UNIVERSITY of RWANDA
COLLEGE OF SCIENCE AND TECHNOLOGY

ACEIoT
Website: www.aceiot.ur.ac.rw
Mail: aceiot@ur.ac.rw

Smart Soil Quality Assessment for Data Driven Fertigation Using Internet of Things and Deep Learning

By:

Judith BIZIMANA
Reference Number: 220000087

A dissertation presented to the African Centre of Excellence in Internet of Things (IoT), University of Rwanda as partial fulfilment of the requirements for the Master's degree in Internet of Things-Embedded Computing Systems.

Supervised by: Dr. Kayalvizhi Jayavel

Dr. Alfred UWITONZE

November, 2021

Student Declaration

I hereby declare that this dissertation is my original work and has not been submitted for any other degree or professional qualification.

Judith BIZIMANA

220000087

Signature:

Date: 30th November, 2021

Bonafide Certificate

This is to certify that the project entitled “Smart Soil Quality Assessment for Data Driven Fertigation Using Internet of Things and Deep Learning” is a record of original work done by Judith BIZIMANA with registration number 220000087 in partial fulfillment of the requirement for the award of masters of sciences in Internet of Things in the College of Science and Technology, University of Rwanda, the Academic year 2020/2021

This work has been submitted under the guidance of Dr. Kayalvizhi Jayavel and Dr. Alfred UWITONZE

Main Supervisor: Dr. Kayalvizhi Jayavel

Co-Supervisor: Dr. Alfred UWITONZE

The Head of Masters and Training

Dr. James Rwigema

Signature: ………………………………

Date: ……………………………………

Acknowledgments

I first thank the Almighty God for the good health, resources and for allowing me to undertake this degree. I thank my beloved Husband and Children for their constant support and encouragement that lightened the load.

Special appreciation goes to my supervisors Dr. Kayalvizhi Jayavel and Dr. Alfred UWITONZE for their support and guidance. It is through their efforts that I have been able to undertake this study. They have constantly given me the skills, knowledge and direction that made this research successful out of their busy schedules. I wish to thank African Center of Excellence in Internet of Things, College of Science and Technology, University of Rwanda, especially the ACEIoT authorities for allowing me to pursue this Masters and for the skills they gave to me.

Special thanks also go to all my friends and colleagues for being there when needed and who helped me through my master's studies journey. This would have been difficult without the support of those around me helping in different ways. I am indeed forever grateful.

May God bless you all.

ABSTRACT

Internet of things (IoT) in conjunction with artificial intelligence techniques are increasingly being used in different sectors, particularly in agriculture ~~it~~ is used to satisfy the need of increasing farm productivity to meet the rapidly growing demand for food due to rapid population growth. Ensuring data driven solutions is an essential step toward increasing productivity while at the same time enhancing utilization of resources. There is a need to ensure efficient usage of both water and fertilizer to conserve the environment and reduce costs. Even though attempts have been made to come up with smart irrigation and fertilization solutions, there is still a need to incorporate latest sensing and data analytic technologies. This study therefore presents a prototype for an Internet of Things (IoT) and a deep learning driven solution for smart fertigation. Soil moisture and soil nutrient data are collected in real time by sensors in a farm, data is then processed on an Advanced RISC Machine (ARM) Cortex 4 based Arduino Nano 33 BLE sense and a deep learning model used to predict when to irrigate. In case deficiencies in soil nutrients are detected, an alert is sent to the farmer via Global System for Mobile communication (GSM) module to add the needed fertilizer to the water. The irrigation valve is automatically actuated based on the predictions and from time to time. Upon successful implementation, this system will reduce water and fertilizer wastages while increasing productivity.

Keywords: IoT, Smart farming, smart irrigation, deep learning, smart fertilization;

LIST OF ACRONYMS

AI- Artificial Intelligence

BLE- Bluetooth Low Energy

CSV-Comma Separated Values

DSS- Decision Support System

FAO- Food and Agriculture Organization of the United Nations

GND- Ground

GPRS- General Packet Radio Service

GSM- Global System for Mobiles

ICT-Information Communication Technology

IDE- Integrated Development Environment

IoT – Internet of Things

LCD- Liquid Crystal Display

LDR- Light Dependent Resistor

LED- Light Emitting Diode

LED- Light Emitting Diode

ML- Machine Learning

NN- Neural Network

NPK- Nitrogen, Phosphorous and Potassium

SGD- Sustainable Development Goals

SVM- Support Vector Machine

LIST OF FIGURES

Fig 3.1: Research steps

Fig 3.2: Map showing data collection area

Figure 3.3: machine learning steps

Figure 3.4: Tensor Flow Lite

Fig. 4.1: System block diagram

Fig 4.2: Arduino Nano BLE Sense

Fig. 4.3: Soil NPK Sensor

Fig 4.4: Soil Moisture Sensor

Figure 4.5: GSM Module

Fig. 4.6. Mini Water Pump

Figure 4.7: Relay

Figure 4.9: MAX485 Connection pins

Figure 4.10: Connected of the pump and Arduino

Figure 5.1: Calibration Graph

Figure 5.2: Soil conditions

Figure 5.3: Effects of optimization

Figure 5.4: Accuracies achieved by using different data and algorithms

Figure 5.5: Accuracy by number of epochs

Figure 5.6: System prototype

Figure 5.7: Prediction output

Figure 5.8: Moisture sensor reading

TABLE OF CONTENTS

Student Declaration ii

Bonafide Certificate iii

Acknowledgements iv

ABSTRACT v

LIST OF ACRONYMS vi

LIST OF FIGURES vii

CHAPTER 1 1

INTRODUCTION 1

1.0 Introduction 1

1.1 Problem Statement 3

1.2 Aims and Objectives 4

1.2.1 Aims 4

1.2.2 Specific Objectives 4

1.3 Hypothesis 4

1.4 Research Questions 4

1.5 Study Scope 5

1.6 Significance of the Study 5

1.7 Organization of the Document 5

CHAPTER 2 6

LITERATURE REVIEW 6

2.1 Smart Irrigation Systems 6

2.2 Smart Fertilization Systems 7

2.3 Use of Artificial Intelligence in Irrigation and fertilization 9

CHAPTER 3 11

RESEARCH METHODOLOGY 11
3.1 Research Steps 11
3.2 Data Collection 12
3.3 Machine Learning Steps 13
3.4 Software Tools 15
3.5 System Development Model 16
CHAPTER 4 18
SYSTEM ANALYSIS AND DESIGN 18
4.1 System Analysis 18
4.3 System Hardware Components 20
4.4 System PDL 25
4.5 Deep Learning Model design 26
4.6 System Setup 28
CHAPTER 5 31
SYSTEM RESULTS, ANALYSIS AND DISCUSSSIONS 31
5.1 Data Collection Sensor Calibration 31
5.2 Deep Learning Model Evaluation 32
5.3 System Prototype results 36
5.4 Comparison to Existing Solutions 39
CHAPTER 6 40
CONCLUSION, RECOMMENDATIONS, AND FUTURE WORKS 40

CHAPTER 1

INTRODUCTION

1.0 Introduction

In Rwanda, just like other African populations, the majority of rural households, approximately 96%, rely on agriculture as a direct and only source of income [1]. However, low productivity and resource wastages are increasingly being witnessed. In arid and semi-arid areas, a concern that is consistent among farmers of different crops and animals is the efficiency in water usage management. One way of ensuring the efficient management of this scarce resource is to automate the irrigation process using latest technologies. In addition to the concern of water wastages, the blind application of fertilizers leads to wastages as well. In an attempt to solve these and other challenges, Government of Rwanda has put in place many policies to improve the development of this sector for example the ICT4Ag (ICT for Agriculture) strategy with a mission to provide a conducive environment for the development, adoption and use of ICT [2]. The use of ICT in Agriculture [3] is one way of reaching a large number of people and can help ensure accelerated productivity and increased efficiency in the agricultural sector. With ICT farmers and other stakeholders can be provided with the needed and appropriate information on time through the development of webpages and another interface through which such information can be accessed. Farmers will also be able to improve their skill and knowledge through ICT driven learning programs. This will also lead to improved access to information and job opportunities.

Internet of Things (IoT) [4] and Machine Learning (ML) [5] provide capabilities that can be exploited in enhancing data driven farming a concept referred to as smart farming. With Smart farming traditional agricultural practices are replaced by the use of automated management systems and equipment. Smart agriculture [6] combines information and communication technology (ICT) and the emerging technology of the Internet of Things (IoT) and to improve the technologies use in agricultural production and to enhance the optimization of different management models. This can in the long run lead to reduced usage of agricultural resources and thus increase the productivity in this sector. With IoT various sensors and devices are installed in the farms to monitor various soil and environmental parameters with the collected near real-time data being sent to the internet for storage and visualization[7]. The farmers have capabilities of viewing the conditions of the farm irrespective of their positions. The collected data can be integrated with data from other sources and analysed by the farmers so as to make quick informed decisions. This can further be improved by using artificial intelligence (AI) for predictions and automation of functions [8].

IoT has been used to improve irrigation systems and to ensure data driven fertilization as stated in [9]. For example, an automated irrigation system in which the soil moisture condition is monitored and maintained at desired levels by the use of an automatic watering system [10], a Raspberry Pi is used in an IoT based smart irrigation solution. In this system a webcam is used for monitoring plan growth and the controlling of the watering system done [11], The presence of soil nutrients is monitored and analysed based on the principle of colorimetric. Custom designed NPK sensors are used to collected data from the field with the collected data being sent to Google cloud for storage and visualization. To determine deficiencies in the sensed data a fuzzy logic inference system is used. Such solutions show the capabilities of IoT which can further be exploited. However, there is a need to also use latest AI techniques to improve efficiency thus the use of deep leering is presented in this study. Deep learning (DL) was selected due to the ability of DL algorithms to learn high-level features from data. This capability makes DL perform better as compared to other traditional Machine Learning (ML) algorithms [12].

This study, therefore, presents a prototype for an IoT and a deep learning driven solution for smart fertigation. Soil moisture and soil nutrient data are collected in real time by sensors in a farm, data is then processed on an ARM Cortex 4 based Arduino Nano 33 BLE sense and a deep learning model used to predict when to irrigate. In case deficiencies in soil nutrients are detected an alert is sent to the farmer via GPRS/GSM module to add the needed fertilizer in the water. The irrigation valve is automatically actuated based on the predictions and from time to time. Upon successful implementation this system will reduce water and fertilizer wastages while increasing productivity.

The data used for training the machine learning model was collected by STES group a commercial IoT company in Rwanda that offers smart irrigation for six months. This presented solution is seen as an improvement to the existing system that is based on threshold values which does not take into account the changes in soil quality over time.

1.1 Problem Statement

Agriculture is reported to be the main economic activity in Rwanda by FAO [13] It is estimated that over seventy percent of people in Rwanda are engaged in Agriculture with over seventy-two percent of citizens who work being employed in the Agricultural Sector. In Rwanda, Agriculture contributes to 33% of the national GDP and has been instrumental to the growth of the GDP and a rate of 7% since the year 2014. The major exports are coffee and tea while, the most produced crops are sweet potatoes cassava, beans, maize, plantains, and potatoes. Some major agricultural exports from Rwanda to other East African countries are cassava flour, dry beans, rice, maize flour, potatoes, poultry maize, and live animals [13].

