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AN INTEGRATED PRECISION AGRICULTURE SYSTEM EMPLOYING IOT AND MACHINE LEARNING

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Abstract – One of the key industries that strategically contributes to maintaining food security is agriculture. However, as the world's population grows, so do agri-food needs, necessitating a shift from conventional farming practices to smart agriculture practices, also known as agriculture 4.0. Agriculture 4.0 has a lot of potential, but to fully realize that potential, it is important to recognize and handle the issues and difficulties that come with it. Crop yields has been the cornerstone of international progress for many years. In order to meet this demand, producers will need water to irrigate the land; yet, because to the population growth and increased demand, farmers will need a strategy that modifies their operating procedures. The collecting and evaluation of data sets has gotten simpler with the introduction of artificial intelligence and IoT. This research promotes a clever, flexible irrigation technique that may be applied in a wide range of circumstances while consuming little power and spending little money. Machine learning techniques are the foundation of this approach to sustainable farming. We used a variety of sensors (soil moisture, heat, and volume of water) to accomplish all of this in an environment that supports increased plant proliferation for weeks. The sensor system makes use of the Raspberry Pi series, which enables it to detect variations in the soil's moisture levels. The algorithms built on top of deep learning are used to calculate the outcome. This technology can also assist in lowering loss with in coming years because water is squandered for long periods of time as a consequence of misinformation. The performance of the proposed method is further investigated by utilizing different machine learning algorithms like KNN, SVM, Neural networks for the analysis of variation of real time data from normal data sets.

Keywords - — IoT, Raspberry Pi, Ultrasonic sensor, PIR sensor, NOOBs, Soil Moisture Sensor, ZIGBEE, Machine learning techniques.

1. Introduction

“Agriculture is without a doubt India's most important source of income. More agricultural productivity is required as the world's population grows. In order to provide further help. As agricultural productivity increases, so does the demand for fresh water for irrigation. Agriculture currently accounts for 83% of total water usage in India [1].

Inadvertent water waste stems from unplanned water consumption. This shows that there is an urgent need to create technologies that reduce water waste without putting farmers under strain.

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During the last 15 years, farmers have begun to use computers and software systems to manage their financial data, keep track of their transactions with third parties, and more efficiently monitor their crops [2]. Agriculture is rapidly becoming a very data intensive industry in the Internet era, where information plays a key role in people's lives, with farmers needing to collect and evaluate a huge amount of information from a diverse number of devices (e.g., sensors, faming machinery, etc.) in order to become more efficient in production and communicating appropriate information" .

With the introduction of open source Raspberry PI series and inexpensive moisture sensors, it is possible to build systems that can analyze soil water level and irrigate areas or landscapes as appropriate.

Agriculture 4.0, sometimes referred to as smart agriculture, is a type of crop cultivation that monitors, assesses, and reacts to changes within the same environment as well as other natural features. Agriculture 4.0 study's main objective is to provide a decision-support system for directing the whole agricultural industry in order to improve resource profitability and environmental conservation. Utilizing spatial analysis and agricultural health monitors, Agriculture 4.0's early phases involve forecasting the application and consequences of various fertilizers.

1.1 Smart Agriculture:

The fourth industrial revolution, commonly known as "Industry 4.0, is revolutionizing and remaking every industry. It is a strategic initiative that combines cutting-edge disruptive digital technologies to enable the digitization of the industry [7]. These technologies include the Internet of Things (IoT), big data and analytics (BDA), system integration (SI), cloud computing (CC), simulation, autonomous robotic systems (ARS), augmented reality (AR), artificial intelligence (AI), wireless sensor networks (WSN), cyber-physical system (CPS), digital twin (DT), and additive manufacturing (AM) [8]. The use of these technologies in agriculture is giving rise to agriculture 4.0, also known as smart farming, digital farming, or agriculture, which is the next generation of industrial agriculture [7].

To solve several issues with agricultural food production related to farm productivity, environmental impact, food security, crop losses, and sustainability, smart agriculture gives farmers a wide range of instruments (shown in Fig. 1). For instance, farmers may connect to farms remotely regardless of location or time using IoT-enabled systems made out of WSNs to monitor and control agricultural operations. Autonomous robots can be employed to support or complete monotonous jobs at farms, while drones outfitted with hyper spectral cameras can be used to collect data from a variety of sources on farmlands. To aid farmers in making decisions, data analytics techniques may be utilised to analyses the collected data with computer programs.

The same is true for a wide range of parameters related to environmental factors, weed control, crop production status, water management, soil conditions, irrigation scheduling, herbicides, and pesticides, as well as controlled environment agriculture, which can be monitored and analyzed in smart agriculture to boost crop yields, lower costs, improve product quality, and maintain process inputs" [8].

2. Related research on IoT based smart agriculture

In this current period of increased food demand, “agriculture 4.0 produces higher yields with lower input costs, labor costs, and environmental damage [7,8]. One of the top 10 agricultural revolutions during the 1990s is called "agriculture 4.0" [9]. Through distributed management techniques, agriculture 4.0 enhances the organization of farm inputs (such as fertilizers, fuel, seeds, and herbicides). Agriculture 4.0 divides huge fields into zones, and instead of administering irrigation, fertilizer, seeds, and other agricultural inputs uniformly as in the past, each zone now receives customized management inputs based on its unique location, soil type, and management records. Therefore, Agriculture 4.0 seeks to revolutionize crop yield and farm profitability through improved control of agricultural inputs.

Due to current food production and PA, a sharp increase in the use of contemporary computers and electronic technology is anticipated in [10,11]. Internet-of-Things (IoT) and cloud computing are two fundamental ideas that have emerged as a result of the development of information and communication technology (ICT) [12]. Both ideas are included in Agriculture 4.0 and are anticipated to be applied broadly in the near future. An IoT-based cloud platform may be utilised for research and development in the fields of precision and ecologically sustainable agriculture [13,14,15]. The implementation of a sustainable agriculture research and development network for crop, forest, and water monitoring, the creation of emission control and mitigation strategies, the textcolorblueanalysis and quality control of food, the management of land quality, as well as improved healthcare[16], can be the subject of such projects.

Smart agriculture is perfect for IoT because of its highly integrated, broad, all-encompassing, and open nature [17–19]. The IoT smart agricultural platform allows for the integration of automation tools from different businesses. These pieces of technology are easily adaptable to the farm's smart system, enable data transmission between various components, and offer automation capabilities using common internet procedures. [20] presented Agri-IoTas as a highly customized IoT-based online platform for innovative data analysis solutions that are affected by these benefits and the potential of IoT for smart farming, taking into account the dearth of universally applicable, efficient, and well-proven frameworks.

