Advanced Machine Learning Techniques for Irrigation System

A Thesis submitted

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

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by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis, entitled "**Advanced Machine Learning Techniques for Irrigation System**" in fulfillment of the requirements for the award of the degree of Doctor of Philosophy in the department of computer science and engineering and submitted in Galgotias University, Greater Noida is an authentic record of my own work carried out during a period from Aug 2017 to September 2023 under the supervision of **Dr. Avneesh Kumar.**

The matter embodied in this thesis has not been submitted by me for the award of any other degree of this or any other University/Institute.

Mrs. Angelin Blessy J

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

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ABSTRACT

The Water Energy Food (WEF) nexus is an interdependent approach which provides mutual integration for a sustainable ecosystem. WEF ecosystem nexuses provide the solution to achieve long-term environmental, economic and social goals. Particularly, an effective irrigation system optimizes the usage of water, reduces the consumption of energy and increase the food production. An advanced water management system required for agriculture because huge amount of fresh water is wasted while doing the irrigation. An irrigation system is the process of managing water for helping the plants to gets efficient way. The different types of irrigation system used for agriculture such as surface, micro, Drip, and etc. An effective irrigation system required proper requirement analysis. The wireless system, IoT and sensors used to help the requirement and environments analysis. Recent technologies such as IoT, machine and deep learning help to analysis the present and future requirements of water and nutrition of plants.

Water and energy consumption in the agriculture industry is not accurately calculated, water efficiency and planning are crucial. An irrigated field waste an enormous quantity of water in irrigation system. The integration of current technology offers a solution for water management and for establishing the right irrigation plan. In this thesis concentrated irrigation requirement analysis using the different parameters for crops. Particularly in this research used banana cultivation for experimental setup and data collections.

In this thesis three methodologies used for irrigation requirement analysis and prediction of water requirements. The first methodologies used IoT sensors, reinforcement learning and KNN algorithms for model creations. The second methodology used cloud storage, long short-term memory (LSTM), and adaptive network fuzzy inference system (ANFIS) techniques and transfer learning used for requirement prediction for irrigations. Using the LSTM algorithm short term requirement is analysis, ANFIS is used to calculate the long-term requirement analysis's and Transfer learning used to reuse the pre-trained model form one farm to other form for better predictions. The third methodology used reinforcement learning KNN algorithm model in the federated learning environments. Using the federated learning better optimized model is created and updated the model using the different parameters. Using this model user data not shared with other farmers.

The proposed methodologies were implemented using the banana dataset and datasets are collected form location is 8.2473502, 77.2743729,345 (Kanyakumari, Tamil Nadu). The experiments are evaluated using R^2, MSLE and accuracy. Using the first methodology 30 to 40% of water is optimized compared to the manual water irrigation. Using the second methodology at 8, 16, 24, 32, and 48 h requirements were predicted. Using the third methodology the accuracy of the predictions was increased from 92.1% to 97.2 %.

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ANGELIN BLESSY J

CHAPTER 1

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
CPU	Central Processing Unit
CNN	Convolutional Neural Network
DDPG	Deep Deterministic Policy Gradient ().
DRL	Deep Reinforcement Learning
DT	Decision Trees
GDP	Gross Domestic Product
DDQL	Double Deep Q-Learning
FedCS	Federated Client Selection
FedAvg	Federated Average
GPS	Global Positioning System
IoT	Internet of Things
KPIs	key performance indicator
k-NN	k-Nearest Neighbors
KMO	Kaiser-Meyer-Olkin
LEPA	Low Energy Precision Application
LED	Light- Emitting Diode
LoRa	Long-Range Radio
LSTM	Long Short-Term Memory
ML	Machine Learning
M2M	Machine to Machine

PSO	Particle Swarm Optimization
PPO	Proximal Policy Optimization
PCA	Principal Component Analysis
RFID	Radio Frequency Identification
RL	Reinforcement Learning
RSTM	Root-Mean-Square Error
SS-VRT	Site-Specific Variable-Rate Sprinkler
SC	Spearman correlation
SMP	Soil Matric Potential
SVD	Singular Value Decomposition
SDG	Stochastic Gradient Optimization
SVM	Support Vector Machines
SDI	Subsurface Drip Irrigation
SSTI	Subsurface Textile Irrigation
SWAMP	Smart Water Management Platform
UAVs	Unmanned Autonomous Vehicles
WEF	Water–Energy–Food
WIFI	Wireless Fidelity
WSN	Wireless Sensor Network

LIST OF PUBLICATIONS

i. J. Angelin Blessy and A. kumar, "**Smart Irrigation System Techniques using Artificial Intelligence and IoT**," *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, Tirunelveli, India, 2021, pp. 1355-1359, doi: 10.1109/ICICV50876.2021.9388444. (**Scopus**)

ii. Angelin Blessy, Avneesh Kumar, "**Banana Irrigation System and Scheduling based on Reinforcement Learning,**" International Journal of Engineering Trends and Technology, vol. 70, no. 8, pp. 394-400, 2022. Crossref, https://doi.org/10.14445/22315381/IJETT-V70I8P240. (**Scopus**).

iii. Blessy, Angelin, Avneesh Kumar. "**Sustainable Irrigation Requirement Prediction Using Internet of Things and Transfer Learning**" Sustainability 15, no. 10: 8260, 2023. https://doi.org/10.3390/su15108260, (**SCIE, Scopus**) (**IF: 3.9**).

iv. Blessy, Angelin, Avneesh Kumar. " **An effective Irrgation Model for Banana Agriculture using Federated Learning**", Agriculture. (Under Communication).

Chapter I

Introduction

1.1. Introduction

Due to an expanding population and the need for food production, the agriculture sector utilizes around 70% of fresh water [1]. A huge amount of water and energy is wasted in irrigation systems. A total of 40% [2,3] of water is wasted because of evaporation, poor water management and poor irrigation systems. The water–energy–food (WEF) nexus is an interdependent approach which provides mutual integration for a sustainable ecosystem. Particularly, an effective irrigation system optimizes the usage of water and reduces the consumption of energy. WEF ecosystem nexuses provide the solution to achieve long-term environmental, economic and social goals. Effective, sustainable water utilization is achieved for irrigation systems and reduces water usage. In addition, due to global changes, lower rainfall rates, and climatic changes, a huge amount of water is also required for plants. Requirement analysis and management of water supply to plants are important to research in today's agricultural society. Based on varying environmental changes, water requirements for plants are managed using an irrigation system. Different water-optimization techniques and effective water-management systems are used to reduce water usage and achieve an effective water-requirements prediction system for plants, to increase production yields. Effective irrigation and scheduling systems are needed for society, and they increase productivity and reduce water usage.

Energy conservation and water management are crucial in today's society. Precision irrigation reduces energy utilization while managing water use. The irrigation system is made up of a system for observation, storing, processing, and making decisions. Data from actual grounds, including soil moisture, soil temperature, weather, and environmental variables are collected using IoT components. With the help of several parameters, we can optimize the demands and reduce energy use. The IoT components' observed data is kept in a cloud environment. Machine learning methods anticipate irrigation system performance using data from cloud environments. In-depth irrigation system models and decision-making based on numerous data are presented in this thesis. Agriculture is the primary consumer of both fresh water and electricity.

Seventy percent of the water consumed worldwide is used for agriculture. Out of this, only around 25% of the water and power are used efficiently; the remainder is lost. For a range of jobs in agriculture, including planting, sowing, spraying, weeding, and harvesting, water and electricity are used. As a result, there is a significant amount of trash produced along with the consumption of fresh water and electricity. Therefore, the optimization solutions consume less water and electricity . The productivity of crops is also increased by proper water use. Due to these elements, civilization needs efficient water use and ways of optimization.

The most recent effective technology applications lower the usage of water and power in many different industries. Various electronics components, techniques, and optimization algorithms are introduced by researchers from different domains. All industries will benefit from today's Internet of Things (IoT) and machine learning technology, which will help cut energy use and increase production. IoT and machine learning have a variety of applications in several industries, including agriculture, road transportation, and optimization. This method integrated machine learning and IoT for energy efficiency and appropriate irrigation techniques for utilizing water. The Internet of Things (IoT) is an assortment of mechanical, firmware-based, and programming-based devices that are connected to one another. Data is collected using IoT devices and handled through cloud computing. The process of machine learning is automated that boosts output by taking lessons from the past. Effective machine learning methods include Bayesian statistics, neural networks, k-Nearest Neighbors (k-NN), support vector machines (SVM), decision trees (DT), and other mathematical models. The use of these mathematical learning models enables efficient analysis and judgment for particular purposes.

The following are the three phases of processing for energy management and efficient irrigation system use using IoT and machine learning:

i. Data collection, transmission, and gathering

ii. ii. The layer of intelligence and data processing

iii. The application layers

The layers above have a variety of elements and functions. Data transmission and collection are done in the first stage. Data processing receives information collected from fields or agricultural grounds. Sensors are used as certain physical components for data collection and processing. The main parts of the data collection process and transmission are Mobile data or Wi-Fi connections, local data processing using the ZigBee network, Wireless sensor Nodes (Single Sensor Node, Multiple Sensor Node), controlling components, Raspberry Pi, and other actual motors are managed by physical devices. The second layer is the processing of data layer, where the gathered data is processed using artificial intelligence and machine learning methods. Using the second layer, decisions are made. The application layer, the third layer, receives data from the second layer. Based on the output of the second layer, improvements, and enhancements for the third layer are planned. The complete data set is maintained in the cloud for preparing the future. Figure 1.1 displays the layers, IoT components, and machine learning method for realistic systems of irrigation representations.

Figure 1.1, data processing structure is divided into layers, each of which has its own unique set of challenges. The main problems with layers and structure in general are as follows.

i. There are certain manual components in the irrigation systems as a whole.

ii. Getting data from bottom layer and conveying it to the top levels is one of the more challenging tasks for the integration component of each layer.

• Combining various handling levels.

• Calculation of the water content and slope of each particular piece of land.

• On the basis of atmospheric action, humidity, and rain, water optimization is selected.

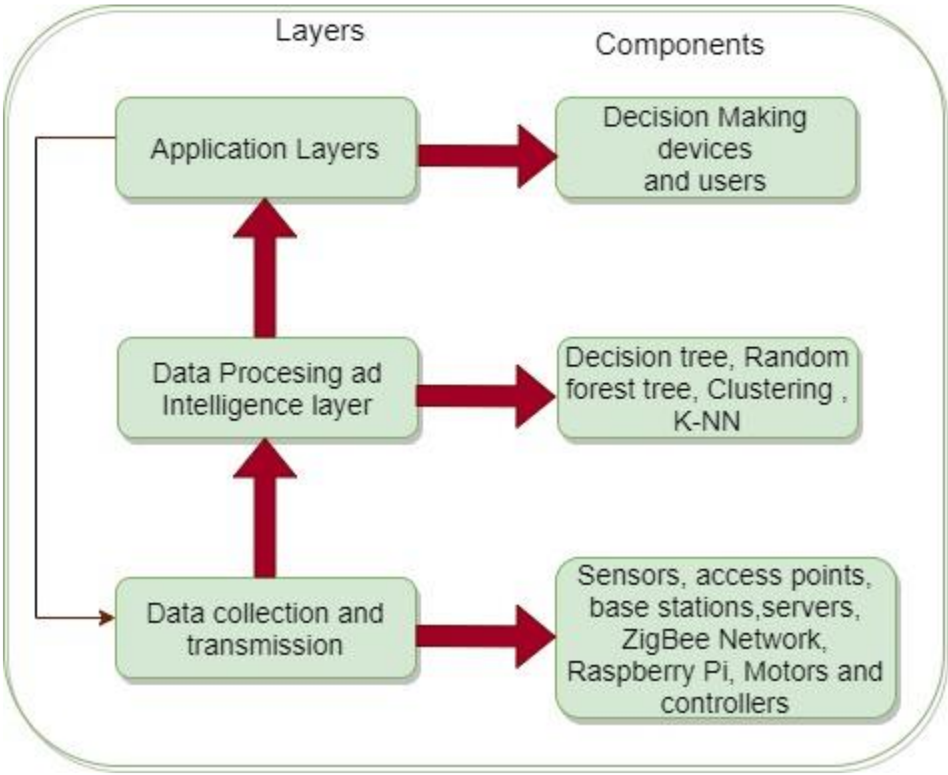


Figure 1.1: Layers and Components of irrigation system

They are the principal considerations that go into the different irrigation system projects. The quantity of moisture in the ground and plant soil, monitoring of land slopes, maximum plant use, month-by-month water usage, and best use based on power utilization were all considered in this suggested study.

1.2. Irrigation System

Multiple container, pump, and sprinkling device types are used to artificially add water to the soil. Irrigation is widely employed in areas with variable rainfall, dry spells, or imminent drought. There are a variety of irrigation methods available that uniformly distribute water throughout the entire area. All types of water can be used for irrigation, including groundwater from spring or water wells, surface-level water from rivers, lakes, or dams, as well as water from untraditional sources such as wastewater that has been treated or water that has been desalinated. In order to lower the risk of contamination, it is essential for farmers to protect their agricultural water source. As with any groundwater withdrawal, users of irrigation water must take care to prevent pumping groundwater out of an aquifer more quickly than it is filling [4].

1.2.1. Types of Irrigation System

Surface irrigation

The earliest and most widely utilized type of irrigation is surface irrigation. In order to moist and permeate the soil, aerial (flood, or level basins) irrigation networks convey water across the highest point of agricultural lands. There are several different types of surface irrigation, include raise, boundary strip, and reservoir irrigation. A frequent phrase for irrigation that causes or almost causes flooding of the cultivated land is "flood irrigation.” This has historically been widely used method for irrigating agricultural land, and the majority of the world still use it. Where irrigation source water levels permit, dikes, which are normally filled with earth, are used to regulate levels. This is a typical sight in rice fields with tiers, also known as "rice paddies," whenever the method is applied to control or flood each area's water supply. In other cases, either human or animal power is used to pump or elevate the water above the level of the land. Surface irrigation typically has a poorer water application efficiency when contrasted with different kinds of irrigation [5].

Micro-irrigation

Micro-irrigation is a technique in which each plant or the region surrounding it is, treated to a little discharge of water that is dispersed via a network at low pressure of pipes in a specified sequence. Other names for it include trickling irrigation, low volume irrigation, and confined irrigation. This set of irrigation techniques includes subsurface drip irrigation (SDI), conventional drip watering with individual contributors, micro spray or micro sprinkler cultivation, and mini-bubbler irrigation.

Drip Irrigation

Sometimes referred to as trickling irrigation, drip (or micro) irrigation, carries out what its name implies. This mechanism receives water at the roots, drip by drip. Water is slowly applied to plant roots or areas around. This method of irrigation may be the most water-saving one if runoff and reduced evaporation. Efficiency of field irrigation with drip watering is normally between 80 and 90 percent when done correctly. To further reduce evaporation and distribute nutrients, contemporary agriculture typically uses plastic mulch and drip watering. Fertigation is the name of the procedure.

Sprinklers for irrigation

In order to irrigate the field using sprinklers water is routed to a few central spots throughout the field for overhead irrigation or other purposes. Sprinklers, sprays, or guns that are mounted above the ground on risers that are permanently erected are used in solid-set irrigation systems. Rotating sprinklers with a higher pressure are known as rotors, they are propelled by impact, ball drives, or gear drives. You can make rotors fully or partially revolve. Guns typically have nozzle sizes between 10 and 50 mm (0.5 to 1.9 in), work at exceptionally high pressure of 275 to 900 kPa (40 to 130 psi), and flow rates of 3 to 76 L/s (50 to 1200 US gal/min). In industrial settings, guns are employed for irrigation in addition to activities like logging and dust suppression.

Additionally, moving platforms that are hosed to a water source may have sprinklers attached to them. Mobile sprinklers are unattended irrigation systems on wheels that automatically pass through locations like parks, sports fields, cemeteries, meadows, and small farms. Most of them employ a section of polyethylene tubing looped around a steel drum. The sprinkler is propelled around the field by irrigation water or a miniature gas engine as the tubing is coiled around the drum. The mechanism turns off as the sprinkler returns to the reel. They are extensively used for irrigation, dust control, and waste water application on land and are commonly referred to as "water reel" moving irrigation sprinklers. Others pull the sprinkler platform with a rope while pulling a flat rubber hose behind them.

Pivot centre

Sprinklers are positioned along the length of numerous pipe segments (often composed of aluminum or galvanized steel), which have been affixed to one another and held up by trusses, in centre pivot irrigation. The pipe is mounted on towers with wheels. Water is supplied to the system, which circulates in a circle, near the arc's pivot point at the middle. Any sort of terrain can be irrigated thanks to the widespread use of these systems. The next image shows that sprinkler heads in more recent systems can detach.

In order to prevent evaporative losses, the majority of centre pivot systems as of 2017 have drips hanging from a U-shaped pipeline connected at the highest point of the pipe with spraying nozzles which are situated just a few feet (at most) above the crop.

The water can be dispersed between crops using drag hoses or bubblers in addition to drops. Crops are usually seeded in a circle to conform to the centre pivot. This kind of system is known as a LEPA (Low Energy Precision Application) system. The majority of centre pivots were initially operated by water. Both hydraulic and electrical motor-driven devices (Reinke, Valley, and Zimmatic) took their place. GPS components are commonly seen in modern pivots.

Watering via lateral movement (side roll, wheel line, wheel move) Several pipes are linked together, each with a 1.5 m-diameter wheel mounted in the centre and sprinklers spaced out along its length. Water is supplied by a big hose at one end. When one strip of the field has received enough irrigation, the hose is disconnected, the water is eliminated from the system, and the assembly is moved either by hand or with the help of a specially designed mechanism to move the sprinkler systems to another spot along the field. Now the hose can be reconnected. Up until the entire field has been watered, the procedure is repeated in a pattern.

Since this approach doesn't automatically move across the field like a central pivot does, it needs to be manually filled with water, rolled to a new strip, and then again manually filled with water. Most systems use aluminum pipe that is 100 or 130 mm in diameter (4 or 5 inches). The pipe functions as an axle to turn all of the wheels as well as a conduit for water to move through. The wheel line is rolled by the clamped-together pipe sections under the supervision of a drive system, which is frequently positioned in the centre of the wheel line. Each wheel's location may need to be adjusted manually if the system becomes out of alignment.

Wheel line systems have height restrictions on the crops they can irrigate as well as a cap on the amount of water they can convey. A lateral move system has the benefit of being composed of readily separated components that, as the line is altered, adapt to the shape of the field. They are used most often in tiny, rectilinear, or unconventionally shaped areas, in steep or rugged terrain, or in places where labour is reasonably priced.

lawn irrigation system

A permanent installation, as compared to hose-end emitters that can be moved, is a feature of a lawn sprinkler system. Sprinkler systems are put on lawns at homes, businesses, cemeteries, schools, public parks, and golf courses. Since aesthetics are so important in a landscape, the majority of these irrigation systems' components are hidden beneath. The number of zones in a typical sprinkler system for a lawn will depend on how much water the water supply can hold. Each zone will contain a distinct portion of the terrain. Typically, the microclimate, plant life type, and system of irrigation type are used to break up the landscape. In addition to sprinkler zones, an outdoor watering system might include bubblers, drip irrigation, and additional components.

Even if manual systems are still in use, the majority of a lawn sprinkler system's irrigation controller, often known as a clock or timer, can automate the system. The bulk of automation systems employ electric solenoid valves. These valves are wired to the controller and can be found in one or more zones. The valve opens when the controller delivers power to it, letting water flow through the sprinkler within that zone.

Pop-up spray heads and rotors are the two most typical sprinkler designs used to wet lawns. Rotors have a number of spinning streams, while spray heads have a set spray pattern. Larger areas are covered by rotors, whereas smaller ones are by spray heads. Golf course rotors can occasionally be so big that just one sprinkler and the valve will fit are combined to create a "valve in head." If applied to a turf area, the tops of the sprinklers are flush with the ground. Upon pressurization of the system, the head will raise above the surface and water the targeted area until the control valve closes, shutting the zone off. The sprinkler head retracts back into the earth when the lateral line is not anymore under strain. Sprinklers can be installed on risers above ground to be flush-set like in a lawn area or even higher pop-up sprinklers in shrubbery or flowerbeds regions.

Sprinklers Irrigation

Hose-end sprinklers come in a variety of varieties. Numerous them are scaled-down copies of huge agriculture and gardening sprinklers that can be connected to a garden hose for use in irrigation. Others have a sled base made to be dragged while connected to the hose, while some have a spiked base that allows them to be quickly trapped in the ground.

Subirrigation

When the water table is high, field crops have been sub irrigated for a very long time. This technique raises the water level table artificially so that moisture can be introduced to the soil from the plant rooted' bottoms. These systems often feature drainage structures and are situated on continuous grassland in lowlands or valleys of rivers. A network of weirs, gates, and pumping stations enables for the management of the water table by raising or lowering the amount of water in a system of ditches.

Subirrigation is sometimes used while growing plants in commercial greenhouses, typically used for plants in pots. Pumps from below draw water up, it is absorbed, while any additional water that remains is taken away for reuse. The usual procedure is to flood or run a water and nutrient solution through a trough for 10 to 20 minutes before pumping it into a container for storage once more for later use. In greenhouses, sub-irrigation calls for fairly pricey, high-tech management and equipment. Reduced system upkeep and automation, labor cost reductions, and nutrient and water conservation are all advantages. In both theory and practice, it works similarly to irrigation in subsurface basins.

The self-watering container is another kind of subirrigation, sometimes called sub irrigated planter. It involves employing a wicking material, like polyester rope, to suspend a planter above a reservoir. The wick is elevated by the water's capillary action. The wicking bed is a comparable method that also utilizes capillary action.

Subsurface irrigation for textiles

Subsurface Textile Irrigation (SSTI), a technique, was developed especially for subirrigation in a variety of soil types, from desert sand to deep clay. An impermeable base layer (usually made of polyethylene or polypropylene), a dripping line flowing down that foundation, an additional layer of geotextile on top above the drip line, and then a narrow impervious layer on top of the geotextile makes up an ordinary subterranean textile system for irrigation (see diagram). Contrary to conventional drip irrigation, up to two meters away from the dripper, the geotextile transfers water along the cloth, therefore the emitter spacing in the drip pipe is not crucial. It is effective to generate an artificial water table.

1.3. IoT for Irrigation System

In cloud environments, data collection and storage are done using the Data Collection and Transmission layers [6]. Table 1.1 and Figure 1.2 present the essential elements and the functions of each element. Data is gathered using a number of sensors in the WSN settings. Prior to sending the data to the cloud environments, the WSN environments internally process it. To keep track of the condition of the soil and land in diverse contexts, a number of detectors and electronic inclinometers are employed. Using a digital inclinometer, the research circumstance reveals a slope and distortion pattern. The slope's stability may be easily checked, and a digital inclinometer can also send status alerts. The data collection process using various sensors is shown in Figure 1.3.

Figure 1.2: IoT Components of Irrigation System

Table 1.1: Components of smart irrigation system

S.No	Components	Usage
1	F-28	Use of a soil sensor to control soil moisture
2	RS485, HPT675	Evaluation of the water condition
3	THERM200	Temperature of the soil
4	HTM2500LF	Measure water vapour and humidity
5	SHT11	Root Moisture
6	WSN	Surveillance, Monitoring and transmission
7	M2M (ZigBee)	Personal communication network
8	Digital Inclinometer	Gradient and slope of land measured.

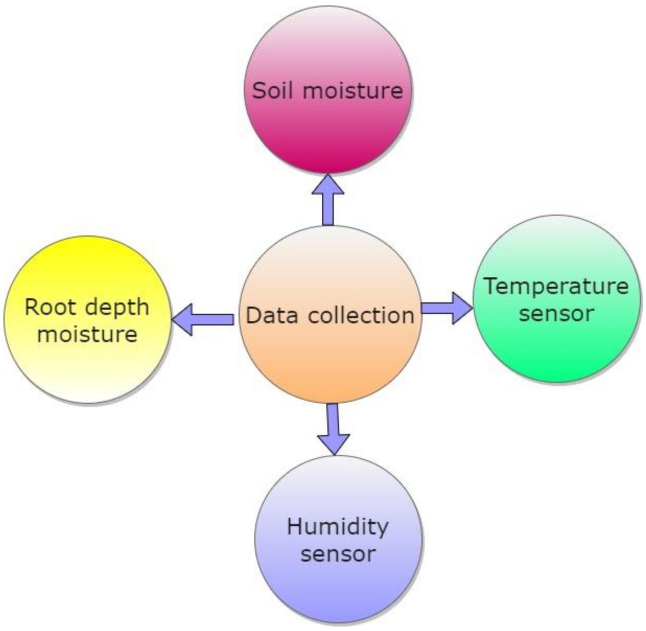


Figure 1.3: Data Collection from various sources

The different types of sensors are used to absorb and measure the irrigation environment for an effective irrigation. The some of the dominant sensors and components are as follows.

Moisture sensors: Soil moisture sensors estimate soil moisture. They might be handheld probes or stationary sensors. The field has fixed positions and depths for stationary sensors, but numerous locations can measure the soil moisture using portable probes.

Temperature Sensors: Temperature sensors measure greenhouse humidity, light, and more. Farmers can use a sensor to determine when the greenhouse temperature dips too low to grow tomatoes. The sensor will inform them to turn on heaters or plug-in radiators to keep the greenhouse warm. Plant development and health depend on soil temperature. In addition to temperatures, a temperature sensor may measure soil moisture. Wet or dry crop cultivation benefits from temperature-based sensors. They measure soil thermal energy to determine plant growth conditions.

Digital Inclinometer: It measures an object's tilt, relative to gravity. Precision farming relies on inclinometers to optimize plough performance. Farmers can optimize seedbed preparation and crop growth by correctly measuring plough inclination to ensure equal depth and furrow formation. The Plough Digital Inclinometer aids precision farmers in many ways. This unique technology has several benefits and uses:

- Plough Digital Inclinometer provides exact inclination measurements to help farmers maintain regular ploughing depth across the field for optimal crop growth and seedbed preparation.

- With wireless connectivity and data transfer, the inclinometer lets farmers monitor plough performance in real time and make on-the-spot modifications. Real-time feedback improves efficiency and reduces errors.

- Plow inclination data from the inclinometer can be evaluated to learn about field conditions, soil profiles, and ploughing technique improvements. This data-driven strategy helps farmers optimize their farming operations.

Humidity Sensors: Electronic humidity sensors monitor atmospheric humidity at minimal cost. Also called hygrometers. Absolute, relative, and specific humidity can be measured. Relative and absolute humidity sensors are classed by kind. Air humidity measures water vapor. Relative and absolute humidity are calculated. In industrial and medicinal settings, relative humidity matters. Humidity over thresholds can cause control system failure and weather prediction inaccuracies. Measurement of humidity values is crucial for security and safety. Humidity sensors measure humidity. Air temperature is measured through relative sensors and above 100 degrees Celsius, this sensor is useless.

WSN: A wireless connection module links many sensor nodes in the wireless sensor network (WSN). These nodes can self-organize and be deployed precisely or randomly because they can process, transmit, and sense. Sensor nodes in a WSN are field-scattered. Each node collects and routes data to produce a view of the controlled field from above. Data is transmitted to a base station for treatment via direct or indirect sensors utilizing a multi-step architecture. When data analysis and decision-making need external network communication, a gateway network can be used by the main station [7].

An ad hoc network with three primary tasks is a wireless sensor network:

i. Sensing: Nodes gather the required data.

ii. Communication: Nodes exchange information with one another, the console, and the base station.

iii. Computing with algorithms, hardware, microcontrollers, and programs.

Some of the WSN characteristics include are as follows:

i. Numerous sensor nodes (from a few tens to thousands).

ii. Scalability: WSN protocols are designed to work well with varying network sizes and node counts, enabling them to thrive in various scenarios, including increased workload and network growth, enhancing their potential for various applications.

iii. Self-operation in remote or hostile places without supervision.

iv. Easy to use.

v. Limited sensor node power and storage.

vi. Node failure handling: Wireless sensor networks face diverse environmental circumstances in hostile or inaccessible settings.

To meet this difficulty, the WSN protocol stack offers techniques for handling node failures in difficult situations.