A major problem reported in Rwanda is that in a majority of irrigated farms the systems are operated manually. Current technologies can be used to develop automatic irrigation systems to replace the traditional irrigation methods. In a manually operated system a farmer is expected to manually turn on and off the motor so as to irrigate, this most of the time leads to wastages of electricity and power. An IoT based solution can be used to overcome the problem by automatically turning ON and OFF the motor based on monitored soil conditions [14]. With such a solution the operation of the motor will mainly depend upon the moisture condition, soil condition and the conditions of the atmosphere. In attempts to measure the above parameters different sensing technologies can be exploited for example; soil temperature sensors, soil humidity sensors and soil moisture sensors. So as to better manage farms soil conditions can be monitored in real-time and regular updates sent to the could for analysis and visualization [9].

In addition, FAO reports [13] that low levels of productivity for both crops and livestock due to low input use, poor production techniques and inefficient farming practices. Farmers apply fertilizes blindly and sometime do not use them when needed. This can be attributed to the lack of soil fertility monitoring mechanisms. Soil fertility sensors can be used to assess the soil fertility in real time and guide the farmers accordingly.

Thanks to the advancement of new technologies, the use of IoT and AI have been exploited in solving the problem. Such technologies are used to automate the soil quality assessment process so as to reduce the the intervention of farmers, different sensors like soil humidity sensor, soil NPK sensor, soil PH sensor, soil moisture sensor, and soil temperature sensors among others, are used and the sensors are connected to a microcontroller units (MCU) in which data is processed and other parts of the system actuated accordingly [15]. Such systems automatically control water system for irrigation land and also send alerts to farmers on the current soil fertility levels. However, the existing solutions are mainly based on threshold for example the BAZAFARM [16] in Rwanda which are not very effective for solutions that monitor parameters that change overtime like soil conditions. In addition, the solutions are based on a cloud dependant architecture which also lead to increased costs for the farmers and can also not be deployed in areas with connectivity challenge. To overcome this challenges, we therefore propose the use of our IoT and deep learning based solution that aims to solve the mentioned challenges.

1.2 Aims and Objectives of the Study

1.2.1 Aims

The aim of this thesis research is to design and prototype an IoT and deep learning based smart fertigation system so as to enhance data driven farming in Rwanda.

1.2.2 Specific Objectives

The specific objective that guided the study are:

i. To design an IoT system for an automatic irrigation based on real time soil parameters.
ii. To train a deep learning model for a smart irrigation system.
iii. To put in place an online cloud database for storing data on soil moisture and soil nutrient collected from a farm by an IoT device.
iv. To prototype an IoT and AI driven smart fertigation system.

1.3 Hypothesis

Our hypothesis is that the integration of IoT and AI can increase the efficiency of smart fertigation system and thus further reduce on wastages and costs.

1.4 Research Questions

The research question that the study addresses are;

i. What are the techniques and tools used in soil quality assessment?
ii. Which are the the existing solutions used for smart irrigation and soil fertility prediction?
iii. Are there opens source IoT and AI technologies that can be used in a smart fertigation solution?
iv. Which is the best way to design and prototype an IoT and AI driven smart fertigation system?

1.5 Study Scope

Due to time and resource constraints the prototype was tested in a lab environment. The data used for training the AI models will be based on historical data collected by STES group company in Rwanda.

1.6 Significance of the Study

This thesis research is a contribution to the existing knowledge, most of the studies on smart irrigation and fertilization do not use deep learning algorithms that can run on a local device without the need of connecting to the cloud as presented in our study. Agricultural authorities will also be able to use the collected data for decision making and planning.

The implementation of the system will help solve the existing problems and reduce wastage of water and fertilizers. This will also lead to improved production and reduced costs.

The system will also contribute towards the achievement of Sustainable Development Goals (SDGs): (i) Goal 1, no poverty as Agriculture is one of the major sources of income in many African countries, the famers will be able to produce more hence better returns; (ii) Goal 2, improved production will ensure farmers have enough to sell and eat reducing hunger.

1.7 Organization of the Document

The rest of this thesis report is organized as follows: In the next chapter related literature is reviewed, the methodology for the study is presented in chapter 3, Chapter 4 presents the system design and analysis; Chapter 5 presents the System Results, analysis and discussion, in Chapter 6 a conclusions are drawn and recommendations given. Lastly the references and the appendix are outlined.

CHAPTER 2

LITERATURE REVIEW

This section outlines a state of the art analysis of existing related solutions. First smart irrigation systems are reviewed followed by a review of smart fertilization systems and lastly an analysis of how artificial intelligence is applied to improve such systems.

2.1 Smart Irrigation Systems

To begin with, a system for automating and monitoring irrigation consisting of soil moisture sensors, soil temperature sensor, a raspberry pi as the MCU and a water pump is proposed. In this solution smart phones are used to communicate. The solution considers plants and the amount of water they require at different stages of growth. Based on the calculated water requirement the plants are irrigated accordingly [17] . Just by irrigating based on the water requirements for the plants alone may not mean that optimal levels of required moisture is reaches. Some water will be lost in the soil by environmental factors. The use of smart phone for communication is also not appropriate for remote locations where ownership and connectivity are a challenge hence the need for improvements.

Secondly, a smart irrigation system has been developed [18]. In the solution sensors including water level sensor, soil moisture sensor, and soil temperature sensors are connected a MCU. The MCU receives data from the sensors on the underlying atmospheric and weather conditions, pre-process the data and based on the information turns on the relay and in turn automatically actuate the water pump. This solution uses threshold values to actuate for irrigation. This does not take into account the trends and gradual change of soil properties.

Thirdly, a system for irrigation smart farms that remotely monitors and controls irrigation drips using a mobile phone in a wireless sensor network (WSN) is proposed. In this solution the sensing devices communicate to the base station via ZigBee. A web based user interphase is used visualization of data from the server where real-time sensed data is stored [19]. The use of mobile phones is a challenge for remote location in Africa necessitating the need for improvements of this solution.

Last but not least, an automated irrigation system has been proposed [20]. In the solution existing soil and water conditions are monitored by soil moisture sensors, soil pH sensors, soil humidity sensor, water pressure sensor. The collected data from the sensors are displayed on a Liquid Crystal Display (LCD). For communication between a farmer and the field devices a GPRS/GSM module is used. The farmers get information on the current status of their farms either through an sms or a customized webpage. This solution is based on threshold values that are not recommended for time series data hence the need to use AI.

Even though these solutions are an improvement from the manual irrigation processes. There is also a need to integrate machine learning to enable predictions for a more efficient data driven process thus the need for this study.

2.2 Smart Fertilization Systems

These systems are mainly focused on ensuring fertilizers are applied only when needed and in right amounts. First, an intelligent system that allows farmers to get relevant information on climatic changes as monitored by IoT devices with an aim of improving the fertilization of the soil is presented. Mobile phones and websites are used to handle the information [21]. This solution can help in guiding the farmers in the usage of fertilizers it however does not integrate this to an irrigation process to ensure maximum utilization of resources.

Secondly, in a related solution data is collected from the farm by an IoT device and sent to a cloud based database for storage. Big data analytics is applied on the collected data to draw meaning in relation to the crop fertilizer requirements, market requirements, stock requirement etc. Data mining techniques are applied to do the predictions and the information sent to farmers via a mobile application [21]. The use of a mobile app may be challenging to rural farmers hence the need for alternative notification methods. Training on the cloud also means additional connectivity and energy costs.

Moreover, so as to improve yields in agriculture and effectively schedule irrigation and fertilization on the basis of forecasted weather, existing environmental conditions and crop requirements a generic IoT framework is proposed. In the solution the design of affordable fertilization and irrigation system is targeted by ensuring that fertilizers are directly fed to the roots of the plants and thus reduce on the amount of fertilizer needed to reduce on costs and soil health. The farmers are able to get information in their local languages via a mobile phone [22]. The use of a mobile application in this solution in this solution makes it challenging to implement in a rural setting.

In addition, a novel method that uses Wireless Sensor Network and Internet of Things in Farming is presented. Soil humidity sensor and soil Moisture sensor ae used to monitor soil properties with data being stored in an IoT server. Based on the real-time soil parameters a solenoid valve is switched ON and OFF for drip irrigation. In an attempt to avoid insufficient or overdose in the application of fertilizers, a nutrient quantitative analysis is done based on requirments. It also alerts the user by sending SMS (Short Messaging Service) through GSM to the user on fertigation date and pesticides spraying date [23]. This solution applies the use thresholds that does not take into account a progressive change in soil parameters. Moreover, the solution does not integrate soil fertility sensors which are important in determining the soil properties.

Lastly, a Light Emitting Diode and a Light dependent resistor are used to design a novel NPK sensor for an IoT based solution. Monitoring and analysing of the nutrients present in the soil is done through the principle of colorimetric. The collected sensed data from different fields is sent to a Goggle cloud database for storage and fast retrieval when needed. So as to detect a deficiency in a given nutrient, fuzzy logic is applied [23]. This solution does not integrate to an irrigation system and with the customized sensor it is not easy to tell the exact amounts of NPK in the soil hence the need for improvement.

Such solutions show the potential IoT and machine learning in fertigation. However, there is a need to not only notify the farmers via a cheap solution but also use more advanced ML techniques so as to predict when to apply the fertilizers and integrate the process to the irrigation function so as to reduce wastages.

2.3 Use of Artificial Intelligence in Irrigation and fertilization

Different Artificial Intelligence (AI) techniques have been used in improving irrigation and fertilization efficiency. First, an IoT based agricultural application Decision Support System (DSS) model is proposed. This solution leverages the analysis of smart watering equipment data using deep analytics with an aim of improving water usage and developing field productions in the agricultural fields. The analysed data is collected from the thing speak cloud platform. An evaluation and demonstration of the efficiency of the proposed model was done through the use of machine learning prediction model approaches. So as to also show the efficiency of the system, a comparison of the proposed model with other classifiers was done and the result showed the efficiency of the system [23].

In another solution, the system uses a pH Meter, DHT11 and Soil Moisture sensors, to obtain soil humidity, soil moisture, and soil acidity (pH) data. XBee is used in the data acquisition process and the collected data forwarded to a gateway for filtering. After that the gateway will send data to the hosting server that will run the fuzzy algorithm to govern the actuator to be able to do watering automatically [24]. Similarly, a Fuzzy logic controller is used to compute input parameters (e.g. soil moisture, temperature and humidity) and to produce outputs of motor status. In addition, the system also switches off the motor to save the power when there is an availability of rain and also prevents the crop using panels from unconditional rain [25]. Also, an Internet of Things based irrigation system that works at reducing the frequency of irrigation while increasing the rate of production through the use of fuzzy logic is proposed [26].

