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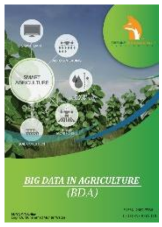

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RESEARCH ARTICLE

THE POTENTIAL FUTURE OF AGRICULTURE FOR SMALL FARMS: SUPERVISED MACHINE-LEARNING SMART IRRIGATION CONCEPT FOR VEGETABLES

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ABSTRACT

Sustainability is a crucial concept in agriculture and agricultural production. Since there is an intense competitiveness and risk in the sector, technical advancements are essential for improved development and sustainability. Small farms require cost effective solutions to match the standards of bigger producers, which essentially means best yields on crops, both in terms of quantity and quality. It is crucial to consider water crisis, climate change, and quality farm care when designing new solutions for agriculture. This study proposes the automation of farm irrigation systems based on a supervised machine learning model (SVM, Logistic Regression) that is cost-effective and precise response to farming demands. In order to show the practicality of this proposed new technology, an application was developed to represent the model results. The application created was for the user to be able to use the model to predict and control the valves in an irrigation system. This work is a potential solution for small farms in a country like South Africa, where sustainable farming is taking rise.

KEYWORDS

soil moisture; crops; irrigation; IOT; rainfall; Machine Learning; Logistic Regression; Support Vector Machine.

1. INTRODUCTION

Agriculture contributes to the damage of biodiversity through changing natural ecosystems to extensively managed systems and bringing pollution such as greenhouse gas emissions (Dudley et al., 2017). Therefore, research on sustainability is of interest in the agricultural sector. Sustainable agriculture producers aim to incorporate three key goals into their work: a healthy environment, economic viability, and social and economic equality. That et al. define sustainable agriculture as "the ability of a crop production system to continuously produce food without environmental degradation" (Tahat et al., 2020). Sustainability in agriculture incorporates many categories but the most prominent category is digital agriculture. Digital agriculture has become the source of new systems that support sustainable agriculture globally. Basso and Antle argue that the global food system must become more sustainable, and therefore propose that digital and geospatial technologies to monitor, assess and manage soil, climatic and genetic resources as the way forward. The article further demonstrates how to handle this problem by balancing the economic, environmental, and social components of sustainable food production (Basso and Antle, 2020).

Farming and agriculture are an essential part of a country's economy, and thus contribute a significant amount into the GDP of countries. Therefore it is important to find new solutions and innovations for the sector (Borowski). To tackle sustainability issues such as climate change, starvation, and malnutrition, technologies in agriculture are developed and to also keep up with the new revolution (Tyagi, 2017). It is wise to develop cost effective technologies that can be available to big and small enterprises in agriculture. These farming technologies help in production, yields and detection of issues (Delgado et al., 2019). New concepts of agricultural practices are given the name "smart" because they employ 4th industrial revolution (4IR) technologies (Fox and Signe, 2021). Smart agriculture is a novel concept and an intriguing area of research in the present, moreover research suggests that the future of agriculture is in smart irrigation. Smart agriculture employs data-intensive techniques to boost crop yields while lowering its environmental impact (Obaideen, 2022). However it remains to be the slowest growing domain, and therefore this opens a gap for a significant amount of Research & Development activities to achieve the sustainable goals, both at the industrial level and at the fundamental level of agriculture research (Vij et al., 2020). Numerous innovations, particularly in irrigation, have been established in agriculture, and automating old irrigation techniques may increase agricultural productivity by several time (Farooq et al., 2020).

The majority of irrigation systems are manually controlled and typically mechanized, and semi-automated processes are used to replace these outdated systems (Debo-saiye et al., 2020). Irrigation methods that are currently available include drip irrigation, terraced irrigation, and ditch irrigation (Oluwasegun et al., 2022). These techniques are thought to be effective, but the rising drive for higher agricultural output, poor performance, and diminishing agricultural water supplies are elements of the global irrigation picture that demand adjustment (Malik and Dechmi, 2019). If a machine-controlled irrigation system is routinely used, these issues will be addressed effectively. In terms of yields, either too much or too little irrigation is a concern, and as a result, automation is essential. This is an issue that can be corrected by adjusting the water quantities in the soil and utilizing machine learning, and good irrigation ensures long-term water usage (Ward et al., 2008). A study was conducted using several sensor modules and microcontrollers such as the Raspberry Pi, Arduino (mega/uno) and It depicted irrigation based on soil topography and weather patterns (Silalahi et al., 2021). As a result, the study investigates an inexpensive and straightforward technique for automating irrigation systems utilizing machine learning and the internet of things (IOT). Improving automation technology for irrigation automation in irrigation offers benefits such as optimized water usage, improved accuracy and consistency, and remote monitoring and control. By harnessing

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technology and data-driven approaches, automation contributes to sustainable farming practices, resource efficiency, and ultimately, the economic viability of agricultural operations.

