Journal of Computer Science
https://dergipark.org.tr/en/pub/bbd

ISSN,e-ISSN: 2548-1304
Volume:IDAP-2022, pp:165-176, 2022
https://doi.org/ 10.53070/bbd.1172774
Research Paper

Monitoring Plant Growth with Image Processing Methods and Artificial Intelligence Supported Agriculture System

Anıl SEZGİN*[1], Vesile KÜÇÜK[1]

[1]Bilgisayar Programcılığı Bölümü, İstanbul Esenyurt Üniversitesi, İstanbul, Türkiye

(anilsezgin@esenyurt.edu.tr, vesilekucuk@esenyurt.edu.tr)

Received:Sep.08,2022 Accepted:Sep.16,2022 Published:Oct.10,2022

Abstract— The use of smart technologies is gaining importance in solving the problems experienced in the field of agriculture. An important aim of the studies is to ensure the cultivation of agricultural products in greenhouse environments. In this way, growing agricultural products in greenhouses controlled by smart systems by creating suitable soil and climatic conditions and facilitating people's access to these products has become an important research and application topic. This study aims to follow the cultivation of a product and determine suitable growing conditions by using image processing techniques, machine learning methods, and the Internet of Things.

Keywords : *Image Processing, Machine Learning, Internet of Things, Sensors*

1. Introduction

Agriculture has an important place in the country's economy, it has become much more than a simple way of feeding the ever-increasing population. The anticipated challenges when it comes to the need to double the food supply in agriculture now equate the importance of agricultural sustainability with ensuring food security.

Smart agriculture is the whole of methods and technologies that aim to give higher quality products by sensing the control parameters of agricultural areas. By determining the control parameters, these parameters are read with the help of various sensors and the large amount of sensor data obtained is transferred to a central computer or server for processing. According to the information obtained from the processed data, it is ensured that the agricultural area has the resources it needs.

Accurate data analysis on the farm plays an important role in increasing operational efficiency and productivity. The data consists of sensor data, audio, image, and video. Image processing methods are used in many areas such as disease detection on leaves, stems, fruits, fruit quality, irrigation, and weed detection. Recently, image processing and the Internet of Things (IoT) are used together in agriculture to obtain higher quality crops and reduce crop errors.

Many negative situations such as soil erosion, intense water consumption, and the emergence of food-borne diseases are encountered in field agriculture practices. To minimize these negative situations, automation systems have been introduced in agriculture and greenhouses. Today, most of the agricultural and greenhouse automation work on a timer basis. Thanks to these timers, water, and nutrients are pumped into the plants at certain intervals. However, different parameters need to be controlled for this system to work efficiently as an intelligent autonomous. This study aims to create the necessary infrastructure for the autonomous operation of agricultural and greenhouse systems, to follow up the products with image processing methods, to process the data coming from the camera and other sensors, and develop a smart system by applying different artificial intelligence techniques.

Technology and artificial intelligence can provide solutions to agricultural activities (w/o soil) in the following areas:

- Tracking product development with IoT: Every day, large amounts of data can be generated both structured and unstructured forms, such as historical weather, soil reports, precipitation, and pest infestations. With IoT systems, these data can be perceived and processed to make predictions to increase efficiency. Both proximity and remote sensing technologies are used for intelligent data fusion. One of the uses of these data is the soil testing. In remote sensing, the sensors are located at high locations or in satellite systems, while in proximity sensing, the sensors must be in contact with the ground or in very close distance. this makes it possible to make soil characterization at a particular location.

- Image-based foresight generation: Precision agriculture is one of the most discussed and researched areas in agriculture today. Images obtained from drone based or fixed cameras; field analysis, crop monitoring, dredging of fields, etc. can help with issues. IoT technology and computer vision Technologies can be used together to make healthier and faster decisions. Fueled by data from camera images, the system can generate real-time alerts to accelerate precision agriculture.

The things that can be done with image processing are:

1. Disease detection: The obtained images are subjected to a preprocessing stage and the leaf images are divided into areas such as background, disease-free part, and diseased part. The diseased part is then clipped and sent to the server for further diagnosis.

2. Harvest detection: To determine the ripeness of green fruits, images can be taken under white / UV-A light. It can create different color values and harvest levels according to the crop/fruit category.

3. Agricultural field management: By using high-resolution images obtained from the air (drone, etc.) an area map can be created and real-time forecasts can be made during the growing period by determining the areas where the crops need water, fertilizer, etc. This greatly aids in resource optimization.

- Identification of crops: Soil condition, weather, seed type, infestation in a particular area, etc. Technological solutions based on many parameters advise farmers on choosing the best quality crops and hybrid seeds. The recommendation can be given not only for internal factors but also for external factors. Examples of these external factors are market trends and prices. In this way, it can support farmers to make informed decisions.
- Monitoring crop health: Hyperspectral imaging is the measurement of energy reflected from surface materials in a narrow and contiguous multiple wavelength bands. LiDAR, on the other hand, is an advanced technology for detecting the distance of objects using laser light. Thanks to these two technologies and remote sensing techniques, crop measurements can be made in very large areas. These technologies can also be used to monitor crops throughout their entire lifecycle, including anomaly reporting.
- Automation and irrigation: In classical agriculture, irrigation is carried out based on manpower. Machines trained on soil, weather, quality, and the types of crops to grow can automate irrigation and increase overall yields.