Agri-IoT enables thorough, automated data processing and analysis based on real-time data streams from numerous sources, such as sensor systems, security cameras, high-speed images from drones, online weather forecasting services, social media streams for rapid event detection, such as threats, floods, and earthquakes, as well as information, notifications, and alerts from governmental organizations [21-24]

In order to help farmers make decisions nearly instantly in reaction to changes and unforeseen events, agri-IoT integrates and analyses data streams similar to those mentioned above. Aspects of these consumer end-use applications include intelligent irrigation, intelligent soil fertilization, intelligent pest control, and intelligent diagnosis of plant illnesses [25-27]

For instance, since grapevine downy mildew regularly causes significant damage to Montenegro's vineyards, a smart sprinkler system is essential for forecasting the illness. This illness has in the past caused a full cessation of productivity for a number of years. Smart systems have been

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developed as a result, allowing producers of grapevines to accurately determine when to spray the vines with the required fungicides.[28].

IoT has begun impacting a wide range of domains and businesses in order to increase efficiency across all business sectors [28–35], from manufacturing and construction to public health and safety, communications systems, electricity and energy, and the farming industry. This has been made possible by IoT characteristics including an efficient framework for communication that is used to communicate with smart devices like sensors, automobiles, smartphones, and more.

Agriculture 4.0 solutions are designed and delivered using a wide variety of interdisciplinary technologies ("Enabling The Smart Agric [36]"). Numerous industry participants, such as telecommunications service providers, producers of agricultural machinery and vehicles, software developers, data analysts, and suppliers of sensing technologies frequently participate in this diversification.

IoT may create answers for a number of traditional agricultural problems, including drought response, yield enhancement, irrigation, and pesticide management, through the use of smart agriculture.[37-39] The world must have more arable land in order to meet the rising demand for food, but during the past 40 years, one-third of this agricultural area has been lost owing to deforestation and pollution" [40].

3. Technologies of Smart Architecture

3.1 Systems for agriculture powered by the Internet of Things

The term "Internet of things (IoT) describes a vast network of interconnected computers, sensors, home appliances, and other equipment that are all connected to the internet and each have their own individual identities and capacities for remote sensing and monitoring.The goal of IoT integration in agriculture is to provide farmers with the automation and decision-making tools they need to integrate information, goods, and services to increase productivity, quality, and profitability. Numerous research are conducted and presented about the development of IoT ideas in the agriculture industry.Periodic monitoring of environmental and soil parameters is done using GPRS or mobile communication technologies (2G, 3G, and 4G). Additionally, HTTP, WWW, and SMTP are the communication protocols that are most frequently utilised in agricultural scenarios. Cloud computing methods are used in the service layer to store data. The application layer then uses this data to create intelligent applications that farmers, agricultural specialists, and supply chain professionals may utilise to increase farm monitoring capacity and productivity. The goal of IoT integration in agriculture is to provide farmers with the automation and decision-making tools they need to integrate information, goods, and services to increase productivity, quality, and profitability. Numerous research are conducted and presented about the development of IoT ideas in the agriculture industry. The various layers of internet of things is shown in fig 1.

3.2 Wireless Sensor Networks in agriculture

IoT systems commonly employ a technology known as a wireless sensor network (WSN). It may be described as a collection of widely spaced sensors that monitor the environment's physical circumstances, store the data momentarily, and transfer the information to a centralized point [22]. Fig. 2 depicts the overall architecture of WSN. Multiple sensor nodes coupled by a wireless connection module make up a WSN for smart farming. These nodes may self-organize, self-configure, and self-diagnose thanks to a range of skills (such as processing, trans- mission, and feeling). There are several WSN kinds, and they are divided into categories according on the settings in which they are used.

There are several WSN kinds, and they are divided into categories according on the settings in which they are used. These include wireless multi-media sensor networks (WMSNs), mobile wireless sensor networks (MWSNs), underwater wireless sensor networks (UWSNs), and terrestrial wireless sensor networks (TWSNs).Agricultural applications frequently employ TWSN and UWSN. TWSNs deploy nodes above the ground that are equipped with sensors to capture data from their surroundings". The second type of wireless sensor network is its underground counterpart, or WUSNs, in which sensor nodes are buried in the earth. Lower frequencies easily pass through the earth in this environment, while higher frequencies are severely attenuated.

3.3 Cloud Computing in agriculture

The National Institute of Standards and Technologies (NIST) defines "cloud computing (CC) as a model that enables universal, practical, on-demand network access to a shared pool of reconfigurable computing resources (e.g., networks, servers, storage, applications, and services) that can be quickly provisioned and released with little management work or service provider interaction

Datacenter (hardware), infrastructure, platform, and application are the four levels that make up the core architecture of CC as seen in Fig. 3 [24]. Each of these levels is associated with one of the three different cloud service models: infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). Due to its ability to provide 1) low-cost data storage services for

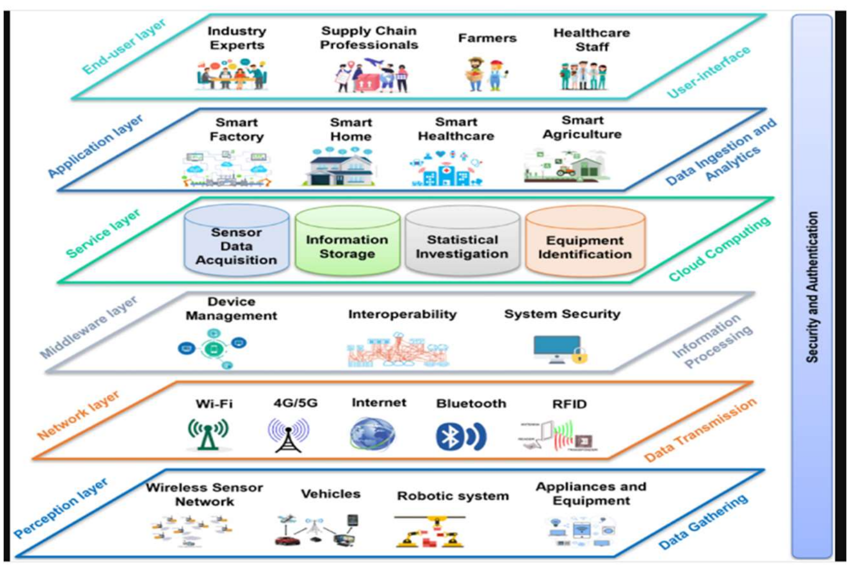

Fig 1 Layers of Internet of things[26]

