Evaluation of an IoT System Used with Sensors for the Recognition of Invasive Plants in Groundnut Crops

Bruno M. Moreno*†, Paulo E. Cruvinel*†, and Augusto G. F. Costa‡

* Embrapa Instrumentation (CNPDIA), São Carlos, SP, Brazil
† Postgraduate Program in Computer Science, Federal University of São Carlos, São Carlos, SP, Brazil
‡ Embrapa Cotton, Campina Grande, PB, Brazil
Emails: bruno.moreno@estudante.ufscar.br, paulo.cruvinel@embrapa.br, augusto.costa@embrapa.br

***Abstract*—Sensors are quite important for data collection from the physical agricultural world, and also a key part of the Internet of Things (IoT) ecosystem. The IoT has enabled monitoring and automation in agriculture, supporting the implementation of precision agriculture applications using sensors in the field. However, the effectiveness of these systems depends on the accurate verification and assessment of network parameters such as connectivity, sensor reliability, and data integrity. Ensuring the proper functioning of IoT devices is crucial to maintaining efficiency, reducing costs, and improving overall agricultural outcomes. This study highlights factors to consider when developing an IoT system based on an experimental field study for pattern recognition of invasive plants in groundnut crops, resulting in classifiers with an accuracy of approximately 80%.**

Keywords-IoT sensor; IoT communication; pattern recognition; precision agriculture; weed management.

I. INTRODUCTION

Since its initial conception, the Internet of Things (IoT) has enabled a range of application possibilities in different areas, as the concept of devices acquiring data from the environment, communicating with each other, and performing actions based on this exchange of information would allow for a multitude of control and surveillance actions, managed locally and in an automated manner. With the new opportunity landscape driven by lower hardware prices, advanced computing, cloud storage, higher speed and lower connectivity costs, current investments in IoT applications are predicted to contribute to an annual global growth of 0.99% Gross Domestic Product (GDP) by 2030 [1].

Such applications make use of a variety of sensors capable of wireless communication with other devices. The main objectives of these sensors are to obtain information of interest from the external physical environment, sample internal signals from the system, and interpret the data, allowing decision-making performance [2]. Sensors must be part of a wireless network with other devices, not necessarily connected to the Internet, as there is data exchange. Therefore, it is important to highlight that there are three key points in IoT systems: capture and processing of data collected by sensors; communication between devices; and aggregation, processing and interpretation of data from different sensors.

Sensors used in IoT can vary greatly, as long as there is the possibility that their output can be transmitted wirelessly. For agricultural applications, for example, position sensors can be used to detect the location of the device when attached to a drone or an animal; temperature, chemical and humidity sensors to know what the environmental situation is in real time in the field; water quality sensors to monitor water reservoirs; and infrared and optical sensors to monitor crops or livestock in the field [3].

The use of IoT sensors can help address one of the challenges in groundnut (*Arachis hypogaea*) cultivation, which is invasive plant interference, since the crop is highly susceptible to competition due to its slow initial growth [4]. The presence of invasive plants in groundnut crops can result in productivity losses greater than 90% and can interfere with the harvesting process, increasing production costs and potentially impacting product quality [5]. Optical and position sensors can then be used to assist in the use of computer vision, based on the development of systems that recognize invasive plants in the environment and allow specific and localized decisions on how to treat the crop [6].

In the literature, many studies propose methods to combine weed detection and classification with IoT systems. Most of them focus more on processing operations but leave aside IoT assessments and sensor data management, focusing more on hypothetical applications of the algorithms in an IoT model. Kansal *et al.* proposed an IoT-Fog computing-enabled robotic system for weed and soybean classification during normal and foggy seasons, processing well hazy images [7], while Tiwari *et al.* also developed a system using IoT camera sensors and cloud computing for a Deep Learning (DL) weed classification for a public dataset of 12 weed species [8]. On the other hand, Dankhara *et al.* proposed a model using a Raspberry Pi (RPi) 3 with a camera sensor and a sprayer for use with a weed classifier controlled remotely with the help of an Internet connection to an external server [9].

