Hydroponic Nutrient Control System based on Internet of Things and K-Nearest Neighbors

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Abstract— The human population significantly increases in crowded urban areas, causing a reduction of available farming land. Therefore, a landless planting method is needed to supply the food for society. Hydroponics is one of the solutions for gardening methods using water as a nutrition media. Traditionally, hydroponic farming conducted manually by monitoring the nutrition such as acidity or basicity (pH), the value of total dissolved solids (TDS), electrical conductivity (EC), and nutrient temperature. In this research, we propose a system that measures pH, TDS, and nutrient temperature values in the nutrient film technique (NFT) technique using a couple of sensors. We use lettuce as an object of experiment and apply the KNN (k-Nearest Neighbor) algorithm to predict the classification of nutrient conditions. The result of prediction is used to provide a command to the microcontroller to turn on or off the nutrition controller actuators simultaneously at a time. The experiment result shows that the proposed KNN algorithm achieves 93.3% accuracy when

Keywords—Hydroponic; pH; TDS; k-nearest neighbor

I. INTRODUCTION

The Population of the world has increased 1,860 times from the past 12-millennium population [1]. Population increases significantly in crowded urban areas [2]. The increasing population causes the decreasing of open land, where land is needed as media to grow plants and maintain the world population's food supply.

Therefore, a landless planting method needed in rural and urban areas. Hydroponics is one of the solutions to gardening methods without using soil as planting media and using water as a nutrition media [3]. In general, maintaining the quality of hydroponic plants done manually by monitoring the nutrition such as acidity or basicity (pH) value, the value of total dissolved solids (TDS), electrical conductivity (EC), and water temperature. Using the internet of things (IoT) concept, monitoring and controlling can be done remotely through internet media in real-time. The benefits of using IoT [4], IoT can increase plant growth due to maintaining nutritional value (such as pH, TDS, and EC) and reducing plant maintenance costs by around 23% - 70% [5].

Some research done by employing IoT on the hydroponic nutrient control system, such as [6] that applied IoT to monitor pH and nutrient temperature on hydroponic with NFT method which can show the condition of nutrient on the LCD, sent a notification through an SMS gateway, and automated control the actuator pH and oxygen pump. Kularbphttong et al [7] research build an IoT for hydroponics system divided into two parts: the automatic part and manual part, which allows user to manually control the nutrient such as light, temperature and, humidity or the system runs

automatically to check and refill nutrient by self-regulating and displays the graphics of nutrient to the user.

In another hydroponic research [8], IoT was combined with Deep Neural Networks (DNN) to predict nutrient control. The DNN predicts the label based on table control, which has eight labels, and the system output shows the sensor value and predicted control labels with the prediction accuracy percentage.

In another research, predicting using machine learning and IoT conducted by Shekhar [9], the study is a soil-based system and predict the soil condition. The irrigation system is fully automated and uses KNN as a machine learning classification to predict the soil condition.

KNN method known as a simple, easy to use, and can be used in various applications [10]. KNN is also known as a lazy algorithm, which is the calculation of the classification of the test sample is large, use a large amount of memory, so the scoring is slow[11].

Related research by Ashwini et al. [12] uses KNN to predict water quality compare to random forest (RF) method results and tested with several water conditions. KNN classification has higher accuracy than the RF with the same data samples, which indicate KNN can use for water quality prediction and management.

In previous research, paper [13] proposes the uses of fuzzy logic and IoT for monitoring and controlling system. IoT devices use to monitoring plant conditions and water needs, while fuzzy logic uses to control the supply water and nutrition precisely. This research also uses lettuce and bok choy plants and compare the uses of smart control with a traditional method. The result shows that using intelligent control, plants can grow better by validating through the visual look of the plants.

In this research, we propose an NFT (Nutrient Film Technique) hydroponic nutrition control system using the KNN method and IoT. This control system expected to provide accurate calculation results to command the microcontroller to turn on or off the nutrition controllers more than one at a time, such as pH down, pH up, AB nutrition, and filter pump. KNN (k-Nearest Neighbor) algorithm uses for predicting the classification of nutrient conditions so the system can provide information on nutrition conditions to the user. pH and TDS values controlled using pH (Up and Down) solution, nutrients (A and B) to increase the TDS value, and nutrient filter to reduce the TDS value obtained from the pH sensor and TDS sensor.

