa range is drastically affected by the vegetation. In a study conducted in 2017 it was found that the communication range drops from 450 -500m in Line of Sight (LOS) environment to only 50 – 90m in Non-Line of Sight (NLOS) vegetation environment. High temperature also deteriorates the signal. Another outcome of the study was that transmission power has little effect on transmission range but other parameter like Bandwidth (BW), Spreading Factor (SF), Coding Rate (CR) and Carrier Frequency (CF) play important role in determining the connectivity range. LoRa device can be set for different values of Transmission Power (TP), Coding Rate (CR), Spreading Factor (SF) and Bandwidth (BW) in order to meet the tradeoff between transmission power and communication performance. There are almost 6720 possible settings for LoRa device [54, 55, 56, 61].

Table 2.8 Scalability of LoRa in Different IoT Applications [62].

Applications	Transaction Message Period (s)	Payload Size (bytes)	Highest SF	Number of Nodes in New York's 7-kilometer Radius Cell	Number of Nodes for 10% or less in Total Network Losses	% of Nodes Served in One 7 km Radius Cell in New York
Home security	600	20	12	591,773	~1400	0.24
Home appliances	86,400	8	12	1,775,319	~150,000	8.45
Roadway signs	30.03	1	10	9340	~650	6.95
Traffic lights	59.88	1	11	152	~1200	100
Credit machine in grocery	120.48	24.00	12.00	32,05	~280	0.87

As already mentioned by 2025 about 75 billion devices will be connected through wireless communication and with this Low Power Technological LPWAN solution are becoming more and more popular. The two leading technologies in LPWAN are Narrow Band (NB) - IoT and LoRa i.e LoRaWAN. Physical features of the LoRa and NB – IoT technologies are tabulated in Table 2.9. After comparing various IoT challenging factors such as Battery life, coverage range, cost, immunity to interference and latency LoRa is either found better or equivalent in performance to NB – IoT, IEEE 802.15.4, SigFox LPWAN technologies. But in Quality of Service (QoS) NB – IoT wins the race but LoRa is found more immune to interference and fading. Table 2.10

gives the various IoT application and suitability of NB – IoT or LoRaWAN [30, 63, 34, 64, 51, 56, 58, 59].

Table 2.9 LoRa and NB – IoT Physical Features [59]

Parameters	LoRa	NB-IoT
Spectrum	Unlicensed	Licensed LTE bandwidth
Modulation	CSS	QPSK
Bandwidth	500 KHz - 125 KHz	180KHz
Peak Data Rate	290bps-50Kbps (DL/UL)	DL:234.7kbps; UL:204.8kbps
Link Budget	154dB	150dB
Max. # message/day	Unlimited	Unlimited
Duplex operation	--	Half duplex
Power efficiency	Very High	Medium High
Mobility	superior to NB-IoT	
Connection Density	Utilized with NB-IoT	1500 km ²
Energy Efficiency	>10 years battery life of devices	>10 years battery life of devices
Spectrum Efficiency	Chirp SS CDMA better than FSK	Improved by Standalone, band, guard band operation
Area Traffic Capacity	Depends on gateway type	40 devices per household, ~55k devices per cell
Interference immunity	Very High	Low

Table 2.10 IoT Applications with Parameters [59]

Better Choice	Study Cases	Major IoT Categories	Parameters
---------------	-------------	----------------------	------------

LoRa	Logistics tracking Asset tracking Smart agriculture Intelligent building Factories and Industries Facility Management Healthcare Airport management.	IoT industries	device cost, battery life, coverage,
NB-IoT	Wearables Smart bicycle Kids monitoring Pet Tracking Point of sale terminals (PoS)	IoT personal	range, diversity, latency, QoS
Depends on specific requirements	Refrigerators Air Conditioners Microwave Printers Water coolers	IoT appliance	range, coverage, diversity, latency, QoS

Thus, LoRa is a feasible solution for the Internet of This (IoT) to address the long-range, power efficiency, real-time, reliability, network capacity, security, and mobility needs of the IoT. LoRa shares 45% of the commercial market in Low Power Wireless Area Network (LPWAN). Major characteristics of LoRaWAN are given in Table 2.11 [31, 66, 79, 28, 68, 69, 70, 71, 72, 73, 74, 75, 37, 76, 77, 78, 67, 80, 81, 82, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93].

Table 2.11 Main Characteristics of LoRaWAN [51]

Characteristic	LoRaWAN
Topology	Star on Star

Modulation	SS Chirp
Data Rate	290bps - 50kbps
Link Budget	154 dB
Packet Size	154 dB
Battery lifetime	8 ~ 10 years
Power Efficiency	Very High
Security/Authentication	Yes (32 bits)
Range	2-5 km urban 15 km suburban 45 km rural
Interference Immunity	Very High
Scalability	Yes

2.5 AGROMETEOROLOGY AND AGRONOMY

Some of the crucial factors that affect agricultural productivity and irrigation planning are wind speed, wind direction, air temperature, and humidity, along with soil temperature and moisture content. Soil moisture and temperature affect the mineralization of organic matter. In a study on the effect of temperature and moisture on soil nitrogen on three different soils i.e forests, grassland, and cropland revealed that soil is more sensitive to temperature at 25°C and optimal soil moisture found was 80% for nitrogen mineralization. In another research, it was concluded that nitrogen mineralization of soil is more dependent on temperature than soil moisture. It has been observed that the suitable temperature for N mineralization of two soils was 25°C and 20°C. Many of the researchers have found that N mineralization shows continuous increment from 5°C to 35 °C with no optimal temperature. *Figure 2.8*, shows the N mineralization at 9 temperatures – soil moisture levels. Availability of nutrients to plants from soil is primarily governed by diffusion, root interception, and mass flow which are mainly affected by soil temperature, root interception, and mass flow are mainly affected by soil temperature. Soil temperature and moisture greatly affect the availability of nutrients to crops. Soil temperature form 5°C to 40°C is most suitable for ammonification and nitrification but the most optimal soil temperature is from 30°C to 35°C. The availability of Phosphorus (P) is more at 20°C than 13°C due to an increase in the diffusion rate. High soil temperature accelerated the organic Phosphorus (P) mineralization. However higher temperature also has the negative effect of reducing the availability of Phosphorus (P) due to fixation and with every 15°C rise from 5°C to

35°C water-soluble Phosphorus (P) is reduced by 43%. Root growth of crops is also affected by the soil temperature and for many of the crops, 24°C soil temperature has been found suitable for root growth [65, 66, 67, 68, 69]..

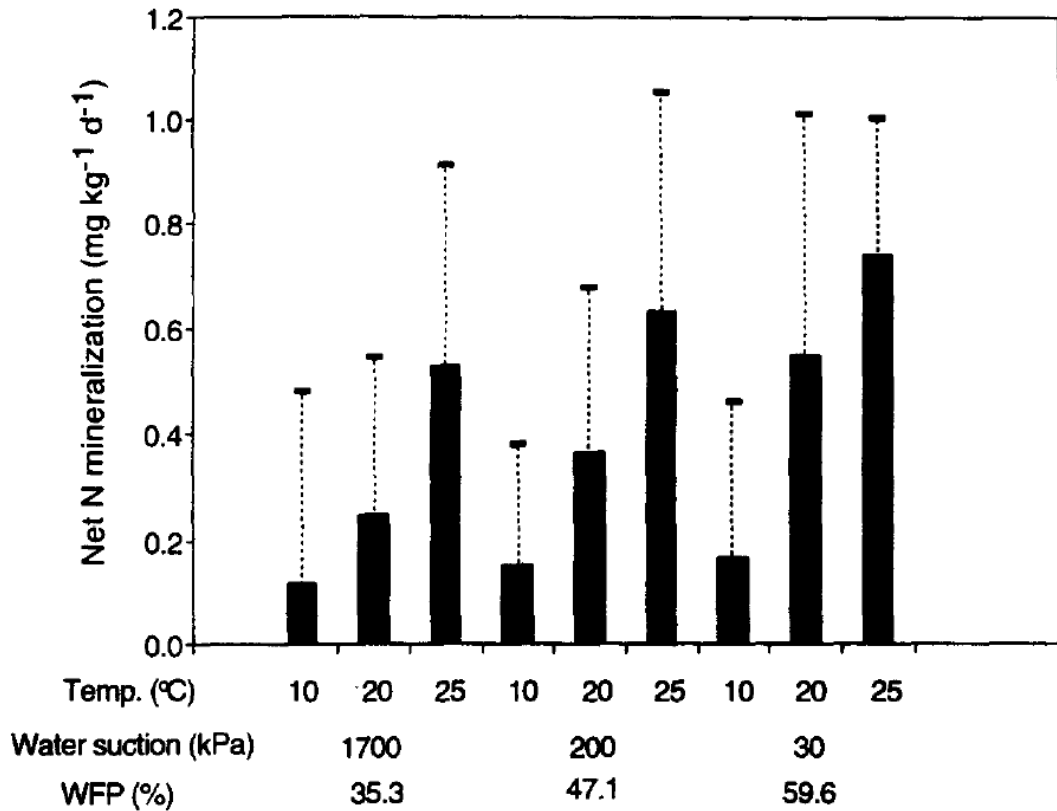


Figure 2.8 Net N mineralization at Different Temperature – Soil Moisture Treatments [66]

Soil temperature has a profound effect on soil and water hydraulic condition, and water uptake by the plants from the soil. There is a decrease in water uptake by plants at low temperatures due to a reduction in root growth, water permeability of the cell membrane, and increased viscosity of water. It was found in one of the research projects that raising the rooting system temperature from 14°C to 26°C increases the water uptake by 30%. An experiment was carried out at six temperature gradients (8°C, 12°C, 16°C, 20°C, 24°C and 28°C) and the result clearly showed the dependency of crop water uptake on root temperature. Water uptake increases up to 16°C and thereafter there was no significant increase but an obvious decrease with a decrease in temperature [70, 71, 72, 73].

Soil temperature is a very important parameter to be monitored in precision Agriculture and is the ratio of energy absorbed to the energy lost by the soil. Soil temperature plays

an important role in determining the soil's physiochemical and biological processes which in turn alter the soil properties or soil processes affecting the plant growth. Organic matter decomposition and organic matter mineralization are determined by the soil temperature which is further affected by the soil water content, soil conductivity, and plant availability. Soil biological activities such as seed germination, plant root growth, seedling emergence, and availability of nutrients are soil temperature-dependent, which further is dependent on the amount of solar radiation received by the soil. Factors having a predominant effect of soil temperature are solar radiations, soil moisture content, vegetation cover, evaporation, soil color, soil mulch, the slope of the land surface, organic matter content, and bulk density. Soil temperature suitable for bioactivity ranges from 10°C to 28°C. An increase in the soil temperature increases soil nitrogen mineralization with an increase in the decomposition of organic matter and an increase in soil microbial activity. Low soil temperature, close to freezing point decreases soil mineralization due to inhibited microbial activity and decreased diffusion of soluble substrates in soil. Most of the soil organisms require temperatures from 10°C to 35.6°C, soil temperatures from 10°C to 24°C is required by the soil macro – organisms, for soil organic matter decomposition most suitable temperature range is from 21°C to 38°C and soil temperature in the range from 25°C to 39°C has increased effect on soil pH. Soil temperature also affects the soil moisture content and it decreases with soil temperature due to decreased water viscosity, allowing more water to penetrate through the soil profile. Shading along with increased soil temperature restricts the penetration of water through the soil profile. Soil temperature also affects plant growth by affecting the water uptake, nutrient uptake, and root growth. With the increased viscosity of water at low temperatures, water uptake by plants is reduced resulting in a reduced rate of photosynthesis. An increase in soil temperature affects nutrient availability by accelerating the soil metabolic activities which in turn stimulates the availability of plant nutrients, changing the soil water viscosity and root nutrient transport. Root growth improves at high soil temperatures as a result of increased metabolic activities of root cells [74, 75, 76].

Factors affecting the plant disease are pathogens, host, and environmental factors as depicted in the disease triangle in Figure 2.9. A series of experiments were conducted on tomatoes to find

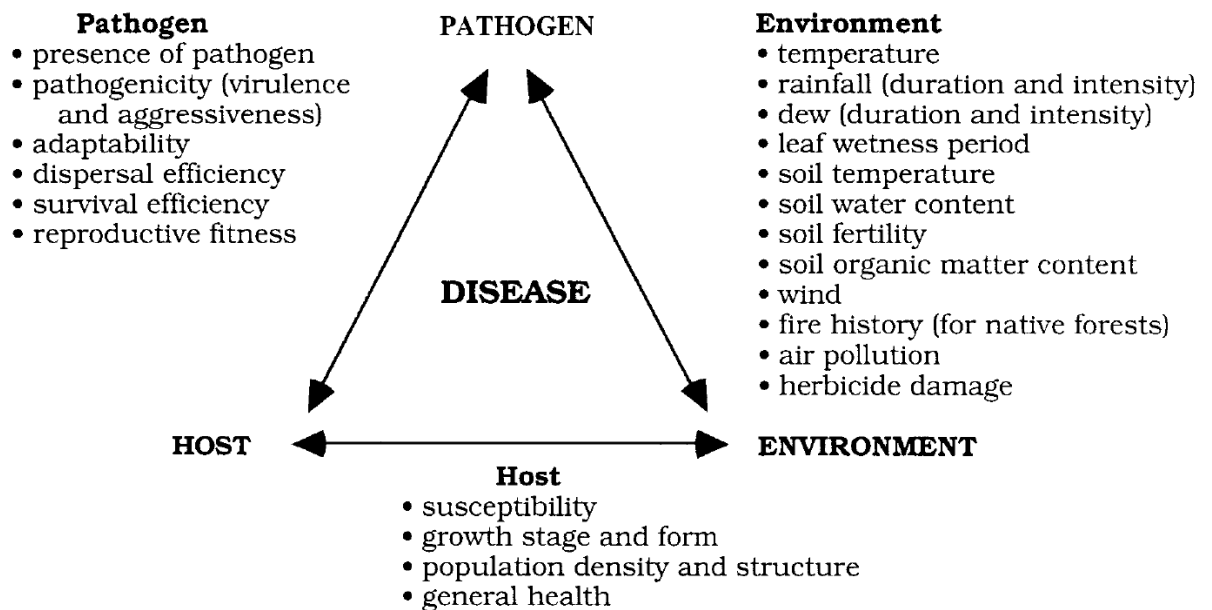


Figure 2.9 Disease Triangle depicting the factors responsible for the occurrence of plant disease [77]

out the effect of soil moisture on the development of disease. The main findings of the study showed that plants develop minimal disease at a temperature range from 27°C to 30°C and is completely immune to the disease in the temperature range from 19°C to 20°C. Similarly, the most suitable soil moisture content for the development of plant disease is from 30% to 33%, and minimum disease conditions are achieved in soil moisture from 13% to 14%. A decrease of soil moisture from maximum disease to minimum disease range results in the reduction of host plant vegetative strength. Soil moisture ranging from 23% to 33% was most favored for plant growth but strong development of disease was observed. Soil moisture from 18% to 19% shows resistance to disease but leads to a reduction in vegetative strength of growth. Plants grown in 13% to 14% of soil moisture showed maximum resistance to diseases but brought the plants near-permanent wilting. Thus, at low moisture content plant loses their resistance to disease, and at soil moisture content nearby to saturation i.e 35% or above plants were immune to disease but the reduction in moisture content result in the development of disease. The most suitable temperature for disease development ranges from 25°C to 30°C. Several works of literature are available to show the effect of air temperature and humidity on plant growth. Solar radiation, air temperature humidity, and evaporation effects the flower and boll production in Egyptian cotton. The primary weather

conditions that have a reasonable impact on crop growth, experimented for rice, are wind speed, air temperature and humidity, solar radiation, and precipitation [77, 78, 79, 80, 81].

The wind is also an important factor and can affect the regeneration and changes in the successional stage of plants. Strong wind can cause damage to crop, urban plants, and forest plants. Many of the crops such as cereals and herbaceous crops including woody plants can recover from damage if there is sufficient availability of nutrients and water. All plants suffer from damage to leaves or young plants due to abrasion, resulting from the wind. In an experiment, *Fetucaarundinacea* Schreb developed ruptured epidermal cells, cracking of cuticle, and smoothing and redistribution of wax deposits damage when exposed to the wind at 3.5 m/s. similar damages were also noted for strawberry *Fragaria sp.*, wild grass *Molinia caerulea*, Moench, and seedling of *Acer pseudoplatanus*. Wind also induces leaf tearing which will result in increased water loss. Crop lodging reduces the yield of cereal crops, and oilseed rape and has a negative effect on grain quality. Damage to crops by wind includes the lodging of wheat, oats, barley, maize, grain sorghum, and oilseed. Losses in yield of about 31% - 80% for wheat, 28% - 65% for barley, 37% for oats and up to 50% for oilseed rape have been reported in different studies. Plant surface temperature is also affected by wind speed. Earlier it was a general viewpoint that transpiration increases with wind speed, but the studies show that increased wind either does not affect the rate of transpiration or decreases it. For C3 plants 30°C temperature is the most optimum temperature for photosynthesis, cell division, and growth and in the temperature ranging from 40°C to 45°C, irreversible damage occurs. C3 plants include crops such as wheat, rice, barley, rye, oat, soybean, peanut, cotton, sugar beet, tobacco, potato, cotton, and all trees and shrubs of the tropics, subtropics, and the Mediterranean [112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131].

In Precision Agriculture, as per the survey of the literature, it has been found that soil temperature, soil moisture content, air temperature, and humidity, wind speed and direction, rainfall, and intensity of solar radiation play very important role in plant/crop growth and irrigation planning in Precision Agriculture based on these parameters may have a great economic impact due to improved irrigation water usage efficiency, crop yield, and crop yield quality. For this, the Internet of Things is the most suitable

technology, but there is a requirement of power-efficient, long-range, cost-effective, scalable, and reliable wireless technological WSN options for real-time and mobile monitoring of important parameters in Precision Agriculture. Many Low Power Wireless Wide Area Networks (LPWAN) technologies are available such as SigFox, Narrow Band (NB) – IoT, GPRS/3G/4G, RFID, NFC, WiFi, Bluetooth/BLE, and many more. After analyzing the pros and cons of all technological solutions available, LoRa win the race and come out as the most favored contender for the IoT for irrigation planning in Precision Agriculture.

2.6 SMART CITIES AND URBAN FARMING

It was in 2007 when the population inhabiting urban centres overtook the rural population. [82]. Humans invented and developed cities intending to ensure security, demonstrate the benefits of living together, short mobility distances, enhanced quality of life, and easy resource management. The population of urban centres or cities around the world is constantly growing, and cities now house half of the world's population, although occupying only about 3% of the Earth's land surface [83, 84]. By 2025, the city's population is anticipated to be 3.59 billion, compared to the world's population of 7.99 billion, according to predictions made in numerous literary works. [85], up to 66% population will be residing in cities and this is as per the United Nations [86], 60%-70% of world population by 2050 [87]. Communication is a vital component of smart cities, including energy communication, information systems, monitoring devices, and service control, among other things [88]. Various works of literature have discussed and emphasized the importance and relevance of Information and Communication Technology (ICT) [139, 140, 141, 142, 143, 144, 145, 146, 147, 132, 134, 148, 149, 138, 150, 151].

ICT has been an important tool to enable smart cities [88], and it is necessary to develop the ICT-based infrastructure for resource optimization. Smart cities has integrated 2.0 technologies with ICT to provide innovative and feasible solutions to urban planning [89], ICT has been utilized in urban area functions such as transportation, healthcare, water, waste, and many more [82] [90]. ICT has been identified as a most critical component in smart city infrastructure [91], ICT, in conjunction with modern

technologies, is the key to smart cities [86], ICT plays a role of key enabling technology for mutating traditional cities into smart cities [92], integrates and coordinates city services, allowing for efficient and rational resource utilization [93]. There is a lack of knowledge and awareness of the trends, concepts, technologies, and links between technology and smart cities [94]. When it comes to defining the smart city, there are several definitions available in various published works of literature, spanning from technological to social factors. In [86, 95, 89, 83, 96, 97, 98, 99, 82, 88] smart city is described as a city that uses digital technology and ICT to boost the city’s development and also improves the sustainability of the city. Electronic and digital technologies, Information Technology, ICT, and the integration of smart ICT and people are the main characteristics of intelligent cities. Education, industry, technical infrastructure, economy, government, environment, participation, living, mobility, and people are all components of smart cities, according to [100]. A smart city is a place where electronic and digital technologies, as well as information and ICT, are used to build a cyber digital knowledge-based metropolis with specific goals as mentioned in Figure 2.10 [92, 99, 101].

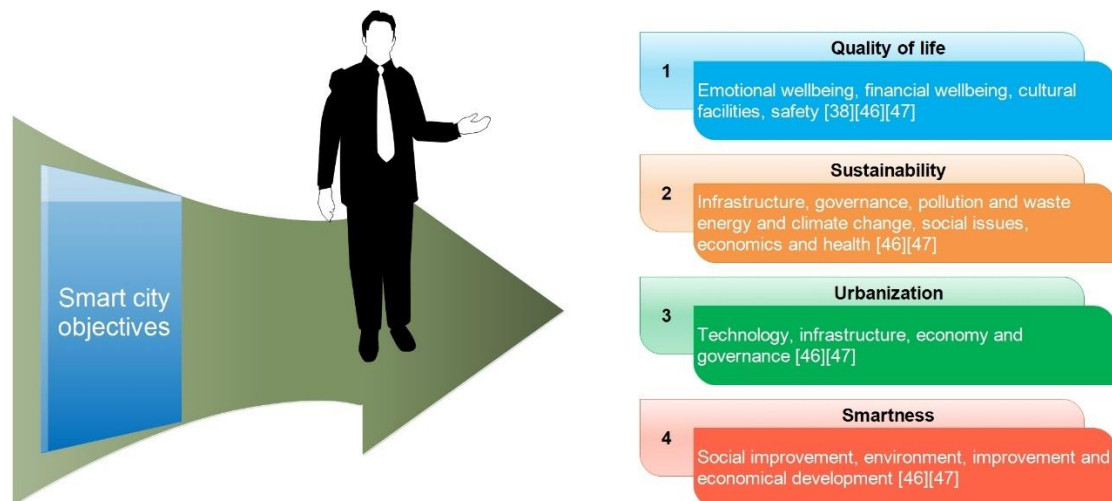


Figure 2.10 Smart city objectives and their aspects [92, 99, 101]

ICT infrastructure along with smart devices and networks supports in the accomplishment of smart cities objective. Six primary characteristics of smart cities have also been highlighted in the literature, including smart economics, smart people, smart governance, smart transportation, smart environment, and smart lifestyle. Each

smart city component or application has its own set of sub-aspects or applications as elaborated in Figure 2.11 adapted from [156, 152, 140, 147, 149, 138, 159, 160, 161, 150, 162, 163, 164].

