

Original papers

IoT based hydroponics system using Deep Neural Networks

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ABSTRACT

Agriculture has the significant impact on the economy of the country. With the practice of modern farming techniques where plants can be grown without the need of soil by means of nutrient solution, Hydroponics and Aeroponics are in the rise. Now towards controlling the hydroponic plant growth, some amount of research has been done in applying machine learning algorithms like Neural Networks and Bayesian network.

Internet of Things allows for Machine to Machine interaction and controlling the hydroponic system autonomously and intelligently. This work proposes to develop an intelligent IoT based hydroponic system by employing Deep Neural Networks which is first of its kind. The system so developed is intelligent enough in providing the appropriate control action for the hydroponic environment based on the multiple input parameters gathered. A prototype for Tomato plant growth as a case study was developed using Arduino, Raspberry Pi3 and Tensor Flow.

1. Introduction

Indian economy is strongly dependent on agriculture. Because of the increase in food demand, labor cost, unpleasant environmental conditions and less area for agriculture, there is an increase in motivation for indoor farming such as hydroponics and Aeroponics.

So, based on the traditional method of growing plants, there is no mention about soil. That means as long as these requirements are fulfilled, plants can grow. This brings the idea of hydroponics farming. This technique uses mineral nutrient solution in a water solvent which allows plant intake of nutrients in a more efficient way than soil. Native plants can be grown with their roots exposed to the nutrient solution. The nutrients provided to the roots come from an array of various sources as shown in Fig. 1.

There are a variety of flowers, vegetables, and herbs that can be grown using hydroponics. The emergence of IoT has allowed farmers to automate the hydroponic culture. Monitoring of water level, pH, temperature, flow, and light intensity can be regulated by the use of IoT. For e.g., during winter, water tends to freeze in some areas which in turn may hamper the cultivation process altogether. Water temperature sensors deployed over the hydroponics farm can sense the temperature loss and alert the farmer accordingly. Similarly, the pH sensor can detect a change in nutrient levels and can pump in the minerals in suitable amounts. An assortment of sensors and controllers like ESP-8266, Arduino and Raspberry Pi, etc. can be used to instrument and automate a hydroponics farm.

So, with this as a background, some amount of research has been carried out by employing IoT in monitoring the hydroponic agriculture. In one such research (Ludwig and Fernandes, 2013), authors have monitored the pH, conductivity, and luminosity of hydroponics system grown plant and information was sent to Microcontroller. Microcontroller here displayed the condition of parameters monitored and controlled the lighting for the plant from the microcontroller using relay switch.

In another hydroponics-based system, a do-it-yourself android/iOS application was developed for the automatic control action (Peuchpanngarm et al., 2016). The application entails the control of sensors for the hydroponic setup for various sensors including temperature, humidity, and ambient lighting. Another advantage of the application is for appropriate planning, timely managing and proper harvesting data recording for the crops. This information recorded from sensors are stored in the Cloud.

In addition to automating the hydroponics by employing IoT technology, there is a need for some intelligence for controlling the hydroponics system. So, towards this machine learning which is a subset of Artificial Intelligence come handy. In hydroponics, machine learning has helped in automating the plant growth where some minimal amount of research has been carried out.

In one research, (Ferentinos and Albright, 2007) authors have constructed the Bayesian network by monitoring the physical event of a hydroponic system incorporating sensors for light intensity, potenz-Hydrogen, electrical conductivity, water level, and environmental

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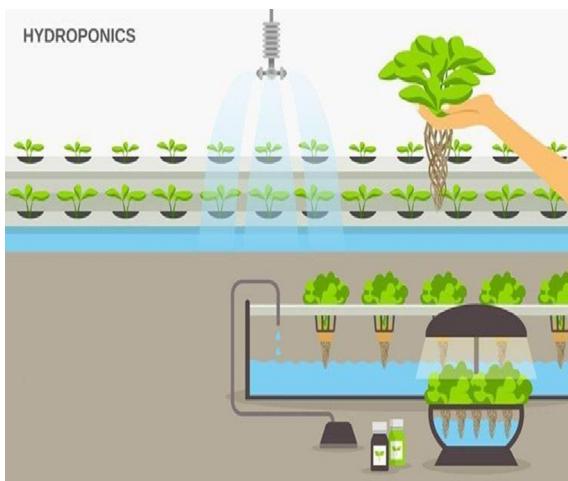


Fig. 1. Hydroponics system.

humidity. These values were used to construct the Bayesian network towards performing predictive analysis for giving output decision in automatically controlling the system. This system provides a GUI for displaying the sensor values as well as controlling the actuators for the farm.

In another research, (Pitakphongmetha et al., 2016) authors have deployed Artificial Neural Network (ANN) in predicting the potenz-Hydrogen and Electrical Conductivity results of the hydroponic setup. Feedforward neural networks developed with several inputs including pH, Electrical Conductivity, temperature, humidity, light intensity, plant age, added acid content and added base content, provides two outputs which are pH and Electrical Conductivity for automatic control of the system.

The challenge with the above-mentioned system is that there has been no intelligence developed in an IoT based hydroponics system. In terms of intelligence in controlling hydroponic environment, these machine learning algorithms were not able to achieve a high level of accuracy, and also these algorithms were proven towards controlling few parameters in a hydroponic environment which were not IoT based. Also, none of the research focused on deploying intelligence at the edge of an IoT based hydroponics system for controlling multiple parameters of the hydroponic environment towards providing appropriate control action. All these motivated towards coming up with an intelligent and automated IoT based hydroponics System with better intelligence and accuracy.

So, the main contribution of this paper are as follows:

- Development of IoT based Hydroponics Control System prototype for tomato plant with sensors interfaced to Arduino and Raspberry Pi3 acting as Edge.
- Development of Intelligence at the edge by deploying Deep Neural Network model towards providing appropriate control action to hydroponics system in real time with higher accuracy.
- Implementation of Deep Neural Network at the cloud towards the classification of control action based on parameters collected from hydroponics system.

The rest of paper is organized as follows. **Section 2** gives a complete literature Review on Hydroponics system followed by IoT and Machine learning. **Section 3** describes the Intelligent IoT based Hydroponics system. **Section 4** details on implementation results and analysis using Deep Neural Network. **Section 5** gives the conclusion and future work.

2. Literature review

Research work pertaining to Intelligent IoT Based hydroponics

system by employing IoT and machine learning technologies are discussed here. So, we would be looking in depth various literature available towards the development of our system. These are discussed below.

2.1. IoT in Hydroponics

IoT refers to the Internet of things towards connecting people, things by means of the Internet and store the data in the cloud for analysis. The emergence of IoT has allowed farmers to automate the hydroponic culture. Monitoring of water level, pH, temperature, flow, and light intensity can be done, and they can be regulated by use of IoT. So, with this in view, quite an amount of research been carried by employing IoT for monitoring and controlling the hydroponic system.

Gosavi (2017) have developed an IoT based hydroponic prototype where the pH, water conductivity and water luminosity monitored by employing sensors like pH, Electrical conductivity and Lumens meter. This information captured by sensors are sent to ARM 7 Microcontroller where continuous monitoring is done for the optimal growth of plants. In hydroponics, the plant needs to be under light for 16 h and in the dark for 8 h. So accordingly, microcontroller have Real Time clock which would control lighting by means of the relay switch. This information displayed on LCD panel connected to the microcontroller.