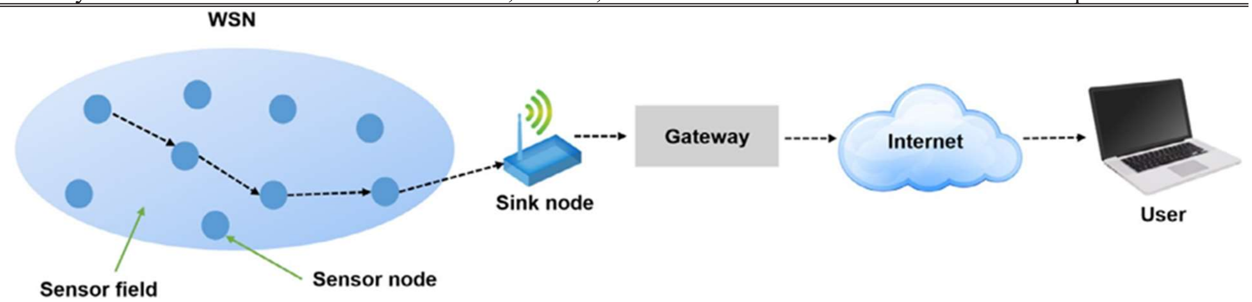

Fig 2 Architecture of wireless sensor network

information gathered from various domains using WSNs and other preconfigured IoT devices, 2) large-scale computing systems to perform intelligent decision-making by turning this raw data into useful knowledge, and 3) a secure platform for developing agricultural IoT applications, cloud computing has attracted significant

attention in the agriculture sector over the past ten years.

The environmental contamination brought on by overuse of pesticides and fertilizers, as well as concerns about the cloud-based agricultural systems safety of agricultural goods, may all be resolved by

However, many farm management systems lack the capacity to support run-time customization in respect to various farmer requirements. Additionally, conventional farm management system applications" struggle to accurately capture agricultural operations since the majority of farm data is typically fragmented and dispersed. Our proposed methodology utilizes Amazon Cloud Computing for data storage and analysis.

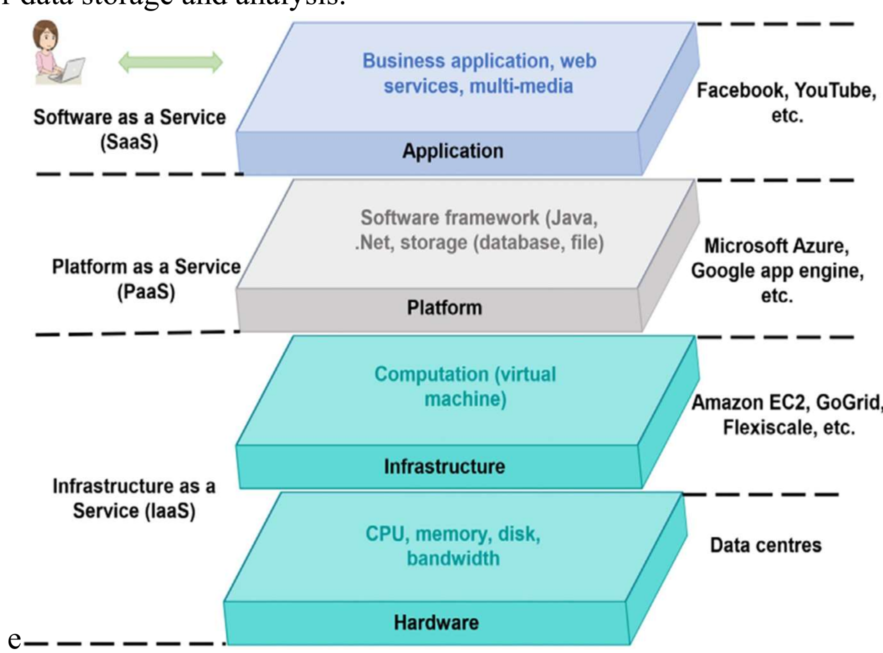

Fig 3 Cloud Computing Architecture

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3.4 Artificial Intelligence in agriculture

The "creation of theories and computer systems that can carry out activities requiring human intellect, such sensory perception and decision-making, is known as artificial intelligence (AI). AI, particularly in the areas of machine learning (ML) and deep learning (DL), is regarded as one of the main forces powering the digitalization of agriculture, along with CC, IoT, and big data. These technologies have the potential to improve real-time monitoring, agricultural harvesting, processing, and marketing while also increasing crop productivity. Many intelligent agricultural systems, such as those that can identify diseases or anticipate yields using machine learning (ML) algorithms, have been created.

3.4.1 Machine Learning

Three major categories may be used to classify machine learning (ML) techniques: Linear regression, regression trees, non-linear regression, Bayesian linear regression, polynomial regression, and support vector regression fall under the category of supervised learning. Unsupervised learning falls under the category of k-means clustering, hierarchical clustering, anomaly detection, neural networks (NN), principal component analysis, independent component analysis, and singular value decomposition (SVD). Reinforcement learning falls under the category of Markov decision process[28].

ML techniques and algorithms are used in the agriculture sector for predicting crop yields, detecting diseases and weeds, forecasting weather (rainfall), estimating soil properties (type, moisture content, pH, temperature, etc.), managing water resources, determining the optimal amount of fertiliser, and managing livestock production

New strategies, like federated learning and privacy-preserving techniques, are being developed to allow digital farming in light of the cyber-security and data privacy problems posed by the digital revolution [29]. These methods avoid exchanging private data samples and create ML models using local parameters, hence reducing security risks.

In the proposed approach different machine learning technologies are compared and analyzed. The technologies that are analyzed are KNN, SVM, Neural Network Naïve Bayes and Logic Regression.

4. Proposed Methodology

A. Context

This give information each process we went through to put the irrigation system in operation. Numerous techniques were required to create this intelligent irrigation system, as shown in Fig.4.

Table 1 Ccompilation of prior research that also included features, observations, and models and employed machine learning algorithms.:

Refrences	Machine Learning Techniques Used	Data sources	Farm type	Model
41	SVM[41]	Maps And Climate	Open	Standard

42.	Boosted Regression Tree, RF[42]	Vegetation Dataset	Open	Standard
43	Recurrent Neural Network[43]	Soil Moisture	Open	Standard
44.	Recurrent Neural Network[44]	Rainfall Data	Open	Standard
45.	Multiple Linear Regression And RF[45]	Wheat Cultivation Data	Open	Standard
46	Artificial Neural Network[46]	Temperature Records	Open	Standard
47.	Artificial Neural Networks[47]	Satellite Images	Open	Standard
48.	RF[48]	Rainfall Records	Open	Standard
49	SVM, RF, Decision Tree[49]	Field Survey Data Of Different Farms	Open	Standard
50	RF [50]	Tap Water Samples	Green House	Standard
51	SVM[51]	Images From A Fruit	Kitchen Garden	Standard
52	Least Squares SVM[52]	Sensor Data	Open	Standard
53	Decision Trees[53]	Sensor Data	Open	Standard
54	RF[54]	Image Data	Open	Standard
55	SVM[55]	Images From A Farm	Open	Standard
56	Least Squares Support Vector Machines[56]	Soil Samples	Open	Standard
57	Extreme Learning Machine-Based Regression[57]	Humidity Data	Open	Standard
58	Bayesian Linear Regression[58]	Rainfall Data	Open	Standard
59	Artificial Neural Network And SVM[59]	Air Temperature, Wind Speed	Open	Standard

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60	Our Approach (SVM,KNN,Naïve Bayes, Logic Regression)	From Agriculture Fields	Open	Standard

Table 2. Qualitative and Quantitative comparisons of existing function based on distinguished features.