Kulkarni *et al.* developed a system capable of acquiring images using a RPi, detecting weeds by a Convolutional Neural Network (CNN) model trained offline, and the weed segments are marked and sent to farmers via email by the Global System for Mobile Communications (GSM) module [10]. Likewise, Farooq *et al.* built a fast and high-performance DL model that required less computing power on a RPi 4 to enable on-device machine learning, using a public dataset for weed detection [11]. All these studies used images acquired from existing databases, not testing the proposed systems in real field conditions using their own sensors, and therefore their IoT specifications and limitations were not considered and prioritized, except for those related to the computational cost of data processing and strategies to reduce it.

Moreno and Cruvinel presented previous studies related to a stereo camera's system using IoT principles, specifying the optical sensor bias correction process [12], and the development of a software based on semantic computing concepts for the segmentation of invasive plants [13]. Expanding the previous studies, this work aims to develop an IoT system for recognizing more than one invasive plant species in groundnut crops capable of acquiring stereo images in a real-field operation, providing processing in real images acquired from wireless commands in an experimental field. Therefore, the limitations regarding handling data obtained by IoT sensors in practical application are considered more carefully.

This paper is structured as follows. Section II presents the materials and methods used, including IoT sensor data insights, IoT communication protocols, camera sensor specifications, and method for recognition of invasive plants. Section III presents the results and discussion of the IoT system developed and the classifiers utilized, with the final conclusions and proposed future works in Section IV.

II. Material and Methods

This section will delve into the specifications and points of interest when collecting and managing data from IoT sensors, important protocols for IoT communication, and specifications of the devices and camera sensors used. Furthermore, an overview of the algorithm for invasive plant recognition is presented, including the experimental setup for collecting and working with data collected by the camera sensors in a real cultivation environment.

A. IoT Sensor Data Insights

The development of IoT systems must take into account the quality and quantity of data generated by sensors in order to generate useful information that can be verified as a whole. Data is also transmitted over a network, and therefore both aspects related to the transmission and storage of this data and those related to the security of the network as a whole must be considered. Therefore, when analyzing sensor data, the following characteristics need to be points of interest in the system development stages:

1) Security: The network and its transmitted data must guarantee the privacy of information, that is, sensor data will only be transmitted to trusted devices. Data cannot be transmitted or captured by other devices outside the configured and trusted network, while data on the network must remain authentic, not suffering from external attacks with the injection of erroneous data packets. Data must also remain intact, considering the transmission errors inherent in wireless networks. Measures that can be taken include Secure Sockets Layer/Transport Layer Security (SSL/TLS), Datagram Transport Layer Security (DTLS), Blockchain and Elliptic Curve Cryptography (ECC) [14].

2) Scalability: Because the sensor network includes data sources from multiple sensors and actuators, it must be scalable to handle the exponential growth of devices and data handling. Latency should not be so high that it hinders processing steps to the point of making operations and decision-making, especially in real time, impractical [15].

3) Bandwidth Availability: Bandwidth can be a bottleneck in the transmission path, resulting in many problems such as sensor data loss, delays and congestion. It is necessary to correctly predict which communication path between devices will have the most information being transmitted or to develop algorithms to be able to dynamically change the bandwidth availability of the paths, creating a reallocation plan according to a set of criteria such as data importance and data volume. If system latency and bandwidth are not critical, a cloud computing scenario can be enough [16].

4) Battery Life: Devices and sensors in an IoT system must be energy efficient and capable of low-power communication with low-cost on-node processing. They can be battery-powered, capable of alerting when power is low to allow for early battery replacement, or harvest energy from the environment, for example, using a solar cell.

5) Data Volume: Due to the large volume of data generated by sensors, it is necessary to pass them through cleaning, noise removal and outlier detection processes to obtain only the relevant information. This volume can generate both an increase in the computational cost of the system in these steps and overload the transmission network. In addition, this data and the processing results can be saved on the devices, which means that their memory and storage capacity must be considered when building the system, even in cases where the data is partially saved in the cloud.

