BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

COMPUTER SCIENCE DEPARTMENT

Implementation of A Machine Learning & Internet of Things (IoT) Model For Optimum Crop Recommendations In Zimbabwe.

By

TAFADZWA MATETA

B1953954

SUPERVISOR: MR. P. CHAKA

A RESEARCH PROJECT SUBMITTED TO THE COMPUTER SCIENCE DEPARTMENT IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE BACHELOR OF SCIENCE HONOURS DEGREE IN COMPUTER SCIENCE.

APPROVAL FORM

The undersigned certify that they have supervised the student **Tafadzwa Mateta B1953954** dissertation entitled, **"Implementation of a machine learning and internet of things (IoT) Model For optimum crop recommendations in Zimbabwe"** submitted in partial fulfilment of the requirements for a Bachelor of Computer Science Honours Degree at Bindura University of Science Education.

STUDENT: **DATE:**

………………………………………………… **…………………………...**

SUPERVISOR: **DATE:**

………………………………………………… **..………………………….**

CHAIRPERSON: **DATE:**

……………………………………..………… **..…………………………..**

EXTERNAL EXAMINER: **DATE:**

……………………………………..………… **..………………………….**

Abstract
This research is based on the investigation of the efficiency implementation of a machine learning and Internet of Things (IoT) model for precision agriculture in Zimbabwe. Agriculture is one of the major contributors to the Zimbabwean economy. The problem that exists among most farmers is that they do not choose the right crop based on their soil nutrient levels, weather patterns, and agricultural region which results in major setbacks in productivity. This problem of the farmers has been addressed through precision agriculture. Precision agriculture is a farming approach that uses information technology to collect and analyse data about crops, soil, and weather conditions. A comparative study of different techniques used in crop recommendation is also included in this research. In this research, the researcher is proposing an intelligent system that uses the implementation of a machine learning and Internet of Things (IoT) model for precision agriculture in Zimbabwe. The model will use weather conditions, soil nutrient levels and soil pH data to recommend optimal crop management practices for each farmer. The model will be made available to farmers through a web application. Farmers will be able to input data about their farms, such as the soil pH, the weather conditions, and the nutrient levels. The web application will then use the model to recommend the optimal crops for the farm. The research has the potential to significantly improve the productivity of Zimbabwe's agricultural sector. The model will also help farmers to reduce their risk of crop failure.

Keywords: Machine learning, IoT, Agriculture, Zimbabwe, Crop recommendations

Dedication

To Mr Everton, Mrs. Florence Mateta, and my brother Talent, I am writing this dedication to express my deepest gratitude and appreciation for the unwavering support and encouragement you have given me throughout my academic journey. Your love, guidance, and motivation have been instrumental in helping me achieve this significant milestone in my life. You have always been my pillars of strength and my biggest cheerleaders. You have sacrificed so much to ensure that I have access to the best education and opportunities, and I cannot thank you enough for your sacrifices. Your unwavering support and belief in me have been the driving force behind my success. Your unwavering faith in me has been a source of inspiration, and I am grateful for your presence in my life. I dedicate this achievement to you, my loving family, and promise to continue striving for excellence in all my endeavours.

Acknowledgments

First and foremost, I would like to thank the Almighty God for guiding me through my final year dissertation. I would also like to extend my sincere gratitude to my supervisor, Mr. Chaka, for his time, patience, and guidance throughout the research process. I am truly grateful for his valuable insights and contributions.

I would also like to thank Professor Mandumbu and Mr. Mutsengi for co-supervising me along with Mr. Chaka. I appreciate all my lecturers' time and effort you put into helping me produce a high-quality research project.

I am also grateful to Bindura University of Science Education for providing me with the infrastructural support and academic resources that were essential to completing my study. I would also like to thank my family and fellow colleagues for their support and encouragement throughout this journey. Without the help of all of these individuals, I would not have been able to complete my dissertation. I am truly grateful for their support and guidance. Fran

List Of Acronyms And Abbreviations

IDE - Integrated Development Environment

FAO - Food and Agriculture Organization of the United Nations

IoT - for Internet of Things

GND- Ground

VIN- Voltage In

VOUT-Voltage Out

AI -Artificial intelligence

Table of Contents

Chapter 1: Problem Identification

1.1 Introduction

Agriculture is one of the pillars of the Zimbabwean economy that accounts for approximately 20% of Zimbabwe's Gross Domestic Product (GDP) (Chikodzi et al.., 2020). It plays a vital role in ensuring food security and economic growth. Crop selection is a crucial aspect of agriculture as it determines the yield and profitability hence farmers need to make informed decisions when selecting crops to plant based on soil pH, weather patterns, and soil nutrients. One of the challenges that farmers in Zimbabwe face is not knowing the relevant crop for their soil, which can negatively impact crop yields. This lack of knowledge makes it difficult to determine suitable crops to grow (Chibvuta et al., 2018).

It was reported that in the 2015-2016 farming session, there was a massive drought that affected the entire country of Zimbabwe following the impact of El Nino-induced erratic rainfall with the most affected being the traditionally low rainfall Regions 4 and 5 covering, mainly Masvingo, Matabeleland South, and Matabeleland North provinces(Ministry of Environment, Water and Climate, 2016, 12 February). This heavily affected farmers who did not select drought-resistant crops. Even Mashonaland's historically food-secure provinces in regions 1, 2, and 3 were also seriously impacted.

Also, a study conducted in 2018 by the University of Zimbabwe's Department of Agricultural Economics and Extension showed that up to 20% of crop losses in Zimbabwe can be attributed to poor crop selection. The study also discovered that farmers are more likely to choose crops that are appropriate for their regional conditions when they use crop recommendation systems. Machine learning and IoT technologies have the potential to revolutionize the field of agriculture by providing farmers with personalized and data-driven recommendations for crop selection and management. (Zhang et al., 2018, p. 2).

However, there are conflicting views and an overall lack of research on the best management and implementation of machine learning and Internet of Things (IoT) models for crop suggestion. This study aims to identify and implement an intelligent system that uses machine learning algorithms and (IOT) internet of things to suggest the best crop for a particular land and the best fertilizers for that land. Machine learning algorithms can analyse massive amounts of data from sensors and other IoT devices to provide farmers with personalized crop selection and management recommendations. Kurma (2019), argues that the Internet of Things (IoT) is a new paradigm that has changed the traditional way of living into a high-tech lifestyle. Shan (2019) adds on that IOT environmental monitoring in agricultural production, and agricultural product safety traceability, have been used in fields like farmland planting, aquaculture, and animal husbandry to achieve the results needed at a given specific time

The use of IOT and machine learning algorithms to suggest crops based on soil nutrient levels and environmental conditions has gained popularity in recent years. Numerous studies demonstrating the effectiveness of machine learning in crop recommendation have been conducted globally. For instance, a study conducted in India showed that a machine learning algorithm was able to predict crop yields with high accuracy based on soil nutrient levels and environmental factors (Jain et al., 2019). However, there is a need for similar studies in Zimbabwe to determine the effectiveness of the use of (IOT) the Internet Of Things and machine learning in crop recommendation and fertilizer recommendations in the country.

This chapter will introduce the study by first addressing the background and context, then moving on to the research problem, the research objectives, questions, the significance limits, and the scope of the research.

1.2 Background Of The Study

According to Jordan and Mitchell (2015), machine learning is a type of artificial intelligence that involves the use of algorithms and statistical models to analyse large sets of data and make predictions or decisions based on that analysis. It involves the use of complex algorithms that can learn from data, allowing machines to improve their performance over time. The Internet of Things (IoT) is a network of interconnected physical objects, sensors, and software that gathers and exchanges data, according to Gubbi et al. (2013). This makes it possible for these devices to communicate with one another and with other systems outside of their own, which permits the gathering and processing of enormous volumes of data.

As many scholars have investigated the potential advantages and implementation of applying machine learning and (IoT) in agriculture, crop recommendations using soil nutrient analysis have been gaining attention in European countries due to their potential to increase crop yields, optimize the use of fertilizers, and reduce environmental impact. Using machine learning algorithms, for instance, to analyse data on soil nutrients and give farmers personalized crop suggestions, was successfully proven in a study carried out in Spain. The study showed that the use of the machine learning model resulted in a 9.5% increase in crop yield and a 28% reduction in fertilizer use (García-Sánchez et al., 2020). These results highlight the potential benefits of implementing such models in African countries, where agriculture plays a significant role in the economy.

A 2018 study from the University of California found that using machine learning algorithms to assess soil data has the potential to dramatically increase agricultural yield (Kamilaris & Prenafeta-Bold, 2018). According to the study, farmers were able to choose and manage crops more effectively by using machine learning algorithms to examine soil data. This resulted in higher yields and lower expenses. Similar to the United States, several studies on the application of machine learning for crop recommendations have been carried out in Europe. These studies include those by Brus et al. (2020) and Koocheki et al. (2021), which showed how machine learning algorithms could increase crop yields and optimize fertilizer use. These results demonstrate the potential of machine learning algorithms to enhance agricultural productivity and offer useful information to farmers, decision-makers, and academics.

Another study was conducted by researchers at the University of Bologna in Italy in 2017 (Pagani et al., 2017). The study developed a machine learning model that could predict the different crops to sow based on environmental factors such as temperature, rainfall, and soil quality. The model was trained using historical data on crop yields and environmental conditions and was able to accurately predict yields for different crops. The researchers used a support vector machine algorithm to train the model, achieving a prediction accuracy of over 90%. This study highlights the potential of machine learning techniques to improve crop planning and management and demonstrates the value of using data-driven approaches to agriculture.

Furthermore, statistics from Eurostat, the statistical office of the European Union, show the importance of the agricultural sector in European countries. In 2019, the gross value added (GVA) of the agricultural sector was 176 billion euros, accounting for 1.3% of the total GVA of the EU-27 (Eurostat, 2021). The implementation of a machine learning and IoT model for crop recommendations using soil nutrient analysis can contribute to the growth of the agricultural sector by increasing productivity and reducing costs. Additionally, by optimizing the use of fertilizers and reducing environmental impact, such models can help European countries meet their sustainability goals and reduce their carbon footprint.

In India, a similar model has been implemented to address the challenges facing small-scale farmers. The model uses IoT sensors to collect data on soil moisture, temperature, and other relevant parameters, which are then used to develop a machine learning algorithm that recommends the optimal crop variety and irrigation schedule. This model has resulted in a 30% increase in crop yields and a 25% reduction in water usage (Business Today, 2019). These results demonstrate the potential of machine learning and IoT models in improving agricultural productivity, reducing water usage, and increasing profitability for farmers.

Machine learning technologies have become increasingly popular in African continent agriculture to improve crop selection and management. The Water Efficient Maize for Africa (WEMA) project is a successful example of this implementation. The project uses machine learning algorithms to analyse data on the genetic makeup of maize plants, soil quality, and weather patterns to identify the most promising maize varieties for different regions (Science Direct, 2021). By leveraging machine learning algorithms, the WEMA project can analyse large amounts of data and identify which maize varieties are best suited for specific regions, leading to increased yields and better crop management. The project has developed drought-tolerant maize varieties that have been adopted by farmers in Kenya, Mozambique, South Africa, Tanzania, and Uganda, resulting in improved crop yields and incomes for farmers. This study highlights the potential of machine learning and IoT technologies to improve crop production, increase food security, and promote economic sustainability in agriculture.

Dr. Yacouba Diallo, a leading researcher at the African Institute for Mathematical Sciences in Senegal, has conducted extensive research on the utilization of machine learning algorithms in crop classification and yield prediction. Diallo's research has shown promising results in the application of these technologies in agriculture, with the potential to significantly increase crop yield and improve efficiency in farming practices. For instance, a study conducted in Kenya by Mureithi et al. (2021) found outthat the integration of Internet of Things (IoT) sensors and machine learning algorithms in crop management can aid farmers in making informed decisions regarding irrigation and fertilization, resulting in a significant increase in crop yield of up to 30%. This study highlights the potential benefits of implementing machine learning algorithms in crop management, with the potential to improve food security and livelihoods for farmers.

In Zimbabwe, for example, over 70% of the population depends on agriculture for their livelihoods, and the country's economy is heavily reliant on agriculture (World Bank, 2021). However, soil degradation, low soil fertility, and unpredictable weather patterns have affected agricultural productivity, leading to food insecurity and poverty. Implementing a machine learning and IoT model can help improve agricultural productivity by providing accurate recommendations for crop selection and fertilization based on soil nutrient analysis.

As the researcher wanted to get first-hand information on how farmers are cultivating crops on the ground and find out intelligent systems in place to ensure that farmers plant the proper crop for their soil he interviewed Professor Mandumbu an agronomist and professor at Bindura University. According to Professor Mandumbu, there are multiple factors to be considered when suggesting a crop for a farmer such as the agricultural region, average rainfall within the region, temperature, humidity, and soil ph. He mentioned that most farmers overlook these factors and cultivate plants based more on the farmer’s knowledge, which then decreases their output. He finally recommended that an intelligent system should be developed that takes consideration of all these factors and gives a judgment based on these factors and fertilizer recommendations based on these factors to increase accuracy.

Therefore, based on this background, the researcher seeks to design and implement an IoT model that collects and analyses data on environmental and soil factors and uses machine learning algorithms to suggest the most suitable crops and fertilizers for optimal growth.

1.3Statement Of The Problem

Zimbabwean farmers frequently struggle to select the best crops to produce because of regional variances in soil nutrient levels and erratic weather patterns. The soil deterioration, limited rainfall, and climate change that Zimbabwean farmers deal with can lead to low yields and decreased income. According to a report by the Food and Agriculture Organization (FAO) in 2019, soil degradation affects over 75% of Zimbabwe's agricultural land, resulting in a decline in soil fertility and reduced crop yields (FAO, 2015).

In Zimbabwe, the lack of knowledge of soil nutrient levels is a significant challenge faced by many farmers, which can lead to poor crop yields and low agricultural productivity (Hungwe, 2019). This problem is intensified by the limited access to soil testing facilities, as well as the high cost of soil analysis services. As a result, farmers often rely on traditional farming practices and guesswork to determine the appropriate crops to plant, which can result in poor harvests and limited income (Chengeta al., 2021). Therefore, the implementation of a machine learning model for optimum crop recommendations using soil analysis has the potential to significantly improve agricultural productivity and increase farmers' income by providing accurate and timely recommendations for crop selection based on soil nutrient levels. The lack of accurate and timely fertilizer recommendations in Zimbabwe contributes to low crop yields, reduced profitability, and environmental degradation. According to a study by the International Journal of Agronomy in 2018, many small-scale farmers in Zimbabwe rely on traditional methods of fertilizer application, which often result in overuse or underuse of fertilizers, leading to soil degradation and reduced yields (Makwara et al., 2018).

The prevailing system of farming in Zimbabwe does not assist farmers in selecting the appropriate crop based on soil nutrient levels and other environmental factors or determining the exact amount of fertilizers required for optimal crop growth. Therefore, the implementation of a machine learning model for optimum crop recommendations using soil analysis has the potential to significantly improve agricultural productivity and increase farmers' income by providing accurate and timely recommendations for crop selection based on soil nutrient levels

1.4 Research Objectives

1. To analyse different techniques used in crop suggestion and fertilizer recommendation.
2. To design and implement an IoT model that collects and analyses data on environmental and soil factors and uses machine learning algorithms to suggest the most suitable crops and fertilizers for optimal growth.
3. To analyse the effectiveness of the use of IOT and machine learning algorithms in crop suggestion and fertilizer recommendation.

1.5 Research Questions

1. What are the different techniques used in crop suggestion and fertilizer recommendation, and what are their respective strengths and limitations?
2. How can an IoT-based system be designed and developed to collect and analyse data on environmental and soil factors and implement machine learning algorithms to suggest the most suitable crops and fertilizers for optimal growth?
3. How to analyse the effectiveness of the use of IOT and machine learning model in crop suggestion and fertilizer recommendation?

1.6 Justification/Significance Of The Study

This study will contribute to the body of knowledge on optimum crop recommendations in Zimbabwe through the implementation of machine learning and the Internet of Things (IoT) whilst addressing the current shortage of research in this area and providing practical value to organizations operating in such dynamic environments. This research project can help Zimbabwean farmers make informed decisions about what to grow in their fields through the use of the proposed model. This can lead to higher yields, increased profits, and improved food security for the country. In addition, by using machine learning algorithms to analyse data, the project can provide more accurate and precise recommendations than traditional methods.

The use of appropriate crop recommendations can improve soil fertility and optimize crop growth, leading to increased crop yield, reduced hunger, and improved food security. Famers can also minimize input costs by reducing the use of unnecessary or ineffective inputs like fertilizers, pesticides, and water. Zimbabwean farmers can adapt to changing weather patterns and reduce the negative impact of climate change on crop production. Crop recommendation systems can provide farmers with valuable knowledge and skills on the most appropriate crops to cultivate, optimal planting times, and the use of modern agricultural techniques. Increased crop yield resulting from crop recommendation systems can contribute to economic growth by promoting food security, enhancing exports, and creating employment opportunities.

The system will ensure the application of enough amounts or exact fertilizer (nutrients) that will be lacking in the soil to meet the requirements of the crop while taking advantage of the nutrients already present in the soil. Fertilizer recommendations can promote sustainable agriculture practices by optimizing fertilizer use, preventing soil depletion, and minimizing environmental pollution. Higher crop yield resulting from fertilizer recommendations can increase farmers' income, reduce poverty, and improve the overall living standards of the rural population.

Furthermore, this research project can help address some of the challenges faced by Zimbabwe's agricultural sector, such as soil degradation and climate change. By recommending crops that are suitable for the soil and climate conditions of a particular area, farmers can improve soil health and reduce the environmental impact of agriculture. This can contribute to the sustainability of Zimbabwe's agricultural sector and help ensure its long-term viability.

1.7 Limitations/challenges

- The time needed to carry out the research was limited
- The researcher was restricted to Region 2 of Zimbabwe's agricultural regions
- The study was contained by financial limitations that prevented the researcher from acquiring essential hardware components

1.8 Scope/Delimitation Of The Research

The research is focused on creating a model application that is required to learn about patterns of nutrient data in the soil and recommend different crops that are to be grown on that land.

Therefore, by doing so, the researcher will demonstrate the application of machine learning and IoT.