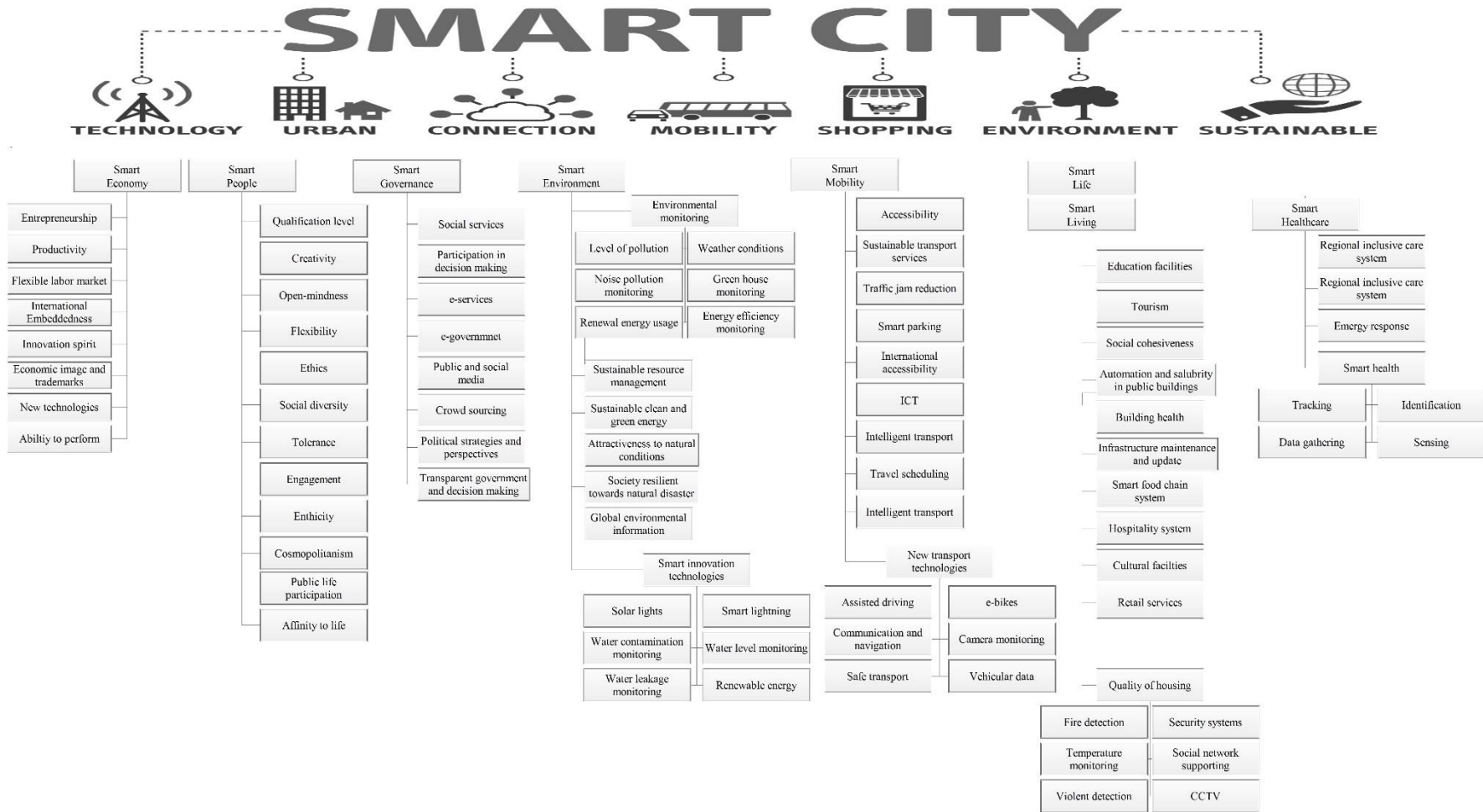


Figure 2.11 Smart city concept and applications [156, 152, 140, 147, 138, 159, 160, 161, 150, 162, 163, 164]

2.6.1 IoT KEY ENABLING TECHNOLOGIES FOR SMART CITIES

Article [102] discusses the smart city model of Barcelona. The authors argue that smart city technologies must be examined in both hardware and application. Furthermore, because of the many technologies and management devices used in smart cities, sensing is heterogeneous. The authors have considered sensing capabilities, gateways, transportation networks, data administration, and front-end applications to be the major parts of a smart city in terms of implementation. The IoT technology utilized in smart cities is termed "Urban IoT," and it intends to offer connectivity infrastructure for citizens to access public services. The capacity to connect multiple technologies of communication infrastructure and to realize unexpected functionality are the characteristics of "Urban IoT" [103, 104].

At the root level of a smart city, the authors have proposed an architecture for "Urban IoT," which includes IoT, sensors, actuators, and a wireless access network. IoT-enabled devices are getting increasingly sophisticated and smarter. Smart, intelligent, and self-configuring items connected over a worldwide network created the framework for a smart city. The IoT provides a unique technique for linking a city's digital services to its residents. According to the network type – scalability, heterogeneity, end-user participation, and adaptability are some of the characteristics of smart cities. RFID, WSN, WiFi, WPNA, WLAN, GSM, 3G, and other smart city technologies are listed in [104].

Smart cities rely on IoT as a crucial technical infrastructure [105], and smart cities are an essential use of IoT [106]. IoT is defined as "a set of technologies for accessing the data collected by various devices through wireless and wired internet networks". The goal of a smart city is to use energy and power efficiency while also providing decent infrastructure for society. The IoT has exploded in popularity. Furthermore, with the growth of various types of networks and technical advancements in the areas of ubiquitous computing, M2M communication, and WSNs [101], the importance of IoT in smart cities is amplified even more. In a smart city, the development of IoT-based technology for diverse functions offers inhabitants sustainable and fulfilling living circumstances.

A smart city is known by a variety of titles, including "cyberville," "digital city," "electronic city," flexibility, and so on. However, the term "smart city" is more often used since it encompasses other city identities. The IoT has been named as the technological foundation of a smart city and possesses three essential characteristics: intelligence, instrumentation, and interconnection [92]. These three characteristics are in line with the objective of tracking, locating, managing devices intelligently identification, monitoring, and timely improvements in communication technologies between humans and machines, or things, or between machines.

The essential enabling smart city technologies for transforming conventional cities into smart cities are ICT, IoT, and Big Data. The integration of IoT into city infrastructure makes the notion of a smart city a reality [107, 92, 95, 105, 106, 107]. The three key technologies—IoT, ICT, and Big Data—recognized in the transformation of a conventional city into a smart city are interconnected since one depends on the other. By linking all other elements of the smart city, ICT is the most important of the three key technologies. Thanks to ICT infrastructure, city services like taxi service and NFC-enhanced credit cards are available [92]. The various communication technologies utilised in the IoT for data transit include NFC, Bluetooth, fibre optics, WiFi, LTE, RFID, 6LowPAN, UWB, Zigbee, GSM, GPRS, and Bluetooth Low Energy. [95, 92, 103, 104, 102]. NFC is mostly utilized for short-range communication, whereas RFID was the first technology used for M2M communication. UWB allows for high-bandwidth transmission within a short communication range. LoRa and SIGFOX are two technologies that have lately found their way into the smart city, in addition to the well-known wireless communication technologies. SIGFOX is an ultra-narrowband radio technology that offers a scalable network for smart cities [95], and the LoRaWAN protocol facilitates interoperability in smart cities. Different communication technologies are described, along with their applications, coverage ranges, and technical specifications, and different WSN technologies used in IoT are categorized based on their coverage ranges and power consumption [108] [109, 110]. Aside from range and battery consumption, IoT communication technologies are classed depending on whether or not they are 3GPP members [111] and whether or not they are licensed

or unlicensed technologies [50]. For IoT applications in smart cities, numerous wireless communication technologies are categorised as presented in Figure 2.12.

2.6.2 URBAN FARMING

Figure 2.11 depicts smart city applications, whereas Figure 2.12 depicts the different main supporting technologies for smart cities. Aside from the applications represented in Figure 2.11, agriculture is one sector that plays an essential role in the economic and environmental protection theme [101] and sustainability target [86] of smart cities, although it is not often recognized as a key component.

The increased city population, poverty, and unemployment are all favourable conditions for urban agriculture growth. Urban agriculture provides food, environmental, and health-related alternatives in urban settings, as well as contributes to the local economy and social integration. Plant cultivation and animal husbandry for consumption and income are examples of urban agricultural operations. "Production in the house or plots in urban or peri-urban regions" is how urban agriculture is technically defined. Urban agriculture feeds the city by utilizing municipal resources and is impacted by unanticipated circumstances such as quality requirements, land contests, and so on. It is critical in improving socioeconomic circumstances in metropolitan areas by increasing food security, health, and the environment. The development of urban agriculture is affected by many factors as shown in Figure 2.13 [87].

Wireless communication technologies

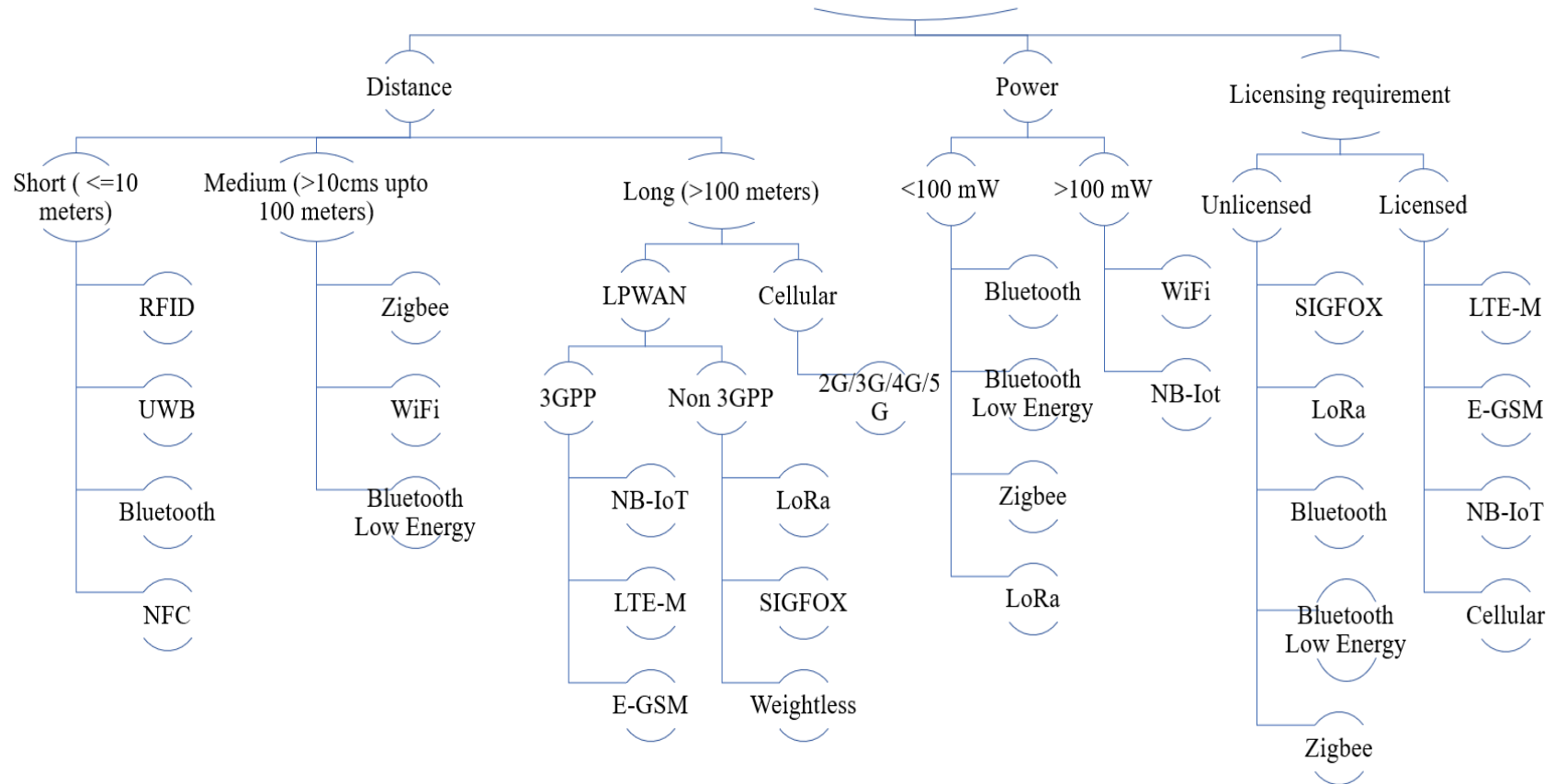


Figure 2.12 IoT wireless communication technology classification [108, 109, 110, 50]

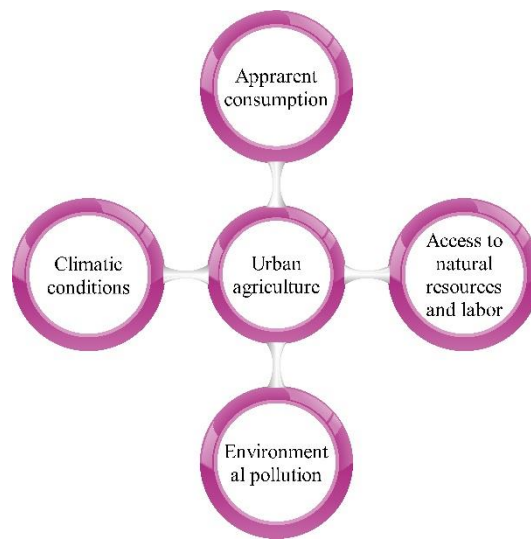


Figure 2.13 Factors affecting the growth of urban agriculture [87]

Urban farming is “food or livestock growth or process that are undertaken within an urban area or around the urban centers with the purpose to generate income”. There are three forms of urban farming: community farming, vertical farming, and rooftop farming. Urban farming may be done on roofs, city grounds, balconies, and vertical walls. Urban farming increases the city's green space, gardens for recreational purposes, and urban reinvigoration while also conserving the city's ecosystem and ecology. Figure 2.14 depicts the four possible benefits of urban agriculture suggested in [112], as well as the related elements.

Livestock management, agricultural cultivation, aquaculture, and poultry are a few examples of urban agriculture activities [113]. Clothing, building materials, and medicinal plants are just a few of the supplementary needs that are expected from urban agriculture. Agriculture has infiltrated city limits, where it is advantageous to trade due to the availability of modern logistics, low-cost labour, and a large scale of production [114]. Farming in cities is also becoming more digital, with "Digital Urban Agriculture" (DUA) leveraging silicon-based gear and software to automate agricultural activities. Urban agriculture has also increased property values by roughly 9% and is credited for reducing food insecurity and enhancing livelihoods by providing easy access to food. It's also intertwined with symbolic and cultural shifts [115].

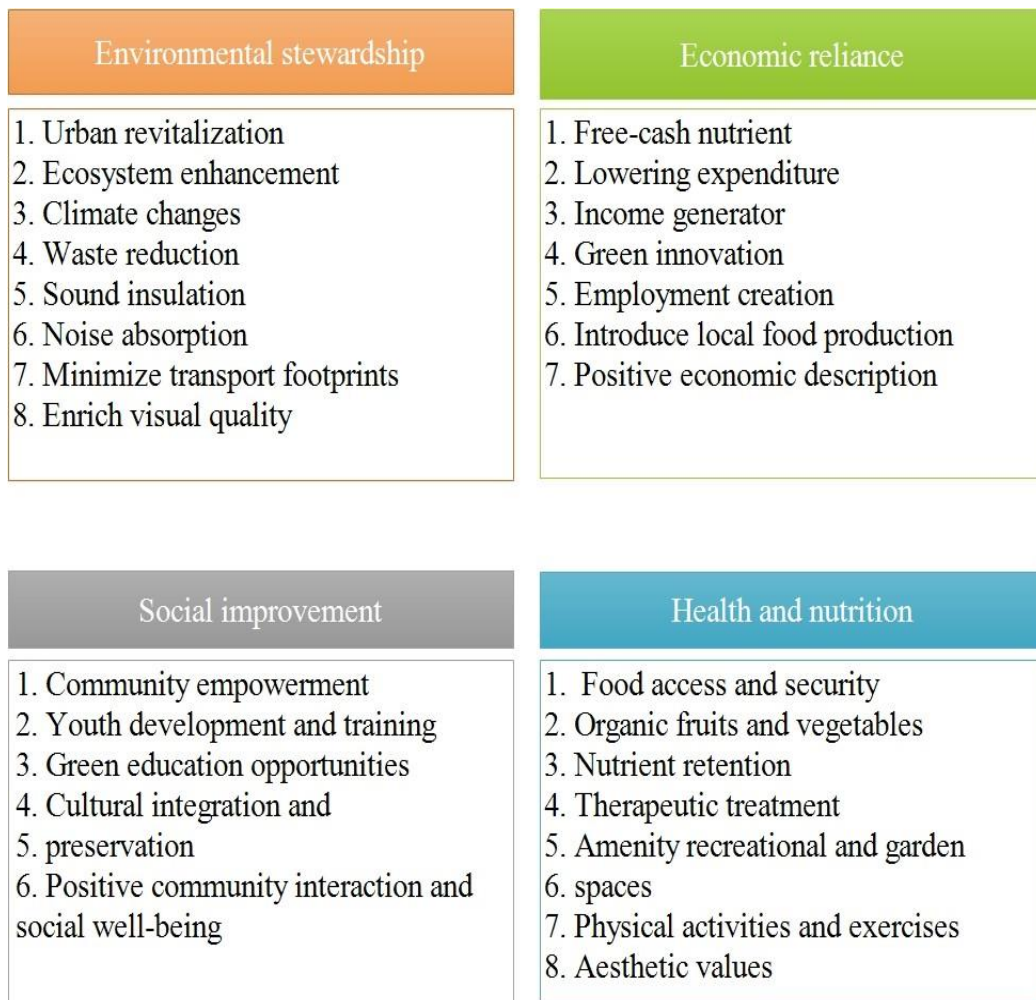


Figure 2.14 Benefits of urban farming [112]

Both rural and urban farming encounter several obstacles, with just a handful of them being universal. High land value, limited land area, and polluted soil are some of the obstacles particular to urban farming discovered by literature review, social establishment, and observations. Learning and adopting new technologies, investment possibilities, transportation, and rapidly dwindling freshwater sources are all major issues for rural farming. Feeding a rapidly rising population, crop damage from birds, inefficient use of agricultural resources such as irrigation water and fertilizers, and quickly dwindling fresh water supplies are just a few of the issues that both rural and urban farming confront. The current project focuses on precision irrigation (the effective use of irrigation water).

2.6.3 IRRIGATION IN URBAN FARMING

Fertilization, pesticide treatment, plant growth regulators, and, most crucially, irrigation is the key operations connected with crop production in agriculture [87, 116, 117, 114]. Water is a critical component of urban plant maintenance, and determining soil type, plant kind, and season has a significant influence on irrigation planning. Many plants need to be watered after they are planted, and if they are not adequately irrigated, they get stressed, affecting their growth. Over-irrigation, like under-irrigation, pollutes other water resources by resulting in food, running off soil nutrients, and necessary chemicals [118]. A range of accessible helpful instruments, like rain and soil moisture sensors, may be used to monitor and regulate both over and under irrigation. It has been observed that reference evapotranspiration-based irrigation adaptation can save up to 62 percent of water when used to predict the irrigation needs of plants or crops [119, 120, 121]. Irrigation is important in areas where plants are not adapted to climatic conditions and need to be irrigated [121].

Water shortage, high dependency on irrigation [11, 12, 122] along with erratic rainfall and high temperatures are some of the obstacles to plant development, and it is discovered that the majority of irrigation water is lost due to inefficient use. Wastewater treatment, which permits it to enter watercourses for irrigation, is one possible solution to the problem. Aside from that, different IoT-based systems are being developed, such as iRain and soil moisture-based irrigation systems. Irrigation is scheduled with IoT-based irrigation systems based on weather predictions and soil moisture estimates, resulting in large-scale resource and energy savings [123] [124]. For better sustainability in urban living, less effective and unsuitable irrigation scheduling must be addressed. Inefficient irrigation planning may lead to a 700% increase in water use. Evapotranspiration and weather station data are used in the article [119] to plan irrigation for the park. In the context of water scarcity and the necessity for efficient water use, the article has also included smart irrigation as a component of the overall concept for smart cities. The indirect method based on reference evapotranspiration and the direct method based on soil moisture sensors are the two different approaches available for predicting plant water needs.

With a growth in the global population and a decline in agricultural areas, providing

enough food to the growing population is becoming increasingly difficult. Precision agriculture is being utilized to raise the efficiency of the agricultural sector. Precision agriculture is a way of increasing the efficiency of agriculture by optimizing food output while minimizing environmental effects. The application of precision agriculture is mostly dependent on three key parameters: real-time monitoring and data collecting, data analysis and decision making, and lastly required treatment of crops depending on the decision. IoT makes it simple to meet all three of these goals. The IoT offers a network architecture with smart and intelligent devices for data collecting, a facility for data processing and decision making, and ultimately the execution of the choice made. Irrigation is one of the most critical parts of Precision Agriculture, and traditional irrigation systems utilize roughly 70% of the freshwater available for human consumption, potentially resulting in water scarcity and environmental effects. Crop-demand-dependent or Crop Water Stress Index (CWSI)-based irrigation scheduling can help to enhance irrigation water efficiency [125]. Precision agriculture in urban farming aids in the management of thermal water stress and energy consumption in the city during the hot season, in addition to increasing irrigation water efficiency.

2.6.4 VARIOUS DIMENSIONS OF URBAN FARMING

The goal of a smart city is to build a smart society with a human-centered approach to sustainable development [126, 106], and a smart city is a foundation for a sustainable environment, quality of life, and excellent resource efficiency [83, 88], and a liveable existence [86, 95, 98]. Thus, smart city development strives to create a sustainable, decent quality of life, and environmental protection, and to achieve these goals, agricultural activities like crop cultivation, livestock management, planting, aquaculture poultry, and so on are described in figure 10. Article [113] makes a substantial contribution by providing food security, health [87], a source of income, enhanced city green space, and urban revitalization [112]. With urbanization and population growth, there is a greater demand for urban agriculture to achieve the goal of a smart city. Figure 10 includes practically all features of a smart city but neglects to add urban farming since, when contemplating a smart city, urban irrigation is slightly overlooked in all published literature. Figure 2.15, taken from [87, 117, 112, 113, 119, 124, 127, 128, 129, 130], depicts the many characteristics of urban agriculture.

Precision agriculture use technology to monitor many agricultural characteristics for optimal planning and resource management. IoT also plays a role in this by collecting data using smart devices, analysing data, and making decisions.