Existing literature demonstrates notable progress in sustainable agriculture through the utilization of digital and AI-based methods. While the concept of proposing a system to meet the cost-effective and precise irrigation demands of the farming industry is not novel, enhancing the automation of these preexisting systems is imperative. The primary objective of this study is to develop an irrigation system by leveraging machine learning techniques, so as to solve water management challenges in irrigation. The system is designed to integrate with an existing irrigation framework, facilitating the automation of irrigation processes. By incorporating data on weather conditions, soil moisture levels, and crop-specific requirements, the system determines whether irrigation is necessary. The paper comprises the following sections: (2) an extensive literature review, (3) a proposed solution and methodology, (4) presentation of results, (5) discussion of challenges and complexities, and (6) a concluding section, along with an exploration of future research possibilities.

2. Literature Review

Automation in irrigation helps optimize water usage by ensuring that irrigation is carried out precisely when and where it is needed. By integrating sensors, weather data, and crop-specific requirements, automated systems can make informed decisions about irrigation scheduling and duration, thereby preventing over- or under-watering. This not only conserves water but also promotes efficient resource management and reduces operational costs for farmers. There are typically different irrigation systems that exist in industry (Namara et al., 2010). Choosing an irrigation system for a location is not always simple and is dependent on a variety of considerations. Often, a site is suitable for multiple irrigation methods, and the final choice is based on factors such as how available water is, the soil, climate, crop, labor force, resources, operating costs, adaptability to farming operations, adaptability for other uses, and personal reasoning of the farmer (Reinders, 2009). This literature review discusses several conventional types of irrigation systems and identifies new irrigation solutions and achievements over the years. The review demonstrates the inadequacies in the existing solutions and justifies the need for further research.

2.1 Irrigation Systems

Drip irrigation systems, center pivot irrigation, sprinkler irrigation, furrow irrigation systems, and terraced irrigation are examples of common irrigation techniques (Bjorneberg, 2013). Drip irrigation systems are made up of a network of tubes with small openings or emitters that can be positioned above or beneath the soil's surface and drip water into it gradually over time (Dustov et al., 2022). A self-propelled center pivot irrigation system makes use of a central pipe with outputs that revolve around a central pivot point. It works in the same way as a sprinkler irrigation system. Sprinkler irrigation systems use a network of pipes to send water in a thin spray to specific areas (Waller et al., 2016). Furrow irrigation is a sort of surface irrigation in which crops are grown along the hills that connect the streams and thin parallel channels are created and filled with water (El-nour, 2020). Terrace irrigation is an old agricultural technology that is being practiced today, mostly in hilly areas. When it rains, a series of steps are carved into the sloping terrain so that water flows from the highest step to the subsequent levels, retaining soil nutrients as it goes (Canyon et al., 2019). These irrigation systems perform well and save water and money, but, lack several crucial game-changing features such as automation and crop specialization. In recent years, researchers and developers have been focusing on automating some of these processes using various technologies. Recent advances in irrigation technology have focused on improving water use efficiency and reducing wastage (Pereira et al., 2020). Smart irrigation systems equipped with sensors and artificial intelligence algorithms enable precise monitoring of soil moisture levels and weather conditions, allowing farmers to optimize water application and minimize water loss (Bwambale et al., 2022). These tools provide valuable data on crop health, water stress, and evapotranspiration rates, allowing farmers to make informed decisions about irrigation scheduling and adjust water application accordingly (Sami et al., 2022). By harnessing and discussing these advances, agriculture can become more sustainable and resilient in the face of water scarcity challenges. It is therefore essential to look at some of the advances that have occurred with regards to irrigation systems.

