# DEVELOPMENT OF AN AUTONOMOUS IRRIGATION SYSTEM USING IoT AND ARTIFICIAL INTELLIGENCE

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**AUGUST, 2023**

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**A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA, IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF MASTER OF ENGINEERING (M.ENG) IN ELECTRONICS ENGINEERING.**

**AUGUST, 2023**

## DECLARATION

I hereby declare that this thesis titled: **"Development of Autonomous Irrigation System using IoT and Artificial Intelligence"** is a collection of my original research work and has not been presented for any other qualification anywhere. Information from other sources (published or unpublished) has been duly acknowledged.

**AKANDE, Thomas Onimisi** …………...…………….

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## CERTIFICATION

The thesis titled: **"Development of Autonomous Irrigation System using IoT and Artificial Intelligence**" by: Akande, Thomas Onimisi (M.ENG/SEET/2018/7623) meets the regulations governing the award of the degree of (MEng) of the Federal University of Technology, Minna and it is approved for its contribution to scientific knowledge and scholarly presentation.

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# DEDICATION

*This work is dedicated to my entire family for their inspiration and immense support to the realization of this great achievement.*

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## ABSTRACT

Agriculture plays a vital role in Nigeria's economy contributing about 23% to the total Gross Domestic Product (GDP) which makes it a key activity after oil. To improve crop productivity, optimum use of scarce water resources and the ability to predict rainfall is crucial in this era. The adoption of emerging technologies to automate irrigation processes is necessary to improve crop productivity. An autonomous irrigation system can be achieved through the synergy between Internet of Things (IoT) and Machine Learning (ML) algorithms, which support automation and improved efficiency in the agricultural field. In this research work, sensors attached to the Microcontroller (ESP32) were used to collect air humidity, air temperature, and soil moisture content parameters. The data is transmitted to the Firebase cloud via the Wi-Fi module of the ESP32. The Firebase cloud contains a trained dataset using Decision Tree Classifier algorithm. The transmitted data from the sensor is compared to the trained dataset and the output is predicted to know if the soil is wet or dry. The ESP32 then obtain data from the Opensource Google weather Application Programming Interface (API), OpenWeatherMap using JavaScript Object Notation (JSON) data to know if there will be rainfall in an hour or not. Based on the data collected from the weather API by the NodeMCU, it then determines whether to trigger the pump for irrigation or not. If the soil is dry and rain will likely fall in an hour, the pump remains OFF and allow the rain to water the field, otherwise, the pump is triggered ON and a calculated amount of water is pumped into the soil. Four machine learning algorithms (Logistic Regression, k-Nearest Neighbours, Support Vector Machine, and Decision Tree Classifier) were selected for the training of the dataset. The prediction accuracy for the Logistic Regression, k-Nearest Neighbours, Support Vector Machine, and Decision Tree Classifier are 81.53%, 88.57%, 81.58%, and 91.31%, respectively.

## TABLE OF CONTENTS


| | | Page |
|---|---|---|
| Cover page | | i |
| Title page | | ii |
| Declaration | | iii |
| Certification | | iv |
| Dedication | | v |
| Acknowledgments | | vi |
| Abstract | | vii |
| List of Figures | | xi |
| List of Plates | | xii |
| List of Abbreviations | | xiii |
| **Chapter One: Introduction** | | **1** |
| 1.1 | Background of study | 1 |
| 1.2 | Problem Statement | 4 |
| 1.3 | Aim and Objectives | 6 |
| 1.4. | Justification for the Research | 6 |
| 1.5 | Scope of The Research | 7 |
| 1.6 | Key Research Contributions | 7 |
| **Chapter Two: Literature Review** | | **8** |
| 2.1 | Introduction | 8 |
| 2.2 | Irrigation | 8 |
| 2.2.1 | Role of irrigation | 9 |
| 2.3 | Internet of Things | 10 |
| 2.3.1 | IoT architecture | 12 |

*2.3.1.1 Perception/Sensing layer* 13

*2.3.1.2 Network layer* 14

*2.3.1.3 Data processing layer* 15

*2.3.1.4 Application layer* 16

2.4 Artificial Intelligence 16

*2.4.1 Types of machine learning* 17

*2.4.2 Machine learning processes* 20

2.5 Review of Related Works 22

**Chapter Three: Research Methodology 26**

3.1 Introduction 26

3.2 Design Components 26

3.2.1 Sensors 26

*3.2.1.1 Temperature and humidity sensor (DHT11)* 27

*3.2.1.2 Soil moisture sensor (FC28)* 28

*3.2.2 Actuators* 28

*3.2.2.1 Relay* 28

*3.2.2.2 Water Pump* 29

3.2.3 Microcontroller (ESP32) 29

*3.2.3.1 Core elements of a microcontroller* 30

3.3 Design Stages 31

3.3.1 Block diagram of autonomous irrigation system 31

3.3.2 Data collection 32

3.3.3 Data processing 32

3.3.4 Machine learning modelling 33

*3.3.4.1 Logistic regression* 34

*3.3.4.2 k-Nearest neighbour* 34

*3.3.4.3 Support vector machine* 35

*3.3.4.4 Decision tree* 36

3.3.5 Rainfall prediction 37

3.3.6 Cloud storage (Firebase) 38

3.3.7 Power supply 38

3.4 Flowchart of Autonomous Irrigation System 38

3.5 Project Setup 40

**Chapter Four: Results and Discussion** **41**

4.1 Introduction 41

4.2 Analysis of Machine Learning Models 41

4.2.1 Logistic regression prediction accuracy 41

4.2.2 kNN prediction accuracy 42

4.2.3 SVM prediction accuracy 42

4.2.4 Decision tree prediction accuracy 43

4.3 Results of the Autonomous Irrigation System 44

4.4 Discussion of Results 47

**Chapter Five: Conclusion and Recommendation** **48**

5.1 Conclusions 48

5.3 Recommendations 48

5.4 Contribution to Knowledge 49

**References** **50**

## LIST OF FIGURES


| | Pages |
|---|---|
| Figure 2.1: Internet of Things | 11 |
| Figure 2.2: IoT connected Devices | 12 |
| Figure 2.3: IoT Architecture | 13 |
| Figure 2.4: Types of Machine Learning | 17 |
| Figure 2.5: Supervised Learning | 18 |
| Figure 2.6: Unsupervised Learning | 19 |
| Figure 2.7: Reinforcement Learning | 20 |
| Figure 2.8: Machine Learning Processes | 20 |
| Figure 3.1: Temperature and Humidity Sensor (DHT11) | 27 |
| Figure 3.2: Soil Moisture Sensor (FC28) | 28 |
| Figure 3.3: Relay Internal Diagram | 29 |
| Figure 3.4: Water Pump | 29 |
| Figure 3.5: ESP32 Functional Block Diagram | 30 |
| Figure 3.6: Complete Block Diagram of Autonomous Irrigation System | 31 |
| Figure 3.7: Logistic Regression Plot | 34 |
| Figure 3.8: k-Nearest Neighbours Representation | 35 |
| Figure 3.9: Support Vector Machine Representation | 36 |
| Figure 3.10: Decision Tree Representation | 37 |
| Figure 3.11: Flowchart of Autonomous Irrigation System | 39 |
| Figure 4.1: Result of Logistic Regression Algorithm | 41 |
| Figure 4.2: Result of kNN Algorithm | 42 |
| Figure 4.3: Result of SVM Algorithm | 43 |
| Figure 4.4: Result of Decision Tree Algorithm | 44 |
| Figure 4.5: Result of Autonomous Irrigation System I | 45 |
| Figure 4.6: Result of Autonomous Irrigation System II | 46 |

## LIST OF PLATES


| | Pages |
|---|---|
| Plate I: Autonomous Irrigation Setup | 40 |
| Plate II: Packaged Autonomous Irrigation System | 40 |

## LIST OF ABBREVIATIONS

| | |
|---|---|
| IoT | Internet of Things |
| ML | Machine Learning |
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| NodeMCU | Node Micro-Controller-Unit |
| JSON | JavaScript Object Notation |
| LCD | Liquid Crystal Display |
| GSM | Global System for Mobile Communication |
| WSN | Wireless System Network |
| k-NN | k-Nearest Neighbours |
| SVM | Support Vector Machine |
| DT | Decision Tree |
| IDE | Integrated Development Environment |
| SDK | Software Development Kits |
| GPS | Global Positioning System |
| HVAC | Heating, Ventilation, and Air Conditioning |
| DAS | Data Acquiring System |
| NFC | Near-Field Communication |
| RL | Reinforcement Learning |
| NTC | Negative Temperature Coefficient |
| IC | Integrated Circuit |
| BaaS | Backend as a Service |
| XML | Extensible Markup Language |
| NodeMCU | Node Microcontroller |
| Apps | Applications |

# CHAPTER ONE

# INTRODUCTION

## 1.1 Background of the Study

Agriculture which is as old as man has been the most important practice from the beginning of human evolution. It is one of the main aspects of human survival as it is the main source of food (Ogunti, 2019). Irrigation and agriculture are intricately related as the former and the latter go hand in hand. The reason for this bond is because water is very essential and vital for the survival of any form of life. Irrigation is the application of controlled amounts of water to plants at needed interval in order to grow crops. Irrigation is soil moisture dependent because soil moisture is recognized as one of the main drivers for plant bionetwork (Ogunti *et al*., 2018). Soil moisture content is a prerequisite for crop growth, and excessive soil moisture content may bring about rot to the roots of crops, take away a lot of fertilizer which can cause water pollution, stop gaseous exchange between soil and the atmosphere which reduces root respiration and root growth. Water is critical for seed germination and uptake of nutrients by the plant and therefore, optimum level of moisture must be ensured for healthy growth of the root and overall development of the crop (Amalraj *et al*., 2019). The practice of irrigation has always been an ancient practice which has evolved through different stages. For example, our forefathers watered their farms with the aid of buckets and watering cans while flood irrigation and sprinkler irrigation are part of the types of irrigation that are still being practiced today. These systems have been hit with several setbacks such as leaching off of soil nutrients, erosion (mainly due to flood irrigation), wastage of volumes of water, and many other deleterious effects on the farm (Ogunti, 2019).

In agriculture, irrigation is an important factor as rainfalls are unpredictable and uncertain. One of the major constraints to development of sustainable agriculture in West Africa is the over-dependence of farming systems on rainfall, which increases the vulnerabilities of production systems to climate change and variability. Recurrent droughts and unpredictability of rainfalls make farmers very vulnerable to climate-related risks (Boansi *et al*., 2019). In Nigeria, a developing nation, tremendous effort is focused on improving agricultural productivity. As the contribution of agriculture to Gross Domestic product is declining nowadays, we are in urge to increase crop productivity with efficient and effective water usage. Oluwaseyi (2017) is of the opinion that a strong and efficient agricultural sector has the capacity to enable a country to feed its growing population, earn foreign exchange, generate employment and provide raw materials for industries. The unavailability of these information with regards to water can be assumed to have reduced the average Nigerian farmer to a seasonal farmer that can only function with the cycle of the rainfall. There exists a demand for colossal technical knowledge to make irrigation systems more efficient (Rajalakshmi and Mahalakshmi, 2018). Agriculture in the face of water scarcity has been a big challenge. The global irrigation scenario is categorized by increased demand for higher agricultural productivity, poor performance and decreased availability of water for agriculture. These problems can be appropriately rectified if we use automated system for irrigation (Remalatha *et al*., 2016). Developments in improving water availability on farmlands are seen in the investments in drip irrigation facilities as a climate-smart option in West Africa particularly for the production of high value vegetables (Wanvoeke *et al*., 2016). Crops like maize, sorghum and millet are only cultivated at certain time of the year. In agricultural domain through the development of a knowledge management system, enquiries of farmers with regards to crop behavior and the environment, can be answered with the help of multimedia which can be made easily accessible. The application of Information and Communication Technology (ICT) has provided the opportunities for widening and promoting agriculture on several aspects and domains in developing countries (Ogunti, 2019).

The global population is set to touch 9.5 billion by 2050 (Cruz *et al*., 2018) with a greater proportion of this growth happening in the developing countries of which Nigeria is one. So, to feed this much population, the farming system must embrace Internet of Things (IoT). Against the challenges such as extreme weather conditions and rising climate change, and environmental impact resulting from intensive farming practices, the demand for more food has to be met. Cruz *et al*. (2018) suggested a reference model for an IoT middleware platform that would support intelligent IoT applications. IoT based solutions are proving very helpful in many dimensions of the agricultural landscape, and these intelligent solutions could also be fruitful in smart irrigation with optimum utilization of water (Goap *et al*., 2018). Soil moisture, precipitation, and evaporation are the essential parameters for designing a smart irrigation system. Smart farming based on IoT technologies will enable growers and farmers to reduce waste and enhance productivity ranging from the quantity of fertilizer utilized to the number of journeys the farm vehicles have to make. In IoT based smart farming, a system is built for monitoring the crop field with the help of sensors. This affords the farmers the capability to monitor the field conditions from anywhere. IoT- based smart farming is highly efficient when compared with the conventional approach. Automated irrigation systems can be very economical in this regard as it helps to conserve water. However, the savings from automatic irrigation systems can go beyond that. Manual irrigation targets plant roots with no significant degree of precision. In disparity, automated irrigation systems can be programmed to discharge more precise amounts of water in a targeted area, which promotes water conservation. The goal of technology is to make the lives of human beings easier and simpler as long as the sun rises. It therefore endeavors to extend the chain of electronic life to the famers and provide a means of reducing the cost incurred during manual means of monitoring and irrigation, save time and energy, cater for the ever-increasing competition of water with urban domains in developing countries.