An expert system using AI has been implemented in using the Naive Bayes method and machine learning which operates on sensor data captured in agriculture. This work was useful in monitoring the quality of fertilizer, pesticides and the amount of water to be irrigated in the crops [27]. In another solution, an IoT device is used to sense the agricultural data and it is stored into the Cloud database. Cloud based Big data analysis is used to analyze the data fertilizer requirements, analyse the crops, market and stock requirements for the crop. Then the prediction is performed based on data mining technique which information reaches the farmer via mobile app [28].

In addition, various calculations and channels are created to gain and handle the hued pictures of the dirt examples. These created calculations are utilized to separate various highlights like tone, surface, and so on diverse soil types like red, dark, dirt, alluvial, and so on are thought of. The grouping utilizes Support Vector Machine, AI method. SVM looks to correct a perfect hyper plane between the classes and uses simply a bit of the readiness tests that lie at the edge of the class transports in feature space (support vectors) [29]. Lastly, a proposal is presented that targets to develop a low cost intelligent system for smart irrigation. It uses IoT to make devices used in the system to talk and connect on their own, with capabilities like: admin mode for user interaction, one-time setup for irrigation schedule estimation, neural based decision making for intelligent support and remote data monitoring [30].

Due to the increasing availability of labeled datasets there is a move to deep learning methods for more accurate prediction systems that can lead to an improvement to the solutions. This study therefore proposes the use of deep learning based models. The study also explores pruning and quantization techniques so as to make the models lighter to run on embedded devices.

CHAPTER 3

RESEARCH METHODOLOGY

The methods, tools and processes and steps undertaken in the research are outlined in this chapter. The research steps are first presented followed by the AI model training steps and lastly the selected system development method used in developing the prototype.

3.1 Research Steps

The research process began in the month of January 2021 with a review of related literature in an endeavour to identify a gap for further study. After an idea of a possible topic was developed and a further literature review and the writing of a research proposal done. The research proposal was presented and approved in March 2021 there after the research process proceeded as presented in figure 3.1

Fig 3.1: Research steps

3.2 Data Collection

Due to the limited time data used for the study was collected in collaboration with STES group a commercial company in Rwanda that offers smart farming solution. The data was collected for a period of 6 months from March 2021 to September 2021, of interest was soil moisture data and when the crops were irrigated. Microsoft excel was used to format the data and remove fields that were not needed for our solution.

This data was collected from KABOKU -KAGITUMBA Irrigation scheme. Kagitumba irrigation scheme where 35 devices are installed in about 70ha with 6pivots for irrigation. Figure 3.2

Fig 3.2: Map showing data collection area

3.3 Machine Learning Steps

The machine learning steps followed the normal steps undertaken in any machine learning algorithm. Figure 3.3 shows the steps

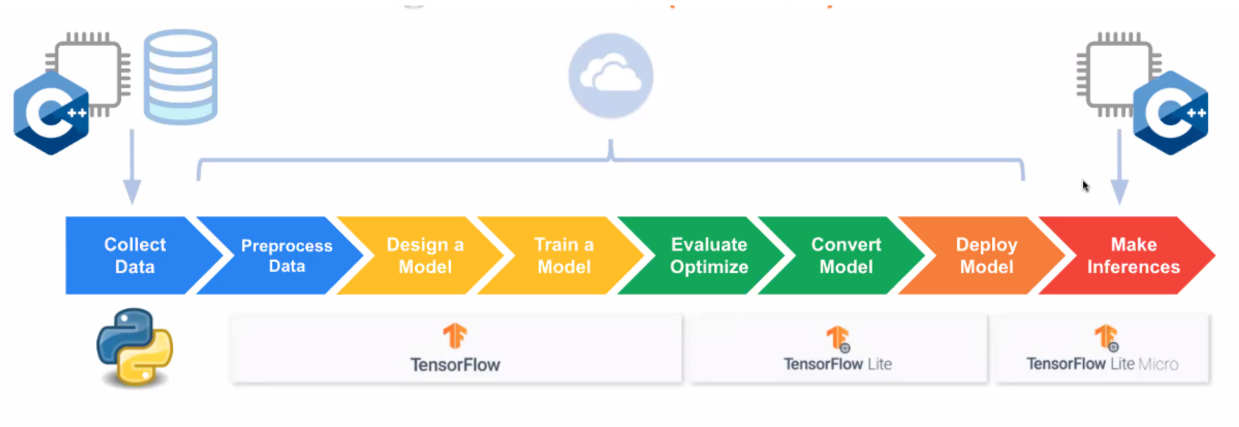

Figure 3.3: machine learning steps

A. Data Collection

The machine learning steps began with data collection. The quality and quantity of data determined how accurate the model would be. Data was collected for a period of 6 months to ensure there was enough data for training. The sensors were also calibrated from time to time to ensure quality was maintained through the process.

B. Data Pre-processing

The collected data was cleaned in preparation for training. Fields that were not needed were deleted, dealt with missing values, corrected errors and removed duplicates. The data was the converted into JSON format and uploaded into the cloud based machine learning platform. The data was also separated into validation set and training sets. The data was the pre-processed so as to generate features for training.

C. Model Design

After pre-processing the machine learning mode was designed, the inputs to the model training were the soil moisture level and soil temperature raw features of the data were selected and a

Keras Neural Network selected for training the model with the expected output being a classification as to whether the is a stress condition in the soil or ideal condition

D. Model Training

The model was then trained. At this stage different number of epoch, dense layers and learning rates were experimented till the optimum training parameters were reached. The on device resources needed by the model were also tested. This step also included hyperparameter tuning, used to tune model parameters for improved performance.

E. Evaluation and Optimization

The test data was used to evaluate the performance of the model on unseen data. This unseen data is meant to be somewhat representative of model performance in the real world, but still helps tune the model (as opposed to test data, which does not). The model was also optimized for performance in an embedded device

F. Model Conversion

After evaluation the model was converted into a tiny machine learning model that can run on an embedded device in readiness for deployment.

G. Make Inferences

Using further (test set) data which had, until this point, been withheld from the model (and for which class labels are known), were used to test the model in both the cloud environment and on the embedded device; a better approximation of how the model will perform in the real world.

3.4 Software Tools

The following software tools and platforms were used in the study

A. Arduino IDE

The open-source Arduino Software (IDE) [31] makes it easy to write code and upload it to the board. This software can be used with any Arduino board.

B. Tensor Flow Lite

Tensor Flow Lite [32] is an open-source, product ready, cross-platform deep learning framework that converts a pre-trained model in Tensor Flow to a special format that can be optimized for speed or storage. This will be used in training and deployment of the prediction model for irrigation. Figure 3.4 give the steps in the working of tensor flow light

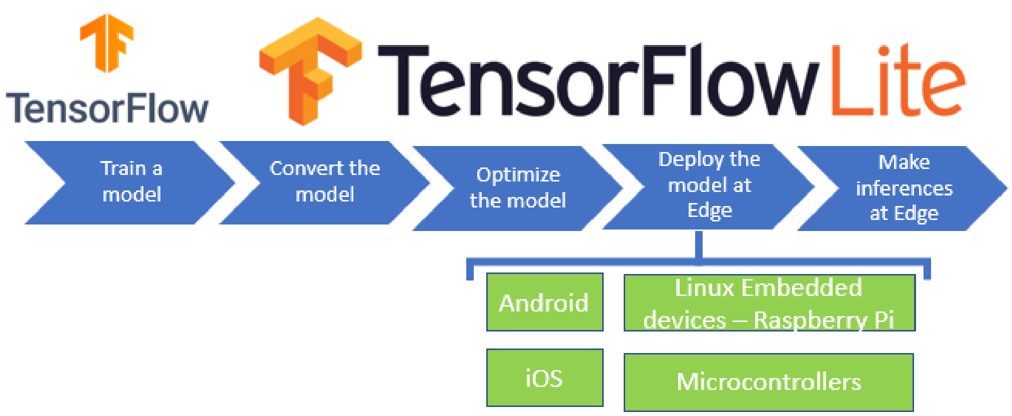

Figure 3.4: Tensor Flow Lite

C. Things Speak

ThingsSpeak [33] is an IoT analytics platform service that allows you to aggregate, visualize, and analyze live data streams.

3.5 System Development Model

The Prototype model was selected as the prototype development model. The basic idea in Prototype model is that instead of freezing the requirements before a design or coding can proceed, a throwaway prototype is built to understand the requirements. This prototype is developed based on the currently known requirements.

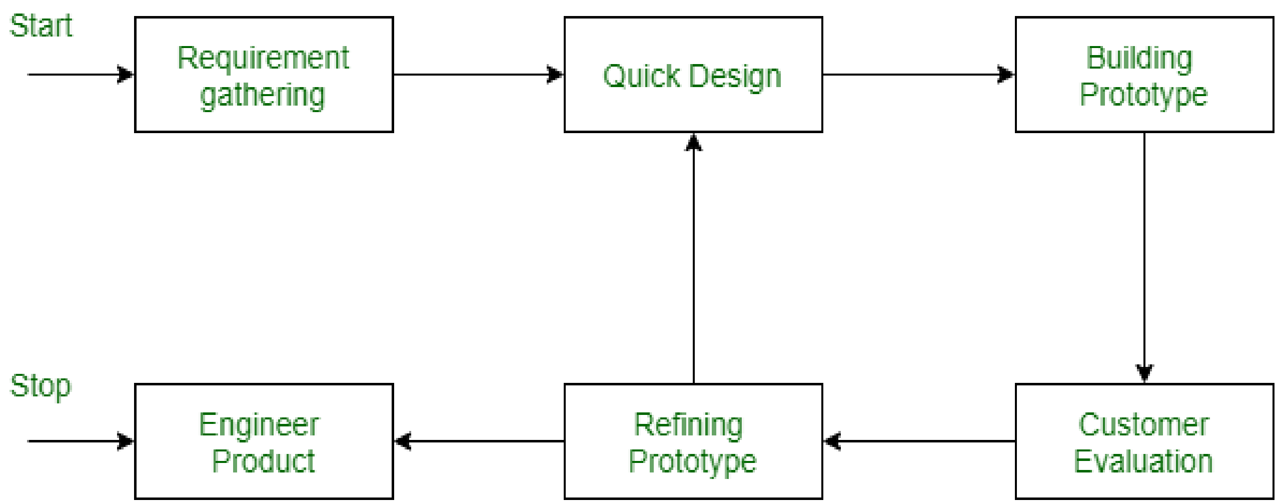

Figure 3.5: Prototype model

Advantages of Prototype model:

- Users actively participate in system development.
- The users can get a better understanding of the system functionalities.
- It is easy to detect error early enough during the development cycle.
- Quick user feedback is presented from time to time hence better solutions developed.
- It is easy to identify missing functionalities during development.
- It is easy to identify confusing and difficult functions.
- Validation of requirements and the Quick implementation of, incomplete, but functional, application possible.

Disadvantages of Prototype model:

- Building a system by implementation and repairing can be involving.
- Scalability beyond the initial plans functionalities are added.
- Incomplete application.
- Incomplete or inadequate problem analysis.