2.2 Advances in Irrigation Systems

Kumar et al., suggested a smart irrigation system in 2018. Kumar et al. developed a framework where the soil moisture content during dry and wet conditions are detected using moisture sensors, the humidity is calculated, and irrigation occurs using a PC-based LabVIEW system connected to an IOT network of other devices, and an automatic water inlet setup (Kumar et al., 2016). Temperature, humidity, and sunlight are monitored and recorded. The study conducted experiments with diverse soils appropriate for various crops under various environmental conditions that control plant development and enable data to be gathered often and with little work. Although this technology may be an automatic irrigation system with information storage, it does not make decisions solely on its own.

Agrawal and Singhal's concept for a home automation system involves the use of commonly available, low-cost, and energy-efficient components such as raspberry pi, Arduino microcontrollers, XBEE modules, and relay boards, where simply sending an email to the system may be used to water plants in both large agricultural areas and little gardens. A smart drip irrigation system was created using solenoid valves and ultrasonic sensors. The authors make no mention of the irrigation automation they use. Furthermore, its approach omits historical data on past operations of the system (Agrawal and Singhal, 2015).

The irrigation control system developed by Zaier et al., is completely automated and wireless, eliminating the need for irrigation quantity and timing decisions. All of the farm's fields may be accessed using the TCP/IP protocol, according to their contribution. A host computer is linked to a Single Collecting Node for data collecting in each farm. Apart from one designated Master Node, every node in a crop is connected to the XBEE network and is regarded as a Slave Node. The irrigation management and monitoring application is installed on the farm's host computer, which keeps track of the crop conditions and controls the valves with timers and thresholds (Zaier et al., 2016). Researchers in farming have developed good and efficient systems but new solutions have emerged with better improvement and most implement technologies of the 4th industrial revolution. In the field of irrigation, decision-making solutions have been introduced, revolutionizing the optimization of water usage through data analysis and prediction. Machine learning enables real-time recommendations for irrigation scheduling, utilizing historical data to enhance water efficiency and crop productivity (Abioye et al., 2022). Integration with sensors and IoT devices allows dynamic adjustment of irrigation parameters, conserving water and minimizing environmental impact. Additionally, machine learning facilitates anomaly detection and early warning systems, helping farmers prevent water wastage and mitigate crop damage, ultimately improving system reliability. These advancements have addressed numerous challenges in irrigation, as documented in the literature, showcasing the availability and functionality of various types of systems.

2.3 The Application of Machine Learning in Irrigation Systems

There are a variety of commercial systems that are automated and can capture soil, plant, and weather data in real time, but they may not be efficient because they lack machine learning algorithms or data-driven mathematical models that can interpret the raw data and provide figures. According to Chlingaryan, Sukkarieh, and Whelan, machine learning (ML) is a fast-developing technology for irrigation systems that are based on precision, due to its capacity to reciprocate human like behavior to make decisions while also tackling a number of variables, that are nonlinear, and time-variant problems in managing irrigation (Chlingaryan et al., 2018). A study describes machine learning models to be useful decision support tool for the rational and sustainable use of freshwater resources. Traditionally, farmers decide whether or not to irrigate based on their prior observations; however, the advances in ML, irrigation conclusions can be made with more accuracy by using the idea of anticipating the water requirements of crops based on the forecast of weather and soil conditions (Wei et al., 2022). ML in irrigation being a new concept there are still gaps in the research in terms of parameters and types of learning involved. ML models toward smart irrigation management have been a big focus of study and promising results have been observed (Balducci et al., 2018). Using sampling from a labeled test dataset, a supervised ML technique uses a function to map the input with the output in order to estimate the mapping function and then when a new input is received the output variables are predicted. A typical example of supervised learning is seen on Figure1. To improve irrigation volume, timing, scheduling, soil moisture prediction, and weather forecasts, the most popular supervised learning techniques such as K nearest neighbor (KNN), decision trees (DT), support vector machine (SVM), and random forest (RF) are utilized (Jain et al., 2021).

