Design and Development of Rover with Robotic Arm-based Soil Moisture Sensor and Live Camera for Plant Health Monitoring

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Abstract

In agriculture, it is crucial to monitor the health and moisture levels of soil and plants in order to maximize crop yields and detect diseases at an early stage. However, traditional methods of monitoring often involve manual labour and are time-consuming, making it challenging to collect real-time data. To address these limitations, a solution has been proposed: a rover equipped with a robotic arm-based soil moisture sensor and a live camera for capturing images of plants. The robotic arm is an automated mechanical arm that can be controlled remotely. In the context of the rover, the robotic arm is equipped with a soil moisture sensor. This sensor measures the moisture content of the soil by analyzing relevant parameters such as electrical conductivity. By utilizing the robotic arm, the rover can navigate different locations within the field, enabling efficient and accurate measurement of soil moisture levels. Furthermore, the rover is equipped with a live camera capable of capturing high-resolution images of plants in real-time. The camera can be mounted on the rover and positioned at various angles to capture comprehensive images. These images provide valuable visual information about the plants' health and condition, allowing for the detection of diseases, nutrient deficiencies, and other abnormalities. By combining the robotic arm-based soil moisture sensor and the live camera, the rover system aims to provide a solution that automates and streamlines the process of monitoring soil moisture levels and detecting plant diseases. This technology significantly improves agricultural practices by providing real-time data, optimizing resource utilization, and enhancing crop productivity. Further, we have used SVM classifier to identify the pest & type of disease in cotton plant. Image acquisition devices are used to acquire images of plantations at regular intervals. These images are then subjected to pre-processing using median filtering technique. The pre-processed leaf images are then segmented using K-means clustering method. Then the color features(mean, skewness), texture features such as energy, entropy, correlation, contrast, edges are extracted from diseased leaf image using gray scale matrix (GSM) in the texture & then compared with normal cotton leaf image. The Support Vector Machine (SVM) classifier is used to classify the pest & Disease in cotton crop.

Keywords: Plant Health, Soil Moisture , Rover with Robotic, Live Camera.

1.Introduction

The agricultural sector faces numerous challenges, including the need for improved water management and precise monitoring of soil conditions. Soil moisture plays a critical role in crop growth and health, as it directly influences the availability of water to plant roots. Traditional methods of soil moisture measurement involve manual labor and time-consuming processes, which often yield imprecise results. Additionally, visual monitoring of crops is vital for identifying growth patterns, detecting diseases, and optimizing resource allocation.In the realm of agriculture, the constant need to optimize crop productivity and efficiently manage resources has led to the development of advanced technologies. One such innovation is the integration of rovers equipped with robotic arm-based soil moisture sensors and live cameras. This cutting-edge solution combines the capabilities of robotics, sensing, and imaging to provide real-time data on soil moisture levels and visual insights for precision agriculture. The integration of robotic technologies into agricultural practices has gained significant momentum in recent years. Researchers and engineers have explored various solutions to automate data collection and enhance decision-making processes for farmers. Early attempts to develop robotic systems for agriculture primarily focused on autonomous navigation and crop harvesting. However, as the importance of soil moisture management and real-time monitoring became apparent, the inclusion of soil moisture sensors and live cameras in rovers emerged as a logical progression.The need for a Rover with a robotic arm-based soil moisture sensor and live camera arises from the limitations of conventional agricultural practices. Manual soil moisture measurement methods are labor-intensive and time-consuming, rendering them inefficient for large-scale farming operations. Moreover, relying solely on visual inspection by farmers often results in missed opportunities for early disease detection or timely intervention. By combining the functionality of a rover, a robotic arm, soil moisture sensors, and live cameras, farmers can obtain accurate data and visual information remotely, allowing them to make informed decisions promptly.The significance of the Rover with robotic arm-based soil moisture sensor and live camera lies in its ability to revolutionize agricultural monitoring and management. The integration of robotic technologies streamlines the process of soil moisture measurement, making it faster, more accurate, and less labor-intensive. The inclusion of live cameras facilitates real-time visual monitoring, enabling farmers to identify crop health issues, detect pests or diseases, and optimize irrigation practices. This comprehensive approach enhances crop yield, reduces resource wastage, and promotes sustainable agricultural practices.The motivation behind developing a Rover with a robotic arm-based soil moisture sensor and live camera stems from the desire to empower farmers with advanced technologies to overcome challenges and maximize productivity. By automating data collection and providing real-time visual information, farmers can take proactive measures to mitigate risks, optimize resource allocation, and make informed decisions. This innovative solution also reduces reliance on manual labor, allowing farmers to allocate their time and efforts to other critical tasks, thereby increasing overall efficiency.