Changes that can be observed by image analysis within the scope of this study are as follows:

- The growth of the plant
- Plant health
- Detection of diseases in the plant
- Detection of insects on the plant

In this study, nutrients and water are kept in tanks, and measurement and monitoring of the values in these tanks are important in terms of resource use. Thus, the feeding process of the plant can be carried out according to the changes in the plant and the condition of the resources in the tanks. Measurements made in the tank: water temperature, pH, conductivity.

It is aimed to adjust the use of resources by monitoring the plants and environmental conditions in the agricultural system in the same way. Measurements made for the plant and its environment: image, CO_2, temperature, light, humidity, pH value. The automation system developed with the data obtained as a result of the measurements made from these 3 different points is fed.

The plant whose development was observed within the scope of the study is lettuce. The reason why this plant is preferred is that the growing conditions of the lettuce can be achieved more easily, it yields in a short time (2-3 months) and the change in it can be detected more easily with image processing.

This paper proceeds as follows: in the 2. section, previous studies in this field are mentioned. In 3. section, the experimental environment and processes created in this study, are mentioned. The results are described in section 4. In the 5th and 6th sections, the study and the results are discussed.

2. Related Work

The Internet of Things has taken place in many sectors such as industry, health services, logistics, and education. IoT connects the real world and the virtual world over the internet and uses it as a communication and information exchange tool.

It is estimated that the number of people in the world will reach 9.5 billion in 25 years. This increase in population is expected to increase the demand for food. This, combined with declining arable land, dwindling natural resources and unpredictable weather conditions, is making food security a major concern in most countries. The world is turning to the use of data analysis and IoT to meet food demands in the coming years (Dlodlo and Kalezhi, 2015).

Wireless sensor networks (WSN) have been used for many years in the fields of precision agriculture, environmental monitoring and traceability for food production and smart agriculture. (Wang et al., 2006) (Amin et al., 2004), The ability of wireless sensor networks to configure, self-organize, diagnose and improve makes it preferable for food industry and smart agriculture. WSN is a system of microcontrollers, RF transceivers, sensors and power supplies (Wang et al., 2006). However, IoT; WSN integrates various existing Technologies such as RF identification, middleware, cloud computing, and end-user applications (Manrique et al., 2016).

There are different examples of IoT applications in agriculture. These examples are crops and livestock (Benaissa et al., 2017), machinery (Oksanen et al., 2016), irrigation and water quality monitoring (Cheiochan et al., 2017) (Zhang et al., 2017), weather monitoring (Kodali et al., 2016), soil monitoring (Kodali et al., 2016) (Na et al., 2016), disease and pest control (Zhang et al., 2014) (Lee et al., 2017), automation (Giri et al., 2016).

Table 1 contains IoT-based solutions developed for agriculture.

Table 1. IoT-based solutions for agriculture

IoT Solution	Service
OnFarm	Tool which is focused on farm management that processes and analyzes data from multiple sources.
Phytech	Provides IoT platform for direct detection, data analytics, facility status, and recommendations.
Semios	IoT platform for orchards focusing on pests, cold (frost), disease, and irrigation
EZfarm	An IBM project focusing on water management, soil monitoring, and plant health.
KAA	Provides platforms for remote crop monitoring, livestock tracking, mapping, predictive analytics for crops and livestock, smart logistics and storage, animal feeding and production statistics.
Cropx	Provides adaptive irrigation software services that increase crop yields, and save water and energy costs.

IoT studies in agriculture mainly focus on monitoring, tracking, machine control, precision agriculture, and greenhouse production.

2.1. Monitoring:

Various parameters can be monitored in agriculture with IoT. These parameters vary depending on the agricultural sector being considered. Several environmental factors affect farm production in crop farming. It helps to understand the farm's patterns and processes to obtain such data. Examples of these data are, leaf wetness, temperature, rainfall, humidity, soil moisture, solar radiation, climate, pest movement, salinity, and human activities (Zhao et al., 2010). Obtaining such detailed records enables optimum decision-making to improve the quality of farm products, minimize risk and maximize profits. For example, solar radiation data provides information about plant exposure to sunlight. Here, the farmer can determine whether the plants have been properly exposed or overexposed. Soil moisture content provides information about soil moisture, which can help control soil conditions and reduce the risk of plant diseases. Accurate forecasting of climate change and precipitation can increase productivity, as well as timely. These estimation data obtained can reduce the labor cost and help the farmers in the planning phase. In addition, pest movement data can be collected in real time and shared with the farmer, which can advise farmers on pest control and take preventive measures (Rubala and Anitha, 2017).

2.2. Tracking:

Thanks to the Internet of Things technology, the efficiency of the companies' supply chains can be increased by product tracking. With this technology, agricultural companies can make better decisions and thus save time and money. By using RFID and GPS technologies, location tracking can be done both indoors and outdoors (Li, 2011).

It is possible for consumers to see all movements of the product by monitoring their production and supply chains. The traceability of these movements gives confidence to the consumer about product safety and health. Thanks to this data collected by the Internet of Things, consumers can have information about the entire life cycle of the product, from the point of origin to the place where it reaches their hands. (Huang and Liu, 2014) (Mainetti et al., 2013).

There are important factors such as soil and water that affect the growing environment of an agricultural product. Thanks to the tracking of the product with IoT, both harmful situations can be detected and production, storage and transportation conditions can be monitored. Monitoring these situations and conditions reduces the risks that may endanger the health of consumers.

The quality and quantity of crops depends on the conditions of production. These conditions are affected by fertilizers, pesticides and pests. Monitoring production conditions and crops can help farmers and agricultural companies increase the efficiency of their production and supply chains.

