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An IoT-Based Smart Real Time Sensing and Control of Heavy Metals to ensure optimal growth of Plants in an Aquaponic Set-Up

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Abstract.

The concentration of heavy metals that needs to be maintained in aquaponic environments for habitable growth of plants has been a cause of concern for many decades now as it is not possible to eliminate them completely in a commercial set-up. Our goal is to design a cost-effective real-time smart sensing and actuation system to control the concentration of heavy metals in aquaponic solutions. Our solution consists of sensing the nutrient concentrations in the aquaponic solution, namely calcium, sulfate and phosphate and providing them to the Machine Learning model hosted on an Android application. The application outputs the appropriate iron and copper concentrations that can be tolerated for optimal growth of plants in an aquaponic set-up and controls the dispensing systems to maintain these desired heavy metal concentrations.

The Machine Learning algorithm used in this case is pre-trained on the top three nutrient predictors selected from a dataset containing the nutrient profiling of samples recorded from three aquaponic farms over the course of a year in South-East Texas based on the output of a pipeline of Feature Selection models like the pairwise correlation matrix, ExtraTreesClassifier and Xgboost classifier. This pre-trained ML classification model, which in our case is a Radial Support Vector Machine, is hosted on a cloud platform and would output the recommended levels of iron and copper in real time through an Android application considering the concentrations of phosphorus, calcium and sulfur as inputs. These recommended values were maintained with the help of an array of dispensing and sensing units, thus monitoring these parameters in a closed loop system.

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Keywords.
Aquaponic, ExtraTreesClassifier, Machine Learning, Xgboost, closed loop system

Introduction:

Over the last few decades, hydroponics and aquaponics-based systems have been used as a promising alternative to traditional agricultural techniques as they use 50 to 70% less water owing to the recyclability of the system [1][2][3]. Adding to it, they have shown great efficiency as they require less pest control and are less affected by the harsh climatic weather conditions, leading to an increase in the yield of the produce. As we are moving towards an era of digital agriculture, efforts are being made to design smart IoT based hydroponic systems to be implemented on a commercial scale.

There have been some recent studies using predictive approaches in the field of alternate agriculture to increase the yield of produce in a sustainable manner. Some of the studies have been stated as follows. In [4], the sensor values in the greenhouse were recorded in an aquaponic system and the fish count extracted using R-CNN algorithm were given as inputs to the AutoML algorithm to trigger the actuators needed to control the environmental parameters. In [5], Dhal et al. designed a Machine Learning based smart IoT system for sensing and controlling the concentrations of ammonium and calcium depending on the season using a feedback loop to have sustainable growth of fish and plants in a single set-up. In [6], a comparative study of Machine learning based approaches were conducted on images of lettuce to study what diseases can be incurred in the growth process. Similar studies have been conducted by Hiram Ponce et al. in [7] and Yadav et al. in [8] using Deep Convolutional Neural Networks for feature extraction on the images of leaves to detect nutrient deficiency in tomatoes and foliar disease in apple plants respectively. Having stated the above, very few studies have been conducted on the effect of heavy metals on the growth of crops in a hydroponic set-up which is the main purpose of our research.

In [9], the effect of biodegradable chelating agents SS-EDDS was studied on the uptake of heavy metals while growing sunflowers in hydroponic solution and it was concluded that it enhanced the uptake of non-essential metals from the solution. On a similar note, Mahanta et al. [10] conducted a study for growing soybeans in hydroponic solution and concluded that the seeds treated with plasma activated water had a significant lower uptake of heavy metals compared to the ones that were just treated with tap water. In [11], Michalska et al. conducted a study on the effect of lead and cadmium on the growth of three variants of lettuce in hydroponic culture and how it affected the absorption of macro and micronutrients in their root and shoot system. Furthermore, in [12], Peralta-Videa et al. did a study on the uptake of environmental heavy metal uptake by plants and the detrimental effects of arsenic, cadmium, and chromium on human body. Having stated that, the main goal of our project is to design a Machine-Learning based IoT system to output the heavy metal concentrations that can be tolerated in a commercial hydroponic system for optimal growth of lettuce depending on the concentration of nutrients measured in real time. The basic functionality of the prototype is to sense and regulate the nutrient parameters using a closed-loop system so that the heavy metal concentration in the hydroponic solution stay within permissible limits.