2. Literature Survey

Tian, Yongding, et al. (2022) proposed intelligent robotic systems for structural health monitoring in the construction industry. They discussed the various applications of these systems, such as damage detection, condition assessment, and real-time monitoring. The authors also highlighted future trends in the field, including the integration of artificial intelligence and machine learning techniques. However, the paper did not explicitly mention any drawbacks or limitations of their proposed work.

Bej, Gopinath, et al. (2022) presented a real-time robotic vision application for health monitoring of paddy plants. Their work aimed to enhance the monitoring and management of agricultural crops. The system utilized robotics and computer vision techniques to analyze visual information from the plants, enabling early detection of diseases and nutrient deficiencies. However, the paper did not specify any drawbacks or limitations associated with their approach, such as accuracy issues or challenges in practical implementation.

Devanna, Rosa Pia, et al. (2022) developed an in-field automatic identification system using a farmer robot for pomegranates. Their work aimed to improve efficiency and reduce labor costs in the agricultural sector. The robot employed sensors and computer vision algorithms to identify and locate ripe pomegranates, facilitating selective harvesting. However, the paper did not discuss any potential drawbacks or limitations of their proposed system, such as the performance in different lighting conditions or the adaptability to different varieties of pomegranates.

Basri, Mohd Ariffanan Mohd, and Muhamad Azizi Adnan (2022) presented an autonomous agriculture robot for plant monitoring using the Internet of Things (IoT). Their work focused on integrating IoT technologies to enable real-time data collection from sensors placed on the robot, allowing farmers to monitor the health and growth of crops remotely. However, the paper did not mention any specific drawbacks or limitations of their proposed system, such as the scalability of the IoT infrastructure or the robustness of the robot's navigation algorithms.

Sankarananth, S., and R. S. Arun (2022) introduced a smart cable-driven parallel robot assistant for individual plant care in farming. Their work focused on developing a robotic system capable of precise and controlled movements for tasks such as pruning, watering, and fertilization. However, the paper did not discuss specific drawbacks or limitations associated with their proposed robot assistant.

Ummadi, Vinay, Aravind Gundlapalle, and Althaf Shaik (2022) presented an autonomous agriculture robot for smart farming. Their work aimed to improve agricultural practices by integrating robotic technologies for various tasks, including crop monitoring, irrigation, and pesticide application. However, the paper did not explicitly mention any drawbacks or limitations of their proposed robot for smart farming.

Poojari, Mohan, et al. (2023)focused on computational modeling for the manufacturing of a solar-powered multifunctional agricultural robot. Their work aimed to optimize the design and manufacturing processes of the robot, considering factors such as energy efficiency and operational capabilities. However, specific drawbacks or limitations of their computational modeling approach were not discussed in the paper.

Khan, Arfat Ahmad, et al. (2022) presented a cost-efficient environment monitoring robotic vehicle for smart industries. Their work aimed to develop a robotic vehicle capable of monitoring various environmental parameters in industrial settings. However, the paper did not explicitly mention any drawbacks or limitations associated with their proposed robotic vehicle.

Chen, Gerry, et al. (2022) proposed a hybrid cable-driven robot for non-destructive leafy plant monitoring and mass estimation using structure from motion. Their work focused on developing a robotic system capable of estimating plant mass and monitoring plant health without causing damage. However, the paper did not discuss specific drawbacks or limitations associated with their proposed hybrid cable-driven robot.

Vulpi, Fabio, et al. (2022) explored the use of RGB-D multi-view perspectives for autonomous agricultural robots. They investigated the integration of RGB-D cameras and multi-view techniques to enhance the perception capabilities of agricultural robots. However, the paper did not explicitly mention any drawbacks or limitations of their proposed approach.

3. Proposed Method

Figure 1 shows the proposed block diagram of rover with live camera and soil moisture sensor system. The robotic arm with soil moisture sensor, live camera for plant image capturing, disease detection and classification algorithms, left and right motors with a motor driver, and the 6-channel transmitter and receiver work together to enable remote-controlled movement, soil moisture measurement, plant imaging, disease detection, and classification for agricultural or scientific purposes.

