A Smart Hydroponics Farming System Using Exact Inference in Bayesian Network

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***Abstract*—Smart farming is seen to be the future of agriculture as it produces higher quality of crops by making farms more intelligent in sensing its controlling parameters. Analyzing massive amount of data can be done by accessing and connecting various devices with the help of Internet of Things (IoT). However, it is not enough to have an Internet support and self-updating readings from the sensors but also to have a self-sustainable agricultural production with the use of analytics for the data to be useful. This study developed a smart hydroponics system that is used in automating the growing process of the crops using exact inference in Bayesian Network (BN). Sensors and actuators are installed in order to monitor and control the physical events such as light intensity, pH, electrical conductivity, water temperature, and relative humidity. The sensor values gathered were used to build the Bayesian Network in order to infer the optimum value for each parameter. A web interface is developed wherein the user can monitor and control the farm remotely via the Internet. Results have shown that the fluctuations in terms of the sensor values were minimized in the automatic control using BN as compared to the manual control. The yielded crop on the automatic control was 66.67% higher than the manual control which implies that the use of exact inference in BN aids in producing high-quality crops. In the future, the system can use higher data analytics and longer data gathering to improve the accuracy of inference.**

***Index Terms*—Actuators; Bayesian Network; Hydroponics; Internet of Things: Machine Learning; Sensors**

I. INTRODUCTION

As smart machines and sensors crop up on farms and farm data grow in quantity and scope, farming processes will become increasingly data-driven and data-enabled. Rapid developments in the Internet of Things (IoT) are propelling the phenomenon of what is called Smart Farming [1]. Monitoring and controlling agricultural production and feed by using advanced sensor systems are further applications of IoT. Such systems will ensure the health of plant origin products intended both for human and animal consumption [2]. Although IoT is getting momentum to enable technology for creating a ubiquitous computing environment, special considerations are required to process huge amounts of data originating from, and circulating in, such a distributed and heterogeneous environment. Collecting and analyzing the data circulating in the environment is where the real power of IoT resides. To this end, applications utilize machine learning and data-mining techniques to extract knowledge and make smarter decisions [3]. To assess the future using these data streams, high-performance technologies that identify patterns in the data as they occur is needed. Once a pattern is recognized, metrics embedded into the data stream drive automatic adjustments in connected systems or initiate alerts for immediate actions and better decisions. On the other hand, hydroponics is one of the farming technologies that was considered as the quickest growing sector of agriculture and can govern food production in the future. Hydroponics farming fully provides the right amount and type of nutrients that the plants need at a right time and can be installed indoor to maximize available space. Soil related problems were solved by hydroponics like growing plants that needed hard-to-maintain soil conditions, minimal weeding and easier to harvest. By combining hydroponics with IoT, this can lead to successful crop harvest and potentially improve growth quality.

This paper makes the following contributions: (1) developed a sensor network that monitored and gathered information from the hydroponics farm; (2) generated a predictive analysis model using Bayesian Network that automates the hydrophonics farm system; (3) developed a web interface that served as the graphical access in monitoring and controlling the farm and (4) performed tests and analysis in order to identify the reliability and improvement gain of the system as compared to manual hydroponics farming.

The rest of the paper is organized as follows. Section II presents the related work. In Section III, we discuss an overview of smart hydroponics system. In Section IV, we discuss the testbed deployment and results gathered. Finally, Section V concludes the paper.

II. RELATED WORK

Relevant works has been published in designing and implementing smart farming. A conceptual model and system design for decision support of smart farming with network sensor applications in order to perform necessary tasks required for farmers has been proposed with a comprehensive model using IoT approach which will be applied to agriculture [4]. On the other hand, Agri-IoT, a semantic framework for IoT-based smart farming applications, which supports reasoning over various heterogeneous sensor data streams in real-time. It can integrate multiple cross-domain data streams, providing a complete semantic processing pipeline, offering a common framework for smart farming applications. It also supports large-scale data analytics and event detection, ensuring seamless interoperability including online information sources and linked open datasets and streams available on the Web [5]. Another work specified a farm management system that takes

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advantage of the new characteristics that future Internet offers. These come in terms of generic software modules that can be used to build farming related specialized modules [6]. Another work build an autonomous gardening robotic vehicle which automatically identifies and classifies the plant species using feature extraction algorithms. It measures the key parameters for gardening such as temperature, humidity, heat level, wind speed, wind direction and soil moisture. The data acquired from the on-board sensors of the gardening rover are sent to the cloud storage platform on a regular basis. Based on the acquired data and history, future predictions are made to maintain the garden more effectively and efficiently. A website and an android application are developed for monitoring and controlling the rover from a remote area [7].