M2M (ZigBee): The ZigBee Alliance developed the wireless communication system known as ZigBee (ZigBee Specifications, 2020). It depends on the IEEE 802.15.4 standard (IEEE Standard for Information Technology, 2006), which specifies the number of communication protocols used in the design and creation of an individual local area network that is wireless with minimal power radio waves with a low data rate (IEEE Std, 2011). Zigbee is also perfect for frequent and intermediary data transmissions from an input device or sensors because it operates at frequencies of 915 MHz, 868 MHz, and 2.4 GHz and has a data rate of 250 kbps [8].

1.4 Artificial Intelligence for Irrigation System

Several machine learning approaches were used in agriculture for data analysis and prediction goals. Environmental data, irrigation control, and moisture analysis are forecasted and offered recommendations for the future with the aid of machine learning. Using a genetic algorithm, irrigation planning was carried out in this study. Utilize this tactic to increase production and determine various watering recommendations. The contributors of offered genetic algorithm-based solutions to problems with consecutive irrigation. The genetic model that was proposed provided a non-constant schedule-based approach. A weekly irrigation strategy and supporting information, such as meteorological and metrological data, were proposed by the different researchers. Based on this irrigation recommendation, the data analysis methods of boosted extrapolation and classification are recommended. As a result, the accuracy of both classification and regression is 93 and 95 percent, respectively. The optimal irrigation allocation method was developed for location-based water demand. The genetic algorithm for optimizations is used to introduce a new irrigation strategy using data from the previous day. In order to schedule irrigation, the sensor data was examined using Intelligence IoT's and K-NN machine learning technology. The entire procedure is automated, and data exchange takes place via machine-to-machine communication. IoT was used to introduce the work of machine learning for agricultural development. To forecast the pertinent irrigation-related variables in this study, decision trees are used. Logical regression was occasionally used by the researchers of to anticipate the water requirements. Predictions of wind speed, the outside temperature, and moisture are made using based on the decision trees. The SysFor [9] provides superior results and higher prediction accuracy as compared to the decision tree. The support vector machine method was employed to predict the demand for irrigation, albeit the proposals' level of accuracy is rather poor.

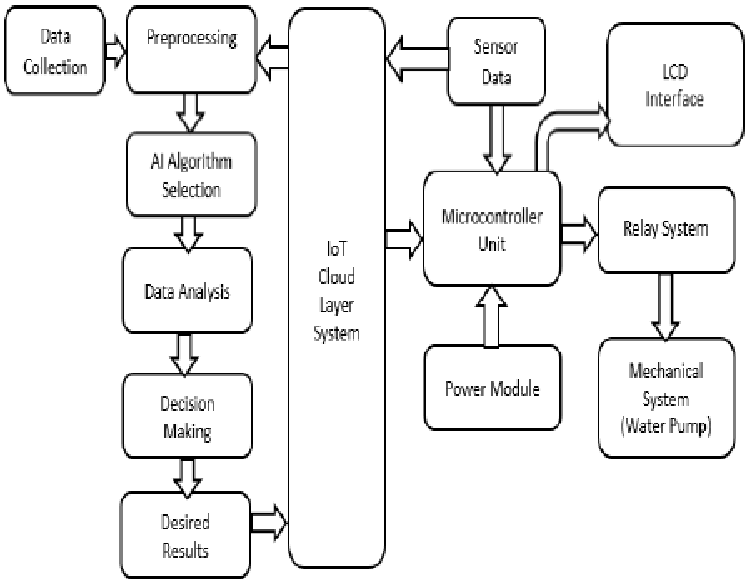


Figure 1.4: Gentral Block Strcutre of Irrgation System

The general block structure diagram is shown in Figure 1.4. This diagram shows each necessary building block. When the system first starts, raw data is used. This raw data may be generated or it may come directly from the available sensors, depending on the demands of the system.

The quantity of soil moisture can be determined using a sensor that detects soil moisture. Data can also be gathered using several pre-packaged datasets. This data is pre-processed or cleaned so that only the right data can be generated as system input. The devices are taught using any AI-based algorithm based on the data that has been collected, weather patterns, soil conditions, etc.

After doing a data analysis on the processed data, decisions regarding the necessary data will be made. The relevant data will be transmitted to the microcontroller or CPU unit through IOT layers as the desired results. Well-known microcontrollers include the Arduino Uno and Raspberry PI. A power module supplies electricity to each component. The microcontroller will process the data before transmitting it to the mechanical system. Relays are a particular class of current converter that convert an input signal into the needed current signal. Pumps of water can be used as irrigation system output devices.

1.5 Motivation of Research

The main motivation of this research reduces the fresh water usage, increase the soil dampness, increase the good yields and reduce the energy usage. The some of the main key points for motivations are as follows.

i. The major consumer of fresh water and power is agriculture. Around the globe, 70% of water is used for agriculture. About 25% of this is efficiently consumed, with the balance being wasted, including water and power [1,2,3].

ii. Due to the irregular irrigation system, the 50% of yields of agriculture is reduced and increase the cost.

iii. Due to the irrigations, the energy usage is increased.

iv. Keep the soil moisture in required level of cultivation.

These are the some of the main motivations of this research. Due to this research decrease the water and energy usage. The alternative advantage of this research is increasing the productivity.

1.6 Scope of the Research

The main scopes of the research are as follows:

i. Smart irrigation system is friendly platform interface to learn easily to farmers.

ii. Provide high accuracy water requirements and avoid waste of water.

iii. Due to automatic process, the required manpower is very less.

iv. The IoT and sensors devices are accurately measure the soil moisture.

v. Easily control and detect the humidity, temperature and find the requirements.

vi. The effective water system produced better quality of yields and improves the benefits in term of cost.

vii. The manual process is decreased and automatic process is increased.

1.7 Objectives of the Research

In this research, created four objectives for an effective model to irrigation model and fulfilment the requirement of crop.

i. To create an effective irrigation model and scheduling of crop.
ii. To predict the short- and long-term sustainable prediction requirements of the irrigation system.
iii. To shares the sustainable requirements of the prediction using the cloud environment and shares the features with the nearest farmers for better requirements prediction.
iv. To create an effective model using different farmers data, without sharing data.

1.8 Problem Statement

The water and energy consumption in the agriculture industry is not accurately calculated, water efficiency and planning are crucial. The irrigated fields waste an enormous quantity of water. The integration of current technology offers a solution for water management and for establishing the right irrigation plan. For smart agricultural areas, the Internet of Things and machine learning techniques are successfully applied. In this research focus on water optimization model, an effective short- and long-term requirement of water prediction of irrigation system, updation of predicted time series data and shared the effective method to nearest cultivation fields to better model for an effective irrigation.

1.9. Experimental Setup and Description

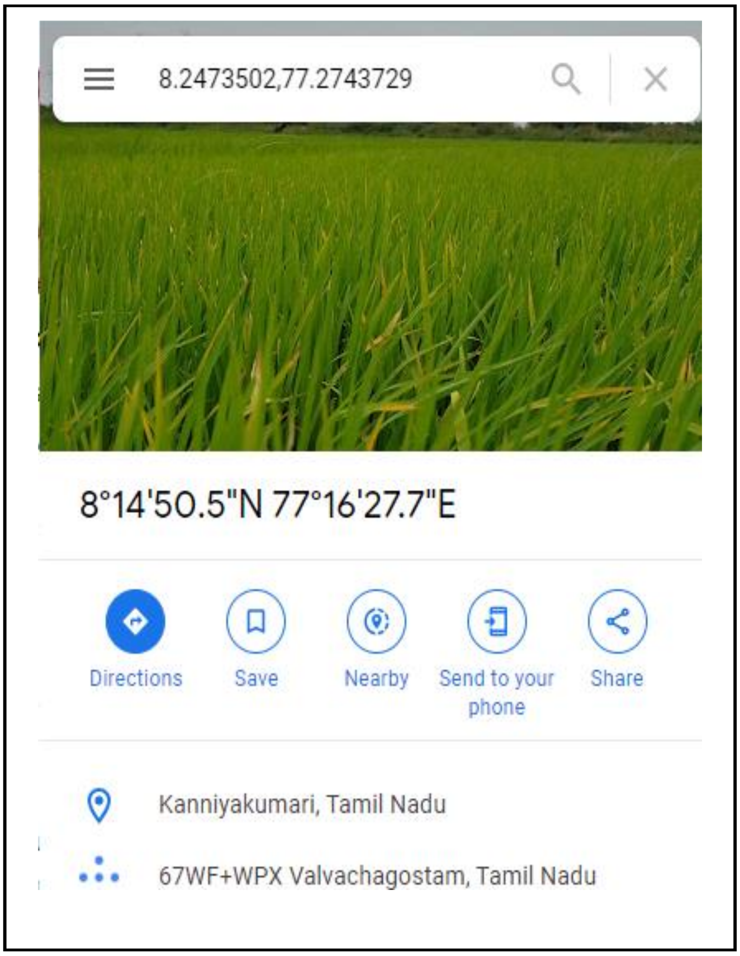


Figure 1.5: Sample collected location

Table 1.1 components are interconnected together and data is collected from each source of the location and roots. The collected data is stored in cloud environment and processed using the computational intelligence. The sample data, soil moisture, surrounding information are collected from the kanyakumari district, India. The sample collected location and experimental location is shown in Figure 1.5. The longitude and latitude of the experimental performed location is 8.2473502, 77.2743729,345. In this location early paddy cultivation was being done, but, currently, banana cultivation is done, here. Especially, thses two species of banana cultivation is being done in these areas, which are Ethapazham/Nendram Pazham/Nendrapazham/Changalikodan is Plantain Banana and Red dacca (Australia), Red banana, 'Red' banana (USA), and Claret banana are all names for this fruit in the English language. In addition to banana species, some regions also grow tapioca or Maravalli Kizhangu or cassava plant cultivation is also done. This location has, two ponds on either side. So, apart from April, May and half of June, we always have water facilities available in this location. So, this location is chosen for this cultivation and one more reason is that, it always has water facilities which are required for proper banana cultivation.

1.10 Outline of the Thesis

This thesis contains six chapters as well as references and three appendices. Chapter 1 contains the introduction, scope, motivation, problem definition and dataset description.

Chapter 2 presents the analysis of water requirements of irrigations and roots length of plants.

Chapter 3 presents a literature survey of the past works in smart irrigation system which is related to the machine learning, deep learning, and comparison of various methods, challenges and future direction of research.

Chapter 4 presents a requirement model prediction for smart irrigation using deep reinforcement learning and KNN algorithm.

Chapter 5 presents a short and long term water requirement prediction model using LSTM and ANFIS algorithm with transfer learning for an effective prediction model.

Chapter 6 presents a model for share the effective predicted model and with features to nearest farming land using federated learning.

Chapter 7 presents an experimental set up and performance evaluation, results and analysis.

Chapter 8 concludes and describes the possible extensions of this work.

Chapter 2

Statistical Analysis of Water Requirements in Irrigation

2.1 Introduction

Due to inefficient water management, a significant amount of the available water is lost during irrigation. It is necessary to have models that can estimate future water requirements in order to achieve better water management in irrigated areas. In this chapter, we construct a crop details and root information's and water management in India, with suitable qualities. We also include some relevant attributes. The rise in average temperature across the planet during the past century has contributed to a widespread decrease in the amount of water that has been restored across continents. For instance, over the years 2002–2016, worldwide endorheic systems saw a significant water loss equivalent to approximately 106.3 Gt yr-1. This loss can be attributed to reductions in surface water, soil moisture, and groundwater levels. In addition to rapidly expanding industry and urbanisation, as well as rapid population increase, there is a steady rise in the demand for water resources. This circumstance puts a significant strain on the water resources of the region, particularly in areas that already suffered from an exceptional deficit of water.

This chapter 2.2 presents different crop and corresponding root length for managing water. And section 2.3 presents different water management statics in India and finally the 2.4 presents the summary of this chapter.

2.2. Soil and Crop Root Analysis for Irrigation

Electrical resistance devices are able to provide an estimate, of the moisture in the soil. The electrical characteristics of the soil are subject to change if there is a shift in the moisture content of the soil. The presence of salts and fertiliser in the soil can make electrical resistance detecting devices very sensitive. Typically, soil tension is determined by a solid-state electric resistance measuring device that also detects soil matric potential (SMP). The resistance is read by a sensor of this type whenever there is a change in the soil tension, which is a function of the moisture content of the soil. The typical range of measurement for a soil tension sensor is 0 to 239 kPa. The greatest amount of water which the soil can store is indicated by an outcome of 0 kPa. The fact that the soil has a value of 239 kPa, suggests that it is dry. It is possible to estimate the amount of water holding capacity that has been lost based on the tension measurements (in kPa). Table 1 provides a description of one form of depletion in water holding capacity that can occur across a variety of soil types. It is possible to predict irrigation recommendations and time based on the depletion results. This will help to ensure that the soil's moisture content is just right for the development of plants [10].

Table 2.1: Depletion of water in soil types

Soil texture	Depletion in water holding capacity (kPa)		
	30%	50%	70%
Sand	20	30	60
Loamy Sand	25	40	67
Sandy Loam	28	50	80
Silt Loam	80	150	250

When it comes to installing soil moisture sensors, there are a few things to keep in mind. It is recommended that sensors be installed in the spaces between plants in a row's representative section. to keep the soil moisture sensors from being placed too close to the edge of a wheel track or lane. Additionally, it is important to avoid placing sensors in portions of the field such as the summit of a hill, low sections, and the field's edge, which are not indicative of the majority of the landscape. It is essential to position the soil depth sensors in the appropriate locations. It is important for the user to take into account the root depth of the crop. For instance, the root system of maize can generally grow up to a depth of 36 inches in the soil. The depths of six, eighteen, twenty-four, and thirty-six inches are suggested for measuring the amount of moisture in the soil. The usual optimum root area moisture absorption levels for various kinds of crops are described in Table 2. It is essential to keep a close eye on the soil depths at which effective moisture extraction can occur in order to increase the precision of the irrigation scheduling. The sensor's immediate surrounding' little soil volume is sampled

Table 2.2: Plants and Roots Length

Crop	Effective root zone depth (inches)	Crop	Effective root zone depth (inches)
Alfalfa	36	Peppers	18
Asparagus	36	Potatoes	18
Apples	30	Pumpkins	24
Beets	18	Radish	6
Blueberries	18	Strawberries	6
Carrots	18	Sorghum	24
Corn	24	Soybean	24
Cucumber	18	Snap beans	18
Eggplant	18	Spinach	6
Grapes	36	Squash	24
Lettuce	6	Sweet Potatoes	18
Melons	24	Tomatoes	24
Onions – bunch	6	Watermelons	24
Peas	18	Wheat	24

and measured by soil moisture sensors. Therefore, the method of installing the sensor is quite important to the process of acquiring correct results.

The study of roots is vital not only for enhancing and raising overall food production but also for preventing damage to the environment and combating the effects of climate change.

i. Roots are responsible for the finding water and nutrients and the efficient utilisation of those resources by the plant. It is possible to draw conclusions about the significance of roots to plants based on the fact that approximately half of the food that plants produce are used to nourish its roots. The productivity of a plant or crop is directly proportional to the degree, to which its roots make optimal use of water and nutrients.

ii. The pollution of the environment that is produced by the runoff wasted fertilisers, which leads to the eutrophication of aquatic systems, is a source of concern for the environment. The overuse of water for irrigation, which leads to the depletion of groundwater and surface water reserves, is another contributor to the unsustainable nature of farming practises.

iii. Roots are an essential part of the natural ecosystem because they contain a significant amount of carbon. As a result, research on roots is becoming increasingly prevalent in all-natural ecosystems.

Root systems have evolved to have distinct morphologies, topologies, distribution patterns, and architectural structures so that they can do all of their tasks. Each root system is customised for its expected lifespan, geographical location, and particular kind of soil.

2.3. Water management Statistics in India

The yield that an agricultural operation ultimately produces is highly dependent on the quality of the water that is used practically for every step of crop production. If plants are not given the proper amount of water, even high-quality seeds and fertilisers will not allow them to reach their full potential. The availability of sufficient water is critical to the process of animal husbandry as well. It goes without saying that the availability of water is essential to the fishing industry. India's share of the world's population is approximately 17%, despite making up about 4% of the world's freshwater resources. These water resources are dispersed across a large portion of the country with a huge discrepancy. Water supplies are being subjected to greater demands as a result of India's rapidly growing population, the deteriorating quality of the country's already existing water resources as a result of pollution, and the added demands of supporting India's exploding industrial and agricultural expansion have led to a situation in which fresh water availability is roughly constant while use of water is quickly increasing. This situation has led to a situation in which India is facing a water crisis. Surveys carried out by the Tata Institute of Social Sciences (TISS) revealed that the majority of urban cities suffer from a lack of available water. Ground water supplies provide close to forty percent of India's urban areas' water requirements. Because of this, most communities are experiencing a staggering 1–2-meter annual decline in their underground water tables. As a direct result of water scarcity, the ecosystem, including lakes, rivers, wetlands, and other fresh water resources, has a number of negative repercussions.

In addition, over use of water can result in a scarcity of water; this is a problem that frequently arises in regions that rely heavily on irrigation agriculture and causes damage to the environment in a number of different ways, including an increase in salinity, the contamination of nutrients, and the deterioration and disappearance of marsh and floodplain areas. In addition, the scarcity of water complicates the process of flow management required for the rehabilitation of urban streams. The ineffective water resource management system in India, along with the effects of climate change, has resulted in an ongoing water deficit. According to the OECD's environmental outlook for 2050, India would be experiencing severe water shortages by the year 2050. Agriculture in India accounts for 90 percent of the country's water consumption, despite rapid ground water depletion and inadequate irrigation systems.

In terms of agricultural production, India is ranked second worldwide. Agriculture, together with industries like forestry and fisheries, contributed 50% of the labour force and 13.7% of the nation's gross domestic product (GDP) in 2013. The irrigation infrastructure consists of a network of canals that draw water from rivers, wells, tanks, and other rainwater collection equipment. These products are used for agricultural purpose. In India, the ground system currently covers 160 million hectares (ha) of cultivated land, making it the largest. 22 million hectares (ha) of this total are irrigated by canals, while 39 million hectares (ha) are irrigated by ground water. However, the monsoon continues to be crucial for approximately two thirds of Indian agriculture.

2.3.1. Irrigation in India

Because India is a country that places a significant emphasis on agriculture and more than 55 percent of the population relies on agriculture for their livelihood, many of India's state governments are providing financial and other incentives to ensure that water is available for irrigation. These include the following: Free energy is being provided by the state government of Punjab in Northern India for the purpose of pumping ground water. In addition, the western Indian states of Gujarat and Maharashtra both provide generous subsidies for the installation of solar pumps. There are differences in the amount of water used for irrigation due, among other things, to the differing geographical conditions that exist in different regions of the nation. Rocky landscape with deep aquifers, sandy deserts, and rough mountains are the types of environments that typically have very inadequate irrigation facilities. This is because the cost of collecting water from these types of environments can be rather high. The areas with highest percentage of irrigation are, by a wide margin, possess the fertile alluvial plains that have permanent rivers and potable groundwater as well, as the regions that receive less than 125 centimetres of annual precipitation.

At this moment, approximately 84% of all of the available water is used for irrigation. The consumption of water by the industrial sector is approximately 12%, while that of the domestic sector is approximately 4% of the total available water. Because irrigation is expected to continue to be the main consumer of water, the maxim "per drop more crop" is an absolute necessity. In order to increase the area that is irrigated while also conserving water, the efficiency with which water is used which needs to be improved. Over the past few decades, India's irrigation system has undergone significant growth and development [11].

2.4. Summary

This chapter presented the analysis of water management and root depth for different plants. This analysis helps to fix and estimate the requirements of water and availability sources for irrigation in India. The Table 2.1 and Table 2.2 shows the different soil water observation and roots length. The roots lengths are used to mange the sensors and are useful to calculate the estimation of cost in irrigation systems.

Chapter 3

Literature Survey

3.1 Introduction

This chapter introduces various existing techniques, supporting concepts and advantages and disadvantages of different irrigation methods. With the aid of various computing approaches, including IoT, neural networks, and artificial intelligence, the smart irrigation system combines software, hardware, and firmware. Due to the efficient use of resources and creation of yields, it is crucial and necessary for civilization. Effective methods are required to monitor moisture levels, improve yields, and optimize water use. The use of the Internet of Things and artificial intelligence to create intelligent irrigation systems for agriculture is discussed in this article. This page presents the various parts, the modern irrigation system, many comparison metrics, and its requirements. Finally, many topics, difficulties, and the direction of future research in the smart irrigation system were highlighted.

Smart agriculture requires irrigation, and efficient resource management is crucial. According to the World Bank, agriculture will require 70 percent more freshwater in the future [12]. As a result, when doing research using various approaches, it is crucial to take effective water usage and water optimization for agriculture into account. Currently, the smart system is a valuable concept for managing resources in a variety of fields, but it has a significant impact on agriculture in particular. These sectors include energy efficiency, disease prediction, management, and irrigation systems. The combination of sensing, control, activation, analysis, and decision-making based on several automated processes is what is known as a smart system [13]. The automated operations rely on a variety of cutting-edge new techniques, networking know-how, sensing powers, and intelligence computations. So, enhance harvests and efficiently utilize the water with the aid of a creative technique. When cutting-edge technologies and intelligent irrigation techniques are applied, less freshwater is used in agriculture. Machine learning and the Internet of Things concepts enable centralized data processing, analysis, and decision-making from various omnipresent sensors [14]. An irrigation system is used in the agricultural process to artificially distribute resources like water. This irrigation technique is mostly employed in regions with low rainfall to keep the soil warm and moist. In agricultural fields, the artificial irrigation technology prevents the growth of weeds and undesirable plants. The two types of irrigation systems are traditional irrigation systems and modern irrigation systems. The traditional irrigation system makes use of irrigation cans and buckets. The most popular traditional irrigation methods, such as basin, furrow, strip, and basin irrigation, which doesn't need any special technical knowledge. But the cost of using a traditional watering system is high. Modern irrigation system was developed by extending the conventional irrigation system with the aid of contemporary technologies. The three types of irrigation systems are currently in use. They are drip irrigation system, pot irrigation system, and sprinkler irrigation system [15]. The contemporary irrigation system has a wide range of extra uses. Irrigation systems, historical controllers, location-based weather measurement controllers, signal-based controllers, etc. are a few examples of the numerous types of weather evapotranspiration controllers. Depending on how the soil moisture sensor controller is configured, the irrigation is separated into suspended cycle irrigation systems and liquid on-demand irrigation. The use of elements and traits has produced a number of notable divisions, including the ones mentioned above. Figure 3.1 depicts the various sensing and regulating methods used in contemporary smart irrigation technology.

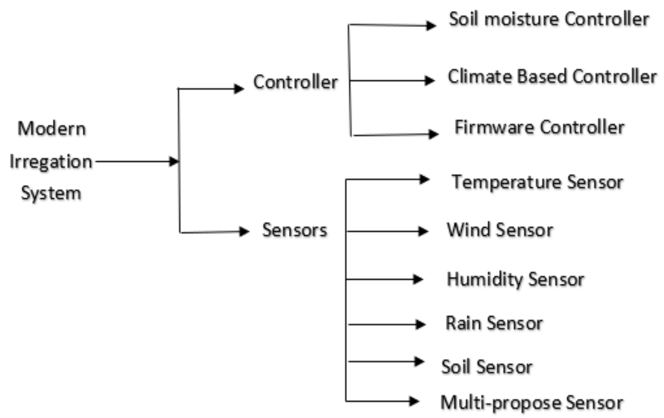


Figure 3.1: Various controller and sensors in Smart irrigation system

Increased yields and lower water and financial expenses are two key benefits of current smart irrigation systems. The automated smart irrigation system made use of a number of modern technologies, including big data [16], the internet of things [17], wireless sensor networks [15], cloud computing [19], artificial intelligence and machine learning [20], etc. Computing methods, sensors, automatic controllers, satellite data, flow meters and valves, WSN, batteries, and other parts are the essential components of smart irrigation systems. Figure 3.2 depicts the contemporary irrigation system in broad strokes.

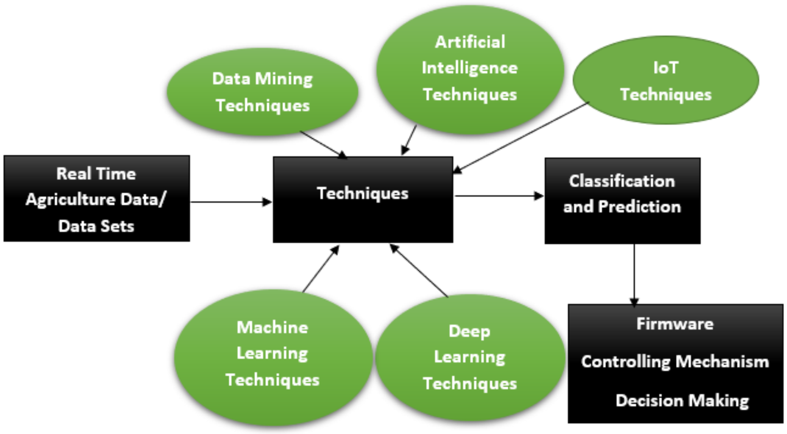


Figure 3.2: Modern irrigation system Techniques

The modern irrigation system has different steps such as i. Real-time data collection ii. Applying techniques iii. Classification and prediction iv. Controlling and decision making.

The organization of the chapter is consisting of section 3. 2 is about the intelligence system method, Section 3.3 consists of various machine learning methods analysis, Section 3.4 consists of various techniques for irrigation system using IoT and machine learning, Section 3.5 various metrics for analysis of irrigation methods. Section 3.6 consists of various issues, challenges, and future direction, and finally 3.7 Summary of the chapter.

3.2. Intelligence System for Irrigation System

Although they are occasionally used synonymously, the phrases intelligent and smart have different connotations. Both technological aptitude and the capacity to use previously learned knowledge are traits of intelligent people. Being intelligent is having the capacity to learn and use new concepts and abilities. Achieving highly intelligent systems requires the ability to learn preferences, routines, and precise situational diagnosis. They also require an organized method for learning, making decisions, and responding to their environment, as well as the ability to recognize the dates, times, and locations of significant events. Smart irrigation systems estimate or measure TAW depletion to restore the crop's water needs and reduce resource waste [21].

These systems usually use initial setup that is unique to the site, execute schedule updates, and incorporate scheduling and necessary cycles when they are programmed. Intelligent irrigation systems optimize crop watering by using artificial intelligence (AI) methods [22]. These systems analyze current data, form conclusions based on prior knowledge, and pick up behavior patterns from their surroundings. If a system, like an intelligent irrigation system, demonstrates intelligence traits that are comparable to human intellect, then we can assess it as intelligent. According to this definition, a virtual creature formed exclusively from software, or a physical entity composed of both hardware and software, with the purpose of performing tasks is called an intelligent agent. Intelligent agents are autonomous

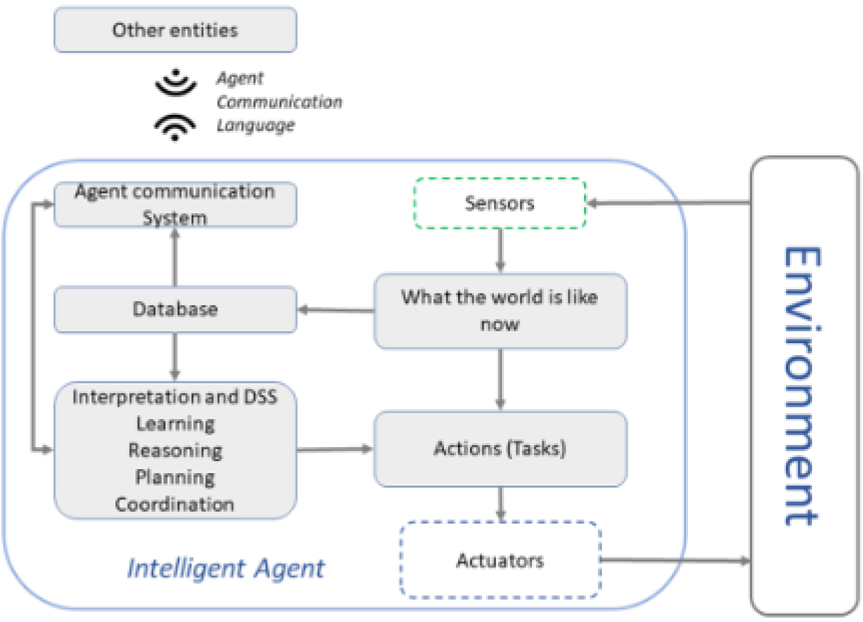


Figure 3.3: General structure of an intelligent agent.

entities that have the capacity for thought, deduction, learning, and information updating. They exhibit social, proactive, and reactive skills as well. When a performance measurement is used to determine how an agent should behave in relation to the environment in which it is positioned, that agent is said to be acting rationally. Figure 3.3 depicts the intelligent agent's components, including sensors for collecting environmental data, actuators for changing the environment, and a framework for interpretation and judgment (with or without AI). Moreover, a representative has the capacity to adapt, learn, coordinate, and plan. It also contains communication mechanisms with other agents to exchange information. An intelligent agent's core components for irrigation applications are shown in Figure 3.4, where information on the crop's hydric conditions is gathered utilizing a variety of sensors [23].