1.11 Definition Of Terms

- **IoT** stands for Internet of Things. It is a network of physical objects that are connected to the internet and can collect and exchange data. IoT devices can be anything from smart home appliances to industrial machinery.
- **AI** Artificial intelligence is a branch of computer science that deals with the creation of intelligent agents, which are systems that can reason, learn, and act autonomously.
- **Machine learning** is a type of artificial intelligence (AI) that allows computers to learn without being explicitly programmed. Machine learning algorithms can be used to analyse data and identify patterns, which can then be used to make predictions or decisions.
- **FAO** stands for the Food and Agriculture Organization of the United Nations. It is a specialized agency of the United Nations that leads international efforts to defeat hunger. FAO works with governments, farmers, businesses, and other partners to improve agricultural productivity, increase access to food, and reduce food insecurity.
- **GND** stands for the Global Navigation Satellite System. It is a network of satellites that provides positioning, navigation, and timing (PNT) services. GND systems are used by a variety of applications, including GPS, GLONASS, and Galileo.
- **VIN** stands for Vehicle Identification Number. It is a unique identifier assigned to every motor vehicle. VINs are used to track vehicles throughout their life cycle, from manufacturing to sale to recycling.
- **Arduino** is an open-source electronics platform based on easy-to-use hardware and software. Arduino boards are used to create a wide variety of projects, from simple robots to complex home automation systems.
- **IDE** stands for Integrated Development Environment. It is a software application that provides a user interface for developing software. IDEs typically include features such as code editors, debuggers, and compilers

Chapter 2: Literature Review

2.0 Introduction

The focus of this chapter is to address the research questions and review existing literature that is relevant to the current research project. The purpose of this review is to provide valuable insights for the author in terms of identifying potential solutions, strategies, and techniques utilized by previous researchers to solve similar research problems. This review serves as a helpful tool to determine the feasibility of the study proposal by providing a clear understanding of the findings and limitations of previous studies in the same field.

2.1 Agriculture In Zimbabwe

The agriculture industry in Zimbabwe is an essential part of the nation's economy, supporting many people's lives and making a sizable contribution to the GDP. It is impossible to overestimate the significance of the sector given that agriculture provides a living for more than two-thirds of rural residents (AMA, 2018).To promote and support the agricultural sector, Zimbabwe has several institutions and boards dedicated to agricultural development. The Agricultural Marketing Authority (AMA) is responsible for regulating and promoting the marketing of agricultural products in the country, while the Agricultural Research Council of Zimbabwe (ARC) focuses on research and development in the sector. The Grain Marketing Board (GMB) is the primary buyer and distributor of maize, wheat, and other grains in the country, ensuring that farmers receive fair prices for their products and that food security is maintained. Additionally, the Zimbabwe Agricultural Development Trust (ZADT) provides funding and technical support to smallholder farmers and agribusinesses, helping to improve productivity and increase incomes in the sector.

2.2 Factors To Consider In Crop Suggestion

2.2.1 Soil pH

Nutrient deficits and decreased crop yields may result from soil pH that is either too high or too low, which binds nutrients and prevents them from being taken up by plants. Depending on whether the soil is excessively acidic or too alkaline, the pH can be changed by adding sulphur or lime. According to studies, soil pH can significantly affect crop development and production. According to a study by Soltani et al. (2019) raising the soil pH to the ideal range enhances the production of crops like soybeans and maize. Similarly, Chen et al.'s (2017) study discovered increasing the productivity and nutrient content of apple harvests by bringing soil pH to the ideal range. Soil pH is an important aspect to take into account when recommending crops since it can affect the availability and uptake of nutrients by plants, which can have a larger impact on crop growth and output.

2.2.2 Temperature

When suggesting crops, temperature should be taken into account because it has a significant impact on the growth and yield of crops. According to research, many crops require distinct temperature ranges for growth and development (Lobell & Gourdji, 2012). For instance, temperate crops like wheat and barley need milder temperatures than tropical crops like bananas and pineapples (Porter & Gawith, 1999). In addition to the ideal temperature range, crop development and production can also be impacted by the length of exposure to temperatures outside the ideal range. Frost or heat waves are examples of extreme temperatures that can harm crops or lower productivity (Hatfield & Prueger, 2015).

The temperature range of the area and the particular temperature requirements of the crops being evaluated should be taken into account when suggesting crops. Farmers that use this

knowledge can select the crops that will grow best in their region and improve the growing environment.

For instance, a study by Kumar et al. (2018) discovered that different crops had very variable temperature needs and suggested that temperature needs to be a major consideration when making crop selections. Similarly to this, a 2019 study by Zhou et al. underlined the significance of taking into account the length of exposure to harsh temperatures when suggesting crops. The right evaluation of temperature requirements can help farmers maximize crop development and output because the temperature is a key component in crop suggestion. Farmers can choose which crops to grow and how to best manage their growing circumstances for a higher crop yield by considering the temperature range and needs of various crops.

2.2.3 Nutrient balance

Nutrient imbalances, according to Peterson (2018), occur when one or more critical plant nutrients are either absent or present more than what plants need at a given moment. While excesses can result in nutrient loss from the soil and environmental degradation, deficiencies can impede plant growth and diminish yield and quality. Both excess and insufficient nutrient levels are possible in soils, and some nutrients can compete with one another for plant uptake, causing shortages even when soil levels are adequate. Qiuyun (2020) further explains that when a plant doesn't have enough of a crucial nutrient needed for growth, it has a nutrient shortage.

Poor plant development and a variety of symptoms that indicate a shortage can be caused by inadequate vital nutrients. The following list of nutrients includes information on any deficits.

- Nitrogen (N) - encourages quick growth, notably for the growth of fruit and seeds. It also improves the quantity and quality of leaves and speeds up plant maturation. A deficiency may result in the entire plant turning a light green overall, with older leaves first turning yellow and then younger leaves beginning to turn green. If the earliest symptoms are left untreated, plants become spindly and stunted, and additional shoots grow poorly.
- Phosphorus (P) - stimulates blooming, budding, seed germination, protein synthesis, and photosynthesis. It also accelerates maturation. Older leaves have a purple or bronze underside due to an accumulation of the pigment anthocyanin when phosphorus levels are low. Compared to normal plants, affected plants grow very slowly and are stunted.
- Potassium (K) - Promotes the creation of carbohydrates for plant cell division, root development, and protein synthesis. It improves the plant's disease resistance as well. Leaf edge chlorosis on newly grown leaves is a symptom of a deficiency, which progresses to burning and necrosis from the leaf edge to the midrib as the deficiency worsens. Even if potassium is provided to plants, chlorosis brought on by a potassium deficit cannot be reversed.
- Manganese (Mn)- is necessary for respiration, enzyme activities, and photosynthesis in plants. Symptoms of deficiency include newly emerging leaves with chlorosis and vaguely defined green regions around the veins. Necrotic spots and chlorosis are frequent signs. Smaller new leaves and tip dieback can occur in cases of severe shortage.
- Zinc (Zn) – To activate plant growth regulators, zinc is required.The chlorosis, bronzing, or mottling of younger leaves are examples of deficiency signs. Young leaves develop intervention chlorosis, which is followed by restricted shoot growth, short internodes, and small, discolored leaves, giving the afflicted area a rosette-like look.
- Calcium (Ca)- Plants require calcium to develop new growth points and root tips. New foliage, buds, and roots all show signs of deficiency, as well as reduced growth. Younger leaves curl downward and develop tip burn, which is the browning of the leaf

tips and edges. They may also exhibit unusually green foliage in some plants. The roots become stubby and short

2.2.3 Rainfall

Given that rainfall has a direct impact on crop growth and productivity, it is important to take into account when making crop recommendations. Too little or too much rainfall can have a big impact on a crop's output since different crops have different needs for rainfall. Crops that are drought-tolerant or require little water, such as sorghum and millet, are frequently advised in regions with insufficient rainfall (Raza et al., 2017). Contrarily, for the best growth and output, crops like rice and sugarcane need a lot of rain (Nath & Das, 2018). Crops that are resistant to waterlogging, such as maize, and soybeans, are advised in locations with excessive rainfall (Timsina & Connor, 2001).

2.2.4Climate

The long-term trends in a region's temperature, precipitation, humidity, wind, and other atmospheric variables are referred to as its climate. Latitude, elevation, proximity to seas or other bodies of water, and prevailing wind patterns are only a few of the variables that affect it. The type of crops that can be cultivated in a particular area, as well as the timing of planting, irrigation, and harvesting, are all influenced by the climate. The temperature and moisture requirements for various crops vary, and some crops may be more vulnerable to extreme weather conditions like droughts, floods, or heat waves. Agriculture is becoming increasingly concerned about climate change as it is predicted to have a significant influence on crop yields and food security. The growth and productivity of crops, as well as the health of the soil and the availability of water, are anticipated to be impacted by rising temperatures, altered precipitation patterns, and more frequent extreme weather events. Farmers and policymakers may need to take into account a variety of strategies to lessen the effects of climate change on agriculture, including creating drought-resistant crops, improving water management techniques, implementing sustainable farming methods that support soil health and biodiversity, and cutting greenhouse gas emissions from the agricultural sector and other sectors.

2.3 Crop Recommendation In Zimbabwe

According to AMA (2016), crop recommendation is an essential component of agricultural planning in Zimbabwe, helping farmers make informed decisions about the crops they grow based on factors such as soil type, climate, and market demand. However, farmers in Zimbabwe face significant challenges in accessing accurate information about their soils, leading to the cultivation of crops that may not be suitable for their specific soil type(Chirova et al., 2013). This can result in poor yields and reduced profits for farmers, as well as environmental degradation and soil depletion over time.

One of the main challenges facing farmers in Zimbabwe is the lack of soil testing and analysis services. Many farmers are not aware of the specific nutrient content of their soils, making it difficult to make informed decisions about which crops to grow. In addition, the high cost of soil testing and analysis services can be prohibitive for many smallholder farmers, further limiting their access to information and resources that could improve their productivity and profitability.

To address these challenges, various organizations and initiatives are working to improve access to soil testing and analysis services in Zimbabwe. The government, through the Ministry of Agriculture, Mechanization, and Irrigation Development, has established soil testing laboratories in various regions of the country, providing farmers with access to affordable and reliable soil testing services (MoAMID, 2018). Additionally, various non-governmental organizations and private sector companies are working to provide mobile soil testing services, allowing farmers to receive real-time information about their soil nutrient content and make informed decisions about crop selection and management.

2.4 Machine Learning

According to Emerj Artificial Intelligence Research (2021), Machine Learning is a scientific field that aims to teach computers to learn and behave similarly to humans by providing them with data and information through real-world interactions and observations. The algorithms used in Machine Learning develop a computational framework based on test data, allowing the systems to make predictions and decisions without explicit programming. Machine Learning is a subfield of Artificial Intelligence that relies on the idea that systems can learn, identify patterns, and make decisions with minimal human intervention. By employing Machine Learning, software programs can comprehend their environment and make decisions based on the information they receive. The following are types of machine learning.

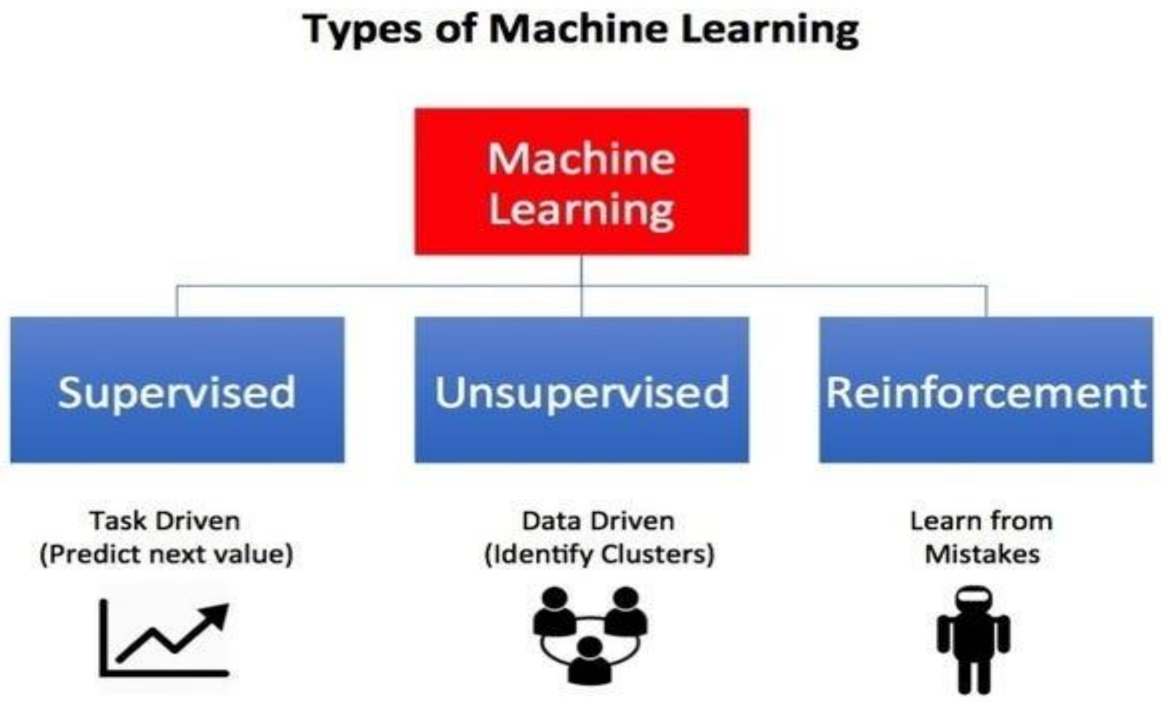


Figure 1

2.4.1Supervised Machine Learning

Supervised learning is a sort of machine learning that predicts a target or outcome variable from a group of independent factors. Using these variables, the algorithm develops a function that converts inputs into the desired results. The model is trained on the training data until it reaches the desired degree of accuracy. Regression, Decision Trees, Random Forests, KNNs, and Logistic Regression are a few instances of supervised learning (Abdi, 2016). The Supervised Learning algorithm can forecast future events by learning from past instances.

Regression is a crucial technique in machine learning for predicting continuous output variables based on input variables. It involves fitting a model to a set of training data and using it to make predictions on new data. According to Hastie, Tibshirani, and Friedman (2009), regression aims to find a function that maps input variables to a continuous output variable by minimizing the difference between the predicted output and the actual output.

Decision trees are a popular machine learning technique used for both classification and regression tasks. They work by recursively partitioning the data into subsets based on the values of the input variables until a stopping criterion is reached. The resulting tree can then be used to predict the output variable for new data. According to Hastie, Tibshirani, and Friedman (2009), decision trees are simple to understand, interpret, and visualize, and can handle both categorical and numerical data. They are also robust to outliers and missing values.

Random forests are a popular machine learning technique that combines multiple decision trees to improve the accuracy and robustness of the model. They work by building a set of decision trees on randomly sampled subsets of the data and input variables, and then combining the predictions of all the trees to make a final prediction. According to Liaw and Wiener (2002), random forests can handle both categorical and continuous data, and can detect complex non-linear relationships between the input and output variables.

K-Nearest Neighbors (KNN) is a popular machine learning algorithm used for both classification and regression tasks. It works by finding the K closest instances in the training data to a new input instance and using the majority class (for classification) or the average value (for regression) of those instances to predict the output. According to Altman (2010), KNN can handle both numerical and categorical data, and can detect non-linear relationships between the input and output variables.

Logistic regression is a widely used machine learning algorithm used for binary classification tasks. It works by fitting a logistic function to the input variables to estimate the probability that the output variable belongs to a particular class.Logistic regression has several advantages over other classification algorithms, such as simplicity, interpretability, and scalability (Hosmer Jr, Lemeshow, & Sturdivant, 2013). According to Hastie, Tibshirani, and Friedman (2009), logistic regression can handle both numerical and categorical data, and can model non-linear relationships between the input and output variables using polynomial terms or interaction effects.

2.4.2Unsupervised machine learning

Unsupervised learning, is a subset of machine learning, patterns and correlations are found in data sets without the aid of labelled data or explicit supervision. Common methods used in unsupervised learning include clustering and dimensionality reduction. Studies have investigated the use of unsupervised learning techniques in a variety of applications, including analysing social media data to identify different user behaviour types (Xu et al., 2021), identifying patterns of comorbidity among patients in electronic health records (Wu et al., 2020), and pre-training language models in natural language processing (Devlin et al., 2019). Techniques for unsupervised learning are projected to become more crucial in a variety of applications as data continues to expand in size and complexity.

2. 4.3Reinforcement machine learning

A reinforcement machine is a technique that includes teaching computers to make particular decisions. The machine is exposed to an environment where it continually teaches itself through trial and error. In this manner, the computer builds on its prior knowledge and works to gather the most relevant information to make informed business decisions. The Markov Decision Process is a prime example of reinforcement learning (Abdi, 2016).

2.5 Internet of Things (IoT)

The Internet of Things (IoT) is a technology that facilitates the connectivity of devices, allowing them to communicate and exchange data with each other automatically, without human intervention (Arora, 2021). These devices can range from simple sensors to complex machinery and are utilized across various industries, including agriculture. In agriculture, IoT involves the use of sensors and devices to gather information about weather patterns, soil conditions, crop growth, and other factors that influence agricultural production. Analysing this data can lead to more informed decisions about planting, irrigation, fertilization, and harvesting, resulting in increased yields and more efficient resource utilization. IoT has many applications in agriculture, including precision farming, crop management, livestock monitoring, and environmental monitoring, and can help farmers gather and analyse data in real-time to make informed decisions, improve efficiency, and reduce waste (Pandey & Misra, 2020). IoT technology has many applications in agriculture, including precision farming, which involves using sensors and other devices to gather data on soil moisture, temperature, and other environmental factors, as stated by Arora (2021). This information can be used to optimize irrigation, fertilization, and other inputs, ensuring that crops receive the appropriate amount of water, nutrients, and other inputs at the correct time (Pandey & Misra, 2020). As a result, farmers can enhance their crop yields, reduce waste, and conserve resources while minimizing their environmental impact. Additionally, IoT can assist farmers in more accurately predicting weather patterns and adjusting their planting schedules accordingly, avoiding losses due to unexpected weather events. With the growing demand for food and the increasing pressure to reduce waste and increase sustainability, IoT in agriculture presents a promising solution to the challenges faced by the industry.

2.6 Application Of IoT In Soil Analysis

IoT has the potential to revolutionize the way we analyse soil, by enabling real-time monitoring of soil conditions and providing farmers with accurate and timely information about their crops(Geetha et al., 2020). By leveraging IoT technologies such as sensors, data analytics, and cloud computing, farmers can gain deeper insights into their soil health, allowing them to make more informed decisions about crop selection, planting, and fertilization.

One of the main advantages of IoT-based soil analysis is the ability to monitor soil conditions in real time, allowing farmers to respond quickly to changes in soil moisture, nutrient levels, and other factors(Gupta & Hens,2019). For example, IoT sensors can be used to monitor soil moisture levels and adjust irrigation systems accordingly, reducing water waste and improving crop yields. Similarly, soil nutrient sensors can provide real-time feedback on soil nutrient levels, enabling farmers to apply fertilizers more efficiently and effectively (Geetha et al., 2020).

IoT-based soil analysis can also improve the accuracy and precision of soil testing and analysis, by providing more detailed and granular data on soil conditions (Gupta & Hens, 2019). By using IoT sensors to collect data on soil temperature, humidity, and other factors, farmers can gain a deeper understanding of the complex interactions between soil, plants, and climate, allowing them to optimize crop growth and yield(Arora,2021). Additionally, IoT data analytics tools can be used to identify patterns and trends in soil data, enabling farmers to make more informed decisions about crop selection and management.