Most of these works that were designed to have a generic IoT-based framework for future smart farming applications. However, only few of them were able to implement an actual farm testbed to verify the performance of the proposed frameworks. In addition, none of these works have considered integrating a hydroponics farm with IoT and used machine learning that performs data analytics to control existing factors governing the growth of the plants. We aim to fill this gap in the literature.

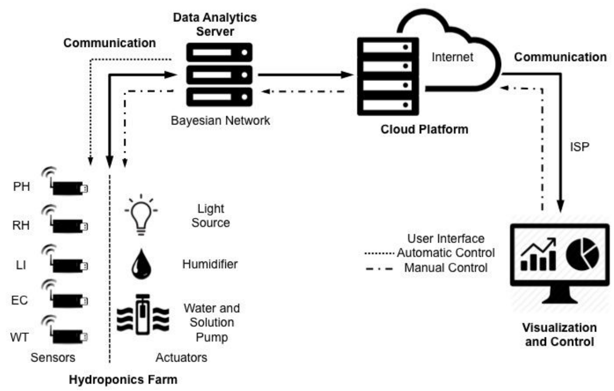

Fig. 1: Overview of smart hydroponics system

III. Overview of Smart Hydroponics System

The whole system is comprise of three major components: sensors, data analytics, and web interface as shown in Figure 1. Hardware includes a hydroponics farm built with a sensor network for the purpose of monitoring and controlling the system. The sensor network is comprise of five different sensors that control different parameters needed for plant growth namely pH level (PH), electrical conductivity (EC), relative humidity (RH), light intensity (LI), and water temperature (WT). Software is composed of the data analytics and a cloud server needed for data storage and predictive analysis. The web interface served as the graphical interface of any user to remotely access the farm.

Plants grown under hydroponics farming extract the nutrients they need from a water based solution. However, not all plants can be produced with this farming technique. Leafy plants are easier to grow and their roots are more lightweight than the other types [8]. Iceberg type of lettuce was used since the growing time of this plant is the suitable to the duration of this study. Since the farming method eliminates the use of soil and focuses on the parameters concerning on the air and water of the system and surroundings, the pH level, electrical conductivity and temperature levels are significant in hydroponics farming. In addition, maintained light intensity ensures the efficiency rate of growing the plant. As data pass through the cloud server, time series charts are being generated and uploaded on the website. The flow and process of the system is shown in Figure 2.

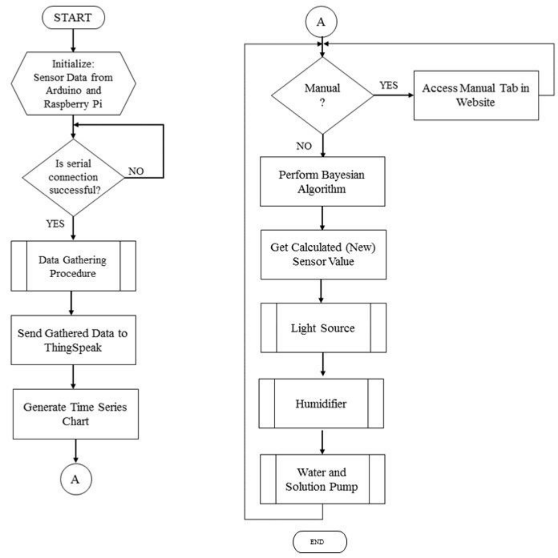

Fig. 2: System flowchart

A. *Construction of Hydroponics Farm*

The construction of the hydroponics farm incorporates a Nutrient Film Technique (NFT) [9] wherein a narrow stream of water containing the dissolved nutrients needed for plant growth was repeatedly circulating past the roots of the plants through a watertight gully, also known as channels as shown in Figure 3. A reservoir houses the water flowing in and out the system and is pump using a submersible water pump. An insect net covers the whole farm in order to reduce the insects and to easily control the humidity around the farm. The hydroponics farm also used an UV plastic roofing in order to reduce the abrupt changes brought by changing weather conditions.