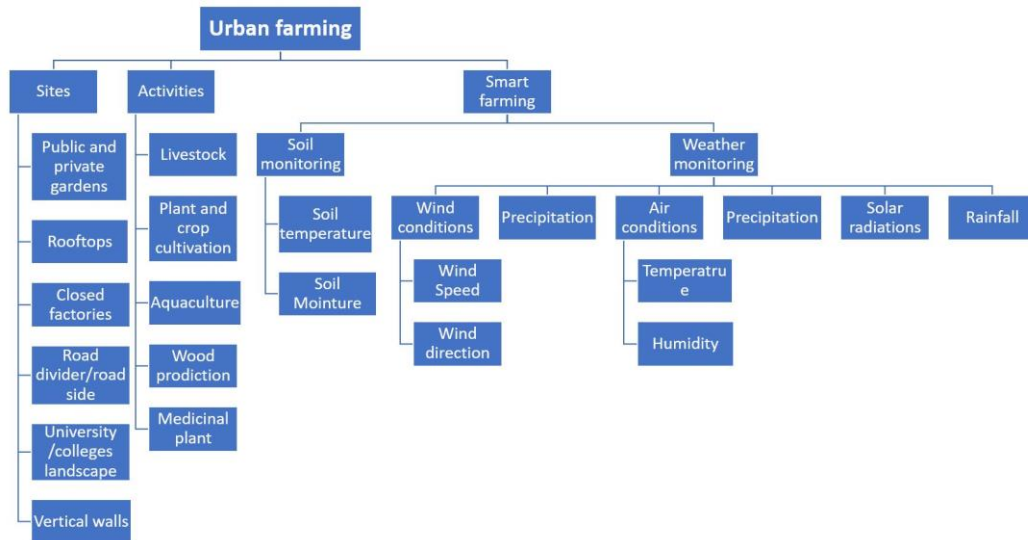


Figure 2.15 Various dimensions of Urban farming [87, 117, 112, 113, 119, 124, 127, 128, 129, 130]

2.7 MACHINE LEARNING

Machine Learning is becoming more and more popular due to increased computational power, enhanced algorithms, and availability of huge and ever-increasing data [131]. Machine Learning can be defined as a technique that enables computers to predict things based on past experiences. With the increased storage and improved processing power of computers, Machine Learning has witnessed magnificent development [132]. One of the definitions of Machine Learning is

“The scientific study of algorithms and computational models on computers using experience for progressively improving the performance on a specific task or to make an accurate forecast.”

In the definition of Machine Learning, the term “*experience*” signifies the available historical information about the task to the learner for developing a prediction model. Machine Learning is a branch of Artificial Intelligence (AI) enabling machines with the capability of learning from past experiences. Using Machine Learning algorithms.

Machines learn directly from dataset sets using computational methods instead of relying on predetermined equations for prediction. Block diagram ML-based systems are given in Figure 2.16. The input to the system is labelled or unlabelled data collected from various sources. The knowledge base of the system helps in deciding the suitable ML algorithm to be used for prediction [133, 134].

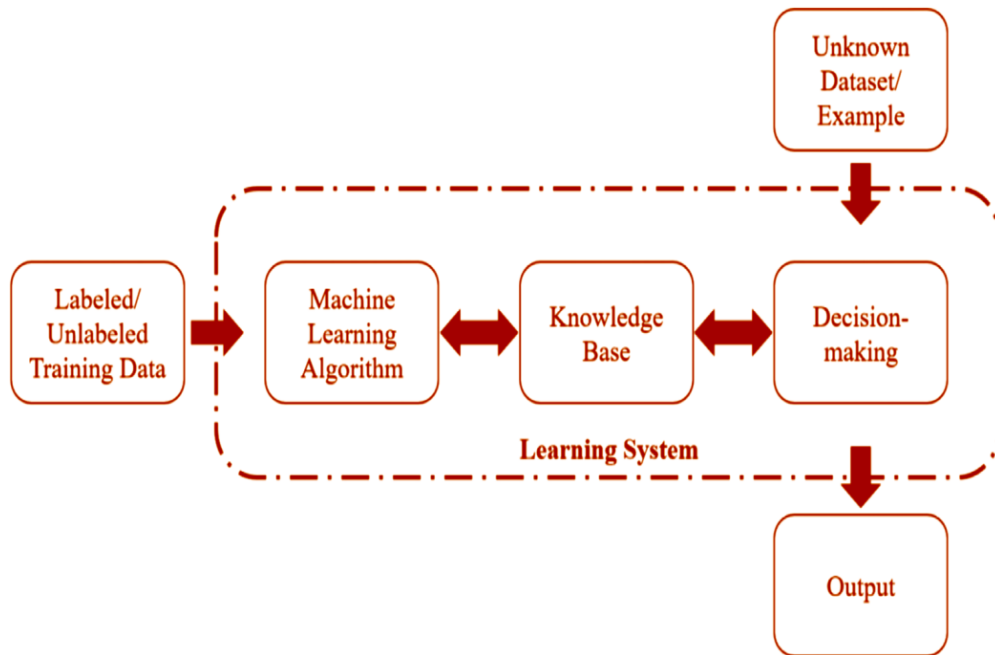


Figure 2.16 Configuration of the ML system [133, 134].

2.7.1 SUPERVISED LEARNING

In supervised learning, a dependent variable is predicted using a given set of independent variables. In this, a labelled dataset is used for the training algorithm for predicting the target variable. Regression, Decision Tree learning algorithms fall under the category of supervised learning.

2.7.2 UNSUPERVISED LEARNING

The unsupervised learning method utilizes the hidden pattern in the dataset to draw conclusions or to make decisions. Unsupervised learning is mainly suitable for applications where the information in the dataset is not clear. In this, there is no dependent variable that is to be predicted. Unsupervised learning is majorly deployed

to group unsorted data. K-means, Clustering are some of the unsupervised learning algorithms.

2.7.3 REINFORCEMENT LEARNING

In reinforcement, the learning machine learns through trial, error, and feedback methods. Machines try to capture the best suitable and accurate knowledge for decision-making. Markov Decision Process is one of the algorithms under reinforcement learning.

There are numerous Machine Learning algorithms under supervised, unsupervised, and refinement learning. The possible Machine Learning algorithms classified under various learning techniques are summarised in Figure 2.17.

2.8 MACHINE LEARNING ALGORITHMS

Machine Learning algorithms are computer programs with the capability to learn from data and improve their performance with experience, with no or minimal human intervention. Learning may include mapping of input to output, and extracting hidden structures in unlabelled (data not tagged with labels) data. This section discusses a few of the most common ML algorithms.

2.8.1 LINEAR REGRESSION

In logistic regression, the relationship between dependent and independent variables is established by fitting the best line. The line that best fits is called a regression line and is given as

$$Y = a * X + B$$

Where:

Y=Dependent variable

a=Slope

X=Independent variable

B=intercept

2.8.2 LOGISTIC REGRESSION

Logistic regression is a classification algorithm to estimate distinct values such as 0 or 1, Y or N. It is used in binary classification problems, to predict the probability of an event between 0 and 1.

2.8.3 LINEAR DISCRIMINATION ANALYSIS (LDA)

LDA is also a classification algorithm but is used when more than two classes are present against logistic regression which is used when only two classes are present. It is most commonly used for feature extraction in pattern classification problems. It is mainly used for the distribution of variables into two or more classes. Figure 2.18 illustrates the classification of objects before and after the implementation of the LDA algorithm. LDA is straightforward in both preparation and application. LDA looks for

1. Which set of parameters best describes the group's association with an object?
2. What is the most effective categorization preceptor model for distinguishing those groups?

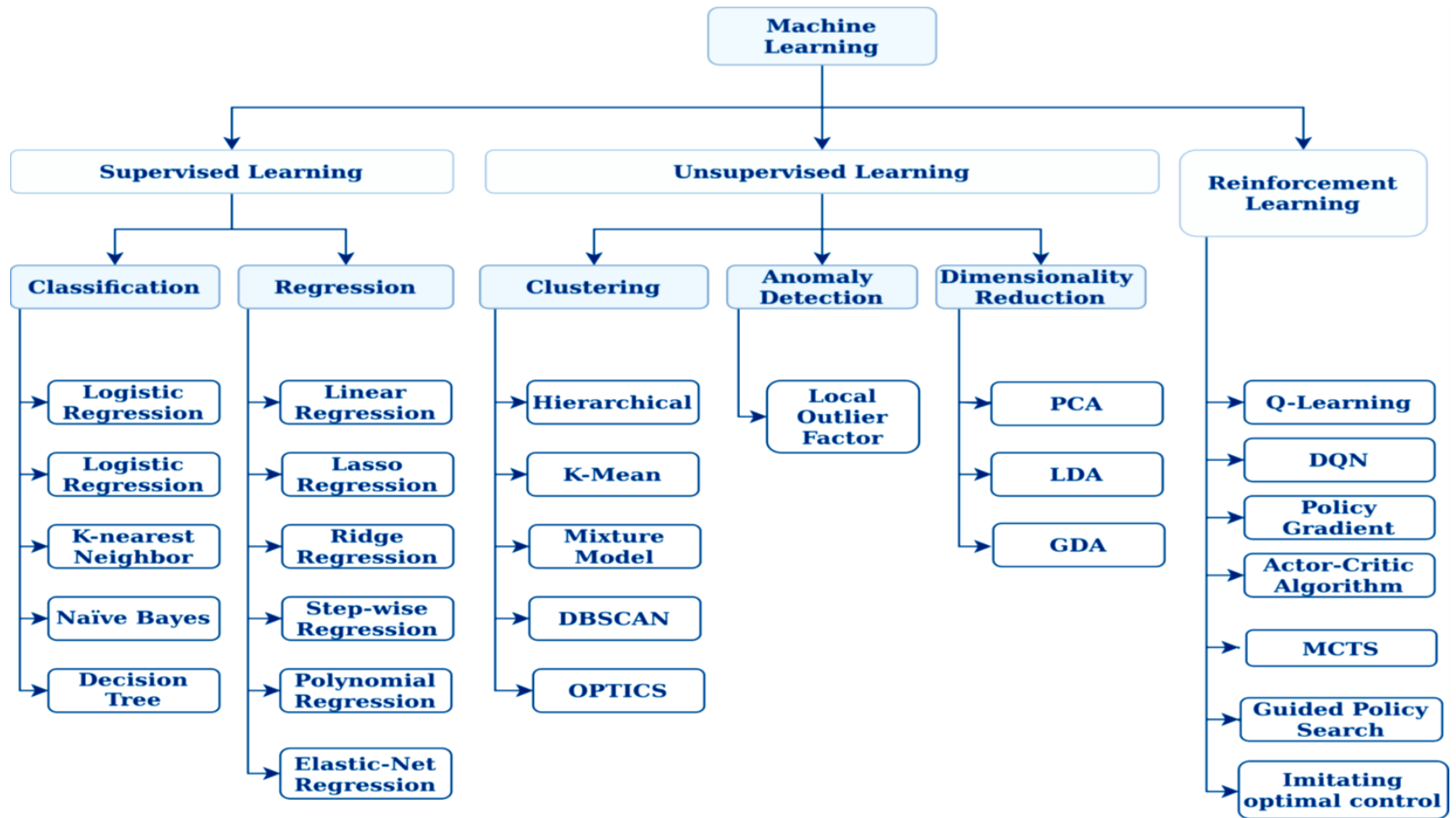


Figure 2.17 Supervised, unsupervised, and reinforcement learning algorithms [134, 135]

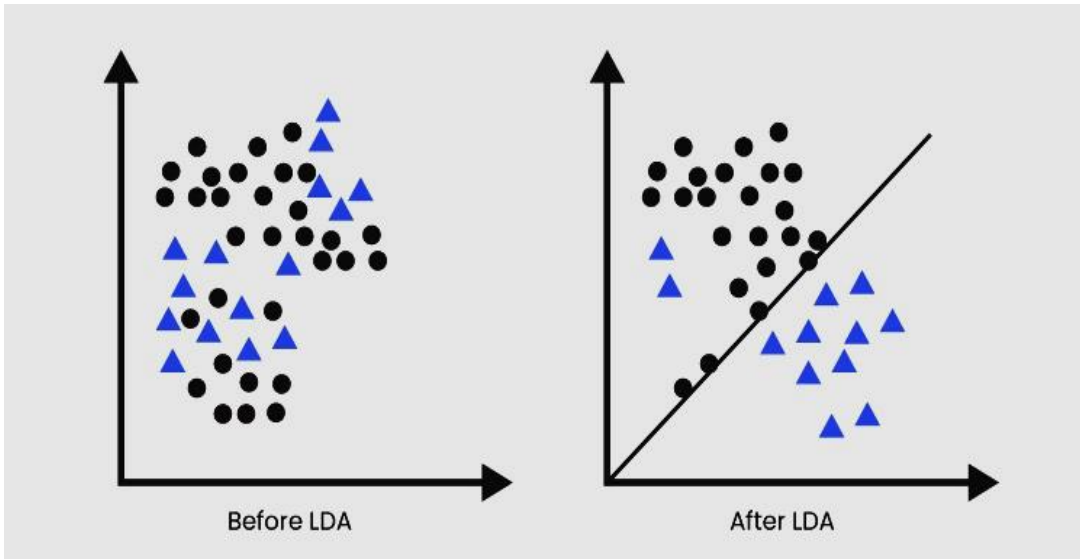


Figure 2.18 Illustration of Linear Discrimination Analysis learning algorithm [136, 137]

2.8.4 DECISION TREE (DT)

The decision tree is used for classification problems and is suitable for both discrete as well as continuous dependent variables. In this, the decision tree is used to illustrate decisions and decision-making. Figure 2.19 give the decision tree for predicting whether the passenger will survive or not from the titanic dataset.

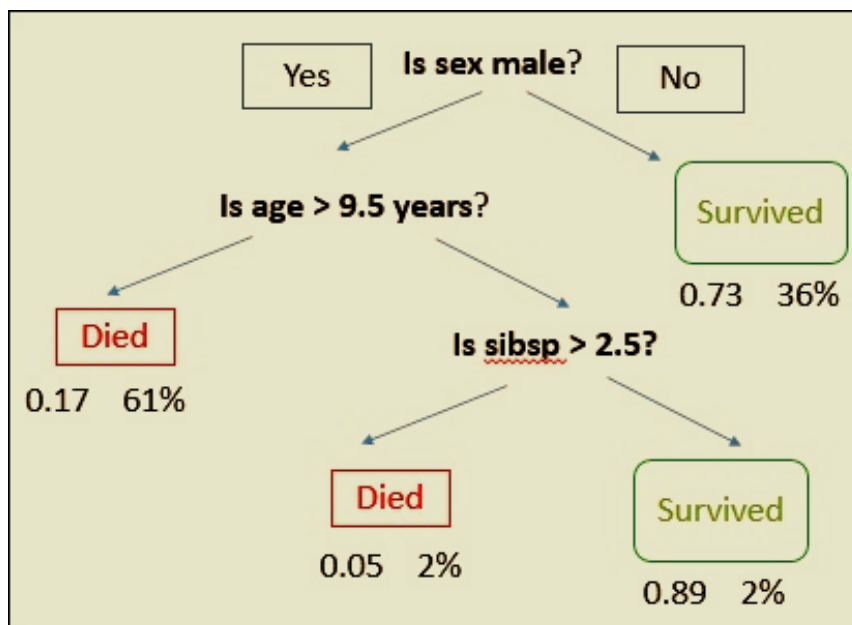


Figure 2.19 Decision Tree [136, 137]

2.8.5 SUPPORT VECTOR MACHINES (SVM)

SVM is a classification algorithm to separates various categories of data by optimizing the line in such a way that the closest points in each group are far away from each other. This vector is assumed to be linear but can take a nonlinear form under certain conditions. Figure 2.20 illustrate the SVM with only two features **Height** and **Hair length**. The line that separates the data into two different classification groups is such closest point in each of the two groups will be the farthest away.

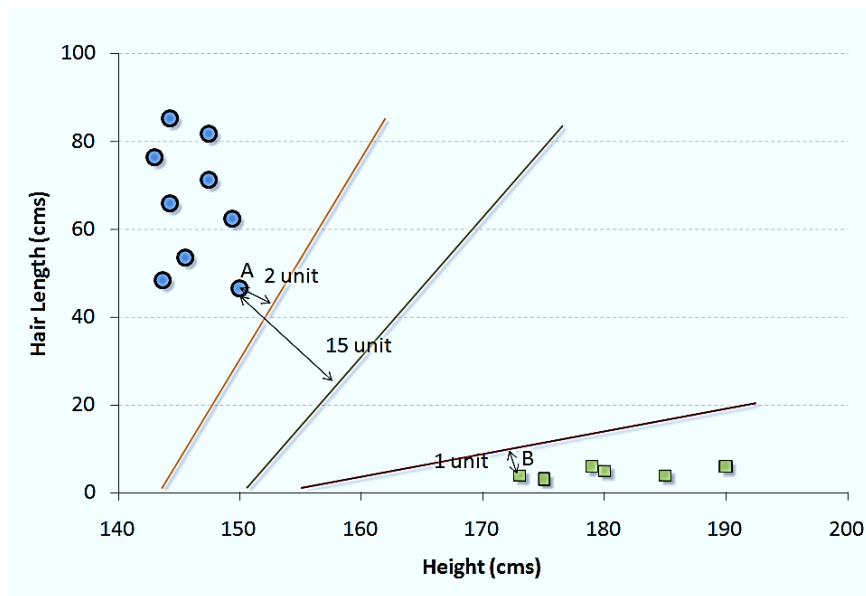


Figure 2.20 Illustration of SVM [136, 137]

2.8.6 NAIVE BAYES (NB)

NB is based on the Bayes theorem and is a classification technique that presupposes that a particular feature present in a class is very much dissimilar to any other feature. NB is simple, useful in handling big datasets, and is known for its good performance.

2.8.7 K-NEAREST NEIGHBOUR (KNN)

KNN classification works by storing all variable cases and classifying the new cases based on the majority vote of its K-neighbours. The functions namely Euclidean, Manhattan, Minkowski, and Hamming distance are used in KNN for assigning a case to a class. KNN can be used for both types of problems i.e., classification and regression

problems Euclidean, Manhattan, and Minkowski functions are used for continuous functions while the fourth one i.e., Hamming distance for categorical variables.

2.8.8 K-MEANS

K-means algorithm is used in clustering problems. Its process follows a simple and straightforward method of classifying a given dataset using a set of clusters with homogenous data points inside the cluster. The data points are heterogenous to peer groups.

2.8.9 RANDOM FOREST

Random forest is a popular ensemble learning algorithm, which takes a few of the “weak learners” and makes them work together to obtain a well-developed predictor. The weak learners are randomly implemented in a decision tree that is combined to produce a powerful predictor-a random forest [136, 137].

2.9 MACHINE LEARNING IN AGRICULTURE

As the world's population continues to grow, the pressure on agriculture will rise. Precision agriculture, often known as digital agriculture, is technology-oriented agriculture, for maximizing the use of agricultural resources such as fertilizers, insecticides, and, most critically, irrigation water. Now with machine learning being used in agriculture, it is possible to gain a better knowledge of the data-intensive processes that occur in the agricultural environment. The machines were given the capacity to learn thanks to machine learning. Figure 4.6 depicts the various areas of agriculture that have benefited from machine learning.

Technology is crucial in many agricultural fields, including animal welfare, livestock management, yield prediction, disease and weed detection, crop quality, species identification, water management, and soil management. Only 10% of the study is focused on water management, whereas over 61% is focused on crop management. However, crop management is influenced by water management, such as water quality and irrigation. Crop production prediction, crop disease detection, crop weed

identification, animal welfare, and a variety of other agricultural applications benefited from machine learning, as shown in Figure 2.21. Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Gaussian Naive Bayes (NB) are some of the machine learning techniques that are commonly employed in agriculture [138].

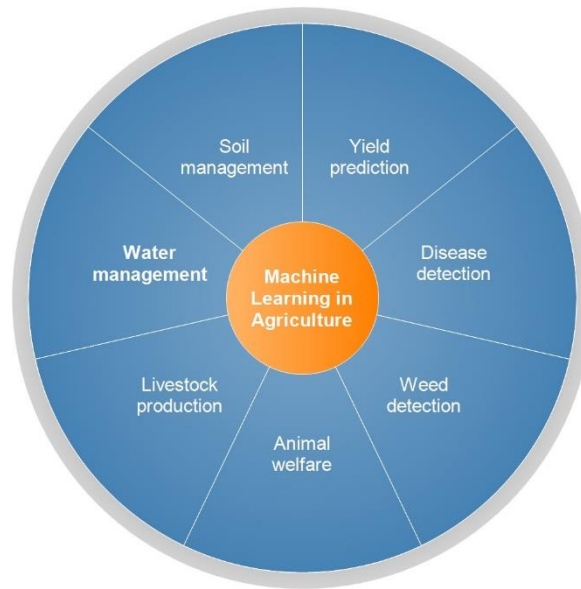


Figure 2.21 Agricultural application utilizing machine learning

Machine learning is an iterative process, and the performance of the system under training improves over time as it gains more experience. Upon successful completion of the training phase, the model that has been trained may be used for classification, prediction, and the generation of fresh testing data. A typical Machine Learning strategy comprises a training dataset that is provided to a Machine Learning algorithm for training. Once the training process is complete, the trained algorithm is used to predict and classify unknown data, and the method is then deployed. Digital agriculture has arisen as a new sector to improve the efficiency of traditional agricultural processes, particularly irrigation, which are currently inefficient. A constant expansion in the global population is placing a growing strain on agriculture, which is causing it to struggle to keep up. New agricultural technologies must be developed to maximize the efficiency with which agricultural resources such as fertilizers, insecticides, and, most significantly, irrigation water are used. As a result, machine learning in agriculture has opened up new avenues for comprehending the data-intensive processes that are

associated with livestock, soil, crop, and water management that are all part of today's agricultural environment. Machine Learning enabled machines to acquire the capacity to learn on their own. Machine Learning has been utilized in Precision Agriculture, according to research and published literature, for soil management, animal management, crop management, and water management, to name a few applications. Figure 2.22 depicts machine learning techniques that are used in precision agriculture for soil management, animal management, crop management, and water management, among other applications. In Figure 2.22, it can be observed that Machine Learning is being used to enhance practically all agricultural operations, including water management in agriculture [133, 138, 139].