Peuchpanngarm et al. (2016) have developed an IoT based autonomous control android/iOS mobile application for the ease of hydroponics. Over here, different sensors are used which are water level sensor, ambient temperature sensor, humidity and light intensity sensor which is interfaced to Arduino. This Pi3 acts as an interface between microcontroller and cloud. The Pi3 controls the hydroponic environment based on the data captured from sensors. In addition, the mobile application provided for monitoring remotely, reminding for harvest, harvest recording, and planning for hydroponic gardening.

2.2. Machine learning in hydroponics

Machine learning is a subset of Artificial Intelligence (AI) that helps in providing computers capability to perform actions on its own after being trained for a particular task. Foremost, for a machine to think like a human mind, it has first to think and learn like a human being. Human mind thinks from the past experiences and past data that is exposed to and based on that the human being takes decision for the future. The machine learning algorithm has various uses in the field of hydroponics towards controlling the plant growth, optimization of Electrical Conductivity (EC) values of the Nutrient solution.

Alipio et al. (Ludwig and Fernandes, 2013) have applied a Bayesian network towards smart farming for monitoring and controlling the environmental events such as light intensity control, potenz-Hydrogen levels, Electrical Conductivity, water level, and humidity. These datasets that were gathered over a period of one month to generate a Bayesian network towards performing predictive analysis for giving output decision for autonomously controlling the system. Also, the system provides two websites for displaying, monitoring and controlling the actuators from hydroponic farms.

Ferentinos and Albright (2007) have applied Artificial Neural Network towards smart farming for controlling potenz-Hydrogen and Electrical-Conductivity levels in Hydroponic setups. Over here Feed Forward Neural Model is applied taking in 9 different input and accordingly producing two output for pH and EC. From these predictive analyses, it is clear that the Neural Network model accurately predicts the values of pH and EC for controlling the hydroponics system.

From the literature surveyed, the drawbacks in the earlier system are that the automation developed employing IoT had no intelligence in producing the appropriate control action for the hydroponic environment based on parameters trained. In terms of machine level intelligence developed in hydroponics, they were not developed for IoT based system. The system here only concentrated on applying machine

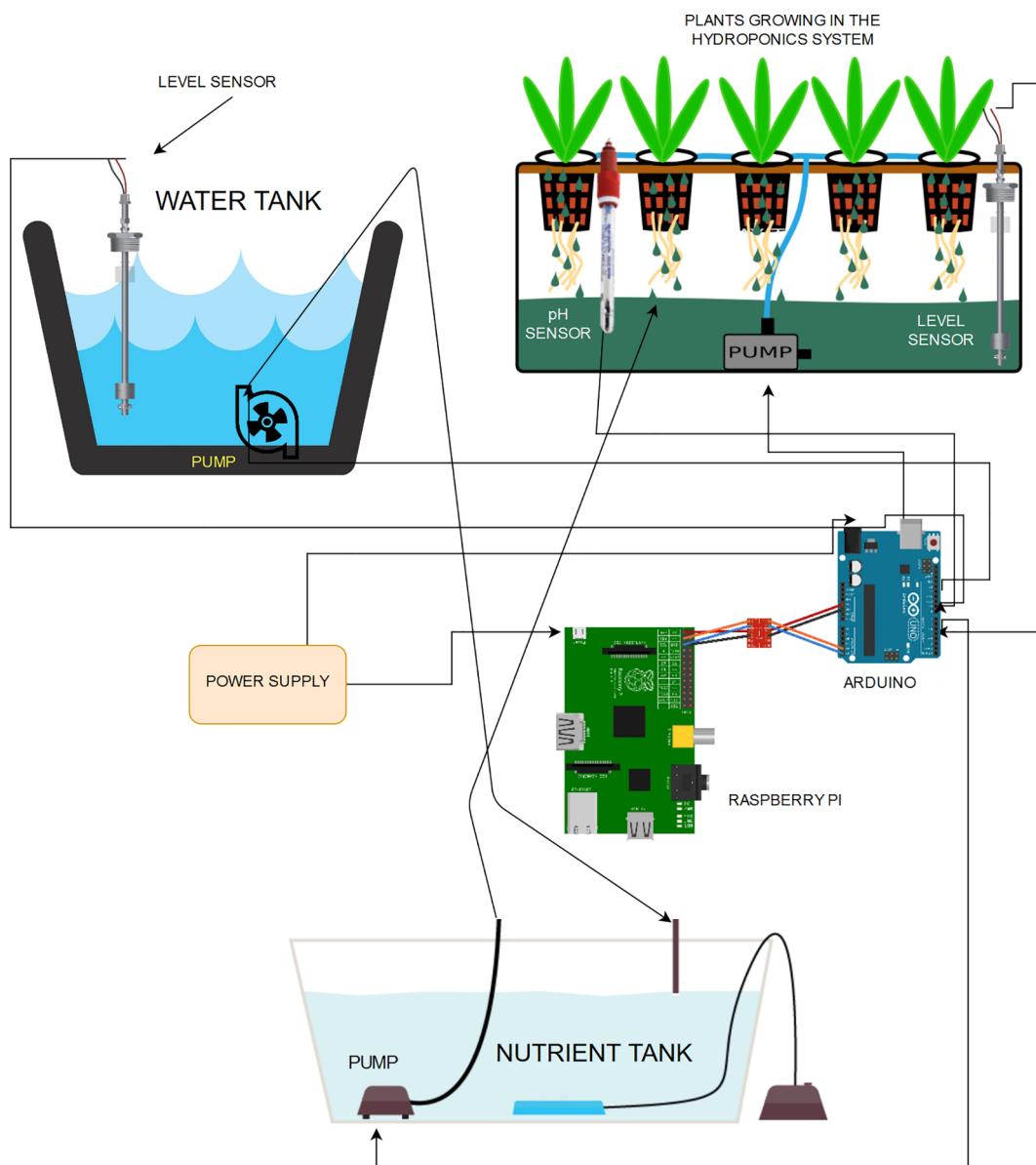


Fig. 2. System architecture of IoT based hydroponics.

learning algorithms like Bayesian and ANN for predicting the appropriate control action based on parameters trained. The work did not focus on controlling the hydroponic environment.

So accordingly, our work focused on developing an intelligent IoT based hydroponics where machine learning algorithm called Deep Artificial Neural Network model deployed at the edge towards predicting the appropriate control action based on real-time parameters gathered from the hydroponic tank. Based on the appropriate control action output, the hydroponic environment be controlled in real time. The Deep Artificial Neural Network machine learning algorithm is used for training the parameters collected in real time from the hydroponic environment in the cloud. We would now see in detail about IoT based Hydroponics system with intelligence in the forthcoming section.

3. Intelligent IoT based hydroponics system

Hydroponics technology has been applied in agriculture for quite some time as evident from the literature (<https://www.epicgardening.com/history-of-hydroponics>). A lot of countries including India has been practicing hydroponics towards farming (<https://en.wikipedia.org/wiki/Hydroponics>).