CHAPTER 4

SYSTEM ANALYSIS AND DESIGN

In this chapter the design for the machine learning model and the embedded system are presented. The first section shows the system level design and system components. This is followed by the design of the deep learning model.

4.1 System Analysis

This subsection gives an analysis of the proposed solution. The functional and non-functional requirements of the system are presented.

A. Functional Requirements

The functional requirements include the product features that must be included to enable the system meet its objectives. These include;

i. The system should be able to collect real-time data from the field on soil moisture, soil NPK and soil Temperature.
ii. The system should be able to predict when to irrigate or not to irrigate based on the soil moisture and temperature readings.
iii. The system should be able to automatically control the water pump based on the prediction of whether to irrigate or not.
iv. The system should be able to transmit the data collected to a cloud platform for future analysis.
v. The system should be able to send an alert via gsm in case fertilizer levels go below the recommended minimums.

B. Non Functional Requirements

The non-functional requirements included quality attributes that affect the behaviour of the system.

i. The system should be available with all working functionalities 98% of the time.
ii. The system should be easy to install and use by all stakeholders
iii. The system should be able to work consistently without failure for 5 years

iv. The should be a possibility of adding additional functionalities without affecting the working of the system
v. The system should be able to operate at minimum power 80% of the time
vi. The system should have mechanisms for ensuring data security and privacy
vii. In case of failure there should be mechanisms for a quick recovery
viii. The system should be able to meet the regulatory requirements of the country

4.1 System Architecture

Sensors collect real time soil moisture and temperature readings, predictions done on whether irrigation or fertilization is needed. In case irrigation is needed irrigation valves are actuated and the parameters observed till the required levels have been achieved. In case there is a need for fertilization a notification is sent to the farmer via GSM on the amount of fertilizer to be added for the next irrigation cycle. The collected data is also sent to things speak cloud platform for future analytics and research.

4.2 System Block Diagram

Figure 4.1 gives the embedded system block diagram showing the embedded components of the system.

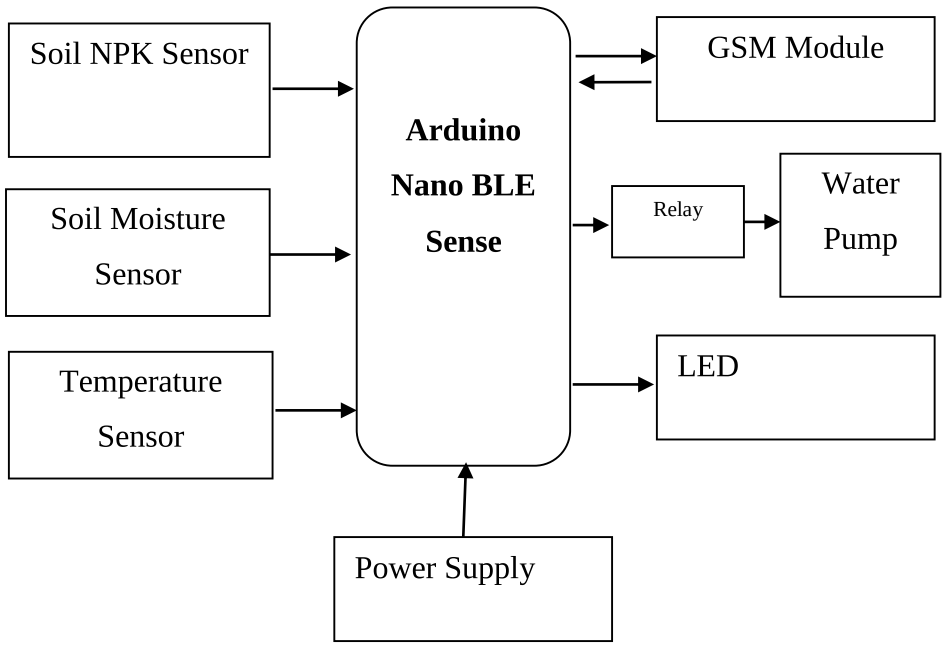

Fig. 4.1: System block diagram

4.3 System Hardware Components

The embedded system is made up of the following components:

A. Arduino Nano BLE Sense

The Arduino Nano 33 BLE Sense [34] combines a tiny form factor, different environment sensors and the possibility to run AI using TinyML and TensorFlow Lite. It is appropriate for creating an embedded ML application or applications that need to use Bluetooth Low Energy to connect a project to a phone. Figure 4.2 shows the pin layout for the board.

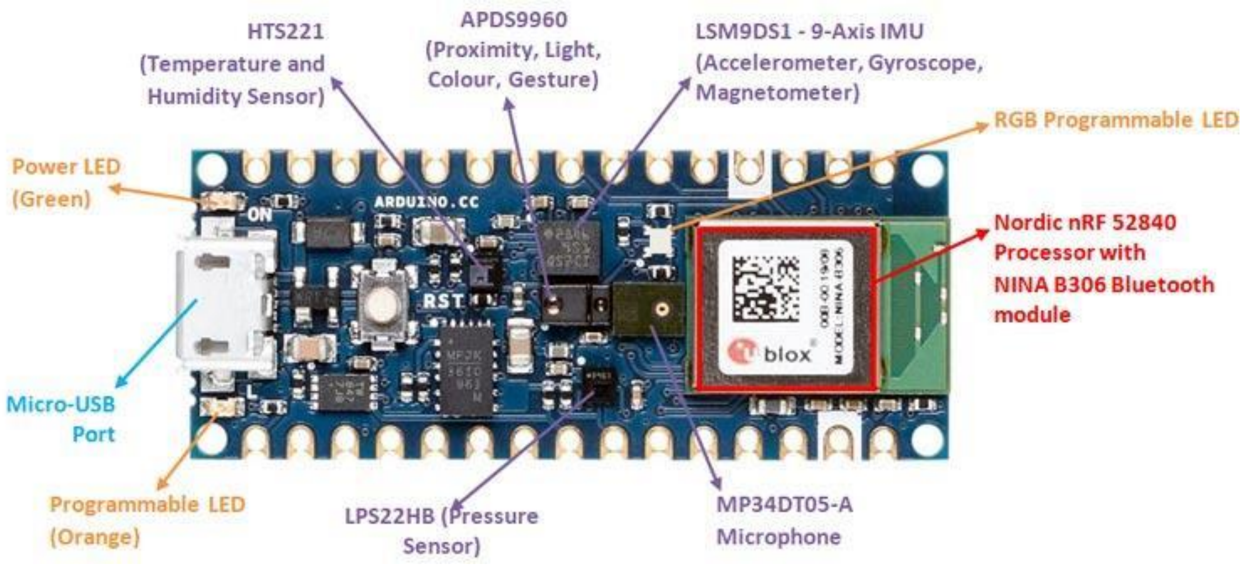

Fig 4.2: Arduino Nano BLE Sense

B. Soil NPK Sensor

The soil NPK sensor is suitable for detecting the content of nitrogen, phosphorus, and potassium in the soil. Figure 4.3 shows the NPK sensor

Fig. 4.3 Soil NPK Sensor

C. Soil Moisture Sensor

The soil moisture sensor consists of two probes that are used to measure the volumetric content of water. The two probes allow the current to pass through the soil, which gives the resistance value to measure the moisture value.

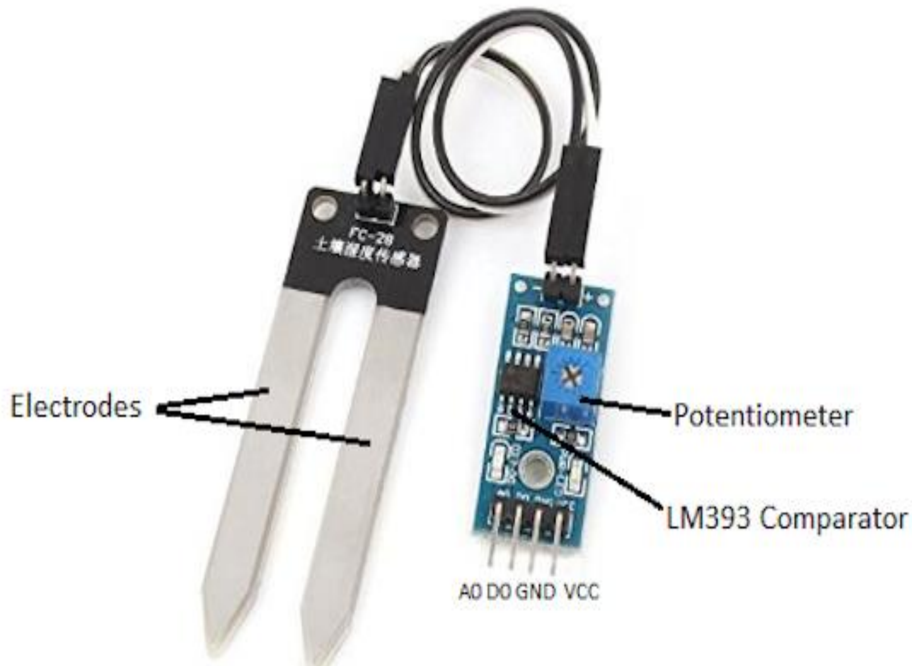

Fig 4.4. Soil Moisture Sensor

D. GSM Module

SIM900 GSM/GPRS shield is a GSM modem, it can be used to accomplish almost anything a normal cell phone can. A SIM900 Model was selected for the project.

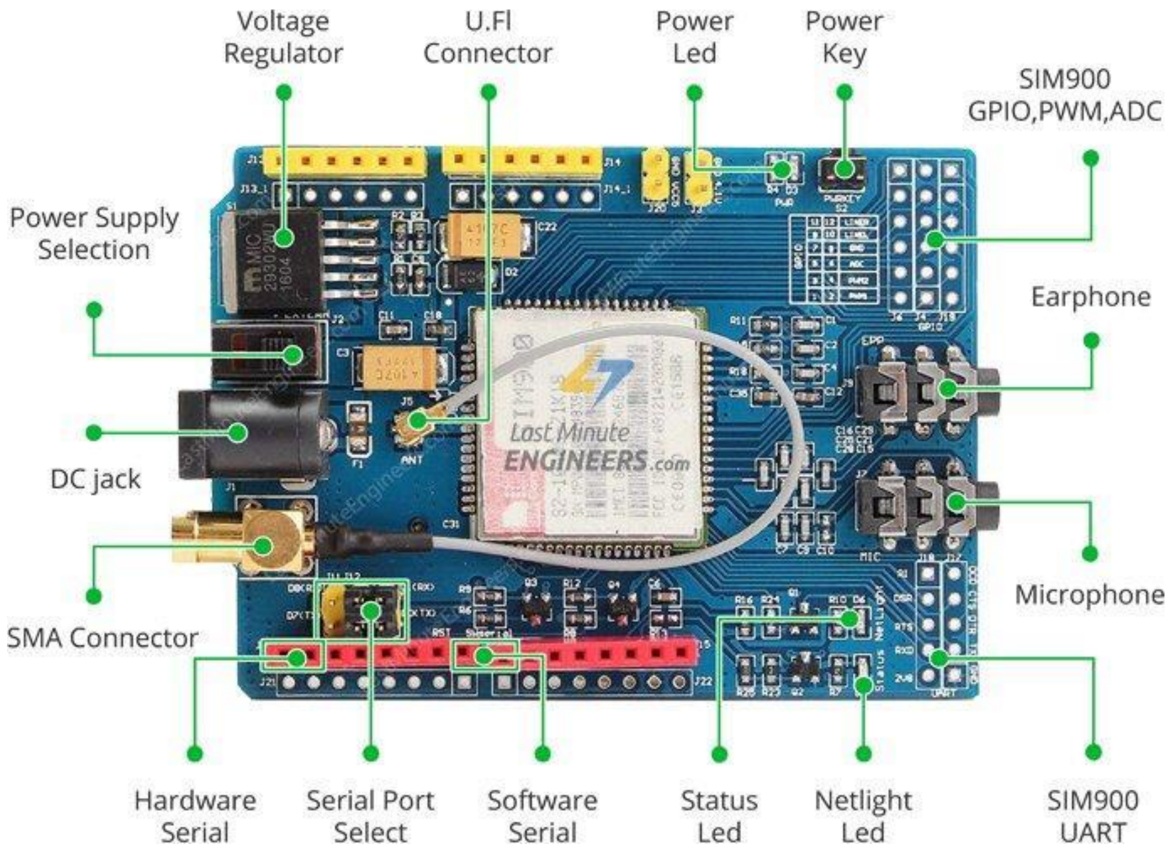

Figure 4.5: GSM Module

E. Water Pump

Micro DC 3-6V Micro Submersible Pump Mini water pump..