B. *Hardware and Sensor Network*

The sensor network is comprise of five different sensors that control different parameters needed for plant growth namely pH level (PH), electrical conductivity (EC), relative humidity (RH), light intensity (LI), and water temperature (WT) as suggested in [8]. These sensors are connected to a microcontroller using Raspberry Pi (Rpi) [10] since it can handle large amount of data and can operate better in

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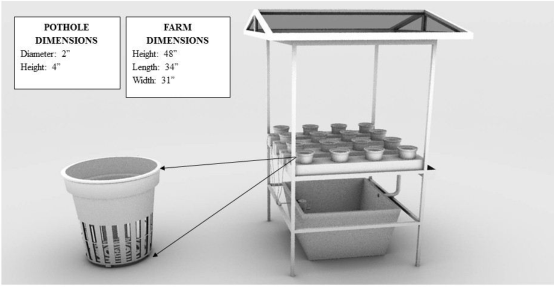


Fig. 3: Actual farm model

tedious processes. Furthermore, it is less expensive, easy to be installed with various types of sensors, and can function as a cloud data logger, which made RPi an ideal microcontroller for the hydroponics system. The performance of each sensor underwent accuracy testing to guarantee that sensors will give accurate data from the farm.

Each of the sensors had its recommended sensing value ranges at which every parameter in the hydroponics system should be met for it to be considered a favorable value for plant growth. Table I shows the approximate threshold value of each sensor as suggested in [8]. The sensors use for electrical conductivity, pH level, water temperature are probed directly onto the reservoir. These measure the current levels and concentration of the solution before pumping the water into the gullies. Meanwhile, the relative humidity sensor is placed on the farm together with the crops in order to monitor the humidity of its surrounding while light intensity sensor is mounted on top of the roofing to properly monitor the incoming light.

TABLE I: Sensor Threshold Values

Sensor	Value/Condition
Relative Humidity (RH)	Min $\cong$ 50 Max $\cong$ 80
Light Intensity (LI)	100-200 $\mu mol/m^2/s$
Water Temperature (WT)	Min $\cong$ 22$°C$ Max $\cong$ 28$°C$
pH Level (PH)	Min $\cong$ 5.5 Max $\cong$ 7.0
Electrical Conductivity (EC)	Min $\cong$ 0.9 mS/cm Max $\cong$ 2.1 mS/cm

C. Data Analytics using Bayesian Inference

In order to make the hydroponics farm autonomous to initiate alerts for immediate actions, this study used Bayesian Networks (BN) to ascertain data transmitted by the sensors. BN is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph which is based on *a priori* probability or Bayes Theorem [11]. The algorithm implements an input-based process wherein the software processed based on the inputs and generate the appropriate output decisions. The algorithm is learning based on the data coming from the different sensors. The greater the number of datasets analyzed, the more accurate the BN prediction will be. After processing the data, the algorithm transmits the decisions onto the cloud server wherein it then transfers the data onto the web interface to monitor and control the system. Figure 4 shows the overview of the BN algorithm used for the automatic control of the farm.

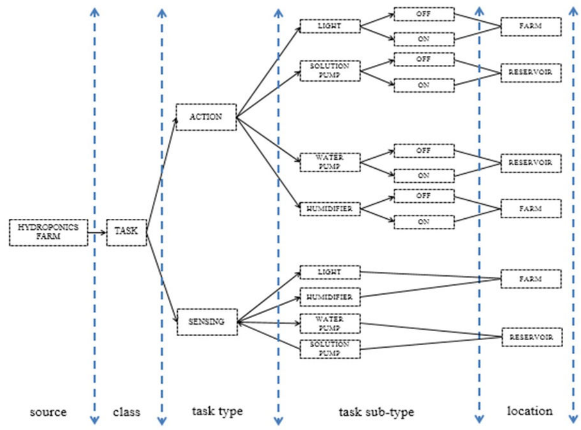


Fig. 4: Exact inference in Bayesian Network

D. Cloud Server and Web Interface

The data gathered from the sensors and the decisions given by BN are transmitted through a cloud server. Using a virtual database, the sensor values to be uploaded to the cloud server were in text format. As a result, file size were smaller and did not require a bigger storage. The incoming data from the sensors are sent to RPi, upload to the cloud server and display in a form of a time series chart. This allows the user to easily track the trend of values in each sensor real-time. Before the user could access the main page, the website ask for the administrators password to ensure privacy and confidentiality of the system. Furthermore, this also serves as a virtual logbook for all the sensor data streams. The web interface are composed of two pages namely automatic control and manual control. In manual control, the user has the authority to change the states of the relay and controlling the operation of any actuator in the system. In automatic control, the decisions based from the BN prediction algorithm are use to control the actuators which make the system autonomous.