[Hydroponics#History](#), <http://hydroponicskenya.com/>, <http://www.scmp.com/magazines/style/travel-food/article/2094791/future-farming-japan-goes-vertical-and-moves-indoors>, <https://www.nasa.gov/missions/science/biofarming.html>, <https://www.nasa.gov/feature/nasa-plant-researchers-explore-question-of-deep-space-food-crops>, <https://www.thebetterindia.com/79003/ajay-naik-goa-hydroponic-farm-software-engineer/>, <https://yourstory.com/2017/12/why-engineer-ajay-naik-sold-his-successful-startup-to-become-a-hi-tech-farmer/>, <https://vegfru.com/profile/ajay-naik/14342>, <http://www.suregrow.in/home.html>, <https://timesofindia.indiatimes.com/city/coimbatore/City-introduced-to-soil-less-cultivation-at-Agri-Intex-2015/articleshow/48120897.cms>, <http://www.futurefarms.in/about/>, <http://www.theweekendleader.com/Success/2643/urban-farmers.html>, <https://gro.io/>, <https://socialunderground.com/2016/08/gro-io-future-urban-micro-farming>, <https://cityfarm.my/>, <https://www.nst.com.my/news/2016/12/197593/cityfarm-helping-farms-grow-urban-homes>, <https://www.greenandvibrant.com/advantages-disadvantages-of-hydroponics>.

Now with the upcoming of IoT Technology, good amount of research done in capturing parameters by employing sensors and controlling the hydroponics system for the growth of plant (Ludwig and

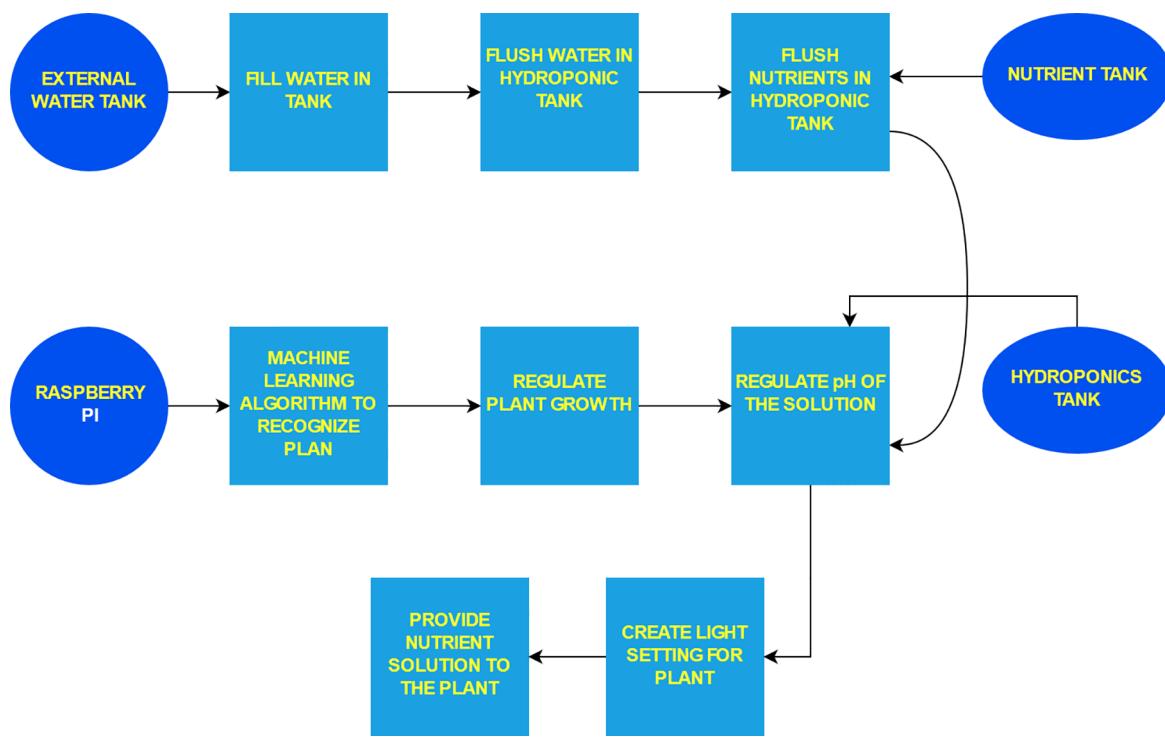


Fig. 3. Data flow diagram.

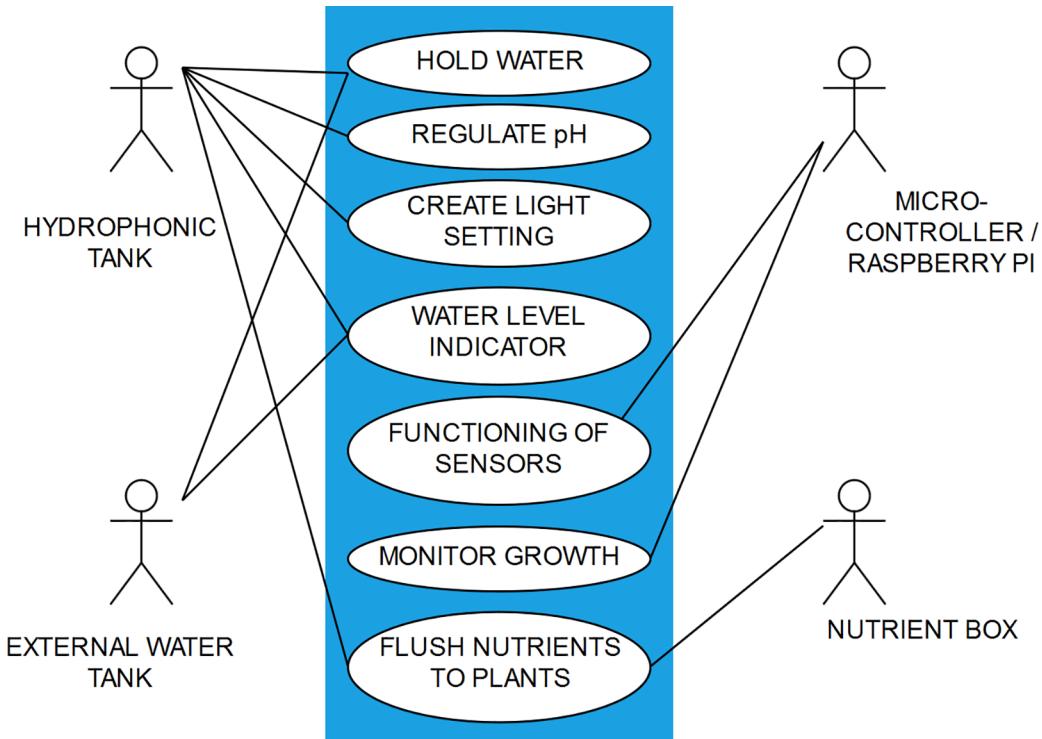


Fig. 4. Use case diagram.

Fernandes, 2013; Peuchpanngarm et al., 2016; Ferentinos and Albright, 2007). Also, to make hydroponics system intelligent in predicting the appropriate control action needed based on parameters gathered, machine learning techniques like ANN and Bayesian Network employed (Pitakphongmetha et al., 2016; Gosavi, 2017).

In earlier IoT based system, they have concentrated on controlling the hydroponic environment based on sensor data collected from the hydroponic tank using a microcontroller. Also, in terms of machine

learning intelligence, they have concentrated only on algorithmic level output prediction based on parameters collected and not controlling the hydroponic environment in real time. These machine learning were not applied for IoT based system.