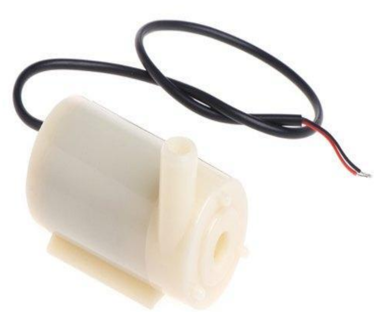

Fig. 4.6. Mini water Pump

F. Relay

This is a 4-Channel Relay interface board that allows one to control various appliances, and other equipment's with large current.

Figure 4.7: Relay

4.4 System PDL

Figure 9 shows the PDL for the embedded system. The Program description language (PDL) is free-format English-like text, which describes the flow of control and data in a program.

```
BEGIN
        Initialize variables
        DOFOREVER
                Sense moisture content
                Sense nutrient content
                Measure soil temperature
                Send values to the cloud
                Run classifier
                IF irrigate predicted THEN
                        DO
                        Switch on pump
                        Light red LED
                        Sense moisture content
                        UNTIL
                        Moisture adequate
                ELSE
                        Switch off pump
                        Light red LED
        ENDIF
        Check nutrient threshold
        IF nutrient low THEN
                        Send notification
                        ENDIF
                Wait 6 hours
        ENDDO
END
```

4.5 Deep Learning Model design

This section outlines the smart irrigation DL model. The first section describes the dataset used for training of the model followed by a description of the training process and thereafter a validation and testing of the model.

A. Datasets

Data used for training of the model was collected with the help of STES Group Rwanda for a period of six months. The data was collected using soil moisture and temperature sensors distributed across a farm in Rwanda. With the existing dataset thresholds are applied to irrigate the farm when stress conditions are detected. Table 4.1 gives a sample of the collected data

Table 4.1: Sample of data collected

ID	**soil_ moisture**	**soil_ temperature**	**battery_ level**	**Date & Time**	**sensor_ id**
6	0	29.3	22	04/02/2021 10:54	C1006
7	0	29.3	22	04/02/2021 10:55	C1006
8	0	28.6	22	04/02/2021 11:00	C1006
9	0	28.5	22	04/02/2021 11:00	C1006
10	0	26.4	86	04/02/2021 12:56	C1006
11	0	26.2	72	04/02/2021 12:59	C1001
12	0	25.8	22	04/02/2021 13:04	C1001
13	0	25.7	22	04/02/2021 13:06	C1001
14	28	23.3	79	04/02/2021 13:35	C1001
15	28	23.3	79	04/02/2021 13:36	C1001
16	28	23.3	79	04/02/2021 13:56	C1001

The dataset included 208,890 observations. The data had to first be cleaned to remove values that had errors also columns that were not needed for the training of the model were removes. Any duplicates were also checked and omitted.

B. Data formatting

The dataset was first separated into two different sets, with the labels, irrigate and no irrigation. Each class had a total of 100,000 observations. 20 % of the data from each class was randomly separated as test data. Data was then converted from CSV to JSON for a convenient upload into the digital signal processing pipeline powered by edge impulse, an embedded ML training platform. In addition, 20% of the data is separated as a validations set leaving the remaining 60% as the training set.

C. Model Training

A Neural Network classifier based on Keras and tensor flow light was used to train the model. A learning rate of 0.0005 with 300 training cycles was applied with 2 dense layers were used with 20 and 10 neurons respectively. The code below describes the model architecture.

D. Training Output

From the validation set a training performance accuracy of 91.7% was achieved with a loss of 0.22. Table 2 shows the confusion matrix for the validation set.

TABLE 2: VALIDATION SET CONFUSION MATRIX

Results	Irrigate	No_Irrigation
Irrigate	96%	4%
No_Irrigation	18.2%	18.8%
F1 Score	0.94	0.86

The resulting model was also small enough to run on an embedded device with a projected RAM usage of 1.7K and a ROM requirement of 17.3K. The model is packaged into a tiny library that can run on an Arduino ARM cortex boards.

4.6 System Setup

Different components of the systems were set as follows

A. Soil Moisture Sensor

The sensor is connected in an analogue mode; the sensor gives us a value from 0 to 1023. The moisture is measured in percentages, the sensor connected as follows;

- VCC of the soil moisture sensor to 5V of the Arduino
- GND of the soil moisture sensor GND of the Arduino
- A0 of the soil moisture sensor A0 of the Arduino

B. NPK Sensor

The NPK Sensor can measure in a range of 0-1999 mg/kg and can operate on a power range of 9V-24V. The MAX485 TTL is used to interfaces the soil nutrient sensor with the Arduino board.

The module is connected to the Arduino as follows;

- RO = Receiver Output. Connects to a serial RX pin on the Arduino
- RE = Receiver Enable. This is for Active LOW and Connects to a digital output pin on a
- Arduino.
- DE = Driver Enable. This is for Active HIGH and it is connected to RE Pin.
- DI = Driver Input. This Connects to serial TX (Transmission) pin on the Arduino
- VCC = 5V
- B = Data ‘B’ Inverted Line. Common with the B
- A = Data ‘A’ Non-Inverted Line. Connects to A on far end module
- GND = Ground

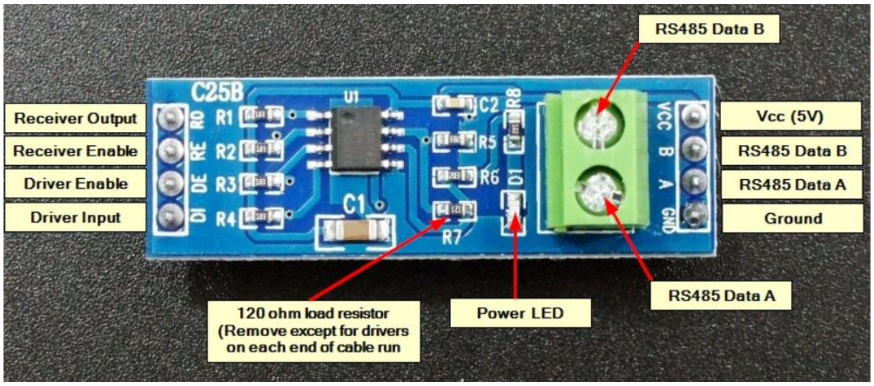

Figure 4.9: MAX485 Connection pins

The NPK is connected to the MAX 485 module as follows;

- ❖ VCC – Brown wire, connected to a 9V-24V Power Supply.
- ❖ GND – Black wire, connected to the GND of Arduino.
- ❖ B Pin- Blue wire, connected to the B pin of MAX485
- ❖ A PIN- Yellow Wire, connected to the A pin of MAX485.

C. Water Pump

The water pump is connected as follows;

- ❖ IN (Signal) of the relay connected to D8 of Arduino
- ❖ VCC of the relay connected to 5V of Arduino
- ❖ GND of the relay connected to GND of Arduino
- ❖ Extra wire from the pump (red) connected to COM of the relay
- ❖ Black wire from the pump connected to 12 v power supply
- ❖ N0 of relay connected to 12v power supply

Figure 4.10: Connected of the pump and Arduino

CHAPTER 5

SYSTEM RESULTS, ANALYSIS AND DISCUSSSIONS

In this section different results from the study are presented, analysed and discussed. In the first section data collection sensor calibration is presented, the deep learning model evaluation results are the outlined and discussed and lastly the results from the prototype presented.

5.1 Data Collection Sensor Calibration

The sensors deployed in the field by STES Group Rwanda for data collection were calibrated to verify the precision and reproducibility of sensor measurements. Sensors that are calibrated are the prerequisite for precise, reliable and reproducible measurement results. Calibration was don as it is one of the key prerequisites for effective quality assurance. The table 5.1 and figure 5.1 show the results during calibration in for a section of the farm.

TABLE 5.1: CALIBRATION DATA

Sno	% of water	**Soil Moisture**	**Soil Temperature**
1	0	0	26.1
2	0	4	27.08
‘3	5	6	27.9
4	10	7	27.2
5	15	10	26.8
6	20	14	26.3
7	25	21	25.8
8	30	28	25.3
9	35	31	25.2
10	40	34	24.3
11	45	35	24.2
12	50	36	24.6
13	55	37	24.8
14	60	38	24.8
15	65	38	24.8

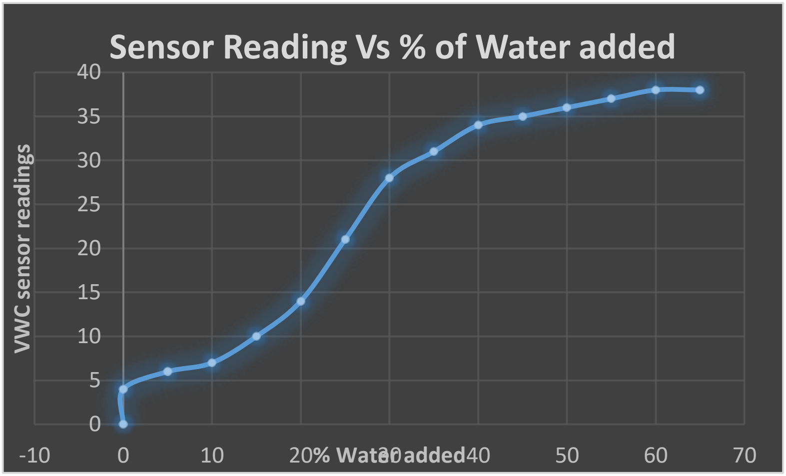

Figure 5.1 Calibration Graph

The conditions in the soil were classified as shown in figure 5.2. The classified conditions include; Extreme stress condition, Stress condition, Field capacity, Excess condition. For the stress and extreme stress conditions irrigation was needed.