Cardoso, Gloria, and Sebastiao (2021) developed a model using Random

Forest, a neural network and SVM to improve agricultural irrigation timing decisions through the use of real-time data and ML, based on sensor and meteorological data. The algorithms identify the best time of day to irrigate. The two most accurate, well-optimized models are XGBoost (87% accurate) and RF (84% accurate) (Cardoso et al., 2020). Kumar, Surendra, Mohan, Valliappan, and Kirthika developed a model using a logistic regression algorithm for an Internet of Things based Smart Irrigation. Based on the information supplied by various sensor devices, the model is utilized to estimate the daily irrigation water requirements. The application for remote monitoring makes the forecast data available (Kumar et al., 2018). Other algorithm models such as Principal Component Regression (PCR) can be employed as seen in a paper, where increases in the irrigated area and the coverage of the irrigation service are part of the model's data envelopment analysis (DEA) integration, which helps to optimize water consumption, management, staff, and water costs (Zema et al., 2018).

In this study, a ML model is proposed for irrigation management using soil moisture data and the type of crop. Irrigation for different crop types is vastly different, it is essential to note how much water each crop can retain, and this can be related to the soil moisture. The crops chosen for this experiment are beans, chilies, and potatoes.

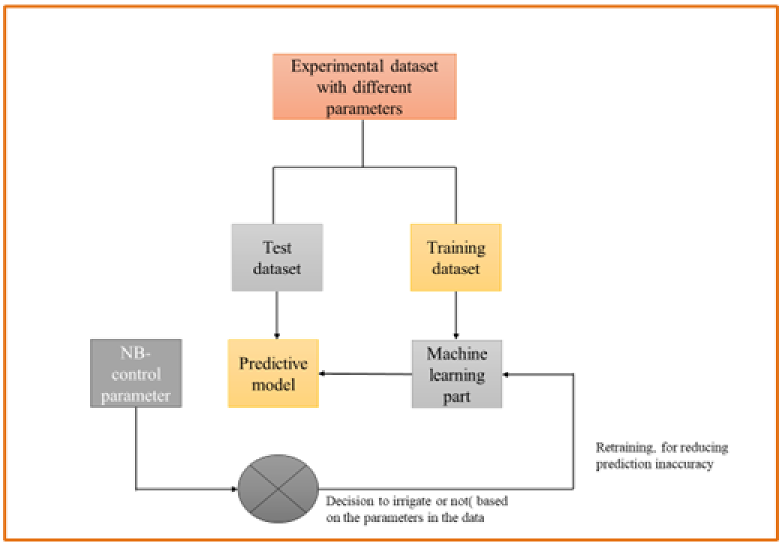

Figure 1: An irrigation system's supervised learning block diagram.

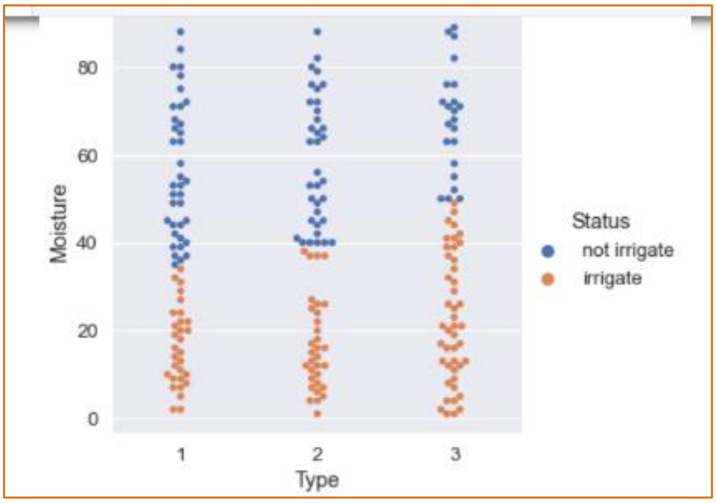

Figure 2: Finding the outliers in that dataset.

3. Proposed Methodology

3.1 Data and Data Processing

An accurate and relevant dataset must be created in order to create the proper algorithm that can forecast if irrigation at that given time is necessary. To design and create a random database for the chosen crops. A studies were used as a guideline for the values of ideal soil moisture for each crop, beans, chili, and potatoes respectively (Saleh et al., 2018; Cheena et al., 2018; King et al., 2020). The parameters chosen were the crop type and the soil moisture value. These contain the properties "soil moisture" determines if the current ground conditions are favorable or unfavorable for sustainable irrigation, " Irrigate" indicates whether irrigation is required, and "not Irrigate" shows whether the property did not need irrigation. Based on the sensor data gathered, these values were picked randomly to diversify the data set. To determine which data points are the most crucial and which ones shouldn't be considered during training, the dataset needs to be plotted to determine whether the data was random as expected or if more data points were required to randomize the data, in order to optimize the dataset and leading to the elimination of noise Figure2 shows the plot and relation of the parameters. Two data sets were created for training and testing. Figure3 shows the flowchart of the described methodology.

