SOIL ANALYSIS ROBOT: LOW-COST SOIL SENSOR AND EDGE AI FUSION

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ABSTRACT

Robots are developed and used more and more in agriculture every day, for various tasks like harvesting, planting, disease detection, plant treatment, etc. but there is a considerable gap in soil analysis even though it is one of the most important parts of agriculture if farmers want to have good crops. There are laboratories that do soil analysis but the process for farmers is laboring and time-consuming, and developed systems and robots from other researchers are usually very expensive due to the cost of sensors and overall robot. Taking this into consideration, we developed a simple mobile robot equipped with a low-cost soil sensor to collect the necessary parameters of soil for farmers, and also an edge device that runs an AI model to perform soil analysis with a camera which will help to make final information more reliable, given the fact that low-cost sensors have a bad reputation for reliability and precision. One of the advantages of this system is that the whole sensor and camera combination for measurement can be adapted very easily to any other existing mobile robot, and the overall cost of the measuring system including the edge device is less than 100 euros, which makes it a lot less expensive compared with other existing systems with still good results in the end. The ultimate goal at the end is to create an almost sensorless device that can perform soil analysis just by a camera and can be used in almost any agricultural robotic system.

1 INTRODUCTION

One of the hot topics in robotics development is in the field of agriculture, especially since the pandemics begin and people realize the importance of robotics and automation to replace some of the human labor. A systematic review of agricultural robotic systems made by Oliveira and others [1] shows that developed robots in that field are mainly focused on plants including plant treatment, disease detection, harvesting robots, sowing and planting robots, etc. One of the interesting findings of that review was the existence of a very large trade-off between the quality and the price of the cameras that are used in agriculture robotics since one of the main sensors on these robots is the camera.

Based on that review and our personal research, we see that there is a gap in soil analysis in robotics, knowing that as this process is crucial in agriculture, especially before planting and treating the plant further. Also, there is existing research that shows that in both emerging [2] and developed countries [3] there are barriers that keep farmers from adapting the latest technologies and robotic systems from applying them in their daily work. One of the leading reasons for that is the high cost of such systems.

Taking into account the gap of robotics in soil analysis, the unsolved problem of price/quality tradeoff for cameras in agriculture, and, high prices as one of the main barriers to adopting robotics in agriculture, we propose a modular device for robots that will tackle these issues. The main idea of such a device [better to give the device a name] is to be easily adapted for different robots as a modular part to use a combination of a low-cost camera and soil sensor yet still provide a detailed analysis of soil and terrain before and after planting. To compensate for the quality of the camera, we will be using different artificial intelligence (AI) algorithms in order to have better results even with a low-cost camera.

2 RELATED WORK

Łukowska et al [4] present a six-wheeled mobile robot that is designed to collect soil samples from the terrain and generate a report about soil properties at the end. Even though the robot's main purpose is specified to analyze the soil, authors mostly focus on the mechanical design and function of the robot and very less on how the robot is supposed to gather the soil data and what type of data will be processed. The authors suggest that the robot will carry the "laboratory" and will analyze the soil on the board of the robot without the need to send it to classic laboratories for results. A similar four-wheeled autonomous robot is developed by Ünal et al [5] which focuses specifically on measuring the electrical resistivity (ER) of soil and mapping it on a database based on which location it was measured. The developed robot is about 150kg, and in the size of a small motorbike, and uses the Wenner four-probe measurement method to measure ER in real-time, without the need of collecting samples of soil. Also, a differential global positioning system was used for real-time mapping and helped the robot position itself in the terrain. The same measurement method was used by Krishnan et al [6] but for a different purpose, to detect underground water on soil. Even though the same Wenner four-probe measurement was used, the robot overall is simpler since it is using Arduino as the main controller and simple GPS for mapping the location of detected water sources on the soil.

An interesting approach was made by Yan et al [7] with AgriRover, as they claim to bring space technology robotics to precision farming. Authors believe that technology used on robots such as ExoMars [8] or Curiosity [9] can help to collect soil parameters for large fields and as such help in increasing the overall quality and productivity of crops. Based on that, they developed a four-wheel robot that has a soil sample collecting mechanism, similar to other robots mentioned before in this chapter, and also an onboard soil nitrogen analyzer which is made possible by using laser-induced breakdown spectroscopy (LIBS). Robots also have an onboard Zed camera which is used for object detection to help the robot navigate easier through the field. Also, the same system to measure the nitrogen level with LIBS was analyzed in much more detail by the same author in another paper [10].