II. METHOD

NFT method selected for the hydroponic system, it has 3 holes of plant net pot and 2 levels of the gutter, while the design is as follows in Fig.1, which divided into 12 parts:

1. Nutrient tank

- 2. IoT module (sensor module and actuator module)
- 3. Sensors (pH, TDS, Temperature probe)
- 4. pH up liquid tank
- 5. pH down liquid tank
- 6. Nutrient A liquid
- 7. Nutrient B liquid
- 8. TDS down pump
- 9. TDS down filter
- 10. Nutrient circulation pump
- 11. Gutter
- 12. Net pot

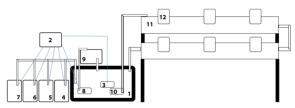


Fig 1: NFT System

This NFT system equipped with a sensor probe controlled by Arduino Leonardo and five pumps controlled by NodeMCU "Fig. 2".

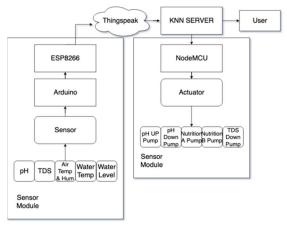


Fig. 2: System Architecture

Arduino sends sensor data to the *thingspeak* platform using *esp8266* as a wireless communication module, and the KNN Server gets the sensor data to classify the nutrient condition and sends the result to NodeMCU at the control module side to give actuator command.

Data collected from *thingspeak* is about 5,750 and labeled using lettuce parameters to create the dataset for k-Nearest Neighbor classification. Data labeling refers to 3 sensor values and lettuce standard values based on research [14], each of these sensors have 3 probability condition such as normal if the values of the sensor are between parameters range, low if the values of the sensor are lower than parameters range, and high if the sensors values are higher than parameters range. Then, if the sensors are 3 and the probability conditions are 3 too, so the nutrient system condition should have 33 = 27 labels probability classification, then with thus 27 labels probability classification, we define it with table 1 as follows.

Table 1. Nutrition Condition Classification

Label	Condition	Solution
Laber	Normal	Chiller off, TDS up & down
1	Normal	pump off, pH up & down
1		pump off
	Normal nu normal	Chiller on
2	Normal pH, normal	Crimer on
	ppm, high temp	Chillen off
3	Normal pH, normal	Chiller off
	ppm, low temp	
4	Normal pH, high	TDS down pump on
	ppm, normal temp	
5	Normal pH, high	TDS down pump on, chiller
	ppm, high temp	on
6	Normal pH, high	TDS down pump on
	ppm, low temp	
7	Normal pH, low	Nutrition ab pump on
,	ppm, normal temp	
8	Normal pH, low	Nutrition ab pump on, chiller
0	ppm, high temp	on
0	Normal pH, low	Nutrition ab pump on
9	ppm, low temp	
40	High pH, normal	pH down pump on
10	ppm, normal temp	
	High pH, normal	pH down pump on, chiller on
11	ppm, high temp	p
	High pH, normal	pH down pump on
12	ppm, low temp	pri down pamp on
	High pH, high ppm,	pH down pump on, TDS down
13	normal temp	pump on
	High pH, high ppm,	pH down pump on, TDS down
14		
	high temp	pump on, chiller on
15	High pH, high ppm,	pH down pump on, TDS down
	low temp	pump on
16	High pH, low ppm,	pH down pump on, nutrition
	normal temp	ab pump on
17	High pH, low ppm,	pH down pump on, chiller on
	high temp	
18	High pH, low ppm,	pH down pump on, nutrition
	low temp	ab on
19	Low pH, normal	pH up pump on
	ppm, normal temp	
20	Low pH, normal	pH up pump on, chiller on
20	ppm, high temp	
21	Low pH, normal	pH up pump on
21	ppm, low temp	
22	Low pH, high ppm,	pH up pump on, TDS down
22	low temp	pump on
22	Low pH, high ppm,	pH up pump on, TDS down
23	high temp	pump on, chiller on
24	Low pH, high ppm,	pH up pump on, TDS down
	low temp	pump on
25	Low pH, high ppm,	pH up pump on, nutrition ab
	normal temp	pump on
	Low pH, low ppm,	pH up pump on, nutrition ab
26	high temp	pump on, chiller on
	, , , , , , , , , , , , , , , , , , ,	
27	Low pH, low ppm,	pH up pump on, nutrition ab
	low temp	pump on

this system has 3 evaluate phase, as can be seen in Fig 3,

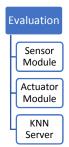


Fig 3: Evaluation phase

1. Evaluate the Sensor Module

The Sensor module evaluated by comparing the values of normal pH and TDS meter where the data sensor sent by Arduino to *thingspeak* and check whether it is updated every 15 seconds.

