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Design and Development of Intelligent Robotic System for Precision Agriculture

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ABSTRACT

Precision agriculture has long been thought to be one of the most difficult fields for robotic farming. Many researchers have already created autonomous tractors, but they have failed owing to their incapacity to comprehend the complexity of the actual world. The primary purpose of this study is to demonstrate the design and construction of an intelligent robotic system capable of collecting real-time environmental data such as AE, leaf index, soil moisture, and picture data and transmitting it to a web server for analysis, categorization, and storage. Four machine learning methods are used in the process: classification, localization, object identification, and segmentation. In the Android Studio environment, a mobile application was designed to monitor the images and submit them to the web CAM server. The suggested model has been interfaced with the mobile application that can be used by smart phones to make a rapid and responsible judgment, allowing farmers to detect and prevent future output losses by allowing them to take safeguards ahead of time. We created and tested a small-scale agricultural robot prototype for precision farming. The experimental findings suggest that it can carry out the basic functions.

Keywords: precision agriculture, AI, Intelligent robot, machine learning, AE, Leaf index.

1. INTRODUCTION

Precision agriculture has long been regarded as one of the most challenging domains for robotic farming. One of the most difficult precision agricultural challenges is integrating emerging technologies like as artificial intelligence (AI), Internet of things (IoT), cloud computing, and intelligence robotics from other fields of study. As a result, the primary goal of using these technologies is to boost agricultural output, efficiency, and environmental impact, among other benefits [1]. Researchers involved in the field of precision agriculture robotics have been working on how a single intelligence robot can carry out one activity at a time or several activities in sequence employing multiple types of tools [2].

Intelligent robots used in precision agriculture can properly navigate from one location to another and vice versa. When deploying a standard robot in an open field, as is the case in most real operations, monitoring system is essential to safeguard the safety of humans, animals, and agriculture plants. The Food and Agriculture Organization (FAO) predicts that the world's human population will reach 9.6 billion by 2050 [3]. Feeding this massive population is often regarded as one of the most significant unresolved issues in terms of human efforts. Agricultural land is fast approaching its maximum in developed countries, and food production must increase by 70% to successfully feed the human population by 2050, based on the European Agricultural Machinery Association (CEMA) [4], the association representing the European agricultural machinery industry.

There is a need for more efficient infrastructure, farms, and production machines capable of saving resources in an ecologically benign, cost-effective, and sustainable manner. Precision farming, which entails combining various methods and strategies to manage differences in the field to maximize crop output, improve company profitability, and assure eco-environmental sustainability, has yielded some significant results. After more than three decades of development, the technologies that underpin precision farming are maturing enough to assist in achieving this aim [5].

Despite substantial research in the field of robotics and control, the adoption of localization plans and techniques in the agriculture industry has received less attention due to the fundamental difference between the laboratory setting and real-world situations [6]. One of the most pressing issues in agriculture today is a labor shortage since people prefer to work in comfortable occupations rather than in the field. The employment of a robotic manipulator is one possible solution to this challenge. However, a key shortcoming of this technique is that single, task-oriented robots can only accomplish the task for which they were developed. Such specialized robots are referred to as "single task targeted robots." Using a robot of this type results in low utilization because the robot is only employed at specific times. For example, an apple-harvesting robot may be employed for roughly one month out of the year, while the rest of the time the robot generates no cash for its owner.

The contribution of this work is the design and implementation for intelligent robotic system capable of completing several tasks. The robot can collect real time environmental data of AE, leaf index, soil moisture and image data and sends to the web server for analysis, classification, and storage. The process consists of four machine learning strategies, namely classification, localization, object identification, and segmentation. A mobile application has been developed in Android Studio environment to monitor the images and send them to the web CAM server. Further, this work describes a robotic platform for precision agriculture that uses computer vision (IP web CAM) and image processing algorithms for the automated recognition of weeds and colors, as well as for visual navigation and obstacle avoidance. The proposed model has been interfaced with mobile application to be used by smart phones to make a quick and responsible judgment which can help the farmers instantly detecting and preventing future production losses by enabling them to take precautions beforehand.

2. RELATED WORK

The use of intelligent robots to undertake precision agriculture operations has considerably enhanced production over the years because of the usage of AI to accomplish various tasks such as spraying, harvesting, and planting. Navigation solutions will be required to improve crop output and quality while lowering agricultural expenses. These will give optimum and autonomous navigation capabilities that is entirely based on a field coverage strategy, making intelligent robot navigation a key method. Researchers have given several optimization perspectives about field completion time, costs, ideal field coverage, and many more. For example, to find a path for agricultural robots to shorten field completion time with the goal of boosting field capacity while decreasing operational time and expense. The objectives have been simplified to a single goal, with the focus being to complete the field as quickly as possible [7].