So accordingly, we here have developed an Intelligent IoT based hydroponics system for Tomato plant as a case study by employing Deep Neural Network. Deep Neural Network is an advancement of Artificial Neural Network with more hidden layers and proved to

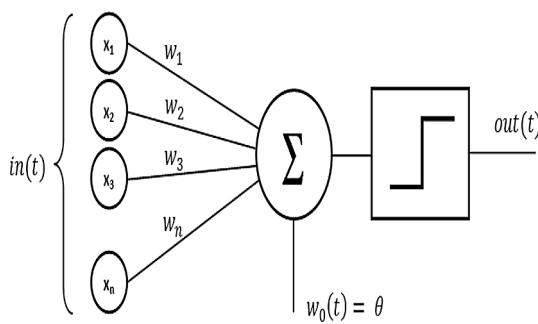


Fig. 5. Perceptron in ANN.

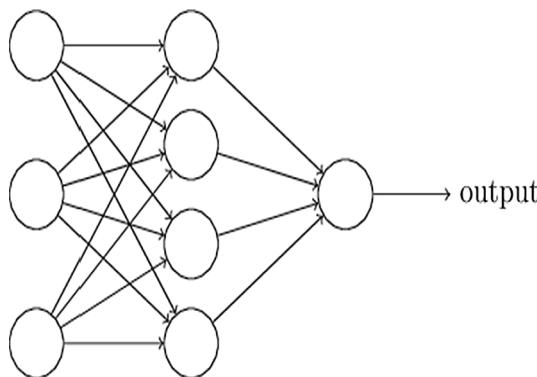


Fig. 6. ANN with a single hidden layer.

achieve better accuracy compared to ANN. Also, in here the system captures the parameters like pH, Temperature, light intensity, humidity, Level which are monitored and accordingly analyzed by applying Deep Neural Network for predicting the appropriate control action towards controlling the hydroponic system which is classified into eight labels. The data captured with the appropriate control action labeling are stored in the cloud. These are implemented using Arduino Microcontroller, Raspberry Pi3, and Tensor Flow. Details on IoT system architecture and Deep Neural Network are explained below.

3.1. System Design

The system design and architecture of Intelligent IoT based

Hydroponics system is shown in Fig. 2. This system here consists of three components. First part is the Arduino part where sensors pertaining to pH, humidity, light intensity, temperature, the water level in hydroponic tank captured sent to the microcontroller. The second part is the Raspberry Pi3 which got the Deep Neural network fitting model which has been trained in the cloud based on the data set collected. The fitting model in the Pi3 would make an intelligent decision in giving the output decision which is further sent to Arduino in activating the appropriate control system pertaining to pumping the water, switching the lights on, switching the fan on and so forth. In addition, the data received by Pi3 sent to Cloud for storage and viewing. Figs. 3 and 4 below show the Data Flow Diagram and Use Case Diagram.

3.2. Deep neural network

The neural system is an artificial neuron known as perceptron. Perceptrons were developed in the 1960s by the researcher Frank Rosenblatt, motivated by prior work by Warren McCulloch and Walter Pitts.

In the illustration shown in Fig. 5, the perceptron has three input sources, x_1 , x_2 , and x_3 . To place it in more exact algebraic terms:

$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{threshold} \end{cases}$$

That is everything to how a perceptron functions!

That is the fundamental scientific model. A way you can consider the perceptron is that it's a device that settles on choices by weighing up prove. It's not an extremely reasonable case, but rather it's straightforward.

Let us take an example here. Assume the end of the week is coming up, and we have heard that there will be a cheddar celebration in our city. We like cheddar and are attempting to choose whether to go to the celebration. We may settle on your choice by weighing up three elements:

- Is the weather great?
- Does your brother or sister need to go with you?
- Is the festival near public transit? (You don't own a car).

We can speak to these three factors by comparing double factors x_1 , x_2 , and x_3 . For example, we'd have $x_1 = 1$ if the weather is great, and $x_1 = 0$ if the weather is terrible. Essentially, $x_2 = 1$ if your brother or

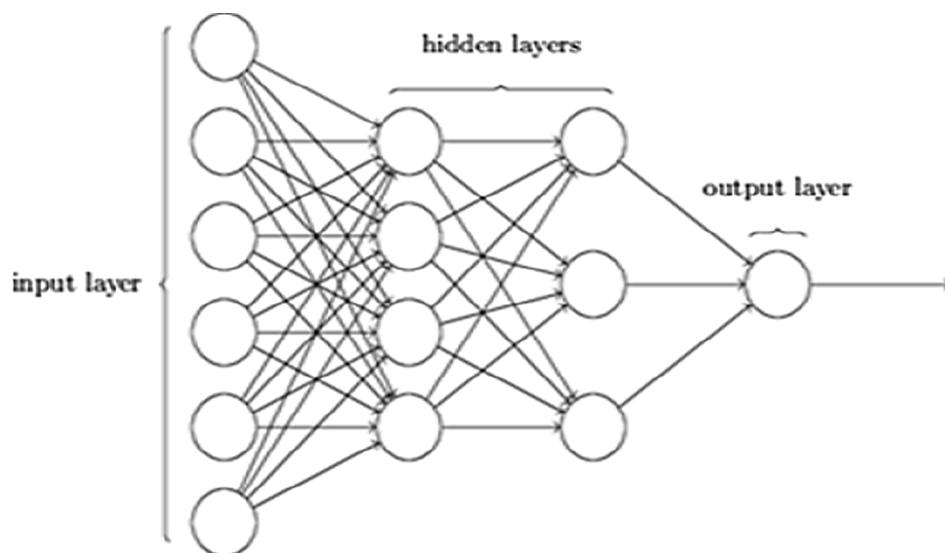


Fig. 7. Deep Neural Network (ANN with two hidden layers).

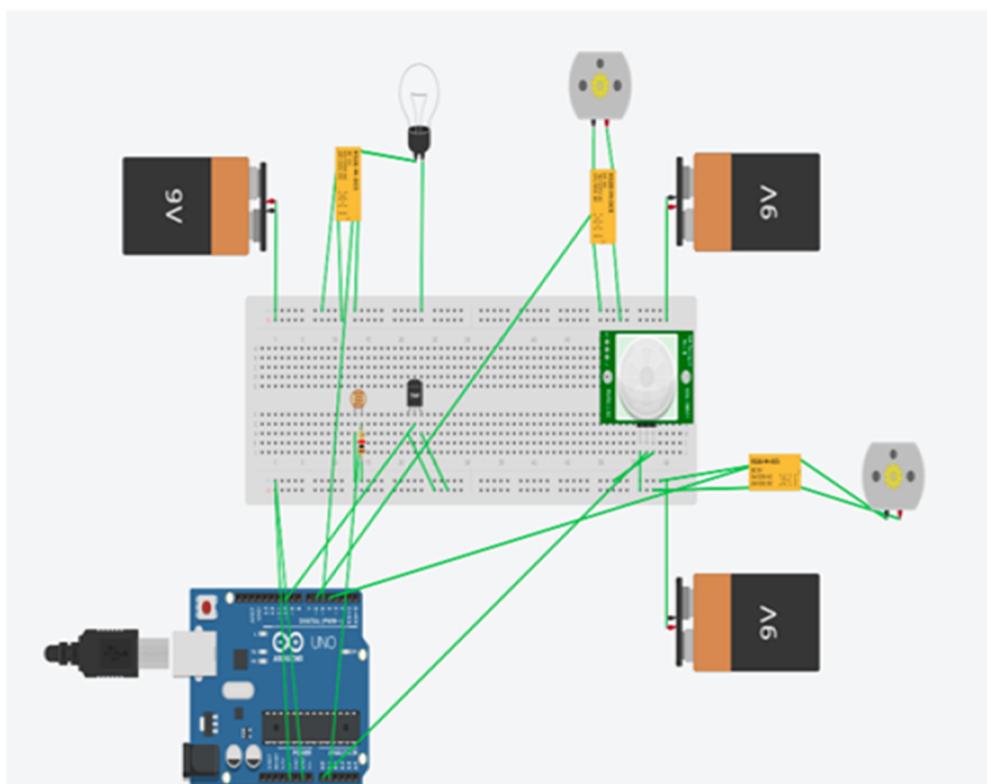


Fig. 8. Circuit diagram.