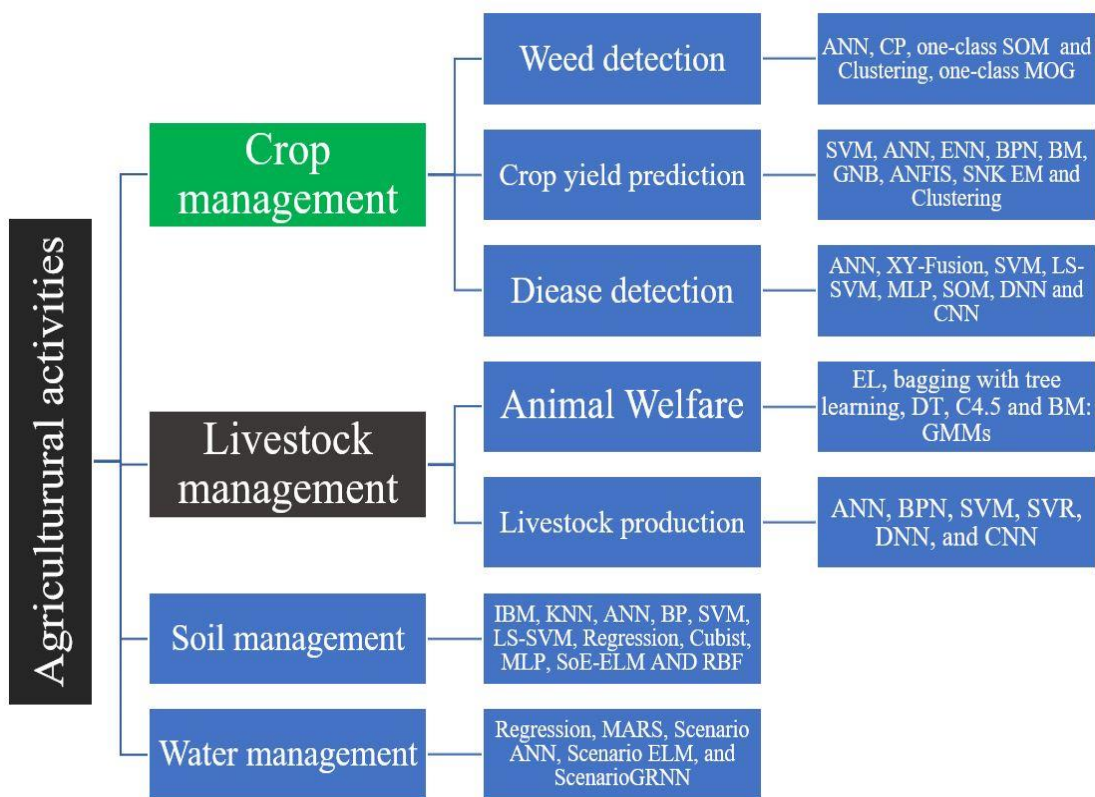


Figure 2.22 Machine Learning algorithms deployed for Agricultural application

Water management, or precision irrigation, is critical because, as previously stated, the world's freshwater resources are limited, and less efficient traditional irrigation methods result in the overuse of irrigation water, as well as changes in soil properties and a reduction in crop yield quality and quality. IoT-enabled machine learning not only

offers irrigation monitoring and control tools but also aids farmers in irrigation planning by anticipating crop water needs for appropriate irrigation. The numerous Machine Learning algorithms utilized for water management in agriculture based on evapotranspiration and dew point temperature are summarised in Figure 2.23 [140, 141, 142].

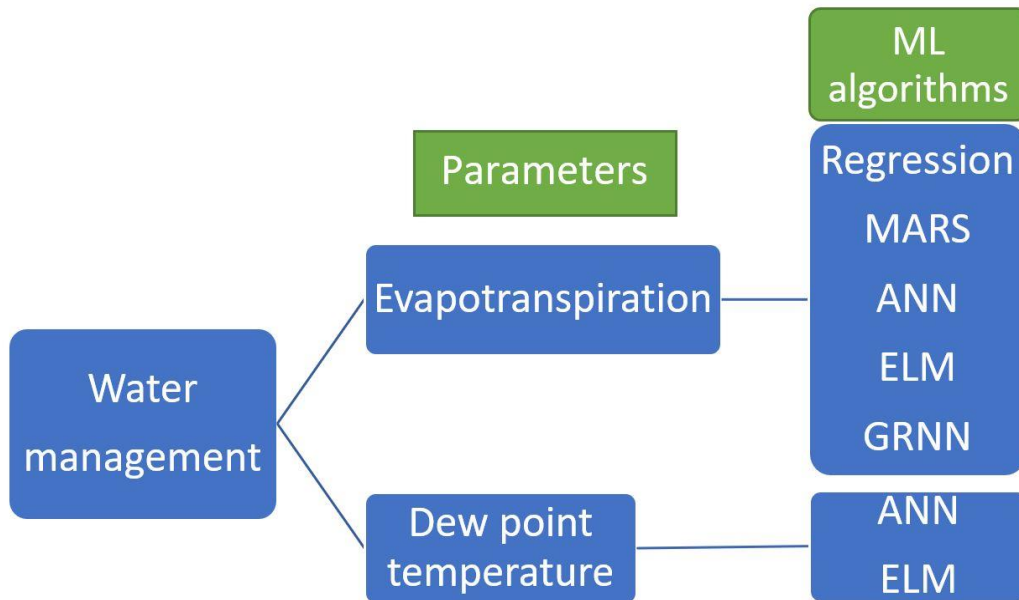


Figure 2.23 Machine learning in water management

In article [132], it is addressed how irrigation planning based on crop water stress management not only makes optimal use of irrigation water but also boosts agricultural productivity. Various applications of machine learning algorithms used for water stress determination are reviewed and different methods for crop water stress measurement which are highlighted in the article are shown in Figure 2.24. Crop water stress estimation makes use of various methods broadly classified into field measurement, remote sensing, and evapotranspiration [139].

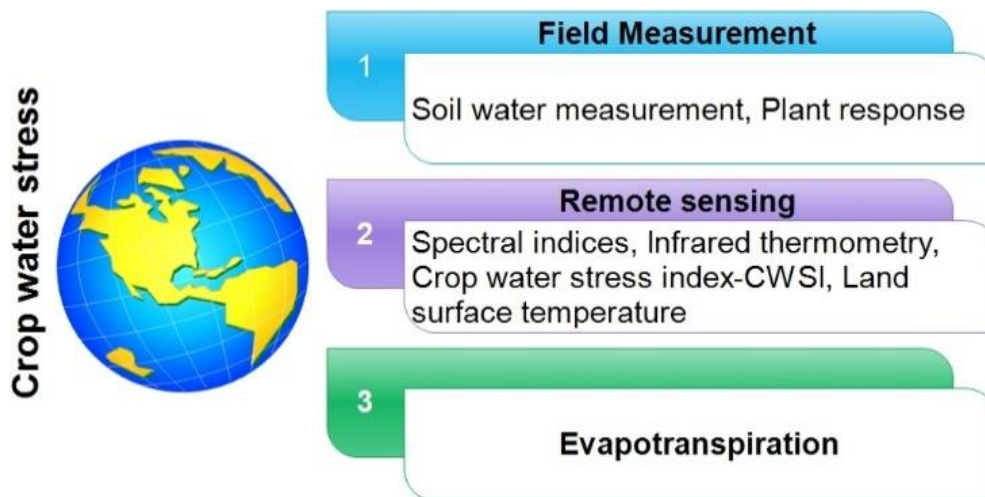


Figure 2.24 Crop water stress measurement methods [139]

Remote sensing, such as satellite imagery and photography, is also utilized to develop more precise precision agricultural systems. Precision agriculture aims to minimize production costs and environmental effects. Weather, soil qualities, irrigation, and fertilizer are just a few of the factors that influence crop output. Much emphasis is placed on Machine Learning 's ability to analyse data from a variety of sources and to cope with non-linear data. The use of machine learning requires little to no human interaction and integrates a superior knowledge-based approach. Machine Learning has been used to identify biotic stress in plants, detect illness in plants, determine physiological and structural features of plants, and recommend automated watering. SVM and KNN are two machine learning techniques that are widely utilized in agriculture [143].

2.10 CONCLUSION

This chapter deals with the literature study on IoT, WSN, LPWAN, LoRaWAN, and the important agrometeorological and agronomy parameters for irrigation requirements for the crop. The chapter explains the historical background of IoT and how IoT has been exploited in agriculture and smart cities focusing the key IoT technologies. This chapter also compared the various IoT wireless communication technologies for their offered capabilities. In the last agricultural parameters playing a decisive role in crop growth and irrigation planning is explored

This chapter also discusses the concept of urban agriculture and the need for PI in urban agriculture. Along with other applications of the smart city such as smart logistics traffic management, smart home agriculture is also an important element of smart cities. In urban agriculture also IoT including ICT, WSN, and Big Data plays an important role. The chapter discusses the definition and important aspects of the smart city to explore the importance and need of urban agriculture. Key enabling technologies for smart cities are provided. In the end, various aspect of urban agriculture is presented. In the end of the chapter, Machine Learning, techniques of Machine Learning, various Machine Learning algorithms, and the applications of Machine Learning in agriculture are presented. Agriculture is used in almost every agricultural practice like crop management, livestock management, soil management, and water management. But the use of Machine Learning in PI is quite limited as identified by a state-of-the-art study.

Chapter 3 DECISIVE SUPPORT SYSTEM FOR PRECISION IRRIGATION (PI – DSS)

"Design is intelligence made visible."

Alina Wheeler

Automated irrigation systems are required owing to shortage and depleting fresh water resources, increasing the irrigation efficiency, agricultural productivity. In chapter 2 it is clearly established that it is not only soil moisture that contributes towards the irrigation planning but soil temperature and weather conditions also have decisive impact on irrigation planning. Most of the automated irrigation system developed only focusses on soil moisture monitoring and uses short distance communication technology to monitor the soil. This chapter presents the design and development of the proposed long-range PI-DSS system.

3.1 PRECISION IRRIGATION

In agriculture an artificially developed ecosystem is used for the breeding of animals and the growth of crops in order to produce food, medicinal herbs, and other goods that support and improve life. Precision Agriculture is the use of technology for gathering and analysing the various agricultural-related parameters for monitoring and controlling agriculture parameters to get better use efficiency, profitability, yield quality, and quantity. It includes keeping an eye on livestock, plants, crops, soil, and meteorological conditions. The effective use of agricultural resources is possible through Precision Agriculture. Irrigation, for instance, is crucial to Precision Agriculture and has a significant impact on the agricultural industry. Around 39 million hectares of land in India are irrigated by groundwater, which provides around 40% of the world's irrigation water. Only 4% of the freshwater resources in the world are in India, and 80% of that freshwater is used for agriculture. Therefore, for lucrative and sustainable agricultural operations, effective irrigation water use through precision agriculture is essential. [11, 12].

Monitoring soil, weather, and plants are important for efficient usage of agricultural resources. Some of the control strategies for precision irrigation in Precision Agriculture are shown in Figure 3.1. The important components of agricultural monitoring are: data collection sensors, data transfer using IoT modules, IoT cloud services, an application server for data analysis, and a monitoring device [144].

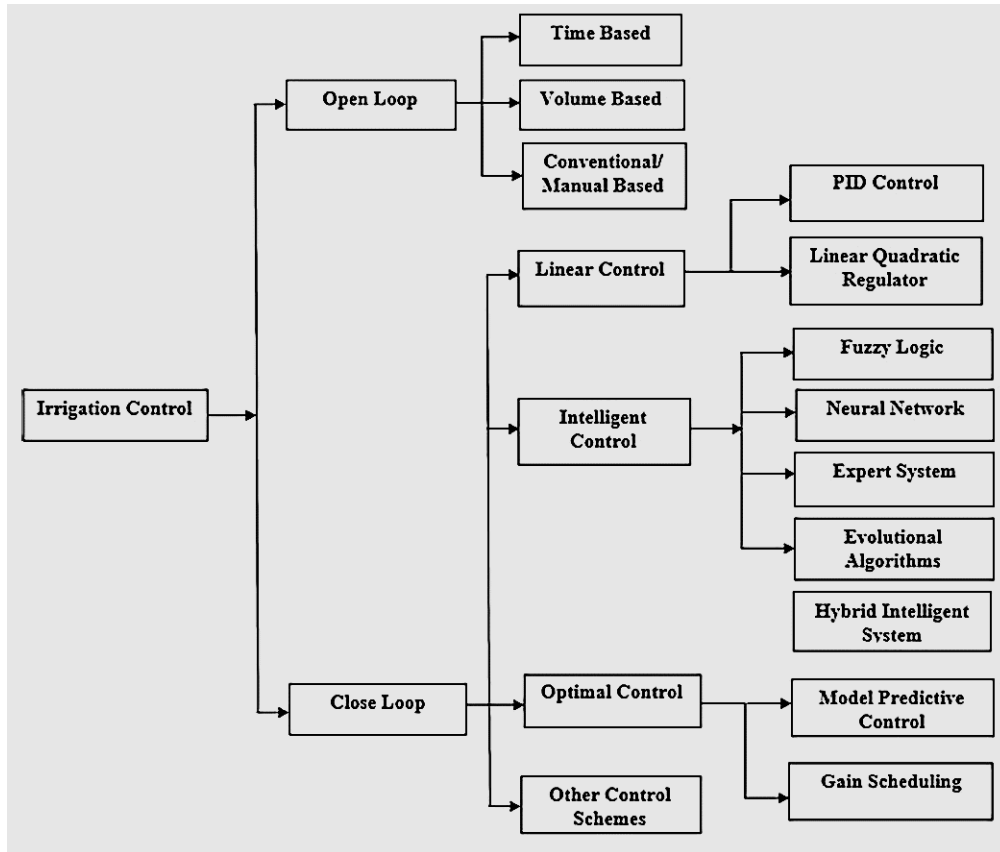


Figure 3.1 Classification of precision irrigation system [103]

3.1.1 PRECISION IRRIGATION PARAMETERS

As already discussed in chapter 2, Soil temperature and moisture, weather conditions - air temperature and relative humidity wind speed, wind direction are the most important parameters in agriculture that directly affect agricultural productivity and irrigation planning. Soil temperature and soil moisture provide the estimation of the availability of soil nutrients to plants. The optimal soil temperature as identified in the literature survey for nitrification and ammonification is 20°C to 25°C and soil moisture is 80%, for nitrogen. Soil temperature has a great influence on the water uptake by plants and

plants take nutrients through water. An increase in rooting temperature from 14°C to 26°C improves the water uptake of plants by 30%.

the temperature and moisture level of the soil are key factors in how quickly crops and plants contract diseases. It has been determined that plants are entirely immune to illness at temperatures between 19 and 20 °C and are less susceptible to disease between 27 and 30 °C. The overall yield of agriculture is also impacted by wind. Crops are harmed by strong winds by leaf tearing, crop lodging, and abrasion, which increases water loss.

It has been determined that 30°C is the optimum air temperature for photosynthesis, cell division, and plant growth. The flower and ball generation in cotton is influenced by air temperature and humidity. According to research on rice and in the literature, the key meteorological factors for crop growth include wind speed, atmospheric temperature and humidity, solar radiation, precipitation, and solar radiation. The most parameters in Precision Agriculture for weather and soil monitoring are soil moisture, air temperature, and air humidity; nevertheless, wind conditions and soil temperature are not given much priority despite having a significant impact on agricultural productivity [77, 78, 79, 80, 81, 145]

According to numerous literary works, soil temperature, soil moisture content, air temperature, air humidity, and wind conditions (both speed and direction) are the significant factors with considerable influence on overall agricultural output, quality, and quantity as well as irrigation need of crops.

3.1.2 PRECISION IRRIGATION MODELS AND CHALLENGES

IoT, WSN, mobile technology, and intelligent agricultural equipment have made it easier for farmers to embrace different Precision Agriculture practices. Using information gathered over a two-year period by 22 soil sensors, an irrigation control system is created. On the dataset, various regression and classification techniques were used. Gradient Booster Regressing provided 93 percent accuracy in prediction out of the Machine Learning algorithms chosen, and Boosted Tree Classifier provided the greatest result with 95 percent accuracy in predicting the irrigation demand. Utilizing

sensors to assess wind speed, humidity, and sun radiation, evapotranspiration—an indirect method—was utilised to calculate the crop's irrigation needs. [146].

Agriculture uses 85% of the available freshwater, primarily for irrigation. Intelligent IoT-based irrigation systems are necessary for monitoring, managing, and scheduling irrigation in order to utilise fresh water in agriculture efficiently. Different intelligent irrigation models have been developed using short-range communication, AI, Machine Learning, and remote sensing. A few of the smart irrigation systems that have been established are included in the last column, along with the issues that still need to be resolved in the current system in order to create a more effective intelligent irrigation system [147].

3.2 PROPOSED PRECISION IRRIGATION DECISIVE SUPPORT SYSTEM (PI-DSS)

1. Currently, available irrigation system mainly focuses only on measuring the presence of water in soil or not. As discussed in chapter 2 and very few of the proposed system considers soil temperature, and wind conditions for irrigation. Also, as elaborated in

majorly do not utilizes the advantages of Machine Learning as part of their irrigation system. With the huge agricultural dataset, Machine Learning plays an important role in decision making for irrigation. The proposed work in the present thesis takes into account both soil as well as weather conditions for irrigation scheduling. The use of Machine Learning makes the system smart and predictive. To enable the system for monitoring large farmland, soil parameters are communicated through a Long-Range Low Power Wireless Sensor Network – LoRa wireless communication technology. While developing a system for monitoring larger farmland, scalability is another important aspect. For scalability the most reasonable contenders are Zigbee and LoRa. But Zigbee suffers from the disadvantage of low range with a maximum range of up to 100m only. The proposed architecture of PI-DSS is given in Figure 3.2. The soil and the weather condition parameters are measured and transmitted to the processing layer via wireless communication link. As already mentioned, many communication

technologies are available given in the Figure 3.2 such as Zigbee, Bluetooth, BLE and many more. Out of the available communication technologies, LoRa is selected for the developed irrigation system. At processing layer, the parameters are processed for irrigation planning. The soil and weather sensor signals are calibrated to soil and weather conditions at soil node end while measuring. The processing layer applies the Machine Learning learned model to the observed soil and weather conditions and provides the decision for irrigation.

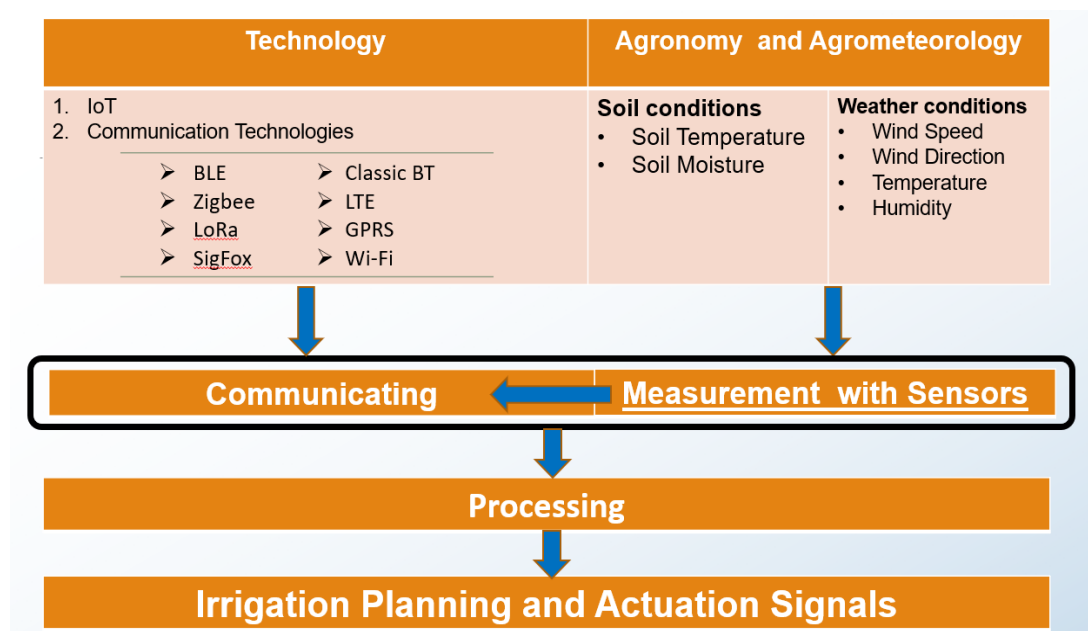


Figure 3.2 Proposed Architecture

3.3 PI-DSS CONCEPTUAL VISUALIZATION

The proposed PI-DSS system is developed around open-source technologies. Figure 3.3 illustrates the conceptual visualization of the developed irrigation DSS with three main elements:

2. Remote soil sensor nodes to be distributed over the entire farmland, for the prototyping two such nodes are developed and tested with soil temperature, soil Volumetric Moisture Content (VMC) sensors. LPWAN LoRa module is used for communication and Arduino open-source board is used for signal processing.

3. Weather station connected implemented using Raspberry Pi, connected to IoT cloud and Machine Learning is implemented for decision-making.
4. Thingspeak IoT cloud for data storage and remote user monitoring.

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Reference	Description	Challenges
[108]	An intelligent Raspberry Pi-based watering system is created. The farm parameters that have been detected includes air temperature and soil moisture. The KNN method is used to forecast the parameters of a farm's observed operations.	<p>The important parameters such as soil temperature and wind conditions are disregarded in the design for irrigation planning.</p> <p>The article does not discuss anything about the sensor networks for monitoring larger fields.</p> <p>Based on observed characteristics, the design makes no attempt to determine the appropriate Machine Learning algorithm for the irrigation application.</p>
[148]	To determine the amount of irrigation required, the farmland's soil moisture, air temperature, humidity, and light intensity were measured. IoT is used to monitor data, and ZigBee is used for short-range data transfer.	<p>The important parameters such as soil temperature and wind conditions are disregarded in the design for irrigation planning.</p> <p>If relatively big farms need to be monitored, ZigBee's restricted scalability prevents it from being used in designs for shorter fields.</p>
[149]	Arduino-based IoT-enabled irrigation system. The developed system used temperature, pH, soil	The important parameters such as soil temperature and wind conditions are disregarded in the design for irrigation planning.

	moisture, and humidity to estimate the irrigation need.	IoT design is complex as a result of using Arduino. System design does not include Machine Learning based irrigation prediction. The system's application in bigger fields is constrained by the short-range wireless communication technology it employs.
[150]	IoT-enabled irrigation system powered by Arduino. The created system determines the irrigation requirement using temperature, pH, soil moisture, and humidity.	The important parameters such as soil temperature and wind conditions are disregarded in the design for irrigation planning. IoT design is complex as a result of using Arduino. System design does not include Machine Learning based irrigation prediction.
[151]	Aa automatic irrigation system was proposed with IoT capabilities based on soil moisture only. The device enables the farmer to keep an eye on the moisture level of the soil and start irrigation as necessary.	The important parameters such as soil temperature, air temperature, and wind conditions are disregarded in the design for irrigation planning. IoT design is complex as a result of using Arduino. System design does not include Machine Learning based irrigation prediction.