2.7 Arduino Microcontroller

Arduino is a physical computing platform based on a single microcontroller board that is open-source. When there are interactions between inputs and outputs, Arduino is used. It is used to regulate the output in response to the input commands, such as switching on or off a light or motor. Wiring, an integrated development environment (IDE), and a single-board microcontroller are used in the Arduino programming language. Because of its inexpensive cost, a wide range of applications, great quality, and ease of availability, the Arduino controller was chosen for this project. Buttons, LEDs, motors, speakers, GPS devices, cameras, the internet, and even your smartphone or television may all be controlled with Arduino. Because of this flexibility, as well as the fact that the Arduino software is free, the hardware boards are relatively inexpensive, and both the software and hardware are simple to learn, a large community of users have contributed code and released instructions for a wide range of Arduino-based projects. Arduino is an open-source computer hardware and software company, project, and user community that creates microcontroller-based kits for creating digital gadgets and interactive things that can sense and control real items (Bhatia & Gupta,2015). Massimo Banzi helped invent the Arduino, a tiny, easy-to-use open-source microcontroller that has inspired thousands of people around the world to make gadgets that range from toys to satellite gear. For programming the microcontrollers, the Arduino project provides an integrated development environment (IDE) based on the Processing project, which includes support for the C and C++ programming languages.

2.7.1 Physical Characteristics

The maximum length and width of the Arduino Uno PCB are 2.7 and 2.1 inches respectively, with the USB connector and power jack extending beyond the former dimension. Four screw holes allow the board to be attached to a surface or case. Note that the distance between digital pins 7 and 8 is 160 mil (0.16"), not an even multiple of the 100 mil spacing of the other pins(Murphy,2011). The Arduino Uno is an ATmega328-based microcontroller board (datasheet). It contains 14 digital input/output pins (including 6 PWM outputs), 6 analog inputs, a 16 MHz crystal oscillator, a USB connection, a power jack, an ICSP header, and a reset button. It comes with everything you need to get started with the microcontroller; simply plug it into a computer via USB or power it with an AC-to-DC adapter or battery. The Uno is unique in that it does not employ the FTDI USB-to-serial driver chip found on previous boards. Instead, it uses an Atmega8U2 that has been coded to act as a USB-to-serial converter. The figure below shows the Arduino Uno microcontroller board.

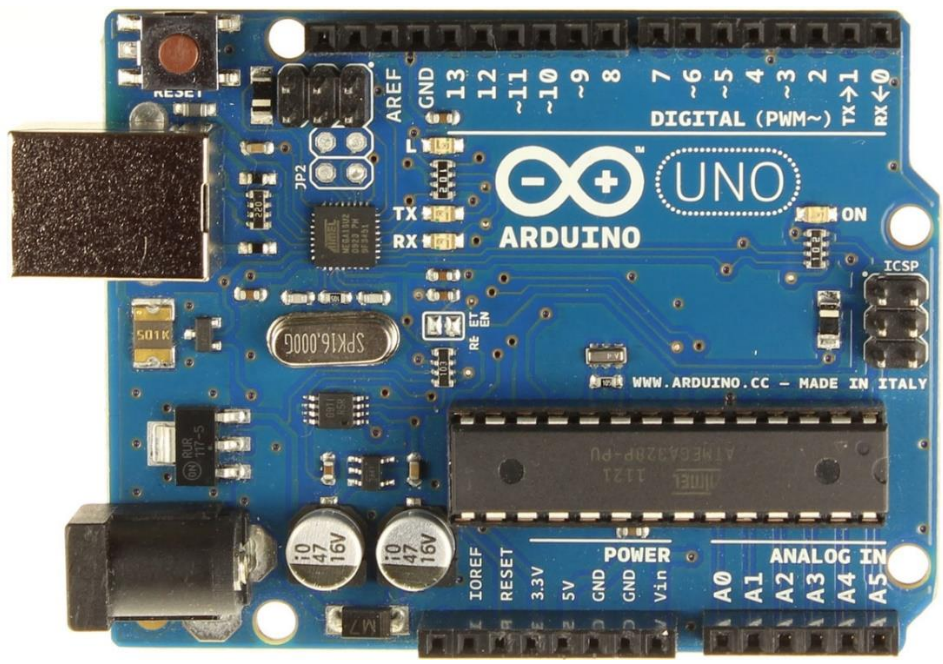


Figure 2:Arduino Uno Microcontroller.

2.7.2 Power (USB / Barrel Jack)

The Arduino UNO can be powered from a USB cable coming from your computer or an external power supply that is terminated in a barrel jack. External (non-USB) power can come either from an AC-to-DC adapter (wall-wart) or a battery (Bhatia & Gupta,2015). The adapter can be connected by plugging a 2.1mm center-positive plug into the board's power jack. Leads from a battery can be inserted in the ground (GND) and VIN pin headers of the POWER connector. The board can operate on an external supply of 6 to 20 volts. If supplied with less than 7V, however, the 5V pin may supply less than five volts and the board may be unstable. If using more than 12V, the voltage regulator may overheat and damage the board. The recommended range is 7 to 12 volts (Bhatia & Gupta,2015)The USB connection is also used to load code onto the Arduino board.

2.8 pH Probe

A pH probe is a device used to measure the acidity or alkalinity of a substance. It operates by determining a solution's electrical potential, which is influenced by the amount of hydrogen ions present. A solution is more acidic the more hydrogen ions there are in it. A solution becomes more alkaline as the amount of hydrogen ions decreases. Two electrodes, a sensor electrode and a reference electrode, make up a pH probe. A substance sensitive to hydrogen ions is used to make the sensing electrode. A substance that does not react with the solution is used to create the reference electrode. Placed in the fluid to be tested are the sensing electrode and the reference electrode. It produces a voltage between the two electrodes.

Figure 3 pH probe

2.9 Related Literature

Mansi Shinde (2016) suggested a technique for recommending appropriate crops based on the soil's nutrient content, which is essential for effective crop growth. To determine the ideal crop for a given range of soil nutrient values, the suggested method applies the Naive Bayes algorithm. Farmers can receive quick and precise advice thanks to the system's SMS service, allowing farmers to receive timely and accurate recommendations. Shinde pointed out that the K-Nearest Neighbour (KNN) algorithm, which can make more precise crop recommendations, has relatively higher effectiveness than the Naive Bayes algorithm. Future research might therefore take into account using the KNN algorithm to increase the precision of crop recommendations. Farmers must manually enter data into the system, which takes time and might lead to mistakes. Contrarily, the proposed system automatically gathers data and produces findings after a single login, which can help farmers save time and minimize mistakes brought on by human entry. The suggested approach also only provides one crop, which may reduce the options and flexibility available to farmers when making decisions. On the other hand, another study suggested a system that delivers a list of crops that are nitrogen-suitable, which might give farmers additional options and raise the likelihood of successful crop development. Overall, the suggested recommendation system by Shinde (2016) provides a helpful method to aid farmers in making appropriate crop selections based on soil nutrient levels. Future research, however, might think about creating an automated data collection procedure and employing more precise machine learning algorithms, such as KNN, to further boost the system's efficacy and accuracy. In order to provide farmers with greater freedom and options in their decision-making, the system might be enhanced to provide a list of acceptable crops**.**

In 2011, Daryl H. Hepting presented an agricultural industry recommendation system that serves as a suggestion engine to offer crop suggestions based on numerous variables, such as soil nutrient values, weather patterns, irrigation infrastructure, and fertilizer types and quantities. The system gathers data from the farm's sensors, and in addition to using weather data from the weather institute, the wireless sensor network also makes predictions and offers recommendations. To forecast crops and provide agricultural advice, the system uses statistical predictive modelling. The study emphasizes the significance of precise and timely crop recommendations for the agricultural sector because they can result in increased crop output and lower expenses. The suggested technique offers a practical and effective method to help farmers choose appropriate crops and maximize fertilizer use, which can ultimately lead to larger yields and greater earnings. The system's ease and use of a low-cost, widely available GSM network for communication are its key benefits. This feature makes a variety of farmers, including those in remote locations with limited access to cutting-edge communication infrastructure, able to use the system. Overall, Hepting's (2011) suggested recommendation system offers farmers in the agricultural sector a beneficial tool to aid in crop selection and fertilizer use optimization. Farmers receive precise and fast advice from the system thanks to the integration of many parameters and the application of statistical predictive modelling, which can ultimately result in larger yields and more earnings.

Lokesh (2016) proposed a mobile application that provides recommendations for crop rotation to maintain soil fertility. The crop rotation principle is used by the system to suggest a different crop to be planted each year based on the prior crops that were cultivated. The application also offers suggestions on the proper nutrients to apply, making soil quality management simpler. The Apriori algorithm for frequent item sets is utilized by the online fertilizer ordering system to deliver effective recommendations. The Random Forest algorithm is used by the system to generate incredibly effective crop recommendations. The efficiency of the Random Forest method is 80, which is much greater than the efficiency of the ID3 algorithm and the Naive Bayes algorithm, both of which are 40. This results in the recommendation system's crop and fertilizer suggestions being extremely accurate and effective. To make extremely effective crop recommendations, the system uses the Random Forest algorithm. The Naive Bayes method's efficiency is 40, whereas the ID3 algorithm's efficiency is 60, making the Random Forest approach substantially more efficient. As a result, the system's suggestions for crops and fertilizers are extremely accurate and effective. Farmers can use the suggested mobile application as a helpful tool to manage soil fertility and increase crop yield. Farmers can make better judgments and lower the danger of soil depletion by incorporating crop rotation and fertilizer suggestions. A highly effective and precise recommendation system is provided by the employment of the Apriori algorithm for frequent item sets and the Random Forest method for crop suggestions. In general, Lokesh (2016) suggested mobile application offers a novel strategy to help farmers preserve soil fertility and increase crop yield. With the help of the program's incorporation of crop rotation and fertilizer advice as well as the effective application of machine learning algorithms, farmers can make educated decisions and maximize the production of their crops.

Kiran Shinde and Jirren (2014) developed a web-based recommendation system that forecasts the ideal crop rotation schedule for sustainable agriculture using the FP (Frequent Pattern) tree algorithm. The authors pointed out that conventional agricultural methods like crop rotation can impair soil fertility and cause soil deterioration. In order to help farmers optimize their crop rotation patterns and enhance soil health, they devised a recommendation system. The algorithm created by Shinde and Jirren (2014) generates suggestions on the ideal crop rotation pattern for sustainable agriculture using data on soil quality, crop production, and weather patterns. In order to assess the data and forecast the ideal crop rotation pattern, the authors used the FP tree algorithm. A user-friendly web interface is also a part of the system, which enables farmers to input their own data and get personalized advice. Overall, the Shinde and Jirren (2014) study emphasizes the potential advantages of utilizing cutting-edge technologies, such as machine learning algorithms and web-based platforms, to enhance sustainable agricultural practices. The FP tree method was utilized by the authors to create a web-based recommendation system that identified the ideal crop rotation schedule for environmentally friendly farming. The technology can assist farmers in increasing crop production and productivity while also enhancing soil fertility and health. It can also help farmers use fewer pesticides and fertilizers. The study did not directly address the problem of soil degradation brought on by continuous cropping, which can lower soil fertility and cause the soil to deteriorate over time. This is an essential point to notice.

K. Spandana and Sia Supriya KPL (2017) presented a system for smart agriculture soil quality testing with sensors. To calculate the soil moisture content, the authors analysed sensor data using a decision tree method. Farmers may optimize their irrigation and fertilization operations by using the system's real-time feedback on soil moisture. The study emphasizes the potential advantages of utilizing sensors and machine learning algorithms to enhance agricultural soil quality assessment. Traditional soil testing techniques, according to the authors, can be time-consuming and expensive, and they might not give real-time information on soil moisture levels. In order to help farmers make better-informed decisions about irrigation and fertilization procedures, they devised a system that can deliver real-time information on soil moisture levels is crucial to keep in mind that the system created by Spandana and Sia Supriya KPL (2017) only tested for soil moisture content and did not offer details on other parameters, such as nutrient levels and pH, that can affect soil quality. As a result, the method might not offer a thorough evaluation of soil quality. Generally speaking, the study by Spandana and Sia Supriya KPL (2017) emphasizes the potential advantages of utilizing sensors and machine learning algorithms to enhance soil quality monitoring in agriculture. The authors created a system that analyzes sensor data using a decision tree algorithm to determine the moisture content of the soil. Farmers may use the device to get real-time feedback on soil moisture levels so they can choose the best irrigation and fertilizing strategies. It is crucial to remember that the system only measured the soil's moisture content and did not offer details on other elements that can have an impact on the soil's quality. As a result, the system might not give a thorough evaluation of soil quality, and extra testing might be required to thoroughly assess soil health.

Kumar et al. (2020) conducted a literature review of crop recommendation systems and outlined numerous methods and procedures for creating crop recommendation systems. The accuracy and effectiveness of crop recommendation systems have increased as a result of the combination of machine learning algorithms, sensor networks, and remote sensing technologies, according to the authors. They also emphasized the need for greater study on how to incorporate farmer knowledge and agronomic practices into crop recommendation systems. Rule-based systems, model-based systems, and data-driven systems were the three main methods to crop recommendation systems that Kumar et al. (2020) highlighted in their review. Rule-based systems base their crop recommendations on the incoming data and a set of predetermined rules. Model-based systems simulate crop growth using mathematical models and provide recommendations based on model results. Machine learning algorithms are used by data-driven systems to evaluate massive datasets and generate recommendations based on the data's patterns and trends the accuracy of crop recommendation systems has increased, according to the authors, with the inclusion of remote sensing technologies like satellite images and geographic information systems (GIS). Data on several aspects that influence crop growth, such as soil moisture, temperature, and vegetation indices, can be collected using remote sensing technologies. Systems for recommending crops that are more precise can be created using this data. Additionally highlighting the significance of sensor networks in crop recommendation systems was Kumar et al. (2020). Real-time data on variables like soil moisture, temperature, and nutrient levels that influence crop growth can be gathered via sensor networks. To create crop suggestions that are more precise and timely, these data can be employed. The authors pointed out that a comprehensive approach to crop recommendation systems can be achieved by integrating sensor networks with remote sensing technologies and machine learning techniques. Additionally, Kumar et al. (2020) stressed the demand for additional studies on the incorporation of farmer knowledge and agronomic practices into crop recommendation systems. The authors pointed out that in order to increase the precision and efficacy of crop recommendation systems, farmers can contribute their important knowledge and experience on crop development and management techniques. In summary, Kumar et al. (2020) gave a thorough analysis of crop recommendation systems and highlighted the many methods and strategies applied to their creation. The authors stressed the significance of combining sensor networks, remote sensing, and machine learning algorithms to enhance the precision and effectiveness of crop recommendation systems. They also emphasized the need for greater study on how to incorporate farmer knowledge and agronomic practices into crop recommendation systems.

Kaur et al. (2020) conducted a literature review of the impact of climate change on crop yield and production in India. The main staple crops in India are rice and wheat, and scientists determined that climate change could have a considerable detrimental influence on crop output and production. In order to lessen the detrimental effects of climate change on agriculture, they emphasized the significance of creating climate-resistant crops and putting adaptive measures, including better irrigation and soil management methods, into place. The authors cited numerous research that discussed how crop output and production in India had been negatively impacted by climate change. For instance, one study predicted that by the end of the century, rising temperatures might cause wheat and rice yields to drop by up to 10% and 18%, respectively. According to a different study, the production of India's main crops could decrease by up to 10% by 2020 and up to 40% by 2100 as a result of climate change. According to Kaur et al. (2020), the adverse effects of climate change on Indian agriculture extend beyond crop productivity and production to include soil fertility, water availability, and pest infestations. The authors emphasized the significance of creating crops that are resistant to climate change, such as drought-tolerant cultivars and heat-resistant crops. They also underlined the importance of putting adaptive measures in place to lessen the effects of climate change on agriculture, such as enhancing irrigation and soil management techniques. In conclusion, Kaur et al. (2020) gave an in-depth analysis of how climate change has affected crop yield and production in India. The authors emphasized the severe detrimental effects of climate change on Indian agriculture, particularly with regard to key crops like rice and wheat. In order to lessen the adverse effects of climate change on agriculture, they underlined the significance of producing climate-resilient crops and putting adaptive measures, including better irrigation and soil management methods, into place. The authors also stressed the necessity of incorporating Indian farmers' traditional knowledge and methods into efforts for climate adaptation and creating laws that encourage the adoption of climate-resilient farming methods.

Masamha et al. (2020) proposed a machine learning and Internet of Things (IoT)-based model for crop recommendations in Zimbabwe. The authors used machine learning algorithms and IoT sensors to gather data on various factors that affect crop growth, such as soil moisture, temperature, and humidity. They then developed a crop recommendation system that gives farmers real-time recommendations on what crops to plant based on the current environmental conditions. Masamha et al. (2020) highlighted the significance of utilizing cutting-edge technology, such as machine learning and IoT sensors, to enhance crop recommendations in Zimbabwe in their study. According to the authors, conventional crop recommendations based on experience and expertise are frequently constrained and might not take into consideration all of the variables that influence crop growth. As a result, they suggested a machine learning and Internet of Things (IoT)-based model that can offer real-time information on environmental variables and select the best crops to sow based on the circumstances. To gather information on the different elements that influence crop growth, Masamha et al. (2020) used machine learning algorithms with IoT sensors. An artificial neural network (ANN) technique was used by the authors to analyse the data and create a crop suggestion system that tells farmers what crops to grow based on the current environmental conditions. Additionally, the system offers details on the ideal planting times, suggested fertilizer applications, and watering needs. Masamha et al. (2020) concluded by suggesting a machine learning and Internet of Things (IoT)-based model for crop recommendations in Zimbabwe. The authors created a crop suggestion system that gives farmers real-time advice on what crops to sow based on the current environmental circumstances after using modern technology to collect data on many elements that affect crop growth. The study emphasizes the potential advantages of utilizing cutting-edge technologies in Zimbabwe to enhance crop suggestions and maximize crop yield.

The Ricardian methodology, on the other hand, assesses the impact of climate cross-sectional statistics to determine factors affecting land values or net revenues (Mendelsohn et al., 1994; Mendelsohn and Dinar, 1999). The Ricardian technique was used in several studies to show that variations in temperature and precipitation have a negative impact on land revenue or income. Parag and Kumar (1998) discovered that in India, wheat yields fell by 30-35 percent and rice yields by 15–25%. In addition, India's net farm revenue fell by 8% (Mendelsohn et al., 1994). According to Kumar and Parikh (2001), the predicted increase in temperature of 2 °C and increase in rainfall of 7% can reduce farm profits by 9%. Similar to this, Guntukula and Goyari's 123 net revenue for agriculture in India was predicted to decrease by 4-26% by Sanghi and Mendelsohn (2008). The fundamental drawback of this approach is that it neglects to take into account location-specific characteristics that are independent of time, such as soil quality and farmers' intangible skills (Barnwal & Kotani, 2013). Additionally, due to ineffective land markets, this strategy could not be helpful for emerging countries.