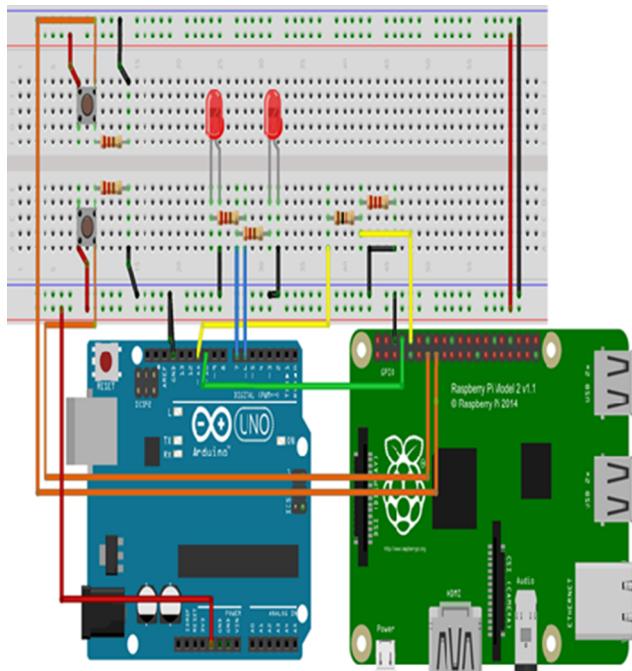


Fig. 9. UART communication.

sister needs to go, and $x_2 = 0$ if not. What's more, correspondingly again for x_3 and open travel?

Presently, assume you totally worship cheddar, to such an extent that you're glad to go to the celebration regardless of whether your brother or sister is uninterested, and the celebration is difficult to get to. Yet, maybe you truly detest awful climate, and it's impossible you'd go to the celebration if the climate is terrible. You can utilize perceptrons to demonstrate this sort of basic leadership. One approach to do this is

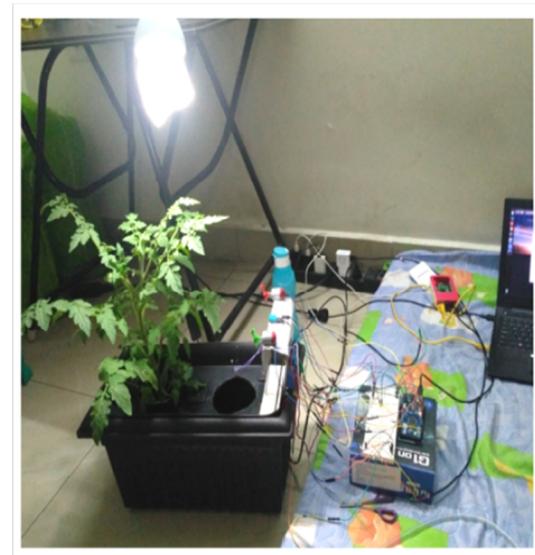


Fig. 10. IoT based hydroponics prototype.

to pick a weight $w_1 = 6$ for the weather, and $w_2 = 2$ and $w_3 = 2$ for alternate conditions. The bigger estimation of w_1 demonstrates that the climate matters a ton to you, significantly more than whether your sweetheart goes along with you, or the proximity of open travel. At long last, assume you pick a limit of 5 for the perceptron. With these decisions, the perceptron executes the coveted basic leadership show, yielding 1 at whatever point the climate is great, and 0 at whatever point the climate is terrible. It has no effect to the yield whether your sibling or sister needs to go, or whether open travel is adjacent. By changing the weights and the limit, we can get distinctive models of basic decision-making.

Fig. 6 shows the general architecture of ANN with a single hidden

Collected Data

The screenshot shows a Google Sheets document titled "Collected Data". The spreadsheet has a header row with columns A through J. Below the header, there are 21 data rows. The first few columns (A-E) contain numerical values for PPM, Water Level, Temp, Humidity, and LDR respectively. The last column, "Label", contains integer values from 0 to 7. A legend is located in the upper right area, enclosed in a dashed blue border. The legend maps each label value to a specific action: 0 (No Action), 1 (pump water), 2 (light on), 3 (fan on), 4 (pump + light on), 5 (pump + fan on), 6 (light on + fan on), and 7 (pump + light on + fan on). The "Label" column in the data rows corresponds to these actions. The "Sheet1" tab is selected at the bottom.

	A	B	C	D	E	F	G	H	I	J
1	PPM	Water Level	Temp	Humidity	LDR	Label				
2	446	110	25	44	21	4				
3	461	343	29	60	45	2				
4	408	344	31	10	2	2				
5	391	92	31	65	45	7				
6	431	238	30	12	628	1				
7	424	167	28	51	38	4				
8	456	358	30	11	393	0				
9	414	135	25	48	27	4				
10	394	357	24	72	0	6				
11	421	358	30	40	685	0				
12	464	211	27	61	19	7				
13	455	351	28	16	50	0				
14	395	330	31	62	14	6			No Action	Action
15	486	168	30	73	276	5	water	325-370	0-320	
16	432	335	27	34	562	0	light	50-700	0-45	
17	402	130	25	12	345	1	fan	9-60	61-80	
18	483	271	26	77	385	5				
19	428	24	30	66	42	7				
20	474	209	28	17	23	4				
21	408	330	28	26	14	2				

Collected Data

This screenshot shows a Google Sheets document titled "Collected Data". The structure is identical to the first sheet, with a header row and 31 data rows. The "Label" column contains values from 2 to 7. A legend is located in the upper right, enclosed in a dashed blue border. The legend defines the following actions: 2 (light on), 3 (fan on), 4 (pump + light on), 5 (pump + fan on), 6 (light on + fan on), and 7 (pump + light on + fan on). The "Sheet1" tab is selected at the bottom.

	A	B	C	D	E	F	G	H	I	J	K
1	PPM	Water Level	Temp	Humidity	LDR	Label					
3102	395	358	24	30	25	2					
3103	411	236	25	14	26	4					
3104	394	363	31	73	442	3					
3105	433	62	31	62	11	7					
3106	416	129	31	16	8	4					
3107	390	363	31	9	15	2					
3108	400	123	30	73	19	7					
3109	427	339	31	10	9	2					
3110	472	347	25	11	13	2					
3111	394	330	28	75	669	3					
3112	427	190	30	65	60	5					
3113	408	363	27	79	78	3					
3114	390	327	26	73	129	3					
3115	474	336	27	9	235	0					
3116	468	57	29	47	44	4					
3117	401	238	31	67	163	5					
3118	466	331	29	79	3	6					
3119	447	336	27	71	142	3					
3120	394	181	26	73	31	7					
3121	443	351	20	58	225	0					

Fig. 11. DataSet with control action label.

layer. The left-most layer is known as the input layer, containing the input-neurons. The right-most layer is called the output layer containing the output neurons. The middle layer is called the hidden layer which contains neither the input neurons nor output neurons. The expression “hidden” maybe sound somewhat secretive – the first occasion

when we heard the term we figured it must have some profound philosophical or numerical hugeness – yet it truly amounts to just “not input or an output.” The system above has only a single hidden layer, yet a few systems have different shrouded layers. For instance, the accompanying four-layer arrange has two hidden layers as shown in

Table 1
Control action with labels.

