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Raspberry Pi as Visual Sensor Nodes in Precision Agriculture: A Study

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ABSTRACT Wireless sensor network applications in the agricultural sector are gaining popularity with the advancement of the Internet of Things technology. Predominantly, wireless sensor networks are used in agriculture to sense the important agricultural field parameters, such as temperature, humidity, soil moisture level, nitrite content in the soil, groundwater quality, and so on. These sensed parameters will be sent to a remote station, where it will be processed and analyzed to build a decision support system. This paper describes the implementation of a wireless visual sensor network for precision agriculture to monitor paddy crop for weeds using Raspberry Pi. Bluetooth 4.0 was used by visual sensor nodes to send the data to the base station. Base station forwarded the data to the remote station using IEEE 802.11 a/b/g/n standard. The solar cell battery was used to power up the sensor nodes and the base station. At the remote station, images were preprocessed to remove soil background and different shape features were extracted. Random forest and support vector machine classifiers were used to classify the paddy crop and weed based on the shape features. The results and observations obtained from the experimental setup of the system in a small paddy field are also reported. This system could be expected to enhance the crop production by giving timely advice to the crop producers about the presence of weeds so that steps can be taken to eradicate weeds.

INDEX TERMS Classifiers, computer vision, precision agriculture, Raspberry Pi 3 model B, shape features, wireless visual sensor network.

I. INTRODUCTION

Lately, new trends have emerged in the agricultural domain with the development in the field of wireless sensor networks. The size and cost of the sensor boards have been reduced to a great extent making it the most preferred technology for precision agriculture. Precision agriculture can be defined as an approach to farm management using science and technology to enhance crop production. As the world‘s population is increasing day by day, farmers need to increase food production. In order to mitigate the looming food security threat which could easily devolve into global instability, large farms increase productivity by exploiting precision agriculture continuously. Precision agriculture with respect to wireless sensor network involves observing, analyzing and controlling some of the agricultural practices remotely. Wireless Sensor Network (WSN) is being explored in the field of horticulture, animal farming, viticulture also. The main goal of using WSNs is to increase the quality and productivity of these sectors.

The main use of WSNs in agriculture is to give a site-specific treatment of the crops thus enabling site-specific crop management. The site-specific crop management reduces overuse of water, fertilizers, insecticides, and herbicides. Sensor nodes are attached to drip which constantly monitoring the water level in the soil. If the water level goes below the threshold, it triggers the drip. Thus reducing unnecessary wastage of water. WSNs can be used to gather soil parameters of farmland over a period of time and then analyze to predict which type of crop is most suitable to grow on that land. WSNs are used to sense various agricultural parameters like temperature, humidity, leaf wetness, soil moisture level, and so forth to predict the occurrence of pests or crop diseases. The prediction of livestock or crop diseases can be done using appropriate soft computing or data analytics. Precision agriculture began in the mid of the 19^{th} century, as shown in FIGURE 1 and since then technologies used in agriculture has evolved to a great extent.

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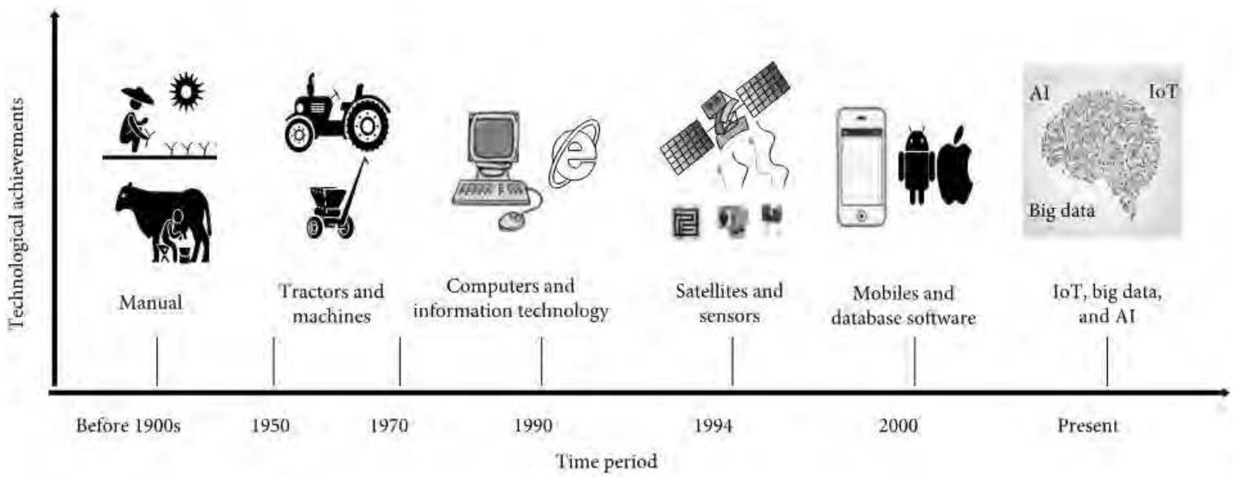


FIGURE 1. Evolution of different technologies in agricultural sector [1].

The sensors in the agricultural sector or any other related sector will be producing a large volume of data continuously and these data are given as input to a soft computing application or to a data analytical application which helps in solidifying research output in precision agriculture. The soft computing techniques and wireless sensor networks together give insights to various issues in agriculture like weather forecasting, crop and livestock disease, irrigation and farmland management. This will help in giving timely advice to the farmers or crop producers that will increase the yield and crop production thus generating revenue. There are three types of architecture of WSNs that can be deployed in farmland based on the movement of the nodes [2]. They are

1) Static Architecture: In this architecture, nodes are deployed at a fixed location and they do not change their positions during the lifetime of the system. A Typical example would be an irrigation management system.
2) Mobile Architecture: In this architecture, nodes are in constant movement throughout the field. An example would be sensors placed on a tractor or drones.
3) Hybrid Architecture: In this architecture, the system consists of both mobile and stationary nodes.