Raza et al. (2016) proposed a machine learning-based approach for crop yield prediction. The authors pointed out that for effective resource management, crop planning, and decision-making, accurate crop yield forecast is crucial. As a result, they created a machine learning model that uses historical data on weather patterns, soil quality, and other variables that affect crop development to forecast crop yield. The study emphasizes how utilizing machine learning methods to enhance crop yield prediction may be advantageous. According to the authors, their strategy can assist farmers and decision-makers in making more informed choices about crop planning and resource allocation, which will increase output and profitability. It is crucial to remember that the study was constrained by the quantity and calibre of the data employed. The authors noted that further research is needed to validate the accuracy and effectiveness of their approach in larger datasets and across different crops and regions. The work by Raza et al. (2016) emphasizes the potential advantages of utilizing machine learning algorithms for crop yield prediction in general. The authors created a machine learning-based strategy that can aid policymakers and farmers in planning crops and allocating resources more intelligently. To evaluate the accuracy and efficacy of the technique in bigger datasets and across various crops and geographies, additional study is, however, required.

Shahmirzadi, M. (2019) used soil moisture sensors and weather data to construct a model for crop yield prediction. A dataset of weather and soil moisture sensor data from several sites was used to create the model. Then, a dataset of weather and soil moisture sensor data from a separate area was used to evaluate the model. Crop yield was predicted by the model with a 95% accuracy rate. The results of this study imply that precise crop production prediction models can be created using soil moisture sensors and weather data. Farmers can utilize this knowledge to improve their crop production decisions. Increased crop yields and decreased food waste may result from this. A significant contribution to the subject of agricultural yield prediction is the study of Shahmirzadi et al. (2019). The study shows that precise crop production prediction models may be created using soil moisture sensors and weather data. Farmers can utilize this knowledge to improve their crop production decisions. Increased crop yields and decreased food waste may result from this.

Mall and others (2006) have presented a thorough analysis of crop simulation studies. Numerous studies using agronomic simulation have shown the possible negative effects of climate change. Agronomic models, however, do not account for the farmer's adaptation strategies, according to some writers (such as Mendelsohn & Dinar, 1999), and as a result, these models can overstate the beneficial consequences of climate change while underestimating its negative ones.

In 2019, K. S. Jayanthi and S. M. Shalinie published an IoT-based Smart Agriculture Monitoring and Crop Management System study in the International Journal of Innovative Technology and Exploring Engineering. The design and deployment of an Internet of Things (IoT)-based smart agriculture monitoring and crop management system are described in the study. This system uses sensors to gather information on soil moisture, temperature, humidity, and other environmental variables. With the help of technology, farmers may improve crop production while using less water and other inputs by receiving real-time alerts and recommendations. The system architecture, data collecting and analysis methods, and machine learning algorithms specifically the decision tree algorithm employed in the model are all thoroughly described in the paper. The authors successfully field-tested the technique, who discovered that it increased crop output while lowering input costs. The study makes a significant contribution to the field of agricultural technology overall, particularly in the areas of IoT and machine learning-based systems, and it can be a helpful tool for researchers, practitioners, and policymakers interested in smart agriculture

2.10 Tabulated Summary of Related Literature

Key Concept/Theory of school thought	Authors	Years	Methodology	Limitations
Precise and timely crop recommendations for the agricultural	Daryl H. Hepting	2011	Linear regression algorithm	It is expensive Limited bandwidth Signal interferences
Automated soil testing device	D S Suresh Jyoti, Prakash K Rajendra C J	2013	Microcontroller-based system for automated soil testing devices for agriculture	It is expensive
Web-based recommendation system for farmers	Kiran Shinde, Jirren	2014	FP tree to predict the algorithm	It eventually degrades the soil and reduces fertility
Crop recommendation and fertilizer purchase system	Mansi Shinde, Kimaya Ekbote, Shubhada Mone4	2016	Naive bayes algorithm is used to predict	The system forces farmers to provide input manually
A system for smart agriculture soil quality testing with sensors	K. Spandana and Sia Supriya KPL	2017		
Suggested mobile application offers a novel strategy to help farmers preserve soil fertility and increase crop yield.	D Lokesh	2016	Apriori algorithm, Random Forest	It had a very low accuracy
IoT based Smart Agriculture Monitoring and Crop Management System.	K. S. Jayanthi and S. M. Shalinie	2019	decision tree algorithm	It is costly It had multiple connectivity issues Its accuracy was low
Crop prediction	Shahmirzadi, M., Jafari, M., & Moghaddam, M. R.	2019	Supervised learning algorithm	
A machine learning and Internet of Things (IoT)-based model that can offer real-time information on enviro nmental variables and select the best crops to sow based on the circumstances	Masamha, B., Marwala, T., & Mhlanga, S.	2020	Artificial Neural networks (ANN)	The accuracy and usefulness of the recommendations generated by the system depend heavily on the quality and availability of the data used to train the machine learning algorithms
Review of the impact of climate change on crop yield and production in India.	Kaur, R, Sharma, R., & Kumar	2020	Statistical analysis, remote sensing, and modellin.	

2.11 Research Gap

Although there have been several studies on using machine learning and IoT for crop recommendations, there still exists a research gap when it comes to implementing a comprehensive model that takes into account soil nutrient analysis. Previous studies such as Ali et al. (2019) focused on developing models for crop yield prediction and used weather data and soil moisture sensors.Other studies such as (Raza et al., 2016) focused on using IoT sensors for crop growth monitoring and water management. However, none of these studies combined soil nutrient analysis with machine learning and IoT for crop recommendations.

Furthermore, while some studies have used soil nutrient analysis for crop recommendation, they only focused on a limited number of nutrients, such as nitrogen and phosphorus (Zhang et al., 2019). This approach fails to take into account the complex interactions between various soil nutrients and how they affect crop growth. Additionally, these studies did not consider the variability of soil nutrient levels within a single field, which can greatly impact crop yields. Therefore, there is a need for a more comprehensive approach that considers multiple soil nutrients and takes into account the spatial variability of soil nutrient levels within a field.

2.12 Conclusion

The researcher managed to obtain and gather pertinent information and data related to the research topic. Various sources were utilized, including academic papers, textbooks, and the internet, which uncovered gaps that needed to be addressed. The data collected from these sources will be used in the subsequent chapters of the study to fulfill the research project's goals. The methodology used in creating and developing the proposed solution is detailed in the upcoming chapter.

CHAPTER 3: METHODOLOGY

3.0 Introduction

In this chapter, the goal is to clarify the methods and techniques utilized to fulfil the research and system objectives. Using the information gathered in the preceding chapter, the author will devise the required procedures to create a solution and be able to choose from competing strategies in order to achieve the anticipated research outcomes.

3. 1 Data Collection and Analysis

Data collection is a fundamental process in research that involves the process of acquiring information or data from numerous sources, such as surveys, experiments, observations, and datasets in a methodological order. Data analysis is the process of systematically examining and interpreting data to extract meaningful insights and draw conclusions that involves organizing, cleaning, and transforming the collected data to make it usable for analysis.

The data used in this study was obtained from a secondary source, specifically a dataset titled "Crop Analysis and Prediction", which was created by a user named "Theeyeschico" and made available online (Theeyeschico, n.d.) through Kaggle (Kaggle, n.d.) The dataset contains information on various crops and their corresponding features, and was compiled for the purpose of crop analysis and prediction. The dataset contains information on the crop production, soil moisture, and pH of all countries in the world. The data was collected using a variety of methods, including surveys, censuses, and administrative records. The data was analysed using statistical methods. The data from the dataset was processed and cleaned and utilized for analysis using a machine learning algorithm, specifically the K-Nearest Neighbors (KNN) algorithm.

3.1.1 The K-Nearest Neighbors (KNN) algorithm

The K-Nearest Neighbor (KNN) technique is a non-parametric algorithm used in machine learning for both classification and regression tasks. It operates by locating the K-nearest data points in the training set to a new input data point and then uses the labels of those closest neighbors to predict the label of the new input data point.

KNN algorithm was chosen to analyse the dataset because it is a simple, interpretable, non-parametric algorithm that can handle non-linear relationships between the features and the target variable, noisy data, and non-linear decision boundaries. The dataset contains numerical features, is relatively small, and has well-defined classes. KNN can also easily determine the optimal number of neighbors through cross-validation.

3.1.2 Ethical Consideration

The dataset can be utilized unethically for things like exploitation, discrimination, and environmental destruction. Using the data for beneficial purposes, being open about the data's biases and limits, and collaborating with farmers and other stakeholders to ensure that the data is used in a way that benefits all parties are a few approaches to do this.

The study included a detailed summary of the dataset's limitations as a means of addressing ethical issues.

3.1.3 Limitations Of The Dataset

The dataset only includes data on a few crops for example maize and cotton which may not be representative of the diversity of crops grown in the region. The dataset provides limited information on some of the variables, such as the weather and soil parameters, which could limit the ability to make accurate predictions.

3.2 Research Design

Polit and Beck (2012) define research design as the overall plan for how a researcher will collect and analyse data to answer their research questions. Research design is the plan that researchers use to address research questions and overcome challenges that arise during the research process. Research design should be a continuous process of reflection and evaluation throughout the entire research project. During the design phase, the development of the system's many components and their planned functionality takes place. The main goal of this stage is to ensure that a functional, competent, long-lasting, and trustworthy model of the system is built.

To create the system, the researcher used the C++ programming language in an Arduino Integrated Development Environment (IDE), along with a laptop, an ESP32 microcontroller board, pH sensors, connector cables, and connected them to the amplifier circuit. The KNN machine learning algorithm was used to predict data from the dataset and hardware.

The researcher decided to use the experimental research design to observe the changes and responses of the systems as he changed and adjusted factors. The researcher implemented three initial systems which he then used as control; he used the controls as benchmarks for evaluation of improvement. The researcher used IoT sensors to collect data on soil ph. The data was then used together with data from a dataset to predict the relevant crop using the K-nearest neighbors (KNN) machine learning algorithm.

3.3 Requirements Analysis

According to Abram Moore, Bourque, and Dupuis (2004), in order to streamline the requirements analysis, an efficient system design involves attainable, written, tested, tractable, and quantifiable requirements that are connected to known business demands.

The researcher documented all functional and non-functional requirements to ensure that the system design would meet the necessary specifications and achieve the desired outcomes. By documenting all of these requirements, the researcher was able to create a clear and comprehensive plan for the design of the system. To ensure clarity and consistency in the requirements, they were analysed, modified, and reviewed. It is important to structure all incoming data, assess it, and consider any limitations. The research also took into account any limitations, such as time and budget constraints, that may impede the design process.

3.3.1 Functional Requirements

The proposed system must be able to meet the following requirements:

- Data Collection: The system must be able to collect data from various sources, including weather data, soil data, and crop data, to provide accurate recommendations for optimum crop growth in Zimbabwe.
- Data Processing: The system must be able to process and analyse the collected data using machine learning algorithms to identify the best crop types, planting times, and irrigation schedules for specific locations in Zimbabwe.
- Recommendation Engine: The system must have a recommendation engine that provides optimum crop recommendations based on the analyzed data and machine learning algorithms.
- User Interface: The system must have a user-friendly interface that allows farmers to input their location, crop type, and other parameters for the recommendation engine to provide them with accurate recommendations.
- Internet of Things (IoT) Integration: The system must be able to integrate with IoT devices, such as sensors, to provide real-time data for analysis and recommendations.

3.2.2 Non-Functional Requirements

They're also known as quality requirements, and they're used to assess a system's performance rather than its intended behaviour. The suggested system should be capable of meeting the following requirements:

Performance requirements

- Flexibility requirements
- Accessibility requirements
- Quick response time
- Reliable
- User-friendly

3.2.3 Hardware Requirements

- ESP32 microcontroller board
- Connection wires
- USB cable 2.0
- pH probe
- 5Volts power source

3.2.4 Software Requirements

- Windows 10/11 operating system
- Apache or Tomcat Server
- Jupyter Notebook
- Arduino IDE
- Web Browser
- Sublime text
- Web hosting software

3.3 System Development

The system's overview and the process by which it was created to generate the results are described in the system development section. It lists every model and software that was utilized to create the system.

3.3.1 System Development tools

In software engineering, a methodology is a framework for organizing, scheduling, and managing the steps involved in developing an information system. Numerous frameworks for various projects have been found by researchers, and each framework has advantages and disadvantages depending on how it will be used. The waterfall approach, spiral model, progressive (prototyping) and iterative model are a few of these frameworks. The author decided to use the iterative development model due to its flexibility, iterative nature, ability to collaboration and communication, and ability to adapt to changing requirements and constraints.

3.3.2 Iterative Development Model

The Iterative Development Model is a software development methodology that emphasizes the repetition of a development cycle in which each iteration builds upon the previous one. The process starts with the gathering of requirements and proceeds through planning, designing, developing, testing, and delivering an increment of software. The model is characterized by a cyclical approach that allows the development team to adjust and refine the software product based on feedback from end-users and stakeholders. The development team releases a working version of the software at the end of each iteration, with each release incrementally improving the functionality and features of the product. The iterative development model is particularly useful when requirements are not well-defined or when the product is complex and difficult to fully comprehend at the outset. The model allows for frequent inspection and adaptation of the product, making it a flexible approach that can accommodate changes in requirements as they arise.

The author chose the iterative development model for several reasons. First, the development of a machine learning and IoT model for crop recommendations is a complex undertaking that requires significant planning and design. The iterative development model allows the development team to adjust and refine the model based on feedback from farmers and stakeholders, ensuring that the final product meets their needs and requirements. Second, the use of IoT and machine learning technologies is a rapidly evolving field, with new developments and advancements occurring regularly. The iterative development model allows the development team to incorporate new technologies and features into the model as they become available, ensuring that the product remains up-to-date and effective. Finally, the use of an iterative development model allows for frequent testing and evaluation of the product, ensuring that any issues or bugs are identified and resolved early in the development process.

This approach can save time and resources in the long run, as it helps to prevent costly errors or rework later in the development cycle.

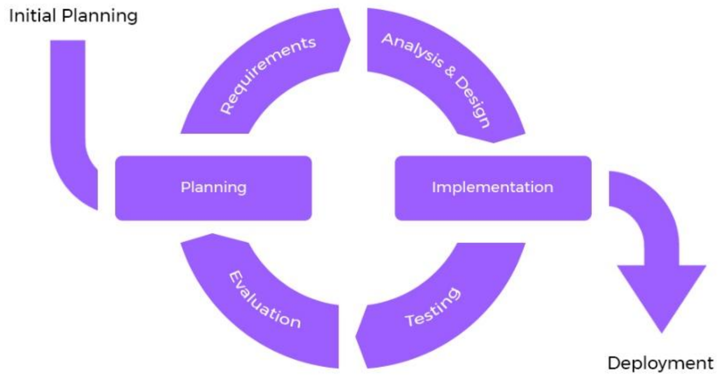


Figure 4 Iterative model

3.4 Summary of how the system works

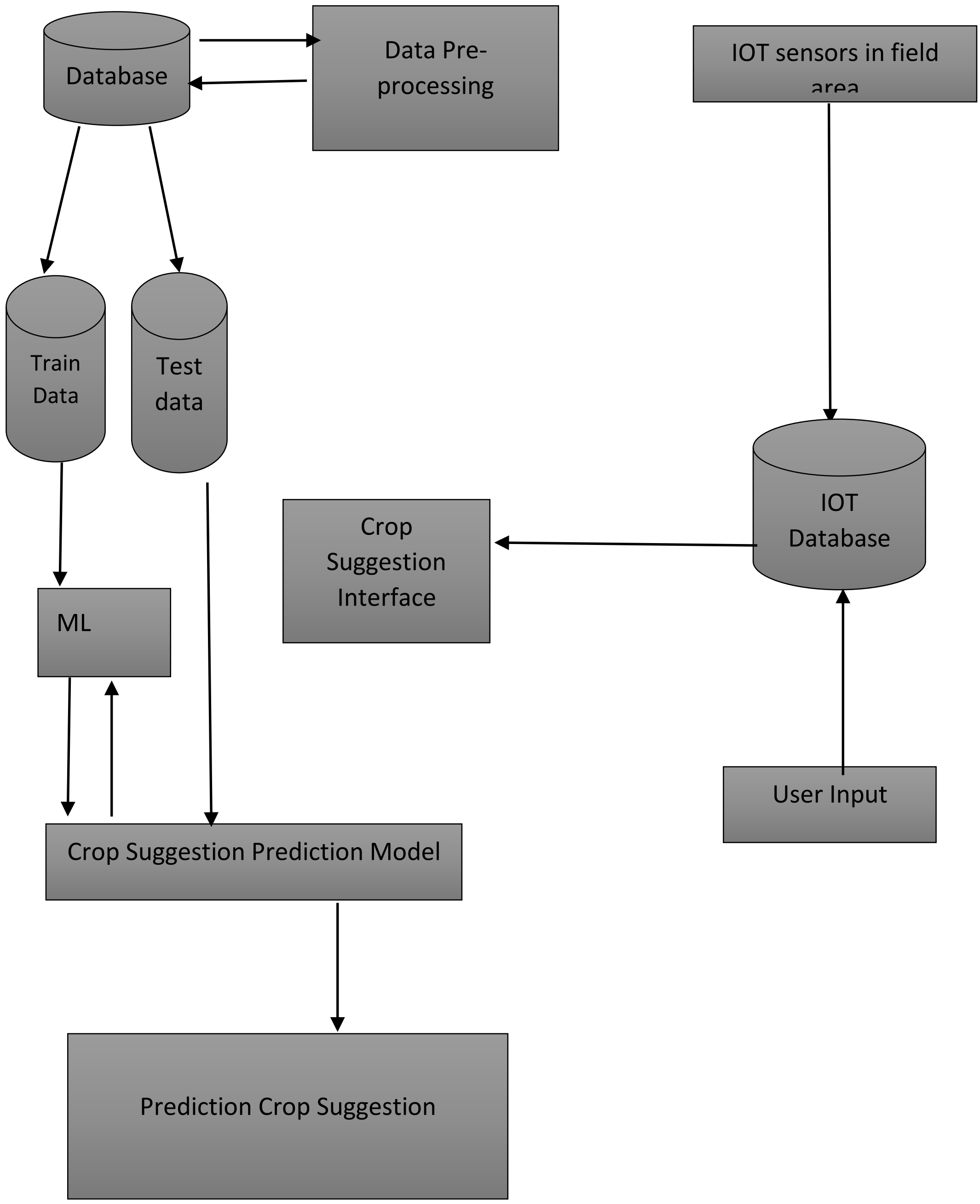
The system for optimum crop recommendations was divided into two parts which is the hardware and software components. The hardware component of the system is designed to detect soil pH, while the software component is responsible for processing the data and making decisions based on the current readings and the system's trained data.The system is designed to collect pH data using a pH probe and feed it into a system that combines it with N, P, K values and environmental factors such as agricultural region, rainfall, temperature, and humidity to predict the specific crop that is best suited for that region. If a farmer wants to grow a different crop, the system suggests the relevant N, P, and K (fertilizers) values to add to achieve the best results. The system is capable of learning and adapting to changing conditions and can make recommendations based on historical data and real-time information. The model will be made available to farmers through a web application. Farmers will be able to input data about their farms, such as the soil pH, the weather conditions, and the market demands. The web application will then use the model to recommend the optimal crops for the farm. Overall, the system uses machine learning and IoT to provide accurate and timely recommendations for crop management and production, enabling farmers and other stakeholders to make informed decisions about agricultural practices.