Label	Action
0	No action
1	Pump water
2	Light on
3	Fan on
4	Water pump + light on
5	Water pump + fan on
6	Light on + fan on
7	Water pump + light on + fan on

Fig. 7 which is called Deep Neural Networks.

To some degree confusingly, and for authentic reasons, such multiple layer networks are infrequently called multilayer perceptrons or MLPs, regardless of being comprised of sigmoid neurons, not perceptrons.

While the plan of the input and output layers of a neural system is frequently direct, there can be significant craftsmanship to the outline of the hidden layers. Specifically, it's impractical to entirely up to the outlined procedure for the hidden layers with a couple of straightforward, dependable guidelines. Rather, neural systems specialists have created numerous outline heuristics for the hidden layers, which enable individuals to conduct they need out of their nets. For instance, such heuristics can be utilized to decide how to exchange off the quantity of concealed layers against the time required to prepare the system.

In Neural systems, the output from one layer is utilized as a contribution to the following layer. Such systems are called feedforward neural systems. This implies there are no circles in the system – data is constantly encouraged forward, never sustained back. On the off chance that we had circles, we had wound up with circumstances where the contribution to the 'o' work relied upon the yield. That'd be difficult to understand. Thus we don't permit such circles.

Neural Networks are able to take in their weights and biases in the gradient descent algorithm. How can we process the slope of the cost work? That is a significant drawback in Neural Networks! A quicker calculation for processing such slope is known as error-backpropagation.

Initially, in the 1970s, the error-backpropagation calculation was proposed, yet its importance was not tested until a paper published by David Rumelhart, Geoffrey Hinton, and Ronald Williams in 1986. The paper contains examples of various neural networks where error-backpropagation has been applied, and it is proved that it works faster

than many other algorithms doing the same calculations.

Importantly the cost change is a most crucial factor in the understanding of neural network model. An articulation for the fractional subsidiary $\partial C/\partial w$ at the cost of work C as for any weight w (or predisposition b) in the system. This shows us how rapidly a change occurs in the weights and biases. Thus, keeping in mind that the articulation is perplexing, it likewise has a delight to it, with every component having a characteristic, natural understanding. Thus error-backpropagation isn't only a concept for learning, but it really gives us point by point bit of knowledge of how biases and weights are changed for the general conduct of the system.

4. Implementation results and analysis

The implementation of intelligent IoT based Hydroponics system involves hardware and software components which are outlined below:

4.1. Hardware components

- **Raspberry Pi** processor controls the Arduino Mega using UART Serial Communication using the A4 and A5 Analog pins on the **Arduino** Microcontroller. Based upon the output from the Neural Network Algorithm, the Raspberry Pi performs specific control action using the sensors interfaced with the Arduino. It is the UART transmitter and works upon the output of the Neural Network Algorithm
- **DHT11 sensor**, which measures the ambient temperature and humidity is interfaced with the Arduino using the digital 10 pin. Based upon the temperature and humidity values, the automatic water sprayer and propeller fans controlled by DC motor function.
- **Water Level Sensor** is interfaced with the Arduino at pin number A0 since it is an analog sensor responsible for measuring the level of water. Based upon the value of the water level, the water pump controlled using a relay board pumps in water into the main tank from the external tank.
- **Photo resistor or LDR** module interfaced with the Arduino microcontroller at pin number A1 is responsible for measuring the ambient lighting conditions. Upon a certain threshold value, the LED bulb controlled using a relay switch is turned ON/OFF as per the need.
- Two **DC motors** with propellers controlled using a 2 Channel Relay switch are responsible for bringing down the humidity level should the need arise. The fans switch on if the humidity exceeds 70%.
- The **DC water pump** is again controlled using a single channel relay

PPM	Water Level	Temp	Humidity	LDR	Label
451	332	24	22	516	0

```

manav@Manav-Lenovo: ~/Desktop/Manav/Projects/Hydroponics
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$ python3 Output.py
For
PPM = 451
Water Level = 332
Temp = 24
Humidity = 22
LDR = 516
The Predicted Label is 0
Prediction : No Action
Prediction Accuracy: 88.50
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$ 
  
```

Fig. 12. Predicted output control action – condition 0.

PPM	Water Level	Temp	Humidity	LDR	Label
402	315	27	27	162	1

```
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$ python3 Output.py
For
PPM = 402
Water Level = 315
Temp = 27
Humidity = 27
LDR = 162
The Predicted Label is 1
Prediction : Pump Water
Prediction Accuracy: 88.55%
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$
```

Fig. 13. Predicted output control action – condition 1.

PPM	Water Level	Temp	Humidity	LDR	Label
406	356	29	57	22	2

```
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$ python3 Output.py
For
PPM = 406
Water Level = 356
Temp = 29
Humidity = 57
LDR = 22
The Predicted Label is 2
Prediction : Light On
Prediction Accuracy: 88.48%
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$
```

Fig. 14. Predicted output control action – condition 2.

switch. If the water level in the main tank falls below a certain level, then this motor pump is activated, and water is pumped into the main tank from an external water tank.

- The **LED Bulb** is controlled using a single channel relay switch. If the LDR values fall below a threshold value of 150, then the relay switch switches on the LED Bulb for optimum lighting condition. The hybrid tomato plant needs 18:6 (18 hrs. light, 6 hrs. dark) or 14:10 (14 hrs. light, 10 hrs. dark) lighting conditions.
- Arduino UNO** – It acts as the receiver for UART communication and is controlled using the RaspberryPi.
- Raspberry Pi** – It is the UART transmitter and works upon the output of the Neural Network Algorithm.

4.2. Software modules

- Raspbian Jessie:** Jessie is the name of the operating system used to run the RaspberryPi. It is based on the Debian Linux Architecture. The present version, Jessie is the name of the character taken from the movie Toy Story.
- Arduino IDE:** The IDE used to code the Arduino microcontroller. It

is based on Java Processing Software and works well on Windows, Linux, and Mac environments. The software is open source.

- Python 3.6:** Python is an interpreted language which is open source. We have used python3.6 throughout our project for developing the neural network code and also coding the sensors interfaced to the Arduino communicating to the RaspberryPi. Python is also used for a Chatbot service in our client that returns the values from the firebase cloud to tell about the present sensor values and thus is quite useful.
- Numpy:** Open source library available for python that becomes relatively easier to control the Arduino using a Raspberry Pi. The Numpy module for Arduino contains the libraries and code for all the sensors that are pushed together at once to the Arduino microcontroller. We need to write specific Python code in the Raspberry Pi that tweaks the sensors that need to be used. The Arduino is connected to the Raspberry Pi using the USB connectors on the Pi.
- Tensor flow:** Open-source library written in C++ by the google brain team at Google. It is used for developing deep neural network programs utilizing the GPU of the system. It is fast and efficient and hence is widely used these days for developing artificial neural

PPM	Water Level	Temp	Humidity	LDR	Label
475	354	29	67	214	3

```
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$ python3 Output.py
For
PPM = 475
Water Level = 354
Temp = 29
Humidity = 67
LDR = 214
The Predicted Label is 3
Prediction : Fan On
Prediction Accuracy: 88.47%
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$
```

Fig. 15. Predicted output control action – condition 3.