Table 1: Dataset Properties.

Feature	description
Crop	Beans, chili, or potato
Soil moisture	mm per day
Output	Irrigating or not

Figure 3: Methodology flow diagram.

3.2 Machine Learning Classification Algorithms

The algorithms for supervised classification are those that will be used in this study. Predicting decision values in the qualitative or category class of a given data point is the process of classification. Two models were created namely, a simple logistic regression and support vector machine (SVM). These were chosen because of the dataset created. The models were both trained using the same dataset and tested with another dataset created. Scikit-learn was employed to research and enhance these algorithms. This is a Python implementation of an open-source machine learning library. The logistic regression model was the next step where a python code was written using the training dataset. The model was used SK learn library for some functionality. The SVM model, training, and fitting of the model was a requirement. Support Vector Machine (SVM) is a supervised learning technique built for outlier identification, regression, and classification in order to suit the dataset that was produced. The two models were then tested using the test dataset. The accuracy of each model was used to see which model was suitable for the next phase.

The chosen model was the transformed to an API using flask as a framework. Flask web application framework uses Python to create API. It is created by Armin Ronacher, the president of Pocco, a global organization of Python aficionados (Uchenna et al., 2021). The Werkzeug WSGI toolkit and Jinja2 template engine form the foundation of Flask. This meant flask was an ideal framework for creating the API since the model is written in python. The flask API was then deployed on Heroku to be able to use the API in the back end of the application to be developed. The next phase was to develop an application which can now be used by the farmer to communicate with the irrigation system and monitor the irrigation process.

3.3 Digital Architecture

The application intends to bring the prediction results to the farmer so the farmer can see if the system is irrigating or not. The application results are intended to send the prediction result to the valves, where "irrigate" sends a signal to the irrigation system valves to open and "not irrigate" sends a signal to keep the valves closed. The application was created using JavaScript functions, with HTML and CSS for styling. The proposed irrigation application architect is shown in Figure 4 below, which depicts the application's flow. For a deeper understanding, see the results for final screen mock-ups. The application requires the user to sign up for use, the first screen includes a signup link. If already signed up the screen the login screen is the first screen. The inputs required once on the home page are the sensor data and the selection of the crop. The model works in the backend to compare the inputs with the training data so give a prediction, the model was used as an API where in functions using Alpine JS and Express JS for the routes. The model was intended to also get some other input from the weather API, but the proposed methodology required changes that will be discussed in the next section of results. The prediction output is seen on the home screen, which also displays the weather. The app also collects soil moisture data, the irrigation status, and the date of irrigation with the weather of that day using SQL and the data can be viewed by the farmer and the developer of the app. This function serves the purpose of future improvements of the application and most importantly the model. A manual on and of button for the valves is necessary for the farmer to gain some control of the irrigation, if there is any malfunction of the model.