Based on the sensor node hardware configurations, WSN architecture is classified as homogenous and heterogeneous architecture. In homogenous architecture, all the nodes are of the same capability whereas, in heterogeneous architecture, nodes have different capabilities. Wireless Visual Sensor Network (WVSN) aids in visual inspection of the crops from a remote site. Visual sensors are scattered all over agricultural land and capture images periodically which are then processed and analyzed for any decision-making process. The WVSNs are usually used to view the growth of plants or crops and also to detect the diseases or pests that affect the crop. Even though WSNs are much popular in precision agricultural applications, there are very few studies that have implemented WSNs using visual or image sensors in precision agriculture. FIGURE 2 shows WVSN implemented in a greenhouse to monitor the plants using ZigBee transmission technique.

A. SUMMARY OF MAIN CONTRIBUTIONS

A facet of precision agriculture is to provide site-specific crop management. This covers different aspects such as monitoring soil, and environmental parameters of a field. Also, it involves monitoring crop for pests such as weeds. For monitoring crop for weeds, automatic weed detection is desirable. The main concern when implementing a WSN for precision agriculture in developing countries like India is that it should be cost-effective and affordable. Raspberry Pi broads are low-cost, easily available, and can be programmed with open source language like Python. Due to its built-in wireless technologies like Wi-Fi and Bluetooth, it can easily integrate and be a part of the wireless visual sensor network. Therefore, this paper makes the first attempt to investigate the potential of Raspberry Pi as visual sensor nodes to monitor the paddy crop for weeds. Our contributions are summarized as follows:

- **WVSN implementation:** We show that Raspberry Pi has the potential to be used as visual sensor nodes for the detection of weeds and can be used in the automation of weed detection in precision agriculture.
- **Classification of paddy crop and weed:** We show that region-based shape feature like Hu's invariant moments [4], geometric shape feature like perimeter, and size independent shape features can be used to classify paddy crop and weed.

II. RELATED STUDY

There are many studies in the literature which have implemented WSNs for precision agriculture.

FIGURE 2. WVSN deployed in a greenhouse [3].

A. WSN FOR PREDICTION/MONITORING CROP FOR DISEASES/PESTS

In [5], a WVSN was implemented in a vineyard to detect the disease or pests affecting the grape crop. In [6], a WVSN was set-up to monitor the pest trap in a greenhouse. The WVSN implemented automatically captured the images of the pest trap and transferred to a remote station where it was processed to know the density of the insects trapped. If the density reached a certain threshold, an alarm was generated. In [7], the WSN network was implemented in a potato farm to monitor the crop and to develop a decision support system based on sensed parameters like temperature, humidity and leaf-moisture level to predict whether the crop is at risk of developing Phytophtora, a type of fungal disease that affects potato crop. In [8], the relationship between the Bud Necrosis Virus and weather conditions of Groundnut crop has been established using a wireless sensor network. This was a project funded by Indo-Japan collaboration. Various environmental parameters including sunshine hours and wind speed were measured and data mining techniques were used and empirically results were evaluated.

B. WSN FOR SENSING IMPORTANT ENVIRONMENTAL PARAMETERS

In [9], an agricultural monitoring system was proposed using a WSN which sensed important parameters like soil information and other environmental information necessary for crop growth. In addition, Closed Circuit Televisions(CCTV) were installed at various places to acquire images of the field. GPS system was used to get the location of the sensors. In [10], the deployment of a WSN in an agricultural environment was explained. This WSN had a gateway with GPRS capability which gathered all the data from the sensors and sent it to a remote station with TCP/IP based communication protocol. The remote station had a web application running which managed all the information and enabled the end user to monitor and take any decision about the environment where WSN was deployed. In [11], a WSN was implemented for the weather forecast. Each node sensed parameters like temperature, humidity and soil moisture. The gateway for the network was implemented using Raspberry pi 3 which forwarded all the sensed data to the remote server. The remote server converted it to a presentable format to the user. The data was then processed to predict weather conditions. In [12], a wireless sensor network was deployed to measure important environmental parameters such as intensity of light, humidity, temperature and water level in the soil. The network had coordinators which bridged the distance gap between sensor nodes and the base station. The routers were placed to extend the range of the network. The communication protocol used was ZigBee. In [13], a cost-effective wireless sensor network was implemented. Microprocessor STM32L152 and wireless modules MRF24J40 and sensors were programmed using Keil-C. The performance of the network was measured using Read-Range, Received Signal Strength Indicator(RSSI), Packet Reception Ratio(PRR) and Link Quality Indicator(LQI) and then compared with commercially available products. The authors reported that their design has the potential for the real world application in the agricultural scenario. In [14], a wireless sensor network was implemented to sense soil quality parameters like conductivity and acidity of the soil so as to determine the quantity of fertilizers needed at regular interval. In [2], a study was made regarding different architectures of the WSN that can be deployed in an agricultural environment. In addition, the study highlights the WSN deployment with respect to Indian agricultural scenario. Authors report that the WSN deployment in India should be a cost-effective one. In [15], a WSN called COMMONSense Net was implemented in the region of Tumkur district of Karnataka which is a semi-arid region. A decision support system was built to predict the water requirement. This project was a collaboration between Dutch and Indian Governments. In [16], a WSN was implemented in a vineyard in Sicily, Italy to monitor the growth of vine crop and also to monitor the micro-climate of the grape crop which helps in scheduling the pesticide treatment and soil treatment at the right time which will reduce the operating costs and thus increase the quality of the grapes. In [17], a low-cost WSN was implemented to save water in agriculture. The WSN along with actuation network technology, Fuzzy rule sets, and numerical soil parameters were used to build context-aware and optimized irrigation schedule. In [18], Received Signal Strength Indicator (RSSI)-based distributed Bayesian localization algorithm based message passing to solve the possible interference because of many obstacles in the environment. Authors report that their work is particularly suitable for large agricultural land for precision farming. In [19], a review was made about various types of energy-efficient WSN implementations made in precision agriculture. The comparison was made between various wireless communication protocols. The state-of-the-art WSN technologies being used in agriculture were reviewed. Also, limitations and challenges of the WSNs in agriculture were exposed for future design considerations. In [20], an air-ground monitoring system was proposed to collect field information. This system consisted of a WSN which was deployed on the field for long term acquisition of soil and environmental parameters. These parameters were then collected by micro unmanned aerial vehicle(mUAV). This mUAV was also equipped with remote sensing (RS) sensors which acquired the images of the field. A ground center station was equipped with 3G/4G technology to receive the data sent by the mUAV. Later, this data was processed and analyzed to guide various agricultural practices. In [21], a context-aware of WSN was proposed. In this paper, authors report that as a fault-tolerant application, WSN in precision agriculture does not require the information from all the sensor nodes. Sensors which are more likely to collect the same environmental parameters are grouped together. Only one of the sensor in this group will sense and forward the sensed information. This increases the lifetime of the network. In [22], various environmental parameters like soil moisture level, light intensity, temperature, humidity, and so forth were sensed and transferred using Wi-Fi to the ESP826612E from which it was forwarded to Things Speak Server, and to the Android phone application. In [23], authors have used the Internet of things(IoT) technology to control the water stress of the crops. An IoT-based WSN was implemented to alert the farmer about the need for irrigation of the crops.