On the other hand, Machine Learning (ML) is an interesting field and which can help in solving real time problems. ML models are extensively used for automation where human intervention is reduced as well as improving performance over a period of time. Adapting new data independently is one new feature found in Machine learning (Kirtana *et al*., 2018). IoT technology is based on connecting application specific objects (with sensors and/or actuators) with Internet and intelligently analysing (using ML) the data received from the objects for making insightful decisions. The ML is a branch of Artificial Intelligence (AI), which helps machines in taking independent decisions (Singh *et al*., 2019). Artificial Intelligence and Machine Learning solutions ensure multiple ways to optimize and mechanize processes, save money and reduce human error for many food industries as well as creating more revenue which prove to be advantageous to restaurants, bars and agricultural industries.

## 1.2 Statement of the Research Problem

Irrigation of plants is usually a very time-consuming activity and for it to be done within a reasonable amount of time, it will require a large number of human resources. Due to the use of technology for irrigation, the majority of human-powered irrigation processes today are labour and time-intensive.(Aishwarya *et al*., 2017). Most of the technology enhanced irrigation systems just irrigate whenever the soil moisture content is low without taking the knowledge of the weather forecast into cognizance, thereby leading to bad water management. Such systems also lack the capability of learning from the data obtained to make prediction for future parameters neither can they work independently without manual input by the farmers. With such technology enhanced irrigation systems, the irrigation control is very limited, and many resources especially water are still wasted, which are responsible for massive losses of water resources since the amount of water available are in excess of the plants' needs (Aishwarya *et al*., 2017). To avoid poor water management, which could reduce yield and ultimately revenue loss, there is need to incorporate Artificial Intelligence and Climate Information System into technology enhanced irrigation systems. Farmers in Nigeria have not embraced the concept of Climate Information Systems in the practice of agriculture talk less of adopting same during irrigations process for crops.

Thus, this research developed an autonomous irrigation system that is adaptive to daily climate conditions, without the need for expensive sensors and costly weather-stations. It incorporates the ability to learn pattern and work independently without manual input.

The system uses sensors to collect air humidity, air temperature, and soil moisture, and transmit the raw data to NodeMCU(Node Microcontroller Unit) to know if the soil is dry by comparing it to trained set of data in the NODEMCU. The NODEMCU then obtains data from the Opensource Google weather API(OpenWeatherMap) using JSON data to know if there will be rainfall or not. Based on the data collected from the weather API, by the NODEMCU, it uses the information to determine whether to trigger the pump for irrigation or not. The real time monitoring report is sent to the cloud where the farmer can access to monitor the condition of the farmland whenever he wishes.

## 1.3 Aim and Objectives

This research aims at developing an autonomous irrigation system using IoT and artificial intelligence. The objectives of the research work are;

i. To acquire soil data parameters in real-time using sensors.
ii. To analyze the acquired data using machine learning algorithm for the purpose of automating the irrigation system.
iii. To predict rainfall using an online weather service for the purpose of weather sensitive irrigation process.
iv. To evaluate the performance of the developed autonomous irrigation system.

## 1.4 Justification of the Research

So far, there have been many advancements in precision agriculture. However, almost all the breakthroughs exclude the use of an intelligent machine-to-machine interaction and rainfall prediction in irrigation. Most of the systems fetched the data at a particular time and responded immediately controlling the valves in the field. There has not been any system that takes the decision based on trained dataset and analyzing real-time data with also the inclusion of rainfall prediction. With these existing systems, human input is still required for the efficient running of the systems, and the fact that rainfall prediction was not incorporated into these systems often leads it to make unintelligent decisions like watering the field when there is the possibility of rainfall in the next minute. This does not only lead to wastage of scarce water resources but could also result in waterlogging which is harmful to the survival of crops. Till now, machine learning has only succeeded in abating crop disease detection, crop management, and crop yielding problems. There is no or meagre research in the field of machine learning techniques that analyze the soil moisture content based on past data fed and controls the irrigation process without any involvement of human work. The study will develop an autonomous irrigation system that is intelligent, energy-efficient, portable, cost-effective, and can be used at any geographic position and responsive to all weather conditions.

## 1.5 Scope of the Research

This study will be limited to the development of an autonomous irrigation system that will irrigate farmlands based on the information obtained from soil moisture sensors and weather forecasts. It is not designed for any specific type of crop.

## 1.6 Key Research Contributions

This research work has produced a weather-adaptive intelligent irrigation system that uses water and electrical energy more efficiently by preventing water loss and waterlog, preserve electrical energy, and minimizing the cost of labour.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Introduction

This chapter presents the background and an overview of the techniques and technologies relevant to the development of this thesis. This chapter aims to link the problems introduced in Chapter one and the method used to solve the problem in the next chapter and to provide a review of related works of literature.

## 2.2 Irrigation

Irrigation is the agricultural process of applying controlled amounts of water to land to assist in the production of crops, as well as to grow landscape plants and lawns, where it may be known as watering. (*Irrigation Definition & Meaning | Dictionary.com*, n.d.). Agriculture that does not use irrigation but instead relies only on direct rainfall is referred to as rain-fed. Irrigation has been a central feature of agriculture for over 5,000 years and has been developed independently by many cultures across the globe.(Shirsath *et al.*, 2017).

Irrigation helps to grow agricultural crops, maintain landscapes, and revegetate disturbed soils in dry areas and during periods of less than average rainfall. Irrigation also has other uses in crop production, including frost protection, suppressing weed growth in grain fields and preventing soil consolidation (Williams *et al.*, 1990). Irrigation systems are also used for cooling livestock, dust suppression, disposal of sewage, and in mining. Irrigation is often studied together with drainage, which is the removal of surface and sub-surface water from a given location.

### 2.2.1 Role of irrigation

The irrigation process consists of introducing water to the soil profile where plants can extract it to meet their needs, mainly evapotranspiration. An important goal of irrigators is to design and manage their irrigation system to optimize placement and timing of applications to promote growth and yield while protecting against soil erosion, salination, water quality degradation, or other detrimental environmental impacts. Since physical circumstances and socioeconomic conditions are site specific, there is no single answer to designing, developing, and managing an irrigation system. In all circumstances, however, the factors and principles involved are universal (Eisenhauer *et al*., 2021).

The practice of irrigation has evolved gradually toward improved control over plant, soil, and even weather variables. The degree of control possible today is still only partial because of unpredictable extremes in the weather. Modern irrigation is a sophisticated operation, involving the monitoring and manipulation of numerous factors impacting crop production. With the continuing loss of suitable land and water and the rising demand for agricultural products, the search for new knowledge on how to improve irrigation and the need to apply this new knowledge have become increasingly urgent. Any attempt to irrigate must be based on a thorough understanding of soil-water-plant relationships (Eisenhauer *et al*., 2021). The movement of water, once applied, consists of a sequence of dynamic processes beginning with the entry of water into the soil, called infiltration. The rate of infiltration is governed by the rate at which water is applied to the soil surface, as long as the application rate does not exceed the capacity of the soil to absorb it. An important criterion for a sprinkler or micro-irrigation system is to deliver water at a rate that will prevent ponding, runoff, and erosion.(Yuvaraju and Priyanga, 2018)

## 2.3 Internet of Things

The Internet is the global system of interconnected computer networks that use the Internet protocol suite (TCP/IP) to link billions of devices worldwide. Nowadays over 63% of the world population uses the Internet. It has had a revolutionary impact on culture and commerce, including the rise of near-instant communication by electronic mail, instant messaging, voice over Internet Protocol (VoIP) telephone calls, two-way interactive video calls, social networking, and online shopping sites. Moreover, Internet connectivity became the norm for many business applications and is today integral part of many enterprises, industrial and consumer products to provide access to information. However, the Internet usage still primarily focuses on human interaction and monitoring through applications (apps) and interfaces. IoT is one of the biggest revolutions of the Internet in which also physical things communicate(Patel *et al*., 2016).

IoT combines the concepts “Internet” and “Thing” and can therefore semantically be defined as “a world-wide network of interconnected objects uniquely addressable, based on standard communication protocols”. The concept was first introduced by the MIT Auto-ID Center to label the development towards a world where all physical objects can be traced via the internet by tagging them with Radio Frequency Identification (RFID) transponders. In the meantime, the meaning is expanded towards a world-wide web of smart connected objects that are context-sensitive and can be identified, sensed and controlled remotely by using sensors and actuators. In the IoT, as shown in Figure 2.1, every ‘thing’ is uniquely identifiable, equipped with sensors and connected real-time to the internet.(Karen *et al*., 2015).

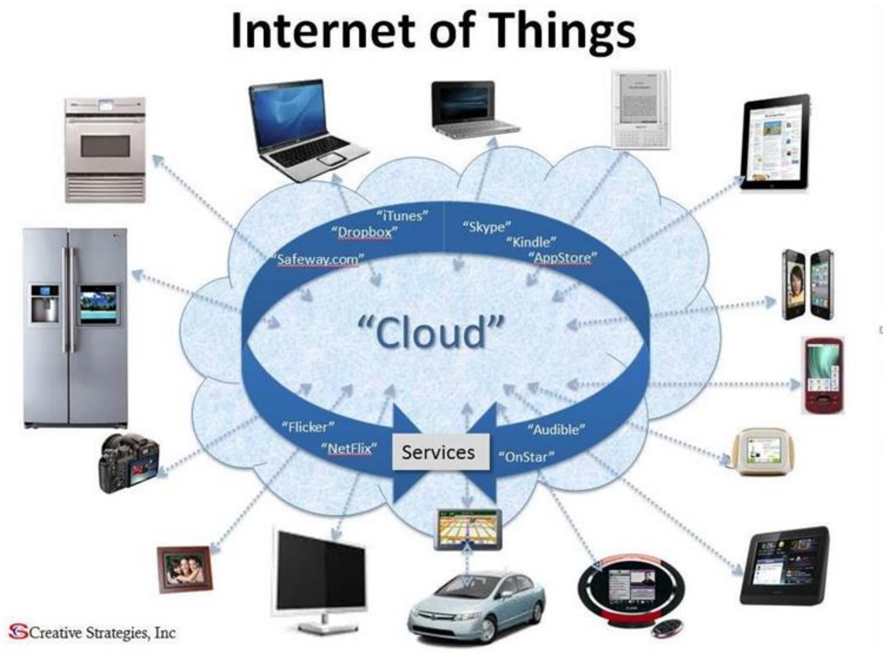



**Figure 2.1:** Internet of Things

As a result, the Internet will be deeply embedded in the daily life of consumers and businesses. Invisible technology operates behind the scenes, dynamically responding to how we want "things" to act. The IoT is expected to be the next Internet revolution. To date, the world has deployed over 13 billion "smart" connected things. The number of IoT devices worldwide as shown in Figure 2.2 is forecast to almost triple from 13 billion in 2022 to more than 29 billion IoT devices in 2030. (*IoT connected devices worldwide 2019-2030 | Statista*, n.d.).