PPM	Water Level	Temp	Humidity	LDR	Label
469	63	28	50	20	4

```
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$ python3 Output.py
For
PPM = 469
Water Level = 63
Temp = 28
Humidity = 50
LDR = 20
The Predicted Label is 4
Prediction : Pump Water and Light On
Prediction Accuracy: 88.56%
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$
```

Fig. 16. Predicted output control action – condition 4.

PPM	Water Level	Temp	Humidity	LDR	Label
403	23	31	64	383	5

```
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$ python3 Output.py
For
PPM = 403
Water Level = 23
Temp = 31
Humidity = 64
LDR = 383
The Predicted Label is 5
Prediction : Pump Water and Fan On
Prediction Accuracy: 88.53%
manav@Manav-Lenovo:~/Desktop/Manav/Projects/Hydroponics$
```

Fig. 17. Predicted output control action – condition 5.

PPM	Water Level	Temp	Humidity	LDR	Label
485	363	31	70	25	6

Fig. 18. Predicted output control action – condition 6.

PPM	Water Level	Temp	Humidity	LDR	Label
450	36	31	67	42	7

Fig. 19. Predicted output control action – condition 7.

network programs.

- **Pandas:** Pandas is mainly used for data mining and cleaning operations. It is highly used for loading and cleaning the data in python. We have used pandas to load csv libraries into the program and hence use it for developing the neural network program.
- **Google Firebase:** Firebase is a SaaS, Software as a Service Cloud service provided by Google. It is free and can be used with your Google account easily. We have used firebase for uploading our sensor data along with the predicted output to the firebase cloud. With the ease of a free cloud service, the values are exported in JSON which can be read easily by the python environment for calculations. Firebase is thus a great software for all cloud applications with a No-SQL feature.

4.3. IoT hydroponics prototype

The complete hardware prototype of intelligent IoT based Hydroponics system involved various sensors, microcontroller, Raspberry Pi3 and UART communication between Arduino and Pi3. The system here comprises of sensors which are pH, DHT11 sensor, LDR, Level that measures the pH, humidity, temperature, Light intensity, and water level. This information is sent to the microcontroller which is sent to Pi3 using UART which got the Deep Neural Network prediction algorithm model for activating the appropriate control

action that is labeled 0–7. The data set collected with predicted control action is sent to Firebase cloud for storage and viewing anywhere. The respective circuit diagram for the complete hardware prototype is shown in Figs. 8 and 9. Fig. 10 shows the complete hardware prototype developed.

4.4. Data analysis using Deep Neural Networks

A lot of machine learning algorithm exist, and accordingly, we here have applied Deep Neural Network which is the advancement of Artificial Neural Network for analyzing the parameters of the hydroponic system for providing the appropriate control action which is labeled 0–7.

So, for our work, we have collected 5000 real-time data from the hydroponic system pertaining to pH, temperature, humidity, light intensity and water level in the hydroponic tank where the plant grows. These data were collected over a few weeks. Now based on the input parameters, two hidden layers created where each hidden layer got 10 neurons or nodes. These input parameters were trained over 10,000 epochs in the cloud and thereby producing the appropriate control action which is labeled 0–7. Now during the training in the cloud, weights were adjusted based on the error produced by applying error backpropagation towards achieving the predicted output. The output here refers to eight control action classification labeled 0–7.

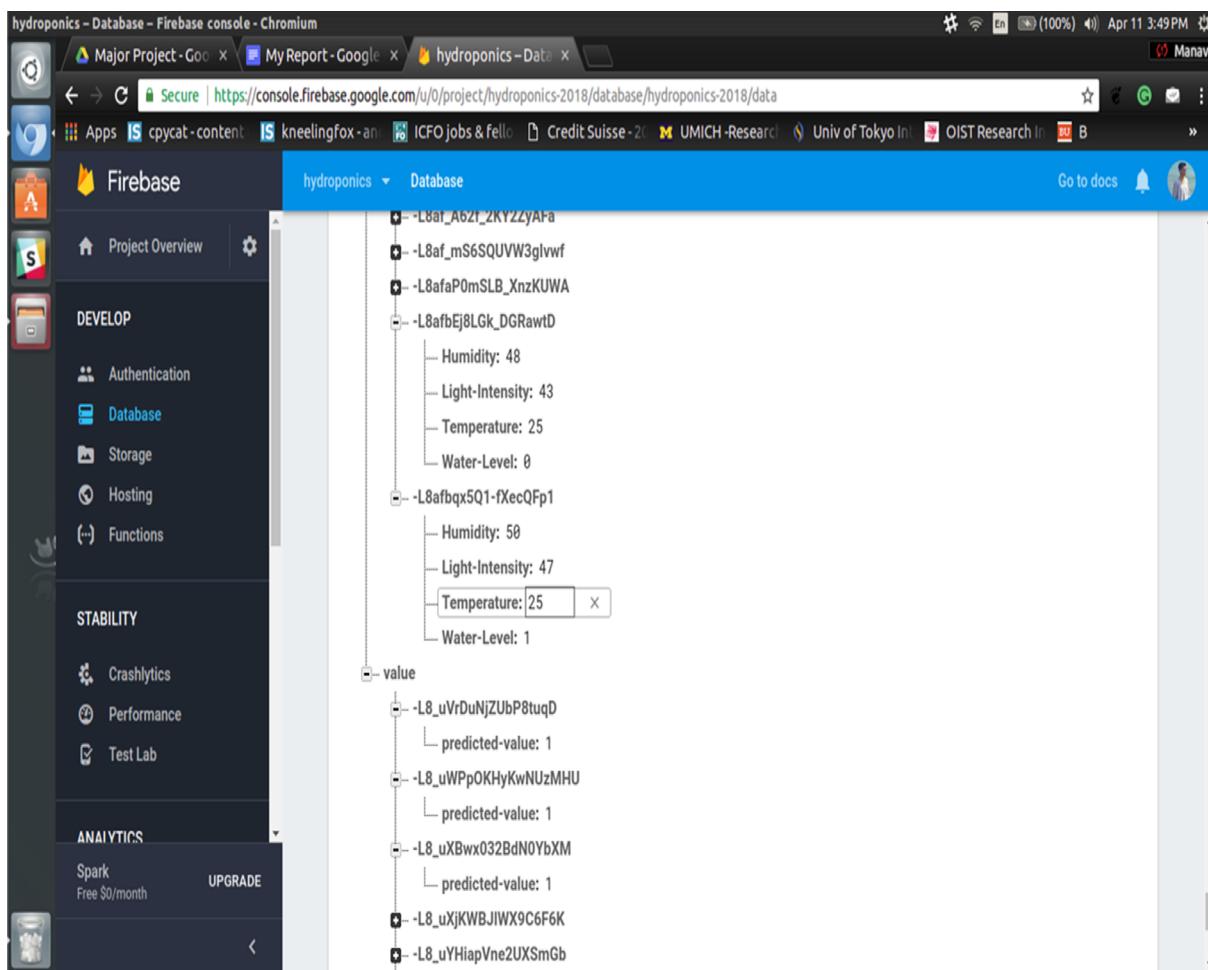


Fig. 20. Cloud storage for predicted output.



Fig. 21. Hydroponic nutrients.

The trained Deep Neural network model is deployed in Raspberry Pi3 which acts as fog in sending the input to Arduino towards producing the appropriate control action to the hydroponic system. The real-time data available from the hydroponic tank and predicted output control

action with the label are sent to cloud for storage and viewing.