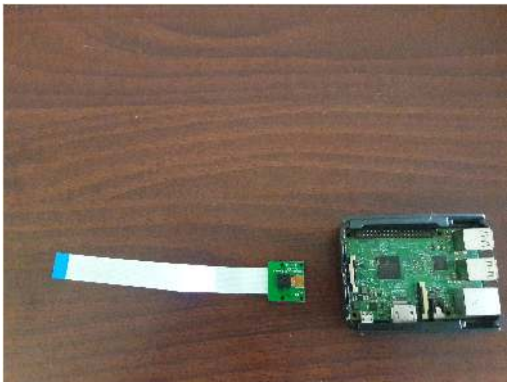
III. METHODOLOGY

A. RASPBERRY PI CAMERA

The huge success of the Raspberry Pi boards led to the development of Raspberry Pi camera module v1 to be used together with the Raspberry Pi boards. The camera module v1 was released in the year 2013. Some of the specifications of the Raspberry Pi camera v1 is listed in TABLE 1. The Raspberry Pi camera is a low-power high-definition small camera that comes with a flat flexible cable which is to be connected into the CSI (Camera Serial Interface) connector. In the year 2016, the camera module v2 was released. For both the iterations, there are visible light and infrared versions. Many programming libraries are available for image processing using the Raspberry Pi camera which can be used for various applications. In this research work, Python APIs have been used to acquire and process images from Raspberry Pi camera. When using the Raspberry Pi in the outdoor environment, it is better to cover the board with a shield to prevent damages from external sources like wind, water, and so forth. FIGURE 3a and FIGURE 3b shows Raspberry Pi 3 model B along with camera module v1 without and with shield respectively.

TABLE 1. Some specifications of raspberry Pi camera module v1.

Still Resolution	5 mega pixels
Sensor	OmniVision OV5647
Image Formats	JPEG (accelerated), JPEG + RAW, GIF, BMP, PNG, YUV420, RGB888
Focal Length	3.60 mm +/- 0.01
Horizontal FOV	53.50 +/- 0.13 degrees
Vertical FOV	41.41 +/- 0.11 degrees



(a)

(b)

FIGURE 3. (a) and (b) Raspberry Pi board with camera.

B. NETWORK ARCHITECTURE AND SENSOR NODES

The system consisted of Raspberry Pi 3 model B as sensor boards interfaced with Raspberry Pi camera board v.1 as an image or visual sensor. The base station was also a Raspberry Pi 3 model B board. The Pi was loaded with Raspbian Stretch operating system. The Pi sensor board was solar-powered. Raspberry Pi 3 model B supports Ethernet, Bluetooth 4.0 and Wi-Fi technologies. Bluetooth was used by sensor nodes and base station to communicate among themselves. The base station and remote station communicated using Wi-Fi. In this study, a laptop was used as a remote station and mobile hotspot was used for Wi-Fi connection.

C. BLUETOOTH 4.0

Bluetooth 4.0 came into existence in the year 2011. It is also known as Bluetooth Low Energy(BLE). This technology operates in the 2.4 GHz band as that of classic Bluetooth. Unlike classic Bluetooth, BLE goes into sleep mode when there is no connection. In addition, it consumes only 3% of the power consumed by Wi-Fi. Therefore, it is very power and cost-efficient when compared to classic Bluetooth. It uses adaptive frequency hopping technique to use any one of the channels from available 79 channels and thus reduces interference problem [24].

D. DESIGN OF THE SYSTEM

The system consisted of static nodes deployed at a fixed location. One of the key design issues in implementing wireless visual sensor network is the placement of the sensor nodes in the field and to decide the number of sensor nodes required. There are two different types of coverage areas in WVSNs namely radio coverage area and sensing coverage area [5]. The radio coverage area gives the distance covered by the communication technology used and the sensing coverage area is the area visible from the visual sensor or image sensor. It is not practical to cover the entire field by the visual sensors due to various factors like cost, the terrain of the land, and so on. This is perfectly fine when implementing wireless visual sensor network for monitoring crops for pests like weeds or diseases. Because weeds usually will be spread throughout the field. So it will be captured by at least one image sensor node and highly unlikely that weeds go unnoticed due to the uncovered regions. In this study, an attempt is made to keep a minimal number of uncovered regions. The field where the system was set-up was about 10m^2. The camera was mounted at a distance of 2m above the ground facing down towards the crops on the field. This resulted in a square sensing coverage area of about 2m X 2m approximately. A good coverage and deployment strategy is necessary for the optimum resource allocation in a WSN thereby reducing the overall cost of the network. Random deployment of visual sensor nodes results in some regions densely or sparsely covered by visual sensor nodes [25] [26]. This, in turn, results in the same target captured by more than one visual sensors. Therefore, information sensed or captured will be very less. Therefore, we have used the formula given by [5] to find the number of sensors to cover an area of about 10m^2. In [5], the sensing area is assumed to be a circle. Therefore, from the square sensing area, the area of a sensing area in the form of a circle was