Reference	Supervised model	Experimental		Simulation	Use IoT Device	Mobility	Power System	Cyber Physical System	Approximate Accuracy
		Edge	Cloud						
[47]	"Linear regression	Yes	Yes	Yes	No	Yes	Yes	No	95%
[48]	KNN, SVM, Logistic	Yes	Yes	No	Yes	Yes	Yes	Yes	90%
[49]	Regression SVM, KNN,	Yes	No	Yes	Yes	No	No	No	92%
[50]	KNN, SVM	Yes	No	Yes	No	Yes	No	Yes	95%
[52]	SVM	Yes	Yes	Yes	Yes	Yes	Yes	Yes"	96%
Our Approach	KNN	Yes	Yes	Yes	Yes	Yes	Yes	Yes	98.8%

To accomplish this, we started by choosing the instruments needed for the model's realisation, beginning with the soil water retention sensor, that displays the quantity of relative humidity, and progressing to the heat and precipitation sensors.
The analysis of prior research done in the field of smart farming is analyzed and shown in the table 1 and table 2. Our approach is also compared and is given that how it is better than the previous approaches.
After connecting the detectors to the "Raspberry Pi board", we can start configuring the panel to manage the detectors in such a manner that the different bits of data may be aggregated and supplied in instantaneously.
"With the aid of specialists in the field of agriculture and among the information recorded by a number of algorithms, we were able to gather several sorts of data, including: Temperature, air humidity, soil humidity, and rainfall data were all gathered by the sensors".
Data collected with water tanks: Suction (On/Off) Specifications
Raspberry Pi Node: This component allows us to communicate with our Arduino card and the base station service.

Node for data preparation: This component is employed to prevent instrument bit streams from becoming divided up.
The “soil humidity, air humidity, temperature, and rain nodes” are used to retrieve specific data from the pretreatment component.
The Inform and Email modules provide appropriate instrument surveillance by transmitting a sequence of alerts.
Existing data unit: Allows for the storage of relevant information.
Dashboard nodes: Enables the viewing of data in real-time.

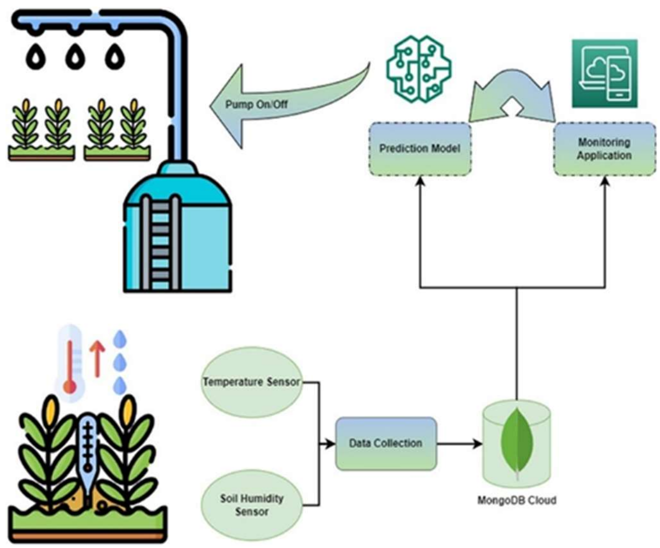

Fig 4: Irrigation System

The entity relationship diagram of the system is shown in fig 5.
B. Classification Models

- **Support Vector Machine (SVM)**

One of the most well-liked supervised learning algorithms, Support Vector Machine, or SVM, is used to solve Classification and Regression issues. However, it is largely employed in Machine Learning Classification issues. The SVM algorithm's objective is to establish the optimal line or decision boundary that can divide n-dimensional space into classes, allowing us to quickly classify fresh data points in the future. A hyper plane is the name given to this optimal decision boundary. SVM selects the extreme vectors and points that aid in the creation of the hyper plane. Support vectors, which are used to represent these extreme instances, form the basis for the SVM method.

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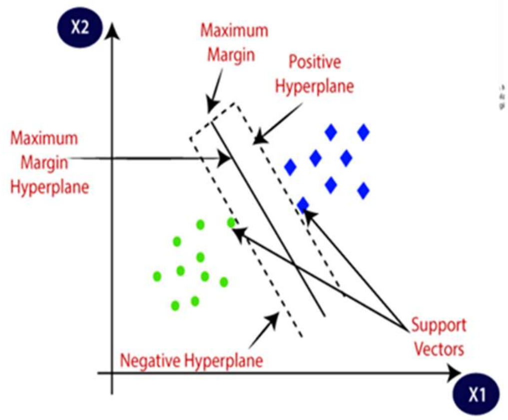

Fig 6 The SVM Graph

The linear SVM used in this study produces the following hyperplane:

$$F(x) = w^T * x + b$$

- Naïve Bayes

Naive Bayesian is a probabilistic machine learning technique based on Thomas Bayes' (1702–1761) Bayes' theorem. The likelihood of A occurring given that B has already happened can be used to describe this theorem. X = (x1,..., xn) represent the features, while Y represent the class variable. The NB algorithm is unique in that it assumes that each characteristic is independent of the others and that modifying one feature will not effect any other. Although it looks straightforward, NB has been shown to be a successful classifier.

- Neural Network

Any arbitrary mapping from one vector space to another vector space may be carried out using the neural network [10]. These neural networks are able to access undiscovered information that was previously concealed in the data but cannot extract it. It should be highlighted that learning in mathematical formalism [14] entails changing the weighting factors to ensure that particular requirements are satisfied. Initially, we introduce the linear model, which is defined as:

$$g(x,w) = \sum_{i=1}^{P} w_i f_i(x)$$

- **Logic Regression**

When the dependent variable is categorical and either (0 or 1), (True or False), or (On or Off), a model called logistic regression is utilised. The logistic process has the following form:

$$p(x)=1/[1+e^{-(x-\mu)/s/s}]$$

- **K Nearest Neighbors**

K-Nearest Neighbors [12] is a straightforward technique that ranks new instances according to a similarity metric after storing all of the existing examples.