A robot that measures both plant and soil parameters is presented by Iqbal et al [11] which also is a four-wheeled robot equipped with Global Navigation Satellite Systems (GNSS) for autonomous navigation, and uses ROS (Robotic Operating System) with Nvidia Jetson Nano as the main processing unit. The robot is also equipped with LiDAR and a depth camera in order to estimate morphological traits of a plant such as height and volume and a manipulator with sensors to measure the temperature and humidity of the soil.

Fentanes et al [12] focus more on the physical properties of the soil such as soil compaction. The authors mention that traditional methods for data collection are costly, laborious, and lack quality information. Instead, they propose an outdoor mobile robot, which is equipped with a penetrometer and generates a 3D map of the soil compaction.

3 OUR APPROACH [Give your system a name and acronym]

[Start with the problem to solve, one sentence to repeat it here is ok]

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[Then introduce the proposed solution] To tackle this problem, we combined a simple mobile robot with a low-cost edge device that will focus mainly on identifying the properties of the soil and provide the necessary information to the farmer. [That this info is crucial, should rather be in the intro]. The nnn system consists of two main parts, sensor and robot control, and edge device with running AI algorithm which uses machine vision to analyze soil type and pH level.

The first part [name it], which contains ATmega328p, will be in charge as a main control unit for both moving the robot in a specific path using encoder data of DC motors and reading soil data such as NPK (nitrogen, phosphorus, and potassium), pH level, and EC (electrical conductivity) of the soil from the soil sensor which will communicate with the microcontroller via the RS-485 module. The soil sensor is mounted in the front of the robot on the specific mechanism (see figure 1) which will push it down to the soil with a DC motor, each time when a measurement is performed. Then measured data will be stored on an SD card in form of a text file ready to be read by the farmer.