6) Exposure Risk: Technical constraints of devices, such as sensor size, make them vulnerable and prone to failure, attack and breakage. Therefore, it is recommended to use protective cases against unwanted external elements, especially for field operations where sensors may be exposed to rain, dust, extreme temperatures and even damage from animals. IoT systems must also be secure so that they cannot be accessed inappropriately or subject to fraud by human action, ensuring reliable information.

B. IoT Communication Protocols

The general structure of an IoT system can be exemplified by Figure 1, in which fog processing can be performed near or at the sensor node. In the Edge Computing node, the data can be stored and processed locally, allowing only useful data to be transmitted to other devices or to the cloud, while the Fog Computing node waits for a considerable amount of local computation, storage, and communication to complete before performing the transmission over the web.

The Bluetooth used communication can support up to 7 devices connected simultaneously, supporting a maximum transfer rate of 1 Mbps, with a signal range of 10 m away from the device indoors and up to 50 m outdoors.

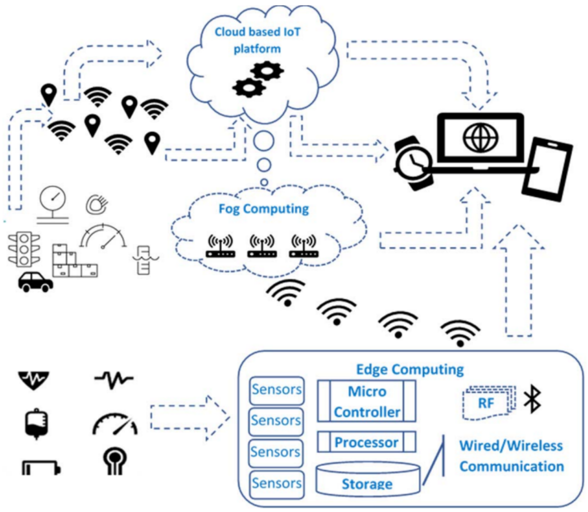

Figure 1: Example of IoT systems structure, with sensor data processing level node [14].

One of the protocols used is Radio Frequency Communication (RFCOMM). The RFCOMM protocol is a serial interface to the Bluetooth transport layer, emulating an RS-232 interconnect cable. RFCOMM is built upon the ETSI 07.10 standard, which allows the emulation and multiplexing of multiple serial ports on a single transport [17]. Additionally, the OBEX protocol (OBject EXchange) is utilized for file transfer, which is a software implementation of the File Transfer Protocol (FTP) network protocol, which runs on top of RFCOMM.

C. Camera Sensor Specifications

For the task of invasive plant recognition, an optical sensor in the visible spectrum is capable of capturing sufficient data. Therefore, an RGB camera and a control device for managing the sensor (responsible for turning on, adjusting settings, and triggering the camera) and the wireless data transmission are required in the development of the IoT system. Thus, the RPi 3 model B+ and Pi Camera v1 were chosen as the device and the sensor, as can be seen in Figure 2.

The use of the RPi in agriculture has been observed because it is a state-of-the-art computer with numerous practical applications in all areas of activity [18]. The embedded computer, combined with its sensors, allows both image capture and processing in the same module, allowing applications in stereo systems and precision agriculture [19]. The RPi requires a 5 V power supply and up to 2.5 A to power itself and the attached optical sensor, with its own operating system installed, the RPi OS, known as Raspbian.

The RPi model has a 64-bit BCM2837B0 Cortex-A53 (ARMv8) processor, 1 GB of SDRAM, and a processor speed of 1.4 GHz. The size of the internal memory is determined by the capacity of the chosen micro SD card, with a minimum of 8 GB being recommended. The RPi supports Local Area Network (LAN) and Bluetooth Low Energy (BLE) wireless communication from a Cypress CYW43455 chip. The Pi camera has a fixed focal length of 3.60 mm, a maximum sensor resolution of 2592 x 1944 *pixels*, and a camera aperture angle of 53.50º horizontally and 41.41º vertically. In addition, the camera's ideal focus is 1 m - ∞ and its signal-to-noise ratio is 36 dB. Another important detail is that the RPi automatically adjusts the camera's brightness and white balance, but if necessary, it is possible to correct these values via software. These and other specifications can be seen in Table I.