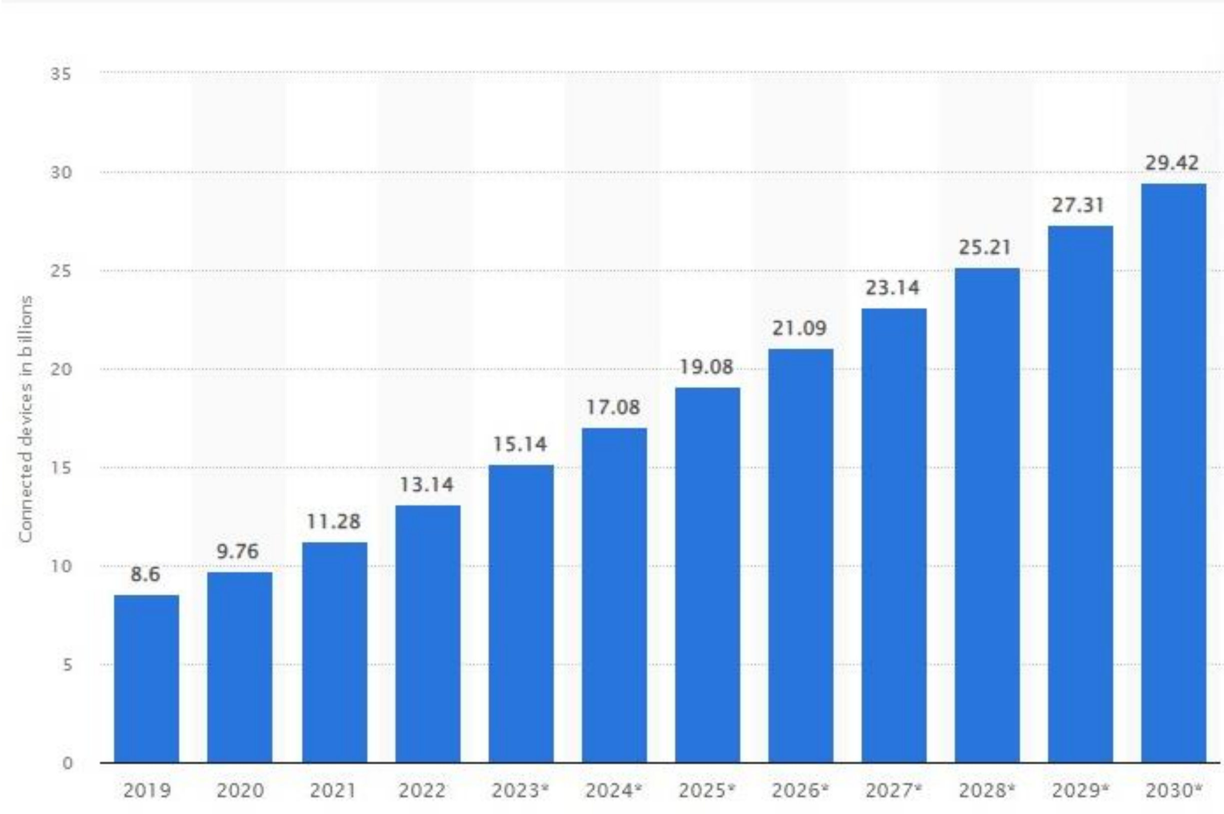



**Figure 2.2:** IoT connected devices

### 2.3.1 IoT architecture

IoT architecture refers to the tangle of components such as sensors, actuators, cloud services, Protocols, and layers that make up IoT networking systems. In general, it is divided into layers that allow administrators to evaluate, monitor, and maintain the integrity of the system. The architecture of IoT is a four-step process through which data flows from devices connected to sensors, through a network, and then through the cloud for processing, analysis, and storage. Figure 2.3 shows the representation of the four-step IoT architecture which is similar to the TCP/IP suite.

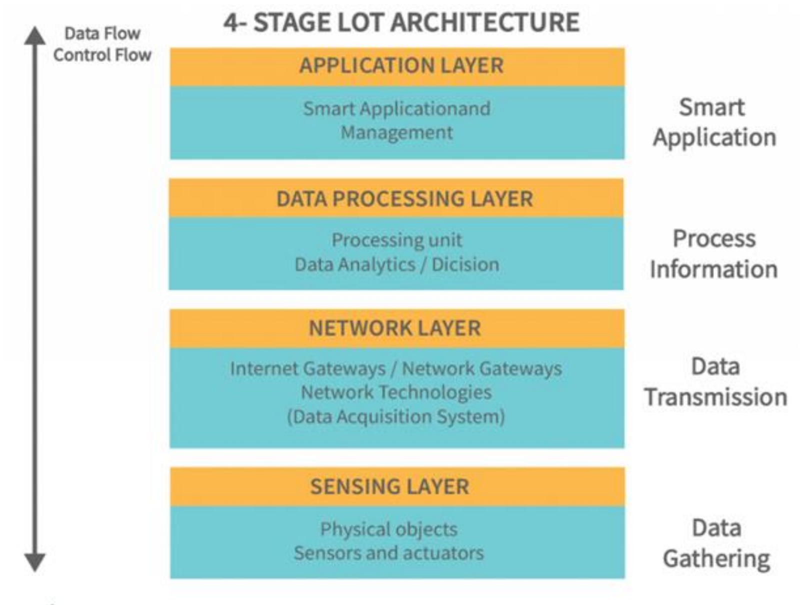



**Figure 2.3:** IoT Architecture

#### *2.3.1.1 Perception/Sensing layer*

It is the foremost layer that is also known as the sensor layer. It implies all types of sensors that can be used in IoT devices. Sensors work to gather minute data from the surrounding environment. They are sometimes also known as 'detectors' as the primary function of sensors is to detect even the slightest changes in the surrounding environment. This allows an IoT device to capture relevant data for real-time or post-processing. They measure particular parameters. Then, they transform signals from the environment sensors interact with them into digital information. Sensors can help create smart premises maintenance systems. The most popular ones that represent the first IoT architecture layer are temperature, pressure, and infrared sensors.(*IoT Architecture - Detailed Explanation - InterviewBit*, n.d.)

i. Temperature sensors: This type of sensor is used in almost any industry. They help control the temperature of water in household heating systems. Also, they are used in refrigerators, computers, and vehicles.

ii. Humidity sensors: They are widely used in Heating, Ventilation, and Air Conditioning (HVAC) systems. Besides, humidity sensors are crucial for industrial premises. It’s vital to maintain the required humidity level to produce certain quality products.
iii. Pressure sensors: With the help of this type of sensor, people can measure the flow of air or liquids. They are used in tech development.
iv. Level sensors: They can be found in almost any car, refrigerator, or household. Level sensors gauge the number of liquids in tanks or gas in the air.
v. Infrared sensors: This type of sensor can detect motion. Infrared sensors are mainly used for security purposes. Also, they help lower the usage of electricity.

Depending on the type of sensor, this small piece of hardware can measure absolutely anything. This can be smoke, motion or even blood pressure. While advanced sensors can measure a range of complexities, some IoT devices have multiple sensors bundled to be able to collect a range of data or perform multiple functions.

#### *2.3.1.2 Network layer*

Network layers provide an overview of how data is moved throughout the application. This layer contains Data Acquiring Systems (DAS) and Internet/Network gateways. A DAS performs data aggregation and conversion functions (collecting and aggregating data from sensors, then converting analog data to digital data). The Network layer transmit and process the data collected by the sensor devices, allow these devices to connect and communicate with other servers, smart devices, and network devices, and handles all data transmissions for the devices. The most popular IoT communication models are the following:

i. Ethernet: It is a secure way to connect IoT devices using a wire. It makes the connection reliable and secure. However, good wire management is required to connect many IoT components using Ethernet.
ii. Wi-Fi: A wireless network is one of the most convenient ways to connect IoT devices. It erases the need to use wires, which works well in small premises. However, Wi-Fi routers have limited signal ranges, making it hard to connect all components of IoT in large premises using Wi-Fi.
iii. Near Field Communication (NFC): NFC is a technology that ensures fast and hassle-free data transfer between two IoT devices. It is rarely used because it needs two devices to be placed in 3 inches or less. Moreover, the data transfer speed is low.
iv. Bluetooth: This technology helps transfer data, consuming low amounts of power. Therefore, it's widely used by IoT devices powered by batteries. Unfortunately, on average, Bluetooth has a short-range signal that makes 30 feet.

#### *2.3.1.3 Data Processing layer*

It is a layer that gathers all the data provided by the perception layers through a network. All the information is stored and analyzed. It is one of the most important layers of IoT because it makes decisions based on data analysis. Also, the application layer interacts with a user to manage and operate their IoT devices. This layer is placed between Network and Application layers in the logical design of IoT architecture. There are two major data processing stages of this layer.

i. Data accumulation: All the data gathered by sensors of IoT devices do not need to be used simultaneously. Therefore, it gets saved on devices' hard drives or transferred to data lakes or different types of databases for further use and analysis. The main goal followed is to sort the gathered data to store it efficiently.

ii. Data abstraction: The gathered data is used for getting helpful insights at this stage. Usually, it's supplemented with data provided by non-IoT devices to get helpful insights. At this stage, data gets unified or reconciled to particular formats. Finally, it gets gathered in one place to make it easy to access for users from different locations.

#### *2.3.1.4 Application layer*

User interaction takes place at the application layer. The user interface is the visible component that is easily accessible and in control of the IoT user. This is where a user can control the system and set their preferences. The more user-friendly this component of the IoT ecosystem is, the easier is a user's interaction. A user may interact with the system via the device itself, or this interaction can be conducted remotely via smartphones, tablets, and laptops.

## 2.4 Artificial Intelligence

Machine learning is a subfield of computer science that evolved from the study of pattern recognition and computational learning theory in artificial intelligence. Machine learning explores the construction and study of algorithms that can learn from and make predictions on data. Such algorithms operate by building a model from example inputs in order to make data-driven predictions or decisions, rather than following strictly static program instruction (Kohavi and Provost, 1998). Machine learning is closely related to and often overlaps with computational statistics; a discipline that also specializes in prediction-making. It has strong ties to mathematical optimization, which deliver methods, theory and application domains to the field. Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms is infeasible (Dönmez, 2013).

In 1959, Arthur Samuel defined machine learning as a “Field of study that gives computers the ability to learn without being explicitly programmed” (Simon, 2013). Tom M. Mitchell provided a widely quoted, more formal definition: “A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E” (Mitchell, 1997).

### 2.4.1 Types of machine learning

Machine learning tasks are typically classified into three broad categories, as shown in Figure 2.4 depending on the nature of the learning “signal” or “feedback” available to a learning system (Russell and Norvig, 2010).

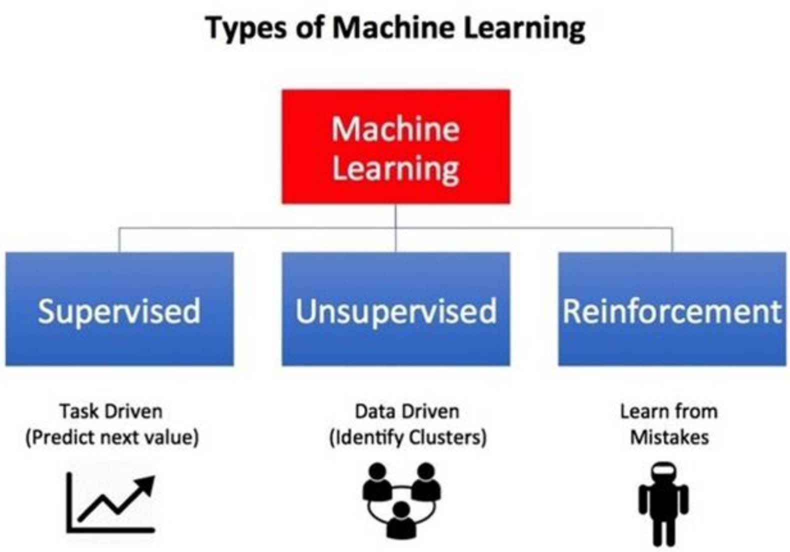



**Figure 2.4:** Types of Machine Learning

i. Supervised Learning: Supervised learning is the type of machine learning in which machines are trained using well "labelled" training data, and on basis of that data, machines predict the output. Figure 2.5 shows how labeled data is fed into machine learning model and the predicted output The labelled data means some input data is already tagged with the correct output. In supervised learning, the training data provided to the machines work as the supervisor that teaches the machines to predict the output correctly. It applies the same concept as .a student learns in the supervision of the teacher(*Supervised Machine learning - Javatpoint*, n.d.).

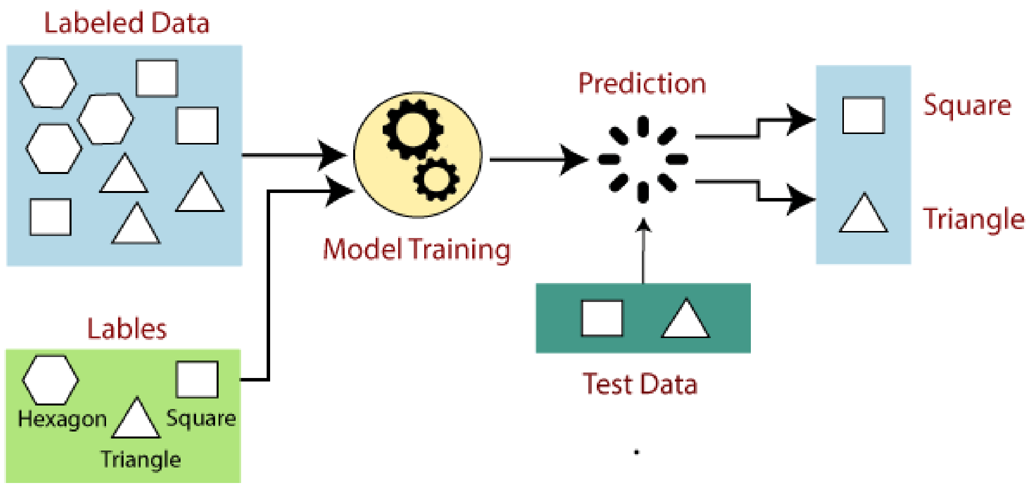



**Figure 2.5:** Supervised Learning

ii. Unsupervised Learning: Unsupervised learning is a machine learning technique in which models are not supervised using training dataset. Instead, models itself find the hidden patterns and insights from the given data. It can be compared to learning which takes place in the human brain while learning new things. It can be defined as a type of machine learning in which models are trained using unlabeled dataset and are allowed to act on that data without any supervision as shown in Figure 2.6.