So based on the above, Fig. 11 below shows the data set collected with appropriate control action labeled 0–7. Table 1 shows the label for the predicted control action.

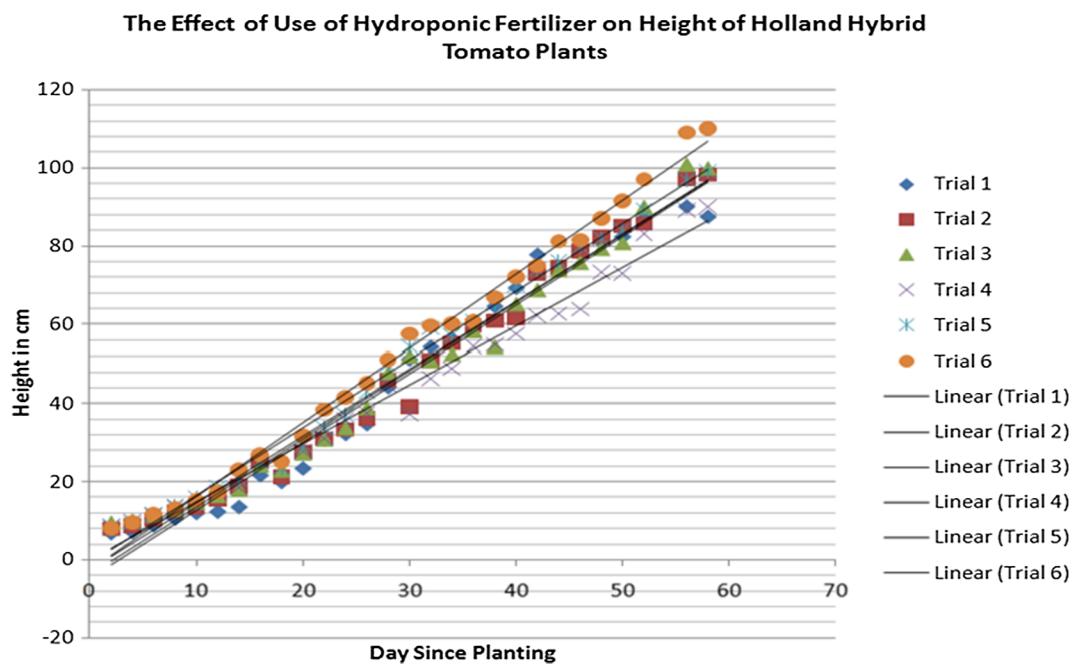


Fig. 22. Effect of hydroponic fertilizer in tomato plant.

The Effect of Use of Hydroponic System Compared to Soil Grown Tomato Plants on Height

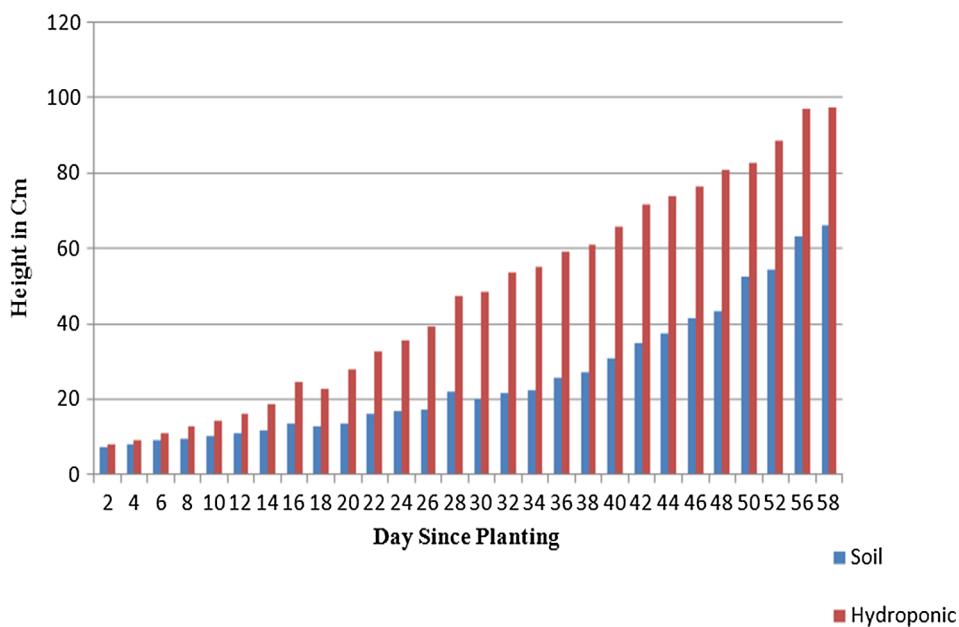


Fig. 23. Hydroponic vs. Traditional soil growth.

Figs. 12–19 below show the screenshot pertaining to control action prediction output based on the input parameters trained in the cloud. The predicted outputs are shown below. Also, the accuracy of the system achieved is 88.50% which shows the best prediction output accuracy based on Deep Neural Network. Lastly, the real-time input data with the appropriate control action label is sent to the cloud for storage which is shown in Fig. 20. Fig. 21 shows the nutrient used in the hydroponic tank for the growth of the tomato plant. Fig. 22 shows the effect of hydroponic fertilizer on the tomato plant. Fig. 23 shows the plant growth in hydroponic versus traditional soil growth. This shows that plant growth in hydroponics is far better in terms of height compared to the traditional soil growth.

5. Conclusion & future work

Agriculture has a significant impact on the economy of the country. Now with the advent of IoT which allows the machine to communicate among themselves, an IoT based automated irrigation system developed where intelligence is pertaining to KNN machine learning deployed at the edge in predicting the soil condition based on moisture towards irrigating the field with water (Shekhar et al., 2017).

Now currently agriculture innovations are more towards hydroponics and aeroponics which allow plants to grow anywhere as hanging or so without the need of the soil. The challenge in such a system is that there is a need for manual monitoring of plants for spraying the

appropriate nutrients to grow efficiently.

So, with the upcoming of IoT, quite amount of IoT based Hydroponic monitoring system developed with a mobile application for controlling too. Now in terms of applying intelligence in terms of machine learning in analyzing the data set captured for controlling the parameters for proper growth of the plant in hydroponic, some amount of research carried in applying Bayesian Network and Artificial Neural Network.

So, with all these in mind for growing a proper plant in hydroponics, we need to control the parameters of hydroponic system autonomously without the need of human. So, we here have developed an intelligent IoT based hydroponic system by taking the tomato plant as a case study. In here five parameters taken as input for controlling the hydroponic environment which is pH, temperature, humidity, level, lighting. These parameters are trained using Deep Neural network towards providing the appropriate control action which is labeled. These parameters are collected in real time over weeks and trained 10,000 times towards achieving the best-predicted output action with an accuracy of 88%. The predicted control action for the real-time data is stored in the cloud. The Pi3 acts as the edge where the Deep Neural network model deployed for producing the predicted output and communicating with the Arduino. This has been developed as a prototype.

In future, the system could be extended by deploying the intelligent IoT based Hydroponic system with Deep Neural Network for other hydroponic grown plants toward achieving higher accuracy. Also, the

system could be extended by growing a more hydroponic plant in different tanks and accordingly training the parameters for producing the appropriate control action by applying intelligence. This could be done on a large scale where the accuracy of the system can be computed for a variety of hydroponic plants with more data set from different plants.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.compag.2018.10.015>.

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