D. Recognition of Invasive Plant

1) Experimental Setup: For the practical experiment, two invasive plants of groundnut crops (cultivar IAC OL3) were chosen for analysis: velvet bean (*Mucuna aterrima*), a plant with broad and dark green leaves; and signal grass (*Urochloa decumbens*), a plant with long and blade-shaped leaves. The experiment was carried out in the municipality of Jaboticabal-SP, Brazil. Pest and disease management was carried out according to specific recommendations for the crop [20]. The groundnut cultivation area selected for the experiment totals 72 m^2 and, to simulate the presence of the invasive plants, they are sown together and separately with the groundnuts. Once grown, field images are captured from this simulation.

2) Feature Extraction: Once collected, the images are preprocessed, filtering out noise and biases derived from the intrinsic characteristics of the sensor.

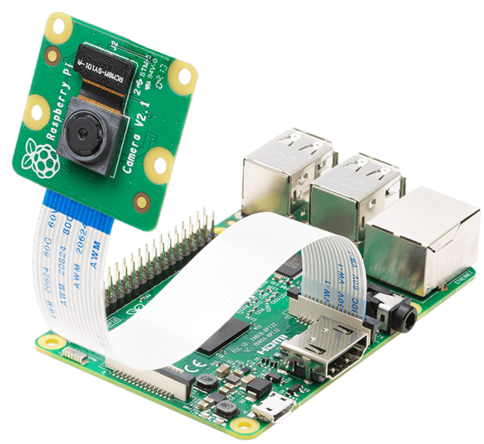

Figure 2: Sensor and connected device.

TABLE I: Pi Camera Characteristics

Size	25 x 24 x 9 mm
Resolution	5 MP
Video modules	1080p30, 720p60, 640x480p60/90
Sensor	OmniVision OV5647
Sensor resolution	2592 x 1944 pixels
Sensor image area	3.76 x 2.74 mm
Pixel size	1.4 μm x 1.4 μm
Optical size	1/4"
Full-frame SLR equivalent	35 mm
S/N Ratio	36 dB
Dynamic range	67 dB @ 8 times gain
Fixed focus	1 m - ∞
Focal length	3.60 ± 0.01 mm
Horizontal field of view (HFOV)	53.50° $\pm$ 0.13°
Vertical field of view (VFOV)	41.41° $\pm$ 0.11°
Focal ratio (F-stop)	2.9

The object of interest is selected from a histogram threshold segmentation, in which the original image is converted to the Hue-Saturation-Value (HSV) color space and a range in the H channel corresponding to the colors of the plants is selected. This method presents a better result when segmenting plants, reducing the impact of variations in illumination and saturation in different images [21]. To improve the result, morphological closing and opening operations are applied to reduce small holes and objects present, respectively.

From this point on, the segmented image is used as a mask on the original image, and based on the intensity of the remaining pixels, the features of the imaged plants are extracted using a texture descriptor and a shape descriptor. The texture descriptor used is based on five Haralick moments: energy, entropy, contrast, homogeneity and correlation [22]. The shape descriptor is the Local Binary Patterns (LBP), applied on the edges of the leaves obtained by the Canny edge detection algorithm [23][24].

3) Pattern Recognition: The descriptor data are grouped into vectors, corresponding to windows present in the image, which are used to train a classifier that assists in the separation of invasive plant species from families. Each window is manually and binary labeled with the presence or absence of each plant. The classifier used was the Support Vector Machine (SVM) [25], varying the internal parameters and dividing the samples into 80% for training and 20% for testing. As the main evaluation metric, the accuracy of the classifier is used, in which the rate of correct predictions is analyzed in relation to the total number of samples tested. Other metrics, such as precision, sensitivity and F-score, are also considered for evaluating the robustness of the classifier, weighting both false positives and false negatives predictions.