It takes an unlabeled input data, which means it is not categorized and corresponding outputs are also not given. Now, this unlabeled input data is fed to the machine learning model in order to train it. Firstly, it will interpret the raw data to find the hidden patterns from the data and then will apply suitable algorithms such as k-means clustering, Decision tree.(*Unsupervised Machine learning - Javatpoint*, n.d.)

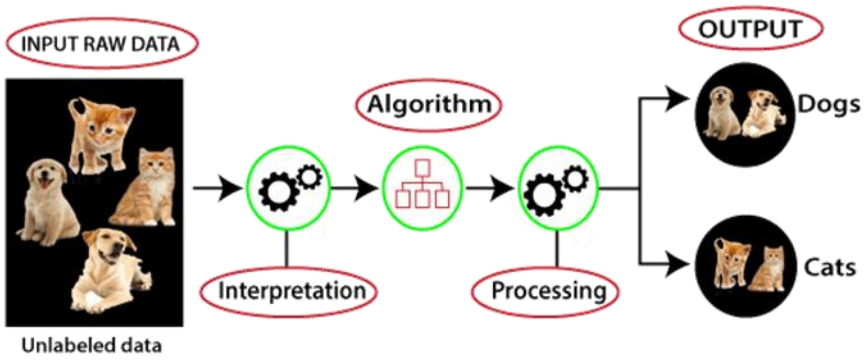



**Figure 2.6:** Unsupervised Learning

iii. Reinforcement Learning: Reinforcement learning (RL) is defined as a sub-field of machine learning that enables AI-based systems to take actions in a dynamic environment through trial-and-error methods to maximize the collective rewards based on the feedback generated for respective actions. In the RL context, feedback refers to a positive or negative notion reflected through rewards or punishments. In Figure 2.7, a computer may represent an agent in a particular state (St). It takes action (At) in an environment to achieve a specific goal. As a result of the performed task, the agent receives feedback as a reward or punishment (R).(*Reinforcement Learning*, n.d.).

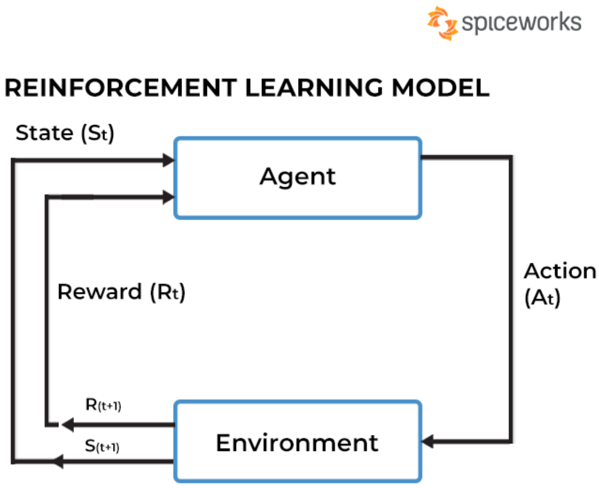



**Figure 2.7:** Reinforcement Learning

### 2.4.2 Machine learning processes

Machine learning processes consist mainly of five stages as shown in Figure 2.8.

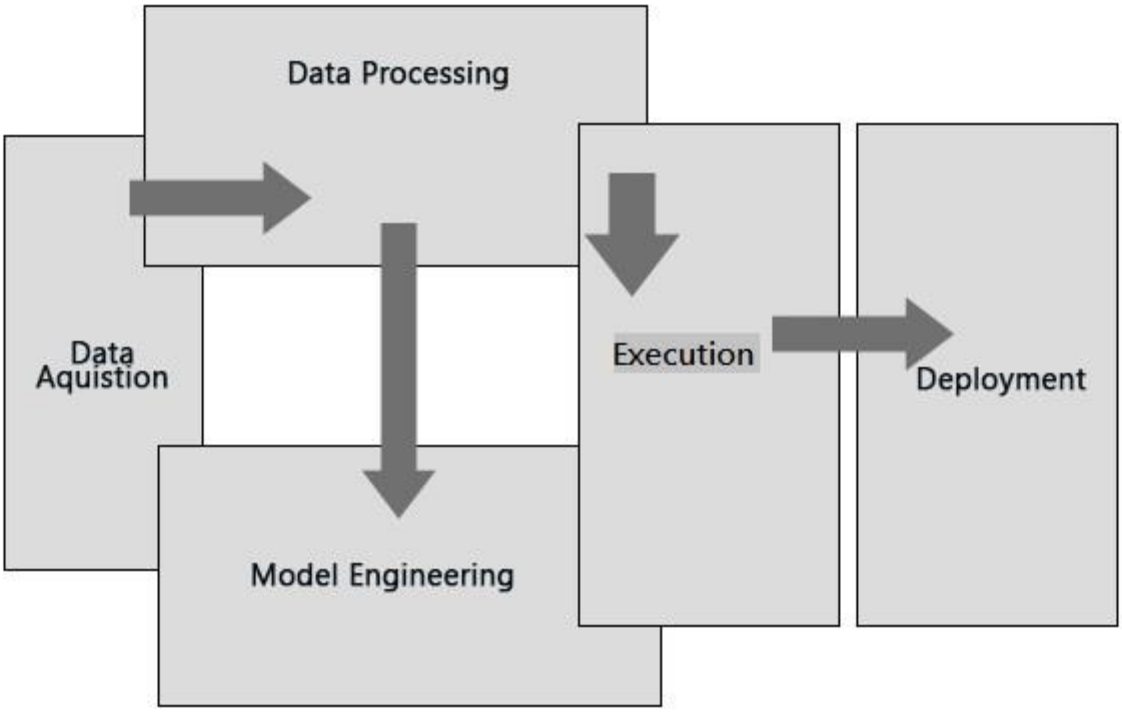



**Figure 2.8:** Machine Learning Processes

i. Data Acquisition: As machine learning is based on available data for the system to make a decision hence the first step defined in the architecture is data acquisition. This involves data collection, preparing and segregating the case scenarios based on certain features involved with the decision-making cycle and forwarding the data to the processing unit for carrying out further categorization. This stage is sometimes called the data preprocessing stage. The data model expects reliable, fast and elastic data which may be discrete or continuous in nature. The data is then passed into stream processing systems (for continuous data) and stored in batch data warehouses (for discrete data) before being passed on to data modeling or processing stages.
ii. Data Processing: The received data in the data acquisition layer is then sent forward to the data processing layer where it is subjected to advanced integration and processing and involves normalization of the data, data cleaning, transformation, and encoding. The data processing is also dependent on the type of learning being used. For instance, if supervised learning is being used the data shall be needed to be segregated into multiple steps of sample data required for training of the system and the data thus created is called training sample data or simply training data.
iii. Data Modeling: This layer of the architecture involves the selection of different algorithms that might adapt the system to address the problem for which the learning is being devised. These algorithms are being evolved or being inherited from a set of libraries. The algorithms are used to model the data accordingly, this makes the system ready for the execution step.
iv. Execution: This stage in machine learning is where the experimentation is done, testing is involved and tunings are performed. The general goal is to optimize the algorithm in order to extract the required machine outcome and maximize the system

performance, The output of the step is a refined solution capable of providing the required data for the machine to make decisions.

v. Deployment: Like any other software output, ML outputs need to be operationalized or be forwarded for further exploratory processing. The output can be considered as a non-deterministic query which needs to be further deployed into the decision-making system.(*Maachine Learning Processes*, n.d.).

## 2.5 Review of Related Works

Ogunti, (2019) designed an IoT Based Crop Field Monitoring and Irrigation Automation System using Arduino and NodeMCU that observe, control and monitor the crop-field environment and based on the information from the sensors (that is, temperature, relative humidity and soil moisture) trigger the watering of the farm, thus making the administrator (farmer) to manage the data in real time. The central node was Thingspeak API and was responsible for passing information to management node via computer or mobile phone. The readings were displayed on LCD screen for farmer to know. However, the system lacks intelligence and ability to predict rainfall which makes it vulnerable to waterlogging.

Kamaruddin *et al*. (2019) Designed an IoT-based intelligent irrigation management and monitoring system using arduino that applied Arduino technology and NRF24L01 as the microprocessor and transceiver for the communication channel, respectively. It developed an IoT, Wireless System Network (WSN) and Android Application that performed both manually and automatically. The manual system utilized a smart phone as a platform where the user can manually perform the watering from long range distance, while the automatic system depends on either the timer setting or the condition of the soil either it is still wet or dry. The decision-making aspect of the project depends on set reference rather than predictive analysis. It also lacked ability to consider weather information before making decision.

Rajalakshmi and Mahalakshmi (2018) developed and implemented an IOT Based Crop-Field Monitoring and Irrigation Automation to monitor crop-field using sensors (soil moisture, temperature, humidity, Light) and automate the irrigation system. The data from sensors were sent to web server database using wireless transmission. The irrigation was automated when the moisture and temperature of the field falls below the brink. The notifications were sent to farmers' mobile periodically. The farmer was able to monitor the field conditions from anywhere. The shortcoming of the system is that it was simply based on a set reference and it also lacked intelligence.

Kissoon *et al.* (2017) designed and implemented a Smart Irrigation and Monitoring System using Microsoft Azure machine learning to process data received from sensors in the farm and weather forecasting data to better inform the farmers on the appropriate moment to start irrigation. The System was based on Arduino-based development board with sensors for collecting air humidity, air temperature, and most importantly soil moisture data. The data collected were used to monitor the air quality and water content of the soil. These raw data were transmitted to the Microsoft Azure cloud platform API and were processed through a machine learning operation which had been trained beforehand, which then informed the farmer through either a web app or mobile app as to when to irrigate. The results obtained from the machine learning processing informed the farmer about the probability of rain and whether he should irrigate or not. The system also enabled the farmer to open the water taps remotely through a mobile application or web app. The limitations of the system are the fact that the farmer has to interact with the system before a decision is taken. Also, the system cannot automatically take decision based on the weather report obtained.

Putjaikal *et al.* (2016) developed an Arduino-based watering and roofing system for outdoor agricultural sites. The system comprised mainly of data where physical factors such as moisture are provided by sensors. The system focused more on the concept of Kalman filtering to remove noise from one sensor to another for obtaining more accurate values. The System used a decision tree model to determine when it is appropriate to start watering. A mobile application was developed for user to obtain the sensor data from the cultivation field and could control the watering and roofing system directly from the phone. The System obtained mainly the physical data from sensors and compare the data with weather forecast using the decision tree model. The decision tree model was devised to allow the author to take decision for watering the crops. The System used node.js library, which is an integration of machine learning libraries in order to compute the decision. This system still requires manual input to complete irrigation processes.

Arvindan and Keerthika (2016) developed an efficient and friendly Arduino-based automatic irrigation system which makes use of Android smart phone for remote control. This System consists of a soil moisture sensor that gave a voltage signal proportional to the moisture content in the soil which is correlated with a fixed threshold value retrieved by inspecting various soils and explicit crops. The data obtained were sent to the Arduino Uno processor connected wirelessly through the HC-05 module to an Android smart phone. The data obtained were displayed on the User Interface of the Android smart phone. The remote control in the Android smart phone was used to manage the irrigation drive system by switching it on and off. This System afforded the farmers to have a better control of their irrigation time but however lacked intelligence and weather forecast abilities.

The limitations and research gaps in the reviewed literatures are further highlighted below;

i. The decision-making process is based on a set reference rather than predictive analysis which is more accurate and efficient.
ii. High error margin in the predicted output.
iii. The systems are not autonomous but still require some level of manual input to function appropriately.
iv. Lack of rainfall prediction which deprived the system from making weather-sensitive intelligent decisions.

Based on the above limitation and research gap, this research aim to design a weather-adaptive autonomous irrigation system capable of making intelligent decision through predictive analysis of acquired sensor data and weather forecast data.

# CHAPTER THREE

# RESEARCH METHODOLOGY

## 3.1 Introduction

The background and an overview of the techniques and technologies relevant to the development of this thesis have been highlighted in the previous chapter. This chapter presents the methods involved in the development of the autonomous irrigation system.

## 3.2 Design Components

To achieve the objective of the research, the following components have been selected after careful consideration of their merit over others.

### 3.2.1 Sensors

A sensor is defined as a device or a module that helps to detect any changes in physical quantity like pressure, force or electrical quantity like current or any other form of energy. After observing the changes, sensor sends the detected input to a microcontroller or microprocessor. Finally, a sensor produces a readable output signal, which can be either optical, electrical, or any form of signal that corresponds to change in input signal. In any measurement system, sensors play a major role. In fact, sensors are the first element in the block diagram of measurement system, which comes in direct contact with the variables to produce a valid output.(*Sensor*, n.d.)