System Description:

While laboratory set-ups are able to measure the nutrient profiles of water samples for specified concentrations, the processing time takes between several hours to a couple of weeks depending on the queue size. Our prescribed design would serve as a convenient tool to access the concentration of the observed hydroponic environment in a timely manner. When activated, the Nutrient Monitoring System (NMS) would monitor the concentration of calcium, phosphate and sulfate when powered on. Each sample would accurately measure and output a signal directly proportional to the chemical's concentration. The main control unit i.e. the microcontroller unit would receive the spectrophotometer's calculations and create a signal which is then converted into human-readable data points and then the values are stored on to the database. A pre-trained

Machine Learning (ML) model hosted on the database is then run on this set of data which then displays the maximum tolerable heavy metal concentrations based on the output of the ML model through an Android User Interface. A full functional block diagram of the entire working prototype is as stated in Figure 1.

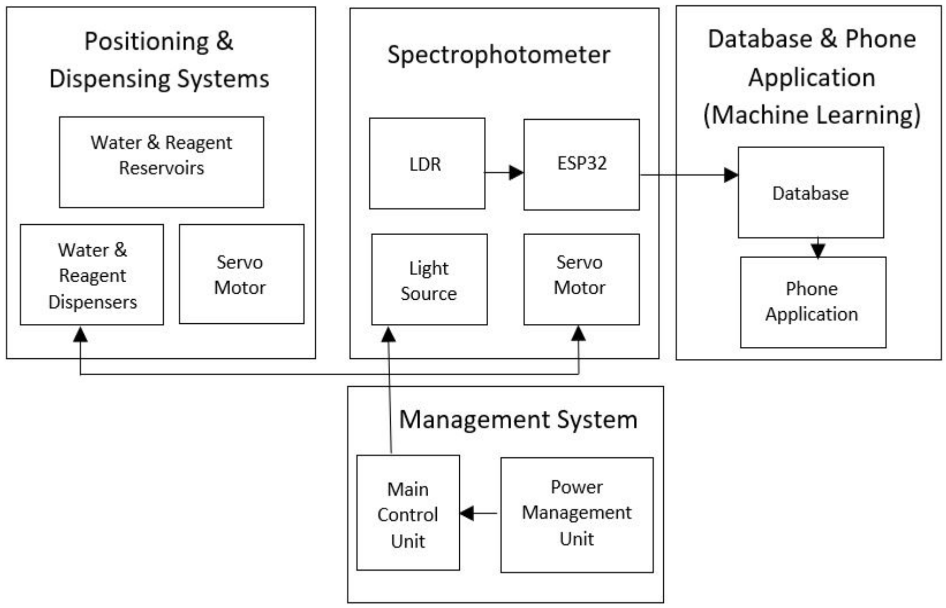
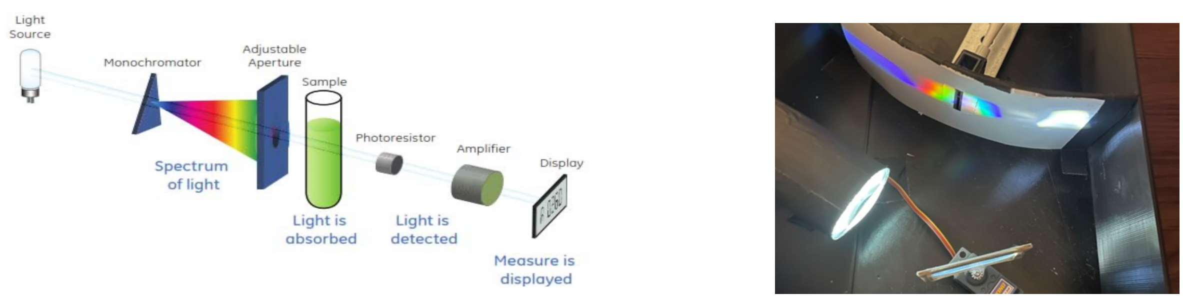


Figure 1. Fully Functional Diagram of the Nutrient Monitoring System

The details of each of the subsystems are stated as follows:

Spectrophotometer system:

The spectrophotometer system consists of a light source that passes through a monochromator i.e. the device that split lights into individual wavelengths and through an aperture. The aperture changes the resolution of the light passing through. The light then goes through and is absorbed by the source in the sample. The light that reaches the detector is the light that did not get absorbed.