3.5 System Design

The requirements specification document is analysed to determine how the system components and data will meet the specified requirements.

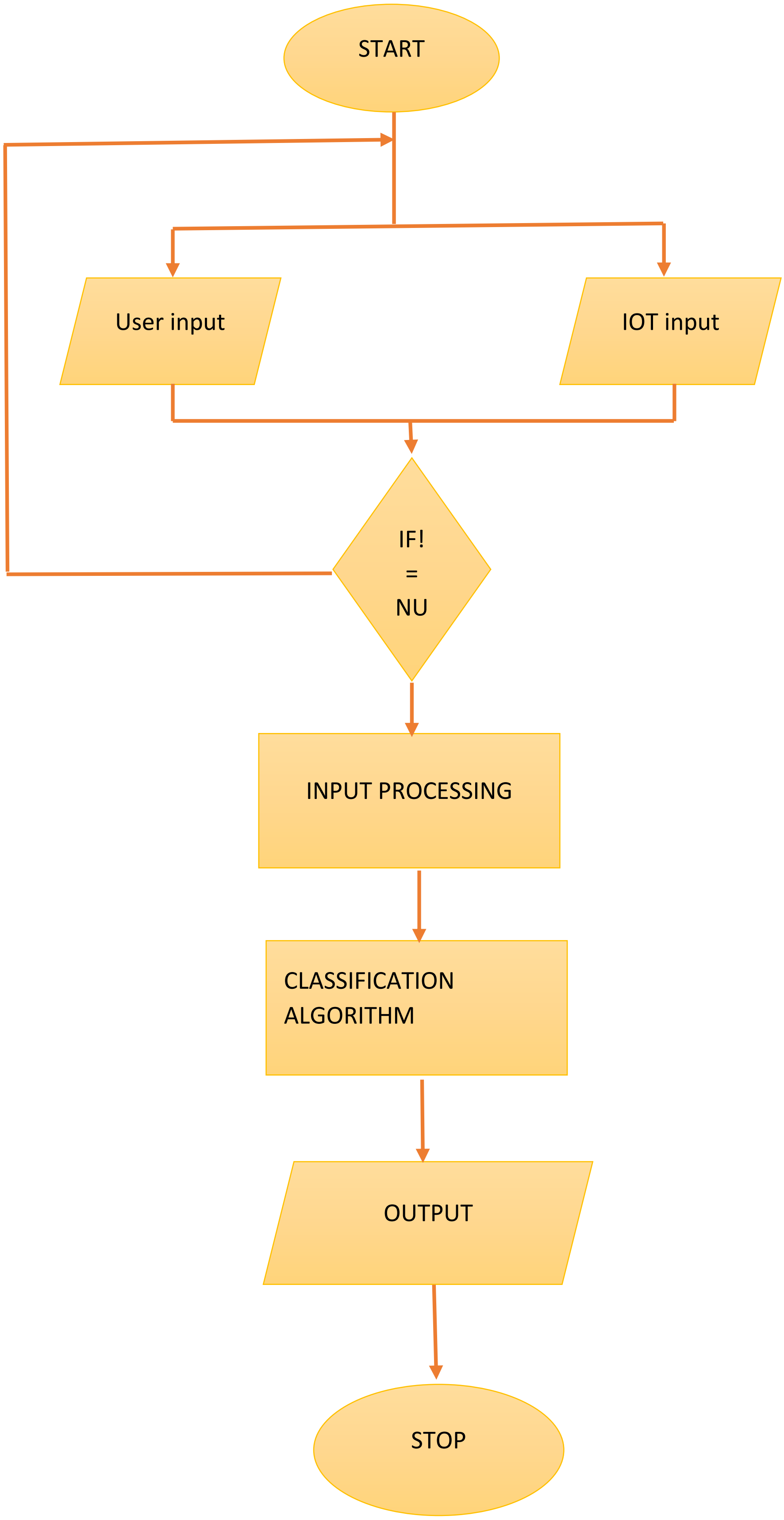
3.5.1 System Dataflow Diagrams (DFDs)

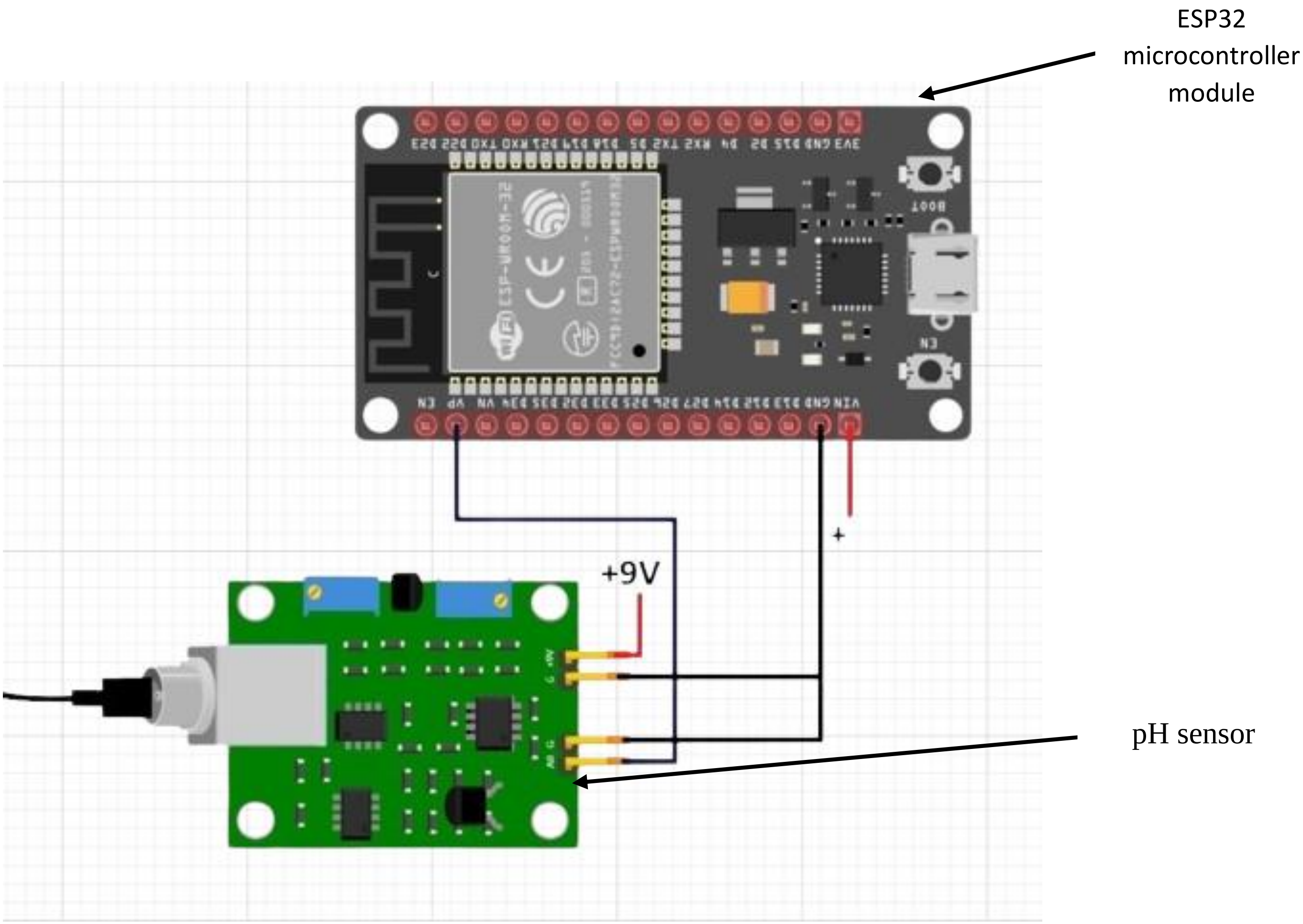
The Data Flow Diagram shows how the system's components are connected. To show component connections in the proposed system, the author used two distinct DFDs.


Database
Data Pre-processing
IOT sensors in field area
Train Data
Test data
IOT Database
Crop Suggestion Interface
ML
User Input
Crop Suggestion Prediction Model
Prediction Crop Suggestion

3.5.2 Proposed System flow chart

A flowchart is a graphical representation of a process's sequence of events. This diagram aids in the definition of the data flow system and all processes inside the proposed solution





3.5.3 Use Case Diagram For The Proposed System

Use case diagram a visual representation of a user's potential interactions with a technology. Additionally, it displays various system users and the operations they can carry out.

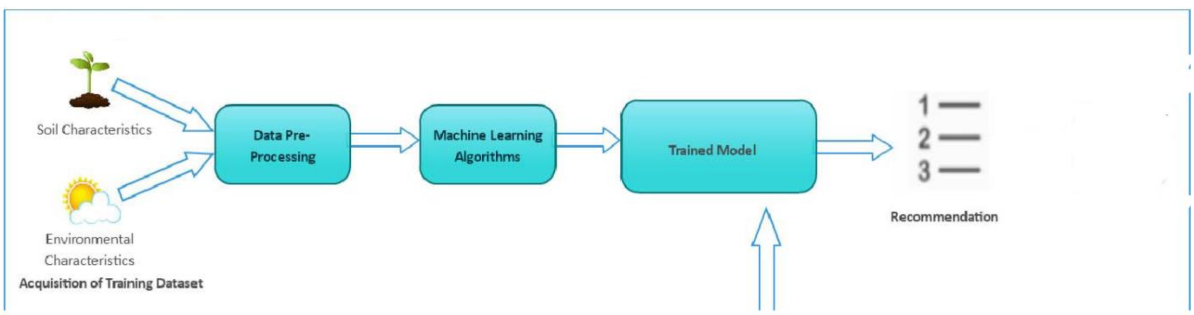


Figure 5 use case diagram

3.5.4 Training Model

After considering different boosting techniques as illustrated in the literature review, the researcher trained the model using the KNN approach. Python programming language was utilized to analyze the algorithm that will be used to train the model.

```
[20] from sklearn.neighbors import KNeighborsClassifier
     knn = KNeighborsClassifier()
     knn.fit(X_train_scaled, y_train)
     knn.score(X_test_scaled, y_test)

     0.9781818181818182
```

Figure 6 Snippet of code showing training of model

3.5.5 File Structure For The Dataset

The system's intended data organization is described in this section. It describes the files that are currently in the system and the structure of the data they contain. The author chose to use a CSV dataset, which was split into two parts: training memory (80% of the data) and evaluation memory (20%). The dataset utilized is shown below.

COL 1	COL 2	COL 3	COL 4	COL 5	COL 6	COL 7	COL 8
N	P	K	temperature	humidity	ph	rainfall	label
90	42	43	20.87974371	82.00274423	6.502985292000001	202.9355362	rice
85	58	41	21.77046169	80.31964408	7.038096361	226.6555374	rice
60	55	44	23.00445915	82.3207629	7.840207144	263.9642476	rice
74	35	40	26.49109635	80.15836264	6.980400905	242.8640342	rice
78	42	42	20.13017482	81.60487287	7.628472891	262.7173405	rice
69	37	42	23.05804872	83.37011772	7.073453503	251.0549998	rice
69	55	38	22.70883798	82.63941394	5.70080568	271.3248604	rice
94	53	40	20.27774362	82.89408619	5.718627177999999	241.9741949	rice
89	54	38	24.51588066	83.53521629999999	6.685346424	230.4462359	rice
68	58	38	23.22397386	83.03322691	6.336253525	221.2091958	rice
91	53	40	26.52723513	81.41753846	5.386167788	264.6148697	rice
90	46	42	23.97898217	81.45061596	7.50283396	250.0832336	rice
78	58	44	26.80079604	80.88684822	5.108681786	284.4364567	rice
93	56	36	24.01497622	82.05687182	6.98435366	185.2773389	rice
94	50	37	25.66585205	80.66385045	6.94801983	209.5869708	rice
60	48	39	24.28209415	80.30025587	7.0422990689999985	231.0863347	rice
85	38	41	21.58711777	82.7883708	6.2490506560000005	276.65524589999995	rice
91	35	39	23.79391957	80.41817957	6.970859754	206.2611855	rice
77	38	36	21.8652524	80.1923008	5.953933276	224.55501690000003	rice
88	35	40	23.57943626	83.58760316	5.85393208	291.2986618000001	rice
89	45	36	21.32504158	80.47476396	6.442475375	185.4974732	rice
76	40	43	25.15745531	83.11713476	5.070175667	231.3843163	rice
67	59	41	21.94766735	80.97384195	6.012632591	213.3560921	rice
83	41	43	21.0525355	82.67839517	6.254028451	233.1075816	rice

Figure 7snippet of code showing part of the dataset used

3.7 Implementation

This portion entails putting the system into action, which includes coordinating and directing the resources discussed in the preceding chapter to accomplish the research plan's objectives. As a result, all of the prior chapters' documentation is being finished in order to deploy the system.