#### *3.2.1.1 Temperature and humidity sensor (DHT11)*

To sense the temperature and humidity of the surrounding of the plant, DHT11 sensor was used. DHT consist of a humidity sensing component, a negative temperature coefficient (NTC) temperature sensor (or thermistor) and an Integrated Circuit(IC) on the back side of the sensor. For measuring humidity, it uses the humidity sensing component which has two electrodes with moisture holding substrate between them. So as the humidity changes, the conductivity of the substrate changes or the resistance between these electrodes change. This change in resistance is measured and processed by the IC which makes it ready to be read by a microcontroller. To measure temperature, these sensors use a NTC temperature sensor or a thermistor. A thermistor is a variable resistor that changes its resistance with change of the temperature.(*DHT11 Sensor*, n.d.). Figure 3.1 shows the image of DHT11. The reasons for this choice are;

i. Low power consumption and excellent long-term stability.
ii. Relatively high measurement accuracy can be obtained at a very low cost.
iii. Built-in ADC, which saves the I/O resources of the control board.
iv. Humidity range of 5 to 95% RH with a ±5% and also a temperature range of -20 to 60°C with a ±2%.

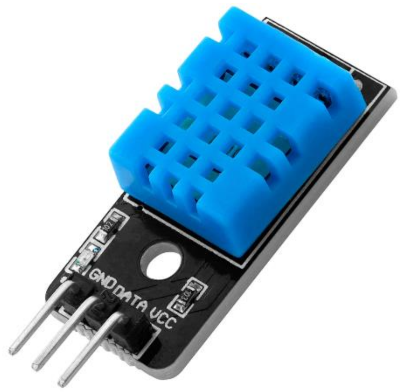



**Figure 3.1:** Temperature and Humidity Sensor (DHT11)

### *3.2.1.2 Soil moisture sensor (FC28)*

This soil moisture sensor module, shown in Figure 3.2 was used to detect the moisture of the soil. It measures the volumetric content of water inside the soil and gives us the moisture level as output. The module has both digital and analog outputs and a potentiometer to adjust the threshold level. The reasons for this choice are;

i. Small, cheap and easily available

ii. Operating Voltage: 3.3V to 5V DC

iii. Operating Current: 15mA

iv. Easy to use with Microcontrollers or even with normal Digital/Analog IC

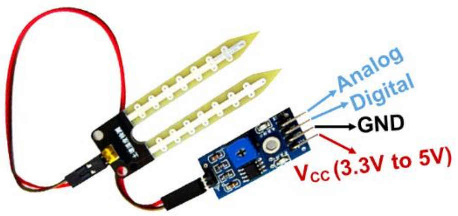



**Figure 3.2:** Soil Moisture Sensor(FC28)

### 3.2.2 Actuators

An actuator is a part of a device or machine that helps it to achieve physical movements by converting energy, often electrical, air, or hydraulic, into mechanical force. Simply put, it is the component in any machine that enables movement.

#### *3.2.2.1 Relay*

Relay is an electromechanical device that uses an electric current to open or close the contacts of a switch. A relay switch has one or more poles, each ofwhose contacts can be thrown by energizing the coil. Normally open (NO) contacts connect the circuit when the relay is activated; the circuit is disconnected when the relay is inactive. These are being operated by using the low DC voltage(5v) and are used to control the on and off operation of the electrical devices like as the motor. Figure 3.3 shows in internal diagram of the relay.

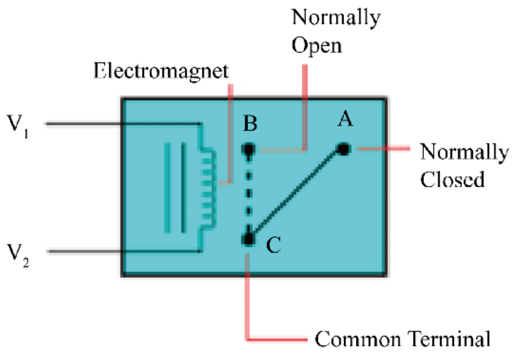



**Figure 3.3:** Relay Internal Diagram

#### *3.2.2.2 DC water pump*

A pump is a device that moves fluids (liquids or gases), or sometimes slurries, by mechanical action, typically converted from electrical energy into hydraulic energy. The model of the water pump used in this system is depicted in Figure 3.4.

**Figure 3.4:** Water Pump Motor

### 3.2.3 Microcontroller (ESP32)

A microcontroller is embedded inside of a system to control a singular function in a device. It does this by interpreting data it receives from its I/O peripherals using its central processor. The temporary information that the microcontroller receives is stored in its data memory, where the processor accesses it and uses instructions stored in its program memory to decipher and apply the incoming data. It then uses its I/O peripherals to communicate and enact the appropriate action.

#### *3.2.3.1 Core elements of a eicrocontroller*

i. The processor: A processor can be thought of as the brain of the device. It processes and responds to various instructions that direct the microcontroller's function. This involves performing basic arithmetic, logic and I/O operations. It also performs data transfer operations, which communicate commands to other components in the larger embedded system.

ii. Memory: A microcontroller's memory is used to store the data that the processor receives and uses to respond to instructions that it's been programmed to carry out.

iii. I/O peripherals: The input and output devices are the interface for the processor to the outside world. The input ports receive information and send it to the processor in the form of binary data. The processor receives that data and sends the necessary instructions to output devices that execute tasks external to the microcontroller.

The main reasons for the choice of ESP32 is it’s incorporated Wi-Fi module, low power consumption, low cost, and dual core. Figure 3.5 shows the internal block diagram of ESP32.

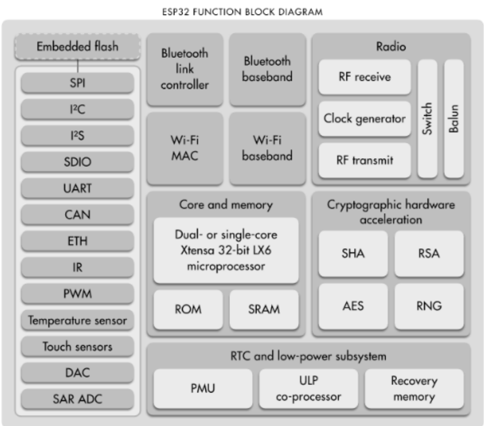



**Figure 3.5:** ESP32 Function Block Diagram(*ESP32*, n.d.)

## 3.3 Design Stages

There are four major design stages involved in the development of the autonomous irrigation system. These were carefully followed and adopted to meet the predefined objectives of this research work. These include: data collection, data processing, machine learning modelling, and rainfall prediction.

### 3.3.1 Block diagram of autonomous irrigation system

The Block Diagram of the Autonomous Irrigation System is illustrated in Figure 3.6. It represents the process flow of the components integrated into the system. According to Figure 3.6, the main board is Node MCU (ESP32) a Wi-Fi module. There are two (2) sensors connected to the NodeMCU. The two (2) sensors are a temperature/humidity sensor (DHT 11) which is used to detect the humidity and temperature of the surrounding, and soil moisture sensor (FC28) which detects the water level in the soil. The cloud that is being used is Firebase which reads and store the real-time database. The desktop app runs the machine learning model through the data obtained from the Firebase and send the prediction back to it. The weather prediction is achieved through the weather API call by NodeMCU. A water pump is also connected to the Node MCU and will receive a control signal from the Firebase to perform any action.

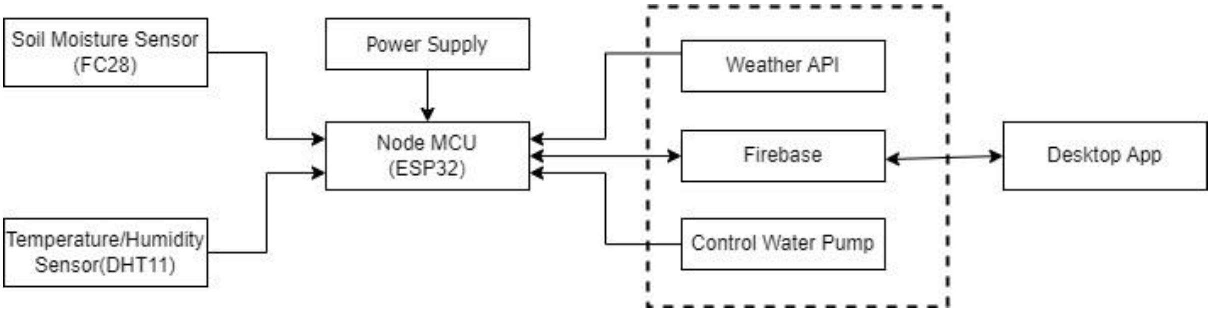



**Figure 3.6:** Complete Block Diagram

### 3.3.2 Data collection

In Machine learning projects, data plays an important role. It is a necessary task to collect the data from all the sensors and storing them correctly in a proper file format so that they can be used when needed to design the various machine learning algorithms on the project. The dataset used for the training of machine learning models was obtain from a reliable source online (*Irrigation Dataset | Kaggle*, n.d.). All the dataset obtained from different sources were subjected to thorough scrutiny to be sure it is in line with the range of data expected from the geographical location of the region being considered. The three parameters of interest for decision to be taken are as follows;

i. Temperature
ii. Relative Humidity
iii. Soil Moisture

### 3.3.3 Data processing

The dataset obtained was collected using sensors and stored in csv(comma-separated values). Data collected contained minor errors which could be due to sensor calibration error resulting to either unavailable or the data sent outside the expected range. In the dataset, some of the cells were having no values in them and machine learning algorithms cannot process accurately any area where data is missing. The reason for the missing data could be due to failure of microcontroller in fetching data or when error code gets printed in the dataset. To remove such type of rows we had used the drop empty row command in the associated python library.

The dataset contains 8914 instances of the data recorded from 23rd February, 2019 to 31st May, 2019. The dataset has five columns out of which the fifth column is the output of the relay that has the status of the relay (When it is OFF(0) or ON(1)). The information about the attributes is as shown below:

i. Timestamp(hh:mm:ss)
ii. Soil Moisture(%)
iii. Temperature($^oC$)
iv. Humidity(%)

### 3.3.4 Machine learning modelling

In choosing the best model for the dataset, the features of the data were carefully considered. Since the output is either a 0 or 1 (either Relay OFF or ON) and there were 3 features on which these were dependent, makes it a classification problem. The following are other key factors considered before adopting any of the classification algorithms.

i. High performance on both small and large dataset.
ii. Simplicity of implementation.
iii. Robust to noisy training data.

Based on the above factors, the following four classification algorithms was selected to train the dataset after which Decision Tree which gave the highest accuracy of prediction was adopted;

i. Logistic Regression
ii. k-Nearest Neighbor(kNN)
iii. Support Vector Machine (SVM)
iv. Decision Tree Classifier (DTC)

### *3.3.4.1 Logistic regression*

Logistic Regression is a binary classification technique, which is used to predict binary outcomes. (Yes/No, 1/0, True/False). Basically, regression technique involves minimizing the cost function by determining the values of weights and biases. Cost is obtained by evaluating error in the predicted value and the truth labels. Gradient Descent is a method which is used in determining those values of hyperparameters (weights and biases), at which the error function has global minima. Once the weights are determined, output so predicted is passed into activation functions. Figure 3.7 shows a Logistic Regression plot. It is simply a sigmoid function, that is,

$$h(x) = \frac{1}{1+e^{-x}} \tag{3.1}$$

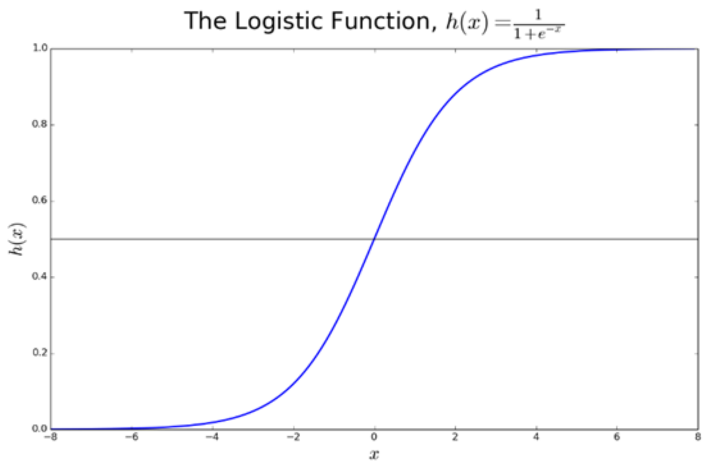
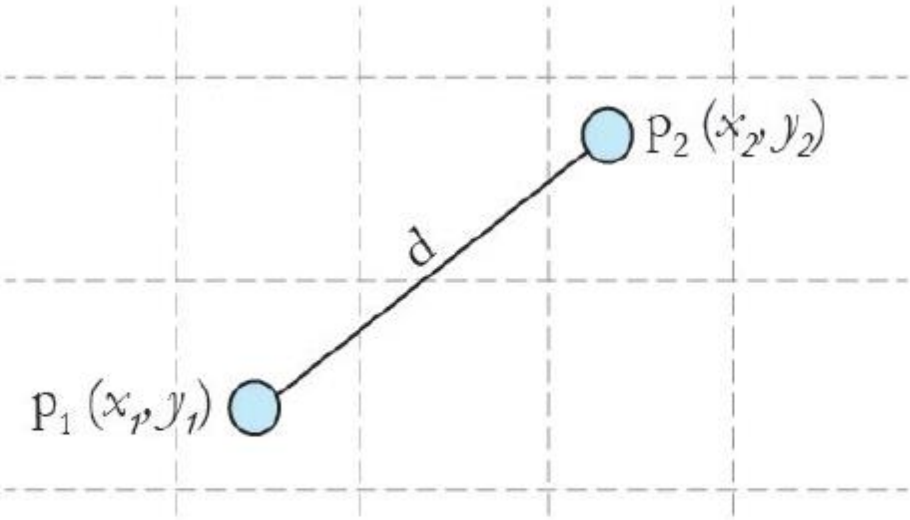