(a) (b)

Figure 2. (a) Set-up of the spectrophotometer (b) Internal Design of Spectrophotometer showing individual wavelengths passing through aperture

From Figure 2(b), it is evident that the light's path starts at the source and goes through the monochromator where it is split up into individual wavelengths. It then passes through the slit (increasing resolution) through the cuvette and reaches the photoresistor. The photoresistor is attached to a voltage divider whose output is dependent on the quantity of light that reaches the photoresistor. This output is finally read by the ESP32 microcontroller and is stored into the database.

To measure the concentration of an unknown sample, a calibration curve has to be made. The calibration curve requires samples with predetermined concentration values to build a line of best fit. Using a preset wavelength (Table 1 uses 610 nm), the device reads the respective absorbance values of each concentrated sample. This creates a set of data points which can be plotted with a line of best fit to create a linear equation. The y value represents absorbance, and the x value represents concentration. Solving the equation for x gives the associated concentration values based on the measured absorbance. Finally, placing a test sample with unknown concentration and measuring the absorbance value from the device, plugging this value into the new equation will give the absorbance of the sample.

The concentration data for the nutrients taken for the experimentation, i.e. Calcium, Phosphate and Sulfate have been shown in a tabular form below.

Table 1: Concentration Data for Calcium, Phosphate and Sulfate

SAMPLE ID	STD0	STD1	STD2	STD3	STD4	STD5	UNKNOWN
TYPE	Standard	Standard	Standard	Standard	Standard	Standard	Standard
CALCIUM							
CONCENTRATION	0.000	28.800	57.600	86.400	115.200	144.000	
WL610.0	0.000	0.210	0.266	0.306	0.358	0.493	
WEIGHT FACTOR	1.000	1.000	1.000	1.000	1.000	1.000	
PHOSPHATE							
CONCENTRATION	0.000	0.516	1.032	1.550	2.060	2.580	
WL610.0	0.000	0.226	0.359	0.478	0.583	0.847	
WEIGHT FACTOR	1.000	1.000	1.000	1.000	1.000	1.000	
SULFATE							
CONCENTRATION	0.000	4.800	9.640	14.460	19.280	24.100	10.000
WL450.0	0.000	0.429	0.753	1.091	1.086	1.432	0.638
WEIGHT FACTOR	1.000	1.000	1.000	1.000	1.000	1.000	1.000

The concentration of Calcium, Phosphate and Sulfate is shown in standard curves below.