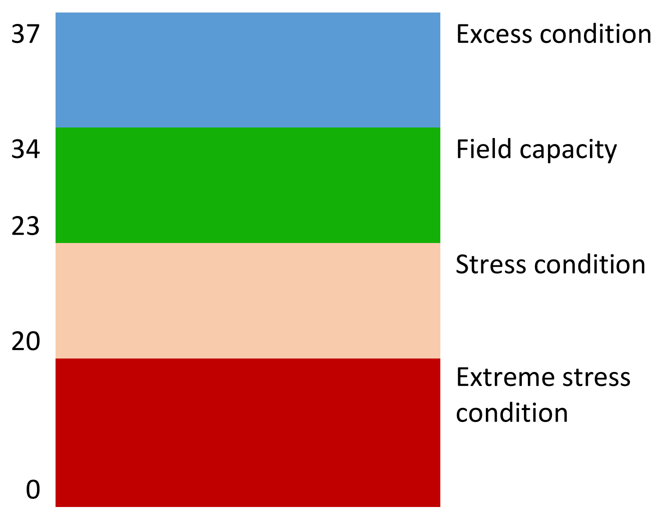

Figure 5.2: Soil conditions

5.2 Deep Learning Model Evaluation

So as to evaluate the performance of the deep learning model. The test data was used for inference on the cloud and on the embedded device and the results were compared so as to determine if optimization affects the model performance. The results were also compared with those best on open source benchmarking datasets and other machine learning algorithms.

A. Inference Results

From the inference results the model was able to predict the need or not need for irrigation with the same accuracies in both the cloud and the embedded device. This shows that the training of a deep learning model for inference in the resource constrained devices do not affect the performance of the model. Table 5.2 shows sample inference results based on test data

TABLE 5.2: TEST DATA INFERENCE RESULTS

Timestamp	Irrigate	No_Irrigation
0	0.86	0.14
1000	0.97	0.03
2000	0.70	0.30
3000	0	1.00
4000	0	1.00

B. Optimization Effects

From the evaluation on test data, the model performed with an accuracy of 93% slightly above that from the validation set which was 91%. However, when the model was quantized by conversion from a float 32 model to an int 8 model. The resources needed on the device reduced while at the same time reducing the accuracy as shown in figure 5.3

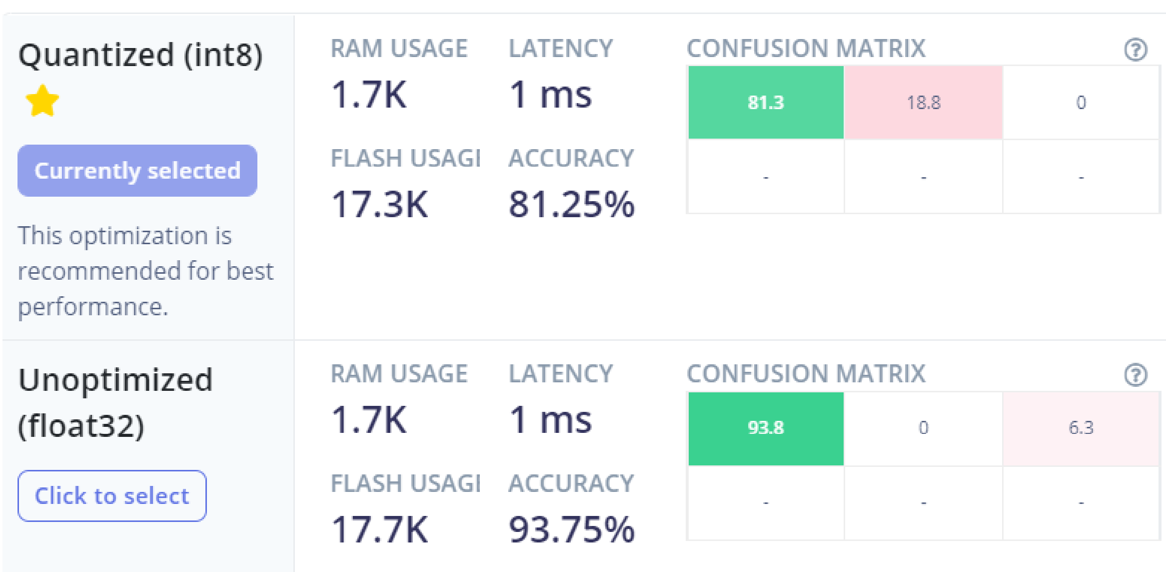

Figure 5.3: Effects of optimization

This shows that in case of a big model one can opt to optimize so as to reduce the required resources. However, this will affect the accuracy and a trade-off must be considered

C. Data set performance evaluation

So as to evaluate the performance of the dataset. A comparison was done with an online open dataset from googled sets. The data was collected from a system with a wireless sensor network that sensed real-time soil moisture and temperature and ML applied to automatically control of an irrigation system. In the system an Arduino board was interfaced with a soil moisture sensor and dht11 sensor and NodeMCU. K nearest neighbour and Naive Bayes Algorithm were then applied so as to predict when to irrigate or not. In our study we use the data for training but explored the used of deep learning with the aim of developing a light model that can run on embedded devices. The results show that our datasets gave better accuracy with an accuracy of 91.7% as compared to 89.1 % for a deep learning model based on the open datasets. In addition deep learning gave better accuracies than other ML algorithms hence support the fact that the dataset used was better than existing model datasets in the areas of study. Table 5.3 and figure 5.4 shows the accuracies achieved with different data sources and algorithms.

TABLE 5.3: MODEL PERFOMANCE ACCURACIES

Results	Deep Learning	K nearest neighbour	Naïve Bayes
Accuracy	89.1%	86.7	88.4

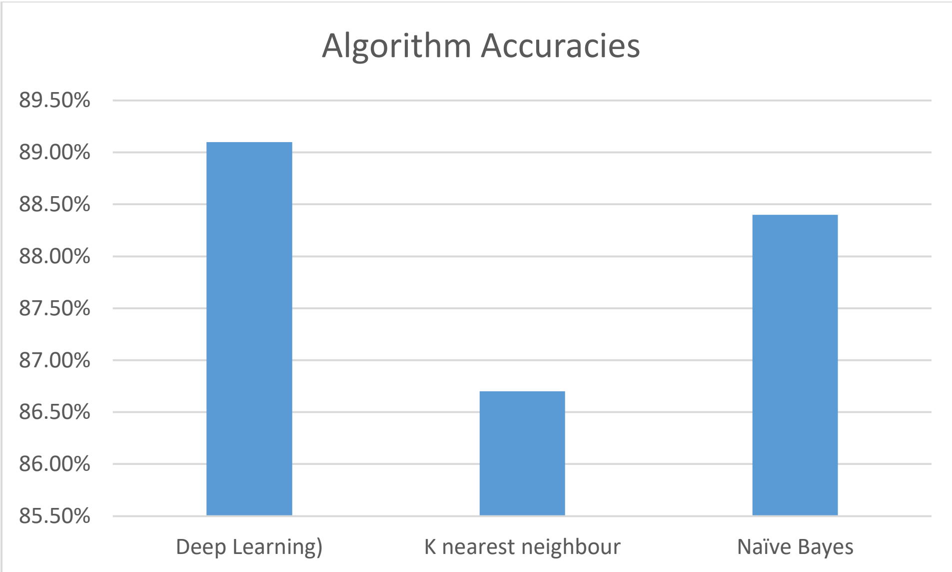

Figure 5.4: Accuracies achieved by using different data and algorithms

D. Effect of training cycles on accuracy

An analysis was also done to find out how the number of training cycles affect the accuracy for the deep learning model. Table 5.4 and figure 5.5 show the results of the analysis.

TABLE 5.4 ACCURACIES BY NO OF EPOCHS

No of Epochs	**Accuracy**
1	30.6%
50	30.6%
100	50.3%
150	77.8%
200	86.1%
250	91.7%
300	91.7%
350	91.7%
400	91.7%

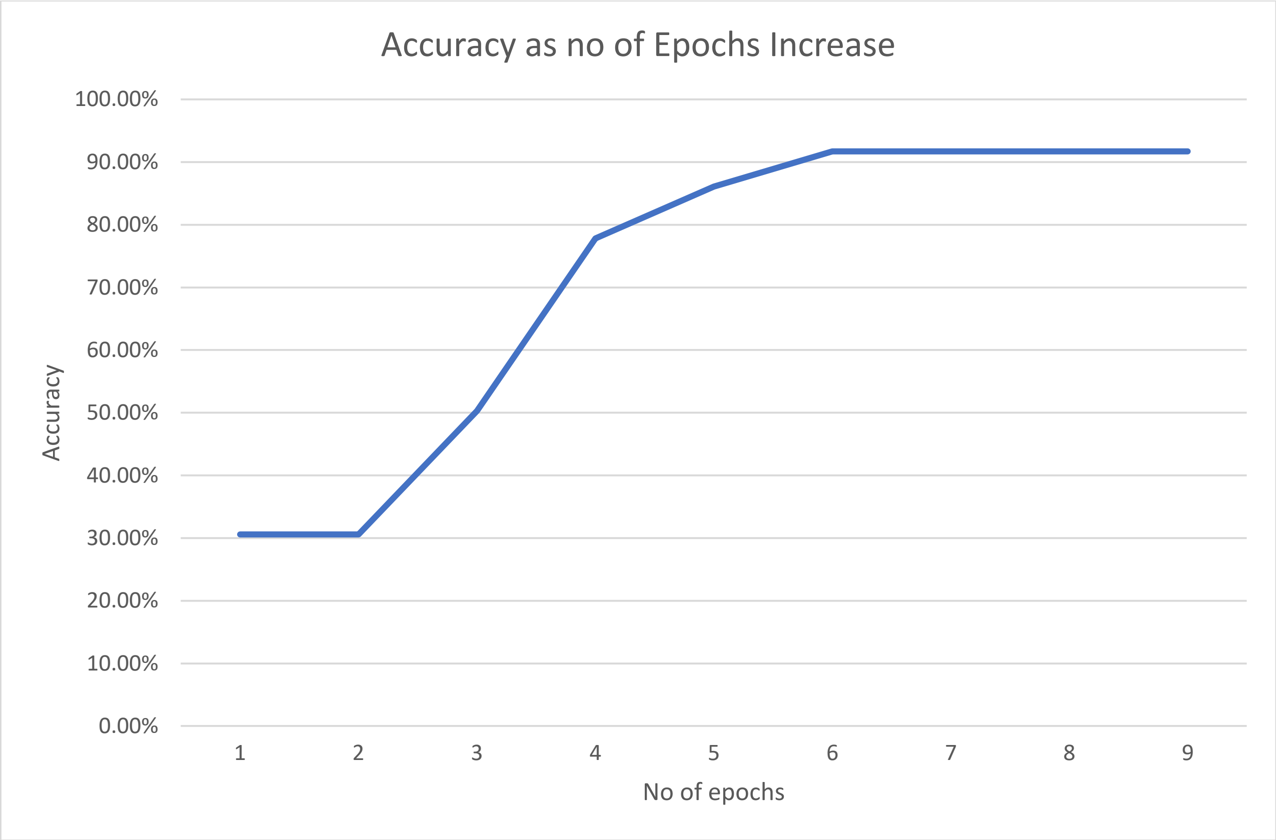

Figure 5.5: Accuracy by number of epochs

From the graph in figure 5.5, the accuracy for them model increases as more training cycles are used. The best training accuracy was achieved at with 300 epochs. After this peak the accuracy did not increase further showing this is the optimum accuracy value.