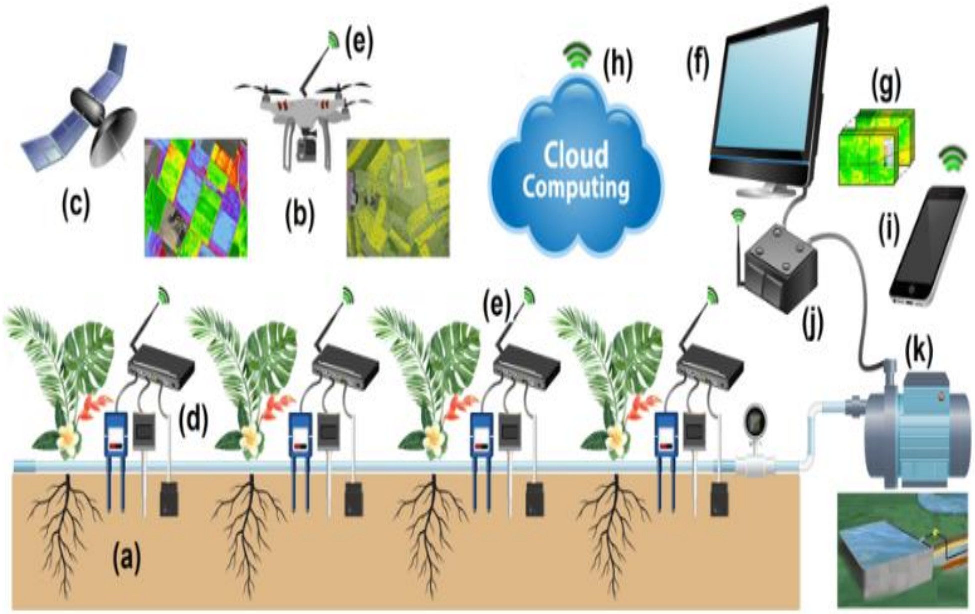


Figure 3.4: Intelligent agent for irrigation applications

To track the physical features of plants, soil, or the surroundings, Figure. 3.4a shows how these sensors are implanted and arranged into nodes or motes. (For instance, temperature, radiation, and relative humidity). Furthermore, information can be gathered through non-intrusive sensing methods to take pictures of the environment using various wavelengths of electromagnetic radiation (thermal, multispectral, night vision, or photometric cameras). Multispectral or radar technologies (e.g., Sentinel2, Landsat, or MODIS) can be used to capture the images using cameras mounted on unmanned autonomous vehicles (UAVs) (Figure. 3.4b), terrestrial systems (ground robots or other ground vehicles), or satellite systems (Figure. 3.4c). To pinpoint the precise location of the measurements, it is necessary to georeferenced the data produced by the sensor nodes or cameras. It is possible to collect data both in live and at predetermined testing intervals.

The sensors' electrical signals, whether analog or digital, must match the recorded physical variables in terms of both magnitude and frequency (Figure. 3.4d). The DAQS collects electrical signals from the sensors, transforms, scales, and conditions them to provide digital data that is stored in a numerical format and is ready for processing or integration. Using wireless communication protocols, the digitalized data used to give crop information is transmitted wirelessly over DTUs (ZigBee, WiFi or Bluetooth). The DTUs, a collection of nodes for wireless sensors made up of modems and antennae, communicate crop data across a network device connected to a central information hub or centralized master system of control (Figure. 3.4e). The central master control system includes a powerful server or machine running specific software integrated in (Figure. 3.4g), which uses artificial intelligence processing techniques to alter and evaluate the information and images gathered from the crops (Figure. 3.4f). The algorithms of the centralized controller system enable for the display of crop data in real-time, interpretation and analysis of data needed to monitor and support irrigated applications, making decisions to provide signals to the actuators that dose water on the field and predicting future crops. Irrigation applications tracking, managing, or remotely controlling, through the internet or cloud computing, agricultural information can be delivered to smartphones, tablets, laptops, and other devices (Figure 3.4h and 3.4i). Additionally, feedback control techniques are used by irrigation control algorithms.

3.3. Analysis of Machine learning methods

This section presents different machine learning techniques related to analysis and predictions of irrigation requirements. Some of the generalized machine learning techniques are as follows. This section, analyses some of the dimensionality detection methods and summarized various machine learning techniques.

3.2.1. Analysis of Dimensional Reduction

The practice of minimizing a dataset's attribute count while keeping as more variance as is practical in the source dataset is known as dimensionality reduction [24]. We do dimensionality reduction as part of the data preparation process before training the model. When a dataset's dimensions are reduced, we typically reduce between 1% and 15% of the variability in the original data, depending on how many components or features we keep. However, don't be concerned about reducing so the most of the variation in the initial data, as diminishing the dimensions will have the benefits follows. Numerous methods of dimensionality reduction can be utilized for a variety of data types and objectives. The graphical representation below contains a list of these methods of dimensionality reduction. The two main groups of approaches for reducing dimensionality are. Those approaches scale back the dimensions, in various types. It is crucial to distinguish between various kinds of techniques. The First one just keeps the essential data while removing the redundant characteristics from the dataset. There are no modifications made to the set of features. Among these examples include backward removal, random forests, and forward selection. The alternate solution to reveals a variety of novel characteristics. The group of features is transformed appropriately. The updated group of features [25] has new data in place of the old ones. This strategy has both non-linear and linear versions. Manifold learning refers to non-linear techniques. Examples of certain non-linear dimensionality reduction techniques include Kernel PCA, t-distributed Stochastic Neighbor Embedding (t-SNE), Isometric mapping and Multidimensional Scaling (MDS). Methods for reducing the linear dimensions include Principal Component Analysis (PCA), Factor Analysis (FA), Truncated Singular Value Decomposition (SVD) (Isomap) and Linear Discriminant Analysis (LDA).The some of the dimensional techniques are shown in Figure 3.5.

Normalization

To prepare data for machine learning, normalization is utilized. The objective of normalization is to use a same scale for all numerical columns in a dataset without allowing for values to fall into distinct ranges. To do this, tables from the dataset are created, and the relationships between the data are identified [26].

Feature Selection

Selecting qualities that are thought to be relevant or important to the issue might be viewed as a beneficial technique. It is also used as a measurement tool for evaluation. It is employed for both assessing metrics that rate different feature subsets as well as for making new feature subset recommendations. M. Banu Priya uses the PSO feature selection approach [27]. As a result, a portion of the final, standardized liver patient dataset is produced. It simply included the key characteristics. A swarm of particle, or basic processes, where every particle substitute for its solution, forms the basis of PSO computation.

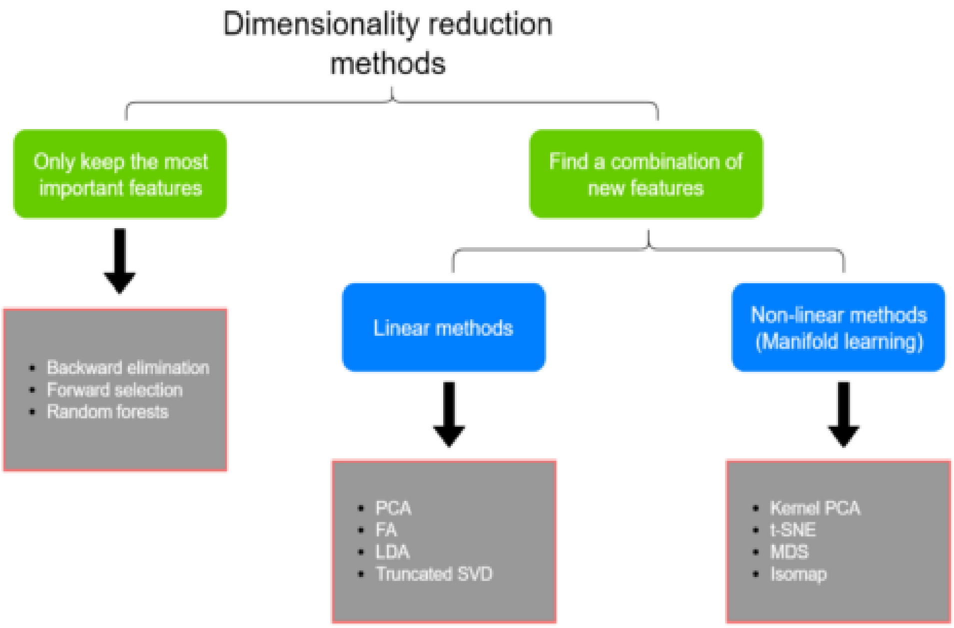


Figure 3.5: Dimensional Techniques

Principal Component Analysis (PCA)

Among my preferred machine learning algorithms is PCA. The PCA is a sequential method for reducing dimensionality (algorithm) that divides a larger group of covariates (p) into a more condensed set of unrelated variables (k) (p), known as principal components, in order to keep the most variation in the given dataset as feasible. For the purpose of dimensionality reduction relating to neural networks, a machine learning technique (ML) known as PCA [28].

Factor Analysis (FA)

FA and PCA are two mechanisms for dimensionality reduction. Factor analysis's goal is not just to lower the dimensions of the data. FA is a valuable tool for identifying latent variables, which are deduced from the dataset's other variables rather than being directly marked in one variable. These hidden variables are referred to as factors [29].

Truncated Singular Value Decomposition (SVD)

Through the use of truncated singular value decomposition, this technique reduces the number of linear dimensions. The data are sparse, where numerous row values are zero, it performs well. PCA, contrasted with, does well with voluminous data. Compact data can also be utilized with truncated SVD. Truncated SVD and PCA differ significantly in another important way: although PCA factors the covariance matrix, SVD factors the data matrix [30]

3.2.2. Machine Learning Techniques

Unsupervised learning is often referred as grouping. In unregulated instruction there is no label, no data set for training, and no known data for output. The guidance is favoring an independent learning strategy and observed by utilizing clustering methods such as PCA and K-Means clustering SVD. This kind of machine learning is agent-based and action-based. State, motivation, and environment. devices and programs that automatically define certain behaviors based on the context's incentive feedback[31].

SVM

SVM, or support vector machine, is a well-versed technique. Both regression and classification make use of it. The calculation generates an ideal hyperplane using the meticulously collected data that arranges fresh samples. [32] has suggested conducting research on the prediction of liver illness using classification systems. In such case, SVM classification performed better than Naive Bayes classification. With a greater accuracy rate of 79.66% than the Naive Bayes algorithm, SVM proved successful. Of the two methods that [33] compared, SVM was able to attain an accuracy of 71%. The SVM structure is depicted in the illustration 3.6.

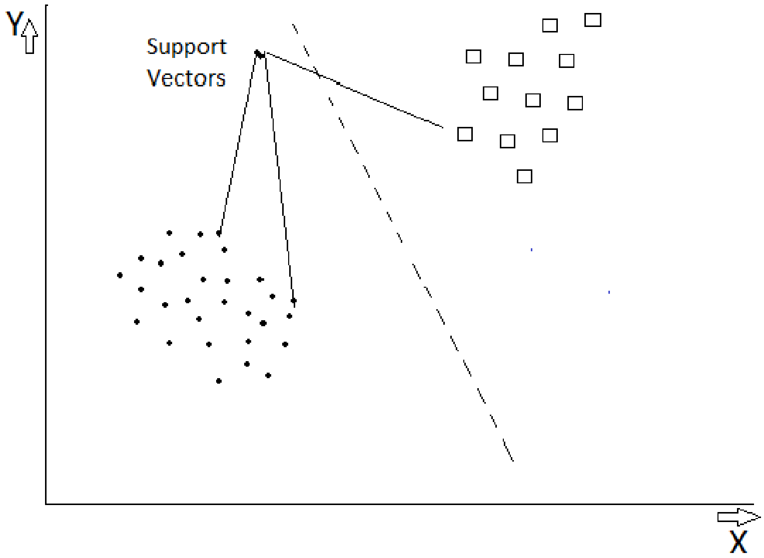


Figure 3.6: Structure of SVM

K – Nearest Neighbor

A non-parametric classification method is K-Nearest Neighbor. Data is classified by determining which of the k examples in the KNN algorithm resembles an input the most. A measurement is used to determine this distance. Bendi Venkata Ramana [34] provided five arrangements computations to identify liver disease. The results of K-Nearest Neighbor also shown a noteworthy level of accuracy. In the AP Liver dataset, it was able to achieve a precision of 97.47% when comparing to other classification methods. The UCLA dataset, it was able to achieve a 62.89% accuracy rate.

Decision Tree

This method has a decision tree which includes specifically, criteria concerning statements. The result could be "true" or "false." To predict the class at the leaf, rules can be obtained using a path that travels from root to the leaf while also using the nodes in motion as prerequisites. The researchers of [35] utilized a variety of techniques to identify liver disease. Decision tree make a respectable precision of 66.14% among the algorithms. The accurate rating of 93.7% was finding using a decision tree technique. To get the best accuracy rate, a decision tree methodology was applied. The structure of Decision Tree in Figure 3.7.

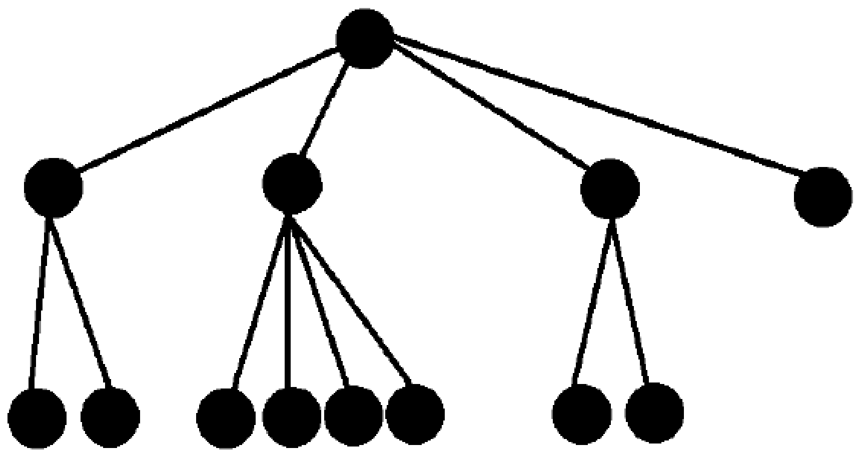


Figure 3.7: Structure of Decision Tree

Random Forest tree

The random forest-based algorithms are come under supervised algorithms and it work based on the set of training dataset with specified features. Both classification and regression may very well benefit from its use. A forest with many trees is essentially created by a random forest tree. It is therefore essentially a collection of various decision trees. The classification process uses a vote system to determine the class. When performing regression, each decision tree's returns are averaged. The Random Forest Tree's Structure shown in Figure 3.8 [36].

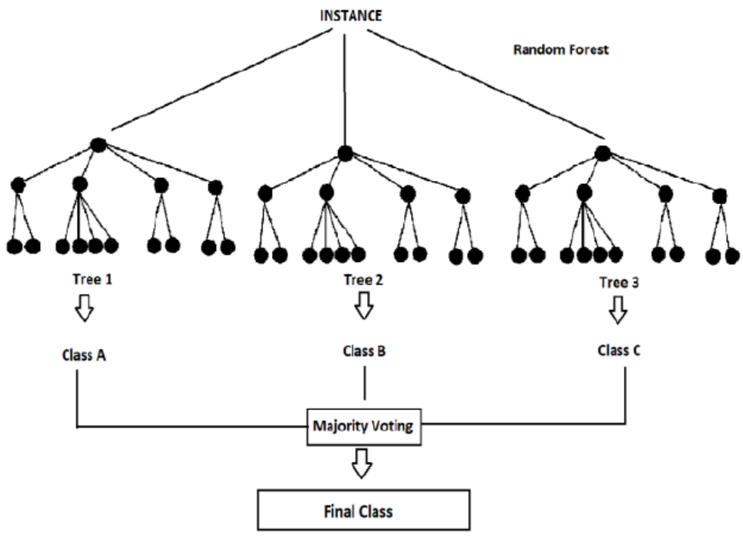


Figure 3.8: Structure of Random forest Tree

2.4 Various Methods and Techniques for Irrigation

To manage intelligent irrigation, a variety of approaches and procedures are employed. The most modern smart irrigation technologies use machine learning, the Internet of Things (IoT), artificial intelligence, and deep learning to build control actions that precisely direct the flow of water to each crop node. These control signals are received by the electronic system or driver, which automatically provides the activation energy required by the actuators, motor pumps, or pumps used to supply precision irrigation learning. These methods can be used to control the soil, the water, and the weather. The information regarding various irrigation system prediction and management strategies is succinctly summarized in this section. The authors of [37] presented a sprinkler-based irrigation system. This method combines a solar panel with a built-in level indicator for the water tank. A statistical analytic strategy for managing water utilizing temperature, moisture, and PH was suggested by the authors of [38]. A little farm and piece of land use this application. According to the authors of [39], IoT components could be employed to automate irrigation water regulation. Water accumulates on the soil's surface using this technique, although other water management concerns are taken. The detailed comparison of different irrigation techniques presented in Table 3.1.

An IoT-based autonomous system to manage irrigation systems was presented by the authors of [40] using a variety of devices, including a Raspberry pi 3, a Wi-Fi node, and a microcontroller. If there is a water shortage, water the ground right away. The authors of [41] created an IoT paradigm for soil moisture monitoring using the Losant platform. Using the MQTT protocol, a low-cost smart watering system to send predicted data via sensors was proposed by the authors of [42]. The node MCU-12E controller regulates the water pump's operation based on the quantity of soil moisture. In [43], the authors introduced a paradigm for IoT-based crop environment monitoring and analysis. This approach effectively addresses the issues with the earlier approach while also conserving time, money, and energy. In order to control irrigation, the authors of [44] suggested using an M2M deployment architecture. Sprinkler irrigation is controlled using M2M technology. Soils are utilized to extract data such as temperature and humidity. Metrological parameters are also employed to choose the irrigation sprinklers. A soil management-based automatic irrigation system was created by the authors of [45]. The microprocessor pumps the water according to the amount of moisture the land needs. The authors of [46] proposed an IoT-based method for autonomous fertigation. The GUI interface in this system is displayed using an SQLite database.

Table 3.1: Components and Advantages of various methods

References	**Components**	**Advantages**
[37] Johar R. et al.,	Solar system and IoT	Water consumption and electricity reduced.
[38] Gupta A. et al.,	ATMega 8 microcontroller and Sensors	Water management and power managed
[39] Gulati A et al.,	Es-8266 WIFI module chip used to manage water.	Water is managed using IoT
[40] Imteaj A et al.,	Automated irrigation system using Raspberry P1. [Microcontroller, WIFI module, GSM, and rely board]	Water shortage is noticed and supplied immediately.
[41]Kodali R.K. et al.,	Soil moisture calculated using ESP-8266 microcontroller, and moisture sensor.	Real time soil moisture calculated using small circuit.
[42] Kodali R.K. et al.,	Water managed using soil sensor, ESP-8266, node MCU-12 E, and MQTT for data transfer.	Measure the soil moisture and to the pumping of water.
[43] Wasson T. et	Monitor and analysis crop environment using RFID	Saved the power, time and

al.,	technology and sensors.	money.
[44] Reche A. et al.,	The M2M deployment model used to control and uses metrological parameters and characteristics are used to manage the soil.	Manage the irrigation of sprinklers.
[45] Padalalu P . et al.,	Monitor the soil water level based on microcontroller (Atmega 328) and Naive bayes algorithm used to decision making.	Based on the recombination, water is supplied.
[46] Abidin S et al.,	Microprocessor, Web-GUI and control communication system managed automated fertigation.	Monitor and manages the farms using Mobile applications.
Krishna K.L. et al.,[47]	Raspberry Pi 2 and intelligence robot used to monitor the soil and other parameters.	Monitor the irrigation environment fields and various parameters are observed
Guru prasadh, J.P. et al.,[50]	ZigBee Modules used to monitor the soil issues.	The soil deficiency alert transferred to the farmer.
Raut R. et al.,[51]	ARM7 LPC2138 processor, 1185 SunRom color sensor, UART, and Solenoid	examined the soil's levels of the three main macronutrients,

	Valves.	potassium (K), phosphorus (P), and nitrogen (N).
J. Gutiérrez. et al.,[53]	Wireless sensor unit, wireless information unit, and web application are used to smart irrigation system.	Automated system was developed for water optimization.
Köks al, Ö. et al.,[54]	Data Distribution Service, Advanced Message Queuing Protocol and Constrained Application Protocol used for farm management information system.	This technique is used to gather and process data, monitor activities, plan, make decisions, and manage the farm.
Cambra Baseca C. et al.,[55]	The IoT based application used to manage and monitor the real time events in the fertirrigation system.	Various events such as wind flow, irrigation events, pressure levels are monitored and decision performed.
Amarendra Goap . et al.,[56]	Using IoT and machine learning soil temperature, soil moisture, air temperature, relative humidity and Ultraviolet (UV) light radiation are monitored.	Intelligence system used to perform the smart decision making.
Khoa TA et al.,[57]	IoT and multi-sensor system	Using this system managed the water.

A moving boat robot to be utilized for monitoring soil moisture and other various environmental parameters was suggested by the authors of [47]. To improve irrigation efficiency, the authors of [48] proposed Internet of Things application and wireless sensor network. In this method, sensors, Zigbee nodes, and green space are used to boost operation. Hardware and software are used. The authors of [49] proposed a sensor and microcontroller-based paradigm for autonomous irrigation and soil PH.

A concept for an intelligent sensor network was suggested by the authors of [50] to identify nutrient shortages in the soil and measure soil moisture. This method is used to provide alerts about deficiency to farmers. The amounts of nitrogen, phosphorus, and potassium were measured and the authors [51] proposed an IoT-based system. These elements produced savings in terms of money, time, and energy. The authors of [52] proposed a paradigm for task management and information gathering for the judgment of the wise farmer. Using this method, task management, planning, and environmental factors are evaluated. A paradigm for simplifying water consumption was proposed by the authors of [53] and it makes use of a web application, a wireless sensor unit, and a wireless information unit, among other things. The authors of [54] provided a number of protocols and hardware elements for running the farm. The authors of [55,56] suggested a model for managing farms and an intelligent decision-making system for managing water. Open-source machine learning-based solutions for smart irrigation were recommended by the authors [56]. Using this method, various irrigation events are tracked.

3.4.1. Reinforcement Learning

The different researchers have proposed different methods for requirement calculation of smart irrigation system. This section presents the related works which supports in reinforcement models, and corresponding advantages and limitations are summarized. The authors of [58] summarized different devices, edge technologies, and software for smart irrigation system. And the authors have summarized different challenges and opportunities for irrigation system. The authors of [59] proposed deep reinforcement learning for irrigation system and solutions are deployed on cloud infrastructure. The main advantages of the proposed work are scalable and practical oriented but this method not considers the surrounding features of prediction and forecasting of requirements. The authors of [60] proposed a hybrid method for prediction and requirement forecasting using IoT and machine learning techniques. The authors are found the requirements within short term and not supported for long term predictions. The implementation was performed using banana tree cultivation and different dynamic parameters. The authors of [61] proposed a DRL-based architecture for scheduling the irrigation system. The experiments conducted for 12 days and requirement of water is reduced to 7.5%.

The authors of [62] proposed an edge computing device and deep reinforcement learning for irrigation system. In this work, different challenges and applications are discussed. For the purposes of energy optimization and water minimization, the authors of [63] suggested a model that utilized Markov Decision and learning by reinforcement. This work is considered only threshold values for prediction and not used any real time data for estimation of requirements. The authors of [64] proposed an irrigation model for rice cultivation and find the uncertainties of weather and produced best irrigation model. The authors of [65] proposed a model using Q-learning and reinforcement learning for effective irrigation system. But the accuracy of the prediction is very less compared to the other methods. The authors of [66] proposed an energy consumption and reduced the water requirement using Marko process and reinforcement learning. The requirement is estimated based on the threshold values and not considered the real scenarios. The authors of [67] proposed deep reinforcement learning for smart irrigation system using real time environment features. In this work the authors are not considered dynamic and uncertain parameters for irrigation. The key benefits of this work, however, are that real-time partial values rather than threshold values were used to estimate the requirements. For the purpose of predicting water usage, the researchers of [68] suggested an RL-ABM framework incorporating Q-learning.

Seven intelligent agents are used to simulate the case study for long-term water management utilizing the suggested framework. The simulated agents categorized into aggregative, forwarded looking, and myopic conservative for learning and action making. But this work is not effective for real time prediction and analysis. The authors of [69] proposed a model called DRLIC and neural network model for optimal learning, current soil requirement calculations and future requirements prediction. The authors of [70] proposed optimized machine learning for smart irrigation using types of plants, different parameters, controlling environments, sensory feedback such humidity, moisture measurement and camera images. The authors of [71] proposed a model to implement OpenAI environment to manage policy, growth, and fertility policy to reduce the environmental impacts. This work is not considered the reality issues for implementations. The authors of [72] investigated reinforcement learning and temporal features for irrigation control system. In this investigation researchers are considered offline data, online data and sensors are used to handle different possibilities of data. In the simulation, crop yields and water expenses are calculated based spatial locations. But in this work temporal features are not considered for the implementations.

The authors of [73] proposed a case study in Portugal using deep reinforcement learning and short-term memory for next day requirement prediction of crop to reduce the water shortage. In this work artificial intelligence, conventional neural network and LSTM are used to training the requirement table of smart irrigation system. The authors of [74] proposed a CNN and DDQL with the help of agent find the immediate requirement of crops and soil moisture. This work, in terms of rewards, answered right away to the demands for other regions and other time-series information. A framework based on behavioral psychology and reinforcement training that describes how the spatial and temporal behavior of resources that are pooled was proposed by the authors of [75]. This work utilizes deep multi-agent reinforcement learning to assist and identify many possible actions in dynamic, changing contexts. The authors of [76] proposed a model for prediction and scheduling for irrigation system using dynamic parameters. Using this work evapotranspiration rate is calculated using the kernel canonical and SVM techniques. The most of the researchers are considered different parameters, threshold values, dynamic parameters are considered for irrigation system. The reinforcement learning also helped to improve the predictions and considered different parameters for predictions. But dynamic parameters and long-time predictions are not considered for in the irrigation system. In this work consider the spatial and temporal parameters in different time intervals and longtime water requirement for smart irrigation system.

3.4.2. Types of Scheduling methods

This Section examines several recent and current developments in irrigation scheduling techniques [77].

i. Feel and appearance.

ii. Gravimetric Method.

iii. Weather- related irrigation scheduling.

iv. Sensor-related irrigation scheduling.

v. Plant-related irrigation scheduling.

vi. IoT technology.

vii. Smartphone APP.

Feel and appearance.

Based on the texture and look of the soil, the most common and efficient method is used. Soil samples are normally collected using a soil probe. Table 3.2 displays the connection between soil moisture and appearance. A rough correlation between field capacity and wilting point is shown in Table 3.2. Each soil type's peak corresponds to a state of zero soil moisture shortage, or field capacity. Each soil type's base corresponds to the level of maximum soil moisture shortage, or the "wilting point." The range of the soil's accessible moisture is also shown by the lack of soil moisture. The table contains broad statistics for a certain set of soils, and it might not be applicable to all soil types. This method lacks precision because it is subjective and not quantitative.