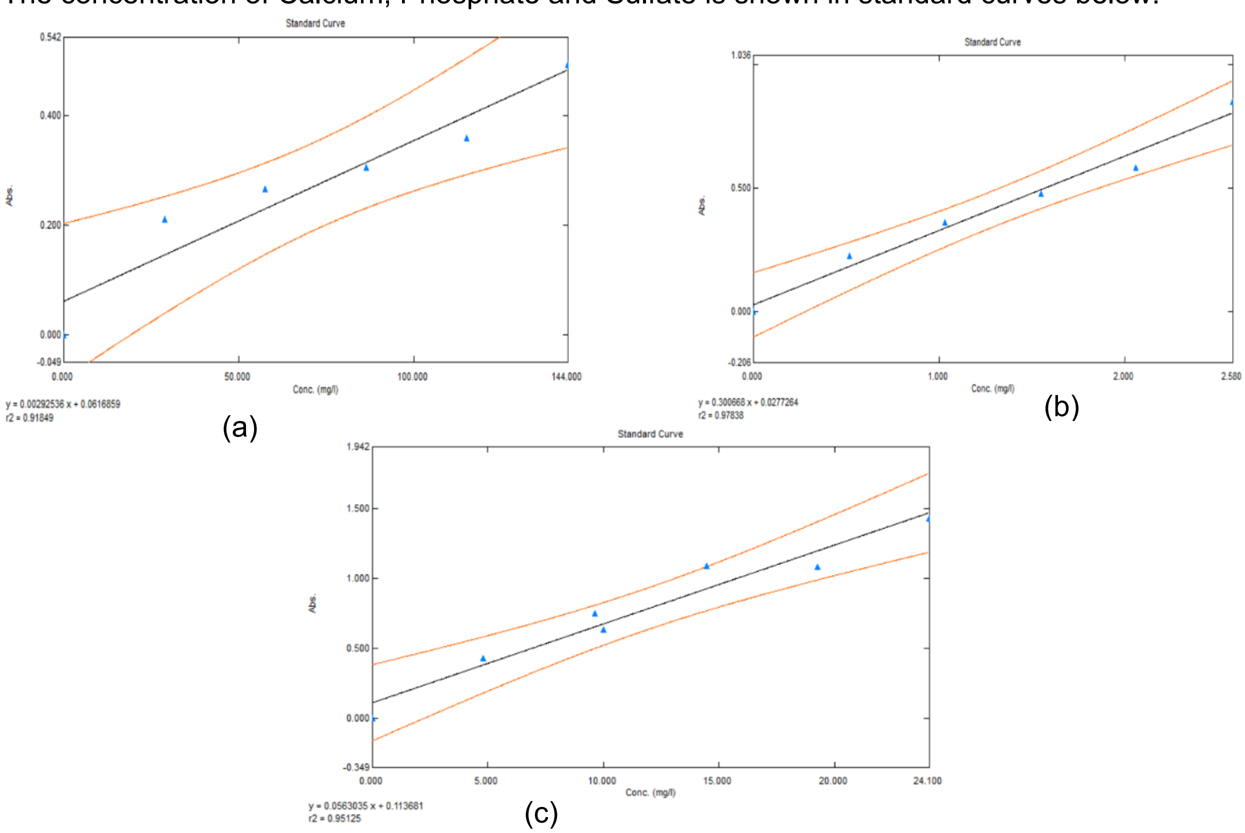


Figure 3: Standard Calibration Curve for (a) Calcium (b) Phosphate (c) Sulfate

Positioning and Dispensing System:

The positioning and dispensing system is an integral part of the Nutrient Monitoring System, allowing for the automation of water filling, reagent filling, and positioning of cuvettes in a spectrophotometer, thereby reducing the amount of necessary hands-on work. The details of the system used to build up the entire unit have been stated below in Figure 4.

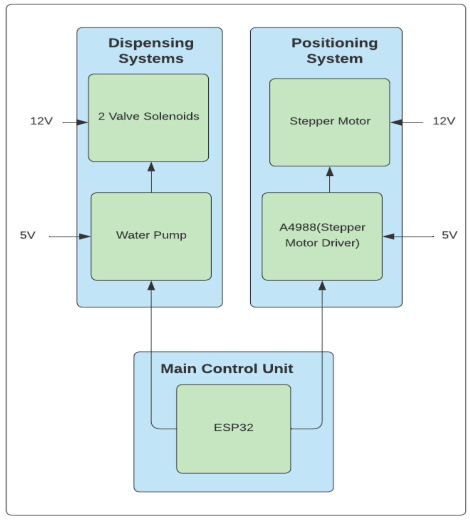


Figure 4: Control Flow diagram of the nutrient Dispensing and Positioning system

In this system, one Nema 17 bipolar stepper motor, two valve solenoids, one A4988 motor driver and one ESP32 microcontroller were utilized to perform each stage of the sequence. For the conveyor system, a stepper motor was used to rotate an arm with a cuvette across the several stages. The dispensing system utilized the water pump to supply both water and a reagent through a tube with a volume of 2mL. Once filled, the upstream valve solenoid closes, trapping the water and reagent mixture in the tube. Then, the downstream valve solenoid opens releasing the water and reagents into the cuvette. To power the stepper motor, a motor driver received 5V from an ESP32 microcontroller and 12V from the power management system. For the motor driver, two digital pins were used to set the stepping type and direction of each motor. For the water pump, the circuit required a PN2222 transistor, 1N4001 diode, and a 250Ω resistor. Using the Arduino integrated development environment (IDE), a sequence of instructions was coded onto the ESP32 microcontroller to perform tasks assigned to the positioning and dispensing system.