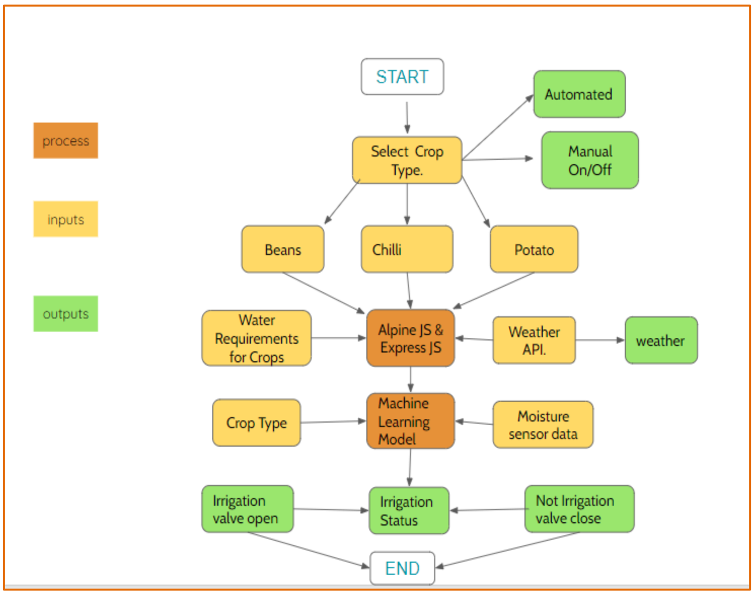

Figure 4: Digital architecture of the application

4. Results and Discussion

An initial dataset from a Kaggle project by Nadhir for Predicting watering the plants was used to analyze the relationship between the chosen parameters (Nadhir et al., 2017). The data set was plotted in python. It was observed that soil moisture is related to rainfall and irrigation. The data plot showed no correlation between the rainfall and moisture according to correlation plots. Figure5 shows the sns. pair plot of the data. There was a need to look into literature related to rain and soil moisture. The soil moisture parameter is important, but the type of crop and its water retention is vital for exceptional yields. This information assisted with creating a suitable dataset from training and testing.

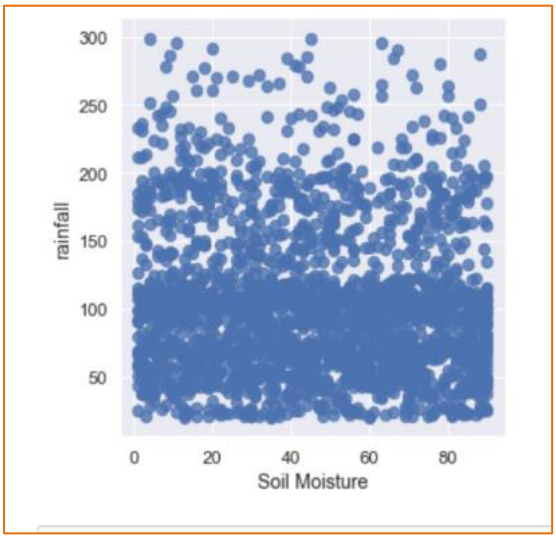

Figure 5: Correlation between the rainfall and moisture.

The dataset created had a y parameter which was the irrigation status (to irrigate or not). This would be essential for training the model. The aforementioned dataset is then used to train the logistic regression model and the SVM model. Accuracy testing is conducted following training. The model is given the new values in order to forecast the result, this is the testing stage.

The SVM model was trained with one parameter, soil moisture. The reason behind this was that the model was not fitting for that created data set with crop types. The model gave an accuracy of 54%. This caused the need to try another dataset with more data points and the crop type parameter. The logistic regression model was then developed using the same data set including the crop type as a parameter. This model gave an accuracy of 87% and the conditions of the ideal soil moisture for each of the chosen crops was used to test this model. This model was turned into a flask API, to be used with the application.

The application was then the next phase of the project. The application was developed using JavaScript, with Alpine JS and Express JS as frameworks. The app is structured in a manner that it enables the user to login. The login screen shows the sign-up link which takes the user to the sign-up page. These can be seen on Figure6 and Figure7.

Following the current screen, the subsequent page is the home page, which allows the user to select the crop type and input the soil moisture. Additionally, the home page presents real-time weather information obtained from the weather API for the user's convenience. Alongside, there is a manual button displayed on the screen, while the tab leading to the history screen can also be found. The primary screen, denoted as Figure 8, serves as the main interface.