III. Results and Discussion

The system was evaluated in relation to the modeling of IoT systems and its experiment in real field application, analyzing the hardware used in its construction and the operational parameters, including the communication protocols and sensor data management. In addition, the results of the classifier for the experimental groundnut cultivation plot were obtained, with its metrics, processed digital images, and application cost analysis.

A. IoT System Evaluation

The IoT system developed consists of two camera sensors each one attached to an RPi with a 32 GB micro SD card, power supplied by a 12 V 60 Ah battery with voltage converted to 5 V, an Android cell phone for user control, and a structure and protective case to house the sensors. The cameras are pointed downwards to correctly capture the crop area. One of the RPis was defined as master, responsible for managing the network via Bluetooth, communicating with the other devices (the slave RPi and the cell phone).

The system was then evaluated, considering each of the topics of interest in IoT sensors. In terms of power, each RPi had a power consumption of around 3 W, and the total system, including other peripherals and converters, reached a maximum of 18 W. Thus, the battery was able to power the system uninterruptedly for 15 hours. The structure in which the sensors are located does not yet have autonomous movement and requires human supervision during its operation. However, if the equipment is coupled to a vehicle, robot or drone, its power supply may be shared with them, requiring a new evaluation of the energy consumption.

Regarding the volume of data, it was decided that each captured image would have a resolution of 1280 x 960 pixels, a resolution chosen so that the digital image would still contain a good amount of information without generating files that require a lot of storage capacity, using the PNG compression format. The data captured by both sensors was stored on the master RPi, because if it were necessary to perform stereo processing of the data, it would already be stored there. In this way, the system was able to save 6,000 images in memory.

To ensure system security, it is connected only to trusted equipment, using each device's Media Access Control (MAC) address and specific ports when creating wireless communication sockets. The devices automatically initiate their connection algorithms and protocols during their boot. If it is necessary to allow pairing of new mobile phones, the embedded systems must be accessed directly, which requires a fixed username and password to access the operating system.

Once communication was established, image capture was controlled via the cell phone, as shown in the pseudocodes in Figure 3. The Android application had buttons that, when pressed, sent a sequence of commands to the Master RPi via Bluetooth and serial communication. Each command consisted of a five word string. This command was used to capture images, transmit files to the cell phone, or shut down the system. The app interface can be shown in Figure 4, and is a Bluetooth serial controller that allows customization by the user, adding buttons and commands as needed.

Each operation had a 15-second delay to ensure that file management operations (especially saving the image file) were performed correctly by the devices. Wireless communication allowed data transmission to be performed uninterruptedly when manually requested by the user, avoiding corrupted files received. If the operator needed to view the image captured on his device only to monitor the system operation, a command could be sent that returned an image with a resolution of 320 x 240 pixels. This option ensured wireless communication during field operations with lower latency, in addition to allowing the user to check the number of images saved in memory based on the file name. In this way, the system was controlled wirelessly and thus able to capture and form a stereo image database relating to the groundnut cultivation field analyzed.

Compared to existing IoT models, the decision was made to store the data on the device instead of sending it to an external server or cloud. Furthermore, capturing real data using the system's own sensors allows for a more problem-focused assessment, acquiring images to train the classifier that represent the real challenges of the weed recognition

```
function IMAGE CAPTURE ON THE MASTER RPI(comd, resol, dir)
begin function
    while True do
        if comd == 'captr' then
            send(comd, Slave)                          ▷ sync trigger
            img ← capture_image(resol)
            save_image(img, dir)
            img2 ← receive_data(Slave)
            wait_operation()
            save_image(img2, dir)
        else if comd == 'send1' then
            send(img, cell_phone)
            wait_operation()
        else if comd == 'send2' then
            send(img2, cell_phone)
            wait_operation()
        else if comd == 'slres' then
            send(lower_resolution(img), cell_phone)
            wait_operation()
        else if comd == 'shutd' then
            send(comd, Slave)
            wait_operation()
            shutdown_system()
        end if
    end while
end function

function IMAGE CAPTURE ON THE SLAVE RPI(resol, dir)
begin function
    while True do
        comd = receive_data(Master)
        if comd == 'captr' then
            img2 ← capture_image(resol)
            save_image(img2, dir)                      ▷ optional
            send(img2, Master) ▷ via OBEXFTP protocol
            wait_operation()
        else if comd == 'shutd' then
            shutdown_system()
        end if
    end while
end function
```

Figure 3: Pseudocode for image capture on both RPis controlled by bluetooth.