The power management system required to supply the required DC voltages to the abovementioned system from a 120 V AC supply has been explained in detail in Figure 8. This system primarily consists of two main steps: an AC-DC conversion system which steps down the voltage from 120 V AC supply to a 24 V DC supply, and a buck converter which takes an input of 24 V from the AC-DC converter and gives two stable output voltages of 12 V and 5 V respectively. The entire schematic of the power management system has been depicted in Figure 5.

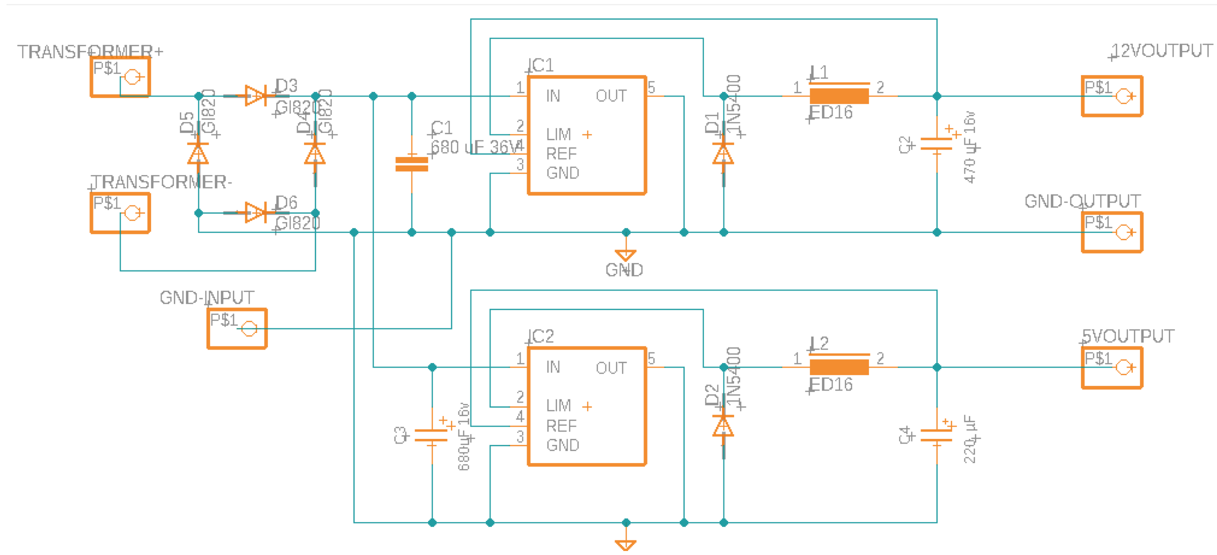


Figure 5: Power Management circuit for the Dispensing and Positioning system

Database and Machine Learning system:

The purpose of the system is to collect data from the spectrophotometer via Wi-Fi on the ESP32 microcontroller, and then send and store that information within a database hosted on Google Firebase. The pre-trained Machine Learning model hosted on the Firebase is run on the calcium, phosphate and sulfate concentrations which are selected through a pipeline of feature selection techniques on a dataset recorded over the course of a year from three hydroponic farms in East-Central Texas.

The water samples were collected on a weekly basis from these farms and were sent to Soil, Forage and Water Testing Laboratory at Texas A&M University to have a nutrient profiling of these samples. The chemical concentrations of calcium, magnesium, sodium, potassium, boron, carbonate, bicarbonate, sulfate, chloride, nitrate, phosphate, iron, copper (all of these measured in ppm) were analyzed from each sample and were appended to the dataset. The final dataset which we used in our case to carry out the initial analysis had a total of 226 observations and 14 predictors.

The concentration of iron and copper were treated as the response variables and the rest 12 predictors were used to carry out the analysis. Initially, we started with treating the entire dataset as an unsupervised approach and used K-Means clustering with the value of K set to 3. Out of the 226 observations in the analysis, 116 observations were classified into Class 0 and 113 observations were classified into Class 1. As the dataset at hand was sparse and the dimensionality was high, a pipeline of Pairwise correlation matrix, XGBoost classifier and ExtraTreesClassifier were carried out on the dataset to find out the most relevant predictors in the analysis. From the pairwise correlation matrix generated, the predictors with more than 90% correlation among them were removed which led to the removal of bicarbonate and sodium concentrations from the dataset. After this, XGBoost classifier was used to generate the feature importance for each of the remaining 10 predictors.