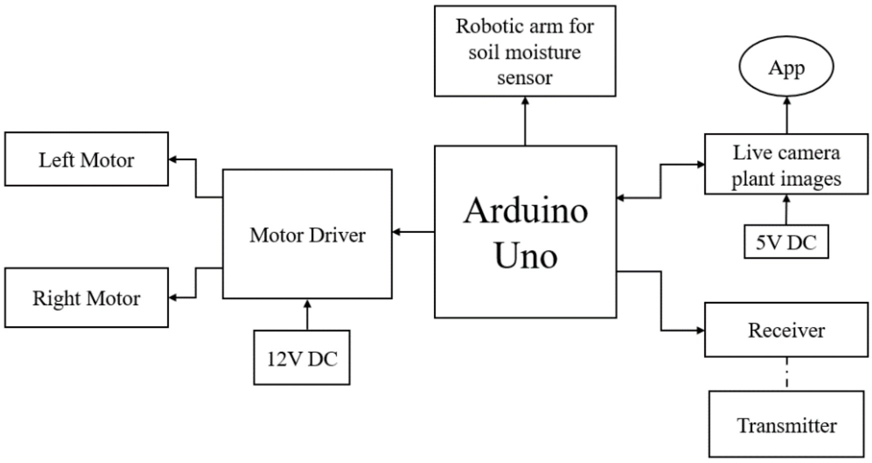


Fig. 1: Proposed block diagram of rover with live camera and soil moisture sensor system.

Step 1: Operational Methodology of the Robotic Arm with Soil Moisture Sensor:

Positioning the Robotic Arm: The operator uses the control system, either through the transmitter or a pre-programmed sequence, to position the robotic arm in the desired location. The actuators or motors of the arm are controlled to move it to the target area where soil moisture measurements are required.

Inserting the Soil Moisture Sensor: Once the robotic arm is positioned, the operator commands the arm to lower or extend the sensor towards the soil. The arm's actuators or motors adjust the position of the sensor and carefully insert it into the ground to a suitable depth, ensuring proper contact with the soil.

Soil Moisture Measurement: With the sensor inserted into the soil, it starts measuring the moisture content. The sensor may utilize various technologies such as capacitive or resistive sensors to detect the moisture levels. It provides feedback in the form of electrical signals, which are transmitted to the control system for further processing.

Interpretation of Moisture Levels: The control system receives the feedback from the soil moisture sensor and interprets the data to determine the moisture status of the soil. It analyzes the electrical signals and applies predefined thresholds or calibration curves to classify the moisture levels as dry, moist, or saturated. This information can be displayed on a user interface or used for further decision-making.

Step 2: Operational Methodology of the Live Camera for Plant Image Capturing:

Camera Orientation: The operator controls the orientation of the camera using the control system. If the camera is mounted on a pan-tilt mechanism, the operator can adjust its position remotely using the transmitter or pre-programmed commands. This allows for capturing images from different angles and perspectives.

Image Capture: Once the camera is properly positioned, the operator triggers the image capture process. The camera captures high-resolution images of plants or specific plant parts, such as leaves or stems. The captured images are then transmitted or stored for further processing.

Step 3: Operational Methodology of Disease Detection and Classification: The captured plant images are processed using computer vision techniques. The images are fed into the control system, which applies machine learning or image processing algorithms to analyze the images. The algorithms extract relevant features or visual markers from the images that are indicative of plant diseases. These features can include color variations, texture patterns, lesion formations, or any other distinguishing characteristics associated with diseases. The control system compares the extracted features with a pre-trained dataset of healthy and diseased plants. The dataset contains labeled images that serve as references for disease identification. By matching the extracted features with the dataset, the system can classify the plant as healthy or identify the specific disease affecting it.

The RGB color images of most frequently encountered Phyto-pathological problems affecting Cotton leaves were captured using camera. Images were stored in.JPG format

Image Pre-Processing and Segmentation

The pre-processing involved the procedures to prepare the images for subsequent analysis. The affected leaf images were converted from RGB color format to gray scale images. Segmentation refers to the process of clustering the pixels with certain properties into salient regions and these regions correspond to different faces, things or natural parts of the things. We proposed k-means segmentation technique to fragment goal areas.- Target regions are those areas in the image that represented visual symptoms of a fungal disease.