5.3 System Prototype results

Figure 5.6 shows the system prototype image. All the components were connected and the functionality of the system tested in a lab environment. The soil moisture and temperature were captured in real-time and the collected values fed into the DL model that correctly predicted when to irrigate or not. Based on the prediction the water pump was actuated to irrigate the farm for a specified duration.

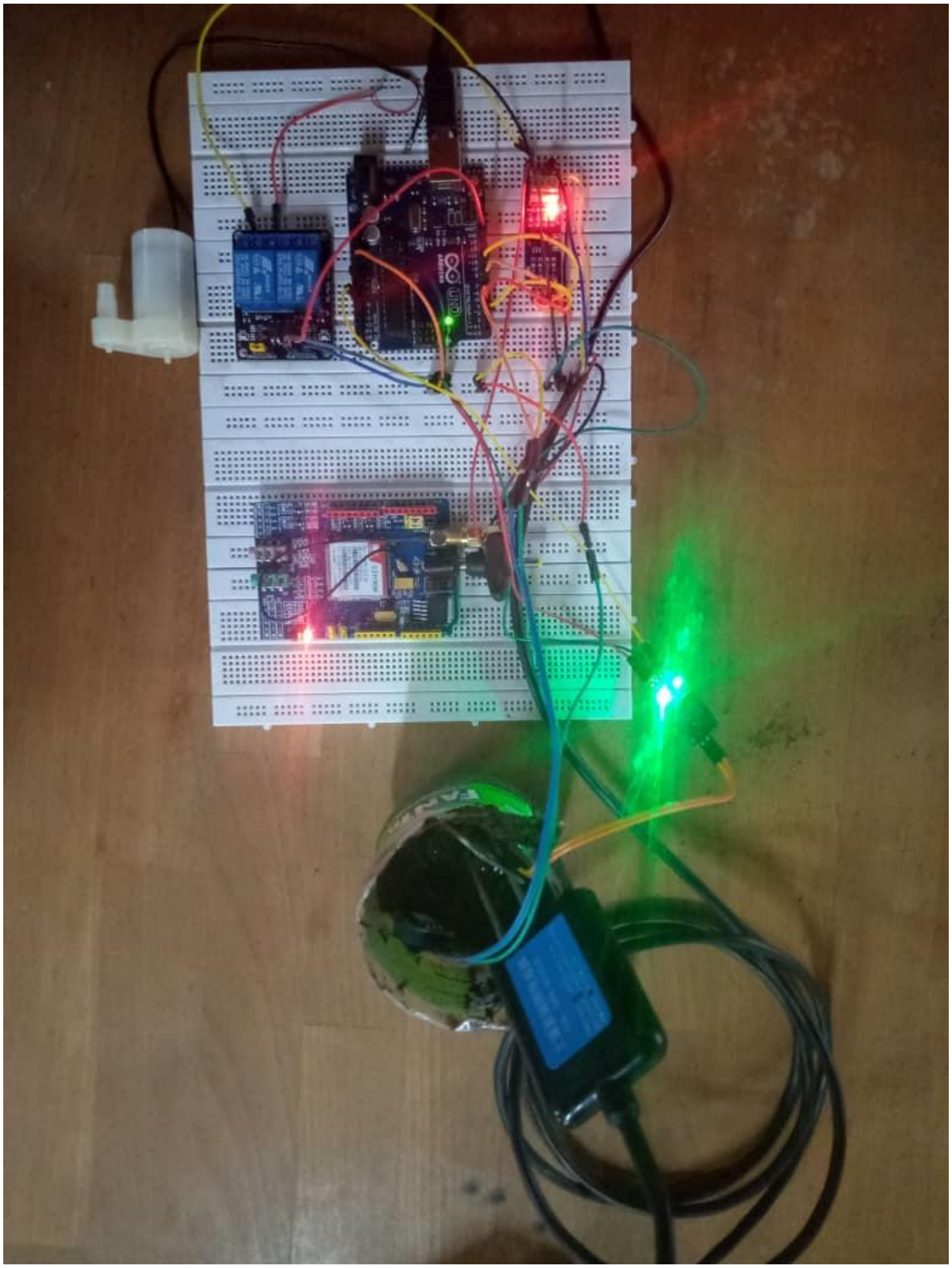

Figure 5.6: System prototype

Some sample outputs from the prototype are shown in figures 5.7 and 5.8. These show that the prototype was able to measure different soil parameters, do the prediction and actuate the pump to irrigate the field

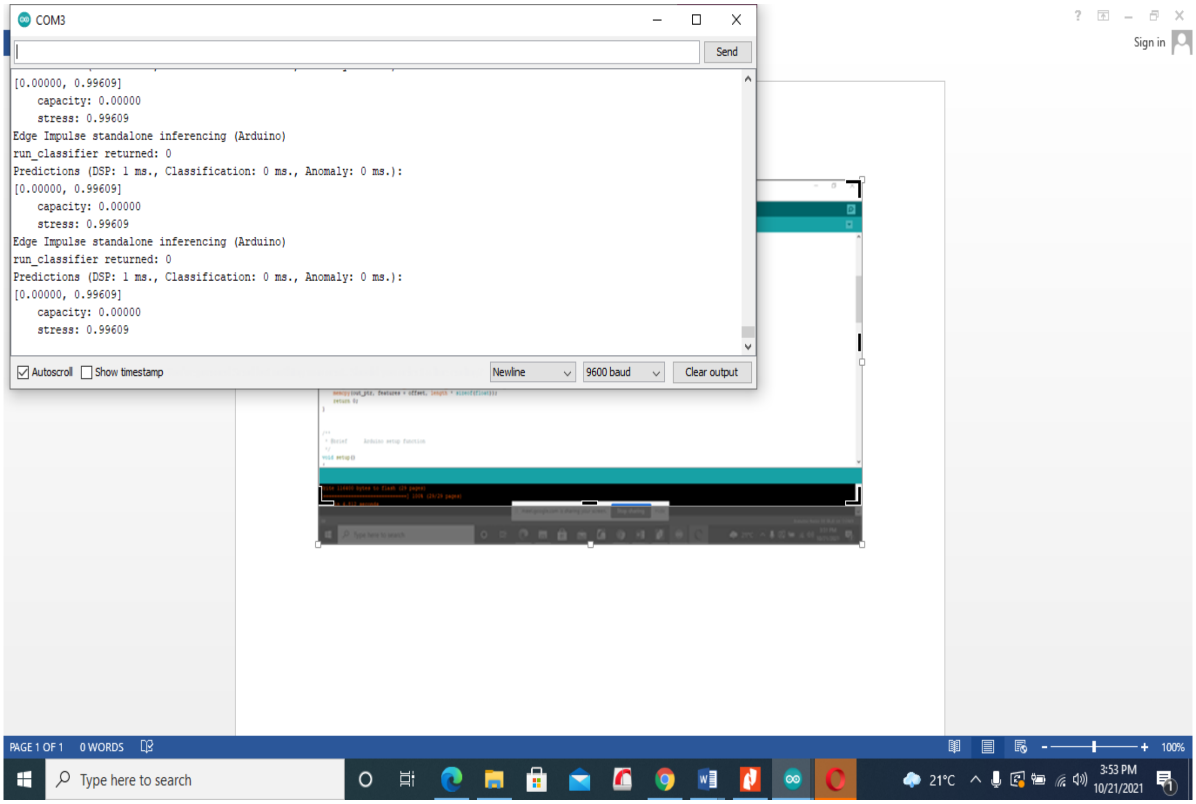

Figure 5.7: Prediction output

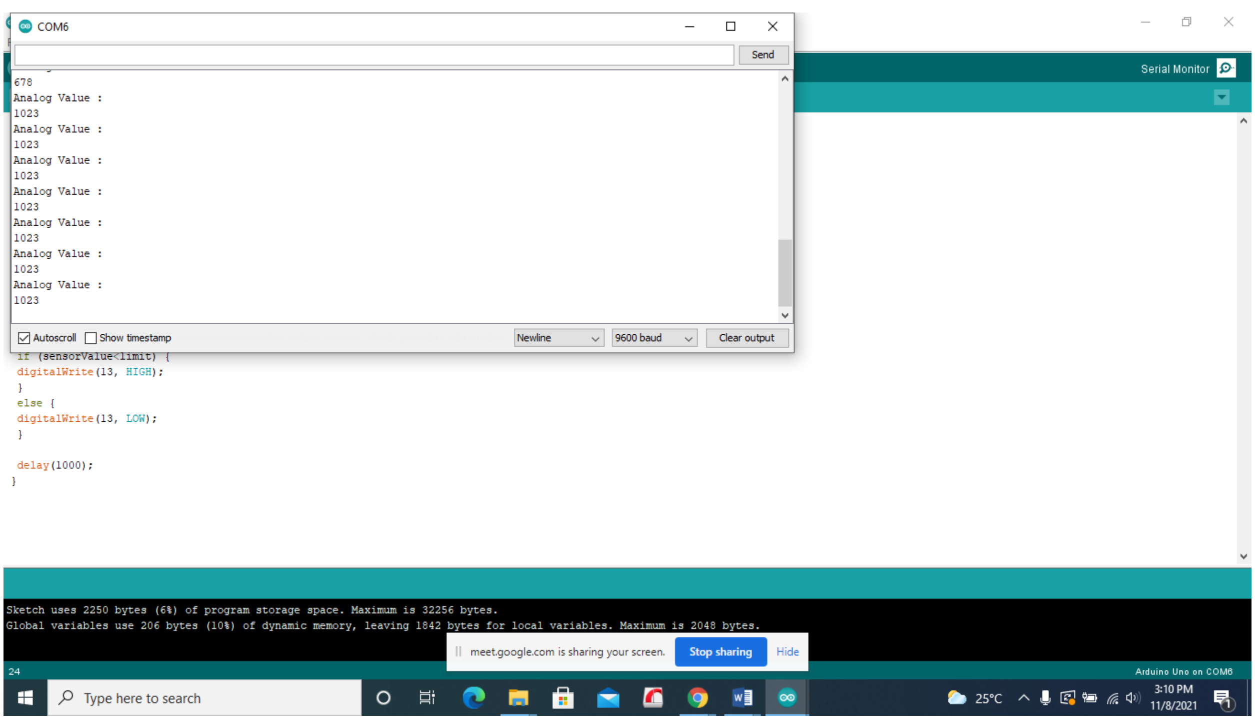

Figure 5.8: Moisture sensor reading

5.4 Comparison to Existing Solutions

So as to evaluate the advantages of our solution over existing solution a comparison was done with the reviewed solutions. Table 5.5 gives the results of the comparisons

Solution	Smart Irrigation	NPK Monitoring	Machine learning	Architecture
Automated irrigation and monitoring system [17]	YES	NO	NO	EDGE
Smart irrigation system [18]	YES	NO	NO	EDGE
Smart farm irrigation [19]	YES	NO	NO	CLOUD
Automated irrigation system [20]	YES	NO	NO	CLOUD
Intelligent farming system [21]	NO	YES	NO	CLOUD
IoT farming system [22]	NO	YES	NO	CLOUD
IoT framework [23]	YES	YES	NO	EDGE
IoT based system [24]	NO	YES	NO	CLOUD
DSS using IoT	NO	NO	YES	CLOUD
Fuzzy based solution	YES	NO	YES	CLOUD
Fuzzy solution	YES	NO	YES	CLOUD
Expert System	NO	YES	YES	CLOUD
Our Solution	YES	YES	YES	EDGE

From the analysis our solution outperforms the existing solutions in the following ways

a) Has the capability of smart irrigation while at the same time monitoring soil parameters
b) Machine learning is used to predict when to irrigate
c) The only solution that uses deep learning, in other solutions either fuzzy logic or naïve Bayes and support vector machine are used
d) For all solutions that use machine learning only our solution applies it at the edge device. This makes our prototype appropriate for the African market where connectivity and energy are challenges. This also helps reduce on operation costs.