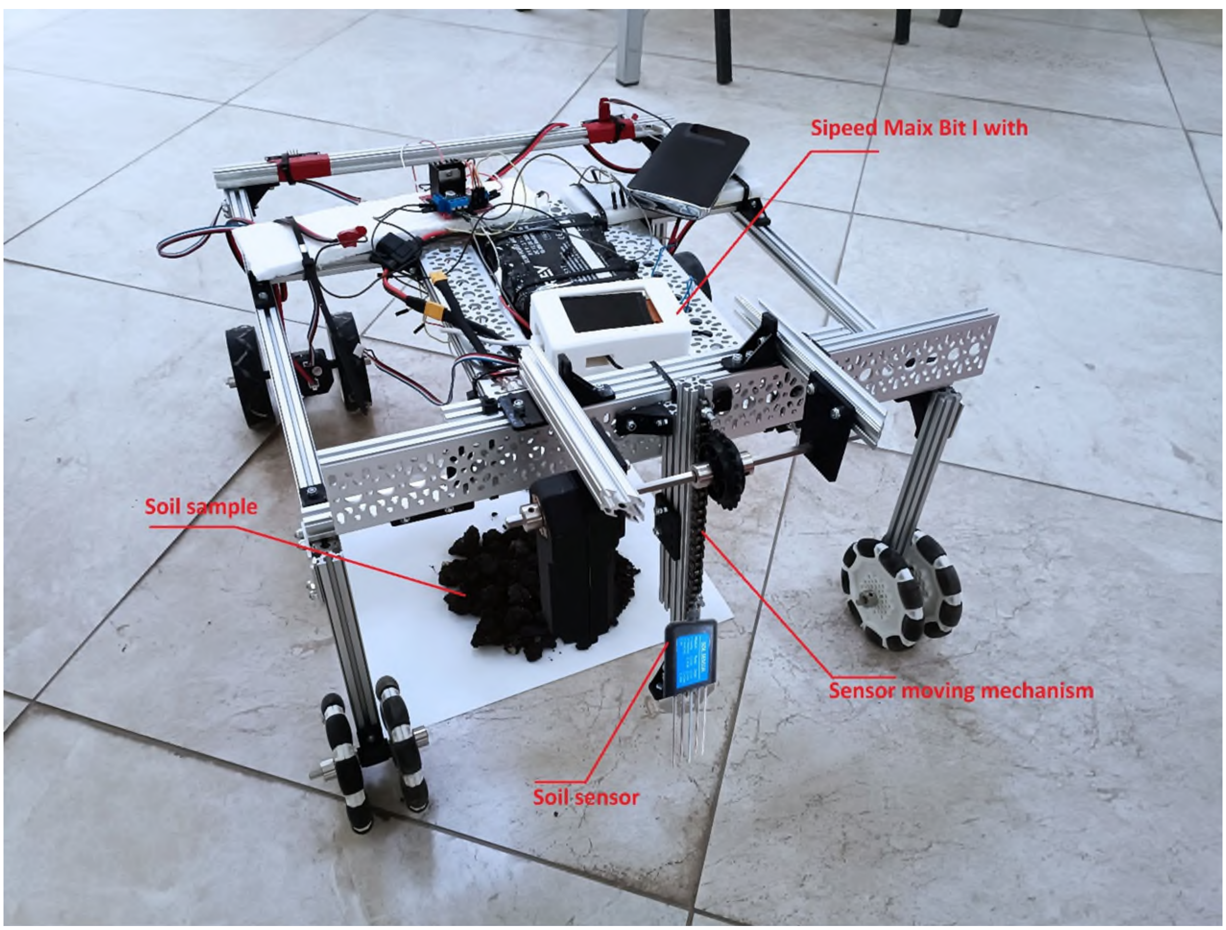

Figure 1. Robot construct [more descriptive. Name of platform, what is all seen]

Since the soil sensor we will use is low-cost and not very precise, we cannot rely 100% on the results that are measured directly from it. To verify the data, we propose an AI algorithm that runs on an edge device and predicts the type of soil and pH level. For soil prediction, an image classifier algorithm can do the job if the training data is good enough in both numbers and quality. The challenge, in that case, is that soil images do not have too many features that can help us to distinguish between types, so the training data is essential in that case. In our case, since the algorithm needs to run on an edge device, we used MobileNet architecture, which is a light version of the convolutional neural network (CNN) created from the TensorFlow library. MobileNet architecture [13] uses depthwise separable convolutions which essentially reduces the number of parameters significantly by keeping the network almost the same in performance compared with complex CNN that has obviously more parameters. That feature makes it possible for us to run that CNN on low-cost edge devices which helps us to predict the type of soil in real-time in the field, without the of powerful computers or laboratory analysis. Prediction of the pH in another hand is a bit more difficult to do just by soil images. Barman and Choudhury [14] explain in their research that they find via linear regression that there is high coloration between the pH value of the soil and the saturation and hue values of the soil images. When these two are used as the main parameters for the artificial neural network model (ANN), the model can predict the pH value of the soil with very high accuracy. And for the ANN model, the best results can be obtained by using the Levenberg-Marquardt algorithm which essentially is a combination of the steepest descent method and the Gauss-Newton algorithm and is generally known as the “trust region” algorithm that finds the minimum of the function over the space of parameters [15].

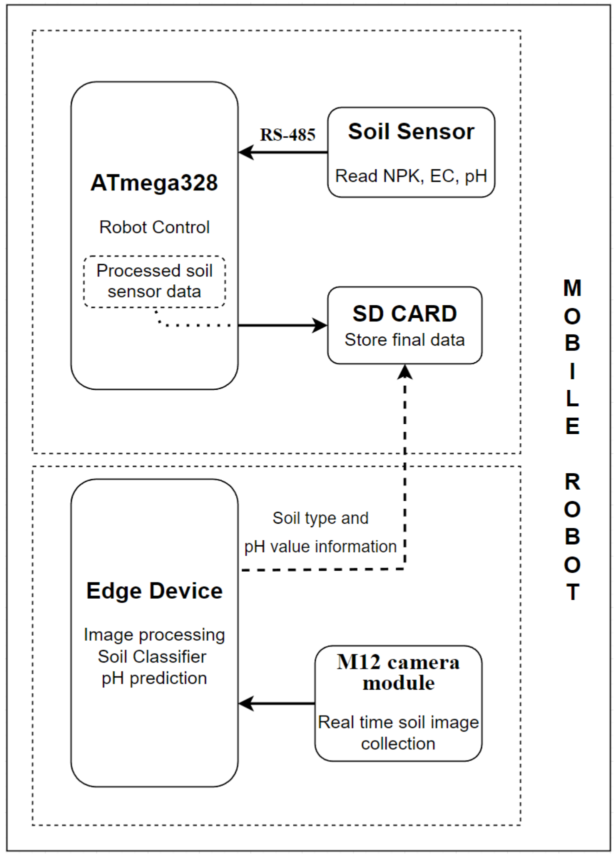

Figure 2. Diagram model of the whole system

As can be seen from the diagram in figure 2, the robotic system, soil sensor data, and SD card module are all connected and controlled from ATmega328, while on the other side, the edge device runs algorithms to classify the type of the soil and the pH level just from images taken from camera. In the end, all the information is collected on an SD card and ready to be read by a farmer.