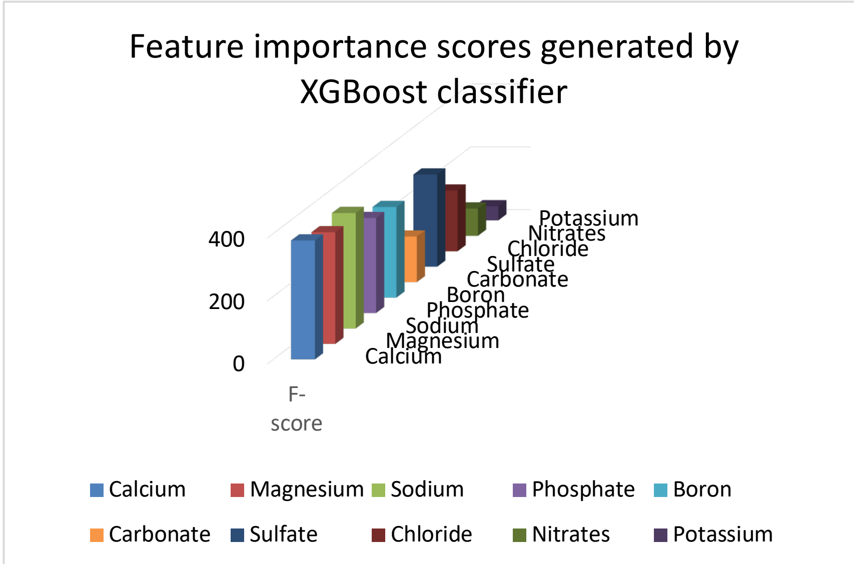


Figure 6: F-scores of the predictors generated by XGBoost classifier

From Figure 6, calcium, magnesium, sodium, phosphates, boron and sulfate were chosen as the top 6 predictors for analysis as they had feature importance over 200. The rest of the predictors were comparatively less important in our resulting analysis, due to which, we decided to eliminate them before proceeding with the application of ExtraTreesClassifier for selection of the top three predictors which were regulated at regular intervals using an IoT based set-up.

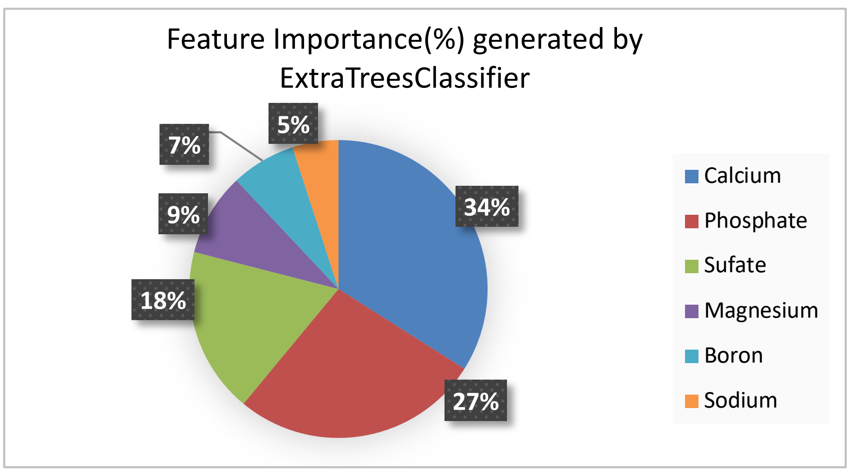


Figure 7: Feature Importance (%) of the top six nutrient predictors

From Figure 7, the feature importance of calcium, phosphate and sulfate were found out to be 34%, 27% and 18% respectively, thereby making up for 79% of the total feature importance in the entire dataset. Therefore, the values of these abovementioned features served as the predictors to be used in the ML model for generating the heavy metal concentrations that can be tolerated in a hydroponic set-up based on the ML output.

As stated before, the entire dataset was treated as a binary classification problem and based on the historical values of the dataset, a certain value of iron and copper that can be tolerated in a hydroponic set-up for optimal growth of lettuce were prescribed depending on the value of the output of the Machine Learning classifier. A 5-fold Cross-Validation with 15 repeats were performed on the dataset to generate the aggregate testing accuracy and selecting the most optimal classifier. The testing accuracy of each of the ML classifiers have been stated in Figure 8.