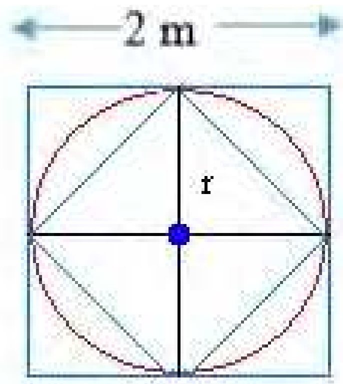


FIGURE 4. Approximating area of a circle from a square.

approximated by the method as follows: A circle of radius ‘r’ is inscribed inside the square as shown in FIGURE 4. Inside this circle, again a square is inscribed. Now, the area of the circle is the average of the areas of the inner square and the outer square. Area of the inner square is the sum of the areas of the four triangles. Therefore, the sensing area ‘S’ is given by

$$S = \frac{\left((2 \cdot r)^2 + 4 \cdot \frac{1}{2} \cdot r \cdot r\right)}{2}$$
$$S = \frac{(4 \cdot r^2 + 2 \cdot r^2)}{2}$$
$$S = 3 \cdot r^2$$

Since ‘r‘ is equal to 1m, the area of the circle is 3m^2. The area covered by a WVSN as a function of image sensor nodes is calculated using (1) [5]. Four image sensor nodes approximately cover an area of about 10m^2.

$$A = n \cdot \pi \cdot s^2 - 0.864 \cdot a_n \tag{1}$$

where s is sensing radius,
n is number of sensor nodes and $n \geq 2$,
$a_n = \sum_{i=1}^{n} (a_{n-1} + (-1)^n)$ and $a_1 = 1$.

The network was implemented using piconets and a scatternet [27] using four Raspberry Pi boards as sensor nodes and one Pi as a base station. Two nodes form a piconet. The deployment of the system is illustrated in FIGURE 5.

The working of the network is explained in two phases namely

- Initiation
- Data Storage

1) INITIATION

The nodes A and B together formed a piconet. B acted as master and A as slave. Similarly, node C and node D formed another piconet. D acted as master and C acted as a slave. A start-up script was made to run the python script to capture the image. Node A captured an image and sent to B. This initiated B‘s image acquisition process. B captured the image

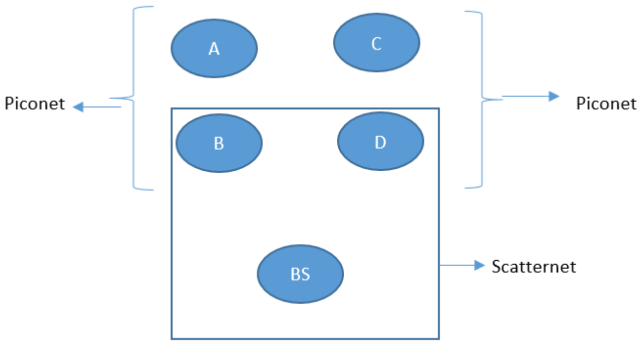


FIGURE 5. An illustration of the deployment.

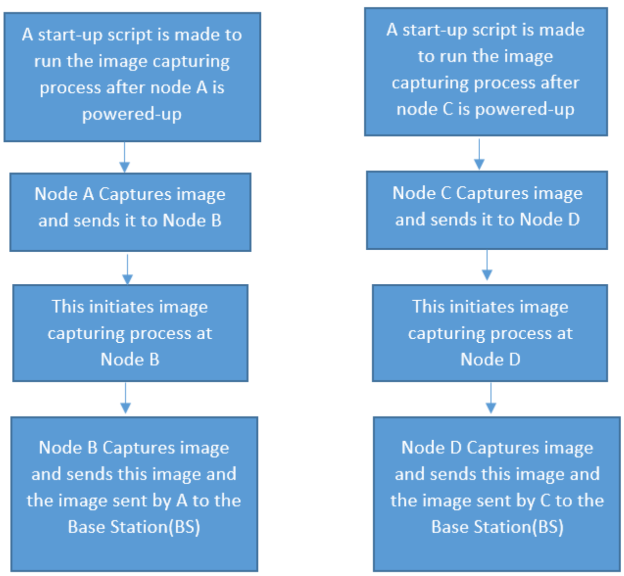


FIGURE 6. Initiation of the image capturing process.

and sent the image captured by it and the image sent by A to the base station. The base station pushed the images as it received from B to the queue. The images were acquired every 12-hours for twenty-five days starting from the eighth day after sowing. The detection of weeds is crucial for the first month where the impact of weed on crop will be high. Same is followed by the piconet formed by C and D. The whole initiation process is summarized in FIGURE 6.

2) DATA STORAGE

The base station received the images from B and D nodes and stored in the queue maintained by RabbitMQ [28], which is an open standard message brokering system. This queue is reliable and persistent. That is, it survives the system restart. RabbitMQ is based on the Advanced Message Queuing Protocol(AMQP). AMQP allows conforming clients to communicate with the conforming messaging middleware brokers. These brokers receive messages from producers also called publishers because they publish the message and consumers are applications which take these messages. Brokers can either deliver the messages to the consumers or consumers can pull the messages from the brokers. In this study, the base station published the message to RabbitMQ server resided in the same machine (base station) and remote station consumed the messages. Use of the message brokering system enabled asynchronous behavior between the base station and the remote station. That is, there was no need for a remote station to be up and running, and available all the time to the base station. Remote station consumed the messages from the queue in the base station every alternate day. The working of the message queue with respect to this work is as shown in FIGURE 7. Exchanges are entities which take messages and route to one or more queue. Direct exchange was used in this study. As soon as the remote station consumed the messages from the queue, acknowledgments were sent to the RabbitMQ server which deleted those messages from the queue. This open standard gives a lot of freedom for the application developers to develop applications as per their requirement. The images taken are of size 2592 X 1944 and stored in PNG (Portable Network Graphics) format. FIGURE 8a and FIGURE 8b show the sample images taken by the Raspberry Pi sensor nodes.