The most important steps in a tracking system are data entry and proper recording of this information. This information should be transmitted uninterruptedly and without loss at all stages of the tracking system. At the end of this whole process, an output is obtained. The entire life cycle of the product is associated with location and time information and recorded in the system (Regattieri et al., 2007).

Monitoring and tracking systems are platforms that can be made available to everyone throughout the supply chain and that provide analysis on the collected data. In this study (Gan et al., 2010), the use of RFID in the process from production to after-sales services is mentioned. The RFID system provides the ability to quickly collect, store and analyze data from long distances.

2.3. Agricultural Machinery:

IoT-based machines used in agriculture can be used to increase crop productivity. With the help of accurate mapping and GNSS data, autonomous operation of machines can be made possible. In this way, crop loss can also be reduced. (Abhishesh et al., 2017). Machinery including vehicles, drones, and robots can be remotely controlled based on available information gathered through the IoT system to apply resources precisely and efficiently to the required farm areas (Tripicchio et al., 2015). Machines can also be used to collect data. These data can help farmers to map their fields to plan programs such as fertilization, irrigation, and feeding (Kaloxylos et al., 2012). For example, CLAAS, an agricultural machinery manufacturer, applied IoT to its equipment, enabling its machines to run in autopilot mode.

2.4. Precision Agriculture:

Precision agriculture is an innovative type of agriculture that combines agricultural production and technology, aiming at the principles of lower cost, maximum income expectation and environmental protection, with the aim of achieving high efficiency in every aspect (Lerdsuwan & Phunchongharn, 2017).

Precision farming relies on a variety of technologies including sensor nodes (Mat et al., 2016), GPS, and big data analytics to achieve improved crop yields. The decision taken in data analytics, irrigation systems, water, fertilizer, pesticides, etc. results in less wasted resources. Precision agriculture, robotics, image processing, meteorological data sensing, etc. presents new challenges for researchers in the field. While precision farming technology can increase yields, training is essential to provide solutions that are easy to use by farmers, while also enabling small and medium-sized farmers to benefit from the systems.

2.5. Greenhouse Production:

In greenhouse cultivation, a controlled environment is provided to the plants. This technique can be applied anywhere at any time, making it possible to grow crops. Wireless sensor networks can be applied in greenhouses to monitor production conditions (Pekoslawski et al., 2013). Studies show that IoT applications in greenhouses provide efficient use of resources. In this way, energy savings can also be made (Dan et al., 2015).

Various studies have been carried out on the use of internet of things technology in soilless agriculture. In their study (Ludwig and Fernandes, 2013), the characteristics of the plant such as pH and brightness were monitored with sensors in the soilless farming system and the data obtained were sent to a microprocessor. By processing the data coming to the microprocessor, the illumination of the production area was controlled with the help of a relay. In this way, it is ensured that the plant receives the light it may need and energy efficiency is achieved.

In the study (Peuchpanngarm, et al. 2016), an automatic control system was developed for soilless agriculture. With the developed applications, data is obtained from the sensors in the environment and it is ensured that the conditions required by the plant can be presented both automatically and manually. Other advantages of the developed applications are correct planning for the product, timely management and determination of the appropriate harvest time.

In addition to automating hydroponics using Internet of Things technology, some knowledge is needed to control the hydroponic system. Therefore, machine learning, which is a subset of artificial intelligence, can come into play at this point. Machine learning methods in hydroponics help automate plant growth.

(Ferentinos and Albright 2002) used various sensors for light, conductivity, pH, humidity and water level to develop a hydroponic farming system. A Bayesian network was created with the data coming from the system. In the Bayesian network, the data obtained from the sensors are checked and predictive analysis is performed to make the decision for the output.

(Pitakphongmetha et al., 2016) used an artificial neural network to predict pH and electrical conductivity results in a hydroponic farming system. In this neural network, plant age, light, temperature, humidity are used as input and it is designed as a feed-forward network. Automatic control of the system can be achieved with the pH and electrical conductivity presented as the output of the neural network.

In the above-mentioned study, a high level of accuracy could not be obtained in the machine learning algorithms used in the environment control in the hydroponic farming system. Studies in this area aim to develop a smart soilless farming system based on the internet of things with higher accuracy.

(Gosavi, 2017), pH, water conductivity, and water brightness; He developed an IoT-based hydroponic prototype, which he monitors using sensors such as pH, electrical conductivity, and lumen meters. This information, captured by the sensors, is sent to the microprocessor, where continuous monitoring is performed for optimum plant growth. In the hydroponic system, the plant should be under 16 hours of light and 8 hours in the dark. The microprocessor has a real-time clock to control the lighting with a relay switch.

The main parameters to be controlled in hydroponic systems are: water temperature, electrical conductivity and pH. By keeping the pH at an optimum level, it will be ensured that the crop absorbs the nutrients in the solution more easily. However, it is not easy to control the pH value in the nutrient solution, as the pH usually changes easily due to ion absorption by the plant roots (Suhardiyanto et al., 2001). Therefore, control becomes complex and uncertain. There are different methods to overcome this problem. Conventional control with a threshold can be used to issue a command to the actuator, but it will be difficult to obtain an exact value required by the system as it cannot cope with uncertainty. A PID controller can be used to remove blur, but this requires a more complex control system. Therefore, fuzzy logic can be used to solve such problems (Abu et al., 2013).