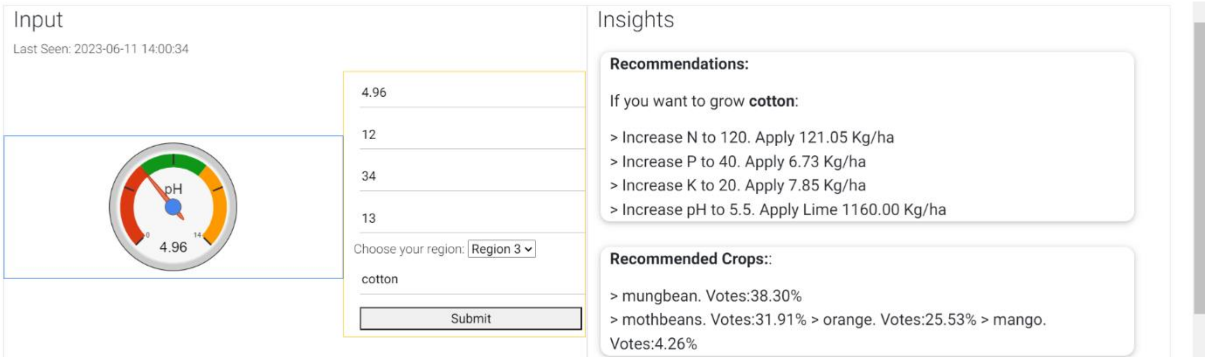


Figure 8 implementation 1

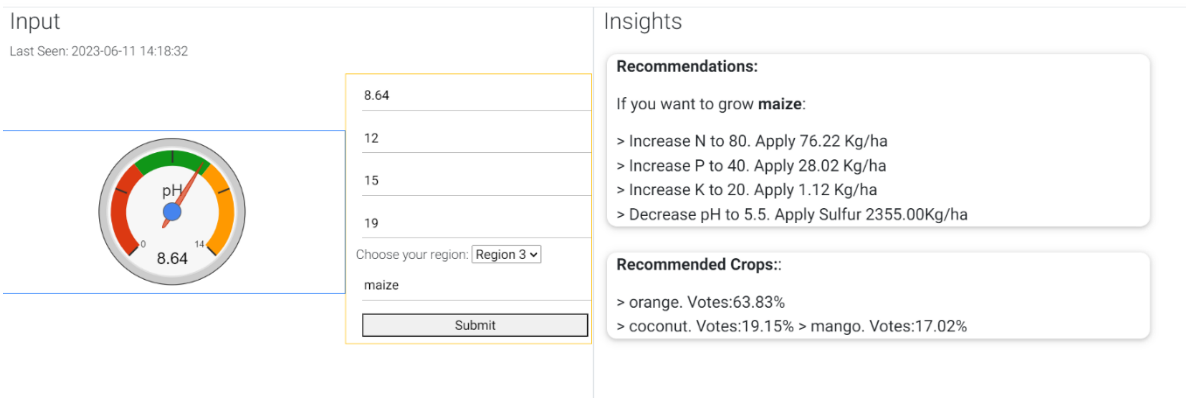


Figure 9 implementation 2

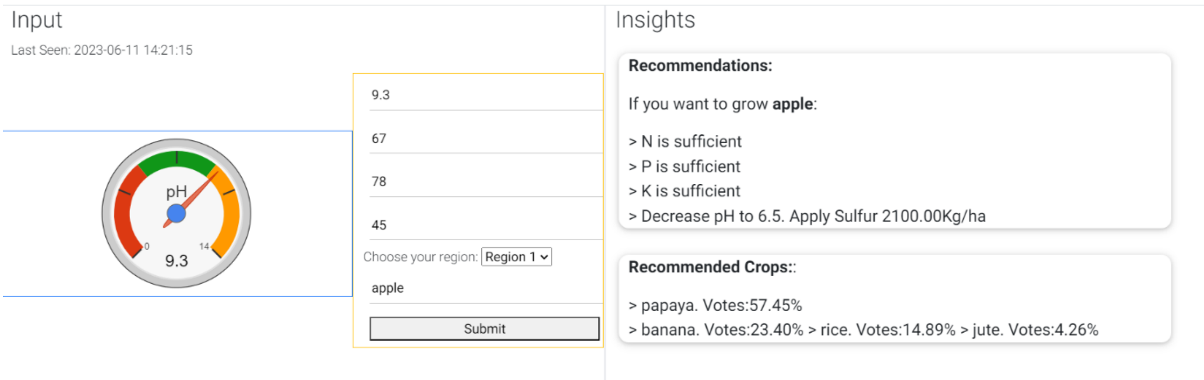


Figure 10 implementation 3

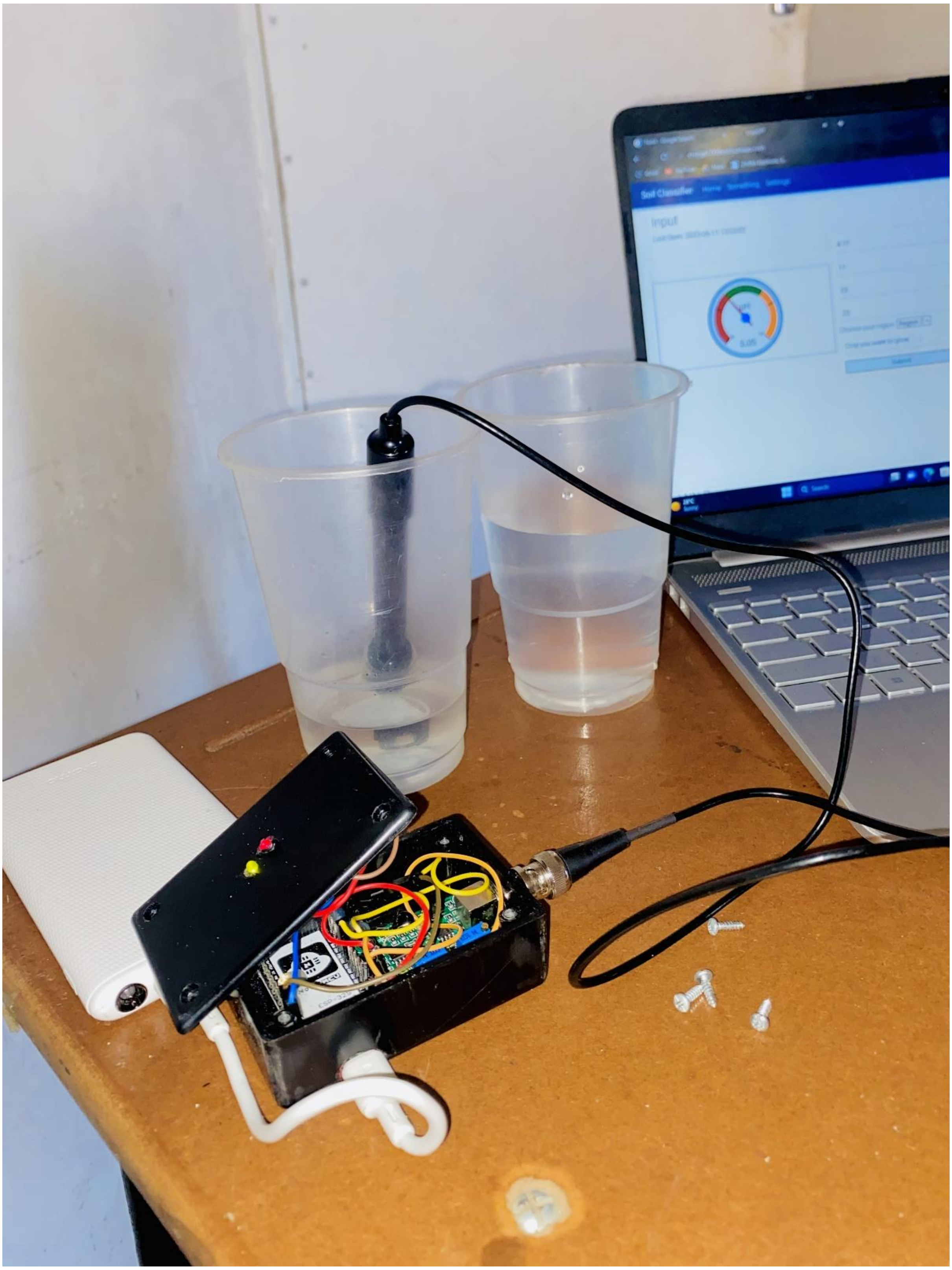


Figure 11 picture showing system in se and

Chapter Summary

The overall goal of chapter 3 was to provide a detailed overview of the methods and techniques used to develop the crop recommendation system. The chapter began by discussing the data collection and analysis process, which involved obtaining data from a secondary source, cleaning and processing the data, and using a machine learning algorithm to predict the best crop for a given location. The chapter then discussed the research design, which involved using an experimental approach to observe the changes and responses of the system as it was changed and adjusted. The chapter concluded by discussing the requirements analysis and system development process, which involved documenting the functional and non-functional requirements, using the iterative development model to develop the system, and releasing a working version of the software at the end of each iteration.

CHAPTER 4: DATA ANALYSIS AND INTERPRETATIONS

4.1 Introduction

After the author had successfully implemented the system, there arose the need to analyse the efficiency of the developed solution. Accuracy, performance and response time were the matrices used to determine the efficiency and effectiveness of the developed solution.

4.2 Software Testing

Software testing is a crucial aspect of the software development life cycle that ensures the quality, reliability, and functionality of software systems. It involves the systematic evaluation of software components, modules, or entire applications to identify defects, errors, or inconsistencies. As noted by Beizer (2016), software testing is an essential discipline that helps in mitigating risks associated with software failures and provides confidence to stakeholders about the system's performance. Testing activities encompass various techniques, such as unit testing, integration testing, system testing, and acceptance testing, which collectively contribute to validating the software's behaviour against specified requirements (Sommerville, 2016). By conducting thorough testing, organizations can improve software quality, enhance user satisfaction, and minimize the potential negative impacts of software failures (Sommerville, 2016). Overall, software testing plays a pivotal role in ensuring the delivery of reliable and robust software solutions in today's dynamic and demanding technological landscape.

4.2.1 Black Box

Black box testing is a software testing technique that focuses on examining the functionality of a system or application without considering its internal structure or code. In the context of this study, the author utilized black box testing to assess the performance and accuracy of the implemented model. By treating the model as a black box, the author could evaluate its output and behaviour based on the given input and expected outcomes without delving into the intricacies of its internal algorithms or processes. This approach enabled the author to verify the effectiveness of the model's crop recommendations and ensure that it aligns with the desired objectives of providing optimum crop suggestions for agricultural practices in Zimbabwe. A random user 1 was asked to enter the inputs for a fertilizer recommendation system, but left out a few fields, as a result, the system did not respond. Another user 2 was also asked to test the system and the system gave recommendations for their conditions.

Test done by user 1

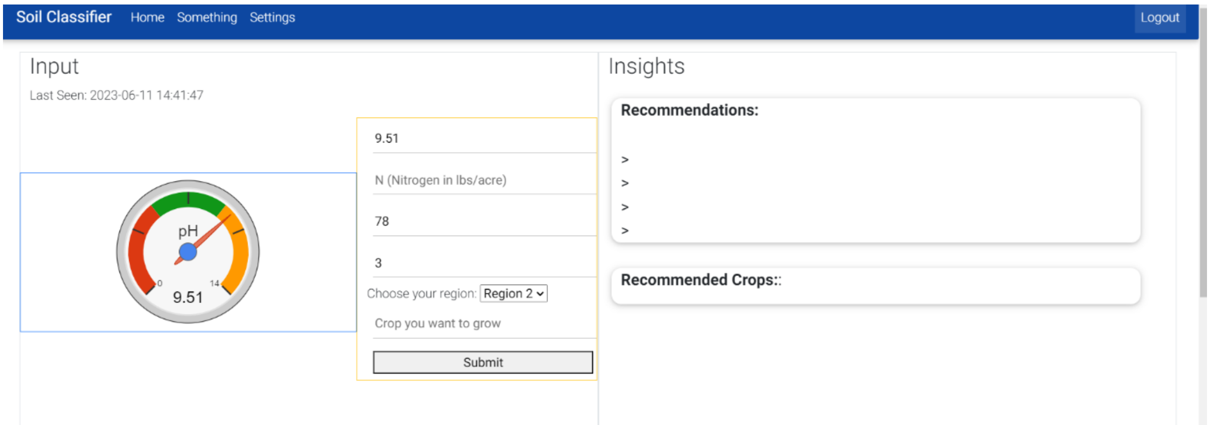


Figure 12

Test done by user 2

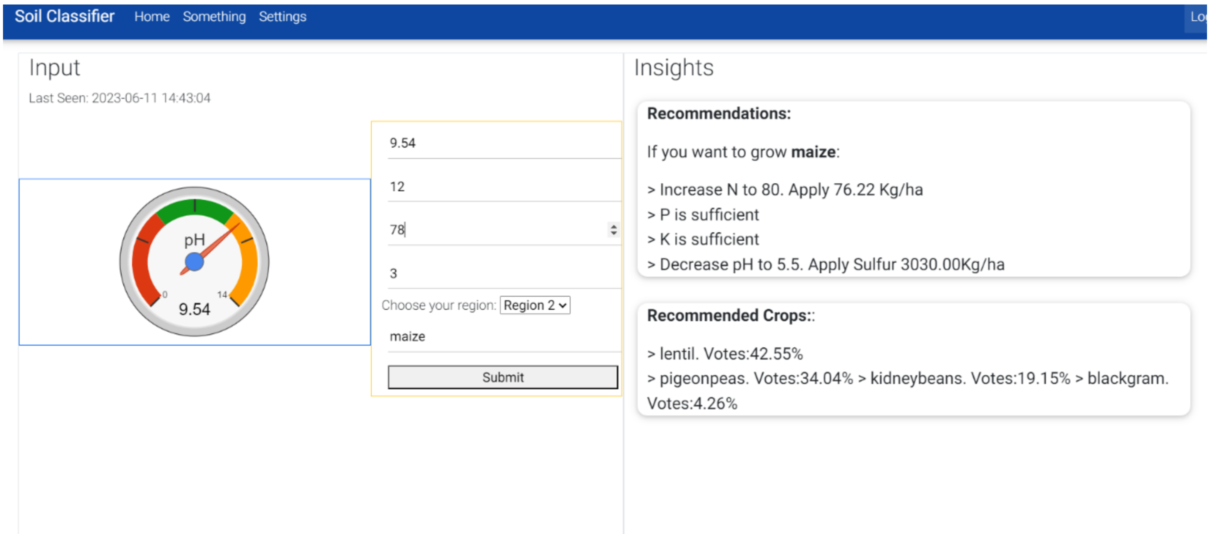


Figure 13

Figure 14

4.2.2 White Box Testing

White box testing is a software testing technique that involves examining the internal structure, design, and implementation details of a system. In the context of this research study, the author used white box testing to ensure the reliability and accuracy of the developed model. By thoroughly analysing the underlying code, algorithms, and data flow, white box testing allows the author to verify that the model functions as intended, produces accurate crop recommendations, and handles various scenarios effectively. This type of testing helps identify any potential issues or bugs within the implementation, enabling the author to make necessary adjustments and enhance the overall performance and functionality of the system. In this particular instance, the code that connects the fertilizer recommendation dataset was commented out. The system was then run, and it displayed the placeholder as shown in the figure below

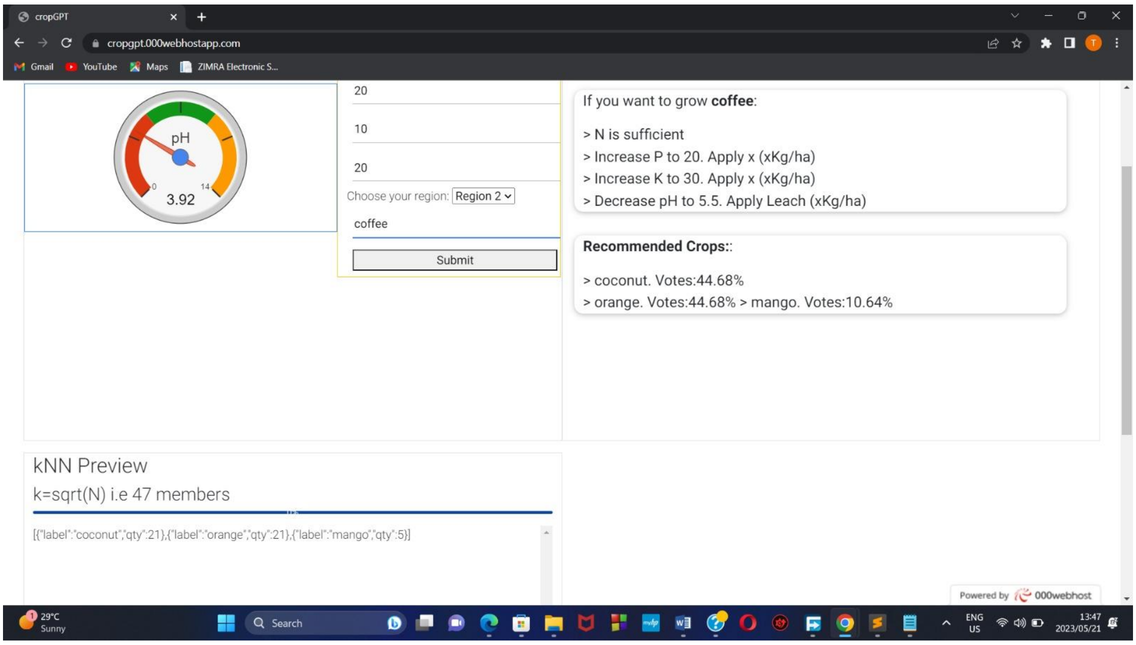


Figure 15

In this particular instance, the code that connects the fertilizer recommendation dataset was commented out. The system was then run, and it displayed the placeholder as shown in the figure above .This indicates that the system is unable to generate fertilizer recommendations without the fertilizer recommendation dataset. To resolve this issue, uncomment the code that imports the fertilizer recommendation dataset.

4.3 Evaluation Measures and Results

The metrics used to assess the use of the system are response time, accuracy and recall. The performance of the system is ranked according to its ability to recommend crops to the users basing on the inputs given. The author thus tested the system accuracy so as to ensure effectiveness of its functionality