Agriculture digital solutions are being developed by researchers. Agriculture has been mastered by humans throughout history since it is essential to our survival. Precision agriculture is now integrating with AI and other technologies. However, integrating technology from multiple knowledge fields is a research problem. New technologies are modifying agriculture and making it into a specific new study topic [8]. Increased degrees of intelligence in precision agriculture are expected to boost efficiency in farming tasks such as harvesting, planting, and pesticide spraying. Furthermore, this parallelism may be extended to farms, which will closely mimic the intelligent manufacturing concept. The intelligent farm concept is a fully automated top layer that produces a totally linked and flexible system that improves system performance through a broader network, learns from new conditions in real- or quasi-real-time, adapts the system to new working situations, and conducts entire production operations autonomously [9].

Precision agriculture operations utilizing intelligent robotics are currently technologically advanced and capable of completing autonomous tasks. Most of these duties involve harvesting, planting, spraying, and crop fertilizers, as well as disease detection and sowing. Furthermore, present agricultural processes have restricted scalability due to factors such as a lack of arable land, water scarcity, underinvestment, environmental concerns, and a labor constraint driven in part by an aging global population [10, 11]. In sum, we are faced with the issue of producing more with less resources. Agricultural robots have been identified as a potential answer to the looming worldwide catastrophe. Increased agricultural robotics are expected to boost efficiency throughout the food production chain [12].

Intelligent robotics for precision agriculture is not a novel concept. Many researchers have previously designed autonomous tractors, but they have not been successful due to their inability to grasp the complexity of the actual environment [13-15]. Most of them embraced an industrial farming method, where everything was known ahead of time and the equipment could only perform in specified ways. The current strategy is to create smarter and more intelligent robots that are sophisticated enough to work in a natural or semi-natural setting [16]. In recognized circumstances, these robots must display rational behavior. As a result, they should have enough intellect ingrained inside them to act reasonably for extended periods of time in a semi-natural environment, unattended. Autonomous robotics is frequently employed in industrial production and warehousing where a regulated environment is required [17, 18]. Driverless robot development has long been a pipe dream in agriculture. The development of these vehicles has received significant attention in recent years [19, 20].

3. MATERIALS AND METHODS

The proposed robot system is a highly effective autonomous, small-scale, ground-based mobile platform that employs powerful computer vision techniques to differentiate between different objects, colors, and plants and can apply a liquid mixture using its spray nozzles. Figure 1 shows the robot's overall design, its hardware layers, system software and their interconnections.