**Figure 3.7:** Logistic Regression plot

### *3.3.4.2 K-Nearest neighbour*

k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms. It classifies the test data point into one of the two classes we have, by calculating its distance from each and every existing data points from both the classes. This distance is called" Euclidean Distance". Class is assigned to the data point will contain the nearest neighbour of that data point. The alphabet 'k' denotes the number of neighbours voting on the rest data point. Figure 3.8 shows the pictorial representation of k-nearest neighbors.




$$Euclidean\ distance\ (d) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{3.2}$$

**Figure 3.8:** K-Nearest Neighbor Representation

#### *3.3.4.3 Support vector vachines (SVM)*

Support Vector Machine is another supervised machine learning algorithm, which also classifies 2 different classes of outputs. It makes the use of supporting planes and separating planes which are collectively known as Hyperplanes. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. The categorization of data by SVM is depicted by Figure 3.9.

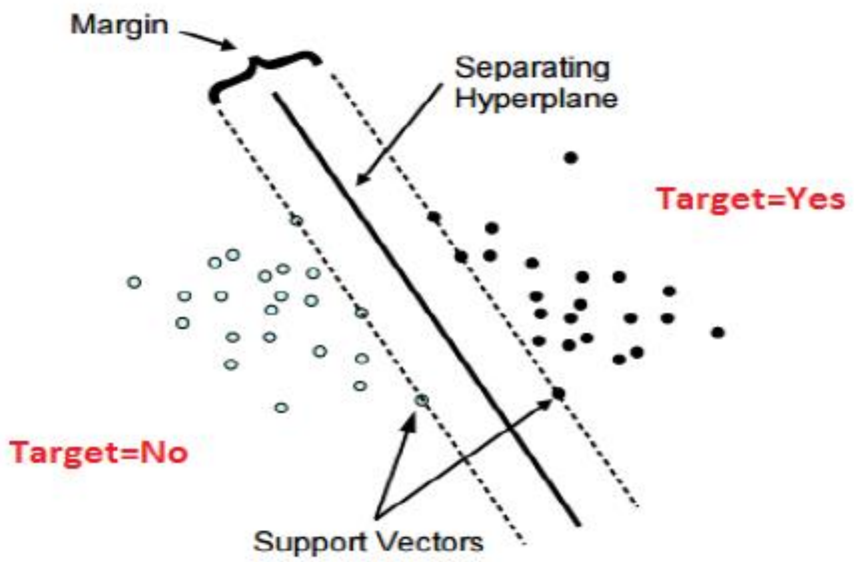



**Figure 3.9:** Support Vector Machine Representation

### *3.3.4.4 Decision tree*

Decision tree is a type of supervised learning algorithm (having a predefined target variable) that is mostly used in classification problems. It works for both categorical and continuous input and output variables. In this technique, we split the population or sample into two or more homogeneous sets (or sub-populations) based on most significant splitter / differentiator in input variables. (*Tree Based Algorithms | Implementation In Python & R*, n.d.). Figure 3.10 shows a Decision Tree representation.

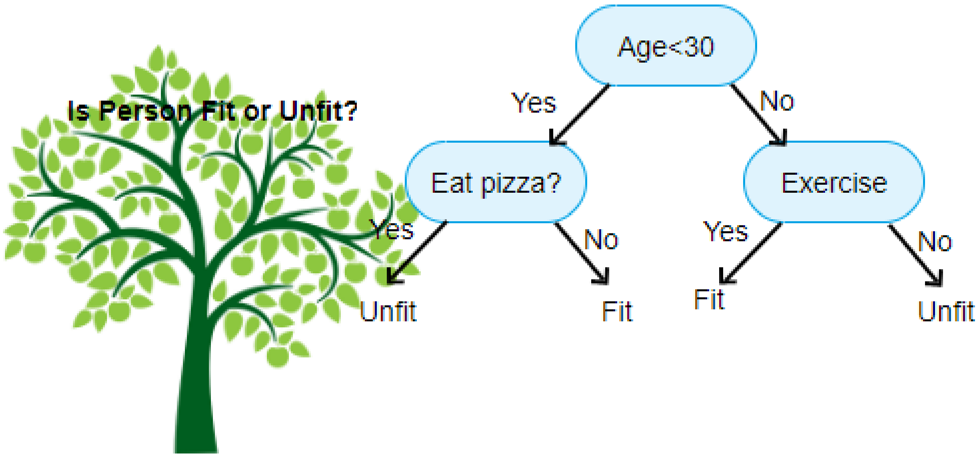



**Figure 3.10:** Decision Tree representation

### 3.3.5 Rainfall prediction

The rainfall prediction aspect of the design will be performed using an online weather prediction platform. OpenWeatherMap is an online service, owned by Open Weather Ltd, that provides global weather data via Application Programming Interface(API), including current weather data, forecasts, nowcasts and historical weather data for any geographical location. The company provides a minute-by-minute hyperlocal precipitation forecast for any location. The APIs support multiple languages, units of measurement and industry standard data formats like JSON and Extensible Markup Language (XML). (*Accuracy and quality of weather data - OpenWeatherMap*, n.d.).

The fields in each API call include the geographical position of the location(latitude, longitude), time zone, time zone offset, time, temperature, pressure, humidity, dew point, Ultraviolet index, cloudiness, average visibility, wind speed, wind direction, probability of precipitation. These parameters are used to forecast weather conditions in days, hours and minutes. For the purpose of this thesis, the hourly call was used to predict hourly rain fall.

### 3.3.6 Cloud storage (Firebase)

Firebase is a Backend as a Service (BaaS) app development platform that provides hosted backend services such as real-time database, cloud storage, authentication, and hosting for static files. It is a cloud hosted NoSQL database that lets you store and sync data between your users in real-time. Sensor reading is transmitted to the firebase through the Wi-Fi module of the ESP32.

### 3.3.7 Power supply

The system is powered by two (2) 3.7V lithium-ion batteries connected in series to give an output of about 7.4V. This output is further stepped down to 5V using a DC-DC buck converter.

## 3.4 Flowchart of Autonomous Irrigation System

The Autonomous Irrigation System is based on IoT and machine learning technology that is capable of controlling the water pump to irrigate water to the farm field and monitor the condition of soil moisture, air humidity and temperature of the farm field. It also incorporates rainfall prediction to prevent water logging on the crop field. The flow of the system algorithm is illustrated in Figure 3.11. The NodeMCU which is the control unit is initialized when the system is switched ON. The NodeMCU reads the input from the sensor and sends it to the firebase. The firebase already contained trained dataset using the Decision Tree classifier algorithm. Through the means of the desktop app, machine learning algorithm is run with the data received from the sensor against the trained dataset and the output is predicted. If the farm field is wet, the predicted output is 0, while the predicted output is 1 if the soil is dry. When a predicted output of 1 is given, the NodeMCU further check through the weather API whether there will be rain in one (1) hour. If there will be rain in one(1) hour, the pump status remains OFF(0) while if otherwise, the pump status turns ON(1) and water is pumped onto the crop field.

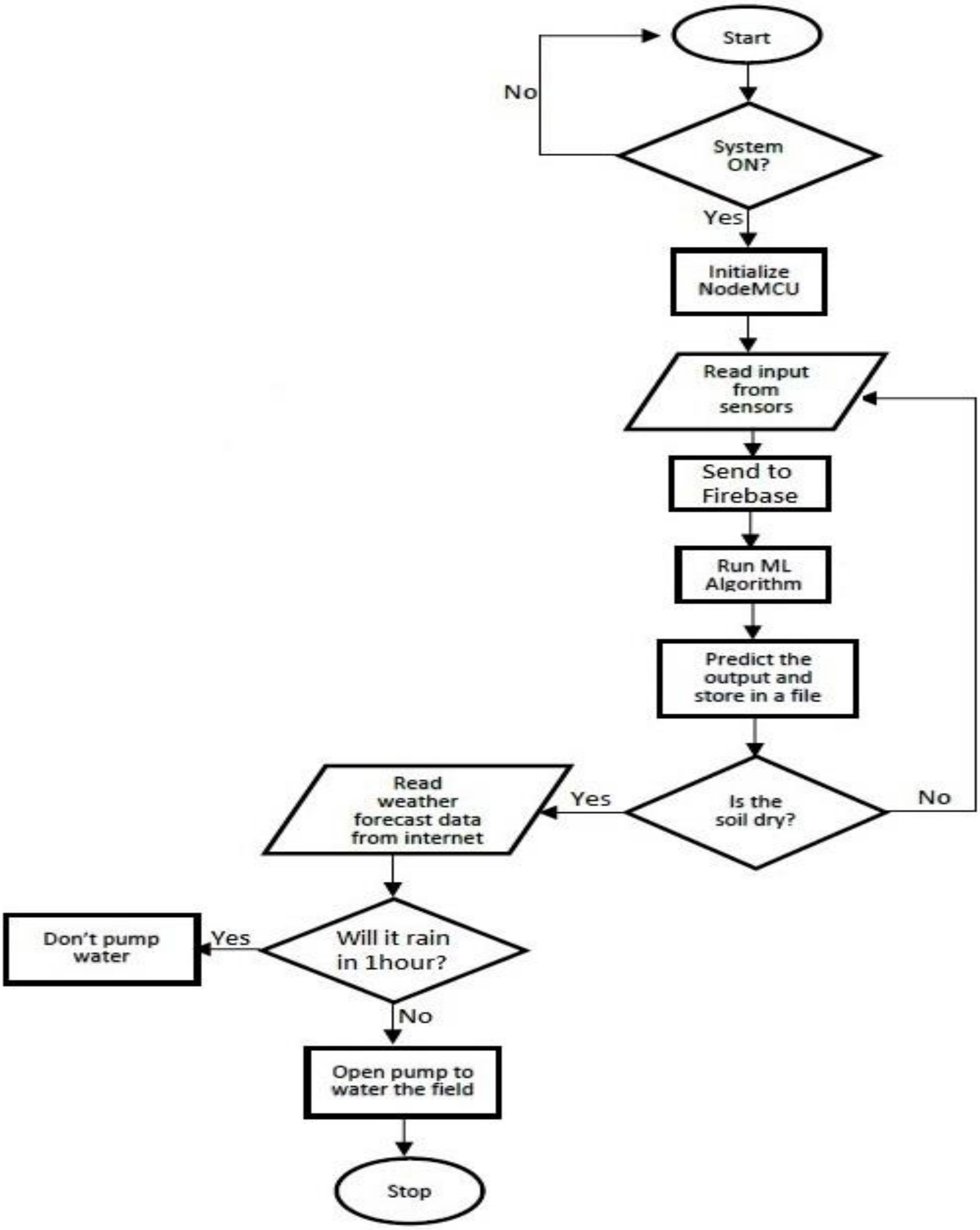



**Figure 3.11:** Flowchart of Autonomous Irrigation System

### 3.5 Project Setup

The entire project was first temporarily connected by means of a breadboard and jumper wires and tested before soldering and soldering on Veroboard and finally packaged. Plate I shows the complete project while the final package is shown in Plate II.