CHAPTER 6

CONCLUSION, RECOMMENDATIONS, AND FUTURE WORKS

This study presents a prototype for a smart irrigation and fertilization system. The solution uses a deep learning model that has been packaged for deployment on an edge device. The edge based architecture for our solution makes it appropriate for the African market where existing cloud based solutions are difficult to deploy due to connectivity challenges.

The deep learning model was tested in different environments and using different data sources, it was also compared against other algorithms applied on similar datasets. The results show that our model performed best with an accuracy of 91.7%. The results also show that the number of training epochs affect the model accuracy and optimization reduces the resources needed on the device to run a machine learning model but affects the accuracy of the model.

We recommend the implementation of this solution as it will indeed ensure the practise of data driven farming and thus help conserve the environment and ensure maximum utilization of resources. This will also lead to reduced operation costs and thus increase profits.

Future works will involve collection of more data so as to tune the performance of the model, development of a model for prediction of the needed fertilizers and the implementation and further testing of the solution

REFERENCES

[1] “National Agriculture Policy,” 2018.

[2] “Rwanda Agriculture 2016 by Kahroy Creative Arts - Issuu.” https://issuu.com/kahroy/docs/rwanda_supplement_sept_2016 (accessed Nov. 19, 2021).

[3] J. C. Aker, I. Ghosh, and J. Burrell, “The promise (and pitfalls) of ICT for agriculture initiatives,” *Agric. Econ.*, vol. 47, no. S1, pp. 35–48, Nov. 2016, doi: 10.1111/AGEC.12301.

[4] “ACM Transactions on Internet of Things,” *ACM Trans. Internet Things*, vol. 1, no. 1, pp. 1–2, Mar. 2020, doi: 10.1145/3379599.

[5] K. Chatzilygeroudis, I. Hatzilygeroudis, and I. Perikos, “Machine Learning Basics,” *Intell. Comput. Interact. Syst. Des.*, pp. 143–193, Feb. 2021, doi: 10.1145/3447404.3447414.

[6] D. Mishra, A. Abbas, T. Pande, A. K. Pandey, K. K. Agrawal, and R. S. Yadav, “Smart agriculture system using IoT,” *PervasiveHealth Pervasive Comput. Technol. Healthc.*, Jun. 2019, doi: 10.1145/3339311.3339350.

[7] W. L. Hsu, W. K. Wang, W. H. Fan, Y. C. Shiau, M. L. Yang, and D. J. D. Lopez, “Application of internet of things in smart farm watering system,” *Sensors Mater.*, vol. 33, no. 1, pp. 269–283, 2021, doi: 10.18494/SAM.2021.3164.

[8] D. Orn, L. Duan, Y. Liang, H. Siy, and M. Subramaniam, “Agro-AI Education: Artificial Intelligence for Future Farmers,” *SIGITE 2020 - Proc. 21st Annu. Conf. Inf. Technol. Educ.*, pp. 54–57, Oct. 2020, doi: 10.1145/3368308.3415457.

[9] E. N. Alam, “IoT in Agriculture Industry,” *J. Sist. Cerdas*, vol. 3, no. 1, pp. 36–42, 2020, doi: 10.37396/jsc.v3i1.57.

[10] S. Rawal, “IOT based Smart Irrigation System,” *Int. J. Comput. Appl.*, vol. 159, no. 8, pp. 7–11, 2017, doi: 10.5120/ijca2017913001.

[11] I. Journal, “IRJET- Smart Irrigation System Using IOT And Raspberry Pi.”

[12] "Deep Learning and Its 5 Advantages | by Magnimind | Becoming Human: Artificial Intelligence Magazine." https://becominghuman.ai/deep-learning-and-its-5-advantages-eaeee1f31c86 (accessed Aug. 17, 2021).

[13] "Rwanda at a glance | FAO in Rwanda | Food and Agriculture Organization of the United Nations." https://www.fao.org/rwanda/our-office-in-rwanda/rwanda-at-a-glance/en/ (accessed Nov. 19, 2021).

[14] K. Singh and R. Kumar, "Design of a Low-Cost Sensor-Based IOT System for Smart Irrigation," *EAI/Springer Innov. Commun. Comput.*, pp. 59–79, 2021, doi: 10.1007/978-3-030-35280-6_4.

[15] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming," *IEEE Access*, vol. 7, pp. 156237–156271, 2019, doi: 10.1109/ACCESS.2019.2949703.

[16] "BAZAFARM TECHNOLOGYy - STES Group Ltd." https://www.stesgroup.rw/bazafarm-technology/ (accessed Nov. 19, 2021).

[17] S. Vaishali, S. Suraj, G. Vignesh, S. Dhivya, and S. Udhayakumar, "Mobile integrated smart irrigation management and monitoring system using IOT," *Proc. 2017 IEEE Int. Conf. Commun. Signal Process. ICCSP 2017*, vol. 2018-Janua, pp. 2164–2167, 2018, doi: 10.1109/ICCSP.2017.8286792.

[18] J. Karpagam, I. I. Merlin, P. Bavithra, and J. Kousalya, "Smart Irrigation System Using IoT," *2020 6th Int. Conf. Adv. Comput. Commun. Syst. ICACCS 2020*, pp. 1292–1295, 2020, doi: 10.1109/ICACCS48705.2020.9074201.

[19] S. B. Saraf and D. H. Gawali, "IoT based smart irrigation monitoring and controlling system," *RTEICT 2017 - 2nd IEEE Int. Conf. Recent Trends Electron. Inf. Commun. Technol. Proc.*, vol. 2018-January, pp. 815–819, Jul. 2017, doi: 10.1109/RTEICT.2017.8256711.

[20] S. (Sri R. I. of T. Anila, R. Nandhini, S. Poovizhi, P. Jose, and R. Ranjitha, "Arduino Based Smart Irrigation System Using IOT," no. December, p. 5, 2017.

[21] R. Maheswari, H. Azath, P. Sharmila, and S. Sheeba Rani Gnanamalar, “Smart Village: Solar Based Smart Agriculture with IoT Enabled for Climatic Change and Fertilization of Soil,” *2019 IEEE 5th Int. Conf. Mechatronics Syst. Robot. ICMSR 2019*, pp. 102–105, 2019, doi: 10.1109/ICMSR.2019.8835454.

[22] R. Prabha, E. Sinitambirivoutin, F. Passelaigue, and M. V. Ramesh, “Design and Development of an IoT Based Smart Irrigation and Fertilization System for Chilli Farming,” *2018 Int. Conf. Wirel. Commun. Signal Process. Networking, WiSPNET 2018*, pp. 1–7, 2018, doi: 10.1109/WiSPNET.2018.8538568.

[23] D. L. Mary and M. Ramakrishnan, “A Novel Approach to Optimize Water and Fertilizers in Agriculture using IoT,” *Int. J. Cybern. Informatics*, vol. 10, no. 2, pp. 57–64, 2021, doi: 10.5121/ijci.2021.100207.

[24] S. A. Karimah, A. Rakhmatsyah, and N. A. Suwastika, “Smart pot implementation using fuzzy logic,” *J. Phys. Conf. Ser.*, vol. 1192, no. 1, 2019, doi: 10.1088/1742-6596/1192/1/012058.

[25] R. S. Krishnan *et al.*, “Fuzzy Logic based Smart Irrigation System using Internet of Things,” *J. Clean. Prod.*, vol. 252, p. 119902, 2020, doi: 10.1016/j.jclepro.2019.119902.

[26] B. Alomar and A. Alazzam, “A Smart Irrigation System Using IoT and Fuzzy Logic Controller,” *ITT 2018 - Inf. Technol. Trends Emerg. Technol. Artif. Intell.*, pp. 175–179, 2019, doi: 10.1109/CTIT.2018.8649531.

[27] S. L. Ullo and G. R. Sinha, “Advances in smart environment monitoring systems using iot and sensors,” *Sensors (Switzerland)*, vol. 20, no. 11, 2020, doi: 10.3390/s20113113.

[28] S. Rajeswari, K. Suthendran, and K. Rajakumar, “A smart agricultural model by integrating IoT, mobile and cloud-based big data analytics,” *Proc. 2017 Int. Conf. Intell. Comput. Control. I2C2 2017*, vol. 2018-Janua, pp. 1–5, 2018, doi: 10.1109/I2C2.2017.8321902.

[29] S. Kiruthika, P. Sakthi, N. Gokul, G. P. Kumar, S. Praveenkumar, and R. Prem, “Monitoring Soil Quality And Fertigation System Using Iot Monitoring Soil Quality And

Fertigation System Using Iot," vol. 12, no. 9, pp. 2884–2893, 2021.

[30] N. K. Nawandar and V. R. Satpute, "IoT based low cost and intelligent module for smart irrigation system," *Comput. Electron. Agric.*, vol. 162, no. April, pp. 979–990, 2019, doi: 10.1016/j.compag.2019.05.027.

[31] "Software | Arduino." https://www.arduino.cc/en/software (accessed Nov. 19, 2021).

[32] "TensorFlow Lite | ML for Mobile and Edge Devices." https://www.tensorflow.org/lite (accessed Nov. 19, 2021).

[33] "IoT Analytics - ThingSpeak Internet of Things." https://thingspeak.com/ (accessed Nov. 19, 2021).

[34] "Arduino Nano 33 BLE Sense — Arduino Online Shop." https://store-usa.arduino.cc/products/arduino-nano-33-ble-sense (accessed Nov. 19, 2021).