Table 3.2: Types of Soils and its Comparison

Moisture deficiency in/ft	Loamy sand	Sandy loam	Loam	Clay loam
0	Leaves wet outline on hand when squeezed (field capacity).	Appears very dark, leaves wet outline on hand; makes a short ribbon (field capacity).	Appears very dark; leaves a wet outline on hand; will ribbon out about one inch (field capacity).	Appears very dark; leaves slight moisture on hand when squeezed; will ribbon out about two inches (field capacity).
0.2	Appears moist; makes a weak ball.	Quite dark color; makes a hard ball.	Dark color; forms a plastic ball; slicks when rubbed.	Dark color; will slick and ribbon easily.
0.4	Appears slightly moist sticks together slightly.	Fairly dark color, makes a good ball.	Quite dark, forms a hard ball.	Quite dark, will make a thick ribbon; may slick when rubbed.
0.6	Very dry, loose; flows through fingers. (Wilting point)	Slightly dark color, makes a weak ball.	Fairly dark, forms a good ball.	Fairly dark, makes a good ball.

Gravimetric Method

Understanding the water movement in the soil depends on the soil's moisture content. The most accurate way to gauge the actual soil moisture level is to take soil samples. To determine the mass of water lost during drying, this approach calls for weighing a sample of soil with a specified volume first, and then weighing it again after it has dried in an oven at 105°C [2]. This technique enables the determination of soil bulk density (g/cm3) and gravimetric water content (g/g). The volumetric water content (cm3/cm3) can be calculated by multiplying the gravimetric water content by the bulk density of the soil [77].

Weather- related irrigation scheduling.

The scheduling of irrigation based on weather is determined by the weather. Evapotranspiration (ET), which powers the weather-based irrigation scheduling approach, is determined by four key meteorological conditions. The radiation from the sun, air humidity, temperature, and wind speed are the weather variables. The bigger the ET, the higher the solar radiation. This is so because the primary energy source for evaporating water is sunshine. Because it can store more water vapor, warmer air has a higher ET. Because the air already holds less water vapor, the ET increases as the air becomes dryer. The ET increases as the wind speed increases. Solar radiation and air temperatures have a major impact on daily ET in areas with humid climates.

Sensor-related irrigation scheduling.

Using a soil moisture sensor is an alternate method of determining the moisture content of the soil. The volumetric water content of soils is often estimated by a conventional soil moisture sensor (cm3/cm3). Without disturbing the soil, soil moisture sensors enable for the monitoring of changes in soil moisture levels over time. To track soil water movement, the sensors can be inserted at various soil depths. There are primarily two varieties of soil moisture sensors. The amount of tension needed for roots to draw water from the soil is measured by soil tension sensors. Based on the electrical characteristics of the soil, a volumetric water content sensor may determine the moisture content of the soil. For the purpose of interpreting these sensor data, it would be beneficial to be familiar with some of the common terminologies used in moisture in the soil monitor-based irrigation scheduling.

Plant-related irrigation scheduling.

Utilizing a sap flow sensor is a typical technique for scheduling irrigation based on plants. Sap flow measures the amount of water, hormones, nutrients, and other substances in the water that pass through a plant's stem. The sensors monitor the heat transported by the sap using thermocouples and a heater. Then, you can translate this to sap flow in grams per hour. Once the sensors are set up and the parameters are established, the system will compute and record the sap flow, which can be downloaded whenever necessary.

IoT Technology

Agriculture 4.0, which incorporates the internet of things (IoT) and the use of big data to enhance procedures and efficiencies, is what the agricultural technology sector is heading toward. There are numerous microcontroller systems that can be used in agricultural settings, including Arduino and ESP 32. To measure soil conditions, analog or digital soil moisture sensors can be coupled to a microcontroller system. A microcontroller system can also measure additional irrigation data, such as water pressure, energy consumption, irrigation system uniformity, and ambient variables, in addition to soil conditions. Using a Wi-Fi, cellular, or long-range radio (LoRa) network technology, many microcontroller systems enable data transmission to a web server.

Smartphone APP.

There are numerous smartphone apps available for scheduling irrigation. In recent decades, many decision-support tools for irrigation scheduling have been developed and are now accessible via mobile apps. For instance, Colorado State University created the irrigation scheduling mobile app WISE (water irrigation scheduling for efficient application), which makes use of evapotranspiration data and the water balancing approach.

3.5. Analysis of Various Metrics for Irrigation System

When determining the effectiveness of the smart irrigation system, several criteria are taken into account. The components of the intelligent irrigation system that control water and soil. The management of soil involves a number of elements, including soil temperature, moisture content, and other variables, including soil conditions and soil dryness. Dew point temperature, evapotranspiration, air temperature, wind temperature, and humidity are only a handful of the numerous factors that influence water management. The smart irrigation model also takes into account prediction accuracy, data transfer rate, and effective utilization. The following formulas are becoming more and more used for quantifying soil and water management [78].

Gravimetric contents of soil = (Volume of soil moisture – Volume of oven-dried soil) / (Volume of oven-dried soil-dried soil)

Volumetric contents of soil water = Volume of Water/ Volume of Soil.

Moisture of the Soil = weight of the moisture of the soil – Weight of the dried Soil/weight of the dried Soil.

Beyond these, different formula and equations are used for getting aggregate, mean, and prediction of present and future values.

3.6. Challenges and Issues of Irrigation System

Depending on the situation, smart irrigation systems must deal with a number of issues and challenges, among others, developing the intelligent system, transferring data transformation, combining hardware, taking decisions, and analyzing data. Some of the difficulties that are covered in this section in varied settings include the following.

i. Because different sensors are used for different things, combining them is a very challenging process. Figure 1 serves as an illustration and illustrates a variety of sensors. It is a difficult procedure to integrate the data from the acquired nodes.

ii. A smart system built on the Internet of Things (IoT) that has several levels of data observation, transformation, and hardware and software interaction. Layer integration has issues with cost and implementation.

iii. Enhance the automated smart irrigation system by reducing irrigation times, reducing water waste, predicting soil moisture levels, and determining the water and nutrient requirements of the soil.

iv. For improved automations in the IoT-based irrigation system, smart automated microcontrollers, efficient irrigation infrastructure, automated switches, and automated pumps are needed.

v. It's important to consider a variety of factors when adopting smart irrigations, such as climate features (soil parameters, moisture, humidity, timing of the rain fall, and future time fall projection).

vi. When implementing, consider the connectivity, smart mobile-based indication, and LED indication functions.

vii. When putting plans into action, it is essential to consider decision-making based on historical data and future predictions.

These are some of the common issues that arise while installing a smart irrigation system. The primary research gap in the numerous publications that have been published is given below.

i. The authors of [37–46] provided guidelines for controlling soil moisture or water efficiency.

ii. Multi-nodes are not included for Water optimization in any of the current methods.

3.6.1. The Future of Research

The rise of new independent systems that make decisions using internet of things, big data, AI, and machine learning, among other advancements, necessitates the enhancement of the present research on smart systems for irrigation.

Future Data Forecast: Predicting the direction of data is an essential task in smart irrigation. However, processing of data in future smart irrigation systems is not covered by the majority of the prior research gathered in the survey work [79].

ii. Smart irrigation infrastructure and weather forecasting connectivity have not yet been shown or put to use.

Smart irrigation uses Big Data, IoT, and AI techniques to assess and predict past, present, and future data, which helps in decision-making.

iv. Improved ecological smart irrigation methods are required.

v. The new data acquisition form and frequency.

vi. When developing and putting irrigation systems with IoT into place for multiple crops, a consistent architecture is required.

vii. The best recommunication system utilizing machine learning and deep learning methods.

3.7. Summary

In future, water and energy constraints will affect many parts of the world, making smart irrigation systems a crucial research area. Nearly 70% of the fresh water, that is available on the planet, is used for agriculture. Therefore, it is essential to optimize water usage and, reduce expenses, conserve energy, and employing an intelligent watering system to boost yields. The components of smart irrigation, the roles of each layer, and a modern irrigation system are all presented on this page. For additional research, section 3.4 provided and compiled several strategies. The section concludes with a discussion of a few challenges and possible future routes for the research.

Chapter IV

Irrigation Prediction Model Using Deep Reinforcement Learning

4.1. Introduction

Water optimization and scheduling are essential for agriculture sector because water and energy usage is not adequately estimated. A tremendous amount of water is wasted in the irrigated fields. The combination of today's technologies provides the solution for managing water and providing the proper irrigation schedule. The Internet of Things and machine learning techniques are effectively used for smart agricultural fields. We proposed an effective water optimization and scheduling method in this paper that makes use of IoT components, the KNN algorithm, reinforcement learning, and person correlation techniques.

The IoT components are used to collect the current requirements and predict the environmental status of the cultivation files. And is also used to transfer the information from the entire cultivation field to control fields. The KNN algorithm captures the nearest features from the cultivation fields. Environmental prediction, awards, or requirements of specific plants are performed using IoT and KNN capabilities. In this work, we applied a smart irrigation system used in banana cultivation. Based on the current prediction, the future requirements of water are calculated in 12-hour time interval from 7 pm to 7 am, and it is calculated for up to 4 days. Compared to traditional cultivation, this proposed method reduces the water usage by upto 24% of the water required.

Globally, 85% of fresh water is being utilized for agriculture as food requirements gradually increase, thus increasing the production of the food chain. The traditional irrigation system has used much water but has given less productivity. So, an effective irrigation system is needed. Still, it is a challenging task in today’s environment because, when we plan for irrigation, we need to consider different scenarios, such as climatic changes, moisture of the plants, wind speed, etc. The water requirement for each plant changes according to the seasons, the growth of the plants, etc. Physically, pouring water for each plant is time-consuming. So, the equalized method of pouring water and irrigation system helps improve the water requirement for plants. Different irrigation methods were used to manage water, such as lateral move irrigation, centre pivot irrigation, irrigation with drips, irrigation by sprinklers, drip irrigation and micro-irrigation, Lawn sprinkler, Hose-end sprinklers, sub-irrigation, subsurface textile, etc [80]. Banana cultivation is the fourth most important crop after wheat, rice, and corn. The banana cultivation is the one of the most cultivation, taking more fresh water in the entire life span. For, example, the water requirement of banana cultivation per day in the litter is shown in Table 4.1[81]. In Table 4.1, cultivation starts

Table 4.1: Month wise Water Requirements for Banana Irrigation [2]

Month	**Water Req. Lit/Day/Plant**
April	5-6
May	4-5
June	5-6
July	6-8
August	10-12
September	8-10
October	6-8
November	10-12
December	12-14
January	16-18

in April and ends in December or January. Initially, the water requirement is low but gradually, it is increased. Morden technologies and techniques are used manage the irrigation system. So, we can efficiently use the irrigation systems, by using the Internet of Things (IoT), Artificial intelligence and its subset, such as machine learning and deep learning, which plays important role to manage the irrigation systems. Various IoT devices and sensors are used to connect and monitor the bottom to top of the plant.

Using IoT, we can easily monitor, control, trace and make the decision also remotely without any delay. Similarly, The Artificial Intelligence is used to take decision automatically.

There are three processing layers of processing techniques is the combination of machine learning and IoT technique which are used for minimize the energy and for the usage of the smart irrigation system. They are: i. Data transferring and collection ii. Intelligence layer, and iii. End Application layers. These three layers consist of different set of components and functionalities. The first stage is Data gathering and transmission. Data is being collected from agricultural grounds and it is being transmitted for further data processing, for which sensors are used. The components which are used for collecting data and for transmissions are, mobile data or Wi-Fi connections, for local data to be processed, the Zigbee Network is used, for collecting data from the ground, the wireless Sensor Node, is used. For controlling the motors, Raspberry Pi, and other controlling components are used. The intelligence and data processing are done in the second layer. In order to process the gathered data, intelligent techniques and machine learning is being used.

In the proposed technique based on the IoT, K-NN and Reinforcement learning method is introduced to manage the irrigation system and reduce water requirements [2]. The main contribution of the proposed hybrid is as follows.

i. The proposed method schedules and optimizes the water using IoT and the Reinforcement learning method.

ii. In this proposed technique, IoT is used to collect the inputs, KNN is used to find the nearest features to extract useful information such as moisture, water requirements, root moisture level, etc. Reinforcement learning is used to minimize the water requirements for the smart irrigation system.

iii. Compared to conventional irrigation systems, 10 to 24% of water requirement is being optimized by this proposed system in terms of long-term irrigation system scheduling.

The remainder of the chapter is as follows: Section 4. 2 presents the associated and current works on smart irrigation techniques. The section 4.3 presents features selection and water requirement prediction using IoT and reinforcement learning. The section 4.4 delves implementation details and result discussion of proposed work with previous dominating methods. And finally presented the summary in Section 4.5.

4.2. Pre-Request Concepts

Software agents can learn how to accomplish their goals with the aid of deep reinforcement learning, which integrates neural networks that are artificial with a learning-based reinforcement framework. It connects states and behaviors to the rewards they provide by combining target optimization and function approximation, to put it another way. All of those ideas, which you may not be familiar with, will be described in greater detail and in plainer language below, based on your own experiences as a traveler through life. Neural networks are not only the key component of recent developments in artificial intelligence (AI) in areas such as data-driven prediction, machine interpretation, and machine vision, but they can also be used in conjunction with reinforcement learning strategies to achieve astounding results, such as DeepMind's AlphaGo, a Go board game algorithm that outperformed the world's winners. You should be cautious about deep RL because of this.

Reinforcement learning is the name given to learnable focused objectives algorithm, through a series of steps how to maximize along a particular axis, such as the number of points scored during a game. Under the right conditions, reinforcement learning systems are capable of superhuman performance from scratch. These algorithms receive rewards when they make the right decisions and penalties when they don't. Reinforcement is when you reward and correct a pet. As opposed to the limited options of a repetitive video game, reinforcement learning algorithms are gradually improving in uncertain, real-world conditions while choosing from an infinite number of possible behaviors. To put it another way, people are beginning to make progress in the real world. If you need to achieve quantifiable KPIs, deep RL might be helpful.

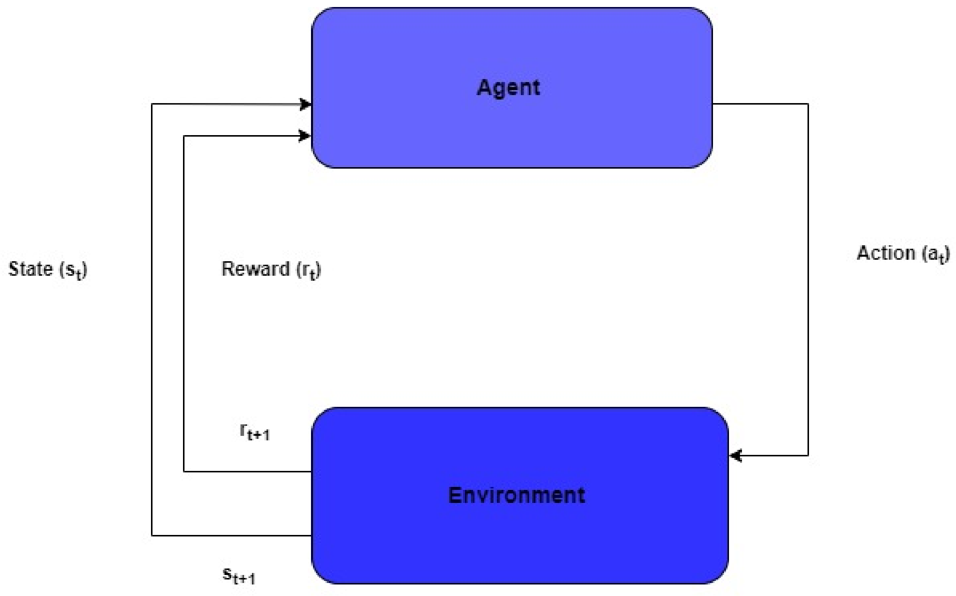


Figure 4.1: Reinforcment Learning

A deep neural network policy that links an input state to an output action and an algorithm in charge of updating this policy make up deep reinforcement learning agents. Popular examples of methods include deep Q networks (DQN), deep deterministic policy gradients (DDPG), soft actor critics (SAC), and proximal policy optimizations (PPO). To optimize the anticipated long-term return, the algorithm adjusts the policy based on observations and rewards gathered from the environment. Neural networks (and/or associated technologies) called Deep Q Networks (DQN) make use of deep Q learning to produce models. Deep Q learning frequently uses generalized policy repetition, which is the mixture of policy assessment and policy repetition, to acquire rules using high dimensionality sensory data. For instance, a well-known deep Q network described by tech publications such as Medium models outcomes using inputs from the senses from video games from the Atari 2600. On the most basic level, the Q network is updated by collecting samples, archiving them, and using them for experience replay.

Deep Q networks, in general, learn to match inputs representing active participants in the region or other seasoned examples with desired outputs. Another notable illustration of how AI makes advantage of the types of interfaces that were previously only employed by human beings is the Atari or chess video game. This is an effective technique for creating artificial intelligence that can perform other complex cognitive tasks or play games like chess at a high level. This is an effective technique for creating artificial intelligence that can perform other complex cognitive tasks or play games like chess at a high level.

Q-learning and Policy variations are used in a reinforcement learning technique known as Deep Deterministic Policy Gradient (DDPG). In order to evaluate actors, DDPG employs a pair of models: the actor and the critic. An actor is a network of policies that gets the state's information as its input and produces the precise action (continuous), as opposed to providing a distribution of probabilities of actions. The critic is a Q-value network that takes state and activity as inputs and outputs the Q-value. A approach that is "off" policy is DDPG. In DDPG, the term "deterministic" refers to the actor computing the action explicitly as opposed to a chance distribution of actions. In the continual activity scenario, DDPG is used. DDPG replaces the actor-critic and is useful in settings with continuous action. By optimizing a stochastic policy in an off-policy way, the Soft Actor Critic (SAC) technique overcomes the distinction between unpredictable policy evaluation and DDPG-style techniques. Although it was published roughly concurrently with TD3, it is not a direct replacement for TD3. Nevertheless, it features the clipped double-Q trick and advantages from smoothing target policies because of the policy's inherent stochasticity. Entropy regularization is one of SAC's key characteristics. Entropy, a gauge of the policy's randomness, and expected return are trade-offs that the goal of the policy is to maximize. This is directly related to the trade-off between exploration and exploitation: when entropy rises, exploration increases, which speeds up learning later on. Additionally, it can stop the strategy from prematurely achieving a suboptimal local optimum [82].

In 2017, OpenAI developed Proximal Policy Optimization (PPO), a set of model-free learning by reinforcement algorithms. PPO algorithms are approaches using policy gradients, which means that rather than putting values on state-action pairings, they search the space of policies. Trust region policy optimization (TRPO) algorithms provide several advantages that PPO methods do not, however PPO algorithms are more broad, easier to construct, and have superior sample complexity. To do this, a new objective function is used.

4.3 Related Work and supporting Existing works

The different researchers have proposed various methods for requirement calculation of smart irrigation system. In this section presented different related works support to reinforcement models, corresponding advantages and limitations are summarized. The different devices, edge technologies, and software for smart irrigation system. And the, authors have summarized different challenges and opportunities for irrigation system. The deep reinforcement learning for irrigation system and solutions are deployed on cloud infrastructure. The main advantages of the proposed work are scalable and practical oriented but this method not considers the surrounding features of prediction and forecasting of requirements. The hybrid method for prediction and requirement forecasting using IoT and machine learning techniques. The authors are found the requirements within short term and not supported for long term predictions. The implementation was performed using banana tree cultivation and different dynamic parameters. The DRL-based architecture for scheduling the irrigation system. The experiments conducted for 12 days and requirement of water is reduced upto 7.5%. The edge computing device and deep reinforcement learning for irrigation system. In this work different challenges and applications are discussed. The Markov Decision and reinforcement learning used for energy optimization and water reduction. This work is considered only threshold values for prediction and not used any real time data for estimation of requirements. The irrigation model for rice cultivation and find the uncertainties of weather and produced best irrigation model. The Q-learning and reinforcement learning for effective irrigation system. But the accuracy of the prediction is very less compared to the other methods. The energy consumption and reduced the water requirement using Marko process and reinforcement learning. The requirement is estimated based on the threshold values and not considered the real scenarios. The deep reinforcement learning for smart irrigation system using real time environment features. In this work the authors are not considered dynamic and uncertain parameters for irrigation. But the main advantages of this work are not considered the threshold values for estimation of requirements and considered the real time partial values. RL-ABM framework with Q-learning is used for water usage prediction. This proposed framework is applied into case study for long time water management and this work is simulated using seven intelligent agents. The simulated agents categorized into aggregative, forwarded looking, and myopic conservative for learning and action making. But this work is not effective for real time prediction and analysis. The DRLIC and neural network model for optimal learning, current soil requirement calculations and future requirements prediction. The optimized machine learning for smart irrigation using types of plants, different parameters, controlling environments, sensory feedback such humidity, moisture measurement and camera images. The OpenAI environment to manage policy, growth, and fertility policy to reduce the environmental impacts. This work is not considered the reality issues for implementations. The reinforcement learning and temporal features for irrigation control system. In this investigation researchers are considered offline data, online data and sensors are used to handle different possibilities of data. In the simulation, crop yields and water expenses are calculated based spatial locations. But in this work temporal features are not considered for the implementations.

The case study in Portugal using deep reinforcement learning and short-term memory for next day requirement prediction of crop to reduce the water shortage. In this work artificial intelligence, conventional neural network and LSTM are used to training the requirement table of smart irrigation system. The CNN and DDQL with the help of agent find the immediate requirement of crops and soil moisture. This work reward wise immediately responded for the requirements to different regions and other temporal data. The behavior theory and reinforcement learning spatial- temporal behavior of pooled resources are managed. This work used to support and find the different possible activities in the dynamic changing environments using deep multi-agent reinforcement learning. The model for prediction and scheduling for irrigation system using dynamic parameters. Using this work evapotranspiration rate is calculated using the kernel canonical and SVM techniques. The most of the researchers are considered different parameters, threshold values, dynamic parameters are considered for irrigation system. The reinforcement learning also helped to improve the predictions and considered different parameters for predictions. But dynamic parameters and long-time predictions are not considered for in the irrigation system. This study considers the spatial and temporal parameters in different time intervals and longtime water requirement for smart irrigation system.

4.4. Materials and Method for Prediction Model

This section presents the required materials and proposed method for prediction and forecasting of smart irrigation system. The proposed irrigation system consists of IoT devices, KNN and deep reinforcement learning. The IoT devises and sensors are used to collect current dynamic information. The KNN collect the nearest features information and deep reinforcement learning used current and future requirement of irrigation system. Using this propose method current and future requirement of water is managed.

4.4.1. Materials

The proposed method consists of two parts such as requirement collection and intelligence part. The data collection is performed using different components such as sensors, IoT devices and transmission devices. Requirement collections are performed using Table 1.1. components [3]. The sample components for data collection are shown in Figure 1.2.

Table 1.1 components are interconnected together and data is collected from each source of the location and roots. The collected data is stored in cloud environment and processed using the computational intelligence. The sample data, soil moisture, surrounding information are collected from the Kanyakumari district, India. The longitude and latitude of the experimental performed location is 8.2473502, 77.2743729,345. In this location early paddy cultivation was being done, but, currently, banana cultivation is done, here. Especially, these two species of banana cultivation is being done in the areas, which are Ethapazham/Nendram Pazham/Nendrapazham/Changalikodan is Plantain Banana and known in English as Red dacca (Australia), Red banana, 'Red' banana (USA), and Claret banana. Aside from certain varieties of banana, some regions also have tapioca or Maravalli Kizhangu or cassava plant cultivation is also done. This location has, two ponds on either side. So, apart from April, May and half of June, we always have water facilities available in this location. So, this location is chosen for this cultivation and one more reason is that, it always has water facilities which are required for proper banana cultivation.

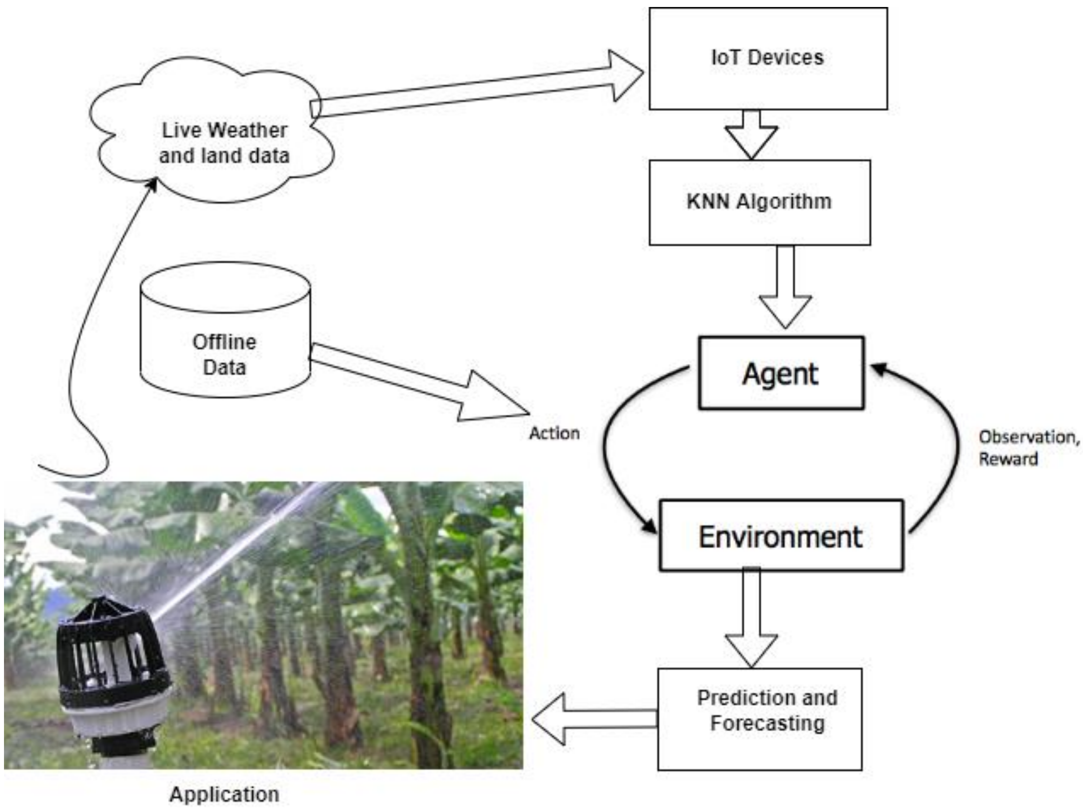


Figure 4.2: Block Diagram Using IoT and Reinforcement Learning

4.4.2. Methodology

The proposed method used IoT devices, KNN algorithm and Deep Reinforcement Learning. The IoT devices are used to connect all the devices, sense all the requirements and communicate between the devices. The nearest required features are managed and collected using KNN algorithm. Reinforcement learning is used to find the behavior of the online and offline data. Based on the behavior and rewards from the data new prediction and decision is performed. The proposed block diagram has shown in Figure 4.2.

To determine the closest values from the anticipated sensors, the KNN algorithm is used. This algorithm is non-parametric that generates real numbers devoid of any presumptions. The dataset or data gleaned from the sources K closest values make up the input. The distance or prediction of the closest neighbour affects the prediction's outcome. The vote of the closest forecast is used to predict the output class. Multiple features and space are present in the KNN training set. The prediction values depend on whether the distance between the features is continuous or discontinuous. Euclidean Distance affects how far apart the feature's predictions are. Equation 4.1 displays the representation of the prediction made by the nearest neighbours using different x parameters.

$$Y = C_n^w\,(x_1, x_2, \ldots, x_n) \qquad 4.1$$

Y - denotes predicted features, *C* - denotes nearest required features, *n* denotes features, *w* denotes weight of different, $\{x_1,\ldots,x_n\}$ denotes different weight. The variations of the features are calculated using Euclidean distance has represented in equation 4.2.

$$D = \sqrt{\sum_{i=0}^{n} (x_i \; - \; x_j} \qquad 4.2$$

D – denotes distance, *n*- denotes number of features *x*, j - and i - various features variations.

Machine learning technique agent interacting with its environment is known as reinforcement learning with series of observations, actions, and rewards. The agent seeks to identify the best possible course of action, or optimal policy that maximizes the total amount of future benefits. The representation of the reinforcement learning and agent with different parameters are shown in the equation 4.3.

$$E = \{S, A, P, R\} \qquad 4.3$$

State space is denoted by S in the equation. A denotes action, P for transition, and R stands for reward function. The state space *S* consists of environmental parameters for irrigation system and it is represented in 4.4.

$$S_t = (W_t, p_t, W_{min}, W_{max}, X_p) \qquad 4.4$$

S_t –It denotes state with time, W_t is the water depth on particular time, W_{min},-Minimum Water depth, W_{max}- Maximum Water depth, X_p- Future prediction of rainfall.