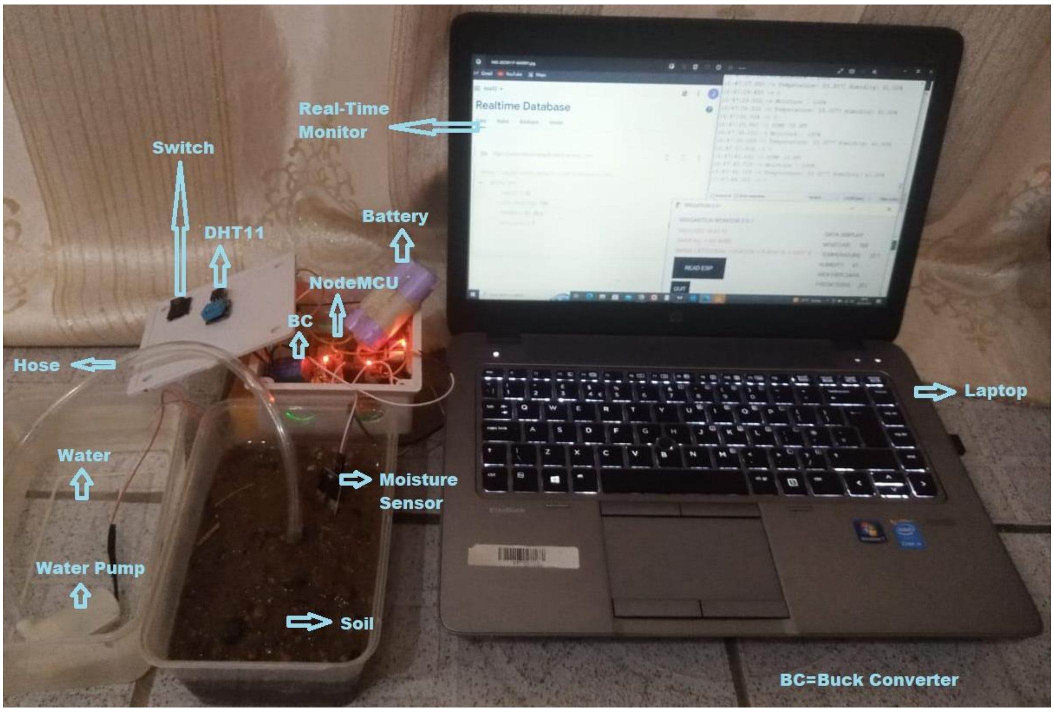



**Plate I:** Autonomous irrigation system setup

**Plate II:** Packed Autonomous Irrigation System

# CHAPTER FOUR

# RESULTS AND DISCUSSION

## 4.1 Introduction

The autonomous irrigation system was carefully designed to meet the required objectives. The entire system was setup and the results obtained are reported and discussed in the subsequent sections of this chapter.

## 4.2 Analysis of Machine Learning Models

Various machine learning models was developed and results obtained. The results obtained using the four selected classification algorithm (Logistic Regression, kNN, SVM, and Decision Tree) are summed up below.

### 4.2.1 Logistic regression prediction accuracy

The prediction accuracy of 81.53% was obtained with the application of logistic regression as shown in Figure 4.1. The dataset was divided into two with 80% of the data used for training and 20% used for testing.

```
In [41]: x_train, x_test, y_train, y_test =train_test_split(x, y, test_size = 0.8)

In [42]: scaler = StandardScaler()
         x_train = scaler.fit_transform(x_train)
         x_test = scaler.transform(x_test)

In [43]:
         model = LogisticRegression()
         model.fit(x_train, y_train)
         predictions = model.predict(x_test)
         predictions
Out[43]: array([0., 0., 0., ..., 0., 0., 0.])

In [44]: df = pd.DataFrame(predictions,columns =['PREDICTIONS'])
         df

In [45]: score = accuracy_score(y_test,predictions)*100
         score
Out[45]: 81.53393157599551
```

**Figure 4.1:** Result of Logistic Regression Algorithm

### 4.2.2 k-NN prediction accuracy

The prediction accuracy of 88.57% was obtained with the application of kNN as shown in Figure 4.2. The dataset was divided into two with 80% of the data used for training and 20% used for testing.

```
In [50]: x_train, x_test, y_train, y_test =train_test_split(x, y, test_size = 0.8)

In [51]: scaler = StandardScaler()
         scaler.fit(x_train)
         x_train = scaler.transform(x_train)
         x_test = scaler.transform(x_test)

In [52]: classifier = KNeighborsClassifier(n_neighbors = 8)
         classifier.fit(x_train, y_train)
         predictions = classifier.predict(x_test)
         predictions

Out[52]: array([0., 0., 0., ..., 1., 0., 0.])

In [53]: df = pd.DataFrame(predictions,columns =['PREDICTIONS'])
         df

In [54]: score = accuracy_score(y_test,predictions)*100
         score

Out[54]: 88.57263039820528
```

**Figure 4.2:** Result of kNN Algorithm

### 4.2.3 SVM prediction accuracy

The prediction accuracy of 81.58% was obtained with the application of SVM as shown in Figure 4.3. The dataset was divided into two with 80% of the data used for training and 20% used for testing.

```
In [13]: x_train, x_test, y_train, y_test =train_test_split(x, y, test_size = 0.8)

In [14]: clf=svm.SVC(kernel = 'linear')
         clf.fit(x_train,y_train)
         predictions = clf.predict(x_test)
         predictions

Out[14]: array([0., 0., 0., ..., 0., 0., 0.])

In [15]: df = pd.DataFrame(predictions,columns =['PREDICTIONS'])
         df

In [16]: score = accuracy_score(y_test,predictions)*100
         score

Out[16]: 81.57599551318003
```

**Figure 4.3:** Result of SVM Algorithm

### 4.2.4 Decision Tree

The prediction accuracy of 91.31% was obtained with the application of SVM as shown in Figure 4.4. The dataset was divided into two with 80% of the data used for training and 20% used for testing.

```
In [116]: x_train, x_test, y_train, y_test =train_test_split(x, y, test_size = 0.8)


          model = DecisionTreeClassifier()
          model.fit(x_train, y_train)
          predictions = model.predict(x_test)
          predictions

Out[116]: array([0., 0., 0., ..., 1., 0., 0.])

In [117]: df = pd.DataFrame(predictions,columns =['PREDICTIONS'])
          df

In [118]: score = accuracy_score(y_test,predictions)*100
          score

Out[118]: 91.3067863151991
```

**Figure 4.4:** Decision Tree Algorithm

### 4.3 Results of the Autonomous Irrigation System

The results obtained at different stages of autonomous irrigation process is displayed in Figure 4.5 and Figure 4.6. The first frame in Figures 4.5 and 4.6 shows the data received at the cloud Firebase as it is being read by ESP32 through the attached sensors. The third frame is from the desktop app where prediction is being made about the water content of the soil. It also displays the condition of rainfall as read from the openweathermap API through ESP32.

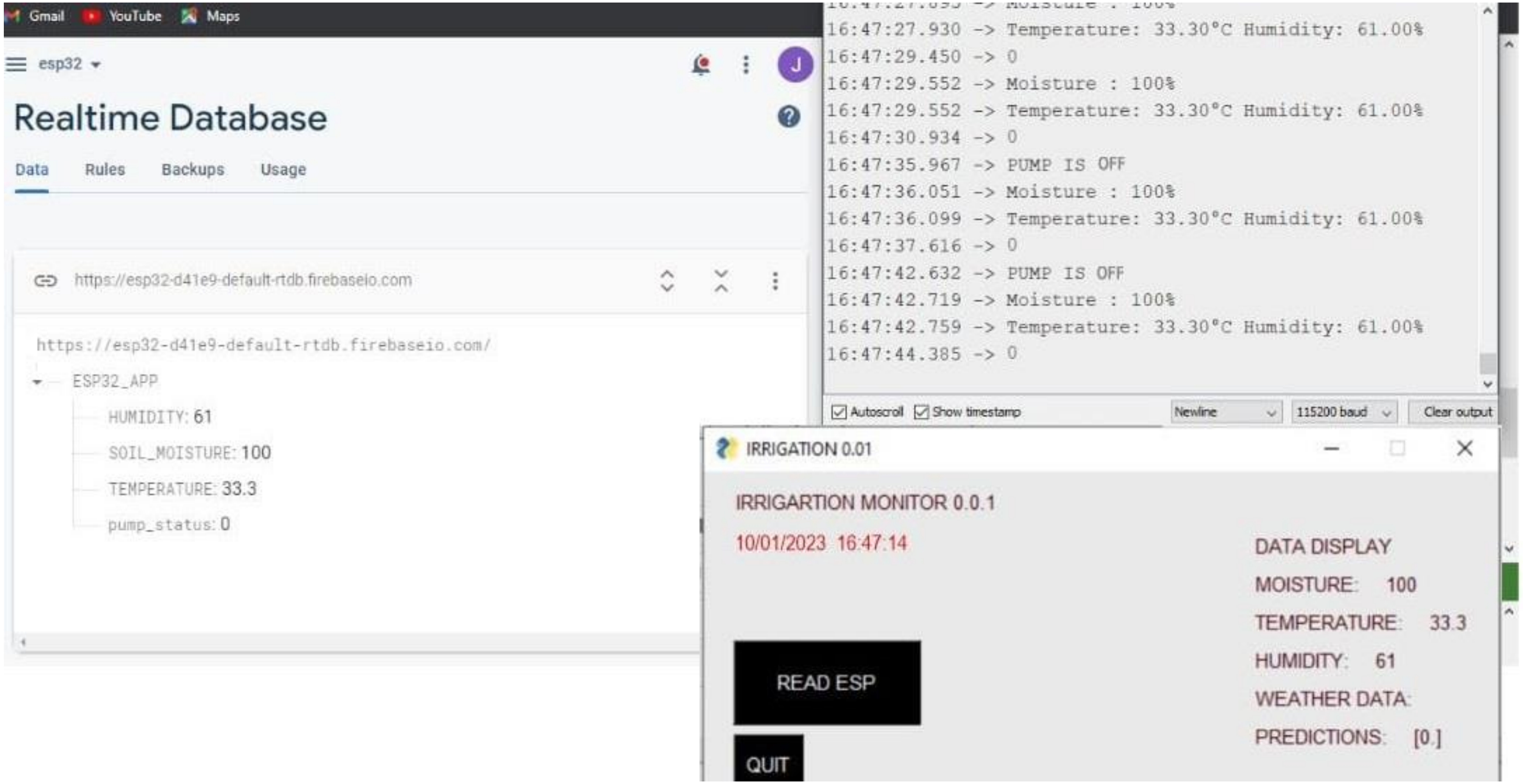



**Figure 4.5:** Result from Autonomous Irrigation System I

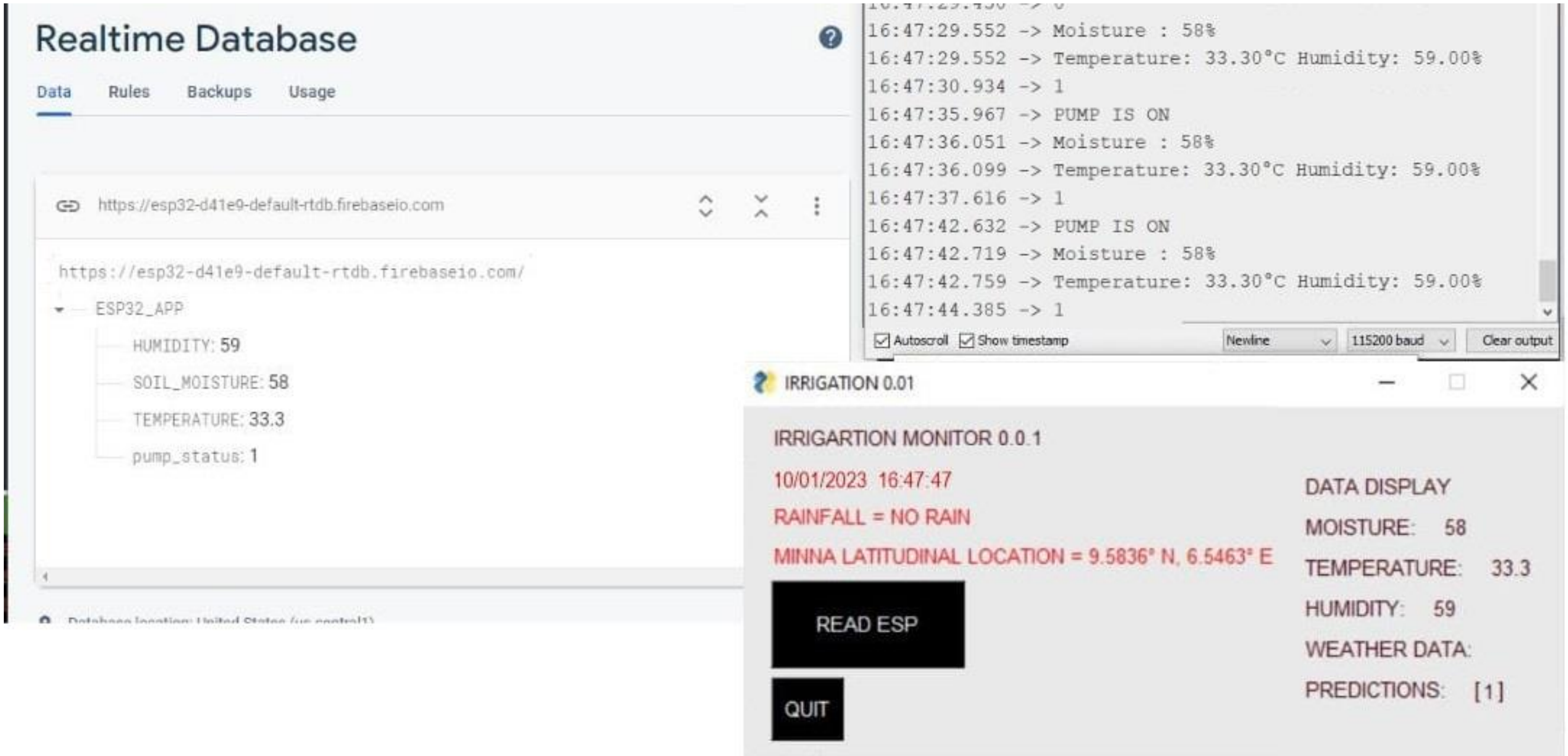



**Figure 4.6:** Result from Autonomous Irrigation System II

## 4.4 Discussion of Results

After applying various models of machine learning on the dataset, the prediction accuracy of SVM is 81.58%, kNN is 88.57%, Logistic Regression is 81.53%, and Decision Tree is 91.31%. Decision Tree was adopted for the training of the dataset.