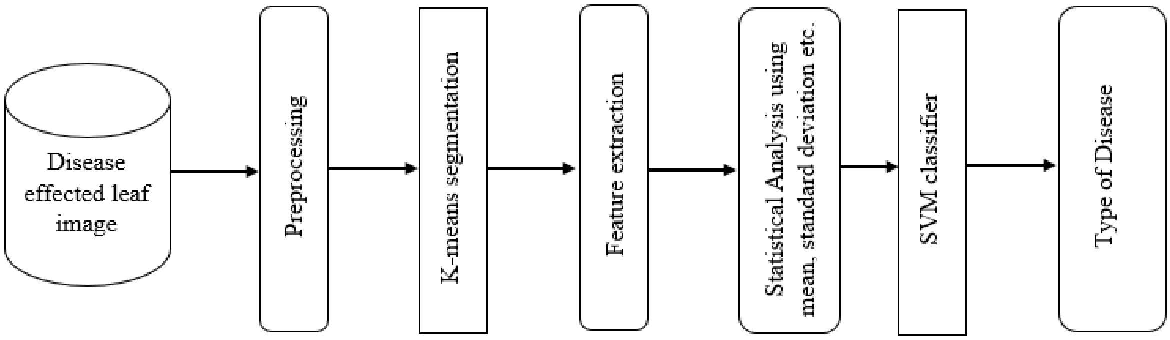


Fig:2. Proposed system of disease identification and classification

Feature Extraction

The symptoms associated with vario0pus Phyto-pathological problems of cotton leaves under investigation visible on the affected leaves were extracted from their respective images using K-means. The image analysis was mainly focuses on the extraction of shape features and their color based segmentation.

The image analysis technique is done using Gray-level co-occurrence matrix. The affected areas vary in color and texture and are dominant in classifying disease symptoms. So, we have considered both color and texture features for recognition and classification purpose. The use of color features in the noticeable light spectrum provided additional image characteristic features over traditional gray-scale representation. GLCM is a method in which both color and texture features are taken into account to arrive at unique features which represent that image.

Statistical Analysis

Statistical analysis tasks are completed to choose the best features that represent the given image, thus minimizing feature redundancy. We have found that only 13 features contribute as discriminating features as this is essential for better classification.

Magnitudes that are workable to guess via the co-occurrence matrix are: energy, entropy, homogeneity, contrast, Mean, Standard Deviation, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM and correlation.

Classification

At present SVM is popular classification tool used for pattern recognition and other classification purposes. Support vector machines (SVM) are a group of supervised learning methods that can be applied to classification or regression. The normal SVM classifier takes the set of involvement data and calculates to classify them in one of the only two separate classes. SVM classifier is trained by a given set of training data and a model is willing to classify test data established upon this model. Most habitual classification models are established on the empirical risk minimization principle. SVM implements the structural risk minimization principle which pursues to reduce the training error and a sureness interval term. A number of submissions showed that SVM hold the superior classification capability in production with minor sample, nonlinearity and high dimensionality pattern identification.

Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that splits among a set of objects having different class association. Classifier that separate a set of objects into their corresponding classes with a line. Supreme classification tasks, however, are not that modest, and regularly more difficult structures are needed in order to make an optimal separation, i.e., correctly classify new objects (test cases) on the basis of the examples that are available (train cases). All the evidence from beyond processes is given to multiclass SVM .The Multiclass SVM were used for cotton disease classification.

K-MEANS CLUSTERING

This section briefly explains the basic theory of K-means clustering. Let $A=\{ai \mid i=1,\dots,f\}$ be attributes of f-dimensional vectors and $X=\{xi \mid i=1,\dots,N\}$ be each data of A. The K-means clustering separates X into k partitions called clusters $S=\{si \mid i=1,\dots,k\}$ where $M \varepsilon X$ is $Mi=\{mij \mid j=1,\dots, n(si)\}$ as members of si, where $n(si)$ is number of members for si. Each cluster has cluster center of $C=\{ci \mid i=1,\dots,k\}$.