4 RESULTS

In the first phase of our experiment, we were able to implement the soil classification module by using a low-cost Sipeed Maix Bit I edge device. We trained and booted the image classifier model into the Sipeed Maix Bit I, and with the help of the M12 camera module, we stream a real-time video with prediction information shown via the TFT display module (see figure 4). To train the classifier model, we prepare a dataset from a total of 785 soil images containing two types of soil as main classes (vertisol and alluvial soil). From that dataset 709 images were used as training data and 79 images as validation data, and the model was trained for 100 epochs with a result of 97% of accuracy.

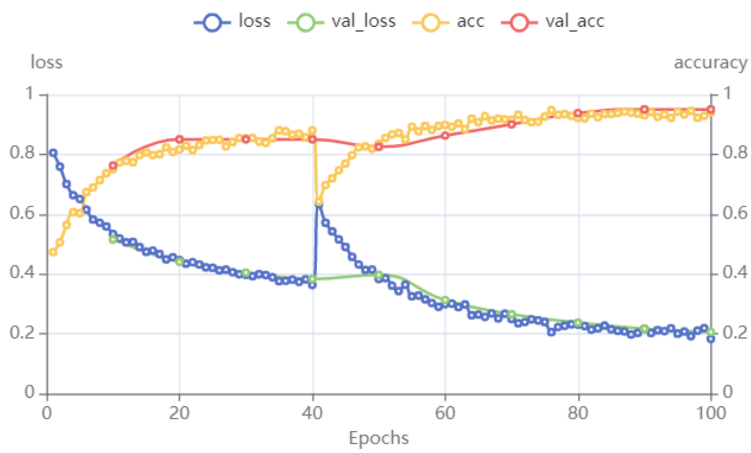

Figure 3. Training results

When we test the model on the device with different soil samples from both types of soil, it shows about 80% accuracy on average, which is still a good result taking into consideration the poor colors that the camera detects.

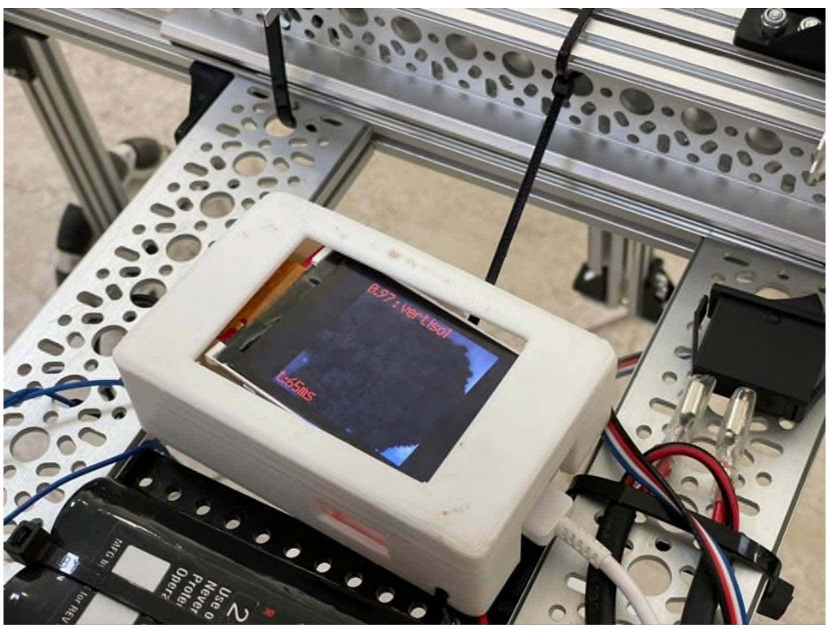

Figure 4. Edge device prediction of soil type

The total cost for all measurements, including sensors, camera, and both microcontrollers for the robot and AI module cost less than 100 euros which can be considered low-cost, especially knowing that the whole measuring system can be easily adaptable to most agriculture mobile robots.

5 CONCLUSIONS

Our robot was able to perform soil measurements with satisfactory results, at a very low cost, and almost fully autonomous which brings solutions to most of the problems and gaps mentioned at the beginning of the paper. One of the main challenges we had to overcome was the poor performance of the camera as we mentioned also earlier, which makes classifying process very difficult since there is not much information for the AI model to analyze from soil images, especially when we try to distinguish two types of soil that look almost identical. But with the right and enough training data, and also with the right training parameters it was possible to overcome that barrier and came up with satisfactory results for such limited resources. Also, the possibility to use the soil measuring system in other robots with only minimum hardware intervention is a huge benefit, especially in lowering the cost by using existing robots and not building an entirely new system.

The next phase is to analyze pH values, which can take a lot more time to prepare the dataset since besides the image of the soil, it is necessary to measure the pH value of each soil sample in order to train the system for pH prediction. Our final aim is to create a robotic system that will analyze soil with almost zero sensors, just by using images taken from the camera.

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