[152]	<p>A irrigation system based on the Internet of Things is created. The variables that are observed to determine irrigation include temperature, humidity, and soil moisture. For irrigation scheduling, the evapotranspiration indirect technique of predicting the crop's water needs has been utilised. For data transfer, the system created makes use of short-range RF communication technology. The technology asserts to be 92 percent more effective.</p>	<p>The important parameters such as soil temperature and wind conditions are disregarded in the design for irrigation planning.</p> <p>IoT design is complex as a result of using Arduino.</p> <p>System design does not include Machine Learning based irrigation prediction.</p> <p>The system only works in smaller fields due to the deployment of short-range wireless communication technology.</p>
[153]	<p>By sensing soil moisture, the Internet of Things-based irrigation system is created. GSM technology for monitoring is used and is developed on the Arduino platform.</p>	<p>The important parameters such as soil temperature, air temperature, and wind conditions are disregarded in the design for irrigation planning.</p> <p>IoT design is complex as a result of using Arduino.</p> <p>System design does not include Machine Learning based irrigation prediction.</p> <p>The usage of GSM makes the system complicated and expensive because it necessitates bringing a mobile phone to the location with an active SIM.</p>



Figure 3.3 The conceptual visualization of PI-DSS

3.4 WIRELESS DATA TRANSMISSION

In WSN network, wireless data transmission technology plays an important role and if one to work on larger scale the major aspects to be considered are distance range, power efficiency and scalability. In precision agriculture for the wireless transmission of agricultural parameters primarily Zigbee and to some extent Bluetooth is being deployed. Although the Zigbee qualifies for scalability and power consumption efficiency but the major drawback is its short range only maximum up to 100 meters, which makes it not suitable for the proposed work to monitor large farmland. Bluetooth is also a short-range technology with 10 meters of range, maximum up to 100 meters for BLE and is not scalable. As discussed in chapter 2, LPWAN including NB-IoT, Sigfox and LoRaWAN are some possible technologies suitable for the proposed work in terms of power efficiency, long distance range and scalability. On the front of cost, both Sigfox and LoRaWAN both qualifies the need of the proposed work. LoRaWAN has been selected for the present work owing to its hardware availability at low cost and programming support with open-source hardware.

3.5 OPEN-SOURCE HARDWARE

There are numerous of open-source hardware available for prototyping to be named few are Arduino, NodeMCU and Raspberry Pi. The advantage of using opensource hardware are they do not come with any design cost and their design can be adapted as per our application both in terms of hardware and programming.

Arduino is one of the most popular open-source hardware but for IoT it is not a suitable choice. Most of the Arduino prototyping boards does not have inbuilt wireless WiFi connectivity to support IoT applications. Connecting the external WiFi modules makes the system design complex and even costly. For the present work Arduino UNO is used being the soil sensor nodes are not to be connected to cloud and LoRa modules need to be connected externally. The layout of the Arduino UNO is provided in Figure 3.4.

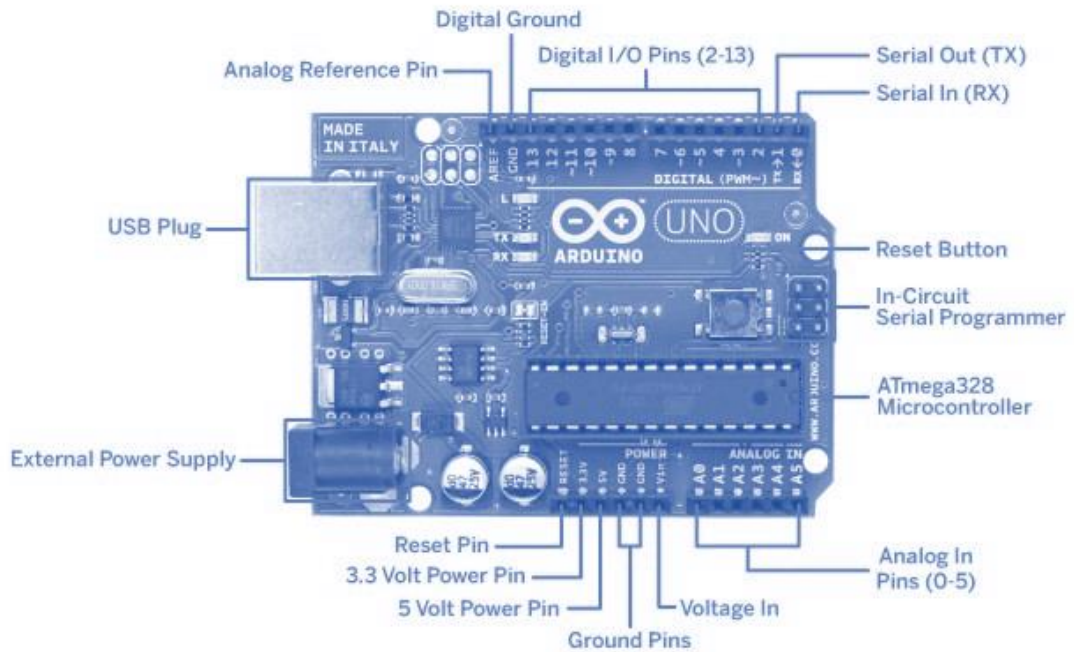


Figure 3.4 Arduino layout [220]

Raspberry Pi is a system based on proprietary technologies and masquerading as an open-source friendly thing. Raspberry Pi is developed around Broadcom ARM (Advanced RISC Machine) Cortex - A53 32 – bit chip and is a Single Board Computer developed by Raspberry Pi Foundation in association with Broadcom. Block diagram of Raspberry is given in Figure 3.5.

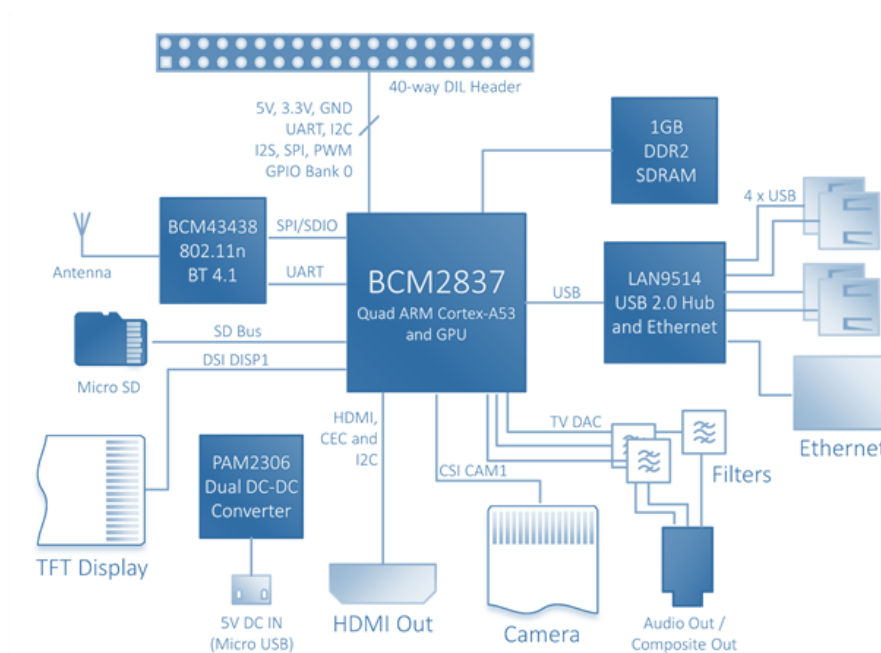


Figure 3.5 Block Diagram of Raspberry Pi [221]

3.6 PI-DSS SOIL SENSOR NODE

In soil measurement, the most measured parameters are soil moisture followed by soil temperature but much less in comparison to soil moisture. As discussed in the literature study, soil temperature plays an important role in water absorption by plants thereby affects irrigation planning, agricultural productivity and soil temperature can be altered through irrigation. For soil moisture, soil VMC sensor VH400 is successfully used in many of the past works of literature [145].

Soil sensor nodes, for the developed irrigation DSS, measure the soil conditions (soil temperature and soil VMC content) and communicate it to the weather station, which along with weather conditions succors in irrigation scheduling. For monitoring open and larger farmland, a network of multiple soil sensor nodes is required to be installed in farmland at a reasonable distance (approximately at a distance of 1mtr to 1.5mtrs, as verified through physical visualization while testing the system.) Figure 3.6 provides the block of the soil sensor node with three main components

1. Sensors
2. Processing board, and
3. LoRa wireless communication module

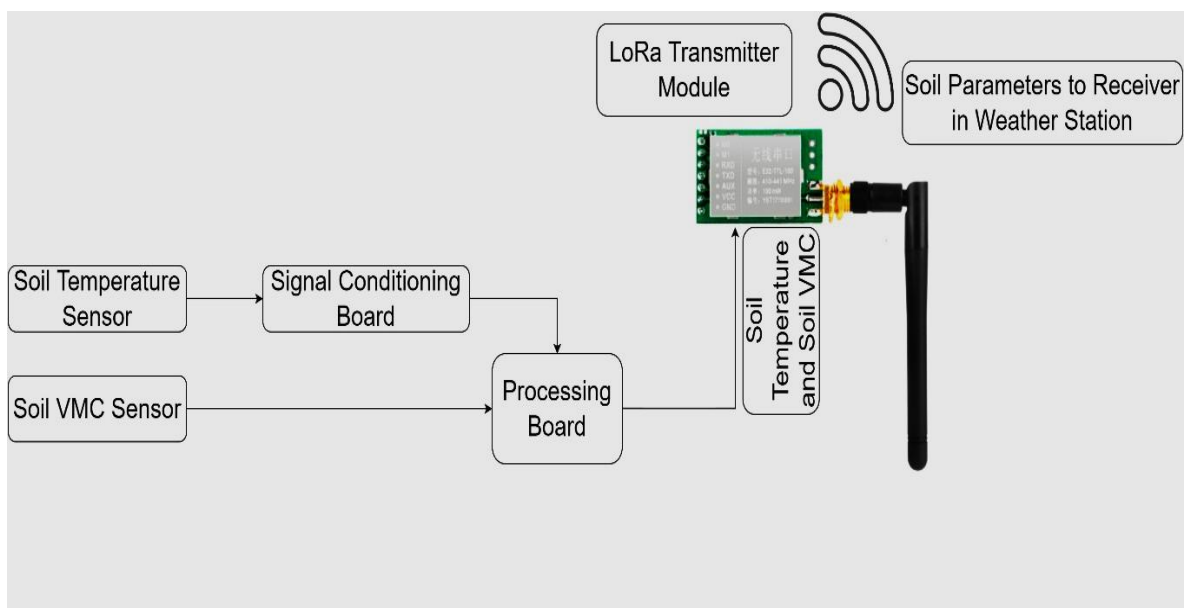


Figure 3.6 Remote soil node with LoRa communication module

Volumetric Moisture Content (VMC), a sensor from Vegetronix that is used in the developed irrigation DSS, senses soil moisture for agricultural land significantly more effectively than a comparator-based soil moisture sensor. In Table 3.1. the calibration formulae based on sensor output voltage are provided. The volume of moisture present or maintained in the soil for a unit volume of soil is known as VMC.

Table 3.1 Soil moisture sensor calibration equations

Sensor output (in voltage)	VMC calibration equation (%)
00 to 1.1	$10xV-1$
1.1 to 1.3	$10xV-1$
1.3 to 1.82	$10xV-1$
1.82 to 2.2	$26.32xV- 7.89$
2.2 to 3	$62.5xV - 87.5$

VMC sensor comes with three wire connections, two wires for the power supply and the third wire provides the output voltage used to estimate the soil VMC with the help of the equations provided in Table 3.1. Figure 3.7 give the pictorial view of the VH400 sensor and Table 3.2 illustrates the important technical parameters of the sensor [154].



Figure 3.7 VH400 sensor

Table 3.2 Technical Specifications of VH400

Power consumption	less than 13mA
Supply Voltage	From 3.5V to 20 VDC.
Power on to Output stable	400 ms
Operational Temperature	From -40°C to 85°C
Accuracy at 25°C	2%
Output	0 to 3V related to moisture content

The temperature sensor DS18B20, which has a temperature range of -55°C to +125°C with an accuracy of 0.5°C, is utilised for the4 developed system. The sensor operates on a 1-wire protocol, making it effective in terms of digital pins and able to be buried in the ground for an extended period of time without being damaged or rusted. Figure 3.8 show the sensor used for sensing soil temperature.

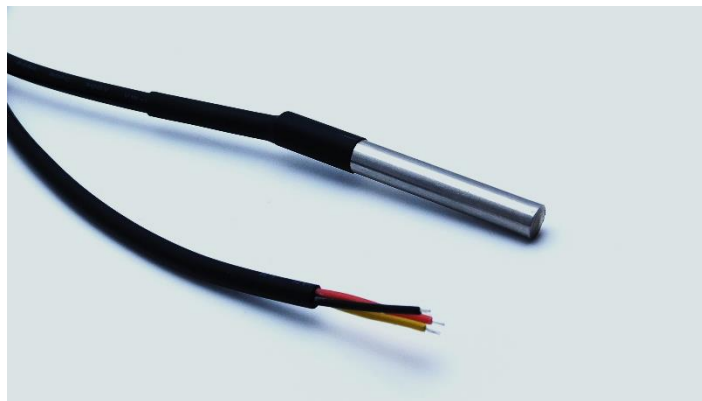


Figure 3.8 Soil temperature sensor

Each soil sensor node is deployed with open-source Arduino UNO hardware for estimating the soil conditions from sensor signals and processing the soil condition and transmitting it through the LoRa module to the weather station. For communicating the soil conditions, the LoRa module is used with communicating the range of up to 8000mtrs (as claimed on the supplier’s webpage). Table 3.3 gives the important parameters of the LoRa module as extracted from Figure 3.9, a snapshot of the supplier’s dashboard. Figure 3.10 gives the LoRa module used in the developed irrigation DSS.

Table 3.3 Important parameters of LoRa module

RFIC	SX1278 SX1276
TYPE	CDMA
Working Frequency	433MHz (Unlicensed in India)
Distance	8000m
Supply Voltage	2.5V-5.5V
Interface	UART

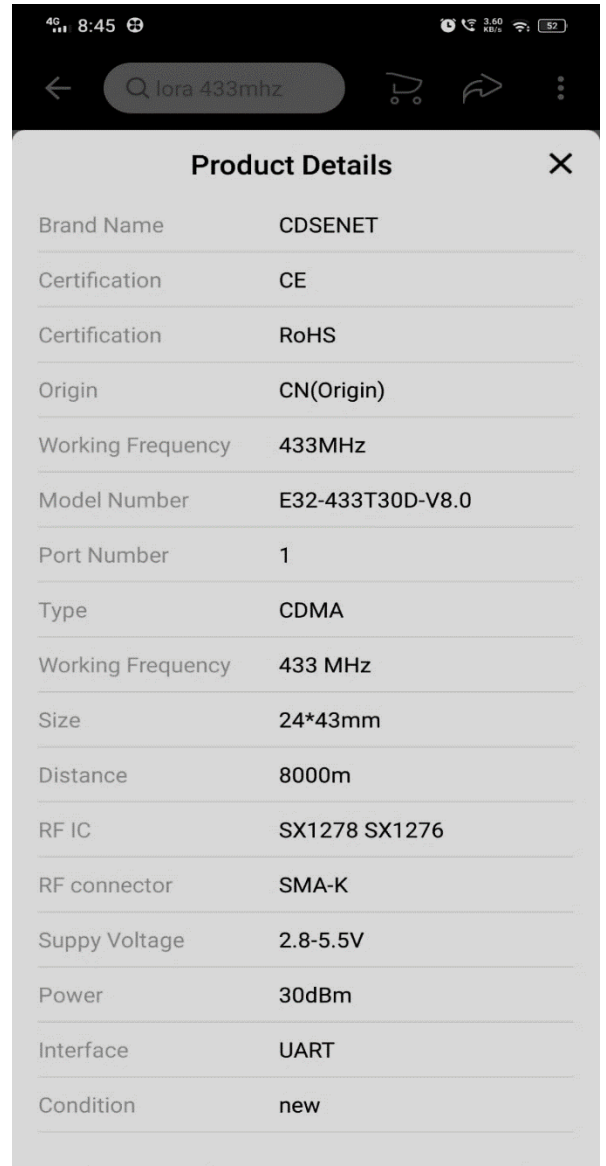


Figure 3.9 Snapshot of supplier's dashboard for LoRa module Specifications [30, 35, 36]



Figure 3.10 LoRa module

The soil VMC sensor, soil temperature sensor, and LoRa module all are interfaced to the main processing board, Arduino UNO. Arduino UNO receives the sensed soil conditions and put in the sense signals to the calibration as required and finally transmits it to the weather station using the LoRa module. The soil sensor node installed in farmland is shown in Figure 3.11.



Figure 3.11 Wireless soil sensor node

The major challenges in developing soil sensor node are communication range, power efficiency and scalability as elaborate in table 3.1. Lora provides solution all of most of the challenges being mentioned in table 3.1 by providing long range for communication with least power consumption and is scalable.

3.7 PI-DSS WEATHER STATION

For weather conditions, the most measured parameter is air temperature and humidity. Very little of the literature takes care of soil temperature and wind conditions in agricultural applications and as discussed in the both plays an important role in agriculture and irrigation planning [145].

The weather station developed is the central unit of the developed irrigation DSS. It senses the weather condition and receives the soil conditions from the soil sensor node network. Each soil sensor node is associated with LoRa address, through which the location in farmland is identified for irrigation planning. With soil and weather conditions, the weather station decided on the requirement of irrigation in a particular sector of farmland. The weather station uses Machine Learning for decision-making and is developed around Raspberry Pi. Raspberry Pi provides the system with sufficient capabilities required to run Machine Learning algorithms and use Machine Learning model along with sensing and receiving the various required weather parameters for irrigation. The weather station is connected to IoT cloud Thingspeak, to which soil and weather conditions are uploaded by the weather station for remote monitoring. Uploading farmland data to the IoT cloud also makes it readily available over the globe for further research by different research communities. All the elements of the weather station are illustrated in Figure 3.12.

IoT cloud, Thingspeak is specifically selected for its availability at no cost to 8-channels. Each channel can be utilized for communicating and visualizing one of the soil or weather parameters. The system utilizes only 6 – channels. Leaving space for 3 add-on sensors for future applications. Also, Thingspeak provides the graphical visualization of the data for easy and better monitoring and in .csv format which is required for further analysis of data or applying Machine Learning algorithms to the received dataset.

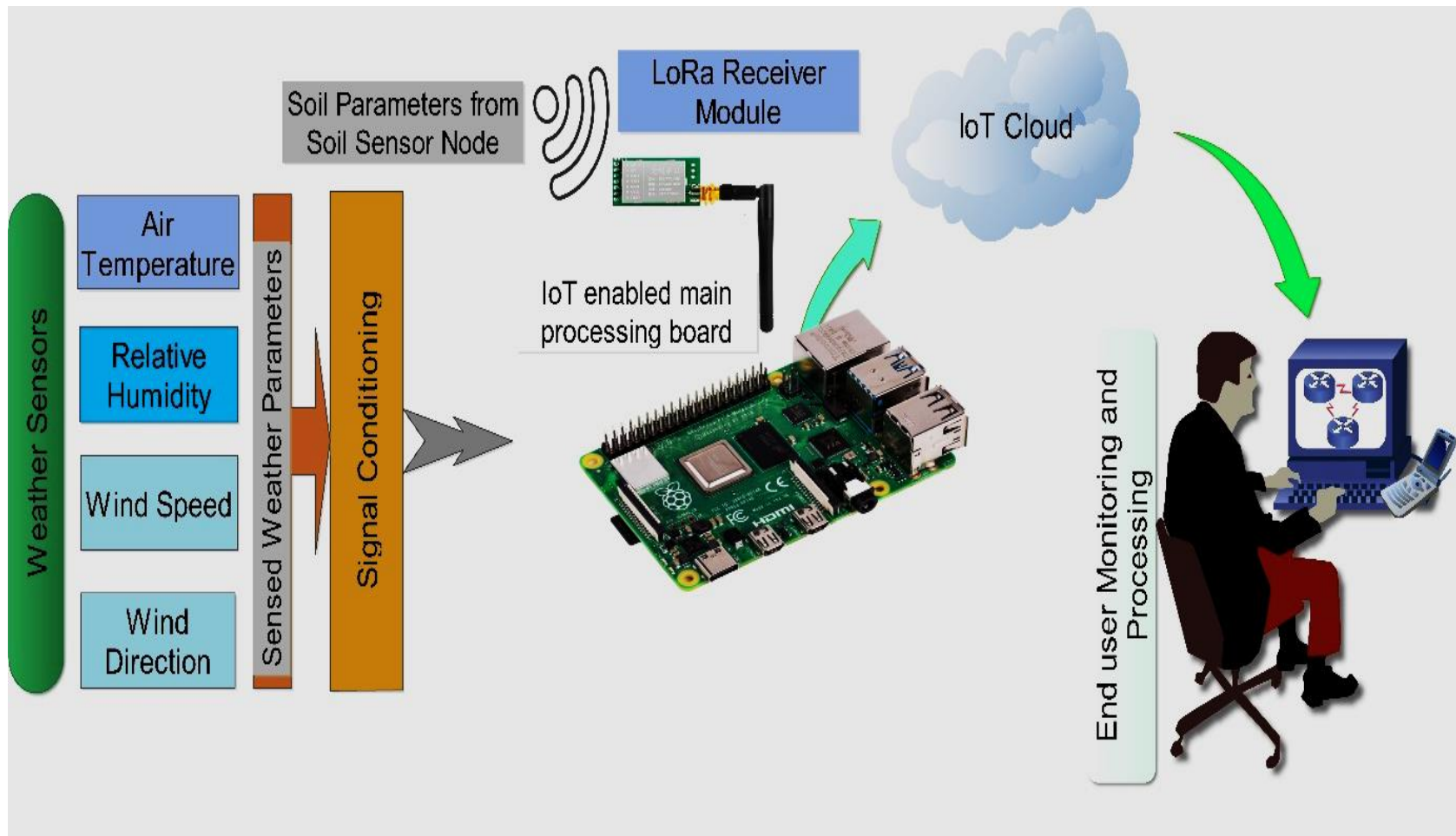


Figure 3.12 Weather Station

Wind speed and direction are measured using the sensor as shown in figure 5.10. The sensor to the left in Figure 3.13 is a wind speed sensor and to the right is the wind speed sensor.