IV. Testbed Deployment and Results

A. Generation of Bayesian Networks (BN)

The generation of BN utilized the data gathered conducted in 27 days which resulted to 6,881 datasets (outliers omitted). Due to page limitation, the resulting simplified BN trees as shown in Figure 5, generated from the datasets of each sensor using Weka 3 [12] data analytics tool. At a certain BN tree of a selected parameter, the large amount of data from the other four parameters were fed to the tree wherein the data were analyzed and decisions were generated. The output of each BN tree was dependent on the other four controlling parameters being fed to their corresponding tree. This is to establish a probabilistic relationship between sensor values as each value were being predicted. Biasing was minimized and the occurrence of human error was minimized as the decisions from BN control each actuators. In this way, the accuracy was improved and the sensor thresholds were achieved real-time.

B. Manual and Automatic Control Comparison

The comparison of each sensor response from automatic control using BN and manual control are shown in Figure 6. In manual control, higher fluctuations on the sensor values were obtained. This was due the minimal supervision on the system since the actuation only relies on the judgment of the user. On the other hand, the trend of values for automatic control using BN is relatively constant. Lesser deviations were obtained since the BN output decisions automatically adjusted the values and control the system. Due to the intricate supervision established using BN algorithm, values for each sensor were maintained over the course of the data gathering. Moreover, this suggested that the implementation of the algorithm was effective in establishing a controlled environment for hydroponics farming.

C. Yielded Crops

For manual control, the low yield is caused by the external factors in which the hydroponics system cannot control such as weather and insects. The dependency of actuators to user is also a factor. For automatic control using BN, the relatively high yield, as compared to the manual control, was due to the automatic-controlled system and the implementation of BN predictive analysis, which was proven to be effective due to the intricate monitoring and controlling of the system. Table II shows the summary of comparison between the crops yielded from manual and automatic controls produced out of 16 total planted lettuce seedlings. In addition, Figure 7 show the actual iceberg lettuces produced from manual and automatic controls, respectively.

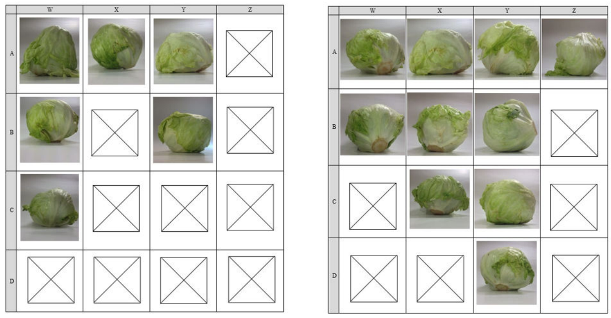
TABLE II: Average Parameter Values of Yielded Crops

Parameters	**Manual**	**Automatic**	**Gain Difference**
Weight (g)	0.35	0.44	27.25 %
Height (cm)	10.58	12.75	20.47 %
Circumference (cm)	35.27	38.52	9.22 %
No. of Leaves	10	14	40.00 %
No. of Yielded Crops	6	10	66.67 %

The BN prediction algorithm generated and utilized during the crop production was able to provide the optimum values required for each governing parameter. This results to a more intricate control over the different parameters which contributes to a higher quality of yielded crops. Since the farmers are eyeing for more sustainable crop production, this integration offers higher crops survival rate at reasonable cost.

D. Dashboard User Interface

The dashboard interface used an IoT cloud platform ThingSpeak [13] as shown in Figure 8 wherein the trend of the



(a) Manual Control (b) Automatic Control

Fig. 7: Actual yielded crops matrix

data from the sensors are being monitored by the user. The graphs were designed for the purpose of easy accessing and monitoring for the targeted users which are the farmers who only requires to view the desired ranges from each parameters. In addition, the design was kept simple and user-friendly. There were two websites made mainly for viewing and controlling purposes. The first website was deployed using Firebaseapp [14]. This only features viewing and monitoring of real-time sensors data stream in time series charts via the Thingspeak platform. The second website is deployed to My NoIP [15] directly to RPi. This features both monitoring and controlling of the actuators in order to correspond from the data coming from the sensors.