4.4.3. Working Process

The proposed work process has represented in the Algorithm 4.1. Initially the IoT devices are used to collect required information’s form the bottom of the layers. The initially all the parameters are considered as the zero. After that in the particular interval initial predictions are performed and initial calculations are performed and required water is pumped using pumping motors. The KNN algorithm collected nearest features and transferred to the reinforcement learning. The required parameters are collected continuously and transferred to processing unit. The entire values are collated using Pearson correlations (PC). The entire step by step process has shown in the Algorithm 4.1.

Algorithm 4.1:

Input: KNN, E, S, A, P, R, Required parameters

Output: Estimated values

1. Initialization
2. Criteria $\leftarrow$ 1
3. For (Criteria $\leq$ 12) do
4. KNN $\leftarrow$ PC(Initial Prediction)
5. E $\leftarrow$ (RL parameters)
6. RL $\leftarrow$ (Rewards and Actions)
7. Action $\leftarrow$ { KNN, Rl_{Para}, E}
8. $Best^{h}_{SR}$ $\leftarrow$ PC { KNN^{n}_{SR} , Rl_{Para} }
9. R (hr) $\leftarrow$ { rewards of Actions }
10. hr $\leftarrow$ hr +1
11. While (hr$\leq$ 12) do
12. Final Action $^{hr}{}_{n}$ $\leftarrow$ R(hr)* $Best^{h}_{SR}$
13. End

4.5 Results and Discussion

The basic experimental setup and material requirements are described in the section 3.1. The basic experimental measurement and number of nodes and other information's are mentioned in the Table 4.2 and training and testing ratios of water requirement has shown in the Table 4.3.

Table 4.2: Experimental Basic Requirements

Parameters	Crop details (Banana)
No of Tree	1000/ Per Acre
Duration	April- Jan
Maximum water requirements of single node in each month	50 Litres
Start of Agriculture	April, 2020
Max Requirements of Water per node	360/400 Litres
Interval of smart irrigation	7 Days

The cultivation starts from April 2020 to End Jan 2020. The starting of the cultivation due to environmental rewards first two months required more water. But after the two-month due to the environmental changes the requirement of the prediction is changed immediately. The experiment values are predicted using following metrics such as spearman correlation (S.C,) Coefficient of Determination (R2), and Root-Mean-Square Error (RSTM). The predicted values are shown in Table 4.5.

Table 4.3: Training and Testing Ratio

Hours	Zone	Min and Max Water Requirements	Training Ratio (70%)	Testing Ratio (15%)	Validation Ratio (15%)	Total
12	1	Min	4900	1050	1050	7000
		Max	3500	750	750	5000
24	1	Min	3150	675	675	4500
		Max	2800	600	600	4000

Table 4.4: Predicted values of R^2 and RSTM using KNN and RL

Zone				
KNN +RL				
epochs	S.C	R2	RSTM	PT(s)
12	0.72	0.95	0.41	16
24	0.61	0.92	0.63	22
36	0.63	0.93	0.43	21
48	0.69	0.94	0.54	35
60	0.96	0.96	0.71	36
72	0.68	0.92	0.45	34

Table 4.4 predicted the different values in different time intervals such as 12, 24 and etc. The processing timing entire structure also has shown in the Table 4.4. The numbers of the hours are increased, automatically the processing time also increased in the different way. The Figure 4.3 has shown the water requirement for at the month of middle and it Shown the initially requirement prediction is low and gradually the requirement of the

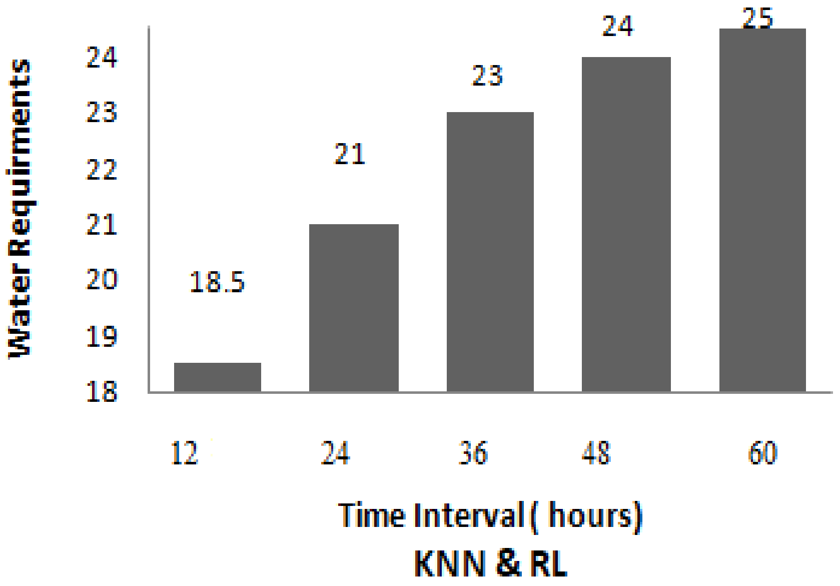


Figure 4.3: Water Requirements in different time intervals

water is increased in the different time intervals. Similarly, every month water requirement of prediction has shown in Figure 4.3. The month wise water requirement has shown in the Figure 4.4. In this graph initially in the month of April cultivation is started and initial time the water requirement is very less. After that requirement of the water is gradually increased in next two months. But in the July and Aug water requirement is reduced due to rain in the cultivation location. Again, at the end of the cultivation the water requirement is reduced.

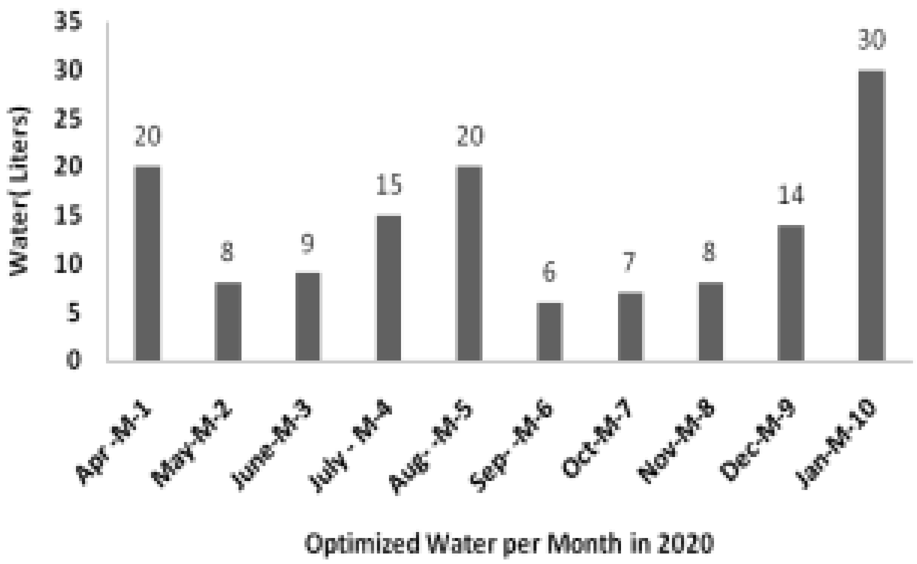


Figure 4.4: Month wise water Optimization of Entire cultivation for one Tree.

4.6. Summary

The proposed technique is based on the IoT, K-NN and Reinforcement learning, which is introduced to manage the irrigation system and reduce water requirements. The main contribution of the proposed hybrid is as follows. The proposed method schedules and optimizes the water using IoT and the Reinforcement learning method. In this proposed technique, IoT is used to collect the inputs, KNN is used to find the nearest features to extract useful information such as moisture, water requirements, root moisture level, etc. Reinforcement learning is used to minimize the water requirements for the smart irrigation system. Compared to the conventional irrigation system, 10 to 24% of water requirement is being optimized by this proposed system in terms of long-term scheduling. This work is extended in three ways: effective knowledge sharing, appending different techniques, and collaborations of predicted parameters. The continual learning technique is used to recommend better predictions. The ensemble learning algorithms are recommended for better appending different prediction techniques. Federated learning is recommended for collaborating in different cultivation fields and sharing the best effective model using the best effective prediction models.

Chapter V

Irrigation Requirement Prediction Using IoT and Transfer Learning

5.1. Introduction

Irrigation systems are a crucial research area because it is essential to conserve fresh water and utilize it wisely. As a part of this study, the reliability of predicting the usage of water in the present and future is investigated in order to develop an effective prediction model to communicate demand. In order to improve prediction, we develop a prediction model and share the updated model with nearby farmers. In order to forecast the irrigation requirements, the recommended model utilizes the Internet of Things (IoT), k-nearest neighbours (KNN), cloud storage, long short-term memory (LSTM), and adaptive network fuzzy inference system (ANFIS) techniques. By collecting real-time environmental data, KNN identifies the closest water requirement from the roots and its surrounding. In order to predict short-term requirements, ANFIS is used. To transfer the new requirements for better prediction, transfer learning is used. Time-series-data updates are predicted using LSTM for future forecasting, and the integrated model is shared with other farmers using cloud environments to enhance forecasting and analysis. For implementation, a period of nine to ten months of data was collected from February to December 2021, and banana tree was used to implement the planned strategy. Four farms, with measurements, were considered at varying intervals to determine the minimum and maximum irrigation needs. The requirements of farms were collected over time and compared to the predictions. Future requirements at 8, 16, 24, 32, and 48 h were also anticipated. The results indicated were compared to manual water pouring, and, thus, the entire crop used less water, making our prediction model a real-world option for irrigation. The prediction model was evaluated using R2, MSLE and the average initial prediction value of R2 was 0.945. After using transfer learning, the prediction of the model of Farm-2, 3 and 4 were 0.951, 0.958 and 0.967, respectively.

Recent technologies are used to effectively manage sustainable irrigation systems and decision-making. Artificial intelligence plays a major role in decision-making and requirement predictions in recent technologies such as IoT. The combination of IoT, the cloud and artificial intelligence constitutes a new methodology for decision-making because interconnected technologies such as firmware and mechanical and programming techniques are used to manage irrigation systems. IoT devices are used to sense the data from their surroundings, a cloud environment is used to process the data, and artificial-intelligence techniques are used to make decisions and predict the time-series data. Importantly, recent machine-learning and deep-learning techniques play a vital role in decision-making systems. Dominant techniques for decision-making include neural networks, KNN, support vector machines, decision tree (DT), LSTM, deep neural networks, etc.

The combination of machine learning and IoT in a smart irrigation system has three layers for processing the entire application [83]: data gathering, data processing and intelligent system, and application layers.

i. Data gathering and transmission: in the first layer of an effective irrigation system, the layer collects all the information using sensors and transmits it using networking devices [84].

ii. Data processing and intelligence layer: in the second layer, intelligence techniques are used for processing and decision-making.

iii. Application layers: the third layer performs planning, optimization and implementations using the second layers' decision [85].

The data-processing layers are used to collect the data and perform the processing steps at the initial stages. The data-processing steps, collect all the inputs from the sensors, atmosphere and other inputs. The data-processing layers apply the initial processing of surrounding information and intelligence techniques. The data-processing layer uses intelligence techniques such as machine-learning models and other statistical techniques to process the data. The application layer helps to connect to the real world. The first and second layers are interconnected to processing and decision-making. Similarly, the second and third layers are connected to decision-making applied to the real world. The previous research [86] shows different challenges and limitations in irrigation systems. Some of the dominant limitations are as follows.

i. The irrigation system must be fully automated from the end-to-end process.

ii. The integrations of different functionalities of irrigation systems cannot be interconnected from data collection to processing.

iii. The real environment inputs (rain, soil moisture and atmosphere inputs) are not interconnected.

iv. The current- and future-requirements prediction still has one of the main research gaps in smart irrigation systems.

v. The predicted feature and requirements are not shared with the neighbour farmers.

To overcome the above challenges, the key contribution of the proposed work is as follows:

i. In this work, IoT sensors and k-nearest neighbours are used to sense and collect the requirements.

ii. We also propose a system to predict the short- and long-term sustainable prediction requirements of the irrigation system using ANFIS and LSTM techniques.

iii. The proposed model shares the sustainable requirements of the prediction using the cloud environment and shares the features with the nearest farmers for better requirements prediction using transfer learning.

iv. The proposed model reduces and optimizes the sustainable irrigation requirements of the crops. It reduces by 42% to 50% the freshwater requirements compared to the previous traditional methods. The proposed work reduces water usage because the short- and long-term usage of irrigation requirements are calculated using the sensors, weather and history. Compared to the previous methods, the coefficient of determination (R2) is better (0.955), and mean squared logarithmic error (MSLE) is less (0.439).

v. Compared to previous methodologies, this work is the first to introduce transfer learning to an irrigation system and forecast irrigation requirements using transfer learning to predict one farm from another. Compared to the previous method of irrigation requirements prediction, our method of LSTM and ANFIS with transfer learning reduces by 30.24% the water requirements in the single node of a banana tree in the implementations. Our method has tuned to consume 1.16% less water in a single banana-tree node than in ref. [85].

The rest of the chapter is organized as follows. Section 5. 2 presents different irrigation methods and requirement analysis methods. Section 5.3 presents the materials, working methodology, and optimized methods. Section 5.4 presents implementation results and comparison with dominant existing methods and the paper finishes with the Section 5.5.

5.2. Related work

This section presents different existing smart irrigation models, frameworks, techniques, machine-learning and deep-learning techniques, transfer learning, and a comparison of different irrigation systems for supporting the proposed work. Different researchers have presented various works related to machine learning, deep learning, the Internet of Things, cloud computing, and highly integrated technologies for smart irrigation. Initial data processing and decision-making are performed using these technologies.

5.2.1. Irrigation Techniques

This section on related work presents how previous techniques are supported for centralized storage, data processing, and decisions. The authors of [87] present an IoT structure for processing, storing, and analysing data using a decision system. An intelligence application system using an IoT system with different dimensions, such as moisture, water evaporation, and land slope, is considered for decision-making processing. The authors of [88] present two models, geography and climatology, and use different parameters for prediction, including moisture, wetness, daily and monthly soil requirements rates, evaporation of moisture and weather reports. The authors of [85] propose a CWSI framework for irrigation management using temperature distributions, and, with the help of this structure, water requirements are reduced. The requirement optimization is performed using time intervals and continuously checking the requirements of the plants. The authors of [89,90] propose an irrigation system using control-based scheduling to manage different factors such as humidity, wind speed, wind velocity, soil moisture, etc. The sensor-based prediction for managing irrigation and soil moisture sensor senses different soil conditions, and mobile applications are used to measure and monitor different activities of the irrigation system. Different recommendation systems such as statistical, machine-learning, and deep learning models are used to manage the prediction. The authors of [91,92] present different activities-based machine- and deep-learning, regression model, GBT and DNN methods to increase the prediction rate. In this model, the accuracy of predictions is increased by 93% ploys thermal images to analyze the various requirements of an irrigation system. Various parameters are measured using thermal images, and leaf potential is calculated. The main drawback of this work is that soil-moisture measurement is difficult to analyze. The authors of [93] propose machine-learning and IoT techniques to manage smart irrigation with the help of different parameters, such as various soil conditions, environmental parameters, temperature and nearest features, which are considered for requirement calculation. The authors of [94] propose a system for optimizing the water requirement of crops using the WSN and different node sensors. Control devices are used to manage the crop using mobile and web applications. With the help of mobile and web applications, soil moisture and future requirements are calculated. The IoT with multiple sensors is used for water management [95,96] using different parameters such as soil properties, moisture, temperature, and rain sensors. In this work, the output is predicted and operated automatically and manually. The authors of [97,98] propose different monitoring and control systems for irrigation systems. Different energy models and IoT platforms are used to analyze parameters and use a decision pumping schedule. The authors of [99] propose a LoRa network structure with an energy-efficient model to cover up to 5 km with smart control. All the information is transferred to different places using the LoRa structure. The various machine- and deep-learning approaches analyze the requirements, moisture analysis, and future recommendations of irrigation systems.

The authors of [83] propose a model, with the help of genetic techniques, to increase yields and analyze various recommendations. The genetic model [100] provides the solution using sequential inputs and non-continuous scheduling. The authors of [87] propose a system using metrological data and created a weekly irrigation-requirement plan using regression and classifier techniques. This system achieves 95% and 93% accuracy using classification and regression techniques. The authors of [101] propose a location-based optimized irrigation system using a genetic algorithm with the help of previous data. The location-based water-requirement analysis for irrigation systems using the KNN algorithm with an intelligent IoT sensor is used to plan irrigation systems [84]. In addition, this work is fully automated with machine-to-machine data transmission for effective decision-making. The heterogeneous data management in irrigation systems uses machine learning and IoT, and this work predicts the requirement for irrigation using the related data. The time-to-time irrigation requirements are also calculated using logical regression analysis. The authors of [102] calculate humidity and temperature using a decision tree. The future requirements for the prediction of irrigation systems are calculated using the SVM algorithm, but the requirements for prediction accuracy are very low. The summary of the different IoT frameworks, models, and machine learning algorithms is presented in Table 5.1.

The authors of [103] present a comparative study for precision agriculture using deep learning and IoT. In this work, authors have gathered and analysed disease, weeds, and soil yields using deep learning techniques. And also, the authors analysed different components of agriculture, such as sensors, UAVs, data acquisition, annotations and datasets used for predictions. Finally, pest detection is performed using VGG16 and transfer learning, which achieves 96.58% accuracy in prediction. The authors of [104] presented the state of the art for managing water using IoT devices. Using the connecting devices, the authors address water-planning and water-distribution issues. This case study is planned with the help of IoT-enabled devices. The author of [105] propose a smart and green irrigation system using gradients and regression trees, which are used for the implementation part. The authors of [106,107] use different parameters such as temperature, humidity and weather data, which are used for the prediction of irrigation requirement. The SVR and K-means are used for soil-moisture prediction.

The different limitations are summarized using the above-related works. Most of the work did not address the requirements of roots, and the nearest features were not considered for the irrigation-system requirement analysis. The recent works do not consider all parameters, such as wind, moisture, and temperature, for requirement prediction. The previous systems need to be integrated with the full automation system. In this work, we planned the different irrigation parameters to predict and analyze the requirement of the irrigation system based on the crop requirements.

Table 5.1: Summary of advantages and Limitations of Previous works

Previous works	advantages	Limitations
IoT framework [84,87,94,101]	The site-specific variable-rate sprinkler irrigation [87] (SS-VRT) used crop and soil conditions for irrigation, KMO [101] is used to analyse the factors of irrigations, SWAMP [84] architecture provides better scalability, Federated learning [94] is used for irrigation without sharing the data, using machine learning.	SS-VRT does not support long-term application, KMO is not considered as a real factor affecting the irrigation, SWAMP is not considered as one of the multiple features for irrigation and the Federated learning.
Irrigation models [85,88,89,102,108]	A sprinkler–solid, centre pivot, travelling irrigator, and micro-spray are used for spatial-based irrigation. Automatic sensors and evaporation-based models are used to predict the requirements.	The spatial-based irrigation model is only supported at particular locations. Central data storage, irrigation scheduling, and root moisture are not considered for processing an effective system.
Recommendation system – Irrigation system [91]	Irrigation performed based on climate change, water availability, and a policy of productivity.	Considers area-wise irrigation and not irrigation technology, makes way for better decision-making.
Optimization and	Genetic algorithm,	Effective sensor

machine-learning algorithms [83,85,87,89,90,100–102]	KNN, logical regression, SVM and decision-tree algorithms are considered for irrigation requirement predictions.	data and data on weather should be combined for effective predictions.

5.2.2. Transfer Learning for Agriculture and Irrigation System

Transfer learning is a knowledge-storing problem which applies similar and related tasks for prediction and classification problems. The transfer of learning is used in different applications, classification problems, knowledge transfer, agriculture, etc. In agriculture [109], it is used in plant disease prediction, species detection, plant-domain-knowledge transfer and plant classification and information sharing. Recently, different researchers have addressed different problems related to transfer learning in agriculture. The authors of [110,111] proposed a knowledge-transfer model to classify different crops and reduce the retraining and labelling time. In this work, authors reduced 20% of the time compared to the normal time.

Similarly, the authors of [112] use transfer learning for weed identification among different plants and achieved an accuracy of 99.29%. Similarly, the authors of [113] propose deep transfer learning for trash classification. In this framework, the authors achieved 94% and 98% accuracy using different datasets. The authors of [114] proposed a model for identifying bale detection using deep transfer learning and a domain-adaptation approach, which transfers the source images to target domain images. The authors of [115] proposed a CNN and transfer-learning model for identifying crop-attacking pests in the early stages of crop growth. Transfer learning is used to create fine-tuned pre-trained models. The authors of [116] propose a transfer learning for transferring a base model, characterized using different samples/features, from one place to another. In this framework, the transfer of features is performed in two places in the context of the irrigation mapping of time-series features in two locations. The authors of [117] propose transfer learning with IoT to train the model better using soil moisture and transfer the soil conditions from one soil to another, with the two soils having different distributions.

The previous works [119–115] on transfer learning are used in classification based on features, which are transferred within the framework and between the models. The authors of [116,117] proposed models for transferring the features from one spatial location to another

5.3. Materials and Method for Requirement Prediction

This section presents the materials and methods for the proposed work. The proposed work uses live data and historical datasets to predict the requirement for the present and future irrigation systems. Live weather data is used to correlate current and future requirements. IoT devices are interconnected for present-requirement collecting, and different components are used for future-requirement collections. The proposed method uses k-nearest neighbours, cloud storage, LSTM, and ANFIS to predict an irrigation system.

The IoT devices must collect the data from the environments, for which KNN find the nearest water requirements from the root and surroundings, and ANFIS predicts short-term conditions. The LSTM is used to predict time-series-data updates for future prediction, and the transfer learning is used to transfer the learning features information from one cultivation field to another.

5.3.1. Materials

In the proposed method, materials are collected in three ways: IoT sensors, past data collected from previous years, and live data collected from the weather data. The sensor and IoT devices are also used to transfer the data from one machine to another and to the cloud environment.

The live-data collection location and the latitude and longitude of the experimental location is 8.2473502, 77.2743729, 345. The data was collected from Kanyakumari, Tamil Nadu, India. This location has seasonal rainfall, and basic requirements were collected using IoT devices. Three basic components, such as IoT devices, gateway and cloud, were interconnected to communicate and transfer data from the physical location to the cloud. Four different fields were used for collaboration and decision-making in the mentioned location. The basic requirements for prediction were measured using various sensors. Figure 5.1 shows the different requirements predictions presented in 3 h time intervals. Similarly, the basic requirements were also measured between 5 h, 8 h and 10 h. The cultivation requirement of the Plantain Banana or Red Dacca (Australia) from the beginning to the end is represented in Table 4.1 The entire cultivation of the species started in February and ended in October. The summarises the basic water requirement from the beginning of February till the end of the cultivation in October. This basic requirement is plotted manually with the help of farmers, and four farmers were involved in the cultivation.

Figure 5.1. Collections of atmosphere requirements.

5.3.2. Methodology

This proposed work used IoT devices, k-nearest neighbours, cloud storage, LSTM, and ANFIS to predict an irrigation system. The IoT devices must collect the data from the environments, for which KNN find the nearest water requirements from the root and surroundings, and ANFIS predicts short-term conditions. The LSTM is used to predict time-series-data updates for future prediction, and the Spearman rank correlation method correlates the needs in different intervals. The proposed work's basic goal is to predict current and future requirements for different time intervals, such as 3 h, 8 h, 12 h and 24 h and 48 h.

The basic structure of the proposed work is presented in Figure 5.2. The proposed structure of the prediction model consists of three main parts: initial-value predictions, integrated prediction model and transfer learning. The initial-requirements prediction is performed using the group of sensors. The group of sensors sensed soil-moisture, root-moisture, and weather data. In the integrated model, KNN, ANFIS and LSTM algorithms were used for sensing nearest values and short-term and long-term predictions. The prediction values and features were shared using transfer learning.

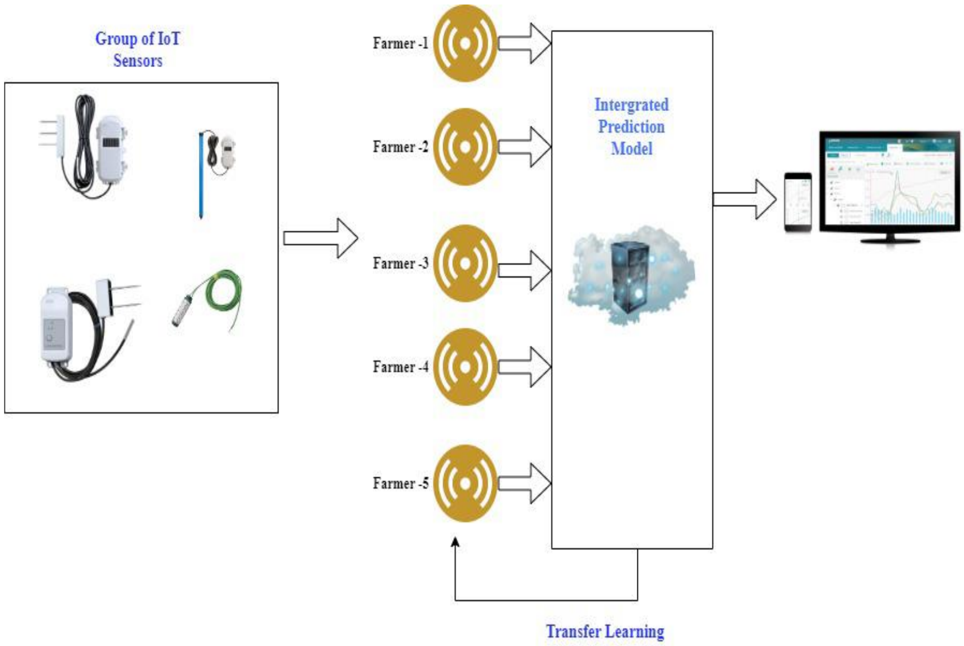


Figure 5.2. Structure of the proposed work

5.3.2.1. KNN Algorithm

KNN is a supervised algorithm to find the nearest values predicted using sensors with many assumptions [118,119]. The dataset inputs considered the real values, taking the values from the certain k nearest distance from the input dataset. The prediction output is the average distance between the input taken and the given sensed input using the average voting of the nearest prediction. The trained data of multiple inputs consist of multiple features, and different classes are labelled using a supervised KNN algorithm. The nearby sensed values depend on the discrete or continuous distance. The different features' relationship or distance between the features is predicted using Euclidean distance. The discrete values, such as soil moisture, atmospheric moisture and weather data, are evaluated using the Euclidean distance. The recommendation of the features is also evaluated and considered as the input value for the integrated prediction model. The Euclidean distance vector evaluated the different region-wise and root-moisture values considered as the input.

5.3.2.2. ANFIS

The ANFIS is an artificial neural network with a combination of neural-network and fuzzy-logic properties. The inference system is a set of if-then rules with non-linear functions [120,121]. The ANFIS was constructed using five layers: an antecedent layer, three hidden layers, and a consequent layer. The antecedent layer is an input layer, and the consequent is an output layer. The three hidden layers are based on rule-based and fuzzy logic applied to these three layers. The first input layer between 0 and 1 is called the "premise parameter". The second layer estimates the income for each neuron using the product operator. The third layer normalizes the input signal, and the fourth layer is fuzzification. The fifth layer is a summarized weighted output layer. The ANFIS is an optimal and intelligent way to manage the energy system [122].

5.3.2.3. Long Short-Term Memory

LSTM is a recurrent neural network which predicts and classifies data requirements using time-series data. It consists of input, output and forget gates. The different gates control the flow of information and help exit and enter the gates. The LSTM predicts future time-series data in short- and long-term predictions [123,124].

5.3.2.4. Transfer Learning

Transfer learning is used to train the system to perform the relevant similar learning of the existing model. The main part of the learning is generalized, and the different scenarios or relevant conditions are transferred from one model to another. The main advantages of transfer learning are saving resources, timing to complete similar learning, increasing the learning model's efficiency, and avoiding the negative prediction from the pre-trained model [116,125].