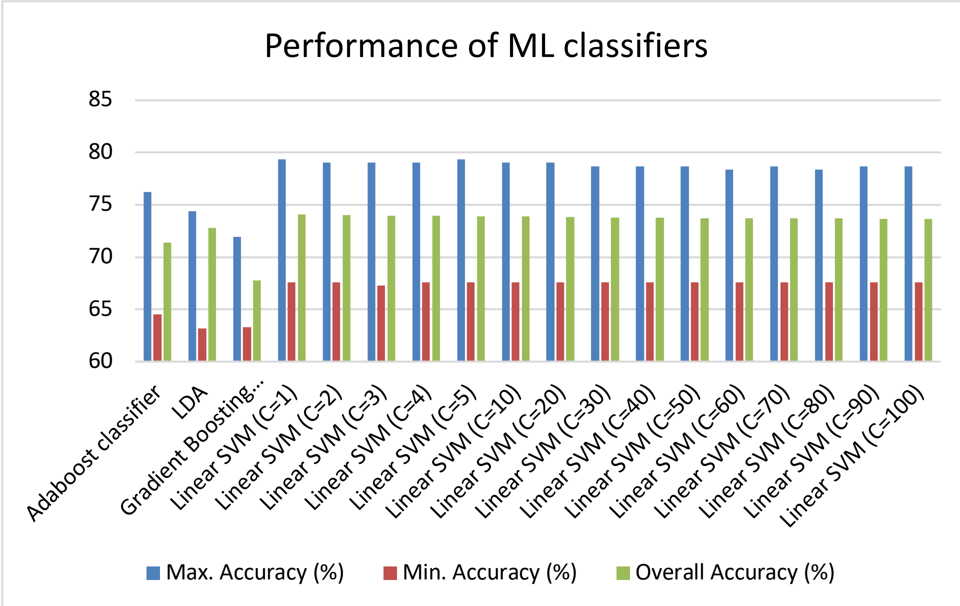


Figure 8: Maximum, minimum, and overall testing accuracy of the ML classifiers on the historical dataset

From Figure 8, it can be concluded that among the three classifiers were used on the dataset, Linear Support Vector Machine outperformed the other classifiers. The value of the highest aggregate testing accuracy was recorded to be 75% in the case of Linear SVM when the value of penalty parameter was set to 10. Therefore, it was decided to proceed with the above stated classifier in our analysis.

Based on the output of the Linear SVM with the concentration of calcium, phosphate and sulfate as inputs to the ML model, a set of maximum tolerable values of iron and copper in the hydroponic set-up were prescribed. The median value of these heavy metal concentrations were computed per class from the training dataset. When the output of the ML model was class 0, the iron concentration and the copper concentration that can be tolerated in the hydroponic environment was 0.03 ppm and 0.006 ppm respectively. Similarly, when the output of the ML model was 1, the iron and copper concentrations that can be tolerated was 2.04 ppm and 0.172 ppm respectively. All these concentrations were displayed through an Android application which have been discussed in the next sub-section.

Android Application system:

The Android phone application serves as a portable display and allows the user to show the appropriate heavy metal concentration value, sorted by measurement date depending on the output of the Machine Learning model hosted on the Firebase. The data recorded through the spectrophotometer is sent to the Firebase (database) through a Wi-Fi connection on the ESP32 module.

Figure 9: Overall connection diagram of dataflow from the spectrophotometer to the Android application

System Integration:

The ideal concentration of calcium, sulfate and phosphate concentration to be maintained for optimal growth of lettuce in a hydroponic set-up are 130 ppm, 125 ppm and 25 ppm respectively. To maintain this concentration in a 450L hydroponic set-up which was used as our test site, 90 g of calcium sulfate powder and 31 g of magnesium phosphate powder are initially added manually to the hydroponic set-up.

After this, the spectrophotometer system designed is used to measure real time values of these nutrients which stores the values on to the Google Firebase where our Machine Learning model is hosted. Based on the value of the ML output, the appropriate values of iron and copper that can be tolerated in a hydroponic set up is displayed through an Android application interface.