Control and monitoring systems of plant production conditions have a fuzzy and complex structure. Fuzzy logic can be used to control the system (Gomez-melendez et al., 2011). This structure can adapt to manage different systems thanks to its learning flexibility and high control features. In their study (Morimoto and Hashimoto, 1991), a soilless agriculture system was established in which pH values can be controlled with fuzzy logic and artificial neural networks. The pH value is an important element for soilless farming systems. The pH value should be kept at appropriate levels for each period of the product. In the study (Fuangthong and Pramokchon, 2018), the control of the system was ensured by following the pH values with fuzzy logic. In the study (Munandar et al., 2017), a real-time monitoring system was designed with fuzzy logic in which the nutritional requirements of the plants are automatically met.

3. Experimental Evaluation

A monitoring and decision-making system is needed to increase productivity. With image processing methods, both the development of the plant can be followed and the negative situations (insect, disease, etc.) that may be encountered during this development can be detected much earlier and intervened. This study aims to develop a system based on monitoring, measuring, and responding to variability in crops. It is aimed that this developed system can work in integration with existing agricultural and greenhouse systems and thus turn these existing systems into autonomous systems.

Manual methods of tracking product development tend to be error-prone. Computer vision and image processing can provide accurate and efficient solutions to support agricultural activities. Machine learning methods and artificial intelligence algorithms will enable fast and accurate analysis of large volumes of data.

With this study, instant changes in the products grown in the system can be followed. In this way, it is aimed to ensure that the harvest can be made on time by notifying the user as soon as the product grows. Thus, depending on the product grown, it is foreseen that new products will be placed in empty places in the system with timely harvest, and more crops will be obtained in the same period.

This work is divided into three phases. The first phase is placing sensors in the system and collecting data, the second phase is placing cameras in the system and processing the images, and the third phase is bringing together all the data and controlling the agriculture/greenhouse system with this data.

This study aims not to develop an agriculture/greenhouse system from scratch, but to make existing systems capable of automated product tracking. Therefore, in the first stage, a planting and irrigation area similar to the systems in the market was prepared. This system consists of pots, circulation motors, tanks, hoses, sensors, and cameras. Figure 1 and Figure 2 show the camera and sensors placed in the system.

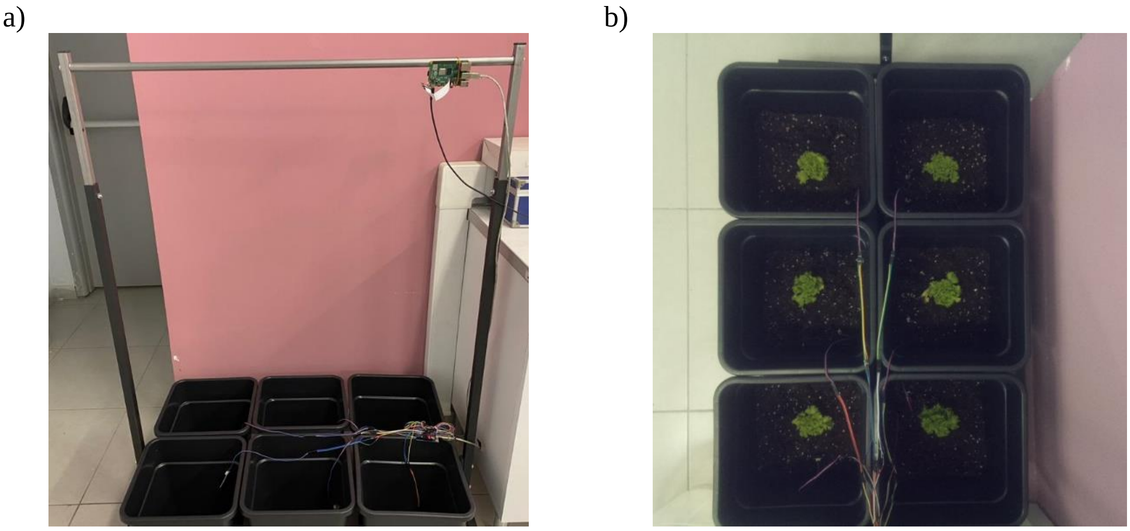


Figure 1. a) Overview of the system b) View from the cameras in the system

In the first phase, sensors were added to the farming system. With the help of the microcontroller, the data coming from these sensors is re-transferred to a local server wirelessly. The reason why wireless communication is preferred here is to avoid complicated wiring in case of too many sensors. A unique name has been determined for each sensor and microprocessor so that it can be determined from which sensor of which product sends the data. Using this unique name, the sensor data is transferred to the local server and from there to the cloud. For example, let's assume that there is a temperature sensor on product A and this sensor reads 220C. The data of this sensor will be sent to the local server as ProductATemperature: 22 and saved to the server with the time stamp. The information about how many seconds intervals the sensor measurements will be made can be changed parametrically. When working with a small number of sensors, it can be sent at very short intervals, but a decision should be made by calculating according to the load that many sensors will put on the server. Depending on the situation, the server features can also be improved and sensor data reading processes can be increased. The sensors in the first phase are classified into 2 different locations: sensors to be placed in/around the plant and sensors to be placed in the water tank.

Sensors placed in the plant and its environment:

- Gas sensor: CO_2, checking whether green leafed plants can photosynthesize healthily by looking at the amount of gas in the environment.
- Temperature sensor: Temperature of the plant and its environment.
- Light sensor: Amount of light on and around the plant.
- Humidity sensor: Moisture on the plant.
- pH value sensor: pH value of the water reaching the plant.

Sensors placed in the water tank:

- Temperature sensor: Temperature of the water in the tank.
- pH value sensor: pH value of the water in the tank.
- Conductivity sensor: Conductivity of water in the tank.
- Dissolved oxygen sensor: Dissolved oxygen amount of the water in the tank.