5.3.3. Working Principle

This proposed work predicts various requirements of irrigation using IoT sensors and weather inputs and helps in finding short- and long-term predictions. The flow of the representation of the proposed work is presented in Figure 5.3. The working process of the proposed work consists of four main parts: data collection from various sources, nearest requirement prediction, short-term prediction (ANFIS), long time-series prediction (LSTM) and predicted knowledge sharing to nearest farms (transfer learning). The working process of the proposed work uses four steps: processing the inputs and storage, short-term prediction, long-term prediction and transfer learning and sharing features from one data source to another data source. Initially, the data is collected from the sensors, with the help of KNN algorithms for predictions. With the collected data, weather forecasts and previous data are used as the input. The processed data is applied for short-term prediction using the ANFIS. The short-term prediction of irrigation recommends water pumping. For long-term prediction, the LSTM technique is used, and, if required, it recommends water pumping. This prediction is performed on a single farm for short- and long-term prediction. Once the farming location requirement is predicted, the features are transferred to another farm for better predictions. The second farm processes the new input data from a particular location and processes the farm 1 features for better performance.

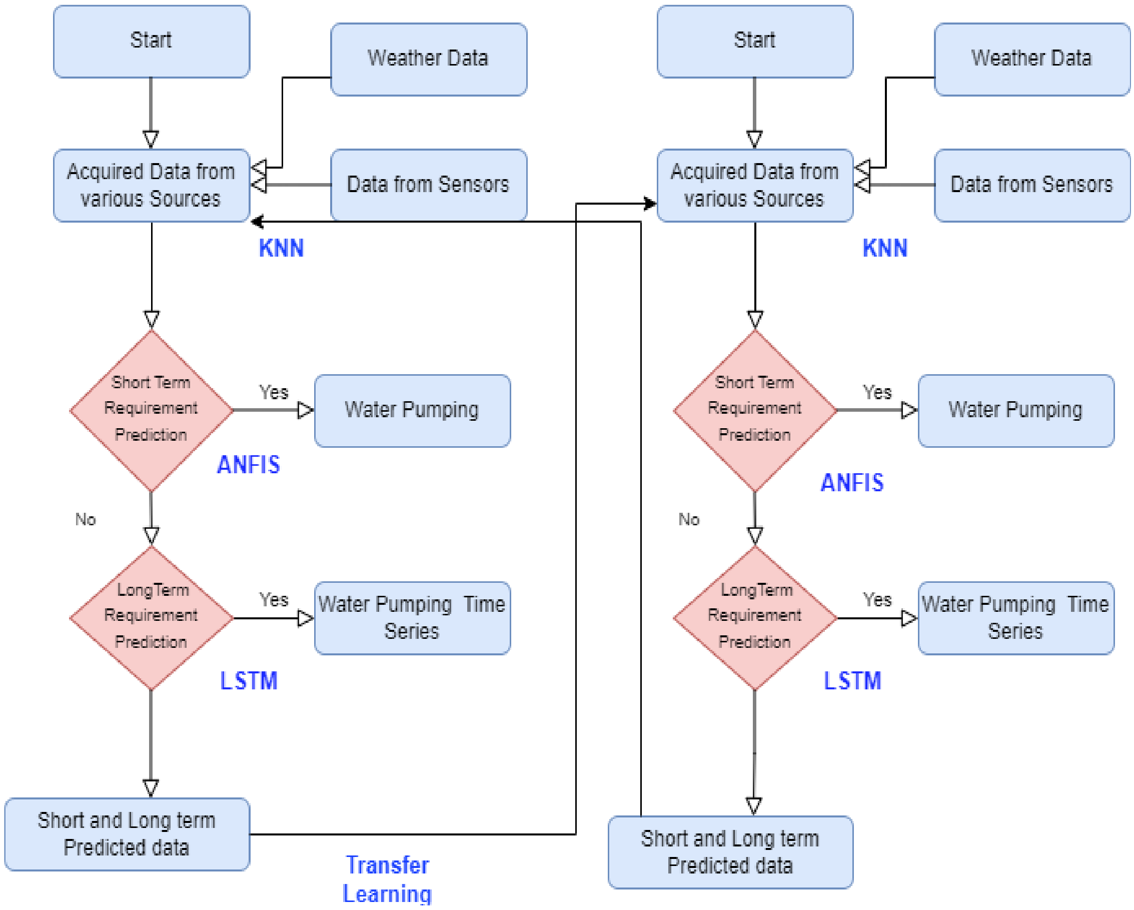


Figure 5.3. Workflow representation of proposed work.

The entire working procedure is described in Algorithm 5.1. The processing steps of the algorithms consist of data processing, and prediction and sharing of knowledge gained from other farmers, as well. Initially, the sensor data from farm 1 and weather data are transferred to the cloud storage. The history data and collected data are initially processed for the prediction of requirements. The processed data predicts the short-term (Sp) and long-term (Lp) requirements using ANFIS and LSTM techniques. Using these techniques and collected data, initial requirements are predicted in the long term and short term. The first farm (X1) gains the knowledge, and so the stored model weight is shared with the nearest second farm for better prediction. A detailed description of the working process is as follows.

Initially the input collected which are collected from various sources of input are, real data, with help of IoT devices, Past data and weather information from the nearest weather stations. In this work we consider four farms for banana cultivations. Each farm is considered as X_1, X_2, X_3, and X_4. The output of four farms with input process model is represented in the equation 5.1.

Algorithm 5.1: Requirement Prediction and Features Transfer

Input: Data Collection Using Sensors (Moisture (Xm),
Weather details (Xw), Temperature (TT)
Farms Prediction Details (X1, X2, X3, and X4)
Output: Short- and Long-term Prediction Details (Sp, Lp)
Generating algorithm Begin:
1. (Moisture (Xm), Weather details (Xw), Temperature (TT) > 0
2. X1, X2, X3, and X4 > 0
3. Calculate (Xm), (Xw), (TT);
4. If (Xm, Xw TT >0)
5. Predict of Each Farm Requirements Details
6. {N = C (Prediction of Nearest features with respect to weights and time)
7. D = {Prediction of distance features between two terminals}
8. Sp = Tp -AP // Short- term prediction
9. Lp = Tp -AP // Long- term prediction
10. End of Each Farm Prediction
11. Share the month wise history data
12. Y = X1 (End prediction of single Farm)
13. Share X1 to X2
14. T = [Y, f(.)] //Start Transfer Learning
15. If X1 > X2 / X2 >X1
16. Share the Y values
17. If (Xw = Rainy)
18. Stop // Stop sharing, Sensors in Sleep Mode

19. End

$$Y = \{X_1, X_2, X_3, \text{and } X_4\} \quad 5.1$$

Each farm used three input sources such as past cultivation data (x_1), weather data (x_2), and current data, collected with the help of IoT and Sensors (x_3). The combination of inputs and output representation of model is shown in equation 5.2.

$$Y = \{X_1(x_1, x_2, x_3), X_2(x_1, x_2, x_3), X_3, (x_1, x_2, x_3), \text{and } X_4(x_1, x_2, x_3)\} \quad 5.2$$

The x_3 is the combination of the nearest features, short term requirement predictions, long time prediction and transfer of knowledge from the one farm to another farm. Initially the nearest features are predicted using the KNN algorithms and nearest features are calculated based on the distance between the roots from the initial prediction to next nearest predictions. The distance is calculated using the Euclidian distance. The mathematical representation of nearest features calculation and distance measurement between the features are represented in the equation 5.3 and 5.4.

$$\mathbf{N} = \mathbf{C}_{\mathbf{n}}^{\mathbf{w}}(\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_n}) \quad 5.3$$

N – denotes the predicted nearest values, *C* - denotes features, *n* denotes different features, *w* denotes weight, $\{x_1, xn\}$ denotes different weight. The distance between the initial root prediction features and next feature distance as follows.

$$D = \sqrt{\sum_{i=0}^{n} x_i - x_j} \quad 5.4$$

D denotes distance, *n*- number of measurement of features *x*, i and j denotes the starting and ending points of moisture measured in the roots. The based on the nearest features, past data and weather information short term inferences are calculated using ANFIS. The inference model and short-term learning prediction are represented in equation 5.5 and 5.6.

$$S_p = \sum_{x=0}^{x} (T_p - A_p)^2 \quad 5.5$$

The Sp denotes short term prediction, Tp denotes the targeted prediction and Ap denotes actual prediction. Similarly, the learning rate of ANFIS representation is as follows.

$$\sigma = \frac{k}{\sqrt{\left(\frac{\delta E}{\delta \sigma}\right) 2}} \quad 5.6$$

σ -denotes the learning rate, k -denotes the learning size, δE- denotes the error rates and $\delta\sigma$- denotes the training data. Based on the equation 5.5 and 5.6, the short-term interference result is, as calculated. If the short-term inference result is not required, long time prediction is performed using the LSTM algorithm. The LSTM algorithm prediction long term series data prediction with the help of three types of the inputs as mentioned in the earlier. The LSTM algorithm consists of three gates, such as forget gate, remember cell, activation sigmoid function and new states of prediction represented 5.7 to 5.10.

$$f_t = \sigma_q (w_f x_t + u_f h_{t-1} + b_t \quad 5.7$$

f_t denotes Activation function, h_{t-1} – denotes previous unit output $t-1$, x_t – denotes input data, b_f denote bias, σ_q denote sigmoid function. The sigmoid function denotes as $S(t)$ is represented as follows.

$$S(t) = \frac{1}{1+e^t} \quad 5.8$$

The remember cell and new state function are, as follows.

$$i_t = \sigma\left(w_i \ (h_{t-1,} x_t\ \right) + b_t \quad 5.9$$

$$S_n = f_t * S_{t-1} + t_t \quad 5.10$$

With the help of KNN, ANFIS and LSTM prediction is done, using, the short term and long-term prediction of the requirements. The requirements of X_1, X_2, X_3, and X_4, are shared using the knowledge transfer. The knowledge transfer, is represented in the equation 511[16]. The initial learning performed from the X_1 ((x_1, x_2, x_3) and predicted values or known value is considered as Y. So, the transferring learning is denoted as

$$T = [Y, f(.)] \tag{5.11}$$

T denotes, learning task transferred to next node or prediction task, Y- denotes the prediction output and f(.) denotes prediction function with different instance. This predicted task is transferred to the other farm using different threshold or different conditions.

5.4. Results and Discussion

For experimental and implementation requirement, the specification is described in Table 5.1 and Table 5.2. Data has been collected form the metrological deportment and banana cultivation research centre of India. Initially, the requirement, such as X_1 is collected from the IoT sensors. Using the sensor, surrounding moisture, Root moisture and humidity values are also collected. And, minimum and maximum water requirements are collected manually from the farmers. The maximum water requirements for a month (50) litres and interval of irrigation (7days) are collected for fixing the threshold values for training and testing. Some of the fixed and basic parameters which are considered for irrigation, is shown in Table 5.2.

Table 5.2: Basic Implementation Parameters

Parameters and requirements	Values
Number of Nodes	4
Number of trees in each Nodes	9/10 Months [Feb- Oct/Nov]
Maximum requirement per month	50 Litres
Irrigation Interval	Feb to November

Minimum Temperature	0 C
Maximum Temperature	37 C
Interval of irrigation	7 Days
Average requirement of water per month	36 Litres

Initially, is the basic requirement of prediction training, testing and validation accuracy which is predicted using the combination of ANFIS and LSTM. The Figure 5.4 represents the accuracy of the training and testing of 97 iteration and 100 nodes data.

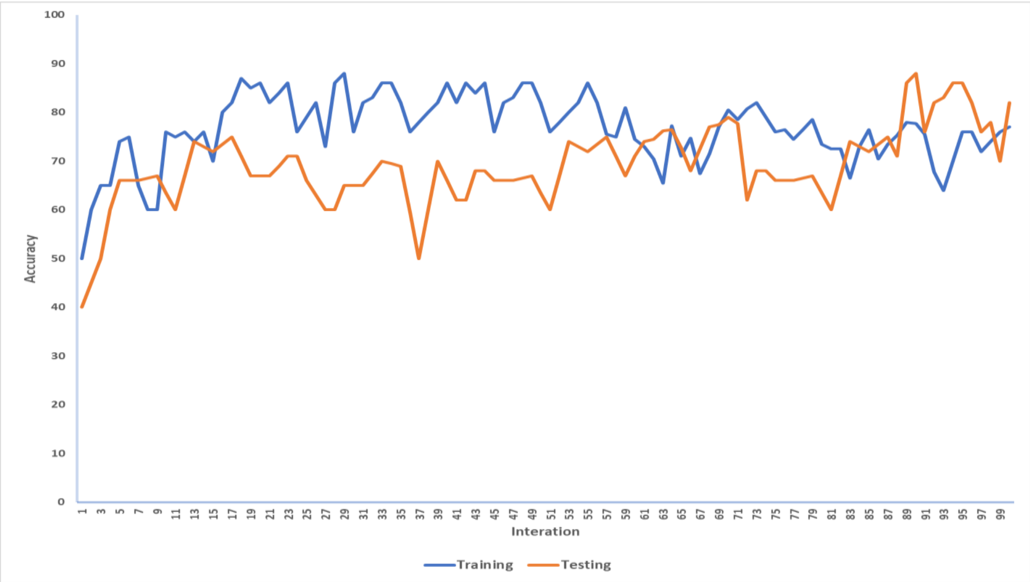


Figure 5.4: Training and testing accuracy of prediction

In figure 5. 2, various live indicators such as temperate, humidity, rain possibility, and wind speed, has been taken for x3 calculation. The past cultivation data (x_1), weather data (x_2), and current data collected with the help of IoT and Sensors (x_3) and root moisture are also calculated continuously with the help of THERM200 and SHT11. In this work, irrigation requirement is predicted in terms of 8 hours, 16 hours, 24 hours, 48 hours and 60 hours. Two main requirements directly affect the requirements, such as temperature and humidity. The year wise temperature and humidity, which is presented in the Figure 5.5 and 5.6.

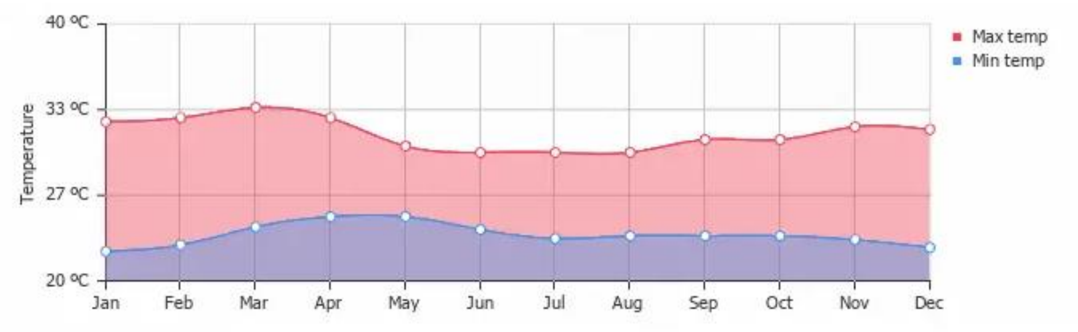
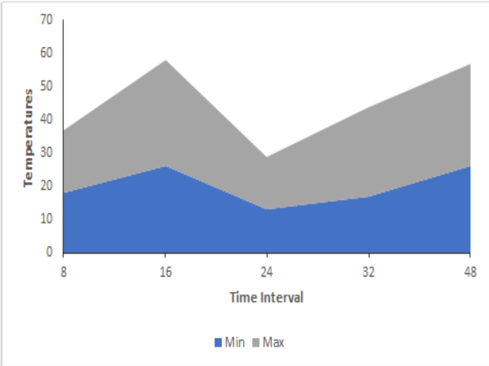


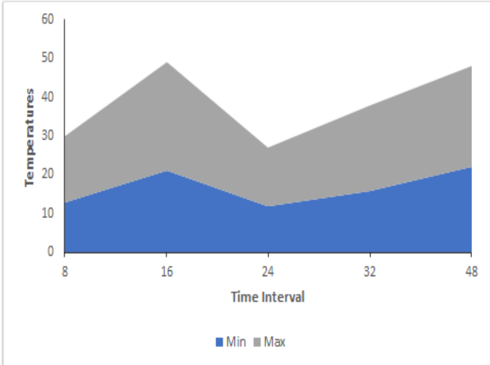
Figure 5.5: Month wise Temperature

Figure 5.6: Month wise Humidity

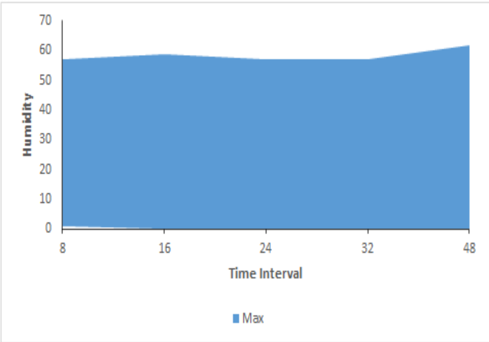
So, in this work three types of the requirements are predicted such as short term (8 hours, 16 hours), long term (, 24 hours, 48 hours and 60 hours) and changes are implemented after transfer learning from the one farm to another farm. The shortest inference result is predicted with the help of ANFIS and long-term prediction is done with the help of LSTM. The shortest-term prediction analysis is done in two months such as march and July. The reason for prediction of March and July is, during march, rain fall is low and in July rainfall starts and thus the atmospheric temperature is low. The moisture and humidity of current and the short-term requirement prediction of march and July requirement prediction, using ANFIS has been presented in the Table 5.3. The shortest-term prediction requirements are shown in the Figure 5.7. Figure 5.5 and 5.6 presents, two main requirements of short- and long-term predictions such as temperature and humidity in-terms of 8, 16, 24, 32, 48 hours. The figure described the minimum and maximum temperature and humidity, and it starts from the 8 am and it continuously measures up to 48 hours.



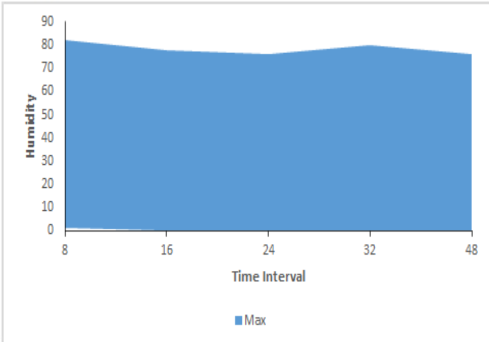
A. March Month Min-Max Temperature



B. July Month Min-Max Temperature



C. March Max Humidity



D. July Max Humidity

Figure 5.7: Minimum and Maximum Temperature and Humidity of March and July Months

Table 5.3: Short-Term Prediction of Requirement

Time Interval		8	16	24	32	48
March	Min (Litres)	2	3	1	2	3
	Max (Litres)	3	4	2	3	4
July	Min (Litres)	0	1	1	0	1
	Max (Litres)	1	2	2	1	2

Based on the minimum and maximum temperature and humidity, the requirements of irrigation for march month and April month are summarized in the Table 5.5. When compared with table 3, the maximum requirement per day in march is 6 to 7 litters and in the requirement, prediction is also according to maximum requirement per day, which is near about 6 to 7 days. Similarly, July also received 2 to 3 litres per day based on the ANFIS prediction. Similarly, the long-term prediction is performed with the help of LSTM algorithm and prediction intervals are 24, 48, 72 and etc. Using the long-term prediction irrigation is performed because generally in the banana irrigation intervals are between 3 days to 5 days. So, based on the long-term prediction irrigation is scheduled. The long-term prediction of farm-1is presented in Table 5.4.

Table 5.4: Long-Term Prediction of Requirement

Time Interval		24	48	72	96
March	Min (Litres)	2	3	1	2
	Max (Litres)	3	4	2	3
July	Min (Litres)	0	1	1	0
	Max (Litres)	1	2	2	1

Based on the Table 5.5 and 5.6, the entire prediction requirements of irrigation in march and April are presented in Table 5.7. This prediction requirement is calculated between four-day intervals. The short-term and long-term prediction is correlated by four-day intervals. Minimum and maximum requirements of irrigation are presented in Table 5.5 and Figure 5.6.

Table 5.5: March and April Irrigation Dates and Requirement -Farm 1

March Time Interval/Irrigation Date		**4**	**8**	**12**	**16**	**20**	**24**	**28**	**Total Requirements**
March	Min (Litres)	2	3	3	4	4	3	4	23
	Max (Litres)	3	4	4	5	5	5	5	31
July Time Interval/Irrigation Date		2	6	10	14	18	24	28	**Total Requirements**
July	Min (Litres)	0	1	1	0	2	3	2	9
	Max (Litres)	1	2	2	1	3	4	3	16

The Table 5.5, 5.6 and 5.6 are the short, long and month wise requirement prediction of Farm 1 prediction. In this prediction, ANFIS and LSTM are used. And based on these two techniques the month wise prediction is presented in the Table 5.7. The Table 5.7 clearly presents the minimum and maximum requirements of irrigation in 4 days' time interval. The four days' time interval is measured with the help of ANFIS and LSTM and corresponding correlation of long and short-term prediction. In the month of March, the humidity, temperature and other parameters such as weather, wind speed and previous year information's are considered for prediction. In the month of march generally the above-mentioned parameters are very high and wind speed also very low compared to the other months in the specified location. So, the maximum requirement of the irrigation is increased in that year and minimum requirement is also similar to the maximum requirements. The difference between the minimum and maximum requirements difference is 8 liters. Similarly, the month of July is monsoon season and it rains in the specified location, so automatically the requirements of irrigation decreases. In the month of July, mostly the requirements are decreased, as the humidity is very less. So, the minimum requirement of irrigation is 9 and maximum requirements is 16. Similarly in next three month, requirements are very less, but during the summer season, the irrigation requirements is very high in the month of April, may and middle of July. The entire year wise irrigation requirements of Farm 1 are presented in the Figure 5.8. In this Figure 5.8, minimum and maximum requirements are summarized in the Farm 1. The maximum requirements are increased in the months of March, April and May.

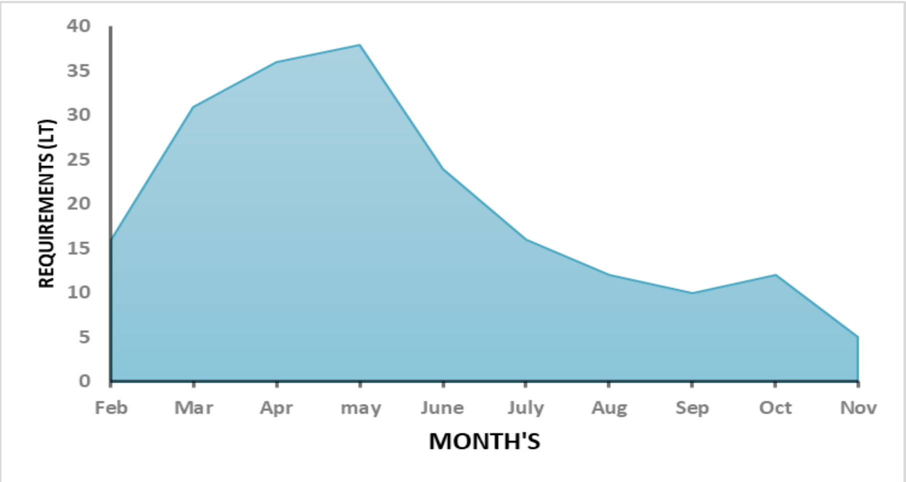


Figure 5.8: Month wise Requirement Prediction of Irrigation -Farm 1

Similarly, with the help of transfer learning, from the Farm 1, prediction is transferred to the Farm 2. Based on the Farm 1, the basic information is shared to the Farm 2. The basic requirements of irrigation in March and April are shown in the Table 8 and year wise predicted results are presented in the Figure 5.8.

The transfer learning helps to reuse the model for new task prediction. Table 5.8 and Figure 9 shows the difference between the first prediction (Farm1) and new prediction (Farm2). Comparing Table 5.5 and 5.7, the requirement prediction is reduced, because, it produced better optimization and saved the irrigation requirements in the two months and overall requirements are also reduced in the farm 2.

Table 5.6: March and April Irrigation Dates and Requirement (Farm-2)

March Time Interval/Irrigation Date		**4**	**8**	**12**	**16**	**20**	**24**	**28**	**Total Requirements**
March	Min (Liters)	2	4	5	4	4	5	4	28
	Max (Liters)	3	5	6	5	5	5	5	34
July Time Interval/Irrigation Date		2	6	10	14	18	24	28	**Total Requirements**
July	Min (Liters)	0	1	1	0	2	2	2	7
	Max (Liters)	1	2	2	1	3	3	3	15

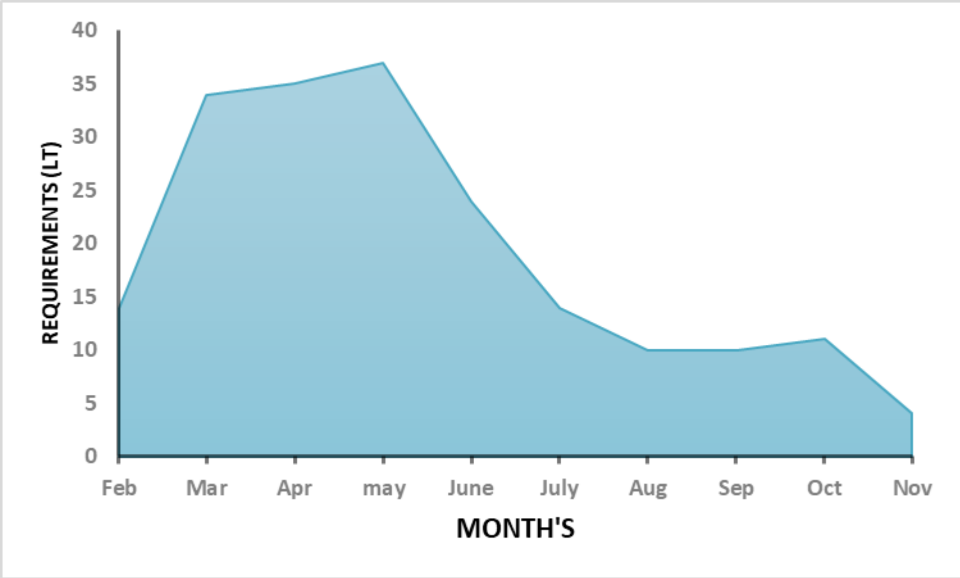


Figure 5.9: Month wise Requirement Prediction of Irrigation -Farm 2

In comparison to the Farm 1 and Farm 2 the requirements of irrigation are reduced to 7 litters per single plant of banana. Farm 1 total requirement is 200 litre per plant and after applying the transfer learning total requirement of irrigation is 193. So, after applying the transfer learning, 7 litre irrigation is requirement has been reduced in the Farm 2. In the overall, irrigation process, every day prediction is transferred form Farm 1 to Farm 2 in 5 minutes time interval, after that Farm 2 irrigation requirement is predicted.

Compared to Farm 1 and Farm 2, the irrigation requirements are reduced to 7 litres per banana plant. Farm 1 total requirement is 200 litre per plant, and after applying the transfer learning total requirement of irrigation is 193. The after applying transfer learning, the 7-litre irrigation requirement has been reduced in Farm 2. In the overall irrigation process, everyday prediction is transferred from Farm 1 to Farm 2 in 5 minutes time intervals delay, and after that, Farm 2 irrigation requirement is predicted.

Table 5.7. Comparison of R2, MSLE and EV.

Epochs	Farm-1			Farm-2			Farm-3			Farm-4		
	R2	MSLE	EV	R2	MSLE	EV	R2	MSLE	EV	R2	MSLE	EV
15	0.92	0.52	0.92	0.93	0.51	0.93	0.94	0.56	0.94	0.95	0.49	0.95
30	0.945	0.48	0.945	0.947	0.48	0.947	0.954	0.47	0.954	0.954	0.45	0.954
45	0.946	0.46	0.946	0.956	0.4	0.956	0.964	0.46	0.964	0.974	0.46	0.974
60	0.95	0.42	0.95	0.96	0.4	0.96	0.967	0.44	0.967	0.977	0.34	0.977
75	0.958	0.38	0.958	0.962	0.38	0.962	0.968	0.35	0.968	0.981	0.33	0.981

The proposed work is evaluated using the coefficient of determination (R^2). The R^2 determines the model prediction measurements when increasing the iterations. Initially, the model was predicted to be 0.920 at 15 epochs and 0.958 at the 75th epochs. After applying the transfer learning, the farm-2, farm-3 and farm-4 values gradually increase. Table 5.7 shows that the model prediction and relationship accuracy values increase after transferring the features.