From the results obtained as shown in Figures 4.5 and 4.6, it was seen how the processes from data collection to decision making was going on simultaneously without the manual input by the farmer. The continuous real-time data reading from the sensors is displayed in the second frames of Figure 4.5 and Figure 4.6. This data is transmitted at the same time to the Firebase cloud as seen from the first frame. The desktop app also accesses these values, run a machine learning algorithm on it and predict the output. A predicted output of 0 means the crop field is wet while 1 means the crop field is dry. This output is transmitted to the ESP32. The ESP32 further checks for the weather forecast from the weather API to determine whether there will be rain in 1 hour. The result shows there will be no rain in 1 hour and the predicted output reflected at the ESP32. It shows above that with the predicted output of 1, the pump status is ON while it remains OFF with a 0 predicted output.

# CHAPTER FIVE

# CONCLUSION AND RECOMMENDATIONS

## 5.1 Conclusion

The Autonomous Irrigation System met the objective to automatically irrigate the crop field without any manual input from the farmer. It is based on the technology of Internet of Things which is integrated with few sensors: temperature/humidity sensor and soil moisture sensor, coupled with real-time weather forecast to control the status of the farm field's soil. ESP32 along with all the sensors detects the current surrounding conditions like temperature, humidity, and soil moisture. These parameters coupled with weather forecast data were used to predict the status of the relay thus making it intelligent, weather-sensitive for any location and eliminating the manpower. The dataset was trained using four machine learning algorithms: decision tree classifier, support vector machine, logistic regression, and k-nearest neighbors. Logistic Regression, k-Nearest Neighbours, Support Vector Machine, and Decision Tree Classifier have prediction accuracy of 81.53%, 88.57%, 81.58%, and 91.31%, respectively. The Decision Tree Classifier was used to train the dataset for this study since it has the highest prediction accuracy. The machine learning and rainfall prediction worked as expected. In the meantime, these sensors are connected to the Internet via the Wi-Fi module. This interconnected activity is to give additional sensitivity to the irrigation system.

## 5.2 Recommendation

An Autonomous Irrigation System that incorporates rainfall prediction has been developed in this research with all the expected objective achieved. This research can further be designed for irrigating specific crops as water requirement for some crops are different.

## 5.3 Contribution to Knowledge

This research work developed a low-cost weather sensitive autonomous irrigation system that use water and electrical energy efficiently by making intelligent decisions using acquired real-time soil and weather forecast data. Data from the plant's surrounding was acquired and forwarded to the Firebase cloud in real-time using low-cost sensors and ESP32. An irrigation dataset was analyzed and trained using four machine learning algorithms where Decision Tree which achieved the highest accuracy of 91.31% was used to automate the process of irrigation. Rainfall prediction was incorporated with an online weather API service (openweathermap) which uses the GPS coordinate of the crop field to give weather sensitivity and intelligence to the irrigation process at any location.

## REFERENCES


*Accuracy and quality of weather data - OpenWeatherMap*. (n.d.). Retrieved June 30, 2021, from https://openweathermap.org/accuracy-and-quality

Aishwarya, T., Chaithra, M., Meghana, M., & Krishnan, R. (2017). *" Raspberry Pi and Arduino Based Automated Irrigation System ."* Visvesvaraya Technological University.

Arvindan, N., & Keerthika, D. (2016). *Experimental Investigation of Remote Control Via Android Smart Phone of Arduino-Based Automated Irrigation System Using Moisture Sensor*. 168–175.

Boansi, D., Tambo, J. A., & Müller, M. (2019). Intra-seasonal risk of agriculturally-relevant weather extremes in West African Sudan Savanna. *Theoretical and Applied Climatology*, *135*(1–2), 355–373. https://doi.org/10.1007/s00704-018-2384-x

Da Cruz, M. A. A., Rodrigues, J. J. P. C., Al-Muhtadi, J., Korotaev, V. V., & De Albuquerque, V. H. C. (2018). A Reference Model for Internet of Things Middleware. *IEEE Internet of Things Journal*, *5*(2), 871–883. https://doi.org/10.1109/JIOT.2018.2796561

*DHT11 Sensor*. (n.d.). Retrieved December 22, 2022, from https://components101.com/sensors/dht11-temperature-sensor

Dönmez, P. (2013). *Introduction to Machine Learning* (Vol. 19, Issue 2). https://doi.org/10.1017/s1351324912000290

Eisenhauer, D. E., Martin, D. L., Heeren, D. M., & Hoffman, G. J. (2021). *Chapter 1 Introduction to Irrigation* (pp. 1–9).

*ESP32*. (n.d.). Retrieved January 2, 2023, from https://components101.com/microcontrollers/esp32-pico-d4-wireless-sip

Goap, A., Sharma, D., Shukla, A. K., & Rama Krishna, C. (2018). An IoT based smart irrigation management system using Machine learning and open source technologies. *Computers and Electronics in Agriculture*, *155*(May), 41–49. https://doi.org/10.1016/j.compag.2018.09.040

*IoT Architecture - Detailed Explanation - InterviewBit*. (n.d.). Retrieved January 2, 2023, from https://www.interviewbit.com/blog/iot-architecture/

*IoT connected devices worldwide 2019-2030 | Statista*. (n.d.). Retrieved December 17, 2022, from https://www.statista.com/statistics/1183457/iot-connected-devices-worldwide/

*Irrigation Dataset | Kaggle*. (n.d.). Retrieved January 2, 2023, from https://www.kaggle.com/datasets/harshilpatel355/autoirrigationdata

*Irrigation Definition & Meaning | Dictionary.com*. (n.d.). Retrieved December 15, 2022, from https://www.dictionary.com/browse/irrigation

Jegathesh Amalraj, J., Banumathi, S., & Jereena John, J. (2019). A study on smart irrigation systems for agriculture using iot. *International Journal of Scientific and Technology Research*, *8*(12), 1935–1938.

Kamaruddin, F., Malik, N. N. N. A., Murad, N. A., Latiff, N. M. azzah A., Yusof, S. K. S., & Hamzah, S. A. (2019). IoT-based intelligent irrigation management and monitoring system using arduino. *Telkomnika (Telecommunication Computing Electronics and Control)*, *17*(5), 2378–2388. https://doi.org/10.12928/TELKOMNIKA.v17i5.12818

Karen, R., Eldridge, S., & Chapin, L. (2015). *The Internet of Things : An Overview* (Issue October).

Kirtana, R. N., Bharathi, B., Priya, S. K., Kavitha, S., Keerthana, B., & Kripa, K. (2018). Smart irrigation system using zigbee technology and machine learning techniques. *Proceedings of IEEE International Conference on Intelligent Computing and Communication for Smart World, I2C2SW 2018*, *Ml*, 78–82. https://doi.org/10.1109/I2C2SW45816.2018.8997121

Kissoon, D., Deerpaul, H., & Mungur, A. (2017). A Smart Irrigation and Monitoring System. *International Journal of Computer Applications*, *163*(8), 39–45.

Kohavi, R., & Provost, F. (1998). Glossary of Terms. *Machine Learning*, *103*(3), 239–248. https://doi.org/10.1023/A

*Machine Learning Processes*. (n.d.). Retrieved January 2, 2023, from https://www.educba.com/machine-learning-architecture/

Mitchell, T. M. (1997). Machine Learning. In *Deep Learning for Robot Perception and Cognition*. https://doi.org/10.1016/B978-0-32-385787-1.00011-7

Ogunti, E. (2019). IoT Based Crop Field Monitoring and Irrigation Automation System. *International Journal of Recent Technology and Engineering*, *6*(3), 124–129.

Ogunti, E. O., Akingbade, F. K., Segun, A., & Oladimeji, O. (2018). Decision support system using mobile applications in the provision of day to day information about farm status to improve crop yield. *Periodicals of Engineering and Natural Sciences*, *6*(2), 89–99. https://doi.org/10.21533/pen.v6i2.183

Oluwaseyi, A. (2017). The Prospects of Agriculture in Nigeria: How Our Fathers Lost Their Way - A Review. *Asian Journal of Economics, Business and Accounting*, *4*(2), 1–30. https://doi.org/10.9734/ajeba/2017/35973

Patel, K. K., Patel, S. M., & Scholar, P. G. (2016). Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies, Application & Future Challenges. *International Journal of Engineering Science and Computing*, *6*(5), 1–10. https://doi.org/10.4010/2016.1482

Putjaikal, N., Phusael, S., Chen-iml, A., & Phunchongharnl, P. (2016). A Control System in an Intelligent Farming by using Arduino Technology. *2016 Fifth ICT International Student Project Conference(ICT-ISPC)*, 4–7.

Rajalakshmi, P., & Mahalakshmi, D. (2018). IOT Based Crop-Field Monitoring And Irrigation Automation. *2018 2nd International Conference on Inventive Systems and Control (ICISC)*, *Icisc*, 478–483.

*Reinforcement Learning*. (n.d.). Retrieved January 2, 2023, from https://www.spiceworks.com/tech/artificial-intelligence/articles/what-is-reinforcement-learning/

Remalatha, R., Deepika, G., Dharanipriya, K., & Divya, M. (2016). *Internet of Things(IoT) Based Smart Irrigation*. *2*(2), 128–132.

Russell, S. J., & Norvig, P. (2010). Artificial intelligence: A Modern Approach. In *2010 The 2nd International Conference on Computer and Automation Engineering, ICCAE 2010* (Third Edit, Vol. 4). Pearson. https://doi.org/10.1109/ICCAE.2010.5451578

Shirsath, P. D. O., Kamble, P., Mane, R., Kolap, A., & More, P. R. S. (2017). IOT Based Smart Greenhouse Automation Using Arduino. *International Journal of Innovative Research in Computer Science & Technology*, *5*(2), 234–238. https://doi.org/10.21276/ijircst.2017.5.2.4

Simon, P. W. and. (2013). Too Big to Ignore : The Business Case for Big Data. *Journal of Chemical Information and Modeling*, *53*(9), 1689–1699.

Singh, G., Sharma, D., Goap, A., Sehgal, S., Shukla, A. K., & Kumar, S. (2019). Machine Learning based soil moisture prediction for Internet of Things based Smart Irrigation System. *Proceedings of IEEE International Conference on Signal Processing,Computing and Control*, *2019-Octob*, 175–180. https://doi.org/10.1109/ISPCC48220.2019.8988313

*Supervised Machine learning - Javatpoint*. (n.d.). Retrieved January 2, 2023, from https://www.javatpoint.com/supervised-machine-learning

*Tree Based Algorithms | Implementation In Python & R*. (n.d.). Retrieved June 30, 2021, from https://www.analyticsvidhya.com/blog/2016/04/tree-based-algorithms-complete-tutorial-scratch-in-python/

*Unsupervised Machine learning - Javatpoint*. (n.d.). Retrieved January 2, 2023, from https://www.javatpoint.com/unsupervised-machine-learning

Wanvoeke, J., Venot, J. P., De Fraiture, C., & Zwarteveen, M. (2016). Smallholder Drip Irrigation in Burkina Faso: The Role of Development Brokers. *Journal of Development Studies*, *52*(7), 1019–1033. https://doi.org/10.1080/00220388.2015.1107048

*What is a Sensor? Different Types of Sensors with Applications*. (n.d.). Retrieved December 22, 2022, from https://www.electricaltechnology.org/2018/11/types-sensors-applications.html

Williams, J. F., Roberts, S. R., Hill, J. E., Scardaci, S. C., & Tibbits, G. (1990). IPM: Managing water for weed control in rice. *Managing Water for Weed Control in Rice*, *44*(5), 7–10. https://doi.org/10.3733/ca.v044n05p7

Yuvaraju, M., & Priyanga, K. J. (2018). An IOT Based Automatic Agricultural Monitoring and Irrigation System. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *4*(5), 58–65.