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If we wish to categorize a case using the KNN technique, the case is voted on by the majority of its neighbors, and it is then allocated to the class with the fewest distances between it and its k closest neighbors [16].

- **Sensor Devices**

Various sensors of many varieties are used to detect environmental conditions such as soil moisture, ambient temperature, dampness, meteorological conditions, leaf perception, and aerial temperature [1]. The installed ecological detectors in watering provide real-time information. The installation time of the second generation soil detector is a little less than four minutes, and it is in manufacturing. In accordance with the surroundings, one or more qualities are taken into account in the irrigation purposes.

- **Irrigation Controllers**

"There are two types of irrigation controllers: open loop controllers and closed loop controllers. Open loop regulator indicates that the conditions, such as irrigation time, frequency, and required amount of water, are pre-set. A closed loop controller is a system that automatically feeds forth data from the controlled item. The system will make judgements on the basis of comparisons of post data and observations of real-time data. Simple to set up. The average sensor installation takes about twenty minutes".

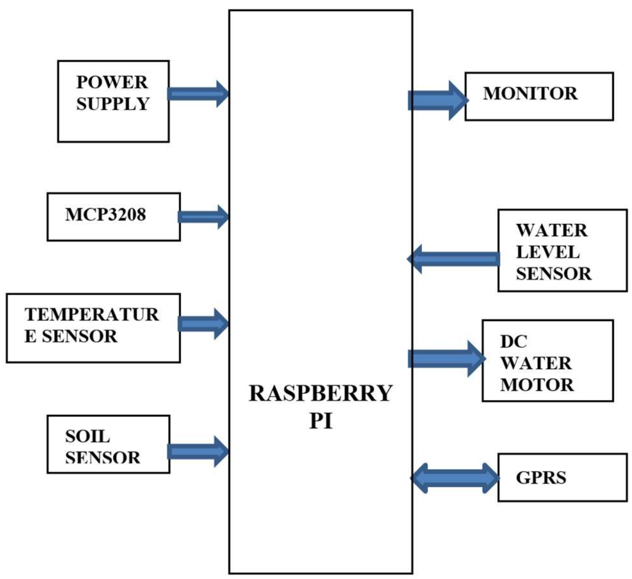

Fig 5: Entity Relationship Diagram

C.Data Set

"We started implementing these devices in various environments with multiple domestic crops in the widespread data gathering for the absolute need of details with the aid of IoT technologies, which are made up of a wide range of automated equipment in the form of detectors capable of self-organization and working to gather information. This was a nearly complete implementation

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of our Dataset implemented to deploy the data using an algorithm to generate a very important data set of our system. We locate the time stamping data, digital data, and incoming data from the centralized sensors at the intersection. Accompanying this growth, we find: soil moisture data, temperature data and water level data

Soil moisture data: This data is provided by an analogue sensor in a data interval ranging from 0 to 1024, with the smallest value being 315 and the highest value being 988.

• Temperature data: These informations are becoming increasingly significant, and it was gathered by means of a temperature detector that displays the temperature in Celsius. We can see that the average temperature gathering is 26 C, and the lowest is 15 C.

• Air moisture data: Using the same sensor that collected temperature measurements, we were able to acquire moisture information for an analytical phase that is as described as: where the lowest value is 36% and the highest value is 80%".

The administration system shown below gives the average value of the system.

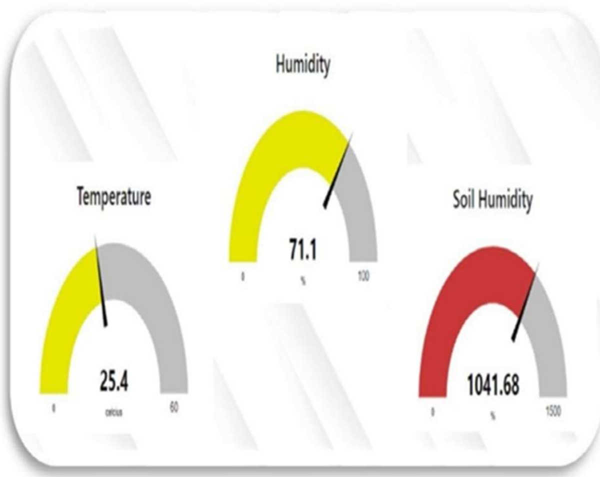

Fig 6: Administration System

5. Apparatus Required

- **RASPBERRY PI3 MODEL B+:**

Fig 7: Rasberry Pi

“The computing power of the Raspberry Pi 2 is six times greater than that of earlier versions. This second-generation Raspberry Pi is equipped with an upgraded BroadcomBCM2836 processor, a potent quad-core ARM Cortex-A7 processor that operates at 900MHz. Additionally, the board has increased storage size to 1Gbyte”.

- **LCD Display**

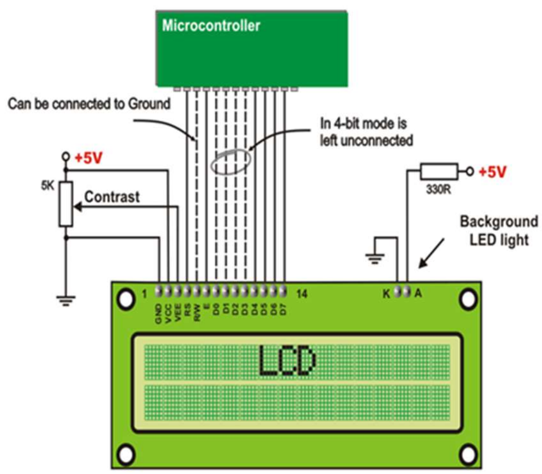

Fig 8 :Combining LCD to micro controller

“Make pin RS=0 to transmit any instruction from table 2 to the LCD, and make RS=1 to deliver data. After that, activate the LCD's internal latch by sending a high to low pulse to the E pin”.

POWER SUPPLY: “The power supplies are made to transform high-voltage AC mains electricity into a suitable short inventory for electronic devices and circuits. A power supply can be divided into a number of blocks, each of which serves a specific purpose. Regulated D.C Power Supply is a type of d.c. power supply that keeps the output voltage constant despite changes in the load or the a.c. mains voltage”.

- **Regulator**

“The output voltages of voltage regulator ICs can be fixed (usually 5, 12 and 15V) or variable. They are rated based on the highest current they can carry. There exist negative voltage regulators, primarily for use with multiple supply. Most regulators include some level of automated overcurrent (also known as "overload protection") and thermal (also known as "heat shields") security”.

- **78XX:**

“The Bay Linear LM78XX is a three-terminal integrated linear positive regulator. The LM78XX is helpful in a variety of applications since it offers a number of fixed voltage levels. The LM78XX typically produces reduced quiescent current and an effective output impedance improvement of two orders of magnitude when used as a zener diode/resistor combo replacement. Possible packages for the LM78XX include TO-252, TO-220, and TO-263”.