5.4.1. Comparison with Other Methods of Estimation and Transfer of Learning

The proposed method was compared to the existing approach, which decreased the water consumption of a single node by 31.4% in the period of 2020. When compared to the previous approach, our method optimized 30.24% of water after applying transfer learning on a single node of the banana tree. Our method was tuned to consume 1.16% less water in a single node of a banana tree. Comparing our suggested method to the manual and technology-based approaches, we find that it optimized 41% to 50% more water in the farm. Using transfer learning, the proposed method reduced from31.4% to 30.24% the water of a single node tree. Tables 5.6 and 5.7 clearly illustrate the optimization of water usage following the implementation of transfer learning. Our proposed work was compared with the recent work [6,105–107], and it optimized the irrigation requirements. Compared to previous work, total water usage is reduced. Table 5.10 shows the water usage of our work and its comparison with previous work. Compared to the previous work, total irrigation requirements were reduced.

Table 5.8. Comparison of Accuracy with Existing Methods.

S.No	Methods	Accuracy
1	GBRT[105]	87.23
2	SVR+ K-Means [106]	88.13
3	LSTM +GBT [6]	92.04
4	RBFN [107]	89
5	Our Method	94

5.5. Summary

This work integrates IoT, machine-learning and transfer-learning techniques to achieve sustainability and predict irrigation-system water requirements. The main finding of this work is that it reduced water usage and transferred the features of the prediction model and exchange for better prediction and requirement analysis. IoT sensor devices collected basic requirements such as humidity, temperature, and moisture. The weather data and past data collected from the banana research centre were used for implementation. The proposed work used ANFIS for short-term predictions, such as 8, 16, 24, etc. The LSTM predicted long-time requirement predictions such as 24, 48, 72, etc. Based on short- and long-term predictions, the entire requirement was predicted in 4 days. In this work, data of two months, March and July, was predicted and analyzed. The entire requirement of overall cultivation was predicted and calculated in the short and long term, with the help of weather and past data. The farm-1 data features were transferred to farm two, and, thus, it predicted the irrigation requirement. Comparing farms 1 and 2, after irrigation, farm 2 had lower irrigation requirements in July, a change from 16 to 15; during May, the requirement increased from 31 to 34. Similarly, comparing the year-wise requirement of farm 1 to farm 2, we see that it reduces the requirements from 200 to 193 for a single banana tree. This work reduces the irrigation requirement and predicts the short- and long-term requirements of an effective irrigation structure at a particular interval. In the future, this approach will be extended to multiple farms. Based on that, the requirements can be optimized. In addition, further implementation of this work is being carried out using Federated learning, sharing the farm data, which predicts and shares the model for further irrigation.

Chapter 6

Collaborative Irrigation Model using Federated Learning

6.1. Introduction

An irrigation is the process of controlling the water usage for agriculture and increase the productivity using an effective cultivation. The researchers are mentioned different usage using the irrigation such as proper utilization of water, optimizing the fresh water usage and avoid water usage, increase the nutrition, landscape plants, grow crops and etc. The different types of the irrigations are used to optimize the water usage such as drip, surface, furrow, Trench, Fertigation and etc. The suitable irrigation types are selected based on the different parameters such as crop type, slop of the land, types of technology and etc. The different types of the crops are used to optimize the water usage such paddy, corn, banana, sunflower and etc. In this work used banana irrigation water usage optimization perform in the different collaborative manner for effective irrigation in the homogeneous environment. The main purpose of this research is to find the effective prediction model for irrigation in the distributed environment using the collaborative manner.

Artificial intelligence includes machine learning as a subset. The various machine learning methods are used to predict the requirement and optimize the irrigation system. The traditional machine learning techniques, the data are centralized and not having privacy, while managing the data. So, recently the federated learning is introduced to manage huge amount of data in the distributed environment with collaborative manner. The federated learning's major benefits are Control over information, data anonymity, manage huge data personally, minimize the risk of data and provide an effective consolidated solution in the distributed manner. So, federated learning-based solution provide an effective solution for irrigation system. The following way the federated learning provides an effective solution in the irrigation system to farmers such as farmer data no need to share own data to others, it provides the consolidated solution from the various nodes, model move and data having privacy, and share the optimize model to other farmers for better solutions.

The organization of this chapter are as follows: The section 6.2 presents the related information about federated learning and its advantages. The section 6.3 presents the definition of the problem, dataset information's used for implementation, algorithms for node selection and aggregations, and working process of proposed work. The section 6.4 presents the implementation details and result and discussion and finally 6.5 presents the conclusion and future work.

6.2. Related Work

While the training data for older machine learning methods must be concentrated in a single computer or data centre, modern science and technology have made the data available everywhere. Data access has become more challenging as a result of governments' increased focus on data protection and the development of rigorous privacy clauses. Data islands are an issue in many sectors since integration encounters strong opposition and sharing is challenging. It will be expensive to adhere to the right to privacy and to consolidate these data in the data centre. The three types of federated learning such as i. Horizontal types of learning, ii. Vertical types of Learning, and iii. Federated transfer learning. The different locations and corresponding data processing presented in Figure 6.1.

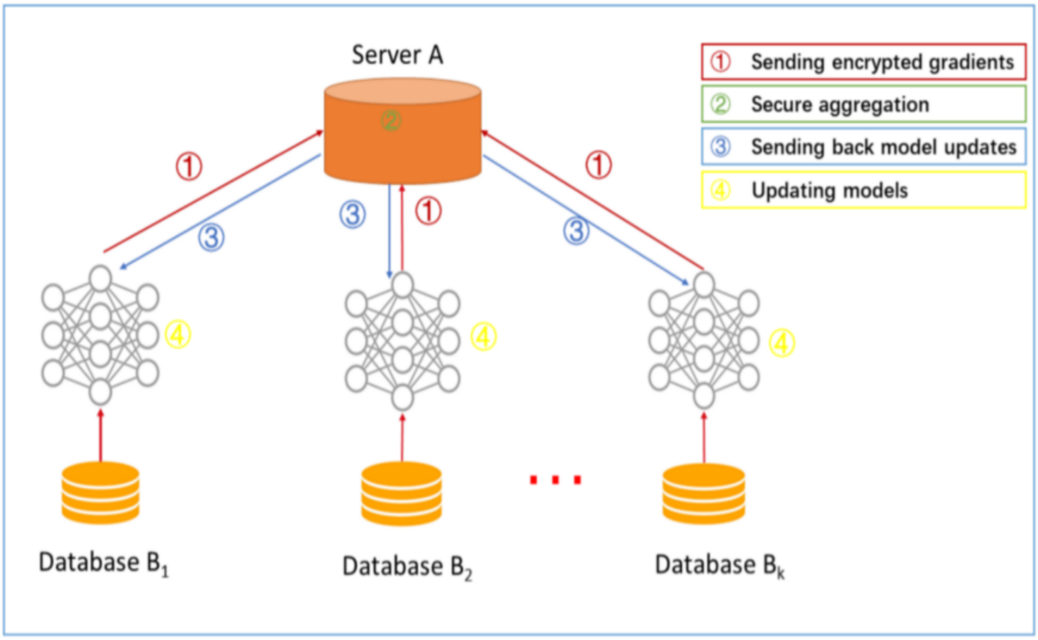


Figure 6.1: Federated learning system for different locations

First, the initialization parameters for the unified model and the identical model specification will be provided to each participant. To train the model, repeatedly iterate the following steps: The structure of the process of federated learning shown in Figure 6.2. The working process of the proposed work has as follows:

i. Each participant (business or device user), after training the model with its own data and determining the gradient, transmits the encrypted gradient correction amount to the server.

ii. The server updates the model by integrating each participant's gradients.

iii. The server sends each participant the model's modified gradient.

iv. The participants revise their individual models.

Because of its straightforward structure, horizontal alliance learning is currently the most popular. The different learning of federated learning are as follows.

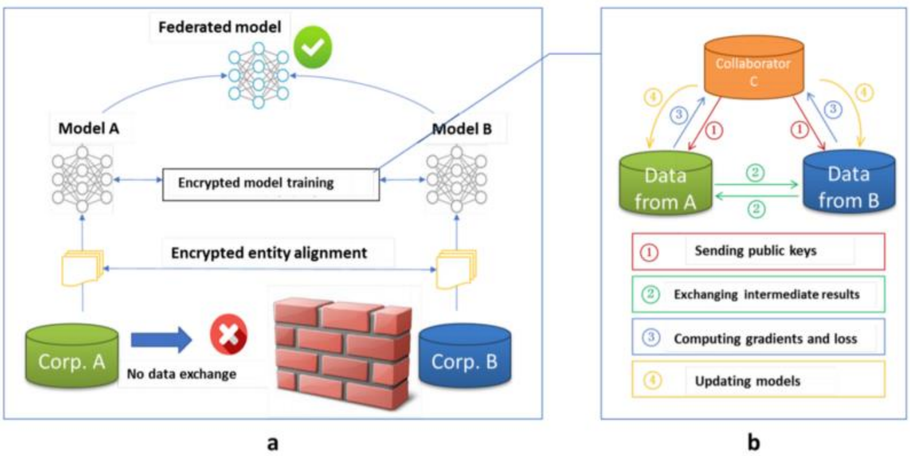


Figure 6.2: Structure of the Processing of Federated Learning

i. Horizontal federated learning

When sample overlap is minimal and feature overlap is substantial, horizontal federated learning is appropriate. For instance, Industries and hospitals in various places may have comparable operations (similar features), but diverse patient populations (distinct samples).

ii. Vertical Alliance Learning

When there is a lot of sample overlap, little feature overlap, and one of the parties also possesses the label that the model needs to predict, vertical coalition learning is appropriate. The different scenarios and corresponding instance, are all locals (the same sample), but the nature of the businesses is distinct (different features). Data transfers to the general public are prohibited by privacy and security regulations. As a result, A and B must utilize encrypted sample alignment technology (also known as encrypted entity alignment) to check the customers that both parties share before using these data for encrypted training.

During the technique, the participants are fully uninformed of the details and characteristics of the other party, and after training, they only receive the model parameters they have independently determined. The vertical alliance attempts to reduce feature overlap, but as long as there are more participants, the process architecture will deteriorate and become more difficult to implement.

iii. Federated transfer learning

When there is relatively little feature and sample overlap among those with data, federated transfer learning may be used. Instead of reducing the data, transfer learning will be employed in this case to overcome the labels and data. insufficient circumstance. The primary difference between horizontal alliance learning and distributed machine learning is that each node (node) is an individual participant (data owner), and as such, the modelling process may be influenced by the engagement of the participant (data owner). Dynamic preference adjustments are conceivable, and the entire learning process is protected by encryption. However, I think that horizontal federated learning is just decentralized learning that has been encrypted.

6.2.1. Advantages of Federated Learning

Dispersed data are used in federated learning to train models. The created models were trained on a variety of data and had minimal latencies without endangering the anonymity of the persons who helped with their creation. Here are a few more advantages to think about:

i. It is team-based by definition.

Federated learning enables mobile phones and other devices to work together to create a prediction model. This approach keeps training data locally on the device rather than uploading and storing it on a centralized server.

ii. Time is saved

Organizations can work together to solve problems using conventional ML models. As an illustration, highly regulated businesses like hospitals can collaborate to train a potentially life-saving machine learning model while safeguarding patient privacy and delivering results more swiftly. It is not necessary to continually gather and combine data from diverse sources.

iii. **It's secure**.

In federated learning, secure aggregation is employed to shield client updates from prying eyes. As a result, the server is unable to determine the value or source of any model updates sent by users. Data attribution and inference attacks are hence less likely. Businesses like financial institutions and hospitals that are subject to strict privacy requirements might profit from the protection it provides because personal data stays local. Since it is simpler to combine data on a single, external server, data is less susceptible to breaches.

iv. A wider range of data is used.

Federated learning facilitates enhanced data diversity because the centralized model continuously learns from numerous organizations and groups rather than a single dataset with a potentially skewed population. The model becomes more inclusive and representative as a result. For instance, in the healthcare industry, federated learning algorithms are trained across several hospitals dispersed throughout several geographies. It makes it easier to develop models that are well-rounded because the patients included in the dataset have a variety of traits, including age, ethnicity, gender, and physical attributes.

v. Real-time predictions are made.

Federated learning produces real-time predictions that are created on the device itself. By doing this, the time that passes between the time that raw data is transmitted back to a central server and the time that the results are sent back to the device is minimized. Because the models are immediately downloaded to the device, the prediction process still works even when there is no internet connection.

vi. It is passive and unobtrusive.

Due to federated learning, the training-related gadgets have longer battery lives. In reality, devices only take part in training while their users aren't using them. As a result, training can be done while your phone is in charge, idle, or in the do not disturb mode.

6.2.2. Federated learning in Irrigation system

Machine learning approaches are deployed using cloud-based centralized systems that process data and perform computational analysis. However, there has been a shift, and interest in federated learning is expanding because of privacy concerns over user-generated data. Devices like local clients, nodes, and sensors can collaborate to build and exchange forecasting models through a process called federated learning, although each device keeps its own data. Data recorded on close or distant gadgets are used to create a global statistical model. Nonetheless, several difficulties related to the literature has mentioned federated learning applications. This includes the difficulties in communicating that arise the use of confidentiality safeguards when transmitting firmware updates from diverse devices that impair model performance and system efficiency. However, spreading the prediction model to other sites is anticipated to yield possible benefits from the implementation of federated learning.

Developing nations, particularly those in Africa and some areas of Asia, are less likely to have adopted smart agriculture methods and digitization. Because most African countries confront infrastructure issues, adoption is slow. For example, many farmers are found in rural locations with low broadband penetration and limited internet connectivity . Therefore, further study is required to develop novel technologies that may be used in underdeveloped nations to apply machine learning to enhance irrigation that is affordable. Among these is the application of inexpensively wide-area communication methods for rural agricultural operations, which includes long-range (LoRa) technology for communication , which fuses federated learning with computing at the edge.

6.2.3. Analysis of Client Selection and Aggregation methods

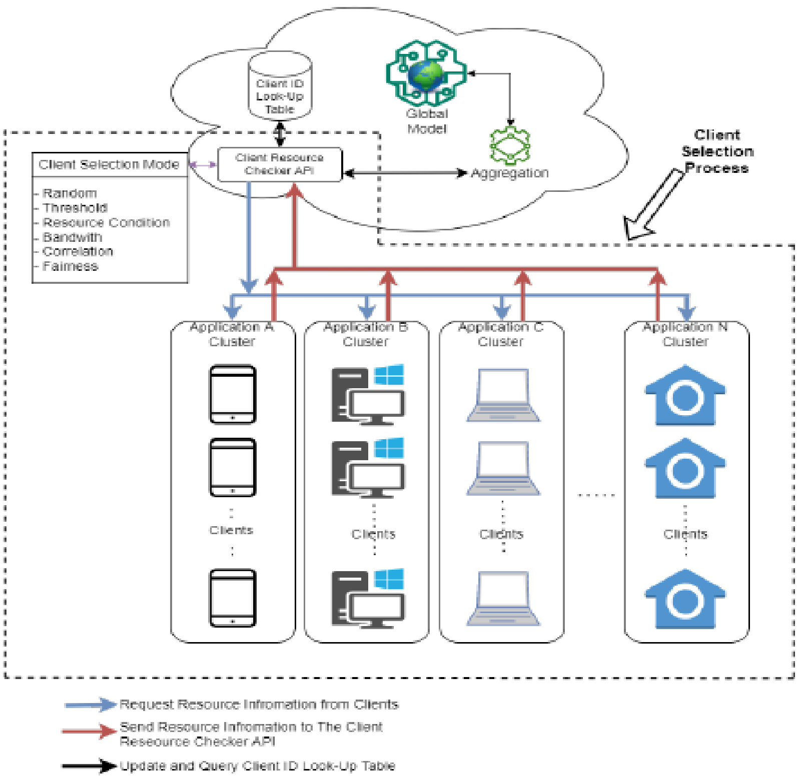


Figure 6.3: Client Selection Process

Node Selection Methods: In federated learning, choosing a client is a common procedure where the device in issue is initially charged and idle. To obtain the accuracy of communication, and the worldwide model, gathered characteristics and weights, and receive the global model, a server or worldwide node is linked to and associated with each authorized edge equipment. Figure 6.3 shows the many features and a general overview of the client decision-making process [126], from enrolment through client decisions. The FedCS [127] was used in this instance as the principal client selection technique, with the aim of actively selecting the client in accordance with the resource condition. The primary flaw in this work was that dynamic scenarios and updating were not taken into consideration during the selection process, which was carried out using random criteria. In order to mitigate this, fewer resources were explored, exploited, and traded inside the mobile network through the use of the multi-armed bandit technique

[128]. This technique reduces learning time, which is one of its key benefits. It is advised for use in future situations to minimize resource utilization in fluctuating FL operations, as it helps handle uncertainty brought on by vast amount of data.

Aggregation Methods: FL's main goal is to create an effective global model by using models acquired through dispersed local data of collaborating clients. The learnt client models' excellent data are then pooled to create an entirely new kind of model known as the aggregation model. Generally speaking, applications such as internet applications and meta-data analysis use both aggregation and rank aggregation techniques in different ways. The majority of the aggregation methods [129] are stochastic and heuristic in nature. In federated learning, aggregation is typically applied at two levels: local device aggregation and federated or cross device aggregation [130].

Local Aggregation: The term "local aggregation" describes the various samples that each client has. It sequentially uses the local parameters and the model parameters. With the use of local streams, it takes into account average loss, computer accuracy, and other parameters for local iterations [131].

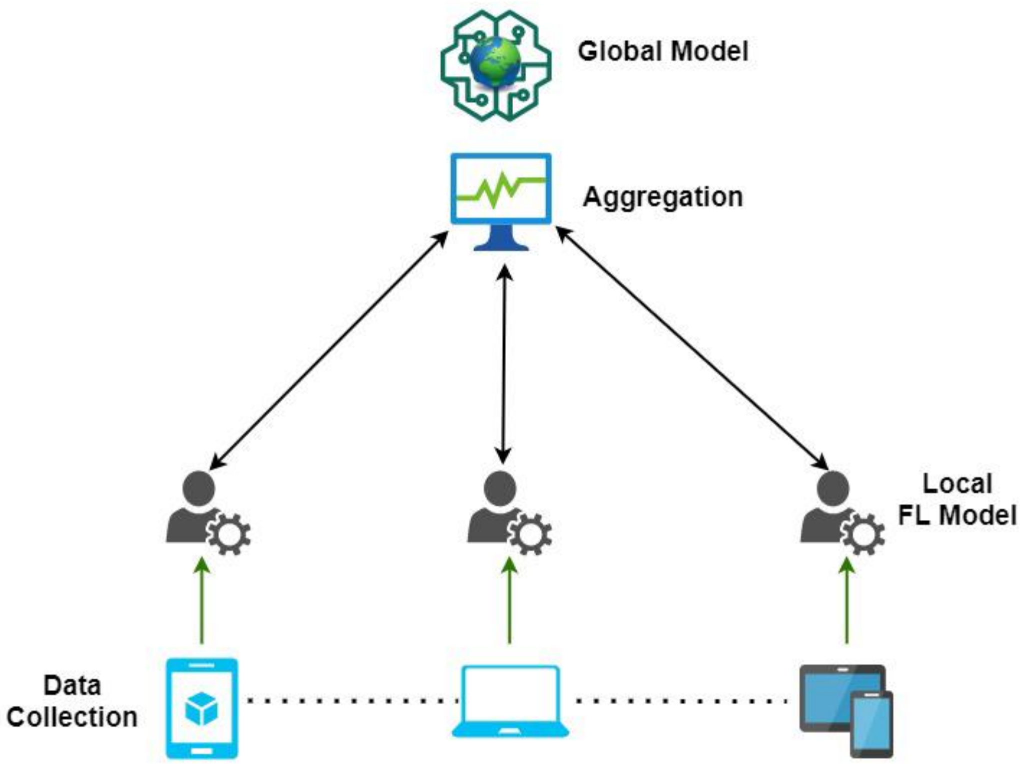


Figure 6.4: Federated Aggregation Structure

Federated Aggregation: Cross-device aggregation is another name for federated aggregation. In order to create a global model, this relates to the accumulation of numerous linked devices utilizes model metrics, averaged client aggregations, and model parameter [131]. Figure 6.4 shows a diagrammatic representation of a Federated Aggregation structure. To develop useful models, scholars in the field have taken into account various federated aggregation techniques over time. Originally, a stochastic gradient optimization was used to introduce federated averaging [132] using four datasets and five different models to average. The foundational paradigm for federated aggregation was this one. Unevenly distributed big nodes were later added by Jakub and McMahan et al. [133] to provide high-quality data for the consolidated algorithm's training. We referred to this procedure as "federated ptimization" or "algorithm." Features, node count, and communication rounds were used in this method's evaluation. Following up on this, Yushi Wang [135] carried out additional research and suggested an asynchronous technique known as CO-OP for combining local samples into global models and training the local model using freshly generated samples. In this work, evaluation factors for communication overhead and model correctness were taken into account.

6.3. Collaborative Irrigation Model

This section presents the objective of the model, dataset information's used for implementation, algorithms for node selection and aggregations, and working process of proposed work presented briefly.

Objective of the Model: The main objective is to create an effective model using different farmers data without sharing for better prediction. A method for training machine learning models on decentralized data, where the data is dispersed among numerous devices or nodes, is called federated learning.

Dataset Information's: The components and data source of the location presented in the Section 1.10. The gathered data is processed with artificial intelligence and saved in a cloud environment. The sample information, soil moisture data, and location data are gathered from the Kanyakumari district in India. In this work we considered 5 farmers (Clients) for implementation.

6.3. 1. Functional Design of Collaborative Model

The proposed model is divided into three sections, including assumptions of federated learning environments, federated learning functional designs and prediction models.

Assumptions of Federated Learning: The implementation assumptions for federated learning model presented in global model and considered 5 clients. The local data is private and was initially shared with clients or local data. The initial model is built and given to all consultants as data is updated on the nearby client disc. Based on the criteria, the client model is run and shared with the aggregations.

Federated learning functional designs: The overall functional requirements of federated learning shown in Figure 6.5. The following are the many steps involved in federated learning:

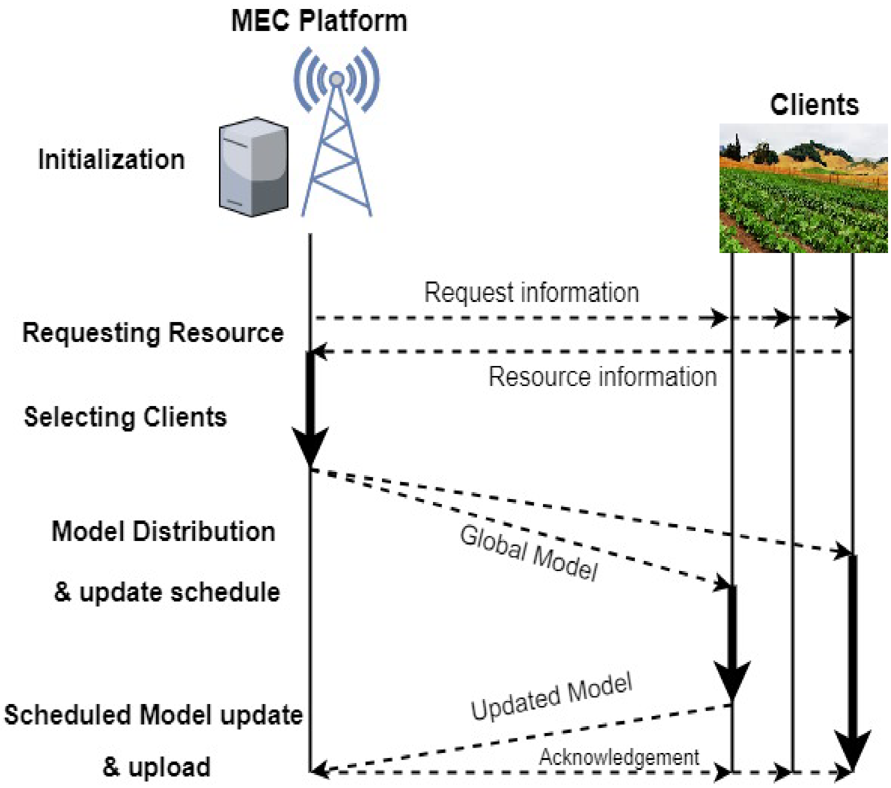


Figure 6.5: Functional Design of Federated Learning

i. Setting up the participant's gadgets.

ii. Request for participation made to the resources.

iii. Client Choice

iv. The parameters' distribution.

v. updating the new parameters and uploading them, and finally.

vi. combining the transferred parameters and weights.

The issues that have emerged as the most important research, with an eye to emerging technologies are client selection, aggregation and optimization, knowledge transfer, and data management with respect to the high requirements for the designing, collaboration, and applications of the FL system model and design.

Prediction Model: The detailed description of the proposed model presented in Chapter 4. The same model is used in global model. The model uses of IoT components, the KNN algorithm and reinforcement learning. The Internet of Things (IoT) components are utilized to gather current needs and forecast the environmental status of agriculture fields. The nearest features from the agricultural fields are captured by the KNN algorithm. IoT and KNN are used to do environmental prediction, awards, or needs for individual plants.

6.3.2. Client Selection and Aggregation Models

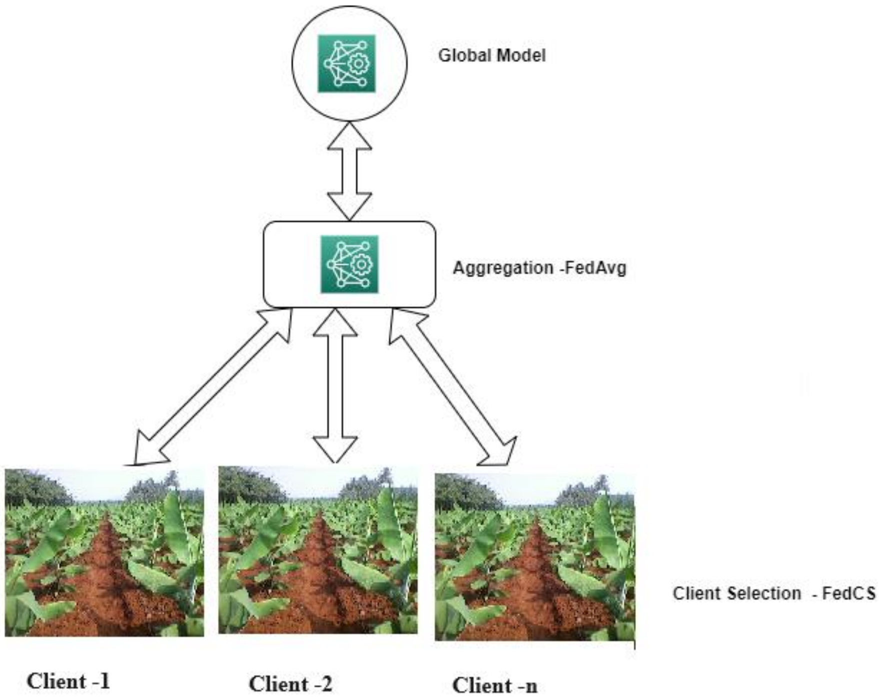


Figure 6.6: Structure of client selection and aggregation

The design of federated learning is the primary concern of this work. The basic structure of the client selection and aggregation process shown in Figure 6.6. The two core elements of the federated learning design are client selection and the aggregation mechanism. The client selection is used to choose the client's genuine client data based on the different conditions such as data updation, density, arrival of data and etc. The aggregation approach effectively brings together the various client-processed data. FedCS [127] algorithms are used to choose the nodes, and Federated Averaging [135] methods are used to determine the average of all the nodes.

Federated Client Selection, commonly known as FedCS, is used to choose the client for the desired job [136]. We select the clients from whom we will collect information at random for this work. The random client selection is used by wireless devices, computational devices, mobile edge devices, and resource information. Initializing the protocol or process, resource requests to participate or client participation, client selection and resource information determination, client distribution and client selection, aggregation of selected device data, and scheduling and uploading of client data are all parts of the client selection procedure. From the client to the global model, this data is continuously being consolidated. The random client selection presented in algorithm 6.1.