A single-board computer was used as the local server. A server with Linux operating system has been installed on this card. A REST service has been developed on this server, where the microcontrollers to which the sensors are connected, can send data wirelessly, and NoSQL technology is used to record the incoming data. Since the amount of data coming from the sensors will be high, the use of relational databases will lead to performance degradation, so NoSQL is preferred. Each sensor data is saved in this database with its unique name and time information.

Records on the local server are transferred to the cloud. Therefore, structures on the local server (REST service and NoSQL) are installed on a remote server. Thus, as long as the system is connected to the internet, it can transfer its data to the remote server regardless of its location. There are 3 main reasons for transferring to a remote server:

- Ability to distribute the workload to the remote server (data processing)
- Remote control of the system
- Transmission of system information to the users

In the second phase of the study, the cameras were included in the system. The images from the cameras placed at an angle to see the products on the agricultural system are instantly transferred to the local server. The local server here and the local server used in the first phase are different from each other. This is because too much data is coming from both sources. A separate local server is used for the data coming from the sensors and a separate local server is used for the camera images. Depending on the number of cameras and sensors to be used, the number of servers can be increased or a single server with a higher processing capacity can be used. The local server containing the images is also located in the same network and has access to the remote server. In this way, if desired, images can be followed instantly over the Internet.

Various image processing algorithms are implemented on the images obtained from cameras and their outputs are recorded both on the local server and on the remote server. Changes that can be followed by image analysis within the scope of this study:

- The growth of the plant
- Plant health

These changes and the algorithms to be implemented can differ according to the type/structure of the product. While parameters such as color and volume are sufficient for some products according to the structure of the products, the number will be equally important for some products.

Image processing methods are implemented on the local server. Data from each frame is recorded and compared with data from previous times. Thus, it can be determined how much the product has changed in the desired time interval.

The first stage of the final phase of the study involved bringing together the data from the first and second phases. Changes are detected by matching the data from the sensors and camera images. Thus, it can be observed which type of changes occur in which sensor values. The second stage of the last phase includes controlling the system according to these changes. By determining the positive ones among the observed changes, the current sensor measurements will be checked and it is ensured that the agricultural system works in the conditions when the positive changes occur. For example, when the product reads the X value in sensor A and the Y value in sensor B, the product has grown by 1% compared to the previous situation and this 1% growth is the highest growth ever. In this case, the values in our positive case are the X and Y values. The control of the system is provided by processing the data from all sensors. Using this data, even a simple artificial neural network can be trained and output to the plant the resource it needs. All data from the sensors is given as input to the neural network and can be matched to the growth rate detected from the camera. In this way, a smart autonomous control system can be developed for the agricultural system. The system is constantly updated with incoming data and training continues. The parameters controlled and reported to the user at this stage are the amount of water, the number of nutrients in the water, temperature, and light parameters.

The water pump engine in the agriculture/greenhouse system is switched with the help of a microprocessor and switch model, allowing water to pass at the desired time and amount. Water and nutrient amounts are also controlled by sensors in the tank.

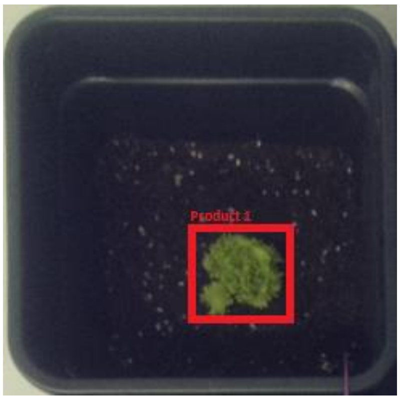
When the items in the tank fall below the threshold values to be determined by the system, the system is activated and the necessary notifications are made to add the missing item to the tank. These threshold values are also determined for temperature and light and reported by the system by observing the changes. The data and outputs obtained in all phases are presented to the user over the cloud. All data sent to the remote server via REST service is kept in the NoSQL database, just like on the local server.

Within the scope of this study, control interfaces and dashboard screens presented to the user were developed. Thanks to these interfaces, all sensor data and camera images can be accessed and the outputs of the system are presented to the user.

4. Results

The growth rate of the lettuce plant was determined by measuring the intensity of the amount of green color. Figure 2 shows the detection of the green color on the image of a product and the marking of the area.

a)



b)

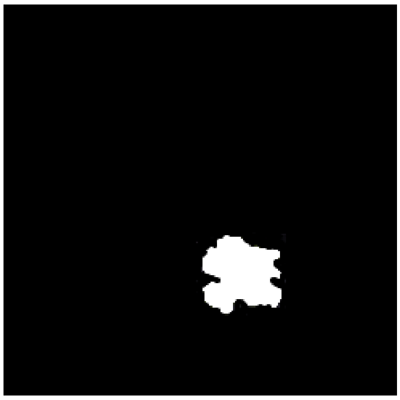


Figure 2. a) Draw a border around the area with green color, b) Image converted to HSV space

Color detection is performed on each image coming from the camera. The size of the area with the green color is calculated and recorded for each image. While the area size information is being recorded, it is matched with the data coming from the sensors at that moment. Table 2 shows sample rows of data collected from sensors and product growth rates. The relationship between the temperature data, which is one of the sensor data, and the growth rate of the plant is shown in Figure 3.