Figure 3.13 Wind direction and wind speed sensor

Important parameters of wind speed sensors are provided in Table 3.4 and the supplier's snapshot for wind speed sensor specification is given in **Error! Reference source not found**. The calibration equation for converting the output voltage of the sensor into wind speed in m/s is

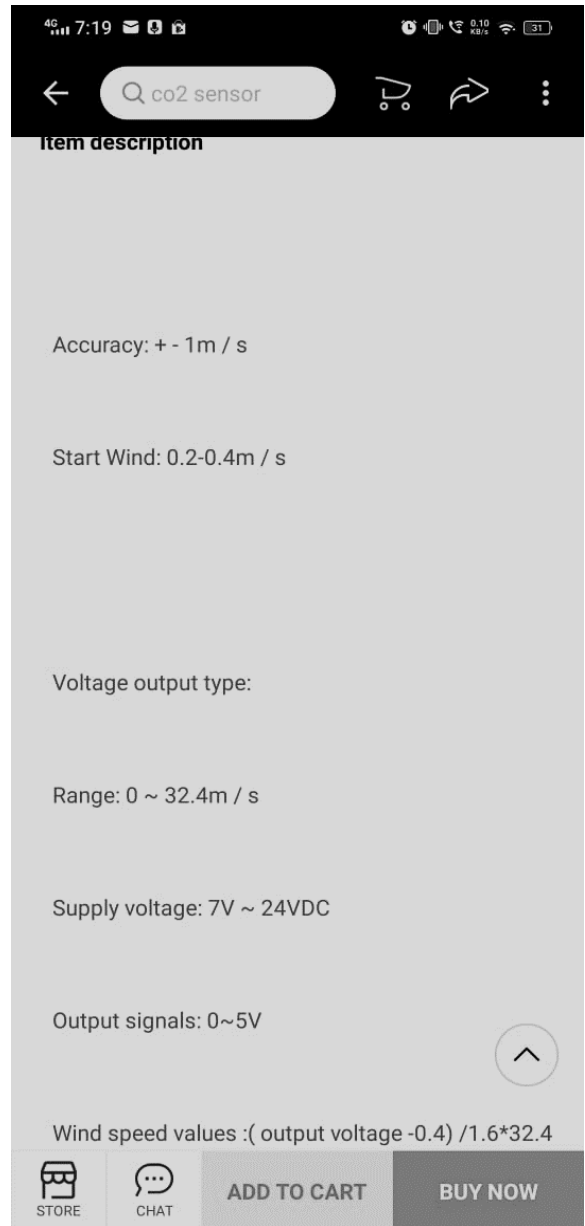
$$\text{Wind speed (m/s)} = (\text{output_voltage} - 0.4)/1.6 * 324$$

For identifying the wind direction, a wind direction sensor is deployed with analog output voltage. Mapping of sensor output with wind direction is demonstrated in Figure 3.14. The analog voltage from the sensor is converted into digital format with ADC. The numerical values mentioned against the direction text show the ADC digital value against each direction. The same is programmed in Raspberry Pi to display the wind direction.

The most commonly used sensor for estimating air temperature and humidity is DHT11 and DHT22. The important technical specification and the difference between the two types of sensors are given in Table 3.5 [154, 155]. The developed weather station uses DHT22 for air temperature and humidity.

Table 3.4 Important parameters of Wind Speed Sensor

Start wind	0.2 – 0.4m/s
Range	0 – 32.4m/s
Accuracy	+/-1m/s
Output type	Voltage
Output signal	0 – 5V



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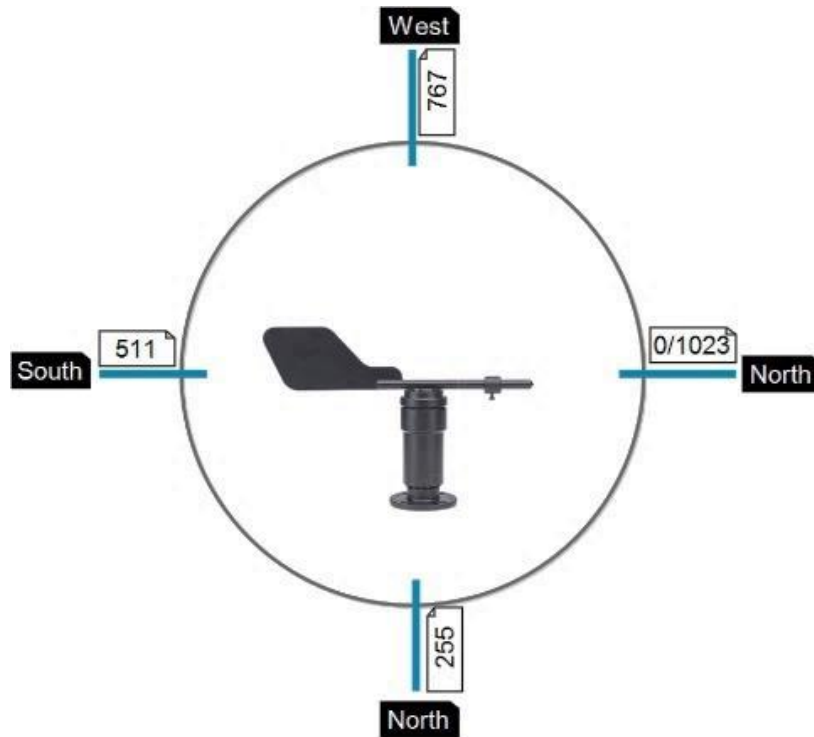


Figure 3.14 Wind direction mapped to sensor

Table 3.5 DHT11 Vs DHT22

Specification	DHT11	DHT22
Temperature range	-20°C to 60°C	-40°C to 80°C
Temperature accuracy	±2%	±0.5%
Humidity range (Relative Humidity)	5% to 95%	0% to 100%
Humidity accuracy	±5%	±2%

The weather station developed and deployed for weather condition measurement is shown in Figure 3.15. The developed weather station is novel in terms of its design, specification, and cost. The juxtaposition of the developed weather station with the weather station design discussed in various literature, provided in different patents, and with commercially available weather stations is provided in Table 3.6, Table 3.7, and Table 3.8 respectively.



Figure 3.15 Weather station at work

Table 3.6 Developed weather station comparison with published literature

Reference/Year	Title	Weather sensors	Data visualization/Storage	WSN technology	Embedded platform	Developed system
[156]/2018	Weather Station Design Using IoT Platform Based on Arduino Mega	Rain, air pressure, RTC, temperature and humidity	LCD/local data logger	WiFi	Arduino Mega	Low cost and power efficient IoT board Wind speed and wind direction sensor Cloud based data logging No local display for energy efficiency Graphical data visualization IoT enabled
[157]/2017	Arduino Based Weather Forecasting Station	Temperature, humidity, and air pressure	LCD/nil	Nil	Arduino UNO	Low cost and power efficient IoT board Wind speed and wind direction sensor Cloud based data logging

						No local display for energy efficiency Graphical data visualization IoT enabled
[158]/2017	Low-Cost Weather Station for Climate-Smart Agriculture	Wind direction, wind speed, temperature, and humidity	MySQL/Cloud	Zigbee	Raspberry Pi	Low cost and power efficient IoT board Cloud based data logging No local display for energy efficiency Graphical data visualization IoT enabled
[159]/2017	Smart Weather Station for Rural Agriculture using Meteorological Sensors and Solar Energy	Light wind direction, wind speed and temperature	LCD/EEPROM	GSM	Microcontroller	Low cost and power efficient IoT board Humidity sensor Cloud based data logging No local display for energy efficiency

						Graphical data visualization IoT enabled
[218] /2014	A reasonably priced automatic wireless weather station that uses Zigbee and has a web hosting option	Air pressure, wind direction, wind speed and temperature	LCD/Local computer	Zigbee	Arduino Mega	Low cost and power efficient IoT board W Cloud based data logging No local display for energy efficiency Graphical data visualization IoT enabled

Table 3.7 Developed weather station comparison with patents

Patent ID	Patent Title	Year	Description	Developed System
US10638675B2	Irrigation controller with weather station	2020	An irrigation controller based on data from a local weather station is the invention.	<p>Designed with IoT technology</p> <p>IoT cloud-based data logging</p> <p>Weather parameters so selected that can assist in predicting irrigation demand using Machine Learning.</p>
CN203465825U	Farmland environment weather information collection system based on Zigbee and GPRS (General Packet Radio Service)	2014	Provides data for the farmland's soil temperature, wind speed, wind direction, illumination intensity, carbon dioxide, and air temperature. For data communication, GPRS and Zigbee are employed as the communication technologies.	<p>Zigbee is only acceptable for short range communication.</p> <p>GPRS is the very infrastructure-oriented resource</p> <p>In the present design weather data of farmland is not user friendly but the developed system uses IoT technology that enables the user to visualize the data in text or graphical form</p> <p>Data can be easily analyzed manually or with Machine Learning</p> <p>IoT cloud-based data logging</p>

US7171308B2	Weather station	2007	Thunderstorms and lightning strikes are two types of weather data provided by the current invention provides.	<p>The developed weather station uses IoT technology for data communication</p> <p>IoT cloud-based data logging</p> <p>The data provided is analysis ready for an advanced tool like Machine Learning.</p>
US7088221B2	Weather station	2006	The design of a weather station with a microprocessor, atmospheric sensors, a memory to store weather data, and a local display unit is discussed in the invention.	<p>For power efficiency the developed system does not use any local display but utilizes IoT technology for data monitoring.</p> <p>Cloud uploaded data is readily available</p> <p>IoT cloud-based data logging</p> <p>Cloud data can be utilized for further analyses using Machine Learning tools or any data analysis tool.</p>
US69679-00B2	Combination clock radio, weather station, and message organizer	2005	The temperature sensor, pressure sensor, and local display for data visualisation make up the weather station in the current invention.	<p>Includes sensors needed to track weather data for irrigation scheduling.</p> <p>The system is IoT enabled</p> <p>No local display for energy efficiency</p>

				<p>IoT cloud based data logging</p> <p>Machine Learning advanced analysis tools can be applied to available data for irrigation demand prediction.</p>
US5920827A	Wireless weather station	1999	A radio transmitter is used to measure and broadcast weather-related parameters. used a local display as well to display data.	<p>Utilises IoT technology to allow for on-demand data visualisation</p> <p>Developed system allows for irrigation planning and prediction (using Machine Learning).</p> <p>IoT cloud-based data logging</p>

Table 3.8 Cost comparison of developed weather station comparison with commercial systems

S. No.	Weather Station Product	Cost/Unit	Make	IoT Feature	Source
1	Automatic Weather Station, for Industrial: ATM1136	70,000	Advance Tec India Private Limited	No	https://www.indiamart.com/proddetail/automatic-weather-station-12477572848.html
2	V Tech Ultrasonic Weather Station for Agriculture: VT-UWS01	120000	V TECH	No	https://www.indiamart.com/proddetail/ultrasonic-weather-station-19054403862.html
3	Portable Weather Station: 110-WS-18	325000	Auro Electronics Private Limited	No	https://www.indiamart.com/proddetail/portable-weather-station-4539296991.html
4	Wireless Weather Station	189000	Nunes Instruments	No	Wireless Weather Station, weather station - Nunes Instruments, Coimbatore ID: 2329258873 (indiamart.com)
5	Automatic Weather Station, for Official	500000	Nevco Engineer Private Limited	No	https://www.indiamart.com/proddetail/automatic-weather-station-13513226588.html

3.8 PYTHON ENVIRONMENT ESTABLISHMENT FOR MACHINE LEARNING

Machine Learning is becoming more and more popular due to increased computational power, enhanced algorithms, and availability of huge and ever-increasing data [131]. Machine Learning can be defined as a technique that enables computers to predict things based on past experiences. With the increased storage and improved processing power of computers, Machine Learning has witnessed magnificent development [132].

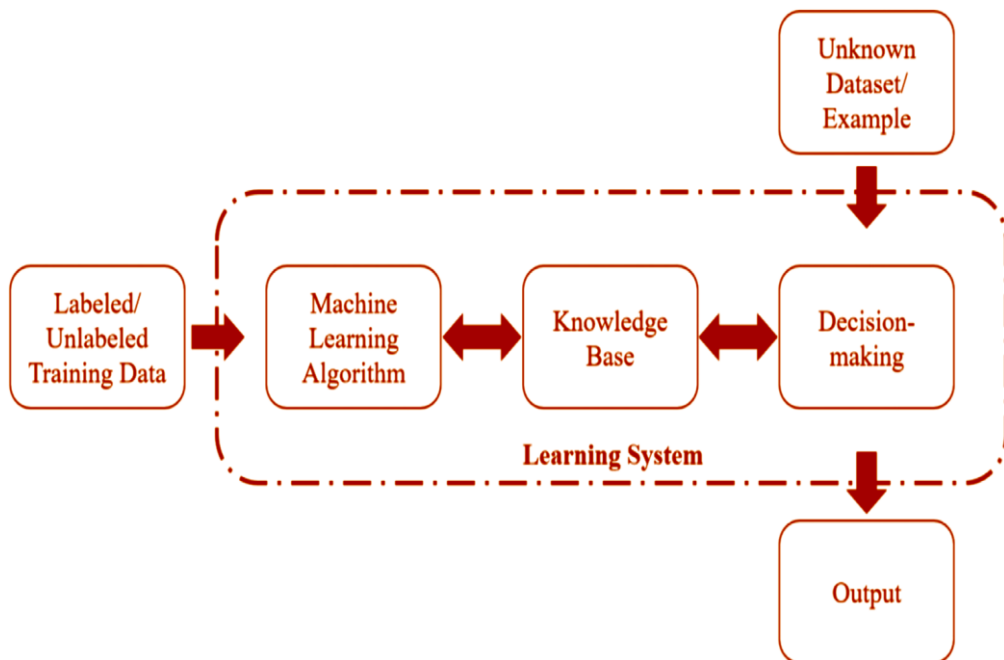


Figure 3.16 Configuration of the Machine Learning system [133, 134].

A few of the advantages of deploying Machine Learning in a system are [160]:

1. Machine Learning algorithms are competent in solving non-linear problems.
2. Machine Learning algorithms provide a mechanism for better decision-making with minimal human interventions.
3. Machine Learning is a powerful tool for incorporating knowledge into a machine,
4. Machine Learning is powerful and a workable framework for data-driven decision-making.

Machine Learning algorithms are broadly classified into three categories namely supervised learning, unsupervised learning, and reinforcement learning [134, 135].

Machine Learning is used in the developed DSS for irrigation to predict and make precise decisions regarding the need for irrigation. The data set obtained with the developed irrigation DSS consists of 5 columns for each measured farmland parameter namely 'air temperature', 'Humidity', 'WindSpeed', 'Volumetric Moisture Content VMC', and 'SoilTemperature' respectively. The Machine Learning algorithms are selected based on literature and are applied to the farmland dataset [196, 190, 196, 197, 197]. The Machine Learning algorithm selected for the study are

- Logistic Regression
- Linear Discriminant Analysis
- K – Nearest Neighbors
- Decision Tree
- Gaussian Naïve Bayes
- Support Vector Machine

Python require some packages to be installed beforehand. The required packages for Python are:

- Python
- Scikit-learn
- Numpy
- Matplotlib
- Pandas

Scikit-learn is the open-source Machine Learning library for Python programming. It implements various regression, classification and clustering algorithms. Numpy library is used to work with multi – dimensional arrays and matrices. It is also used to apply high level mathematical functions to arrays. Matplotlib is a visualization library, used to implement the static, animated and interactive visualization in Python. It creates amazing 2D plots of arrays. Pandas is another Python library primarily for data manipulation and analysis. It includes specific data structures and procedures for working with time series and mathematical tables.

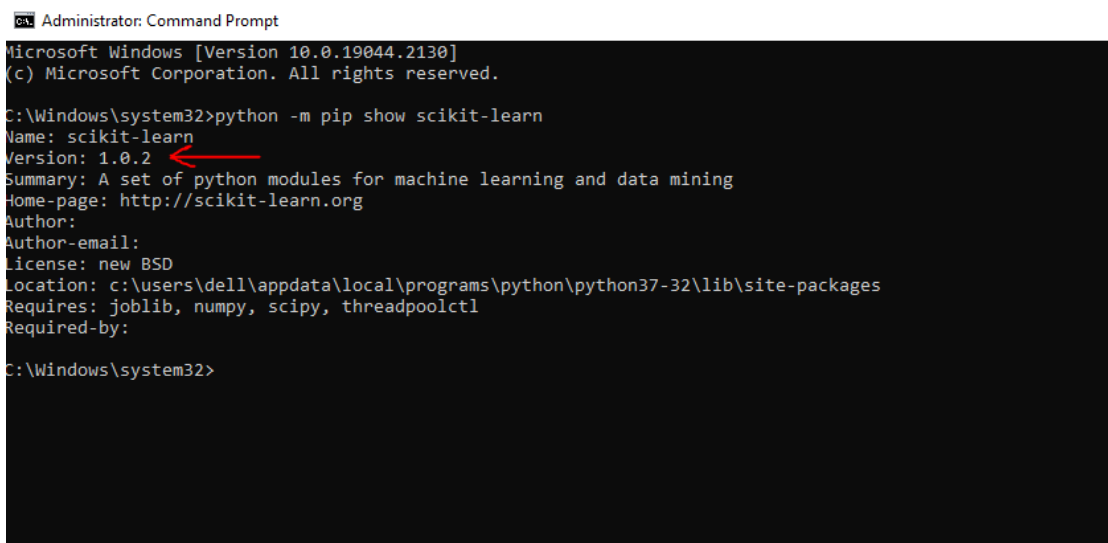
For the present work Python version 3.7.6 has been used. Scikit-learn is a Python package for implementing Machine Learning algorithms. Scikit-learn library for Python supports both supervised and unsupervised learning and is an open-source library supporting cross validation and visualization. To install the library using *pip* following command need to be executed through power shell of windows 10.

pip install scikit – learn

The installation of Scikit-learn can be verified by running below command on power shell

python – m pip show scikit – learn

The Scikit-learn library used for the implementation of the proposed work is shown in Figure 3.17. For further documentation on scikit-learn “<https://pypi.org/project/scikit-learn/>” can be referred.



```
Administrator: Command Prompt
Microsoft Windows [Version 10.0.19044.2130]
(c) Microsoft Corporation. All rights reserved.

C:\Windows\system32>python -m pip show scikit-learn
Name: scikit-learn
Version: 1.0.2
Summary: A set of python modules for machine learning and data mining
Home-page: http://scikit-learn.org
Author:
Author-email:
License: new BSD
Location: c:\users\dell\appdata\local\programs\python\python37-32\lib\site-packages
Requires: joblib, numpy, scipy, threadpoolctl
Required-by:

C:\Windows\system32>
```

Figure 3.17 Scikit-learn version on host machine

The core Python library for array computing is called NumPy. It offers:

- a strong object for an N-dimensional array
- complex (broadcasting) operations
- instruments for combining C/C++ and Fortran code

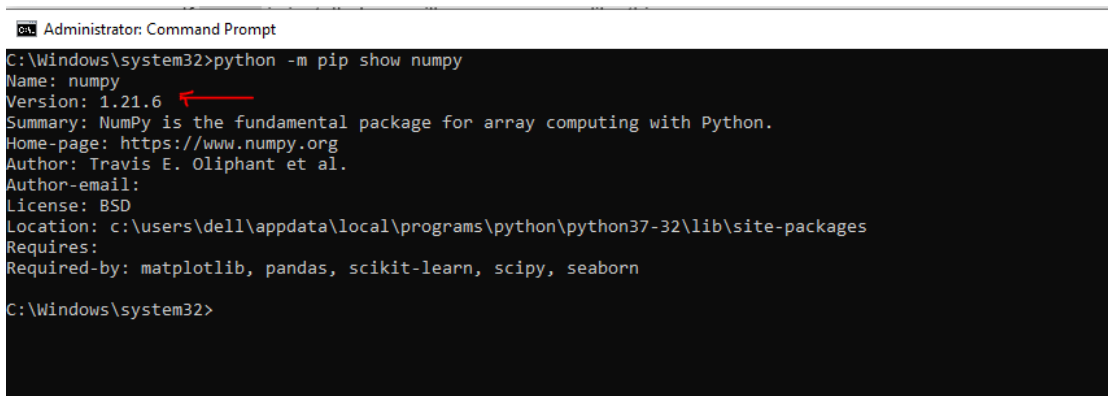
- useful Fourier transform, random number, and linear algebra abilities and a lot more

NumPy is a powerful multi-dimensional data container that has numerous applications outside of science. Data-type definitions are flexible. As a result, NumPy can quickly and easily interact with a wide range of databases. The installation command for numpy is

pip install numpy

numpy installation and version can be verified using the below command and the version of numpy for the proposed work is shown in Figure 3.18. For further documentation on numpy “<https://numpy.org/install/>” can be referred.

python -m pip show numpy



```
Administrator: Command Prompt
C:\Windows\system32>python -m pip show numpy
Name: numpy
Version: 1.21.6
Summary: NumPy is the fundamental package for array computing with Python.
Home-page: https://www.numpy.org
Author: Travis E. Oliphant et al.
Author-email:
License: BSD
Location: c:\users\dell\appdata\local\programs\python\python37-32\lib\site-packages
Requires:
Required-by: matplotlib, pandas, scikit-learn, scipy, seaborn
C:\Windows\system32>
```

Figure 3.18 numpy version on host machine

Matplotlib is a Python library that allows to create static, animated, and interactive visualisations. Matplotlib makes simple things simple and difficult things possible. Produce plots suitable for publication. The library is installed with the below command

pip install matplotlib

Matplotlib installation and version can be verified using the below command and the version of Matplotlib for the proposed work is shown in Figure 3.19. For further documentation on Matplotlib “<https://pypi.org/project/matplotlib/>” can be referred.

pip show matplotlib

```
Administrator: Command Prompt
C:\Windows\system32>pip show matplotlib
Name: matplotlib
Version: 3.5.3
Summary: Python plotting package
Home-page: https://matplotlib.org
Author: John D. Hunter, Michael Droettboom
Author-email: matplotlib-users@python.org
License: PSF
Location: c:\users\dell\appdata\local\programs\python\python37-32\lib\site-packages
Requires: cycler, fonttools, kiwisolver, numpy, packaging, pillow, pyparsing, python-dateutil
Required-by: seaborn
C:\Windows\system32>
```

Figure 3.19 Matplotlib version on host machine

Pandas is a Python library that provides data that is fast, flexible, and expressive. Pandas is an open-source data analysis and manipulation tool built on top of the Python programming language that is fast, powerful, flexible, and simple to use.

pip install pandas

Pandas installation and its version can be verified using the command below and the version of Pandas for the proposed work is shown in Figure 3.20. Further documentation on pandas can be found at “<https://pandas.pydata.org/>”

pip show pandas

```
Administrator: Command Prompt
C:\Windows\system32>pip show pandas
Name: pandas
Version: 1.3.5
Summary: Powerful data structures for data analysis, time series, and statistics
Home-page: https://pandas.pydata.org
Author: The Pandas Development Team
Author-email: pandas-dev@python.org
License: BSD-3-Clause
Location: c:\users\dell\appdata\local\programs\python\python37-32\lib\site-packages
Requires: numpy, python-dateutil, pytz
Required-by: seaborn
C:\Windows\system32>
```

Figure 3.20 Matplotlib version on host machine

3.9 MACHINE LEARNING DEPLOYMENT

The soil and weather conditions measured to are uploaded to the Thingspeak IoT cloud for about a month for testing. The dataset so created is applied to the Python Machine Learning algorithms to learn the pattern. Machine Learning is implemented using the scikit-learn Python package, the detail of other packages used in given in Figure 3.21.

```
>>>
Python: 3.7.6 (tags/v3.7.6:43364a7ae0, Dec 18 2019, 23:46:00) [MSC v.1916 32 bit (Intel)]
scipy: 1.7.3
numpy: 1.21.5
matplotlib: 3.5.1
pandas: 1.3.5
sklearn: 1.0.1
>>> |
```

Figure 3.21 Attribute of Python and ML libraries

3.10 CONCLUSION

In this chapter, the development of PI irrigation DSS is explained. Details of every sensor being used along with calibration are provided. This chapter also compares the developed PI – DSS system with previous designed Precision Irrigation systems. The majority of previous automated PI designs lack the use of Machine Learning exhaustively and ignore many of the farmland parameters. The developed weather station for PI – DSS is compared with developed patents and with commercial weather station for a cost comparison. The last chapter provides the Machine Learning techniques being used and are compared. The overall contribution of the present work can be summarized in the following points.