Algorithm 6.1: Client Selection Method

Require: Index set of randomly selected clients $\mathbb{K}'$

Initialization $\mathbb{S} \leftarrow \{\}$, $T^{\mathrm{d}}_{\mathbb{S}=\emptyset} \leftarrow 0$, $\Theta \leftarrow 0$

while $|\mathbb{K}'| > 0$ **do**

  $x \leftarrow \arg\max_{k \in \mathbb{K}'} \frac{1}{T^{\mathrm{d}}_{\mathbb{S}\cup k} - T^{\mathrm{d}}_{\mathbb{S}} + t^{\mathrm{UL}}_{k} + \max\{0, t^{\mathrm{UD}}_{k} - \Theta\}}$

  remove x from $\mathbb{K}'$

  $\Theta' \leftarrow \Theta + t^{\mathrm{UL}}_{x} + \max\{0, t^{\mathrm{UD}}_{x} - \Theta\}$

  $t \leftarrow T_{\mathrm{cs}} + T^{\mathrm{d}}_{\mathbb{S}\cup x} + \Theta' + T_{\mathrm{agg}}$

  if $t < T_{\mathrm{round}}$ **then**

    $\Theta \leftarrow \Theta'$

    add x to $\mathbb{S}$

  end if

end while

return $\mathbb{S}$

Algorithm 6.2: Federated Average Aggregation Method

Server executes:
initialize w_0
for each round $t = 1, 2, \ldots$ **do**
  $m \leftarrow \max(C \cdot K, 1)$
  $S_t \leftarrow$ (random set of m clients)
  for each client $k \in S_t$ **in parallel do**
    $w_{t+1}^k \leftarrow \text{ClientUpdate}(k, w_t)$
  $w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$

ClientUpdate(k, w)**:** // *Run on client k*
$\mathcal{B} \leftarrow$ (split $\mathcal{P}_k$ into batches of size B)
for each local epoch i from 1 to E **do**
  for batch $b \in \mathcal{B}$ **do**
    $w \leftarrow w - \eta \nabla \ell(w; b)$
return w to server

The aggregation is carried out using the FedAvg [118], often known as the federated average method. This federated aggregation was performed using stochastic gradient optimization (SDG) [118]. This aggregation approach randomly selects the clients for each communication cycle. After each iteration, trained data is collected from the random data. The FedAvg approach uses trained data that is randomly obtained, yet the aggregated results are reliable. The vast number of rounds means that the proposal is more precise in terms of accuracy. The federated averaging client selection algorithm presented in algorithm 6.2.

6.3.3. Working Process of Federated Model for Irrigation

The overall working process of the collaborative learning irrigation model for better model updation steps involved are listed shown Figure 6.7.

i. The clients are first given access to the reinforcement learning model for initial prediction of requirements. The requirement trained using the different samples for predictions.

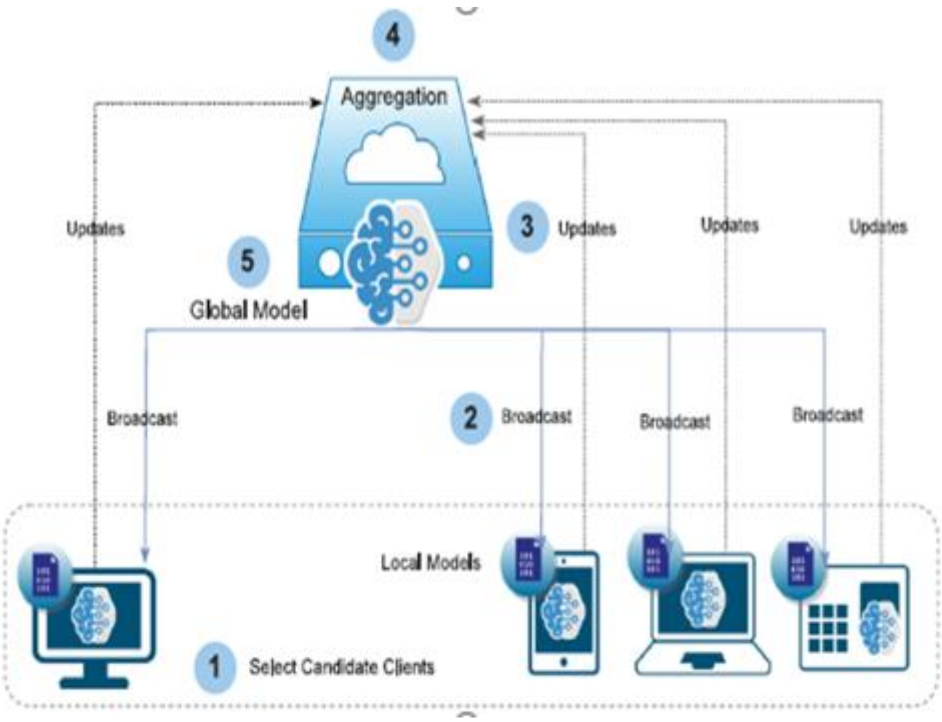


Figure 6.7: Working Process of Federated Learning for an effective model

ii. The initial model transferred to the participants clients. Client data are used to trained the model, and the most recent data and parameters are used to assess its accuracy.

iii. After accessing the client's activities, the global model call for updation from the clients using algorithm 6.1. The random selection algorithms used for client selections.

iv. Clients are chosen at random for aggregation and performed the aggregation in global model.

v. The aggregated parameters and weighted aggregates are added to the overall model.

vi. New accuracy tests are conducted after the clients receives the updated model.

6.4. Results and Discussion

This section consists of implementation details and result and discussion of proposed model. The proposed model used five clients and basic implementation model. The dataset details and model information's are described in the section 1.10 and chapter 4. The implementation steps are presented in section 6.3.3. The accuracy, client prediction model accuracy and aggregated accuracy were presents in Figure 6.8 to 6 .11.

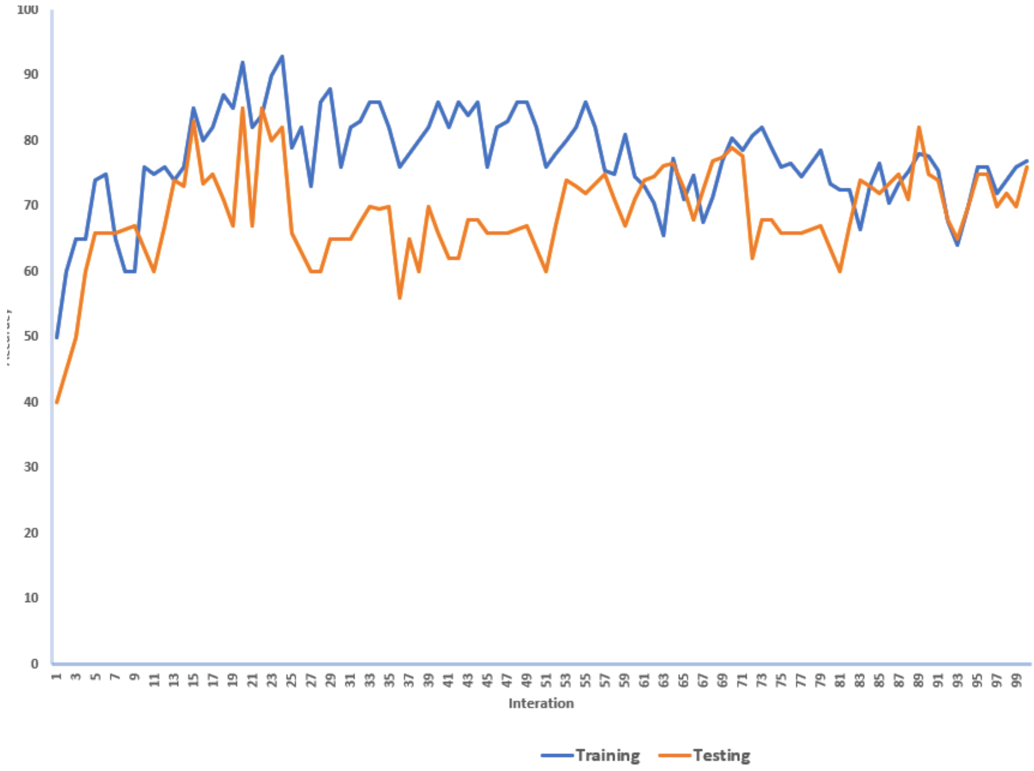


Figure 6.8: Global Model Accuracy for Prediction

Using high-dimensional IoT sensor feedback, deep reinforcement learning model data is used for irrigation requirement predictions. Because deep reinforcement learning applies adaptive amounts of water based on different measures throughout time, so it enhances irrigation requirements in many cropping irrigation systems. The initial training and testing accuracy of the global model of federated learning presented in Figure 6.8. The overall training and testing accuracy of deep reinforcement with KNN algorithm are 77% and 68%. The experiment is conducted using 100 iteration and summarized the training and testing accuracy of proposed system. The training iteration of 25 received highest accuracy is 92% and similarly 23rd iteration provided highest testing accuracy is 83%. This initial training and testing accuracy transferred to the different 5 clients (farmers) local accuracy and requirement of water predictions.

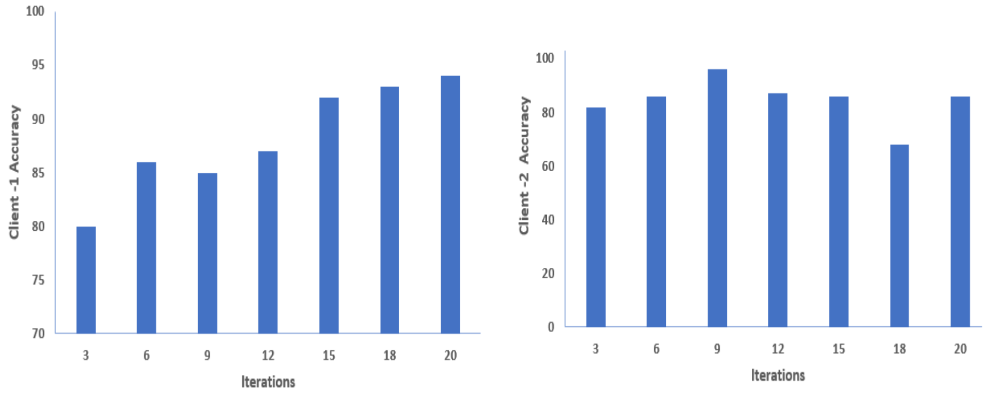


Figure 6.9: Client – 1 and 2 Irrigation requirement prediction Accuracy

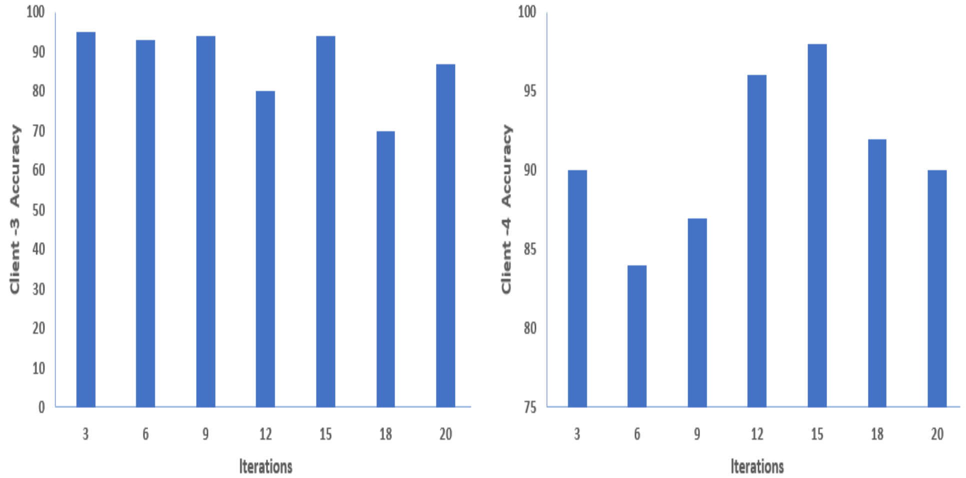


Figure 6.10: Client – 3 and 4 Irrigation requirement prediction Accuracy

The clients and global model performed the testing of requirement prediction using the local data. The server iteratively gathers client model changes in federated learning. Usually, a random selection of clients is made at each cycle. To incentivize clients with high-quality data to participate in the federated learning process, an incentive system grounded in contract theory has been suggested. FedCS random selection is a new protocol that selects more clients with less resource constraints in a single round in an attempt to aggregate more updates. Power-of-choice selection is a technique that uses a random selection process to determine which clients are included in each round's test group for the loss of local data when using the current global model. After that, a few clients with the biggest losses are chosen for round training. In this experiment, considered only client different iteration wise accuracy and requirement of irrigations are calculated. The figure 6.9, 6.10 and 6.11 shown the accuracy of the requirement predictions of irrigation system.

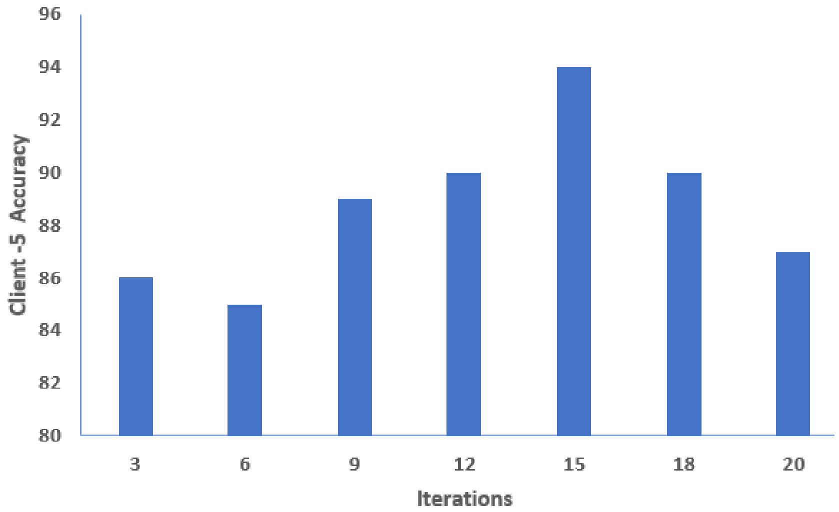


Figure 6.11: Client -5 Accuracy

The sharing of model parameters between clients and servers in federated learning raises the possibility of client historical gradient leakage. In order to address this issue, a technique for the safe aggregation of high-dimensional data has been

Table 6.1: Model, Clients and Aggregation Accuracy

S. No	Different Accuracy	
1	Basic Model Training Accuracy	77
2	Model Testing Accuracy	68
3	Client -1 Accuracy	88.12
4	Client -2 Accuracy	84.4
5	Client -3 Accuracy	87
6	Client -4 Accuracy	91
7	Client -5 Accuracy	88.77
8	Aggregative Model Accuracy	89.2

developed, enabling the server to securely summarise client-provided updates to local models. Furthermore, even in the event that a randomly chosen portion of the clientele abruptly leaves the system, the network's anonymity can still be protected. Applying differential privacy technology to federated learning, which conceals client contributions during training, protects client information. To stop information leaking, federated learning systems can incorporate and combine multiple ways. After different iterations with data privacy and using the local parameters the accuracy of requirement is increased. The summarized accuracy of experiment different iteration presented in Table 6.1. In the client 1 iteration 20th received 94% highest accuracy, but the summary of 20 iteration us 88.12%. The client 2, 9th iteration received 96% highest accuracy, but the summary of 20 iteration us 84.4%. In client 4, 3th iteration received 95% highest accuracy, the summary of 20 iteration is 91%. And similarly, the client 3 and client 5 received 87% and 88.77% respectively.

Finally, the suggested aggregation approach to achieve high global model accuracy with a minimal number of communication rounds. The client selection technique and 20 communication round aggregate pipelines produced 89.2% accuracy for prediction of requirements. Compared to the training and aggregated accuracy, the global model received 12.2% accuracy improved and similarly the requirement of irrigation also updated in each farm. The global model, 20 iteration requirement and after the aggregation the reequipment of water irrigation shown in Table 6.2. The summarized 6.2 Table shown the three types of requirements and shown the optimized requirements.

Table 6.2: Comparison of basic and Aggregated Model

<table>
<tr><th>S.No</th><th>Single Tree Water Requirement for Global Model per month</th><th>Single Tree Water Requirement for Local Client per month</th><th>Aggregative requirement for Month</th></tr>
<tr><td>Client -1 (Farm)</td><td rowspan="5">20 Litres</td><td>24</td><td rowspan="5">20.8 Litres</td></tr>
<tr><td>Client -2 (Farm)</td><td>22</td></tr>
<tr><td>Client -3 (Farm)</td><td>18</td></tr>
<tr><td>Client -4 (Farm)</td><td>19</td></tr>
<tr><td>Client -5 (Farm)</td><td>21</td></tr>
</table>

6.5. Summary

The older machine learning methods have been concentrated in a single computer or data centre, modern science and technology have made the data available everywhere. The federated learning provides data privacy and share the updated effective model to concern clients or farms. In this chapter used IoT components, the KNN algorithm and reinforcement learning for initial global model requirement predictions. The Internet of Things (IoT) components are utilized to gather current needs and forecast the environmental status of agriculture fields. The nearest features from the agricultural fields are captured by the KNN algorithm. The implementation of the proposed work used datasets from the five different locations and transferred the global model. Compared the global model to aggregative model reduced the water requirements and increase the requirement prediction accuracy.

Chapter 7

Result and Analysis of Methodologies

7.1 Introduction

The objectives of the thesis are providing an effective water irrigation to agriculture using the modern devices and an effective machine learning technique. The objectives of the proposed methods are to create an effective irrigation model, to predict the short- and long-term sustainable prediction requirements of the irrigation system, to shares the sustainable requirements of the prediction using the cloud environment and shares the features with the nearest farmers for better requirements prediction and to create an effective model using different farmers data, without sharing data. The proposed methods which were discussed in chapter 4, 5, and 6 are compared with each other in terms of their metrics and performance results analysis are given in the following sections.

The experimental setup is performed using an IoT devices, different dynamic parameters and cloud environments. The section 1.10 provided the detailed explanation about the data sources collected details. The chapter 4 used only collected information's from the 8.2473502, 77.2743729,345. The chapter 5 and 6 used IoT devices collected live dataset, banana research centre dataset for Ethapazham/Nendram Pazham and local dataset metrological dataset for requirement predictions. The chapter 4, 5 and 6 used different soil nature also for calculation requirement of water based on the depletion holding capacity of water. The experimental areas used red loam variety of soil and 1.50 - 2.30% of water holding capacity per foot of soil.

7.2 Results and Performance Analysis

The different crops and corresponding root length provided in Table 2.2. The average banana root length is 21 inches. The performance analysis of irrigation requirements analysis using the different parameters such as accuracy of requirement prediction model, water consumption using manual calculation and advanced machine learning concepts, and requirement calculation of concern plants in different situations.

The parameter and setting of overall comparison of banana irrigation is shown in Table 7.1.

Table 7.1: Common Experimental setup and Parameters

Parameter	Setting
Number of Trees	1000 Per Acre
Duration	April- Jan 2020 Feb -Nov 2021
Starting of Agriculture	April 2020 and Feb 2021
Number of Farms	5
Maximum Water requirements of Single node in each month	40 Liters
Maximum Water requirements of Single node in Entire Cultivations	360/400 Liters
Interval of Smart Irrigation	3 Days

7.2.1 Accuracy of Prediction Requirements

The accuracy of the water requirements calculated using the three methodologies such as deep reinforcement learning with KNN algorithm, initial prediction with LSTM and transfer learning, and initial prediction with federated learning. Using the refinement learning with the help of different stats such as weather information, KNN provided features, and past history data accuracy of the requirement is predicted. In the second methodology using the LSTM algorithm long and short-term requirements were prediction and after applying the transfer learning the accuracy of requirement rate is increased, similarly after applying the federated learning different the aggregate accuracy and different client's accuracy also varied. The overall comparisons of the different techniques and methodologies were presented in Table 7.2 and Figure 7.1.

The overall comparisons show that the DRL and KNN received 92% and this model is considered as the initial level of predication accuracy of water requirements. In this method not used any weather or past history data for requirement predictions.

Table 7.2: Comparison of Techniques and Accuracy

Methodology	**Techniques**	**Accuracy**
Methodology - I	IoT Devices + DRL + KNN	92
Methodology - II	KNN+ANFIS+LSTM	91.3
	KNN+ANFIS+LSTM with Transfer Learning	94
Methodology-III	Client 1 with FL	94.2
	Client 2 with FL	92.1
	Client 3 with FL	93
	Client 4 with FL	96
	Client 5 with FL	95
	Aggregative Results with 20 Rounds	94.6

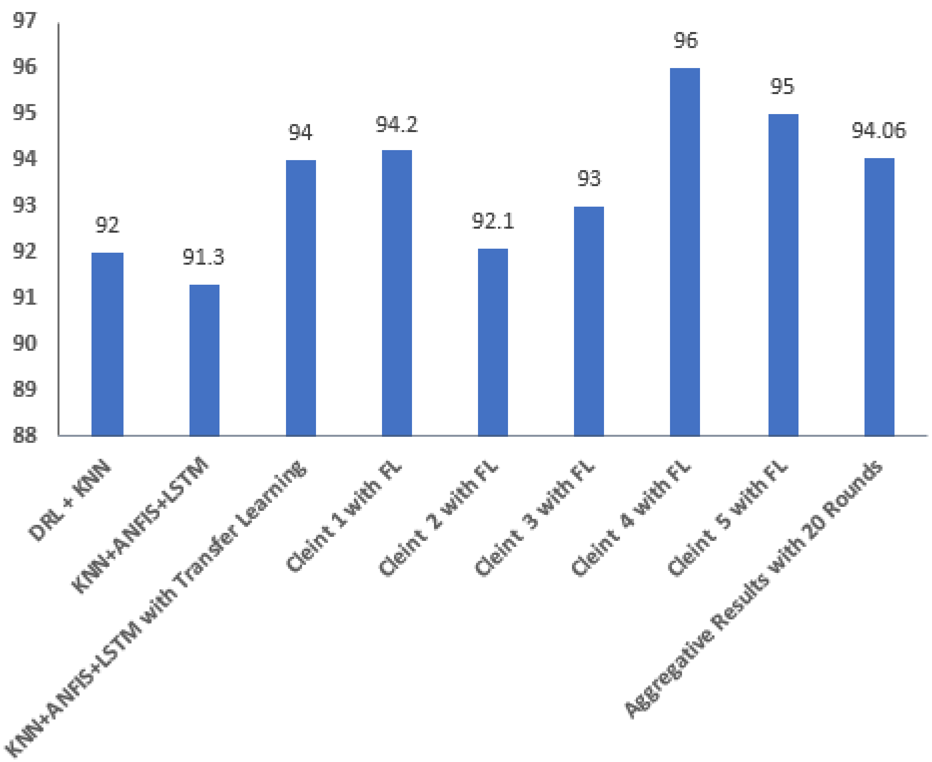


Figure 7.1: Comparison of Accuracy using Methodologies

The IoT sensors devices used for requirements predictions. The long term and short-term requirement prediction are performed using KNN, ANFIS and LSTM algorithms. In this method the weather data and history data used with IoT data. The initial prediction of the requirements is 91.3% and same initial method applied in different farms using transfer learning. After the transfer learning, the accuracy of the prediction is increased input 94% and different between with and without transfer learning is 2%. With transfer learning, 2% of requirement prediction rate is increased. The initial prediction model is applied using federated learning and implemented using the 5 client's setup. The table 7.2 shown the different results of each clients and the aggregated results shown 94.6% improvements. In this federated learning and transfer learning, similar dataset and same division of data contribution is used for implementations. So, the performance of the accuracy is slightly changed. If the dataset and other supporting features are changed, automatically the accuracy also increase.

7.2.2. Comparison of Accuracy with Previous methods

Table 7.3: Overall Comparison of Accuracy

S. No	**Methods**	**Accuracy**
1	GBRT [27]	87.23
2	SVR+ K-Means [28]	88.13
3	LSTM + GBT [8]	92.04
4	RBFN [29]	89.0
5	DRL +KNN	92.0
6	KNN+ANFIS+LSTM with Transfer Learning	94.0
7	Aggregative Results with 20 Communication Rounds	94.6

The accuracy of the water requirement is compared with previous similar methods, but the implementation crops are not used the same. The proposed three methodologies were compared with the recent work [8,27–29], and it optimized the irrigation requirements. Compared to previous work, total water usage is reduced. Table 7.3 shows the requirements prediction accuracy of our work and its comparison with previous work. Compared to the previous work, total irrigation requirements prediction accuracy had increased. The previous methods detailed explanation and technical information's were included in the section 5.2.1.

7.3. Summary

The proposed methods deep reinforcement learning, ANFIS + LSTM with transfer learning, and federated learning method with clients are implemented, trained and tested on various data and different parameters. The two types of the datasets were used for implementation. When we compare our methods and previous methods, the accuracy of the prediction has, increased. The ANFIS + LSTM with transfer learning, and federated learning methods produced effective accuracy and maintained the moisture in the soil for better irrigation.

Chapter 8

Conclusion and Future work

An irrigation is the process of controlling the water usage for agriculture and increase the productivity using an effective cultivation. The researchers have mentioned different usages of the irrigation, such as proper utilization of water, optimizing the fresh water usage and avoiding water usage, increase nutrition, landscape plants, grow crops and etc. Different types of the irrigation are used to optimize the water usage. Suitable irrigation types are selected based on various parameters such as crop type, slop of the land, types of technology, etc.

The main motivation of this research is agriculture is the largest field which consumes fresh water and electricity. Around the globe, 70% of water is used for agriculture. Of this, around 25% water and electricity are consumed efficiently and remaining is being wasted. Due to the irregular irrigation system, 50% of yields of agriculture is reduced and increase the cost. Due to the irrigations, the energy usage is increased. Keep the soil moisture in required level of cultivation. Due to these motivations, in this research three objectives are created to provide the effective solutions such as create an effective irrigation model and scheduling of crop, predict the short- and long-term sustainable prediction requirements of the irrigation system, shares the sustainable requirements of the prediction using the cloud environment and shares the features with the nearest farmers for better prediction and create an effective model using different farmers data, without sharing data. The experiment data is collected form the location is 8.2473502, 77.2743729,345. The species of banana crop is used for implementation and water requirements analysis. Three methodologies were used for implementation.

The first methodology proposed an effective water optimization and scheduling method with the use of IoT components, the KNN algorithm, and deep reinforcement learning. The IoT components are used to collect the current requirements and predict the environmental status of the cultivation files. The KNN algorithm captures the nearest features from the cultivation fields. Environmental prediction, of specific plants are performed using IoT and KNN capabilities. In this method, we applied a smart irrigation system used in banana cultivation. Based on the current prediction, the future requirements of water are calculated in 12-hour time interval from 7 pm to 7 am, and it is calculated for up to 4 days. This method produced 92% prediction accuracy during various levels of requirement predictions.

The second methodology is used to forecast the irrigation requirements, and utilize Internet of Things (IoT), k-nearest neighbours (KNN), cloud storage, long short-term memory (LSTM), and adaptive network fuzzy inference system (ANFIS) techniques. By collecting real-time environmental data, KNN identifies the closest water requirement from the roots and its surrounding. In order to predict short-term requirements, ANFIS is used. To transfer the new requirements for better prediction, transfer learning is used. Time-series-data updates are predicted using LSTM for future forecasting, and the integrated model is shared with other farmers using cloud environments to enhance forecasting and analysis. This method produced, 91.3% prediction accuracy without transfer learning, and with transfer learning, the prediction accuracy increased to 94%.

The third methodology has used collaborative learning mechanism for an effective prediction of requirements. The same first model is used for global model and 5 clients were used for implementation. The client selection is performed using the random selection method and aggregation is performed using the federated averaging methods. The experiment conducted using 20 communication rounds which produced 94.6 aggregate accuracy. Comparing to these three methods, the transfer and federated learning produced an effective performance for better requirement predictions.

This work can be extended, using the effective knowledge sharing in the irrigation system, appending different techniques for hybrid model, and collaborations of predicted effective parameters. The continual learning technique is used to recommend better predictions. The ensemble learning algorithms are recommended for appending different prediction in the model.

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