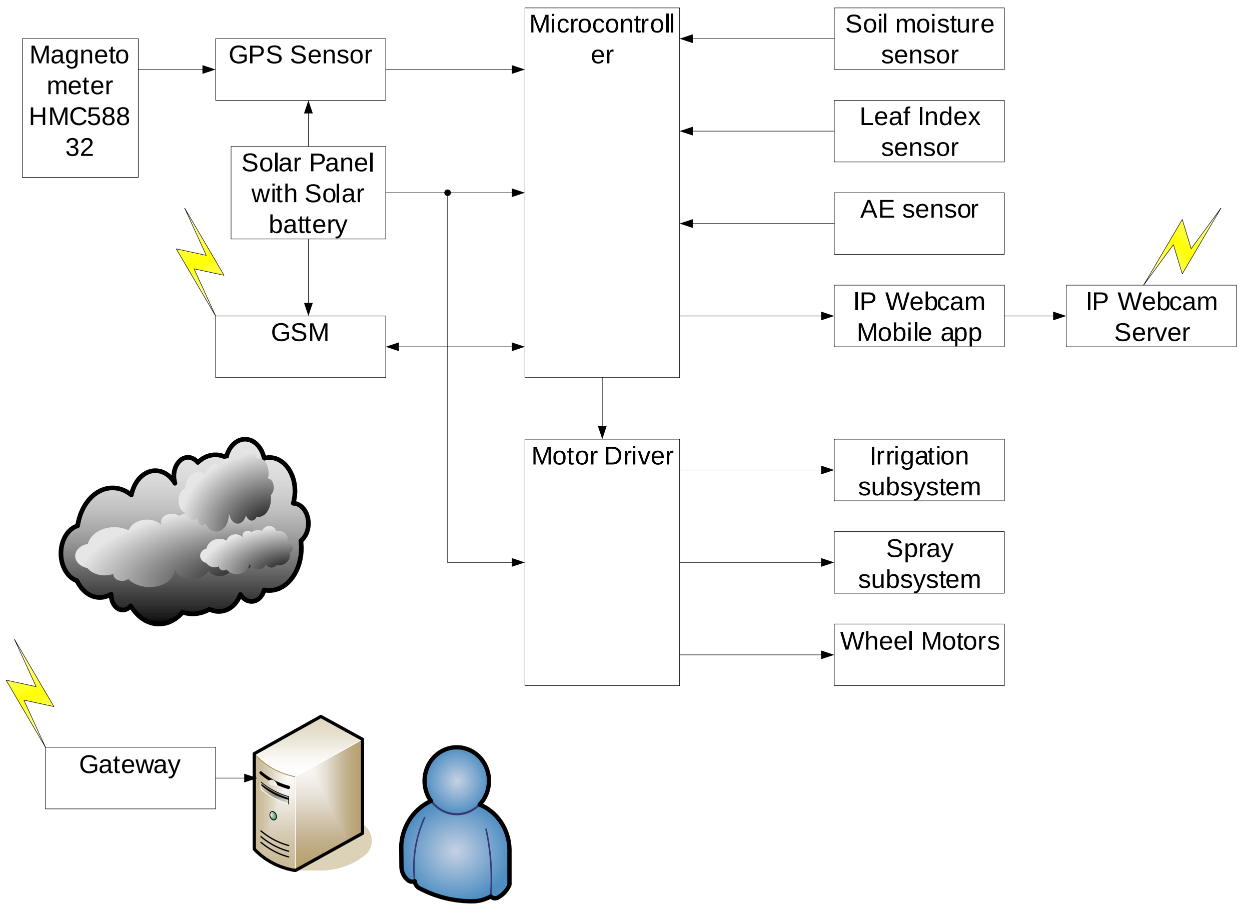

Fig 1: Robot's overall design

3.1 Microcontroller

We utilized the widely accessible Arduino Mega2560 microcontroller to implement computer vision tasks on the created small-scale agricultural robot. It is the core of the robot's highest-level hardware layer. This version of the microcontroller is compatible with many cameras, including the commercially available and the more sophisticated intel real sense depth and tracking cameras.

The Arduino Mega 2560 is an ATmega2560-based microcontroller board. It contains 54 digital I/O pins (14 of which may be used as PWM outputs), 16 analog I/O pins, 4 UARTs (hardware serial ports), a 16 MHz crystal oscillator, and a USB interface. The Arduino Mega2560 includes several communication ports for connecting to a computer, another Arduino, or other microcontrollers. The ATmega2560 has four hardware UARTs for serial TTL (5V) connectivity. A power connector, an ICSP header, and a reset button are all included.

3.2 System Actuators

The motors and motor drivers consisting of irrigation, spray and wheel motors subsystems are included in the lowest layer of the proposed hardware architecture. This layer is responsible for the robot's propulsion and directional control. The intermediate hardware level gives the robot with the capacity for independent movement and path planning. From an application standpoint, the robot must be able to handle clods and bumps, as well as navigate between the furrows using the proper algorithms and without harming the plants. The robot features a four-wheeled off-road chassis with front and rear suspension and a high ground clearance for this application.

The robot's body pieces are designed in Solidworks 2018 and then fabricated using 3D printer. Two brushed DC motors with integrated encoders are utilized for the robot's propulsion system. They have metal gears and are designed to operate on a nominal voltage of 12V. The motors are driven by L298N based motor driver module, which is intended to control two high-power, bidirectional brushed DC motors.

The prototype of the intelligent robot employs a steering MG995 metal gear servo motor for turning left and right. Because the drivers are mounted in a mirror arrangement, the polarity of the power supply to one of the motors must be reversed. Since the motors are DC, reversing the polarity will reverse the rotation of the motor shaft and synchronize the spinning of both motors. PWM signals are used to control the motor driver autopilot. To establish the movement's direction, these signals have varying intensities. A high-level signal will cause the robot to go ahead, while a low-level signal will cause the robot to move backwards.

3.3 Communication System

Several communication systems, which are managed by the autopilot board, were installed on the robot to offer redundant communication and remote control. Some of these systems, like as the GSM and GPS systems are part of the middle layer hardware and are utilized directly by the autopilot board, whilst others, such as the telemetry system and the remote-control receiver, communicate with the autopilot board via various interfaces. The microcontroller and IP webcam at the top layer of the given architecture are responsible for computer vision tasks.

3.4 Sensing Mechanism

The microcontroller manages the hardware components of the middle layer, which are located above the DC motors, motor driver shield, and servo controller. The primary GPS and compass are necessary to send positional data to the autopilot during movement, however the secondary GPS system is optional and is utilized to increase the localization precision. The robot includes sensors for moisture to actuate irrigation system. Leaf index sensor and acoustic emission sensors are integrated to the system for detecting plant water stress and trigger irrigation mechanism.