Fig 9:Voltage Regulator(three terminal)

- **Soil Humidity Detector**

“This is a straightforward moisture sensor that may be used to measure soil moisture. When there is a scarcity of soil moisture, the module outputs a high level, whereas the output is low. By using the sensor, a watering device is created automatically, saving you from having to select and hire garden plant managers. The sensitivity may be adjusted using a digital potentiometer (blue).

Operational voltage range of 3.3 to 5 volts. Simple digital output from a single-chip microprocessor using g and v. easy installation, fixed bolt hole. control board Size of PCB: 3 cm by 1.6 cm; size of soil probe: 6 cm by 2 cm. The red power indication light and the green output indicator light for the digital switch (green) The LM393 chips used by the comparator provide stable operation”.

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Fig 10:Soil Humidity Detector

- **Water Pump**

Fig 11:Water Pump

“A little water pump, this is submerged one. It can hold up to 120 litres of water in an hour and uses just 220 mA of current. It has a power supply range of 2.5 to 6 v and is a tiny, inexpensive water submersible pump. Its operation requires only that you attach a pipe to the motor outlets, submerge it under water, and supply electricity.

6. Software employed

A. Rasberry Pi OS System

An operating system is not included with the Raspberry Pi. New Out of the Box Software, sometimes known as NOOBS (NOOBS stands for New Out Of Box Software), is required for that. It is a system manager that makes downloading, installing, and configuring your Raspberry Pi simple. You may choose from a number of OSes when NOOBS first starts up. The operating systems that are offered depend on the

Raspberry Pi model you are running. For the sake of this article, we'll adhere to the most prevalent Oses operating systems that are accessible on the most recent Raspberry Pi models. Currently, those include Windows IoT Core, OSMC, Open ELEC, Raspbian, and RISC OS”.

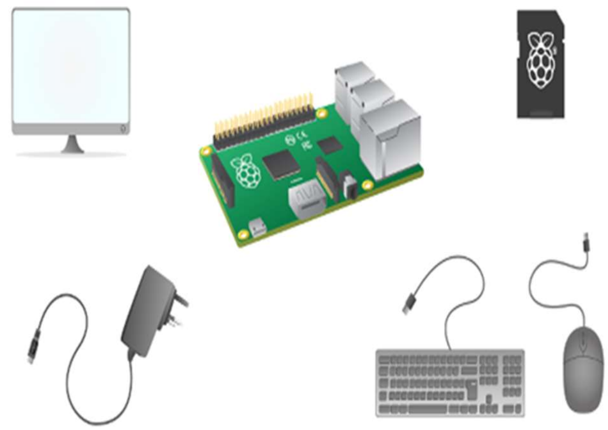

Fig 12 :Rasberry Pi System

The following is the flow chart of the proposed system:

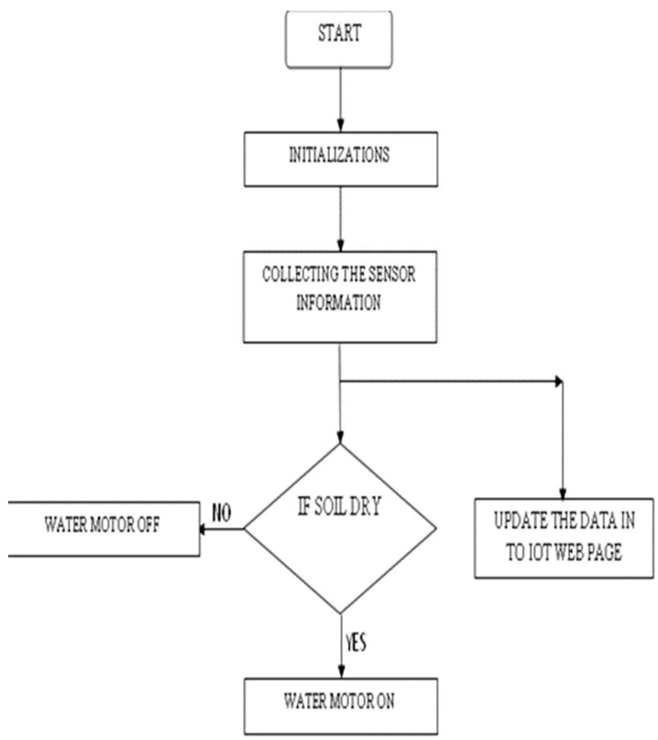

Fig 13: Flow chart of the system

The smart agriculture system acquired is made up of numerous software applications that were designed using a flexible modular development methodology to accept a variety of embedded equipment with minimal driver compatibility. A confluence of modern monitoring systems and digital technologies has evolved as the Internet of things interventions, an agricultural response to the IoT's emergence. RFID, GPS, and remote monitoring are among the detection devices. Device interface and real-time assistance technologies enabled by IoT are assisting the agriculture sector in improving accessibility, cost, dependability, and efficiency. Conventional agriculture industries turn intelligent when they are linked to the Internet and may gather additional information, provide

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information on developments, facilitate information about moisture content, and provide farmers with greater dominance. [5], For agriculture management, the Internet of devices can detect actual data. . Integrated soil moisture monitoring and management, equipment connection and database administration, and research technologies will all be promoted by the Internet of Things [16]. One can acquire crucial data about. There is an existing platform that utilises Bluetooth devices to detect the temperatures and conduct rapid response. This paper's central emphasis is on electronic agriculture possession, communication, and surveillance. "The moisture level of soil is maintained by a wireless sensor and relayed to the receiver end via GPRS. The microprocessor monitors the information obtained at the other end. If any of the characteristics are anomalous, the GSM component is configured to transmit SMS to the farmers cellular device and refurbish the information on the web site".

7. Experimental Setup

"The temperature and soil moisture content are analyzed by wire-less sensor nodes and relayed to the remote end via GPRS. The microprocessor monitors the data received at the other end. If any of the indicators are unusual, the GSM module is programmed to send an SMS to the individuals cellphone and modify the information on the web site. The approach used in this research is designed for worse conditions but to keep track on a regular basis. Whenever a catastrophic state arises, the programme will transmit an emergency notification to the individual".

With MEMS (Microelectromechanical System) being utilized to monitor the position of soil, interaction will occur with the aid of serial communication between the GPRS modem and the microcontroller. A MAX 232, a sequential driver, is used to connect the modem to the microcontroller. The GPRS module allows you to immediately send data to the website. The system block diagram for the monitoring system is illustrated in Fig. The hardware setup for the scheme is depicted in following figures.