- Agronomy and agrometeorology parameters for Precision Irrigation selected after detailed analysis and effect of these parameters on crop irrigation planning and crop health.
- Identification of wireless communication technology after detailed survey and testing of wireless communication technology. The selection is based on scalability, power consumption and distance range.

- Detailed cost analysis of developed weather station to provide cost effective solution to farmers.
- Testing and analyzing the performance of system w.r.t. standard parameter from online weather measuring portals
- Implementing and selection of the best Machine Learning algorithm for better efficiency and least error.
- Validating and analyzing the performance of selected Machine Learning algorithm as trained and tested.
- Comparing the present work with the state of the art work.

Chapter 4 RESULTS AND DISCUSSION

“The only limit to the height of your achievements is the reach of your dreams and your willingness to work for them.”

Michelle Obama

4.1 LoRa RANGE TESTING

The soil sensor node is equipped with Long Range LPWAN LoRa wireless communication module. Through LoRa module the soil parameters are communicated to weather station, where along with weather parameters are analysed for irrigation scheduling and are uploaded on Thingspeak IoT cloud.

The LoRa module deployed in the developed irrigation DSS is shown in Figure 4.1. The LoRa module UART SX1278 deployed works at 433Mhz which is an unlicensed frequency band in India. The supplier’s specification claim range up to 8000mtrs. Practically the LoRa module is tested within Lovely Professional University campus itself and the transmission was found without any error up to 1Km with buildings in between.



Figure 4.1 LoRa Module

For working with LoRa at least two LoRa module are require, one acting as transmitter and other as receiver. The LoRa module deployed work on serial communication UART protocol. Open-source hardware Arduino is used as processing board with each soil sensor node. The transmitter and receiver configuration of LoRa module with Arduino is shown in Figure 4.2. The transmission of data bytes is also demonstrated in Figure 4.2.

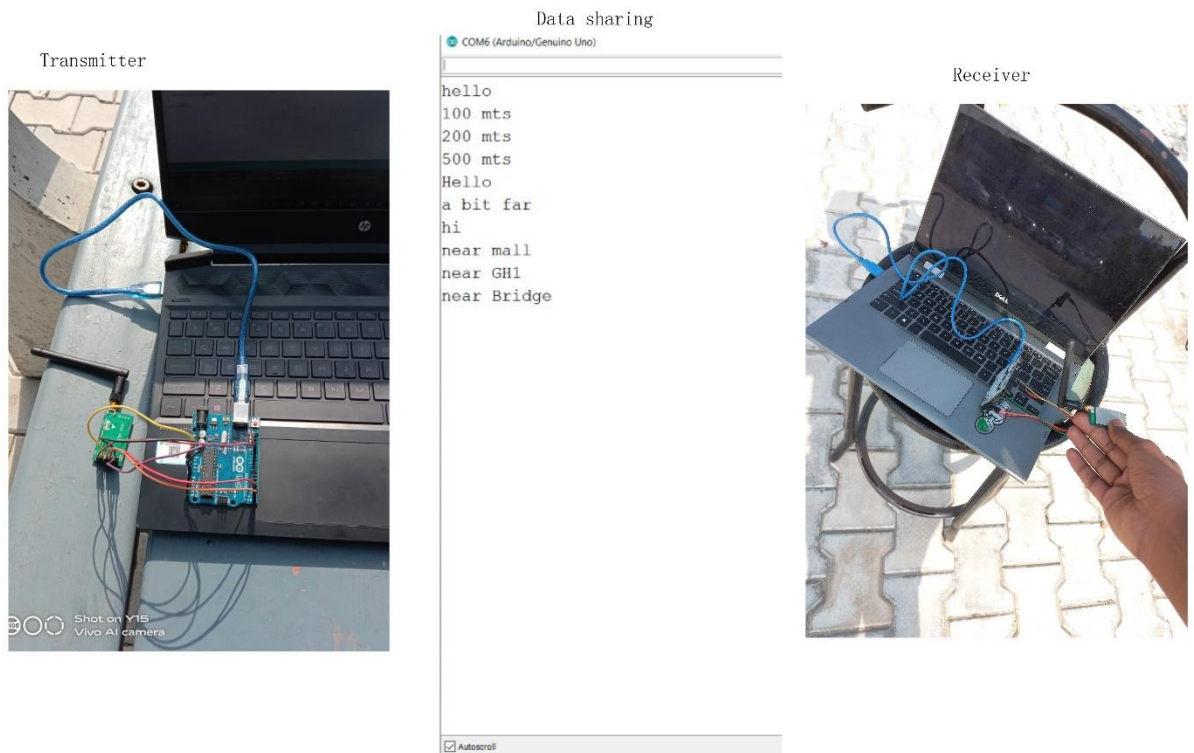


Figure 4.2 LoRa transmitter and receiver

For testing of the range of the communication, two LoRa systems are developed connected with laptop and Arduino IDLE is used for data reception. One is made static and other is move to different location sand the on mobile location sharing is activate for location information. As shown in Figure 4.3, one is place near to block 30 of LPU and till the backside of block 14 the data sharing was good.

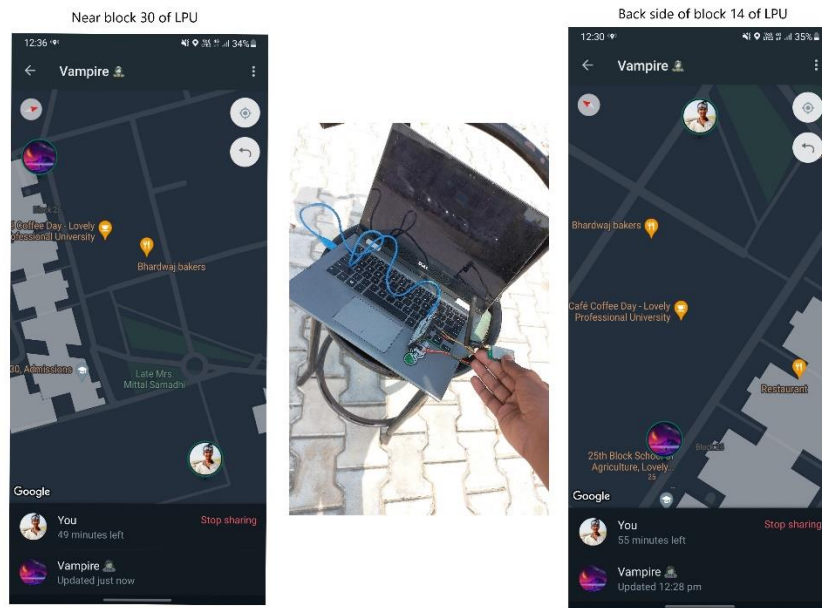


Figure 4.3 LoRa range testing (block 30 to block 14)

To verify the maximum range with obstacle in between, the static node is placed near to the extreme end of block 56 and the second node is continuously moved towards the main gate. The data transmission was proper up to the LPU bridge end towards the main gate, as shown in Figure 4.4. The weather condition under which the range testing of LoRa is done is shown in Figure 4.5. The LoRa and the irrigation DSS is tested under different climatic conditions.

4.2 SOIL SENSOR NODE

The soil sensor node collects the soil condition, particularly soil VMC and soil temperature, using the VH400 for soil VMC and DS18B20. The LoRa module transmits the collected soil parameters to the weather station for further processing. Figure 4.6 shows the soil sensor nodes with the required modules.

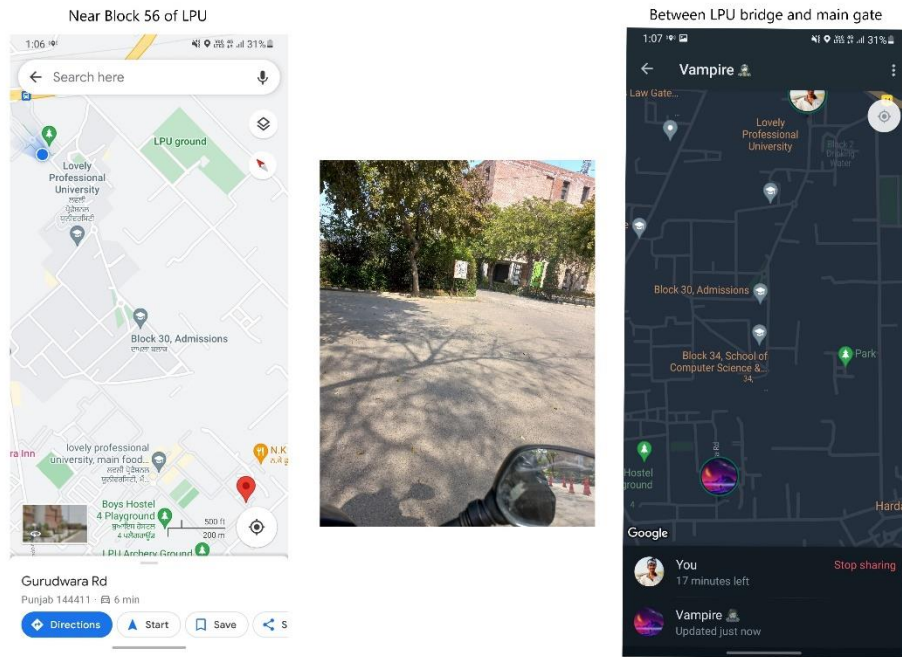


Figure 4.4 LoRa range testing (block 56 to LPU bridge)

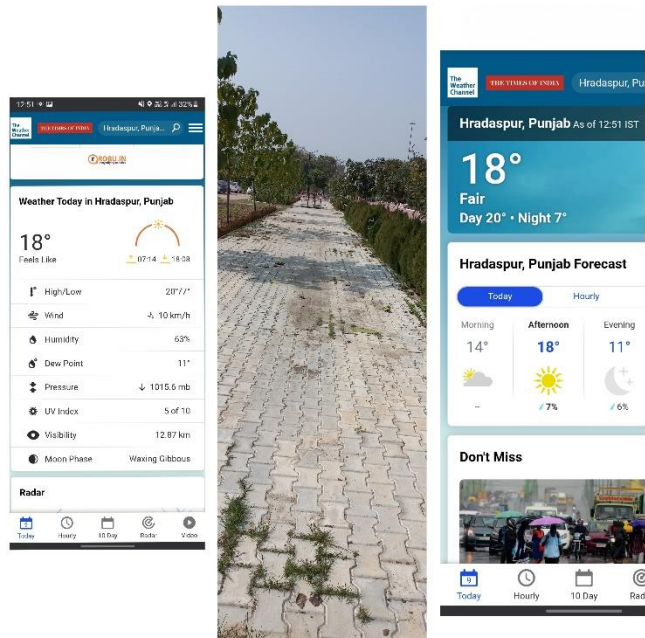


Figure 4.5 Weather condition under which LoRa is tested



Figure 4.6 Soil sensor node deployed in farmland

4.3 WEATHER STATION

Weather station developed tested for continuous three days (14th December 2018 to 16th December 2018) and the information is uploaded on Thingspeak IoT cloud. The graphical visualization of data on Thingspeak is shown in Figure 4.7.

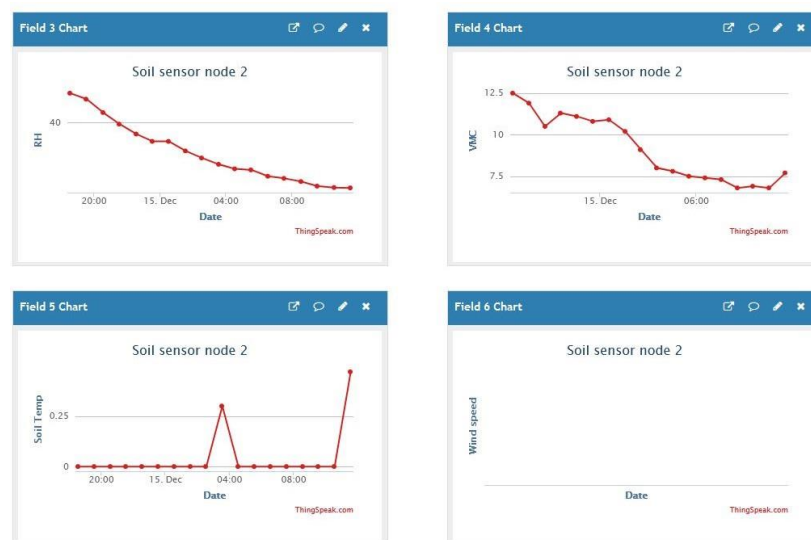


Figure 4.7 Thingspeak data visualization of developed weather station

Practically satisfactory results are obtained from the developed prototype of weather station. The weather station is tested for continuous 3 days from 14th December 2018

to 16th December 2018 at Phagwara, Punjab India with geographical coordinates latitude as 31.199325275018488 and longitude as 75.7736178548299. The weather information from the weather Station is observed for fixed duration of time as shown in Table 4.1 and Table 4.2. Table 4.1 gives the weather data from <https://www.worldweatheronline.com> and Table 4.2 shows the weather data from the weather station prototype.

Table 4.1 Weather conditions from <https://www.worldweatheronline.com>

	Time	Friday	Saturday	Sunday
Temperature	3:00 AM	12°C	12°C	11°C
	12:01PM	21°C	22°C	22°C
Humidity	3:00 AM	50%	44%	33%
	12:01PM	26%	22%	20%
Wind Speed	3:00 AM	4 kmph	9 kmph	8 kmph
	12:01PM	10 kmph	8 kmph	9 Kmph

From the weather data obtained from <https://www.worldweatheronline.com> and measured by the developed weather station prototype for the three-day maximum difference is temperature measurement was about 1.4°C. The difference in humidity between the two sources of information was measured at 2 percent, while the largest variation in wind speed is 1 kmph.

Table 4.2 Weather conditions from developed weather station

	Time	Friday	Saturday	Sunday	Average % Variation
Temperature	3:00 AM	13.3°C	11.8°C	12.4°C	8.41
	12.01 PM	22.2°C	20.7°C	20.9°C	5.54
Humidity	3:00 AM	52%	46%	31%	4.87
	12:01PM	25%	23%	18%	6.13
Wind Speed	3:00 AM	4.5 kmph	10 kmph	7 kmph	12.04
	12:01PM	11 kmph	8 kmph	8 kmph	7.04

4.4 WEATHER AND SOIL PARAMETERS INTERPRETATION

When the different weather and soil characteristics are shown together, as shown in Figure 4.8 and Figure 4.9, there is a strong link between them was observed. The link between air temperature and soil moisture, as well as the relationship between relative humidity and soil moisture, is shown in Figure 4.10 and Figure 4.11, respectively. Data in Figure 4.10 and Figure 4.11 shows that soil moisture follows both the air temperature and the relative humidity, as can be seen from a visual study of the figures. The crossover of the air temperature and soil moisture graphs is predicted because the air temperature increases rapidly during the daytime; but, owing to the soil's water-holding capacity, the same sudden shift in the soil moisture is not expected during the daytime. A similar sort of observation may be made for relative humidity and soil moisture content using the data shown in Figure 4.11. The soil moisture content, on the other hand, seems to be somewhat dependent on both air temperature and relative humidity, as seen by both plots. Figure 4.12 shows a single graph that shows the relationship between soil moisture and air temperature, relative humidity, and soil temperature overall.

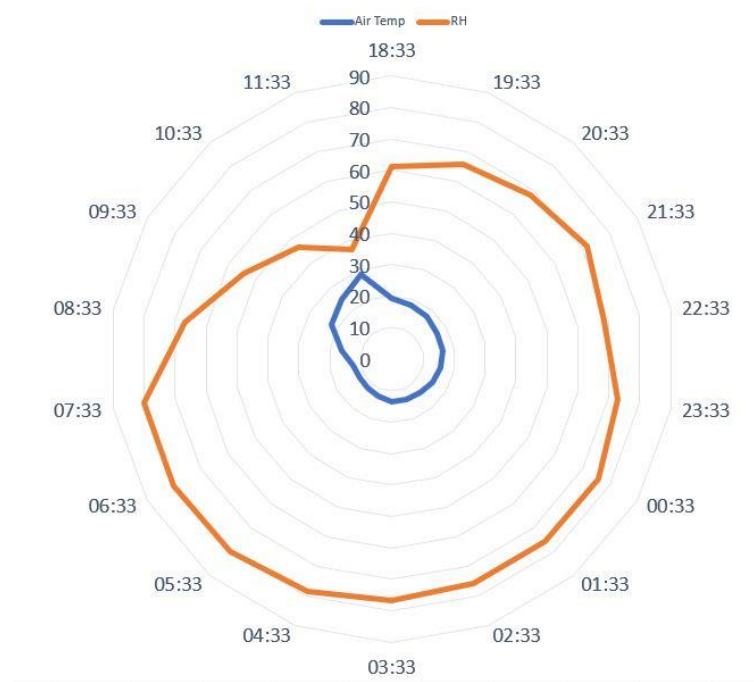


Figure 4.8 Weather parameters

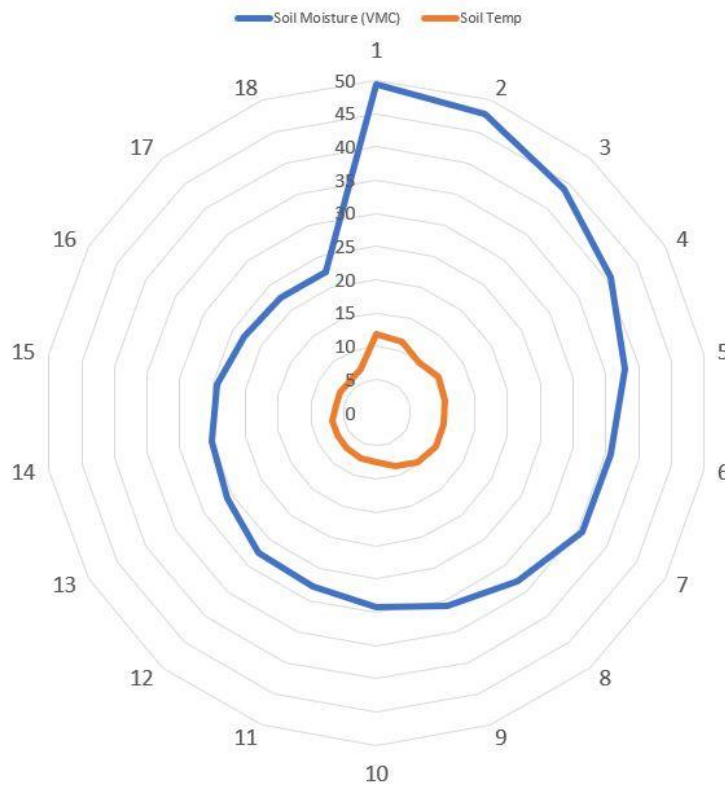


Figure 4.9 Soil parameters

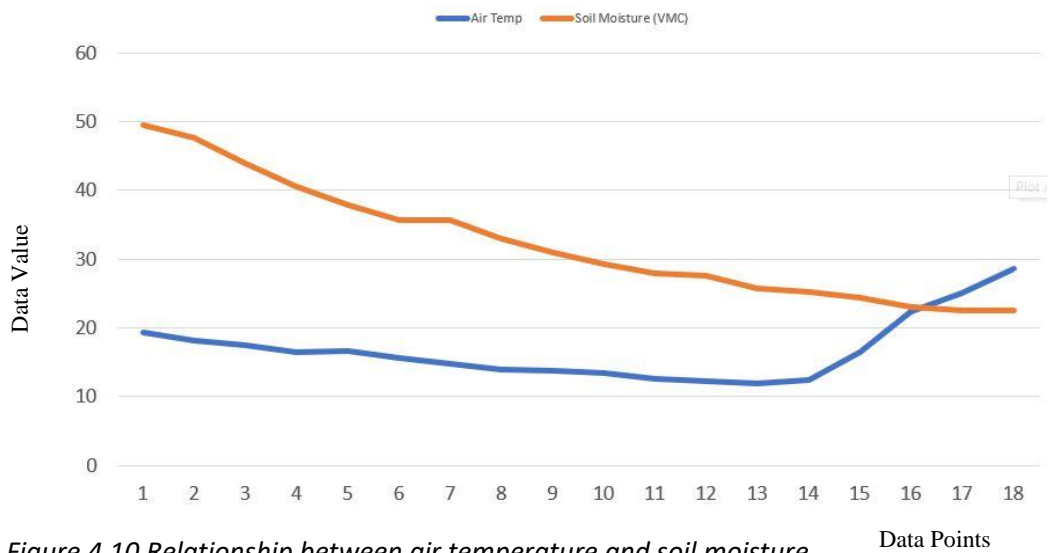


Figure 4.10 Relationship between air temperature and soil moisture

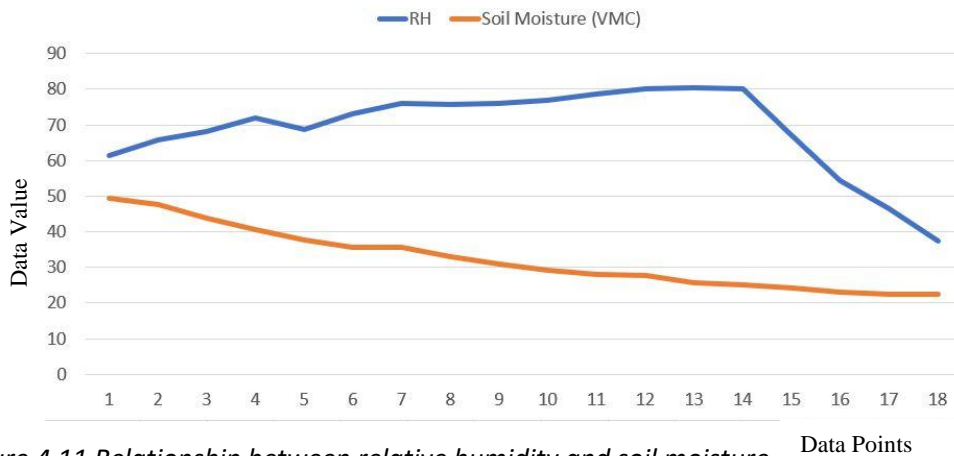


Figure 4.11 Relationship between relative humidity and soil moisture

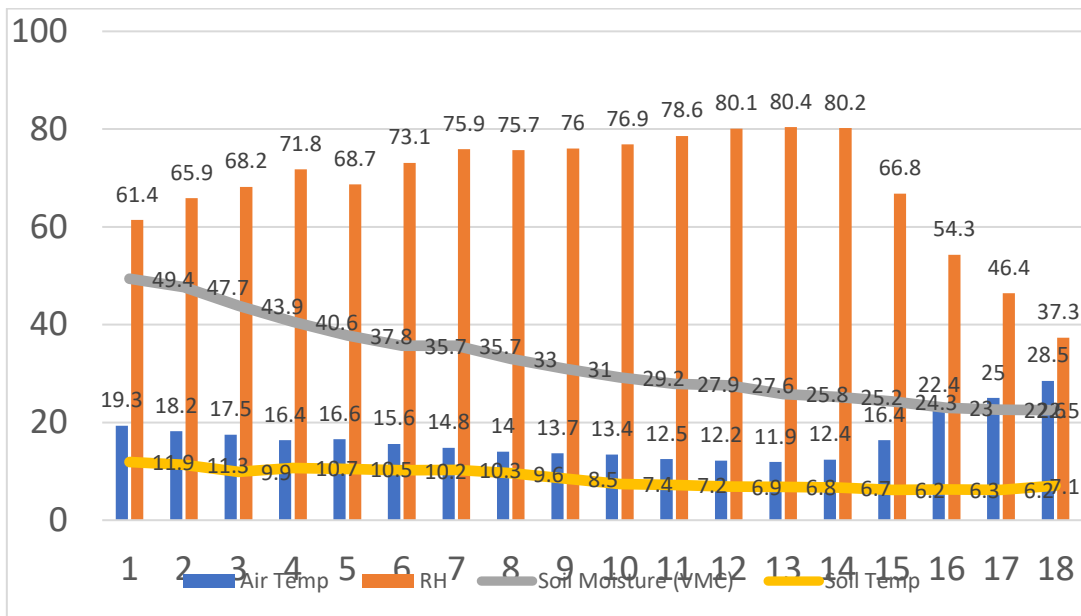


Figure 4.12 Distribution of soil moisture with respect to air temperature, relative humidity, and soil temperature