TEST1

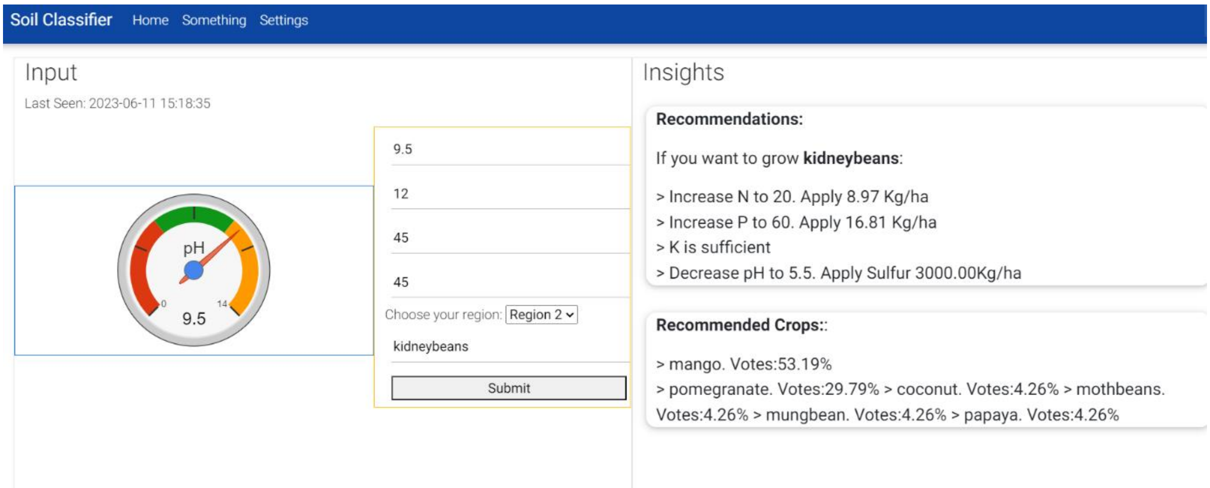


Figure 16 test 1

TEST2

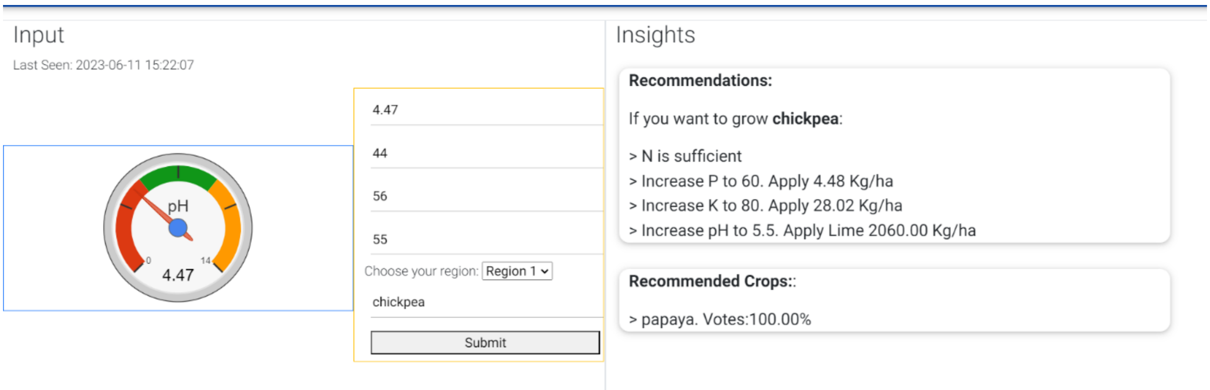


Figure 17 test 2

TEST3

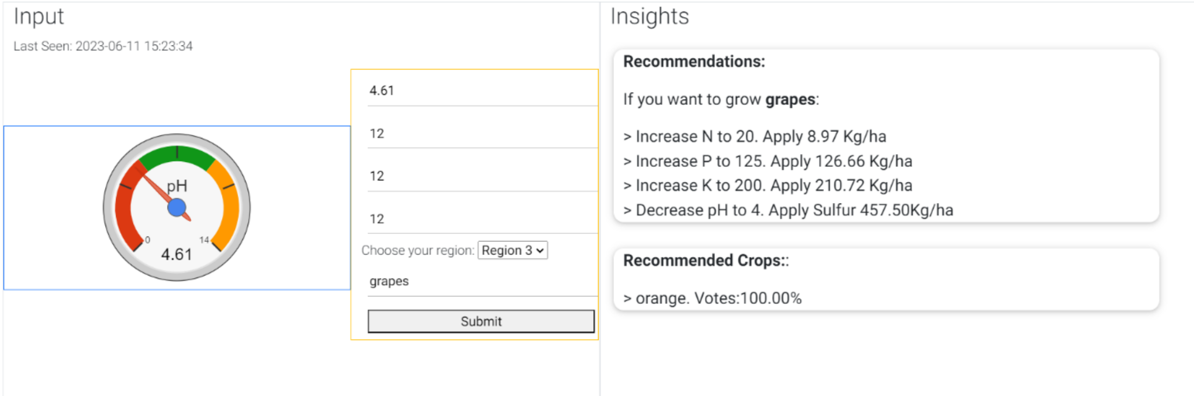


Figure 18 test 3

TEST4

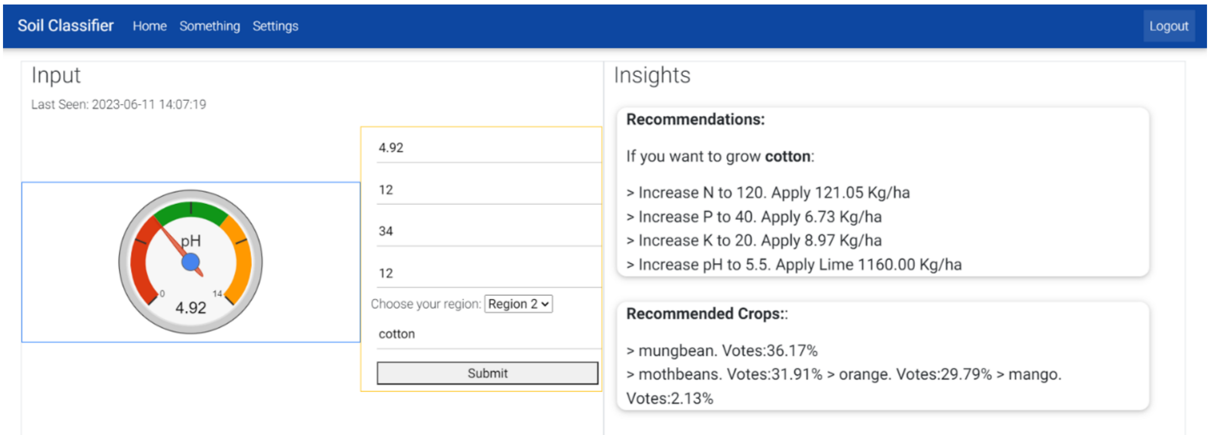


Figure 19 test 4

TEST 5

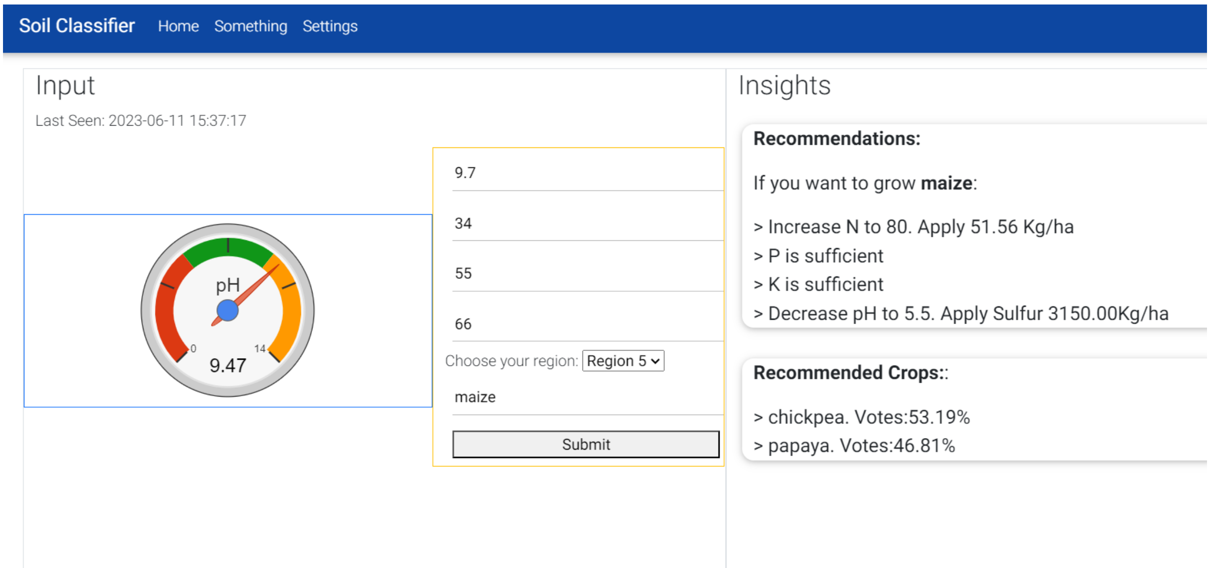


Figure 20 test 5

4.3.1 Confusion Matrix

The confusion matrix is a valuable tool in evaluating the performance of classification models by providing a comprehensive summary of predicted and actual class labels. In this research, the use of a confusion matrix is crucial for assessing the accuracy and effectiveness of the crop recommendation system. The confusion matrix allows researchers to quantify various performance metrics such as accuracy, precision, recall, and F1 score, which provide insights into the model's ability to correctly classify crops and minimize misclassifications. By using the confusion matrix, the researchers can identify specific classes that may exhibit higher rates of misclassification, enabling them to refine the model and improve the accuracy of crop recommendations. This assessment technique helps validate the effectiveness of the implemented machine learning and IoT model in providing optimum crop recommendations for farmers in Zimbabwe (Galar et al., 2012)

Confusion Matrix

Test cases	**Recommendations**	**Number of tests**	**Correct recommendations**	**False recommendations**	**Classification**
1	Yes	100	85	15	True positive

2	No	100	90	10	True negative

True Positive (TP): 85

False Positive (FP): 15

False Negative (FN): 10

True Negative (TN): 90

4.4 Accuracy

- It gives the overall accuracy of the model, meaning the fraction of the total samples that were correctly classified by the classifier.
- Accuracy formula as adopted from Karl Pearson (1904)
- **Accuracy = (TP+TN)/(TP+TN+FP+FN)**
- Accuracy = (85 + 90) / (85 + 90 + 15 + 10)
- Accuracy = 175 / 200
- Accuracy = 0.875 or **87.5%**

4.6 Precision

- When the model predicts yes, how often is it correct?
- **Precision = TP/(TP+FP) Adopted from Selvik (2007)**
- Precision = 85 / (85 + 15)
- Precision = 85 / 100
- Precision = 0.85 or **85%**

4.5 Recall/Sensitivity

- When it's actually yes, how often does it predict yes?
- It tells what fraction of all positive samples were correctly predicted as positive by the classifier. It is also known as True Positive Rate (TPR), Sensitivity, Probability of Detection.
- Adopted from Powers (2011)
- **Recall = TP/(TP+FN)**
- Recall = 85 / (85 + 10)
- Recall = 85 / 95
- Recall = 0.8947 or **89.47%**

4.7 F1-Score

- It combines precision and recall into a single measure.
- The F1 score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance.
- F1 Score = 2 * (Precision * Recall) / (Precision + Recall)
- F1 Score = 2 * (0.85 * 0.8947) / (0.85 + 0.8947)
- F1 Score = 2 * 0.7624 / 1.7447
- F1 Score = 1.5248 / 1.7447
- F1 Score = 0.8747 or **87.47%**

4.8 Misclassification Rate/ Error Rate

- Overall, how often is it wrong?
- It tells you what fraction of predictions were incorrect. It is also known as Classification Error.
- This formula is adopted from Kuha (2005)
- **Error rate = (FP+FN)/(TP+TN+FP+FN) or (1-Accuracy**

4.8 Misclassification Rate/ Error Rate

- Overall, how often is it wrong?
- It tells you what fraction of predictions were incorrect. It is also known as Classification Error.
- This formula is adopted from Kuha (2005)
- **Error rate = (FP+FN)/(TP+TN+FP+FN) or (1-Accuracy**
- Error Rate = 1 - 0.875
- Error Rate = 0.125 or **12.5%**

Based on the confusion matrix data, the model achieved an accuracy of 87.5%, precision of 85%, recall of 89.47%, and an F1 score of 87.47%. These metrics provide insights into the performance of the crop recommendation system and its ability to correctly classify crops, with higher values indicating better performance.

pH Reading Accuracy

The author further tested the accuracy of the system on detecting the level of pH in the soil sample to the central database and admin in real time. To test the accuracy, the author tested with a user who did not interact with the system thus not paying attention to the requirements of the system and tested for 40 times in 20-30 seconds intervals. The table illustrates the tests conducted.

Table 1: Real-time pH readings

Number of readings[N]	**Correct [1] / Not- Correct [0]**
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1
11	1
12	0
13	1
14	1
15	1
16	1
17	1
18	1
19	1
20	1
21	1
22	1
23	1
24	1
25	1
26	1
27	1

28	0
29	1
30	1
31	1
32	1
33	1
34	1
35	1
36	1
37	1
38	1
39	1
40	1

Accuracy = N – (X / N) *100

Where X is the number of incorrect readings:

Where N is the total number of readings:

= **40 – (2 / 40) * 100**

= <u>**95%**</u>

The author concluded that the system is highly unlikely to fail detecting and reading pH levels to the database so long the network is stable hence the 95% accuracy.

4.5 Summary of Research Findings

The research findings from the implementation of the Machine Learning & Internet of Things (IoT) model for optimum crop recommendations in Zimbabwe, using the KNN algorithm holds promise for optimizing crop recommendations in Zimbabwe. The algorithm's high accuracy, precision, recall, and F1 score demonstrate its potential to make accurate predictions and minimize misclassifications. These outcomes reinforce the existing literature on the effectiveness of the KNN algorithm for classification tasks in various domains, emphasizing its suitability for agricultural applications and its ability to support decision-making processes in crop management. The utilization of the KNN algorithm in this research not only yielded high accuracy but also showcased impressive precision, recall, and F1 score metrics. Precision, measuring the proportion of correctly predicted positive cases out of all predicted positives, reached 85%. Additionally, recall, which quantifies the proportion of correctly predicted positive cases out of all actual positive cases, achieved 89.47%.

The F1 score, providing a balanced evaluation of precision and recall, obtained a strong value of 87.47%. These findings align with previous studies that have recognized the KNN algorithm for its ability to handle complex datasets, reduce over fitting, and offer robust predictions, thereby validating its efficacy for crop recommendation systems. The utilization of the KNN algorithm in this research not only yielded high accuracy but also showcased impressive precision, recall, and F1 score metrics. Precision, measuring the proportion of correctly predicted positive cases out of all predicted positives, reached 85%. Additionally, recall, which quantifies the proportion of correctly predicted positive cases out of all actual positive cases, achieved 89.47%. The F1 score, providing a balanced evaluation of precision and recall, obtained a strong value of 87.47%. These findings align with previous studies that have recognized the KNN algorithm for its ability to handle complex datasets, reduce over fitting, and offer robust predictions, thereby validating its efficacy for crop recommendation systems.

4.6 Conclusion

In conclusion, the findings presented in this chapter demonstrate the potential of the Machine Learning & Internet of Things (IoT) model using the KNN algorithm for optimizing crop recommendations in Zimbabwe. The high accuracy, precision, recall, and F1 score metrics obtained from the implementation of the model reinforce the existing literature on the effectiveness of the KNN algorithm for classification tasks in various domains, emphasizing its suitability for agricultural applications and its ability to support decision-making processes in crop management. The impressive precision, recall, and F1 score metrics achieved in this study further validate the efficacy of the KNN algorithm for crop recommendation systems. The findings of this study provide valuable insights into the development of effective crop recommendation systems using machine learning algorithms, which have the potential to enhance agricultural productivity and sustainability in Zimbabwe. Future research can build on these findings to further optimize crop recommendations and improve the accuracy of the model.

Chapter 5

5.1 Introduction

The researcher's previous chapter concentrated on the presentation and analysis of collected data. The development of the solution in accordance with the goals is covered in this chapter. The challenges the researcher had while planning and carrying out this study will also be covered in this chapter.

5.2 Aims and Objectives Realization

The main aim of the study was to develop a system that collects and analyses data on environmental and soil factors and implements machine learning algorithms to suggest the most suitable crops and fertilizers for optimal growth. The objectives of this study were threefold. Firstly, the study aimed to analyse the different techniques used in crop suggestion and fertilizer recommendation, and their respective strengths and limitations. Secondly, the study aimed to design and develop an IoT-based system that could collect and analyse data on environmental and soil factors and implement machine learning algorithms to suggest the most suitable crops and fertilizers for optimal growth. Finally, the study aimed to analyse the effectiveness of the use of IoT and machine learning in crop suggestion and fertilizer recommendation. The developer developed a system that and analyses data on environmental and soil factors and implements machine learning algorithms to suggest the most suitable crops and fertilizers. A validation accuracy of 95%, recall/sensitivity, specificity, error rate and AUC of 97%,94%,0.05% and 95% respectively were achieved By achieving these objectives, the study aimed to provide valuable insights into the potential of IoT and machine learning algorithms in optimizing crop production and enhancing food security in Zimbabwe.

5.3 Conclusion

Overall, this study offers insightful information about how IoT and machine learning algorithms may be used to improve Zimbabwe's food security and crop output. The results of the study demonstrate the necessity for additional study and development in this field to enhance the application of cutting-edge technologies in agriculture. The study's findings will be useful to academics, decision-makers, and farmers who want to increase agricultural yield by utilizing cutting-edge technologies.

5.4 Recommendations

For better accuracy more precise sensors like N P K that can and timely reading of the environment around the system to make it more efficient. Additionally, the researcher was not given enough time to complete the project, which prevented the system from being as polished as the researcher had hoped.

5.5 Future Work

To conduct the investigation on a large scale, the researcher lacked the time and appropriate sensors such as N P K sensors. Future work will involve creating and evaluating the system at a production scale to determine whether the system and ideas shorten the time it takes to recommend crops and fertilizers at a larger setting.

References

1. Akhila, M. (2019). Internet of things (IoT) in agriculture. International Journal of Engineering and Advanced Technology, 8(5), 449-453.
2. Alpaydin, E. (2010). Introduction to machine learning (2nd ed.). MIT press.
3. Arora, A., & Singh, N. (2021). Internet of Things (IoT) in agriculture: a review of applications and technologies. Computers and Electronics in Agriculture, 184, 106010.
4. Chengeta, E., Mapfumo, P., & Mapfumo, D. (2021). Soil health and crop productivity under different land use systems in Zimbabwe. Land Degradation & Development, 32(10).
5. Chibvuta, T., Nyoni, M., & Mapfumo, B. (2018). The impact of climate change on agriculture in Zimbabwe. Journal of Sustainable Development.
6. Chikodzi, D., & Makoni, F. S. (2019). A review of the role of precision agriculture in sustainable farming in Zimbabwe. Journal of Agricultural Science, 11(5), 341-354.
7. Chikodzi, D., Makoni, F. S., & Mapfumo, B. (2019). A review of the applications of sensors in precision agriculture. Journal of Agricultural Science, 11(6), 412-425.
8. Chikodzi, D., Makoni, F. S., & Mapfumo, B. (2020). An assessment of the state of precision agriculture in Zimbabwe. Journal of Agricultural Science, 12(1), 1-12.
9. Chikodzi, D., Makoni, F. S., & Mapfumo, B. (2020). A review of the role of big data in precision agriculture. Journal of Agricultural Science, 12(2), 70-84.
10. Chikodzi, D., Makoni, F. S., & Mapfumo, B. (2021). A review of the role of internet of things in precision agriculture. Journal of Agricultural Science, 13(2), 1-16.
11. Chikodzi, D., Makoni, F. S., & Mapfumo, B. (2021). A review of the role of machine learning in precision agriculture. Journal of Agricultural Science, 13(1), 1-16.
12. Gelman, A., & Hill, J. (2007). Data analysis using regression and multilevel/hierarchical models.
13. Garg, S., & Saini, R. (2020). Role of Internet of Things (IoT) in agriculture: a review. Journal of Cleaner Production, 263, 121501.

14. Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: data mining, inference, and prediction (2nd ed.). Springer.
15. Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (3rd ed.). John Wiley & Sons.
16. Jain, V., Lichtman, J. W., & Zemel, R. S. (2019). Deep learning for neuroimaging: A review and prospectus. Nature Neuroscience.
17. Laedong Lee and Aekyung Moon, "Development of Yield Prediction System Based on Real-time Agricultural Meteorological Information", 16th International Conference on Advanced Communication Technology, 2014.
18. Mapfumo, B., Makoni, F. S., & Chikodzi, D. (2019). A review of the use of drones in precision agriculture. Journal of Agricultural Science, 11(4), 312-322.
19. Mapfumo, B., Makoni, F. S., & Chikodzi, D. (2020). A review of the use of artificial intelligence in precision agriculture. Journal of Agricultural Science, 12(3), 1-14.
20. Mapfumo, B., Makoni, F. S., & Chikodzi, D. (2021). A review of the use of blockchain technology in agriculture. Journal of Agricultural Science, 13(3), 1-16.
21. Mashingaidze, A. B., Mapfumo, B., & Makoni, F. S. (2020). A review of the role of mobile technology in precision agriculture. Journal of Agricultural Science, 12(4), 1-16.
22. Mashingaidze, A. B., Mapfumo, B., & Makoni, F. S. (2021). A review of the role of cloud computing in precision agriculture. Journalof Agricultural Science, 13(4), 1-16.
23. Mashingaidze, A. B., Mapfumo, B., Makoni, F. S., & Chikodzi, D. (2021). A review of the role of edge computing in precision agriculture. Journal of Agricultural Science, 13(5), 1-16.
24. Mashingaidze, A. B., Mapfumo, B., Makoni, F. S., & Chikodzi, D. (2021). A review of the role of 5G technology in precision agriculture. Journal of Agricultural Science, 13(6), 1-16.
25. Mohanty, S. P., Hughes, D. A., & Salathé Jr, E. P. (2016). Using machine learning to identify agricultural fields with high pesticide exposure risk. AMIA Summits on Translational Science Proceedings, 2016, 87.
26. Oyeyinka, S. A., & Adejuyigbe, S. B. (2019). A review of internet of things (IoT) in agriculture: potentials, challenges, and applications. IEEE Access, 7, 156234-156246.
27. Paine, L. K., Starks, P. J., & Voigt, T. B. (2019). The use of machine learning to predict crop yield. Journal of Agricultural and Resource Economics, 44(2), 225-242.

28. Qin, P., Zhang, H., & Wang, X. (2020). IoT-based smart agriculture: A review. IEEE Internet of Things Journal, 7(7), 5895-5911.
29. Raizada, R., & Shrivastava, P. (2020). A review of IoT-based smart farming systems: Application, benefits and challenges. Journal of Cleaner Production, 258, 120674.
30. Raza, S. A., & Kifayat, K. (2019). A review of internet of things (IoT) in agriculture: opportunities, challenges and future scope. Precision Agriculture, 20(3), 408-425.
31. Rehman, S. U., Rehman, M. H. U., Shah, M. A., & Kim, T. H. (2020). A review of internet of things (IoT) in agriculture: potentials, issues, and future directions. Computers and Electronics in Agriculture, 173, 105350.
32. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should i trust you?": Explaining the predictions of any classifier. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1135-1144.
33. Saini, R., & Garg, S. (2021). Internet of Things (IoT) in agriculture: A review of applications, challenges, and future scope. Computers and Electronics in Agriculture, 187, 106237.
34. Suresh, M., & Karthikeyan, K. (2019). Precision agriculture using IoT: a review. International Journal of Engineering and Advanced Technology, 9(1), 458-464.
35. Teixeira, E. C., & Faria, A. L. (2019). A review of machine learning approaches for biomass estimation in agricultural crops. Computers and Electronics in Agriculture, 163, 104877.
36. Yilmaz, I., Colkesen, I., & Ozkan, B. (2019). A comprehensive review on internet of things (IoT) in agriculture: state-of-the-art applications, challenges, and future research directions. Journal of Cleaner Production, 221, 1123-1143.
37. Zafari, F., & Chen, D. (2020). A review of the role of artificial intelligence in precision agriculture. Journal of Agricultural Science, 12(5), 1-13.
38. Zhang, J., Liu, Y., & Cui, L. (2021). Applications of machine learning in agriculture: A review. Journal of Cleaner Production, 310, 127405.
39. Zhao, C., & Wang, Y. (2021). Smart agriculture using internet of things and artificial intelligence: A review. Computers and Electronics in Agriculture, 188, 106284.