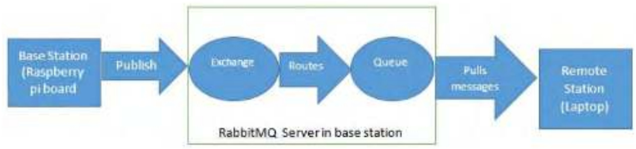


FIGURE 7. Working of RabbitMQ.

IV. SHAPE FEATURE EXTRACTION

Shape features are one of the important features used for the discrimination of crop and weed. Individual leaves or the whole plant can be considered for the shape feature extraction. In this study, the whole plant was considered for shape feature extraction. Grass-type weed and paddy belong to the same family and hence their shape features also resemble to a great extent. Even sedges(a type of weed) also have close similarities with the paddy crop with respect to shape features. The shape of the plants keeps varying as they grow. Therefore, relying on only one shape feature may not be enough for the discrimination of paddy crop and weeds. In this study, different shape features namely, chain codes, size independent shape descriptors, and moment invariants were considered to build an integrated shape feature model.

A. MOMENT INVARIANT FEATURES

An important issue in shape feature extraction is to extract those features which are not sensitive to rotation, scaling and translation. The idea of using moments in shape feature extraction was first used by Hu [4] using algebraic invariants. Since then it is used as one of the important shape features. Hu's moments help in extracting region-based shape features. Connected component algorithm [29] was used to get the

(a)

(b)

FIGURE 8. (a) and (b) Images acquired by Pi nodes.

plant objects from the image acquired by the Raspberry Pi as shown in FIGURE 9b and FIGURE 9c. Successive erosion and dilation were used to remove possible overlapping. For each plant object in the image, seven Hu's moments were obtained to characterize the plant object in order to discriminate between paddy crop and weed. Assume that a binary image f (x, y) denotes a plant object where x and y are pixel coordinates having dimension MXN. Plant object is represented by pixels having value one and soil background is represented by pixels having value zero. The moments of f(x,y) are defined as follows:

$$m_{pq} = \sum_{x=1}^{M-1} \sum_{y=1}^{N-1} x^p y^q f(x, y) \tag{2}$$

where $p = 0, 1, 2 \ldots.$ and $q = 0, 1, 2, 3 \ldots$

The moments are translated by an amount (a,b) are defined as

$$m_{pq} = \sum_{x} \sum_{y} (x + a)^p (y + b)^q f(x, y) \tag{3}$$

The central moments μ_{pq} is given by

$$\mu_{pq} = \sum_{x} \sum_{y} (x - x_c)^p (y - y_c)^q f(x, y) \tag{4}$$

where $x_c = \frac{m_{10}}{m_{00}}$ and $y_c = \frac{m_{01}}{m_{00}}$

When scaling normalization is done, central moment is given by

$$\eta_{pq} = \frac{\mu_{pq}}{\mu^{\gamma}{}_{pq}} \tag{5}$$

where $\gamma = \left[\frac{(p+q)}{2}\right] + 1$

The Hu created a set of seven invariant moments which are not sensitive to scaling, rotation and translation using the equations 2 to 5 given as follows

$$M_1 = \eta_{20} + \eta_{02} \tag{6}$$

$$M_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2 \tag{7}$$

$$M_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{8}$$

$$M_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{9}$$

$$\begin{aligned} M_5 = {} & (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\ & + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) \\ & \times \left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \end{aligned} \tag{10}$$

$$\begin{aligned} M_6 = {} & (\eta_{20} - \eta_{02})\left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{30})^2\right] \\ & + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{03} + \eta_{21}) \end{aligned} \tag{11}$$

$$\begin{aligned} M_7 = {} & (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\ & - (\eta_{30} + 3\eta_{12}) - (\eta_{21} + \eta_{03}) \\ & \times \left[3(\eta_{30} + 3\eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \end{aligned} \tag{12}$$

B. SIZE INDEPENDENT DESCRIPTORS

These are dimensionless and does not depend on plant size, image rotation, and location of the plant. Because the size and shape of the plants (paddy crop and weed) varied due to growth during the study, quantification of the plant shape was extremely difficult in this case. Therefore, size independent descriptors were used in this study. These were calculated using shape features such as area, perimeter, Feret diameters extracted from the connected components obtained after applying erosion and dilation. Five size independent shape descriptors [30] that were used in this study are

- Deviation from the circular shape ‘s1‘

$$s1 = \frac{Area}{\left(\frac{\pi}{4}\right) \cdot perimeter^2} \tag{13}$$

- Deviation from the shape of a square ‘s2‘

$$s2 = \frac{Area}{d \cdot sp} \tag{14}$$

  where d is shortest Feret diameter and sp is Feret diameter perpendicular to d.

- Deviation from the area of triangle ‘s3‘

$$s3 = \frac{Area \cdot 2}{sp \cdot d} \tag{15}$$

- Elongation of the shape ‘s4‘

$$s4 = \frac{perimter}{l} \tag{16}$$

  where l is the longest Feret diameter.

(a)

(b)

(c)

FIGURE 9. **Extraction of plant objects. (a) Paddy field image after removing soil background. (b) Plant object(crop). (c) Plant object(weed).**

- Number of corner points(CP): Number of corner points in an object is found using Harris corner detection algorithm [31].