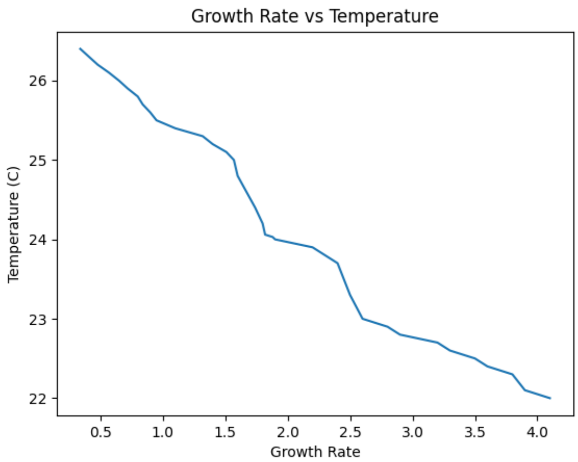


Figure 3. Temperature - Growth Rate Relationship

Table 2. Product growth rate and sensor values

Temperature (C)	Humidity Level (Soil)	Light Intensity	CO_2	pH	Product Growth Rate
26.4	401	422	420	4.7	0.3
26.3	415	583	550	4.7	0.2
26.2	422	588	446	4.7	0.4
26.1	425	786	685	4.8	0.5
26.0	425	632	548	4.8	0.7
25.9	425	564	776	4.7	0.9
25.8	434	558	675	4.9	1.1
25.7	437	643	588	4.8	1.1
25.6	438	773	764	4.9	1.4
25.4	454	535	528	4.9	1.5
25.3	465	592	761	4.7	1.5
25.2	477	705	435	4.7	1.6
25.1	504	756	552	4.9	1.7
25.0	528	457	504	4.8	1.6
24.8	544	808	519	5.0	1.8
24.4	587	422	606	4.9	1.9
24.2	610	743	724	4.8	2.0
24.1	634	667	512	4.9	1.8
24.1	655	690	501	4.7	1.8
24.0	668	496	456	4.7	1.9
23.9	670	713	743	4.9	2.2
23.7	687	750	808	5.0	2.4
23.3	687	803	618	4.9	2.5
23.0	699	735	629	5.1	2.6
22.9	720	476	479	4.9	2.8
22.8	738	458	664	5.0	2.9
22.7	743	460	567	5.1	3.2
22.6	775	629	496	5.0	3.3
22.5	790	466	599	5.3	3.5
22.4	807	741	778	5.2	3.6
22.3	808	804	748	5.3	3.8
22.2	808	737	455	5.2	3.5
22.1	814	606	790	5.4	3.9
22.0	822	768	432	5.4	4.1

A dataset was created with the data obtained from the sensors and cameras. The purpose of creating this dataset is to predict how much growth occurs in the plant at which sensor values. In the dataset, in addition to the columns above, there are unique values assigned to the sensors and the time of each measurement. The average of the measurements made every 12 hours is taken and the growth rate of the plant is determined and calculated by image processing methods.

The neural network has been established to process this created dataset. The artificial neural network model generally consists of three parts: input layer, hidden layer and output layer. 20% of the dataset was reserved for testing and the rest was used for training. The steps of the machine learning pipeline are shown in Figure 4.

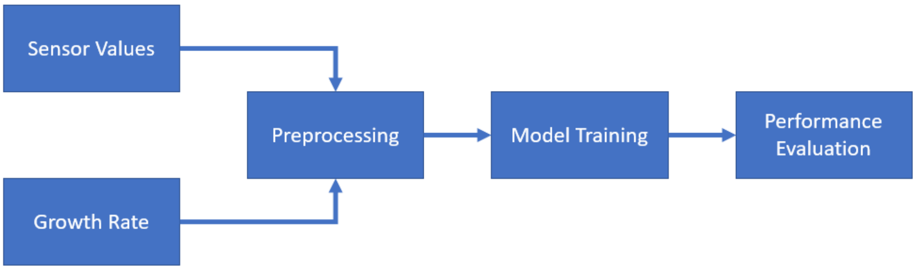


Figure 4. Steps of machine learning pipeline

In the study, the data to be included in the disaggregated groups of the data set, namely training and test data, were randomly selected from among the entire dataset. The maximum number of iterations was determined as 5000, and the training of the network was terminated as soon as it fell below the specified error amount.

Since the data presented to the network is in a very wide range, in different units, and disproportionate, giving it directly to the network will cause the network to be trained incorrectly. At the exit of the network, it was asked to convert it back to its original scale and the results were evaluated in this direction.

The accuracy of the model obtained was 96.2%. To interpret the obtained model, the SHAP technique was used to evaluate the importance of each feature in determining the predicted output.

Figure 5 shows the importance of the features in the dataset according to the developed model. As seen in the figure, the most important feature according to the model, is the temperature. The next important feature is humidity.

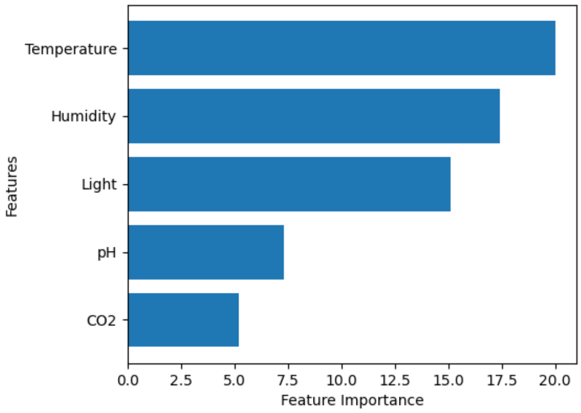


Figure 5. Feature importance

5. Discussion

In the proposed IoT solution within the scope of this study, many sensors were used and measurements were made continuously. A dataset was created with the data obtained from the sensors and cameras and a neural network was applied to this dataset. The importance of features is listed by using the SHAP method.