2. Actuator Module

The actuator module evaluated by measuring the water flow that can be flowed by the pump according to the specified time.

3. KNN Server

Testing the KNN prediction with sensor data based on 27 conditions of nutrient using realtime test data from *thingspeak*, then calculate the accuracy with different k value to get the optimal k accuracy, with the equation below, the accuracy result shown the percentage of tests that are correctly classified by classifier[15].

$$Accuracy = \frac{True\ Classification}{Total\ Classification} x 100\%$$
 (1)

III. PROPOSED HARDWARE DESIGN

A Sensor module consists of several tools and sensors

- 1. Arduino
- 2. Breadboard
- 3. pH sensor
- 4. TDS sensor
- 5. DHT11 sensor
- 6. DS1B820 sensor
- 7. HC-SR04 Sensor
- 8. ESP8266

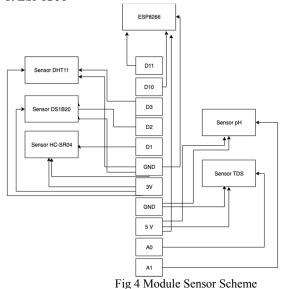


Fig. 4 is a schematic description of the Arduino pin connection to the pin sensor and *esp8266*. There are 3 sensors with digital pins connected to 3.3v pin and ground pin, 2 analog sensors, which is a pH sensor, and a TDS sensor that connected with 5v pin and ground pin. Furthermore, *esp8266* as a wireless communication media connected to D10 and D11 pins which are connected serially and given a 5v and ground voltage

The actuator module consists of NodeMcu, Breadboard Power Supply, 8 Chanel Relay, and 5 pcs water pump with the scheme in Fig. 5

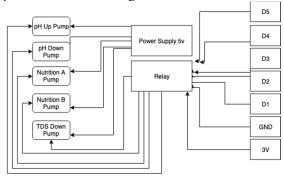


Fig 5. Actuator Module Scheme.

The relay connects with 5 digital pins from NodeMCU to exchange data from pump 1 to pump 5. The relay connected with a 3.3v and GND pin from NodeMCU while the pump gets voltage and GND from the 5v power supply.

Fig 6. is the result of the sensor and actuator module that have been arranged and installed inside the box.

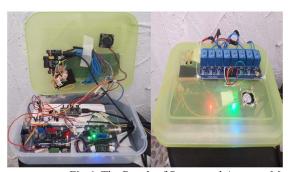


Fig 6. The Result of Sensor and Actuator Module

Once assembled, the sensor and actuator modules installed on the NFT hydroponic system as follows in Fig 7.



Fig 7. NFT system assembled with module

IV. ACTUATOR CONTROL DESIGN

The actuator controlled by using the results of the KNN classification runs on KNN Server in local PC with specification:

- 1. AMD C60 1 GHz CPU
- 2. 1 Gb RAM Memory

- 3. 250 GB hard drive
- 4. OS Windows 7 32bit

Fig 8 shows the actuator control design flowchart.

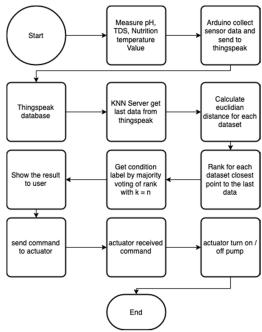


Fig 8. The actuator control design flowchart

The first phase before building the actuator control saves the sensors data from the database with CSV format as a dataset as follows in table 2.

Table 2. Sample of the collected dataset from thingspeak

entry_ id	airte m	hu m	watert em	рН	ppm	ec	wl vl
3276	28.6	63	27	5.9 4	900. 15	1406. 49	15
3277	28.7	63	27.06	6.3	834. 12	1303. 31	15
3278	28.5	60	27	6.0 7	792. 49	1238. 26	15
3279	28.5	63	27.13	6.5 4	849. 18	1326. 84	15
3280	28.6	63	27.06	6.4	835. 27	1305. 11	15

This dataset then classified and labeled manually using a spreadsheet-based on 27 probability classifications, so the labeled dataset created and shown in table 3.