Figure 4: Android application interface for wireless communication.

task. Thus, the results of the classifiers will be more robust when compared to classifiers trained with images that may not accurately represent the variability found in real environments.

B. *Classifier Results*

Sixty-four georeferenced images of 1280 x 960 pixels were obtained, representing the crop field where the plants grew. Each image captured 0.76 m² of the experimental area, forming an 8 by 8 grid. The ideal threshold range for the segmentation process was H channel values between 25 and 70; morphological operations eliminated objects with less than 75 pixels in area and holes smaller than 150 pixels. By dividing the images into square windows of 100 pixels (eliminating the regions where the foot of the device responsible for the capture was located), a total of 6912 samples were obtained (108 per image), of which 5529 were separated for training the classifiers and 1383 for testing. The vector obtained by the feature extraction stage had a size equal to 14 per window.

For the SVM classifiers, three kernels were analyzed: linear, Gaussian and Radial Basis Function (RBF). The kernel functions aim to better deal with non-linear patterns of similarity between elements of the same class. Analyzing all of them and considering the processing time and accuracy, the best configuration for weed classification was the RBF kernel (C = 1000 and $\gamma = 0.01$), with an accuracy of 79.2% for signal grass and 81.1% for velvet bean.

Table II shows the final result of the SVM classifiers for each invasive plant, with the total values and individuals for each class, considering that for the samples the null hypothesis $\mathcal{H}_0$ corresponds to the case of no invasive plant, while the alternative hypothesis $\mathcal{H}_1$ is when there is presence of the invasive plant in the sample window of the image. It can be observed that, although they have good accuracy and precision, the sensitivity for invasive plants is low, which could be improved by using a feature vector with more elements (adding more descriptors at the expense of processing time).

Figure 5 shows an example of the original image, the label used for training, and the results of the classifiers (black is not an invasive plant, false color is). In the labeled image, the green pseudocolor represents velvet bean, the blue represents signal grass, and the red represents other plants (including the groundnut plant).

Regarding the costs of a possible herbicide application, the control of signal grass was considered using Cletodim (0.4 L/ha) and mineral oil as adjuvant (0.5 L/ha) and the control of velvet bean with Imazapic (140 g/ha) and adjuvant (0.25 L/ha). The costs for the control of signal grass were estimated at USD 11.19/ha, and for velvet bean they were USD 51.43/ha. Since the experimental area was 72 m^2, if the product were applied uniformly throughout the area, the total cost of the weed management would be USD 0.45. Using the developed system, the classifiers obtained an area of occupation of signal grass of 4.12%, and of the velvet bean of 14.54%. Thus, if the herbicide application followed the proposed method and applied the product only where there are invasive plants, the cost of weed control would be USD 0.057 for the same area.

 ISBN: 978-1-68558-273-9

TABLE II: SVM classifier results

Classifier	Precision	Sensitivity	F-score	Samples	Accuracy
SVM velvet bean				1383	81.1%
$\mathcal{H}_1$	0.80	0.41	0.54	349	80.2%
$\mathcal{H}_0$	0.83	0.97	0.89	1034	82.8%
SVM signal grass				1383	79.2%
$\mathcal{H}_1$	0.72	0.14	0.23	313	71.7%
$\mathcal{H}_0$	0.80	0.98	0.88	1070	79.6%