C. PERIMETER USING CHAINCODE

Chain code was first proposed by Freeman and Davis [32] and therefore sometimes called as Freeman's chain. It is simply a walkthrough the boundary pixels of a binary object in an image. Say for example we start at a random pixel, if the next pixel is left, instead of saying "move left" we say 7 and to move diagonally down right we say 4. We move always in clock-wise around the shape as shown in FIGURE 10 and hence we can calculate the perimeter of a binary object in an image from the chain code. Since grass-type weed like Echinochloa Crus-galli commonly known as Barnyardgrass mimics paddy crop morphologically [33] and [34], we have used perimeter as one of the shape features so that slight geometric variation between grass-type weed and paddy crop can be denoted by the perimeter.

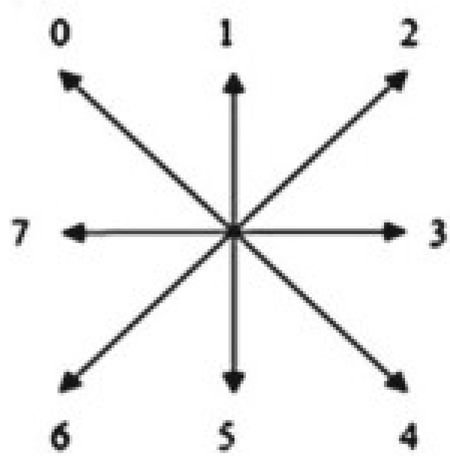


FIGURE 10. **Chain code step calculation.**

The chain code represents the object in a "jagged" way. It is highly unlikely that a real-world object outline will look like the "jagged" binary shape. Therefore, in [35] the authors suggested different weights for odd and even chain codes based on minimum square error for straight lines of infinite length at random orientations. They suggested a new equation as given by (17) to calculate the perimeter.

$$p = count\ (even) \cdot 0.948 + count\ (odd) \cdot 1.340 \quad (17)$$

where $even$ is the number of even chaincodes and odd is the number of odd chain codes.

But later this was improved by [36] by considering the even and odd chain codes, and corner count(cc). Corner count is the number of times the chain code changes the value. So the new equation is

$$p = count\ (even) \cdot 0.948 + count\ (odd) \cdot 1.340 - count(cc) \cdot 0.091 \quad (18)$$

where cc is the number of times chain codes change the value.

But we modified the (18) to obtain a still better estimation of the object perimeter by considering the number of times the chain codes do not change the value. So the modified equation by applying the correction to find the perimeter of an object is given by (19).

$$p = count\ (even) \cdot 0.948 + count\ (odd) \cdot 1.340 - count(cc) \cdot 0.091 + count(ncc) \cdot 0.000132 \quad (19)$$

Algorithm 1 ShapeFeatureExtraction(image)

procedure SoilBackgroundRemoval(image)
 $C \leftarrow image$
 image $\leftarrow$ *convert image to YCbCr colorspace*
 $Ch \leftarrow$ *select Cr channel of the image*
 $Ch \leftarrow$ *setpixels in Ch having value* 16 *to* 120 *to one and rest to zero*
 $Ch \leftarrow Ch \times C$
 comment: Now, *Ch* will contain only greenplants with
 comment: soil background removed
 return (*Ch*)
main
 output (*img*, SoilBackgroundRemoval(*image*))
 Convert img to binary
 $CC \leftarrow$ *connected components of img*
 foreach $x \in CC$

$$\textbf{do}\begin{cases} \textit{Use successive errosion and dilation to remove} \\ \textit{possible overlappings} \\ f1 \leftarrow \textit{Calculate Hu's moments} \\ f2 \leftarrow \textit{Calculate size independent descriptors} \\ f3 \leftarrow \textit{Calculate Perimeter} \\ F(v) \leftarrow f1, f2, f3 \end{cases}$$

 $F(v)$ *as feature vector*

where ncc is the number of times chain codes do not change the value.

From FIGURE 11, we can come to the conclusion that the estimation of the perimeter is improved after applying the correction. Pseudocode for the extraction of shape features is summarized in the Algorithm 1.

V. CLASSIFICATION OF CROP AND WEED

Classification can be defined as a process of assigning classes to the given information. The tasks like identifying a given object in the image, classifying a given object in an image etc. involve a thorough understanding of perceived information. Using this understanding, the presented information is assigned a class. A classifier is a computer agent which performs this type of classification. These classifiers are divided into two broad categories namely supervised and unsupervised. Supervised techniques learn with the help of training data. That is, they will have some prior knowledge. But unsupervised techniques are not based on prior knowledge. In this research work, Random Forest and support vector machine classifiers were used.

A. RANDOM FOREST CLASSIFIER

The tree-based supervised learning algorithm is considered to be one of the best as it provides high accuracy and maps the non-linear relationships effectively. Random Forest [37] is one of the most popular methods among data scientists as it can perform both classification and regression. It also performs well in handling outliers, filling missing values and other essential issues in data analytics. It comes under the ensemble learning model wherein a group of weak learners comes together to form a strong model. In Random Forest multiple trees are built. If the classification of objects is based on features, multiple trees are built. Each tree gives a classification. The forest goes with the majority vote. The following points summarize the steps involved in Random Forest classifier as follows

- First randomly m features are chosen from M features where m<M.
- Using these m features build a node b which will be a root node using the best feature among m features. This is called as best split approach.
- Make node b to have child nodes by using the same best split approach.
- Repeat the steps from one to three until 'p' numbers of nodes have been reached.
- Repeat the steps from 1 to 4 until 'n' trees have been built.
- Test Features are now taken and rules of each tree are applied to predict the class.
- Final prediction is done by considering the majority vote in the forest.

B. SUPPORT VECTOR MACHINE CLASSIFIER

Support vector machine (SVM) [38] is one of the popular supervised machine learning algorithms. It finds a hyperplane in a N-dimensional space (N-features) that distinctly classifies data points. SVM usually tries the find the hyperplane that lies in the middle of the gap between the categories and thus maximally far away from both classes of data. But real data are seldom separable cleanly and thus results in misclassifications. SVM uses kernel function that adds an extra dimension to the data, projecting it from low-dimensional space into higher dimensional space and therefore are more often easily separable. In this study, radial basis function kernel [39] was used.