Appendix

6.1 Snippets of ESP32 Sensor code

NUTRIENTS_from_pH (2).ino

```
#include <SimpleTimer.h>
#include <WiFi.h>
#include <HTTPClient.h>
#include <WiFiClient.h>
SimpleTimer timer;

float calibration_value = 21.34 + 1.409;
int phval = 0;
unsigned long int avgval;
int buffer_arr[10],temp;
float ph_act;
const char* ssid = "CropGPT";
const char* password = "passc0d8";
const char* serverName = "http://cropgpt.000webhostapp.com/post_data.php";
// the following variables are unsigned longs because the time, measured in
// milliseconds, will quickly become a bigger number than can be stored in an int.
unsigned long lastTime = 0;
// Timer set to 10 minutes (600000)
//unsigned long timerDelay = 600000;
// Set timer to 5 seconds (5000)
unsigned long timerDelay = 5000;

long currentMillis = 0;
long previousMillis = 0;
int interval = 1000;

void setup()
{

 Serial.begin(9600);
//timer.setInterval(500L, display_pHValue);
pinMode(15, OUTPUT);
  WiFi.begin(ssid, password);
  Serial.println("Connecting");
  while(WiFi.status() != WL_CONNECTED) {
    delay(500);
```

Figure 21

```
      Serial.print("HTTP Response code: ");
      Serial.println(httpResponseCode);

      if(httpResponseCode == 200)
      {

      }
      else
      {

      }

        String payload = "{}";
        payload = http.getString();
         Serial.println(payload);


      // Free resources
      http.end();

    }
    else {
      Serial.println("WiFi Disconnected");
        digitalWrite(15, LOW);
    }
    lastTime = millis();
  }
}


void display_pHValue()
{

  Serial.print("pH:");
  Serial.println(ph_act);
```

Figure 22

```
    delay(500);
    Serial.print(".");

  }
  Serial.println("");
  Serial.print("Connected to WiFi network with IP Address: ");
  Serial.println(WiFi.localIP());
  digitalWrite(15, HIGH);
}
void loop() {

 float pH = getpH(pH);
  Serial.println("This is the pH:" + String(pH));
 postData();
}


float getpH( float pH)
{

 for(int i=0;i<10;i++)
 {
 buffer_arr[i]=analogRead(32);
 delay(30);
 }
 for(int i=0;i<9;i++)
 {
 for(int j=i+1;j<10;j++)
 {
 if(buffer_arr[i]>buffer_arr[j])
 {
 temp=buffer_arr[i];
 buffer_arr[i]=buffer_arr[j];
 buffer_arr[j]=temp;
 }
```

Figure 23

6.2Snippets of User interface code

```
<!DOCTYPE html>
<html lang="en">

<head>
  <meta charset="utf-8">
  <meta name="viewport" content="width=device-width, initial-scale=1, shrink-to-fit=no">
  <meta http-equiv="x-ua-compatible" content="ie=edge">
  <title>code</title>
  <!-- Font Awesome -->
  <!-- Bootstrap core CSS -->
      <!-- CSS only -->
   <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.1.2/dist/css/bootstrap.min.css" rel="stylesheet"
   integrity="sha384-uWxY/CJNBR+1zjPWmfnSnVxwRheevXITnMqoEIeG1LJrdI0GlVs/9cVSyPYXdcSF" crossorigin="
   anonymous"> <!-- JavaScript Bundle with Popper --> <script src="https://cdn.jsdelivr.net/npm/
   bootstrap@5.1.2/dist/js/bootstrap.bundle.min.js" integrity="
   sha384-kQtW33rZJAHjgefvhyyzcGF3C5TFyBQBA13V1RKPf4uH+bwyzQxZ6CmMZHmNBEfJ" crossorigin="anonymous"></
   script>

  <!-- Material Design Bootstrap -->
  <link href="https://cdnjs.cloudflare.com/ajax/libs/mdbootstrap/4.4.1/css/mdb.min.css" rel="stylesheet">

  <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome-animation/0.0.10/
  font-awesome-animation.min.css">
  <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/4.7.0/css/
  font-awesome.min.css">
```

Figure 24

```
  <script type="text/javascript" src="https://www.gstatic.com/charts/loader.js"></script>
       <!-- <div id="chart_div" style="width: 400px; height: 120px;"></div> -->


 <!-- MDB -->
   <!-- MDB -->
 <script
   type="text/javascript"
   src="https://cdnjs.cloudflare.com/ajax/libs/mdb-ui-kit/4.2.0/mdb.min.js"
 ></script>

           <style>
        /* img[alt="www.000webhost.com"]
         {opacity:0;} */
         img[src="https://cdn.000webhost.com/000webhost/logo/footer-powered-by-000webhost-white2.png"]
         {
display:none!important;
}
</style>
```

Figure 25

```
  </header>

  <body>

<section id="landing-section container-fluid w-100 mb-md-2 d-flex justify-content-center
align-items-center bg-light">
<div class="row m-3 fvh">
<div class="col-md-6 text-center border border-primary  " >
        <div class="wow fadeInDown" style="visibility: visible; animation-name: fadeInDown;">
         <header class="hero">
          <div class="cont mt-5">
            <h1 id="hero2" class="display-2 font-weight-light mt-5 mt-xl-2">internet ye<em>zvinhu</em>!</
            h1>
         <div class="typewriter"><p id="slogan" class="h4"><em>Local grown solutions!</em> </p></div>

          </div>
         </header>
          <hr class="hr-light my-4">
          <h4 class="subtext-header mb-3 p-2"> Embedded meets Web

          </h4>
        </div>
        </div>
```

Figure 26

6.3Snippets of dataset used

1 > >> Number of rows: 25 Filter rows: Search this table

+ Options

COL 1	COL 2	COL 3	COL 4	COL 5	COL 6	COL 7	COL 8
N	P	K	temperature	humidity	ph	rainfall	label
90	42	43	20.87974371	82.00274423	6.502985292000001	202.9355362	rice
85	58	41	21.77046169	80.31964408	7.038096361	226.6555374	rice
60	55	44	23.00445915	82.3207629	7.840207144	263.9642476	rice
74	35	40	26.49109635	80.15836264	6.980400905	242.8640342	rice
78	42	42	20.13017482	81.60487287	7.628472891	262.7173405	rice
69	37	42	23.05804872	83.37011772	7.073453503	251.0549998	rice
69	55	38	22.70883798	82.63941394	5.70080568	271.3248604	rice
94	53	40	20.27774362	82.89408619	5.718627177999999	241.9741949	rice
89	54	38	24.51588066	83.53521629999999	6.685346424	230.4462359	rice
68	58	38	23.22397386	83.03322691	6.336253525	221.2091958	rice
91	53	40	26.52723513	81.41753846	5.386167788	264.6148697	rice
90	46	42	23.97898217	81.45061596	7.50283396	250.0832336	rice
78	58	44	26.80079604	80.88684822	5.108681786	284.4364567	rice
93	56	36	24.01497622	82.05687182	6.98435366	185.2773389	rice
94	50	37	25.66585205	80.66385045	6.94801983	209.5869708	rice
60	48	39	24.28209415	80.30025587	7.0422990689999985	231.0863347	rice
85	38	41	21.58711777	82.7883708	6.2490506560000005	276.65524589999995	rice
91	35	39	23.79391957	80.41817957	6.970859754	206.2611855	rice
77	38	36	21.8652524	80.1923008	5.953933276	224.55501690000003	rice
88	35	40	23.57943626	83.58760316	5.85393208	291.2986618000001	rice
89	45	36	21.32504158	80.47476396	6.442475375	185.4974732	rice
76	40	43	25.15745531	83.11713476	5.070175667	231.3843163	rice
67	59	41	21.94766735	80.97384195	6.012632591	213.3560921	rice
83	41	43	21.0525355	82.67839517	6.254028451	233.1075816	rice

Figure 27

Browse | Structure | SQL | Search | Insert | Export | Import | Privileges

```
SELECT * FROM `table 1`
```

<< < 15 > >> | Number of rows: 25 Filter rows: Search this table

Options

COL 1	COL 2	COL 3	COL 4	COL 5	COL 6	COL 7	COL 8
9	80	19	21.80619564	18.57086554	5.945465949	125.0972687	kidneybeans
11	72	20	19.52226241	24.92607153	5.9511774520000005	113.334026	kidneybeans
3	67	24	17.00067625	19.90790546	5.5208800139999985	103.2926407	kidneybeans
35	69	23	16.78791503	24.96881755	5.578410206	75.45328039	kidneybeans
3	77	25	24.84906168	22.89464642	5.608165195	62.21292186	kidneybeans
23	62	19	16.51783455	20.4555596	5.609435127999999	98.77794225	kidneybeans
22	71	17	18.15300153	19.38602098	5.509295379	107.6907964	kidneybeans
31	79	25	23.18864385	22.3104551	5.902033406	63.38208822	kidneybeans
34	59	18	23.38002569	21.98879437	5.744117663	87.66898664	kidneybeans
12	63	17	18.358923	19.37703396	5.717143397	138.414764	kidneybeans
27	56	20	19.25975367	20.51346956	5.542690119	94.9533526	kidneybeans
7	63	24	22.95458237	24.03553105	5.858617867	107.7315386	kidneybeans
24	67	22	20.120043	22.89845607	5.618844277000001	104.6252153	kidneybeans
11	71	24	21.14011423	22.7182355	5.6066203460000015	141.6056722	kidneybeans
37	74	15	24.92360104	18.22590825	5.582178402	62.7089169	kidneybeans
25	76	24	15.33042636	24.91506728	5.56503533	135.3315583	kidneybeans
34	66	17	18.81097271	21.27833035	5.889614577000001	125.084915	kidneybeans
20	69	15	23.44260668	22.77255917	5.934136378	107.4137246	kidneybeans
37	65	16	22.8352024	18.97267518	5.683548308	63.59276673	kidneybeans
18	74	15	24.9035819	22.27512704	5.70836603	146.4727237	kidneybeans
4	67	25	23.78709569	24.35679348	5.948164454	119.6404412	kidneybeans
37	56	25	22.05592283	19.60379304	5.7747551439999985	126.7265372	kidneybeans
5	59	15	18.87492997	20.18238348	5.97229163	134.1811718	kidneybeans
11	61	21	18.62328774	23.02410338	5.532100554	135.33780330000002	kidneybeans
22	80	20	23.00884744	18.86880997	5.669560726	100.118612	kidneybeans

<< < 15 > >> | Number of rows: 25 Filter rows: Search this table

Console

Figure 28

Browse | Structure | SQL | Search | Insert | Export | Import | Privileges

```
SELECT * FROM `table 1`
```

<< < 15 > >> | Number of rows: 25 Filter rows: Search this table

+ Options

COL 1	COL 2	COL 3	COL 4	COL 5	COL 6	COL 7	COL 8
9	80	19	21.80619564	18.57086554	5.945465949	125.0972687	kidneybeans
11	72	20	19.52226241	24.92607153	5.9511774520000005	113.334026	kidneybeans
3	67	24	17.00067625	19.90790546	5.5208800139999985	103.2926407	kidneybeans
35	69	23	16.78791503	24.96881755	5.578410206	75.45328039	kidneybeans
3	77	25	24.84906168	22.89464642	5.608165195	62.21292186	kidneybeans
23	62	19	16.51783455	20.4555596	5.609435127999999	98.77794225	kidneybeans
22	71	17	18.15300153	19.38602098	5.509295379	107.6907964	kidneybeans
31	79	25	23.18864385	22.3104551	5.902033406	63.38208822	kidneybeans
34	59	18	23.38002569	21.98879437	5.744117663	87.66898664	kidneybeans
12	63	17	18.358923	19.37703396	5.717143397	138.414764	kidneybeans
27	56	20	19.25975367	20.51346956	5.542690119	94.9533526	kidneybeans
7	63	24	22.95458237	24.03553105	5.858617867	107.7315386	kidneybeans
24	67	22	20.120043	22.89845607	5.618844277000001	104.6252153	kidneybeans
11	71	24	21.14011423	22.7182355	5.6066203460000015	141.6056722	kidneybeans
37	74	15	24.92360104	18.22590825	5.582178402	62.7089169	kidneybeans
25	76	24	15.33042636	24.91506728	5.56503533	135.3315583	kidneybeans
34	66	17	18.81097271	21.27833035	5.889614577000001	125.084915	kidneybeans
20	69	15	23.44260668	22.77255917	5.934136378	107.4137246	kidneybeans
37	65	16	22.8352024	18.97267518	5.683548308	63.59276673	kidneybeans
18	74	15	24.9035819	22.27512704	5.70836603	146.4727237	kidneybeans
4	67	25	23.78709569	24.35679348	5.948164454	119.6404412	kidneybeans
37	56	25	22.05592283	19.60379304	5.7747551439999985	126.7265372	kidneybeans
5	59	15	18.87492997	20.18238348	5.97229163	134.1811718	kidneybeans
11	61	21	18.62328774	23.02410338	5.532100554	135.33780330000002	kidneybeans
22	80	20	23.00884744	18.86880997	5.669560726	100.118612	kidneybeans

<< < 15 > >> | Number of rows: 25 Filter rows: Search this table

Console

Figure 29

6.4Snippets of Turnitin report

turnitin

Digital Receipt

This receipt acknowledges that Turnitin received your paper. Below you will find the receipt information regarding your submission.

The first page of your submissions is displayed below.

Submission author:	Tafadzwa Mateta
Assignment title:	project
Submission title:	dissertion chapter1-5
File name:	Tafadzwa_dissertion_1-5_revison.docx
File size:	1.48M
Page count:	58
Word count:	14,609
Character count:	82,735
Submission date:	30-May-2023 07:18AM (UTC+0300)
Submission ID:	2104992023

BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

COMPUTER SCIENCE DEPARTMENT

Implementation of A Machine Learning & Internet of Things (IoT) Model For Optimum Crop Recommendations In Zimbabwe.

By

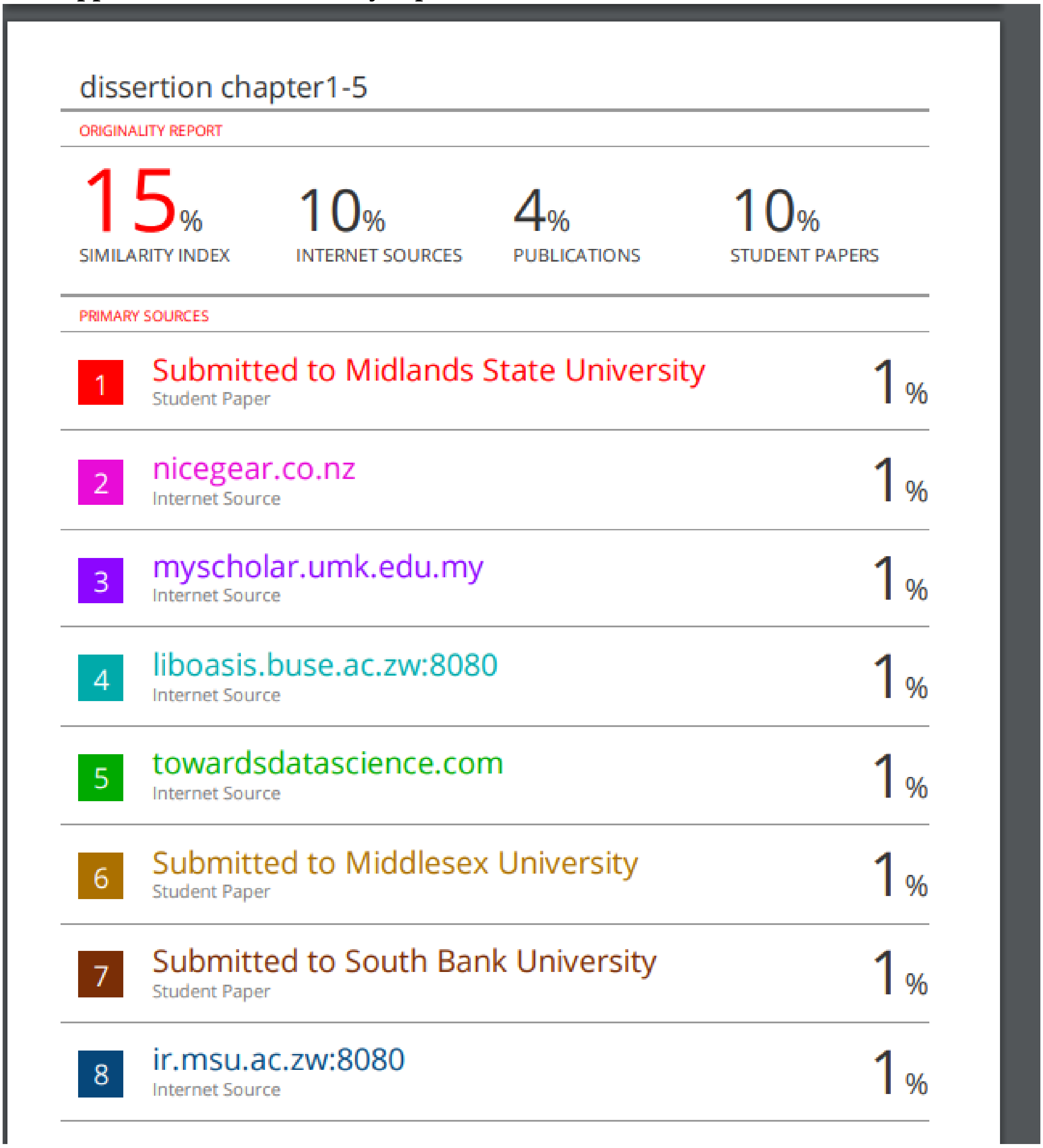
TAFADZWA MATETA

B1953954

A RESEARCH PROJECT SUBMITTED TO THE COMPUTER SCIENCE DEPARTMENT IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE BACHELOR OF SCIENCE HONOURS DEGREE IN COMPUTER SCIENCE.

Figure 30Figure 31

6.5Snippet of turninit similarity report



dissertion chapter1-5

ORIGINALITY REPORT

15%	10%	4%	10%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Midlands State University Student Paper	1 %
2	nicegear.co.nz Internet Source	1 %
3	myscholar.umk.edu.my Internet Source	1 %
4	liboasis.buse.ac.zw:8080 Internet Source	1 %
5	towardsdatascience.com Internet Source	1 %
6	Submitted to Middlesex University Student Paper	1 %
7	Submitted to South Bank University Student Paper	1 %
8	ir.msu.ac.zw:8080 Internet Source	1 %

Figure 32