The complete hardware setup of the proposed system is shown which comprises of a temprature sensor, soil moisture detector, Raspberry PI module which will give indication about the soil moisture content and will upload the data in the amazon server.Fig 14 is showing the complete hardware setup of the system.

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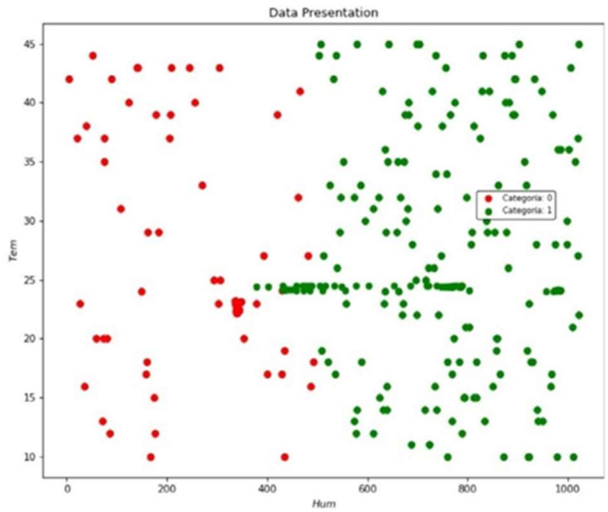

Fig 14 Hardware Setup

8. Results and Discussion

We discover “the empirical observations that are consistently summarised by peer-to-peer identification, which classifies two distinct colours. The first is the colour red as a generic term for knowledge at category "0," as evaluated by the pouring, which depends on a temperature versus and with a humidity deviated towards deactivation. The colour green, on the other hand, represents category "1," which is based on temperature pumping vs being controlled at the same time by active humidity.

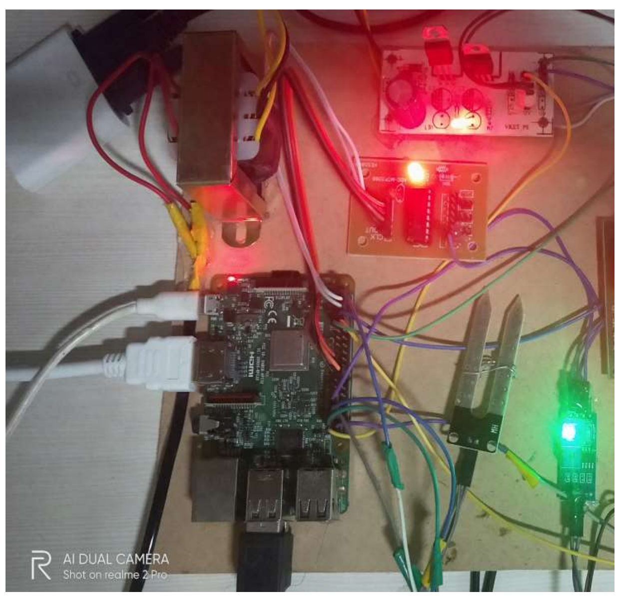

Fig 14 Data Set

A large amount of data is used to present the predefined plant sections, and this data is trained using a variety of methods and algorithms so that it can be extrapolated from past events to better predict future events, determine irrigation system forecasts, and support future trends that will unavoidably manifest. The usage of the neural network algorithm is justified since the likelihood of the output data really occurring depends on the methods used.

Table 3: Results of different analysis

Models	Accuracy
K-Nearest Neighbors	98.9%
Neural Network	95%
Naïve Bayes	94%
Support Vector Machine	93%
Logistic Regression	92%

We can see that the K-NN model signed a rate of 98.9% in a training set compared with Neural Network, Gaussian Naive Bayes, SVM, and logistic regression with successive result warehouse: (95%), (94%), (93%) and (92%). The following table (Table 3) specifically uses the various tests carried out to train the predictions, in a framework of exploration of the relevant data from a pre-sorting which reveals the following results. All of this is done to evaluate the prospective advantages and accurately characterise the data that emerges.

In order to have a better application of our model and to produce greater accuracy, we chose to standardize the data before dividing it into the test data and the training data. We employed a neural network classification method based on a specified number of periods, and we can see both the correctness of the data and the lost data for each period.

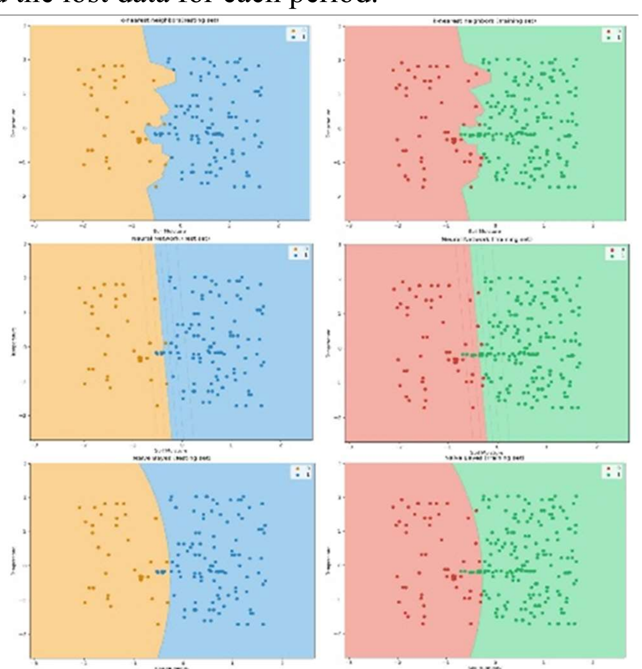

Fig 15 Results of different models

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The figure 16 depicts the output values of Graphical User Interface, the interface which will be available to monitor the different levels like the temperature of the atmosphere at different levels the nature of the soil as if it is dry, moist or normal and also the water level content of the soil if it is high,

Low or moderate.

The result of the temprature, water level and soil moisture content will be uploaded in the IOT web page as per the sensor information and accordingly the decision will be taken by the server if the soil will be dry then it will switch on the motor and if the water content of the soil will be as per the requirements then switch off the motor.