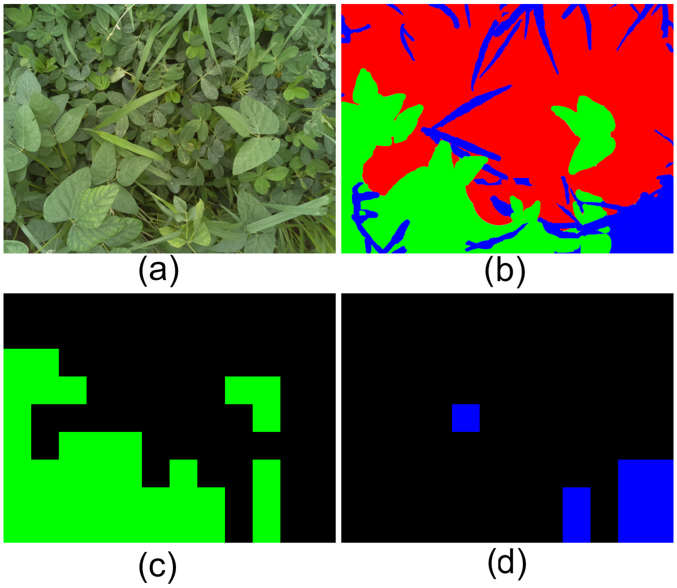

Figure 5: Recognition of invasive plants: (a) original image captured by the system, (b) manually labeled image, (c) classifier result for velvet bean, and (d) classifier result for signal grass.

It is possible to refine even more this result, using the information provided by the stereo sensors-based images to utilize the depth perception of the acquired images in the control of the invasive plants, allowing treatment in layers in relation to the height of the plants.

IV. CONCLUSION

It can be concluded that the use of IoT sensors can aid the task of recognizing and distinguishing the presence of different invasive plants in groundnut crops. This aids in more precise use of herbicides on crops and can be adapted to crops other than groundnuts, reducing the cost and environmental impact of weed control. Considering the decision-making steps, results have proved the usefulness of the developed sensor-based system to operate with great precision and generate information for agricultural management. Besides, important factors in handling IoT sensor data and communication have been observed, leading to a specific protocol and requirements related to security breaches as much as possible, and including functionalities to decrease latency.

The invasive plants classifiers achieved accuracy close to 80%; however, sensitivity can still be improved by refining the descriptors and the image working window. Despite the promising results, the current system is limited by the hardware on-device processing. For future work, it is being considered the integration of the system into Field Programmable Gate Array (FPGA) platform in order to have configurable possibilities related to prototyping based on high performance computing and thus improving the processing cost.

ACKNOWLEDGMENT

This work has been supported by the Brazilian Corporation for Agricultural Research (EMBRAPA), and the Coordenation for the Improvement of Higher Education Personel (CAPES).

REFERENCES

[1] H. Edquist, P. Goodridge, and J. H. and, "The internet of things and economic growth in a panel of countries," *Economics of Innovation and New Technology*, vol. 30, no. 3, pp. 262–283, 2021.

[2] R. Krishnamurthi, A. Kumar, D. Gopinathan, A. Nayyar, and B. Qureshi, "An overview of IoT sensor data processing, fusion, and analysis techniques," *Sensors*, vol. 20, no. 21, 2020, ISSN: 1424-8220.

[3] D. Sehrawat and N. S. Gill, "Smart sensors: Analysis of different types of IoT sensors," in *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, 2019, pp. 523–528.

[4] N. G. Sai and D. Subramanyam, "Impact of weed management practices on weed growth, crop yield and soil microbes in groundnut," *Indian Journal of Weed Science*, vol. 55, no. 3, pp. 340–344, 2023.

[5] Z. Gonzalez *et al.*, "Herbicide selectivity in peanut cultivars," *Journal of Agricultural Science*, vol. 10, pp. 447–447, Jul. 2018.

[6] J. F. S. Gomes and F. R. Leta, "Applications of computer vision techniques in the agriculture and food industry: A review," *European Food Research and Technology*, vol. 235, no. 6, pp. 989–1000, 2012.

[7] I. Kansal, V. Khullar, J. Verma, R. Popli, and R. Kumar, *Paladyn, Journal of Behavioral Robotics*, vol. 14, no. 1, p. 20 220 105, 2023.