This work describes a robotic platform for precision agriculture that uses computer vision (IP web CAM) and image processing algorithms for the automated recognition of weeds and colors, as well as for visual navigation and obstacle avoidance. Supervised machine learning algorithms that are pertinent to the robot's operation were researched and utilized to evaluate its performance. We employ deep learning models for object identification. Their convolutional layers are the crucial component that enables image processing and object recognition. Typically, they are referred to as filters because they take characteristics from the preceding layers to change the input data into a form that is more suitable for representation. The workflow consists of four primary phases: preparation of the environment, preparation of the datasets, training, and implementation of the object detection model. The input dataset is required to have images containing items of interest; for the agricultural robot, the images must contain various types of weeds that are commonly seen in the field.

After gathering the appropriate number of images, they were labeled to indicate to the classifier the location of the object of interest inside the image. The Faster R-CNN is the standard model for object detection using deep learning. The time required to train the model is dependent on the number of images, their resolution, and the technical specifications of the computer device. The final phase of the procedure, following training, is to export the trained model and use it in practice. In some instances, the robot may be required to do independent activities that are more sophisticated. To do this, the robot may be programmed to move autonomously and without predetermined paths, again without injuring the crops. In this instance, the robot's objective is to generate a map of the unknown area and then locate itself on it. This concept is known as the simultaneous localization and mapping (SLAM) problem in the field of computer science. It is also regarded crucial to the field of robotics because its resolution enables robots to become totally independent. SLAM essentially combines two issues that are simple to solve separately: the localization problem and the mapping problem. Currently, it is straightforward to generate a map based on a given position, which is the mapping problem, and it is also relatively simple to determine your location on a known map, which is the localization problem. However, if both problems exist concurrently and must be tackled simultaneously, their combination proves to be difficult and complex. Fortunately, there are multiple known algorithms that can handle the SLAM issue, therefore the research efforts in this field are focused on improving their computing efficiency and providing consistent and accurate estimates of the map and the robot's location. Recent scientific efforts to tackle the SLAM challenge are centered on visual positioning techniques, often known as visual odometry. This method estimates the location of the robot based on the three-dimensional motion of the camera in space. There are two primary approaches to create a visual odometry system: with a single camera (monocular) or with two cameras (stereoscopic). The latter determines the depth by measuring the differences between the corresponding key locations in the pictures captured by both cameras. Visual odometry is a robust approach for autonomous navigation, motion tracking, and obstacle identification and avoidance. It enables a robot to self-localize utilizing just a stream of images collected by the web CAM attached to it.

3.5 Software design

The system was designed with the aid of Unified Modeling Language (UML) and Arduino IDE. The UML is a graphical language for specifying, visualizing, constructing, and documenting the artifact of software systems. Different features to be presented which gives a view of a system that emphasizes the behavior as it appears to outside users.

In addition, A mobile application has been developed in Android Studio environment to monitor the images and send them to the web CAM server for analysis, classification, and storage. The process consists of four machine learning strategies, namely classification, localization, object identification, and segmentation, which are relatively similar yet give distinct results. The robot prototype is depicted in Figure 2. The real time soil moisture and AE sensor readings monitored data are shown in Figure 3 and 4, respectively. The data are changing consistently and reasonably.

4. RESULTS AND DISCUSSION

To enable the robot to recognize various colors, we've written a script that enables the detection of a predetermined color. We have assumed that the red color represents the presence of weeds for the sake of the experiment. After detecting weeds, the robot will spray them with a liquid solution before removing them. It is anticipated that the code used to evaluate the computer vision algorithm would only recognize colors. The process of color recognition needs the conversion of the RGB (red-green-blue) color diagram of the camera's pictures to HSV (hue-saturation-value) format. The requirement to convert color formats arises from the fact that, when representing RGB colors, the color components of a specific item in a picture are proportional to the quantity of light falling on the object. This drastically reduces the color contrast between the items. The HSV color system, which employs hue, saturation, and value, is far superior for picture description. The system is programmed to distinguish two colors of red and green, which are typical in agricultural settings.