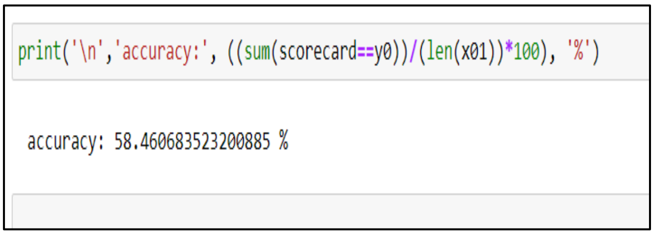

Figure 6: accuracy of the model

Figure 7: Home/Login page

Figure 8: Sign-up page

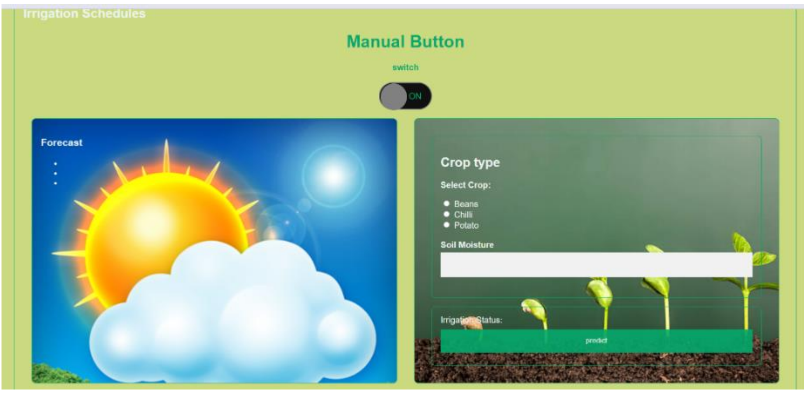

Figure 8: Main- page

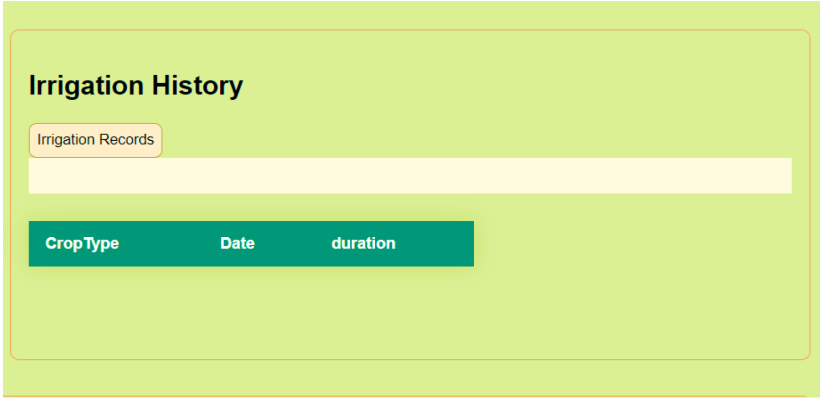

Figure 9: history page

The last screens display the irrigation history, and this information is collected from the inputs and outputs including the weather (Figure 9).

5. Challenges and The Opportunities

5.1 Opportunities

The next phase in this project is to integrate the equipment and the software. An IOT, internet and Wi-Fi solution for connecting the computers needed system. The Raspberry Pi and Arduino microcontrollers are the foundation of the proposed solution. The processing speed, cost, and availability ease of the microcontrollers were taken into consideration. A variety of sensors will be used to continuously monitor the variable factors, and irrigation specific to the type of crop will be carried out [9]. The changeable parameters will be continually checked using various sensors, and irrigation appropriate to and particular to the type of crop will be performed. This would a good solution for the next phase. A wireless sensor network would also be needed for the moisture sensor.

5.2 Challenges

The precision of the forecast is dependent on the setup's appropriate installation. Machine learning algorithms must be taught on enormous amounts of data as well as data from specific regions. Wild animals represent a hazard to the hardware as well, and while they would be identified upon entering the field, they would require personal intervention to avoid any harm to the gear. For the visualization, a dedicated server or network storage is required.

6. Conclusions

The current challenge in irrigation is the combination of water scarcity and inefficient water management. Consequently, the reviewed literature examines existing irrigation systems, their limitations, and the potential of machine learning algorithms in irrigation management. The study emphasizes the necessity for technological advancements in irrigation systems to optimize water utilization, enhance crop yields, and minimize environmental impact. The proposed methodology focuses on developing an irrigation system that utilizes machine learning techniques. By integrating data on weather conditions, soil moisture levels, and crop-specific requirements, the system can make informed decisions regarding irrigation scheduling and duration. The research primarily concentrates on beans, chili, and potatoes as the selected crops. The process of dataset creation and processing, as well as the selection and training of machine learning classification algorithms (logistic regression and support vector machine), are outlined. The results demonstrate an 87% accuracy of the model, and the developed platform provides irrigation decision-making outcomes. Overall, this study underscores the importance of automation and data-driven approaches in agriculture to attain sustainability and economic viability. The proposal to automate farm irrigation systems using supervised machine learning models like SVM and Logistic Regression holds promise for cost-effective and precise irrigation systems in the farming industry, with potential implications for future research and development.

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