Table 3. Labeled dataset sample

no	рН	ppm	watertem	label
1	5.94	723	27	2
2	6.19	970.23	27.06	5
3	6.07	366	27	8
4	6.93	689	27.13	11
5	7.89	935.27	27.06	14

After dataset labeled then Actuator control build as on fig 8, and the detailed steps are,

- 1. Take the previously made dataset and divide it into attributes as X and label as y. y is dependent data, and the attribute is independent data, which is pH, TDS, and temperature sensor data.
- 2. Normalized the X data using the MinMaxScaler function to transform dataset values between 0-1.
- 3. Get the last updated sensors data from *thingspeak*,
- 4. Calculate the last updated using Euclidian distance with each of the sensor's data from the dataset.
- 5. Rank the Euclidian result from the lowest to highest distance. The lowest result indicates the closest distance to the last updated sensors data.
- 6. Classify the result data by counting the majority uses optimal k, which determined later.
- 7. Fig 9 shows the classification result example.



Fig 9. KNN Result

8. Fig 9 shows the label is 1, so the KNN server sends a command to NodeMCU to control the actuator based on solution from table 1 as "Normal Condition" so the actuator will turn the chiller and all pump off.

V. RESULT AND DISCUSSION

KNN evaluation uses realtime data from *thingspeak* by retrieving realtime data for every 25 minutes of data collection from *thingspeak*. Each data calculated uses k value to get the majority rank. The initial range of k values defines by dividing the dataset into 80% data train and 20% test data, then calculating accuracy by carrying out the KNN classification.

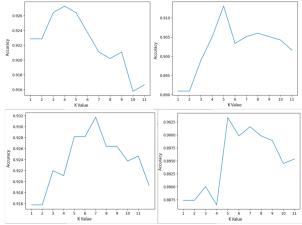


Fig 10. The initial test for k value

Fig 10 shows 4 test result to get the initial k value range, it shows the highest k value is k=5 and decreasing on higher k value, so the test stops at k=11. The next test is retrieving realtime data from *thingspeak* and give several conditions on hydroponic nutrition then use k value range between 1-11. Table 4 above shows the classification result, and the sample classifications result are shown in Fig 11 – Fig 12.

Equation (1) used to get the classification accuracy value from 30 experiments. The highest accuracy value of the KNN classification is 93.3% with k = 5.