[8] S. Tiwari *et al.*, "IoT-enabled model for weed seedling classification: An application for smart agriculture," *AgriEngineering*, vol. 5, no. 1, pp. 257–272, 2023, ISSN: 2624-7402.

[9] F. Dankhara, K. Patel, and N. Doshi, "Analysis of robust weed detection techniques based on the internet of things IoT," *Procedia Computer Science*, vol. 160, pp. 696–701, 2019, ISSN: 1877-0509.

[10] S. Kulkarni, S. Angadi, and V. Belagavi, "IoT based weed detection using image processing and cnn," *Int. J. Eng. Appl. Sci. Technol*, vol. 4, no. 3, pp. 606–609, 2019.

[11] U. Farooq *et al.*, "Lightweight deep learning model for weed detection for IoT devices," in *2022 2nd International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET)*, 2022, pp. 1–5.

[12] B. M. Moreno and P. E. Cruvinel, "An IoT stereo image sensor system for agricultural application," *International Journal On Advances in Software*, vol. 16, no. 3 & 4, pp. 160–171, 2023, ISSN: 1942-2628.

[13] B. M. Moreno and P. E. Cruvinel, "Computer vision system for identifying on farming weed species," in *IEEE 16th International Conference on Semantic Computing (ICSC)*, 2022, pp. 287–292.

[14] S. C. Mukhopadhyay *et al.*, "Artificial intelligence-based sensors for next generation IoT applications: A review," *IEEE Sensors Journal*, vol. 21, no. 22, pp. 24 920–24 932, 2021.

[15] H. Landaluce *et al.*, "A review of IoT sensing applications and challenges using rfid and wireless sensor networks," *Sensors*, vol. 20, no. 9, 2020, ISSN: 1424-8220.

[16] O. Said, "A bandwidth control scheme for reducing the negative impact of bottlenecks in IoT environments: Simulation and performance evaluation," *Internet of Things*, vol. 21, p. 100 682, 2023, ISSN: 2542-6605.

[17] C. Bisdikian, "An overview of the bluetooth wireless technology," *IEEE Communications Magazine*, vol. 39, no. 12, pp. 86–94, 2001.

[18] U. Saeed, M. Waqas, N. Mirbahar, and M. Khuhro, "Comparative analysis of different operating systems for raspberry pi in terms of scheduling, synchronization, and memory management," *Mehran University Research Journal of Engineering and Technology*, vol. 41, pp. 113–119, Jul. 2022.

[19] R. Neves and A. C. Matos, "Raspberry pi based stereo vision for small size asvs," in *2013 OCEANS - San Diego*, 2013, pp. 1–6.

[20] I. J. Godoy *et al.*, "Groundnut – arachis hypogaea l.," in *Instruções agrícolas para as principais culturas econômicas*, ser. Boletim IAC, A. T. E. Aguiar *et al.*, Eds., 7th ed., vol. 200, Campinas: Instituto Agronômico, 2014, pp. 22–27.

[21] C. S. Pereira, R. Morais, and M. J. C. S. Reis, "Recent advances in image processing techniques for automated harvesting purposes: A review," in *2017 Intelligent Systems Conference (IntelliSys)*, 2017, pp. 566–575.

[22] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-3, no. 6, pp. 610–621, 1973.

[23] R. Song, Z. Zhang, and H. Liu, "Edge connection based canny edge detection algorithm," *Pattern Recognition and Image Analysis*, vol. 27, pp. 740–747, 2017.

[24] V. N. T. Le, S. Ahderom, B. Apopei, and K. Alameh, "A novel method for detecting morphologically similar crops and weeds based on the combination of contour masks and filtered local binary pattern operators," *GigaScience*, vol. 9, no. 3, giaa017, Mar. 2020, ISSN: 2047-217X.

[25] T. U. Rehman, M. S. Mahmud, Y. K. Chang, J. Jin, and J. Shin, "Current and future applications of statistical machine learning algorithms for agricultural machine vision systems," *Computers and Electronics in Agriculture*, vol. 156, pp. 585–605, 2019, ISSN: 0168-1699.

 ISBN: 978-1-68558-273-9