6. Conclusion

In this study, an IoT system was designed to successfully track plant growth. Thanks to this system, a dataset was created with the growth rate of the plant and the sensor data during this growth. Then, by training a neural network with this dataset, it has been seen that it can be predicted how much growth has occurred in which sensor values. The accuracy of the model was calculated as 96.2%. Thanks to such a system, information on the conditions under which plants should be grown can be obtained using different image processing and machine learning methods. Thus, the provision of suitable conditions for plant growth in a greenhouse can be achieved autonomously.

Acknowledgment

This study is supported by Istanbul Esenyurt University as scientific research project (BAP) with 2020/02 project code.

References

Abhishesh, P., Ryuh, B., Oh, Y., Moon, H., and Akanksha, R. (2017), “Multipurpose agricultural robot platform: Conceptual design of control system software for autonomous driving and agricultural operations using programmable logic controller,” World Acad. Sci. Eng. Technol. Int. J. Mech. Aerosp. Ind. Mechatronic Manuf. Eng., vol. 11, no. 3, pp. 496–500.

Abu, M.A., and Yacob, M.Y. (2013), "Development and simulation of an agriculture control system using fuzzy logic method and visual basic environment", In 2013 International Conference on Robotics, Biomimetics, Intelligent Computational Systems, pp. 135-142.

Amin, M.S.M., Aimrun, W., Eltaib, S.M., and Chan, C.S. (2004), “Spatial soil variability mapping using electrical conductivity sensor for precision farming of rice,” Int. J. Eng. Technol., vol. 1, no. 1, pp. 47–57.

Benaissa, S., Plets, D., Tanghe, E., Trogh, J., Martens, L., Vandaele, L., Verloock, L., Tuyttens, F.A.M., Sonck, B., Joseph, W. (2017), “Internet of animals: Characterisation of LoRa subGHz off-body wireless channel in dairy barns,” Electron. Lett., vol. 53, no. 18, pp. 1281–1283.

Dan, L., Xin, C., Chongwei, H., and Liangliang, J. (2015), “Intelligent agriculture greenhouse environment monitoring system based on IoT technology,” in Proc. Int. Conf. Intell. Transport. Big Data Smart City, pp. 487–490.

Dlodlo, N., and Kalezhi, J. (2015), “The Internet of Things in agriculture for sustainable rural development,” in Proc. Int. Conf. Emerg. Trends Netw. Comput. Commun. (ETNCC), pp. 13–18.

Ferentinos, K.P., Albright, L.D. (2007), Predictive neural network modeling of Ph and electrical conductivity in deep-trough hydroponics. Trans. ASAE 45 (6), 2007–2015.

Fuangthong, M., and Pramokchon, P. (2018), “Automatic control of electrical conductivity and PH using fuzzy logic for hydroponics system,” in 2018 International Conference on Digital Arts, Media and Technology (ICDAMT), pp. 65–70.

Gan, W., Zhu, Y., and Zhang, T. (2010), “On RFID application in the tracking and tracing system of agricultural product logistics,” in International Conference on Computer and Computing Technologies in Agriculture. Nanchang, China: Springer, pp. 400–407.

García-Lesta, D., Cabello, D., Ferro, E., López, P., and Brea, V.M. (2017), “Wireless sensor network with perpetual motes for terrestrial snail activity monitoring,” IEEE Sensors J., vol. 17, no. 15, pp. 5008–5015.

Giri, A., Dutta, S. and Neogy, S. (2016), “Enabling agricultural automation to optimize utilization of water, fertilizer and insecticides by implementing Internet of Things (IoT),” in Proc. Int. Conf. Inf. Technol. (InCITe) Next Gener. IT Summit Theme Internet Things Connect Your Worlds, pp. 125–131.

Gómez-melendez, D., López-lambraño, A., Ruiz, G.H., Rico-garcia, E., Olvera-olvera, C., and Alaniz-lumbrerasc, D. (2011), “Fuzzy irrigation greenhouse control system based on a field programmable gate array”, African J. Agric. Res., vol. 6, no. 11, pp. 2544–2557.

Gosavi, J.V. (2017), “Water monitoring system for hydroponics agriculture”, International Journal for Research in Applied Science and Engineering Technology, vol. 5, no. 7, pp 234-238.

Huang, L., and Liu, P. (2014), Key Technologies and Alogrithms’ Application in Agricultural Food Supply Chain Tracking System in E-Commerce. Beijing, China: Springer, pp. 269–281, doi: 10.1007/978-3-642-54341-8-29.

Kaloxylos, A., Eigenmann, R., Teye, F., Politopoulou, Z., Wolfert, S., Shrank, C., Dillinger, M., Lampropoulou, I., Antoniou, E., Pesonen, L., Nicole, H., Thomas, F., Alonistioti, N., Kormentzas, G. (2012), “Farm management systems and the future Internet era,” Comput. Electron. Agricult., vol. 89, pp. 130–144.

Kodali, R.K., Jain, V., and Karagwal, S. (2016), “IoT based smart greenhouse,” in Proc. IEEE Region 10 Humanitarian Technol. Conf. (R10-HTC), pp. 1–6.

Lee, H., Moon, A., Moon, K., and Lee, Y. (2017), “Disease and pest prediction IoT system in orchard: A preliminary study,” in Proc. 9th Int. Conf. Ubiquitous Future Netw. (ICUFN), Milan, Italy, pp. 525–527.