Table 4. Realtime Classification Result

No	рН	PPM	Temp	Expected	KNN Label Result										
				Label	k =	k =	k =	k =	k =	k =	k =	k =	k =	k =	k =
1	6.23	150.33	28.1	8	8	2 8	3 8	4 8	5 8	6 8	7 8	8	9	10 8	11 8
2	6.18	953.14	27.69	5	5	5	5	5	5	5	5	5	5	5	5
3	6.17	898.66	27.6	5	5	5	5	5	5	5	5	5	5	5	5
4	6.32	892.03	27.44	5	5	5	5	5	5	5	5	5	5	5	5
5	6.33	819.56	27.38	2	2	2	2	2	2	2	2	2	2	2	2
6	6.45	788.1	27.31	2	2	2	2	2	2	2	2	2	2	2	2
7	6.34	779.45	27.19	2	2	2	2	2	2	2	2	2	2	2	2
8	6.34	724.21	22.75	3	3	3	3	3	3	3	3	3	3	3	3
9	6.41	771.21	24.1	1	1	1	1	1	1	1	1	1	1	1	1
10	6.39	771.07	24.5	1	1	1	1	1	1	1	1	1	1	1	1
11	6.32	744.99	24.81	1	1	1	1	1	1	1	1	1	1	1	1
12	6.44	736.66	25.94	1	11	11	1	1	1	1	1	1	1	1	1
13	6.43	736	25.9	1	1	1	1	1	1	1	1	1	1	1	1
14	6.45	732	25.9	1	1	1	1	1	1	1	1	1	1	1	1
15	6.40	732	25.82	1	1	1	1	1	1	1	1	1	1	1	1
16	6.35	724.92	25.89	1	1	1	1	1	1	1	1	1	1	1	1
17	6.42	741.8	25.90	1	11	11	11	11	1	1	1	1	1	1	1
18	6.33	749.23	25.98	1	2	2	1	1	1	1	1	1	1	1	1
19	6.37	743.65	25.88	1	1	1	1	1	1	1	1	1	1	1	1
20	6.74	727.72	26.06	11	11	11	11	11	11	11	11	11	11	11	11
21	6.60	759.00	26.38	11	11	11	11	11	11	11	2	2	2	2	2
22	6.67	714.94	27.94	11	11	11	11	11	11	11	11	11	11	11	11
23	7.06	632.87	26.13	11	11	11	11	11	11	11	1	1	1	1	1
24	7.15	631.01	27.13	11	11	11	11	11	11	11	11	11	11	11	11
25	8.45	663.89	26.88	11	11	11	17	17	17	17	17	17	17	17	17
26	8.90	674.00	27.00	11	11	11	11	11	11	11	11	11	11	11	11
27	8.63	660.59	26.94	11	11	11	17	11	11	17	11	11	11	11	11
28	8.51	677.97	27.00	11	11	11	11	11	11	11	11	11	11	11	11
29	8.71	700.46	26.88	11	10	10	10	10	10	10	10	10	10	10	10
30	8.54	666.47	26.88	11	11	11	11	11	11	11	17	17	17	17	17
Total True Classification			27	27	26	27	28	27	25	25	25	25	25		
		ACCURAC	CY (%)		90	90	86	90	93.3	90	83.3	83.3	83.3	83.3	83.3

```
pH: 6.23 PPM: 150.33 Water Temp: 28.1
Label k-1: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-3: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-3: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-4: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-5: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-6: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-7: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-8: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-8: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-9: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-10: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-11: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-11: [8]
Normal pH, low ppm, high temp -> Nutrition ab pump on, chiller on
Label k-11: [8]
```

Fig 11. Realtime data testing result sample (true condition).

```
pH: 6.6 PPM: 759.0 Water Temp: 26.38
Label k-1: [1]
High pH, normal ppm, high temp -> pH down pump on, chiller on
Label k-2: [11]
High pH, normal ppm, high temp -> pH down pump on, chiller on
Label k-3: [11]
High pH, normal ppm, high temp -> pH down pump on, chiller on
Label k-4: [11]
High pH, normal ppm, high temp -> pH down pump on, chiller on
Label k-5: [11]
High pH, normal ppm, high temp -> pH down pump on, chiller on
Label k-6: [11]
High pH, normal ppm, high temp -> pH down pump on, chiller on
Label k-6: [2]
Normal pH, normal ppm, high temp -> Chiller on
Label k-8: [2]
Normal pH, normal ppm, high temp -> Chiller on
Label k-8: [2]
Normal pH, normal ppm, high temp -> Chiller on
Label k-8: [2]
Normal pH, normal ppm, high temp -> Chiller on
Label k-10: [2]
Normal pH, normal ppm, high temp -> Chiller on
Label k-11: [2]
Normal pH, normal ppm, high temp -> Chiller on
Label k-11: [2]
Normal pH, normal ppm, high temp -> Chiller on
```

Fig 12. Realtime data testing result sample (with the false condition)

Fig 11 and 12 show the KNN classification solution. The actuator module uses it as a command; Fig 13 shows the actuator module action sample.

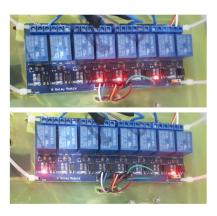


Fig 13 Actuator action sample (A) Up, (B) Down

Fig 13 (A) shows 3 actuator lights on (red light), indicate the actuator module received the command from KNN Server and turn on the nutrition A pump, nutrition B pump, and pH down pump. Fig 13 (B) shows 2 actuator lights on, indicate the actuator module turns the pH Up pump on and TDS down pump on at a time.

VI. CONCLUSION

This research conducted to test the design of a hydroponic system with IoT on a prototype scale that uses a

k-Nearest Neighbor (KNN) to classify nutrient conditions. The evaluated system shows that KNN successful classifies the nutrient condition with several k values. The classification result output can be used in a realtime condition and used as a command to the actuator module. The actuator also can turn on or off the nutrition controller simultaneously at a time according to the label that is classified. More experiments with more data in various conditions can improve system accuracy.

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