C. EVALUATION METHOD

The evaluation of Random Forest and support vector machine classifiers in classifying crop and weed is done quantitatively using confusion matrix [40] which gives us a summary of the prediction done on a classification problem. This essentially tells us how the classification model is confused while making the predictions. TABLE 2 shows the confusion matrix for a binary classification problem or when we have a two-class classification problem. If the classifier outcome is positive and actual case is also positive, then we have a true positive. If the classifier outcome is negative but actual case is positive, then we have a false negative. If the classifier outcome is negative and actual case is also negative, then we have a true negative. If the classifier outcome is positive but actual case is negative, then we have a false positive. TABLE 3 shows evaluation parameters for the confusion matrix for a binary classification problem [41].

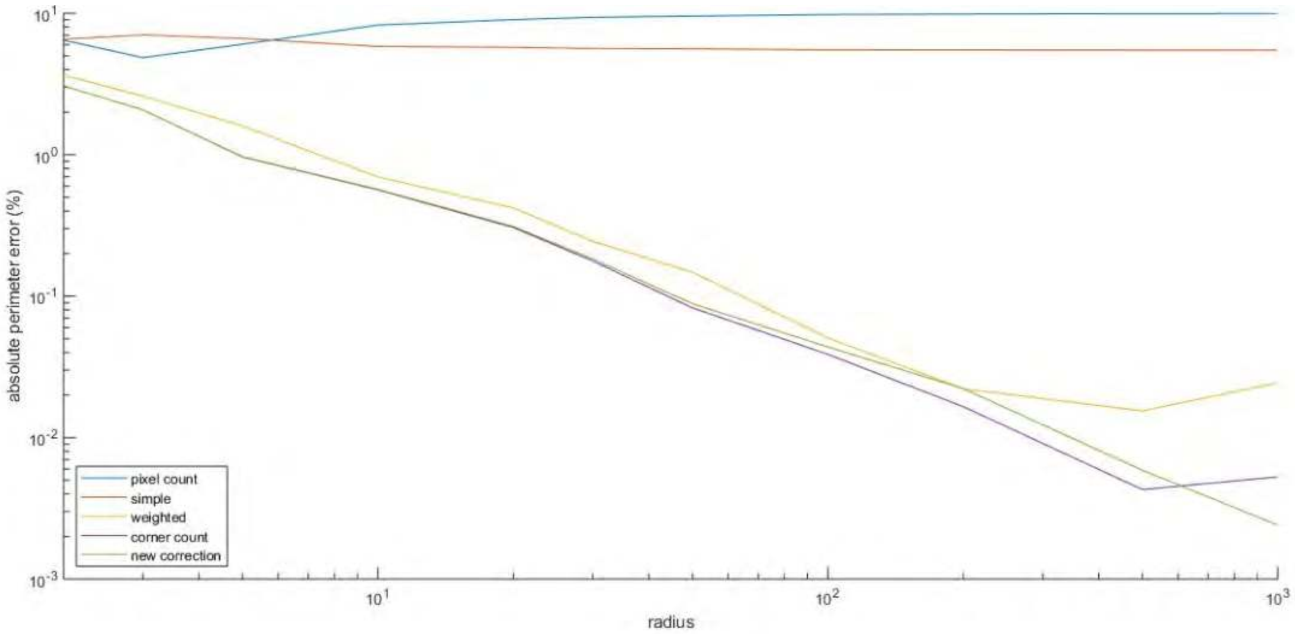


FIGURE 11. The absolute error of different methods including the new correction.

TABLE 2. Confusion matrix.

Predicted Class	Actual Class	
	Weed	Crop
Weed	True Positive(TP)	False Positive(FP)
Crop	False Negative(FN)	True Negative (TN)

TABLE 3. Evaluation parameters for two-class confusion matrix.

Evaluation Parameter	Formula	Describes
Accuracy	(TP+TN)/(TP+TN+FP+FN)	The ability of the classifier to correctly label the class
Recall or Sensitivity	TP/(TP+FN)	Compares positives with ones that should have been positives.
Precision	TP/(TP+FP)	Gives us how many of the positively predicted were indeed positives.
Specificity	TN/(FP+TN)	How effective a classifier in identifying the negatives.
F1-score	(2*TP)/((2*TP)+ FP+ FN)	Relates the real positives with those given by classifier

VI. RESULTS AND DISCUSSIONS

A. CLASSIFICATION OF PADDY CROP AND WEEDS BASED ON COMBINED SHAPE FEATURE VECTOR

The total number of images acquired by the Raspberry Pi was 200 images. The connected component algorithm was used to get individual plants as described in section IV(C). In some instances, we found heavy overlapping between the leaves of paddy crop and weed, and those overlapping which could not be separated were omitted and not considered for classification. We obtained about 788 plant objects. From these plant objects, shape features were extracted. The extracted shape features were used to train the Random Forest classifier and SVM classifier. The size of the training data was 606 and the size of the test data was about 182. Out of 182 plant objects, 133 belonged paddy plants and 49 were weed plants. The result of the Random Forest classifier and SVM classifier is given in TABLE 4 and TABLE 5 respectively. The misclassifications can be attributed to the similarity of grass-type weed and the paddy crop. It is difficult to compare the result of paddy crop and weed discrimination carried out in this study with other published work in the literature because each research work has been carried out for the different crops under different field conditions, different lab conditions and boundary conditions. However, there are studies which have discriminated crop and weed by considering the whole plant. In [42], identification of weeds found in Chilly crop was done with an accuracy of 97% using SVM classifier. In [43], discrimination of carrot crop and weed was done with an accuracy of 84% using Random Forest classifier. In [44], classification of sugar beet crop and weeds was done with above 90% accuracy using SVM, and artificial neural network classifier. This indicates that it is very difficult to develop a general model for crop and weed discrimination, and it largely depends on plant types (crop and weed), field conditions and features extracted.