The other connection from the spectrophotometer system is to the Nutrient Dispensing System which uses two cuvettes each with a dispensing capacity of 2 mL. Both the systems are connected in a closed loop system using a feedback loop, where the spectrophotometer system senses the nutrient parameters from the solution and sends the readings to the dispensing system which releases the nutrient solution if the measured concentrations are less than the recommended parameters. For a single run of the Nutrient Monitoring System (NMS), the sensing and the dispensing units are operated five times and the average value of the nutrient concentrations recorded from the spectrophotometer are stored on to the Firebase which is given as input to the Machine Learning model.

Discussion:

As discussed in the introduction section, the concentrations of heavy metals in hydroponic environments should be as low as possible. In a practical commercial set-up, it is not possible to get rid of these heavy metals completely. Due to this, it was decided to use the median value of iron and copper concentrations per class calculated from the historical dataset that should be maintained in the solution.

For observations belonging to class 0, the recommended concentrations of iron and copper that can be tolerated in the hydroponic solution was 0.003 and 0.006 ppm respectively. Similarly, for observations belonging to class 1, the recommended concentrations of iron and copper was 2.04 and 0.172 ppm respectively. The values of these above stated heavy metal concentrations were maintained as per the input concentration of calcium, sulfate and phosphate concentrations which were regulated with the help of our prescribed Nutrient Monitoring System (NMS).

The effect of addition of calcium and sulfates have been studied in [13] where it was concluded that the dry matter yields of most of the plants under high treatments of calcium sulfate was high compared to the ones with less treatment. It has also been established by many studies that the addition of calcium increases the pH of the hydroponic solution. The effect of pH on the absorption of copper by plants was studied in [14] where it was concluded that increasing the pH of the soil decreased the rate of copper absorption by plants as determined by their shoot biomass and root elongation, thereby reducing the chances of copper toxicity. There have been studies on the effect of copper toxicity in [15] which state that when the concentration of copper increases beyond a certain threshold which in this case was 100 micro-Moles, the relative growth rate decreases as well as severe browning is observed in the leaves leading to necrosis. In [16] and [17], the effect of increased copper concentration leading to a decrease in phosphorus uptake by plants in hydroponic media was studied where significant imbalances in the nutritional values of the plants as well as stunted plant growth was observed.

Similarly, the effect of pH on the absorption of iron by the plants have also been studied. In [18], it has been stated that the pH of the soil should be kept at moderate levels for ferric iron to be freed from ferric oxides and be more available for uptake by plant roots. Similarly, a lower level of pH would mean high uptake of iron by plants which can lead to iron toxicity. A detailed account of the toxic levels of iron that resulted in young plants suffer from increased oxidative stress has been studied in [19] with reduced relative growth rates. The detrimental effect of iron on the phosphate concentrations in growth environments has been discussed in [20] where phosphate deficiency due to excess of iron resulted in inhibition of primary root growth and retarded development of lateral roots. This same observation was reinstated in [21] which stated that a phosphorus depleted hydroponic media for growing barley resulted in iron plaque formation in the root system.

Therefore, having stated the above, it is important to regulate the nutrient parameters as prescribed to control the heavy metal concentrations and achieve optimal growth of lettuce in hydroponic systems. The presence of heavy metals such as iron and copper may reduce the uptake of essential nutrients by the plants in a hydroponic system. This might be detrimental to the growth, sustenance, and yield from lettuce. Regulation of heavy metals can reduce the competitive affinity of plants to the essential nutrients.

Conclusion and Future Work:

In conclusion, a smart IoT Nutrient Monitoring System was designed which was successful in detecting the concentrations of calcium, phosphates and sulfate in real-time and prescribed a specific concentration of iron and copper that can be tolerated for these nutrient concentrations through an User Interface based on the output of the Machine Learning classifier to which these nutrients were fed as inputs.

In the future, data can be recorded from more geographically distinct terrains to create a dataset with more variance in data which would help in formulating a more reliable Machine Learning model. The spectrophotometer which currently measures only three nutrients can be extended to measure more chemical properties of the hydroponic solution. The size of the positioning and dispensing system which currently consists of two dispensing units can be scaled to make a larger system which can be used in larger commercial set-ups. Adding to it, the current prescribed system does not have a way to monitor or regulate the heavy metal concentrations in real time which can be incorporated.

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