Fig 2: Robotic prototype

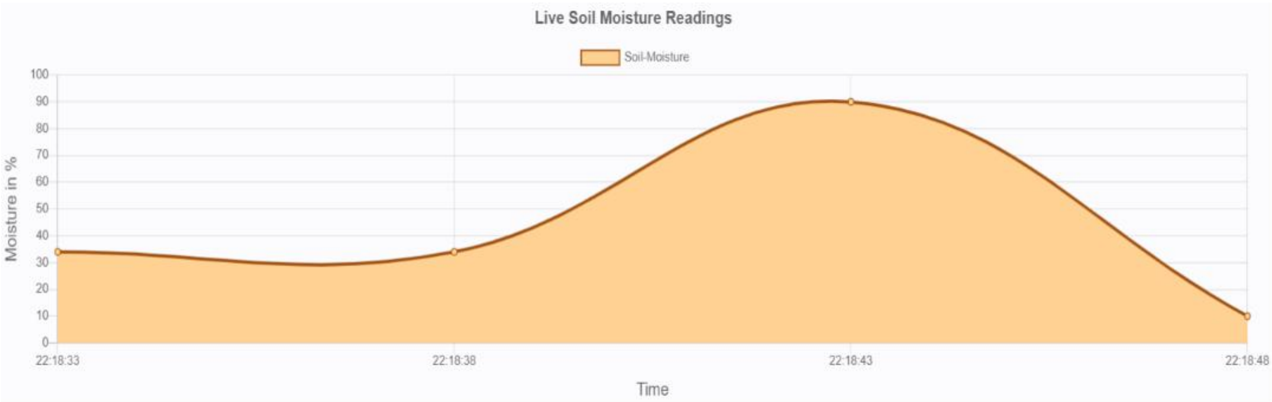

Fig 3: Soil moisture monitoring

Fig 4: Soil moisture monitoring

The color green denotes new leaves and healthy plants, whereas the color red indicates damaged plants. The code defines the bounds for both colors with tight tolerance levels. This enables the computer vision program to distinguish between several color tones. The identification of red and green in a picture needs a comparison of the pixel values to a set of predefined values. If the algorithm identifies green or any other color except red, no action is taken, and the program continues comparing the image's other pixel values. If red is detected, the function spray is run. With this function, a low-level signal is transmitted to the robot's electrical relay switch. The length of the signal is only 3 seconds, and during this low-level signal, the relay closes, activating the sprinkler motor and initiating the spraying process. Once the 3 seconds have passed, a high-level signal is transmitted to the relay, stopping the spraying. The time of the procedure is determined in accordance with the robot's speed of 12 kilometers per hour each minute. For our experiments, the mission planer program is employed to give the robot autonomous navigation capabilities. This program enables the user to predefine a route that the robot's GPS navigation system will follow. Once the specified task has been uploaded to the robot, it may self-navigate across the field and follow the predetermined course. Throughout the task, the robot's computer vision system runs continuously. The computer vision system of the robot has recognized the green color in the video stream as well as the red target. The picture in the middle depicts the robot while it is spraying the target. All testing were successful, and the robot could detect the red target and carrying out the spraying procedure. The robot is totally autonomous if it can construct its own route rather than following the navigation instructions supplied by the Mission planner program. This allows the robot to navigate towards the distant item while avoiding obstacles along the route. In addition, the camera provides the robot with the capacity to compute the distance between objects. The robot is also able to provide feedback with information on the object's distance. The robot can traverse uneven terrain and clods of dirt without destroying the plants, as well as go from row to row without harming the plants. To avoid impediments, the robot will stop moving when an item is identified at a predetermined distance, such as 50 cm.

An additional advantage of the optical navigation system is that the robot can track the rows of crops in the field totally autonomously. Using this capacity, the robot may generate a map of the surrounding region and preserve it for use in future missions. As the method for visual navigation is not dependent on GPS location data, the robot generates its own relative coordinate system and retains its initial position. Based on this initial position, a map of the agricultural field is then constructed. The robot performs self-localization based on its present coordinates, which are related to its beginning location, allowing it to return to its starting position. The robot is also in continual connection with its control station and may send periodic information about its location, allowing the user to follow it remotely in the field.

5. CONCLUSIONS

The technologies that are altering our everyday lives include Artificial Intelligence, Computer Vision, and Robotics. Their potential is enormous, and they are being introduced gradually in locations where it was previously thought to be difficult to do so. To validate this idea, we have provided a prototype of a small-scale agricultural robot for precision farming in this work. The created prototype is in its early assessment phase, but thus far it has exceeded all expectations and shown capable of performing the fundamental duties it was intended to complete. Based on this, we may conclude that it is conceivable to construct small-scale, cost-effective precision agricultural solutions using existing information and communication technology. The robot described in this paper is appropriate for usage in agricultural settings.

Future research work is to update the system to conduct more sophisticated tasks, such as weed eradication, etc. Additionally, the robot will be outfitted and tested with manipulators, such as arms, that will allow it to collect tiny fruits and vegetables.

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