From FIGURE 12 and FIGURE 13 we can observe that Random Forest classifier has outperformed the SVM classifier. This could be attributed to the presence of irrelevant features. Random Forest classifier is immune to irrelevant features and outliers. Also, it can cope up with the unbalanced data easily when compared to SVM. It is also noteworthy to mention that no data preprocessing nor feature selection techniques were used. This indicates that Random Forest classifier can be considered as a powerful tool in classifying paddy crop and weed.

TABLE 4. Confusion matrix showing result of classification by random forest.

Predicted Class	Actual Class	
	Weed	Crop
Weed	37	27
Crop	12	106

TABLE 5. Confusion matrix showing result of classification by SVM.

Predicted Class	Actual Class	
	Weed	Crop
Weed	35	58
Crop	14	75

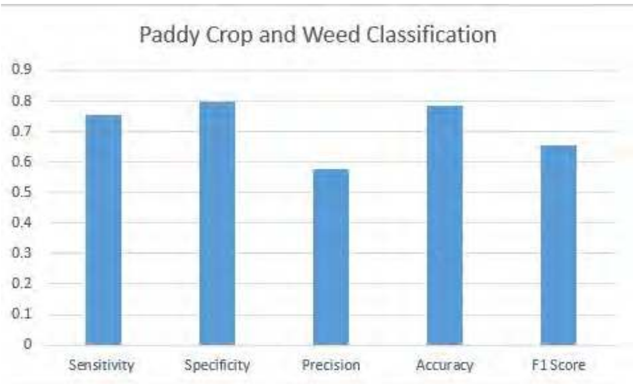


FIGURE 12. Result of classification of paddy crop and weed by random forest classifier.

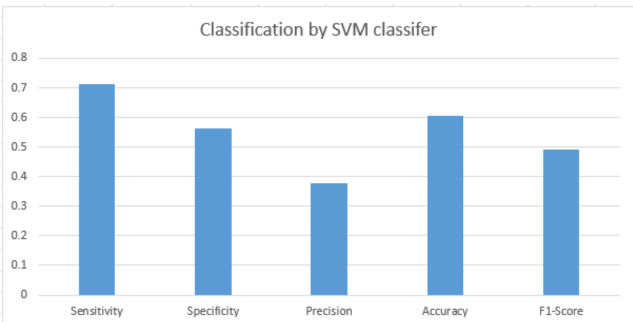


FIGURE 13. Result of classification of paddy crop and weed by SVM classifier.

The shape feature extraction algorithm 1 explained in section IV(C) is suitable for the images taken from transplanted rice fields where there is some distance between the rice plants and weeds growing in between them. Also, it is suitable if the paddy plants are in the early stage of the growth when there is little interference between the leaves of the plants. In this study, only shape features were considered for classification. Better results could be expected by adding extra features like color, and texture features.

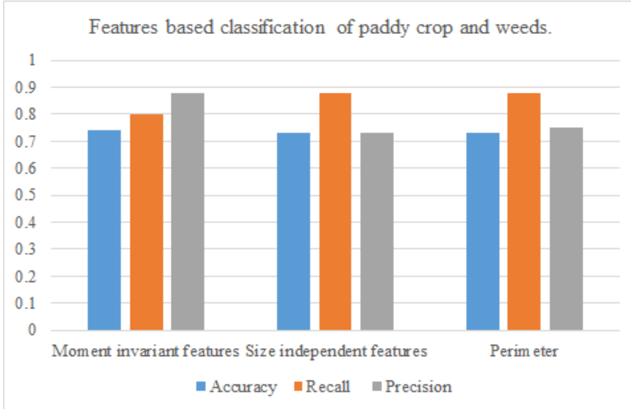


FIGURE 14. Classification result based on individual shape features.

B. FEATURES BASED TRAINING AND CLASSIFICATION.

To find out how these three shape features influence individually in classifying paddy crop and weed, Random Forest classifier was trained with these features separately and tested. FIGURE 14 shows the performance Random Forest classifier in classifying paddy crop and weed using the shape features separately. The average accuracy obtained in this classification was around 73%. We can note that these three shape features when combined together as a feature vector gave good result than as individual features. This could be attributed to the presence of some kind of interaction between the features.

C. OBSERVATIONS FROM WVSN IMPLEMENTED

The following observations were made from the wireless visual sensor network implemented in this study

- Bluetooth 4.0 can be used as communication technology to transfer the images in wireless visual sensor nodes. Chances of data loss due to collision is very rare. In this experimental set-up, no data loss or alteration of the data was observed.
- An average delay of 95 seconds was observed for 1-hop transmission.
- The experimental set-up was power efficient due to the use of Bluetooth 4.0 and solar power.
- The quality of images produced by Pi sensor board is good enough to make an inference from the images using image processing and soft computing technique.
- The Raspberry Pi camera board is very delicate and fragile. Slight mishandling of the camera board will result in the failure of the visual sensor node. Therefore, when handling the Raspberry Pi camera board in an outdoor environment, it has to be well protected from external disturbance factors like wind, water and so forth with the help of a shield.
- Raspberry Pi Zero W model can be used instead of Raspberry Pi 3 model B in order to reduce the cost when installing in large fields.

Through this study, we have shown that a wireless visual sensor network could be developed for monitoring the crops for pests using Raspberry Pi. We intend to extend this network by using various sensors like soil moisture sensors, light sensors, humidity sensors, temperature sensors along with the visual sensors so that a low-cost, full-fledged crop monitoring system is developed. This system could be used to monitor climatic parameters as well as monitor the crops for pests like weeds and diseases by analyzing the images acquired by visual sensors. Also, we intend to classify the types of weeds in the paddy fields so that suitable herbicide is recommended to the crop producers. This could result in the gradual decrease of herbicide-resistant weeds.

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