4.5 THINGSPEAK DATA VISUALIZATION

Two soil sensor nodes were used to test the system, and it was found to be effective at uploading the data to the specified IoT cloud service providers. Figure 4.13 and Figure 4.14 illustrate the Thingspeak data visualisation of the soil sensor for node 1 and sensor node 2 for the internet browser, as well as the weather parameters for each sensor. Any laptop or mobile phone with an internet browser would suffice. While utilizing an internet browser has its advantages, the disadvantages are that the user must go through a lengthy process of logging in and picking a channel each time, and the interface may

be unfamiliar to farmers. Anyone may simply monitor the field conditions using the Android mobile app, which just requires the use of the back and choose buttons. The Thingspeak IoT cloud app for Android devices just needs to be downloaded, installed, and all applicable Thingspeak IoT cloud channels only need to be registered once. There is a mobile interface for the dashboard and field monitoring, as shown in Figure 4.15.



Figure 4.13 Thingspeak data visualization for soil sensor node 1

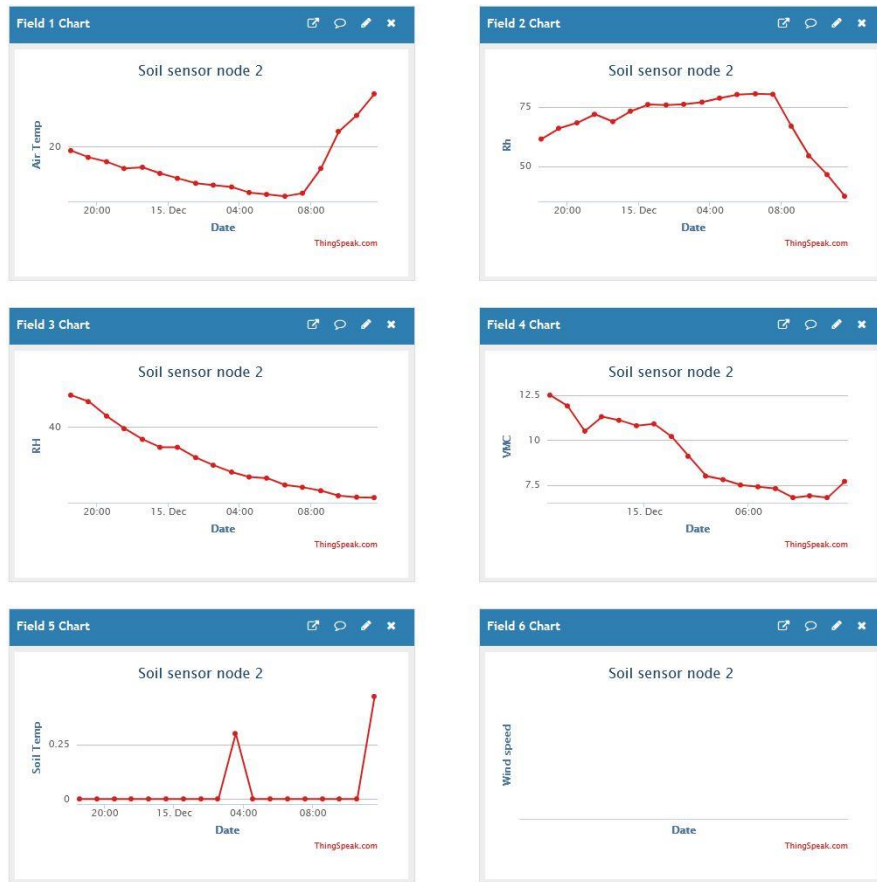


Figure 4.14 Thingspeak data visualization for soil sensor node 2

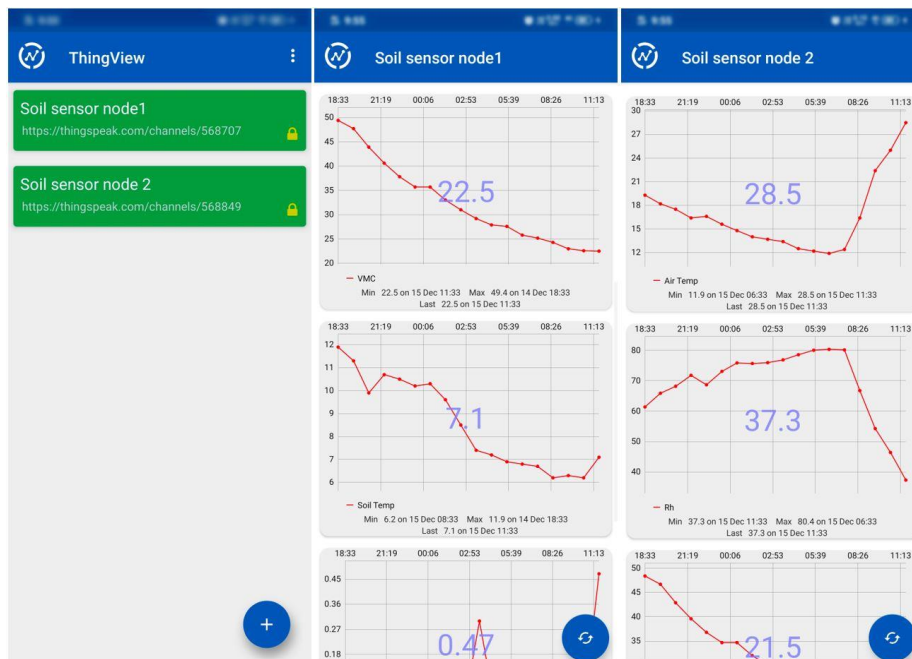


Figure 4.15 Thingspeak data visualisation on mobile device

4.6 MACHINE LEARNING BASED PREDICTION

Six best suited Machine Learning methods are performed to the weather and soil information in order to determine which the best one for the current application. The chosen techniques includes both linear and nonlinear Machine learning algorithms. Amongst the linear algorithms includes Logistic Regression (LR), Linear Discriminant Analysis (LDA) and nonlinear algorithms applied are K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), Gaussian Naive Bayes (NB), Support Vector Machines (SVM). For agricultural applications, the Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Gaussian Naive Bayes (NB) algorithms are frequently utilized. Figure 4.16 shows the multivariate plot and from the figure the relationship between the various soil and weather conditions can be observed. For instance, the air temperature and soil temperature to some extents are linearly related while air temperature and VMC graph shows the scattered dots.

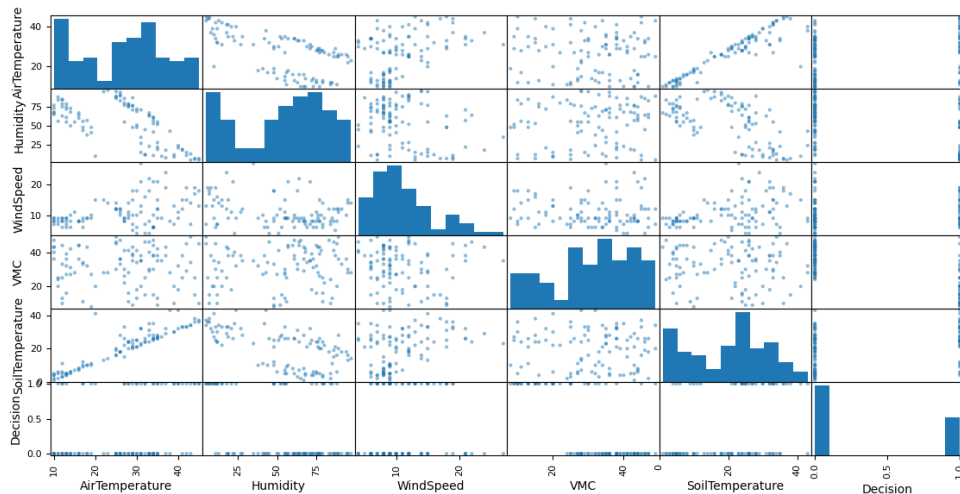


Figure 4.16 Multi-variant plot for soil and weather conditions

The available soil and weather dataset set is divided into two parts (80% and 20%), 80% data segment is used for training, evaluation and selection of best Machine Learning algorithm. While the other 20% data segment is used for validation of the Machine Learning algorithm. LDA gives the accuracy of 91.25%, highest amongst all the six Machine Learning algorithms while SVM accuracy is minimum with only 63.75%. The accuracy of all six Machine Learning algorithms is provided in Table 4.3.

Table 4.3 Algorithms comparison for accuracy in prediction

S. No.	Machine Learning algorithm	Accuracy in Prediction
1	LR	82.5%
2	LDA	91.25%
3	KNN	83.75%
4	CART	85.00%
5	NB	85.00%
6	SVM	63.75%

Following the computation of ML algorithm accuracy based on the training and validation process, the LDA model with 91.25 percent accuracy was chosen. Four instances are used to evaluate the chosen ML method in Figure 4.17 and they are numbered 1, 2, 3, and 4.

```

Soil and weather parameters from data set for decision 1: 1
[[36, 10, 9, 35, 27]] [1]
Required irrigation and system is activated

Soil and weather parameters from data set for decision 0: 2
[[35, 19, 9, 42, 27]] [0]
Irrigation not required and system is deactivated

Random soil and water condition Case 1: 3
[[40, 70, 10, 50, 30]] [0]
Irrigation not required and system is deactivated

Random soil and water condition Case 2: 4
[[40, 58, 5, 26, 30]] [1]
Required irrigation and system is activated
>>> |

```

Figure 4.17 Machine Learning LDA algorithm testing for intelligent irrigation system

Cases in point 1 and 2 are the soil and meteorological conditions from the dataset itself that result in irrigation decisions of 1 and 0. The output from instances 1 and 2 is determined to be correct when compared to the predicted output. Without reference to

the dataset values, instance 3 and instance 4 give the chosen Machine Learning model random values for the soil and weather circumstances. Instances 3 and 4 both result in decisions of 0 and 1, respectively. The Machine Learning model used is able to accurately anticipate the need for irrigation when the decision is compared for the expected outcome based on dataset.

4.7 URBAN FARMING

Although there is little or no literature on Precision Irrigation from a Society 5.0 or smart city viewpoint, there are various irrigation monitoring and control technologies created under the Precision Agriculture paradigm. For the various technical components, Table 4.4 compares the existing state-of-the-art solutions for Precision Irrigation planning with the system given in this research paper. Many of the works of literature cited in table 4 fail to include all of the important and non-redundant weather parameters, such as wind speed, wind direction, air temperature, and relative humidity, as even omitting the wind speed or direction parameter may not provide a complete picture of the weather. Similarly, much of the literature on soil conditions ignores the importance of soil temperature in agricultural planning. Few of the instances given have IoT connection with a PC or any other complicated system, which is an impractical option for agricultural applications. Even though the IoT solutions given are based on the most advanced technology, they are unable to provide a comprehensive monitoring solution for agricultural metrics for field monitoring.

4.8 CONCLUSION

In this chapter the results of the developed PI DSS system are discussed. Range testing of LoRa module along with its technical details, sensing accuracy of weather station is provided in detail. The relation between various measured agronomical and agrometeorological data is presented. IoT cloud data visualization is provided for both laptops and mobile phone. The application of various Machine Learning algorithms on the observed dataset, selection of the best Machine Learning algorithm based on its accuracy of prediction and testing the selected Machine Learning algorithm on random input variable for the developed PI-DSS is discussed. In the end, developed system is

compared with previous state of the art irrigation support system from urban farming perspective also.

Table 4.4 Comparison of existing state-of-the-art solutions for Precision Irrigation with the developed system

S.No.	Challenges	Irrigation automation based on IoT, cloud, and LPWAN in [154, 161, 156, 157, 158]	Irrigation Automation with Zigbee [23, 24, 25]	Irrigation Automation using Bluetooth [29, 26, 146, 159, 162]	Proposed DSS for Precision Irrigation
1	Scalability	Scalable	Scalable	Not Scalable	Scalable
2	Communication Range	Upto 1000 meters	Upto 10 meters	Upto 100 meters	upto 8000 meters
3	Machine Learning	Not considered	Not considered	Not considered	Implemented
4	Weather Conditions (wind direction, air temperature, and relative humidity)	All weather parameter not considered	All weather parameter not considered	All weather parameter not considered	Considers, air temperature, relative humidity, and wind conditions
5	Soil Conditions (Soil Temperature)	Primarily concerned with measuring soil moisture	Primarily concerned with measuring soil moisture	Primarily concerned with measuring soil moisture	Considered, soil VMC and soil temperature
6	Urban Farming	Not considered	Not considered	Not considered	Considered

Chapter 5 CONCLUSION AND FUTURE ENHANCEMENT

*“Research is seeing what everybody else has seen and thinking
what nobody else has thought.”*

Albert Szent-Györgyi

5.1 CONCLUSION

The thesis work develops a system for smart Precision Irrigation by deploying Long Range WSN communication technology and irrigating plants/crops as and when required. This thesis accomplishes the 4 objectives; first being the development of soil sensor node with soil moisture and soil temperature sensor with LPWAN – LoRaWAN technology having good power efficiency and is scalable along with long range of communication. Second objective is to developed a weather station for collecting the weather information. The developed weather station also collects the soil conditions from soil sensors nodes and along with weather parameters uploads the information to IoT cloud. The third objective is to apply the machine learning techniques to enable system to take decision of its own. Fourth objective focusses in comparing the present developed irrigation systems with the already developed irrigation automation system in literature, patent or commercially available systems. The development of the precision irrigation system in the thesis work has been presented into 4 sections – (1) weather station, (2) soil sensor nodes, (3) Thingspeak IoT cloud, and (4) Machine Learning implementation. The various challenges in present automated irrigation systems and the rationale for selecting soil and weather parameters is provided in Chapter 2.

The weather station collects the soil conditions from different soil nodes and along with weather conditions and uploads them on the IoT Thingspeak cloud. The weather station is developed first as it acts as the central unit between soil sensor nodes and IoT cloud. Weather station is equipped with temperature, relative humidity, wind speed and wind direction sensors. Weather station also connects with soils sensor nodes via LoRaWAN

receiver module. The developed prototype weather station produces practically satisfactory results. The weather station was tested for three days in a row from the 14th to the 16th of December 2018 in Phagwara, Punjab, India, with the geographical coordinates 31.199325275018488 and 75.7736178548299. For the three-day maximum difference in temperature measurement, the weather data obtained from <https://www.worldweatheronline.com> and measured by the developed weather station prototype was about 1.4°C. The difference in humidity measured between the two sources of information is 2%, while the largest variation in wind speed is 1 kmph. When the various weather and soil characteristics were displayed together, a strong link between them was discovered. Data shows that soil moisture is affected by both air temperature and relative humidity. The crossover of the air temperature and soil moisture graphs is predicted because the air temperature rises rapidly during the day; however, due to the soil's water-holding capacity, the same abrupt change in soil moisture is not anticipated during the day. A similar observation can be made about relative humidity and soil moisture content. The moisture content of the soil, on the other hand, appears to be affected by both air temperature and relative humidity.

The weather station is developed around quad-core 64-bit Broadcom BCM2837 ARM Cortex-A53 SoC processor Cortex based Raspberry Pi 3 board. The with 1GB of RAM and with 16GB SD card is capable of processing the required information of soil and weather. The architecture selected has inbuilt WiFi which connects the board to internet to upload the soil and weather conditions to IoT Thingspeak cloud. The use of such high architecture is supported as the weather station in addition to reading and uploading the agricultural information, also applies Machine Learning to the soil and weather parameters for decision making.

Soil sensor node collects soil condition, specifically soil VMC and soil temperature, using VH400 for soil VMC and DS18B20 for soil temperature. The LoRa module transmits the collected soil parameters. Both the soil sensors are resistant to rust and other damages, are safe to be buried in soil for years. DS18B20 uses one wire protocol for communicating the temperature value to microcontroller board and has range from -55°C to +125°C with an accuracy of $\pm 0.5^\circ\text{C}$ Accuracy from -10°C to +85°C. As there was no reference data available for the soil parameters, that is why the work relies on

the calibration equation and the development board Arduino and this is an additional challenge this thesis addresses by creating the agricultural data for irrigation planning.

Soil sensor nodes are equipped with LPWAN-LoRAWAN transmitter module and weather station is connected to LPWAN-LoRAWAN receiver module. With the LoRa module, soil parameters are communicated to a weather station, where they are analyzed. The LoRa module deployed works at 433Mhz which is an unlicensed frequency band in India. The supplier's specification claim range up to 8000mtrs. Practically the LoRa module is tested within Lovely Professional University campus itself and the transmission was found without any error up to 1Km – 1.5Kms with buildings in between. The soil parameters are successfully transmitted and received with LoRa module.

IoT cloud Thingspeak allows monitoring up to 8 – channels at no cost with data presentation in excel format and also in graphical format for better visualization. Thingspeak data visualization is provided in Chapter 6. Thingspeak apart from providing the data monitoring and visualization, also creates a repository of agricultural data suitable further for study for irrigation and other agricultural automations system developments. Use of Thingspeak IoT cloud is cost effective being allowing to use 8 channels without and subscription cost.

Machine Learning gives the machine capability to learn from past experiences and makes suitable decisions. In agriculture, Machine Learning has been exploited extensively in most agricultural applications such as soil management, disease detection, livestock management, animal welfare, weed detection, and many more. KNN, SVM, MB, and ENN are a few of the Machine Learning algorithms used in agricultural applications. But there have been few traces in the literature for the deployment of Machine Learning for Precision Irrigation. The dataset so observed with soil sensor nodes and weather station, and available from Thingsperak IoT cloud in .csv format is applied to six different machine learning algorithms, taking into account both linear and nonlinear algorithms, in order to select the best machine learning model. Logistic Regression (LR), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), Gaussian Naive Bayes (NB), and Support Vector Machines are among the linear algorithms used

(SVM). The dataset is split into two parts: training data (80%) and validation data (20%). After applying the machine learning algorithms to the dataset, the accuracy of prediction is calculated using the accuracy score, which is obtained by dividing the number of correct predictions by the total number of predictions. Based on the accuracy score, the top three prediction algorithms are LDA (91.25%), CART (85.00%), and NB (85.00), respectively. SVM gave the least efficiency of 63.75%. Based on the accuracy score, the LDA machine learning algorithms provide the best prediction accuracy for the agricultural dataset, which is 91.25%. Once the system has been learned, random use cases are applied to the model to test it. The system is tested for three different use cases, and the irrigation actuation was chosen correctly.

Agriculture in the modern era is not only limited to rural farming or establishment but has also extended to cities as urban farming and due to large-scale urbanization is the need of today. Urban farming is an important element in smart city development and automation in Urban farming is also required. Urban farming includes all the activities of rural farming but in the city's infrastructure. Urban farming helps in reducing the load on agriculture due to ever increasing population, decreasing agricultural land due to urbanization, providing the mode of living and income in cities, and providing food security and a sustainable development environment in cities. Precision Irrigation is equally important in urban farming as in rural farming affecting the utilization of irrigation water, crop yield quantity, and quality. The various details of urban farming and its components are illustrated in Chapter 2. The present work is equally applicable to urban farming as the technology used provides the required performance in the urban establishment also.

5.2 FUTURE ENHANCEMENTS

Although the researcher has put in his best efforts in the present study, still precision agriculture has wide scope for further research. Like a stepping stone, this research has enough scope for further enhancements. Thus, for future research and in light of the results and conclusions of this study, the following future work may be carried out:

1. Implementing Linux-based Device Driver algorithms for the system to improve overall hardware performance.

2. Analyzing the power efficiency of various power sources for better and longer operational life of soil sensor nodes.
3. Advancing the monitoring with image processing for disease detection and synchronizing the irrigation with the disease detection module. This will help farmers to reduce yield loss and serve society with the growing need of agricultural products.
4. Implementing the Precision Irrigation system with other modules such as Pycom boards, and ARM Ax series processor and comparing their performances.
5. Integrating a water quality monitoring system to helps in maintaining soil salinity and also determining the effect of irrigation on soil temperature. With this the soil pollution can be reduce and also helps in maintaining the soil fertility of the soil
6. Extending the present work to controlling the fencing around the farmland for protecting the crop from wind-related damages such as leaf tearing, bending, cracking, lodging, and many more. This will again will be an added protection to crops and will result in reduces yield losses.

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