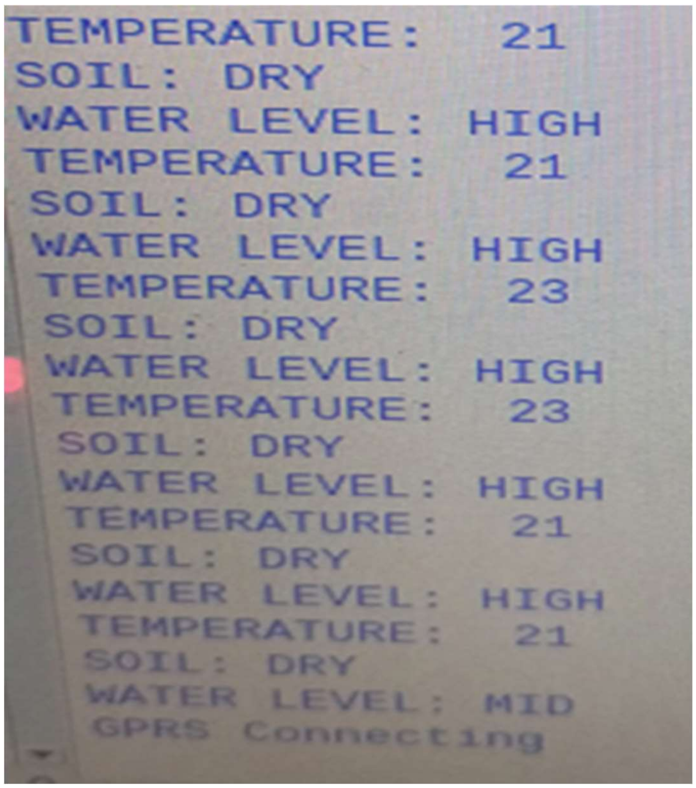

Fig 16: Result of GUI

Fig 17 : Updated result of IoT Webpage.

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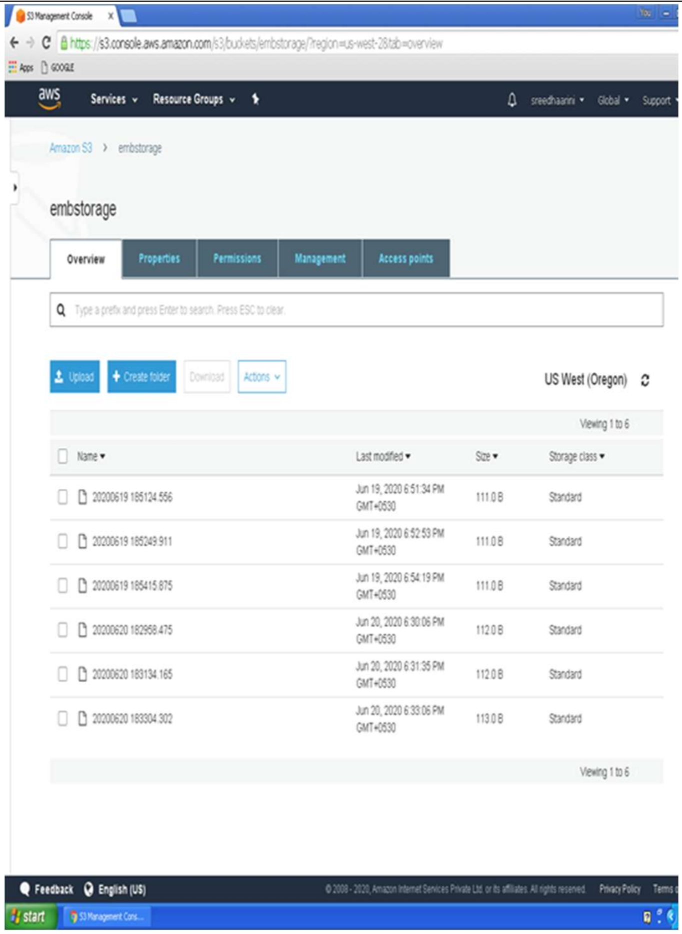

Fig 18 : The graphic depicts how information is maintained on Amazon's web services.

9. Conclusion

The need for next-generation industrial farms and intense production techniques in agriculture has increased in response to growing worries about global food security. Digital technologies made available by the Industry 4.0 programs are at the vanguard of this new agricultural era, offering a wide range of innovative solutions. To boost agricultural yields, lower prices, decrease waste, and preserve process inputs, the scientific community and researchers use disruptive technology into conventional agriculture systems

The world's food demand is predicted to grow by more than 70% by the year 2050, making increased production to fulfil this need a critical first step. It also involves controlling how much water is used for irrigation. In this research, we offer an irrigation forecast that begins with the establishment of a database utilizing an Amazon cloud platform and a data collecting card with several sensors (temperature and humidity sensor, soil humidity sensor, rain sensors).

This made it possible for us to gather a variety of data for use in our internet of things and machine learning decision support models. According to the results, K-Nearest Neighbors has a recognition rate of 98.9% when compared to other models. Finally, we present a web application to group all the tasks completed during this course in order to make it easier to visualise and monitor the

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environment using a basic phone or laptop and to analyse the data in the future in order to take the necessary action.By analysing the soil moisture content, temperature, and other factors in advance and producing the data necessary to take action, the Raspberry Pi operating system and zigbee technology have improved the use of machine learning and IoT.

Appendix 1

Data Availability

Table 1. The software employed in the respective research.

S.no	Software employed	Explanation
1.	Raspberry pi OS	1. The Raspberry Pi does not include a pre-installed system software. 2. NOOBS is a system software administrator that enables downloading, installing, and configuring the Raspberry Pi effortlessly. 3. NOOBS is an acronym that stands for "New Out Of Box Software." Raspbian isthe approved operating system for utilization with the Raspberry Pi. Raspbian is a GNU/Linux distribution created particularly for the Raspberry Pi.
2.	Processing	Processing is an accessible programming framework and developing platform for modifying the code. Although it is extremely versatile and strong, it is mostly em- ployed in the creative arts. Acquirement to create on display using coding is the focus of Processing.
3.	Integrated develop- ment environment(IDE)	An integrated development environment (IDE) is a system software that brings to- gether all of the resources that programmers ought to build and test the code. An IDEoften includes a code editor, a compiler or interpreter, and a debugger, all of which are accessed via a unified graphical user interface by the programmer (GUI). An IDE canbe utilized as a stand in application or even as element of one or more other appropri- ate technologies. The ui enables the programmer to gradually generate and run code, as well as handle reference application code in a uniform fashion. Most IDEs are built to work with arbitrator version control systems like GitHub or Apache Version.
4.	QT creator	QT Creator is an application framework for designing and developing apps utilizing the QT application component. QT Creator enables you to make, execute, and dis- tribute QT apps for pc, integrated, and handheld devices. QT Quick Designer and QTDesigner are two existing graphical processors included with QT Creator. QT Quick may be used to develop logical, contemporary, and agile interface design. You may use the inbuilt QT Designer to create a conventional user interface that is precisely organized and imposes a standard visual appearance.
5.	Python	Python is a programming language that is elevated, interpreted, dynamic, and object- oriented. Python is intended to be a very understandable language. Python’s struc- ture and flexible typing, together with its interpretive orientation, make it an excellentchoice for programming and quick systems integration in a variety of fields. Python provides a lot of coding patterns, spanning object-oriented, declarative, usable, and iterative coding. Python provides the Object-Oriented programming approach, which

		abbreviates code into entities.

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