Lerdsuwan, P., and Phunchongharn, P. (2017), “An energy-efficient transmission framework for IoT monitoring systems in precision agriculture,” in International Conference on Information Science and Applications. Singapore: Springer, pp. 714–721.

Li, L. (2011), “Application of the Internet of Thing in green agricultural products supply chain management,” in Proc. IEEE Int. Conf. Intell. Comput. Technol. Autom. (ICICTA), vol. 1. Shenzhen, China, pp. 1022–1025.

Ludwig, F., Fernandes, D.M., Mota, P., Bôas, R. (2013), Electrical conductivity and pH of the substrate solution in gerbera cultivars under fertigation. Hortic. Bras. 31 (3), 356–360.

Manrique, J.A., Rueda-Rueda, J.S., and Portocarrero, J.M.T. (2016), “Contrasting Internet of Things and wireless sensor network from a conceptual overview,” in Proc. IEEE Int. Conf. Internet Things (iThings) IEEE Green Comput. Commun. (GreenCom) IEEE Cyber Phys. Soc. Comput. (CPSCom) IEEE Smart Data (SmartData), Chengdu, China, pp. 252–257.

Mainetti, L., Mele, F., Patrono, L., Simone, F., Stefanizzi, M.L., Vergallo, R. (2013), “An RFID-based tracing and tracking system for the fresh vegetables supply chain,” Int. J. Antennas Propag., vol. 2013, Art. no. 531364.

Mat, I., Kassim, M.R.M., Harun, A.N., and Yusoff, I.M. (2016), “IoT in precision agriculture applications using wireless moisture sensor network,” in Proc. IEEE Conf. Open Syst. (ICOS), pp. 24–29.

Morimoto, T., and Hashimoto, Y. (1991), “Application of fuzzy logic and neural network to the process control of solution pH in deep hydroponic culture,” IFAC Proc. Vol., vol. 24, no. 11, pp. 147–152.

Munandar, A., Fakhrurroja, H., Rizqyawan, M. I., and Pratama, R.P. (2017), “Design of Real-time Weather Monitoring System Based on Mobile Application using Automatic Weather Station”, International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT), pp. 44–47.

Oksanen, T., Linkolehto, R., and Seilonen, I. (2016), “Adapting an industrial automation protocol to remote monitoring of mobile agricultural machinery: A combine harvester with IoT,” IFAC PapersOnLine, vol. 49, no. 16, pp. 127–131.

Pekoslawski, B., Krasinski, P., Siedlecki, M., and Napieralski, A. (2013), “Autonomous wireless sensor network for greenhouse environmental conditions monitoring,” in Proc. 20th Int. Conf. Mixed Design Integr. Circuits Syst. (MIXDES), pp. 503–507.

Peuchpanngarm, C., Srinitiworawong, P., Samerjai, W., Sunetnanta, T. (2016), DIY sensorbased automatic control mobile application for hydroponics. In: Proc. 2016 5th ICT Int. Student Proj. Conf. ICT-ISPC, pp. 57–60.

Pitakphongmetha, J., Boonnam, N., Wongkoon, S., Horanont, T., Somkiadcharoen, D., Prapakornpilai, J. (2016), Internet of things for planting in smart farm hydroponics style. In: 20th Int. Comput. Sci. Eng. Conf. Smart Ubiquitous Comput. Knowledge, ICSEC.

Regattieri, A., Gamberi, M., and Manzini, R. (2007), “Traceability of food products: General framework and experimental evidence,” J. Food Eng., vol. 81, no. 2, pp. 347–356.

Rubala, J.I., and Anitha, D. (2017), “Agriculture field monitoring using wireless sensor networks to improving crop production,” Int. J. Eng. Sci., vol. 5216, pp. 5216–5221.

Suhardiyanto, H., Seminar, K.B., Chadirin, Y., and Setiawan, B.I. (2011), “Development Of A pH Control System For Nutrient Solution In EBB And Flow Hydroponic Culture Based On Fuzzy Logic,” IFAC Proc. Vol., vol. 34, no. 11, pp. 87–90.

Tripicchio, P., Satler, M., Dabisias, G., Ruffaldi, E., and Avizzano, C.A. (2015), “Towards smart farming and sustainable agriculture with drones,” in Proc. IEEE Int. Conf. Intell. Environ. (IE), Prague, Czech Republic, pp. 140–143.

Wang, N., Zhang, N., and Wang, M. (2006), “Wireless sensors in agriculture and food industry—Recent development and future perspective,” Comput. Electron. Agricult., vol. 50, no. 1, pp. 1–14.

Zhang, P., Zhang, Q., Liu, F., Li, J., Cao, N., and Song, C. (2017), “The construction of the integration of water and fertilizer smart water saving irrigation system based on big data” in Proc. IEEE Int. Conf. Comput. Sci. Eng. (CSE) IEEE Int. Conf. Embedded Ubiquitous Comput. (EUC), vol. 2. Guangzhou, China, pp. 392–397.

Zhang, S., Chen, X., and Wang, S. (2014), “Research on the monitoring system of wheat diseases, pests and weeds based on IoT,” in Proc. 9th Int. Conf. Comput. Sci. Educ., Vancouver, BC, Canada, pp. 981–985.

Zhao J.C., Zhang, J.F., Feng, Y., and Guo, J.X. (2010), “The study and application of the IoT technology in agriculture,” in Proc. 3rd Int. Conf. Comput. Sci. Inf. Technol., vol. 2. Chengdu, China, pp. 462–465.