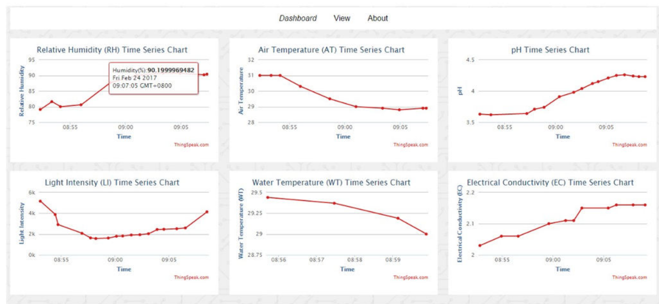


Fig. 8: Time series chart monitoring dashboard interface

For manual control interface, four actuators (water pump, solution pump, humidifier and light source) can be access and controlled via the Internet from the decision and judgment of the user. In addition, that the amount of time in doing the actuations is indefinite for this interface. On the other hand, in automatic control interface, wherein the BN algorithm were executed and the states of the actuators were controlled based on the predicted values, the duration of the actuation was definite since it has a feedback mechanism where it continuously monitors and compares the predicted and current values of each parameter. As long as both of these values were not equal, the actuation continues based from the prediction algorithm.

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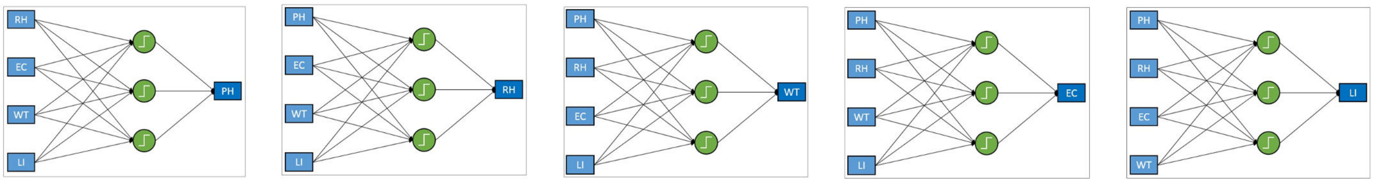
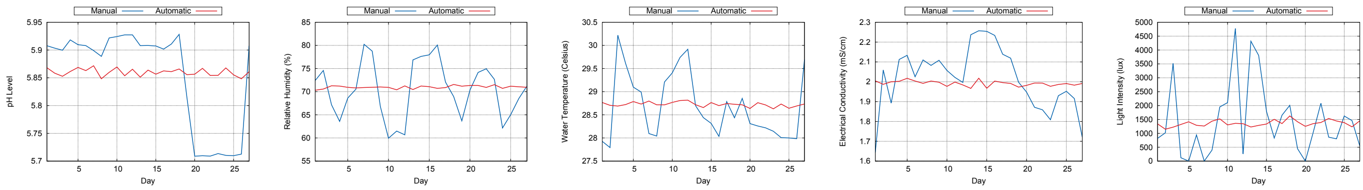


(a) PH (b) RH (c) WT (d) EC (e) LI

Fig. 5: Generated Bayesian Network tree (simplified) for farm automation



(a) PH (b) RH (c) WT (d) EC (e) LI

Fig. 6: Comparison of sensor data responses between manual and automatic controls

V. Conclusion

This work design and implement a smart NFT hydroponics farm using inference from Bayesian Network. The sensor network composed of pH, light intensity, electrical conductivity, water temperature and relative humidity sensors were used to gather data from the farm. The data received from the sensors are process and are sent to an IoT platform. Actuators such as water pump, solution pump, humidifier and light source were triggered in order to adjust the systems parameters. Smart farming was integrated with Internet of Things (IoT) by analyzing the large amount of data sent from the sensors. These datasets gathered for almost one month were used to generate BNs which then performs predictive analysis that gives output decisions to autonomously control the system. Two websites were deployed for viewing, monitoring and controlling the actuators from the hydroponics farm. It is concluded that the crops yielded from using the automatic control is better than the crops yielded from manual control due to computed gain differences between 20% to 60% for all parameters used to evaluate good quality crops. Due to realized real-time data automatic acquisition and data analytics of hydrophonics farm parameters and biological information, the farmers can achieved good economic and ecological benefits, and the great significance to the development of modern agricultural information-based intelligence. In the future, in order to effectively improve the system, the data gathering procedure must be longer as larger data would have produce better results for data analytics.

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