Flowchart for K-Means Algorithm

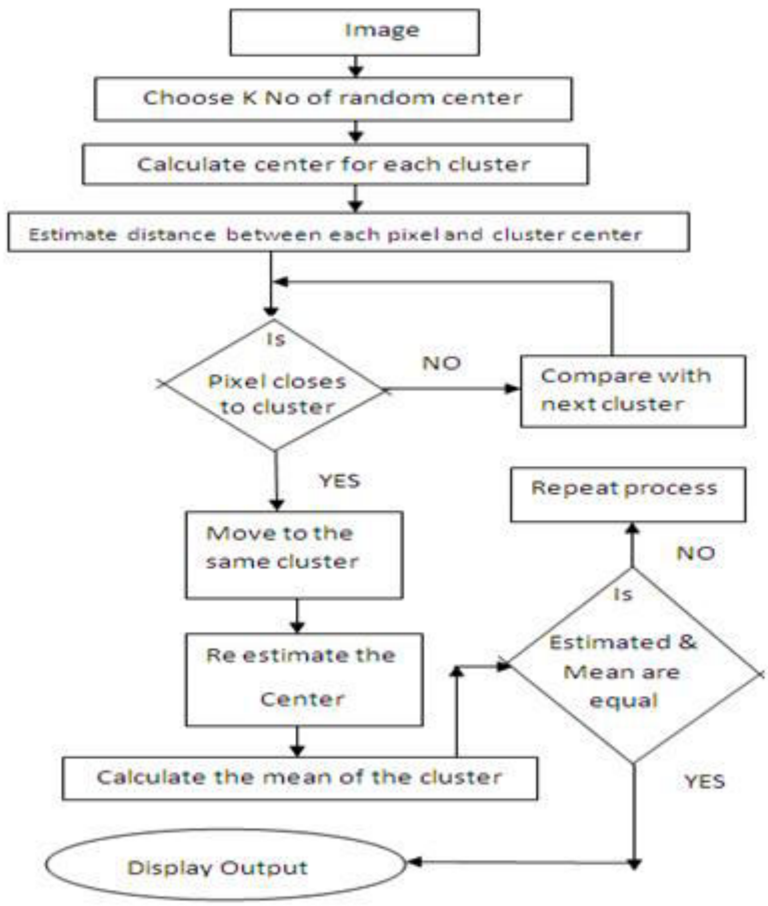


Fig. 3. Flow chart of k-means clustering

K-means clustering algorithm can be described as follows

1. Initiate its algorithm by generating random starting points of initial centroids *C*.

2. Calculate the distance *d* between *X* to cluster center *C*. Euclidean distance is commonly usedto express the distance.

3. Separate *xi* for *i*=1...*N* into *S* in which it has minimum *d(xi,C)*.

4. Determine the new cluster centers*ci* for *i*=1...*k* defined as:

$$C_i=\frac{1}{n_i}\sum_{j=1}^{n(s_i)} m_{ij} \in s_i$$

5. Go back to step 2 until all centroids are convergent.

The centroids can be said converged if their positions do not change in the iteration. It also may stop in the *t* iteration with a threshold ε if those positions have been updated by the distance below *ε*:

$$\left|\frac{c^t-c^{t-1}}{c^t}\right|<\varepsilon$$

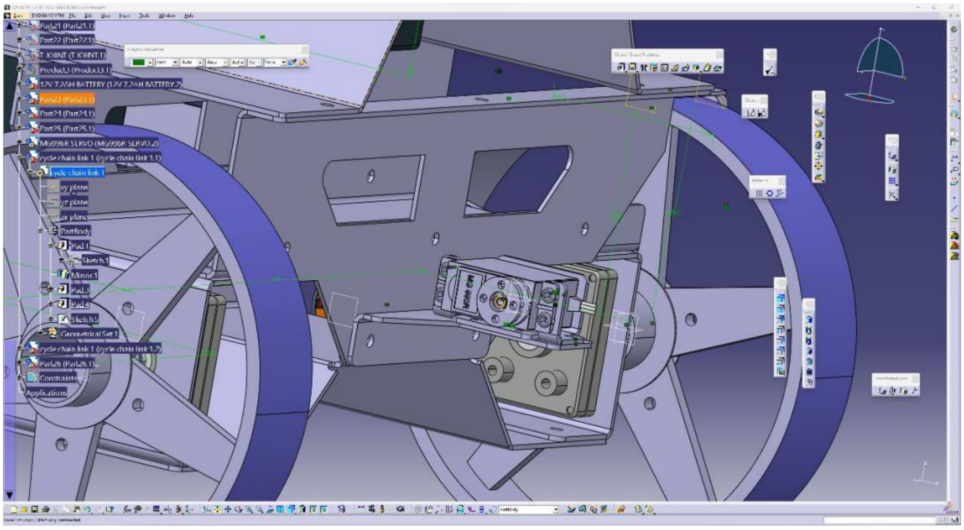
GLCM

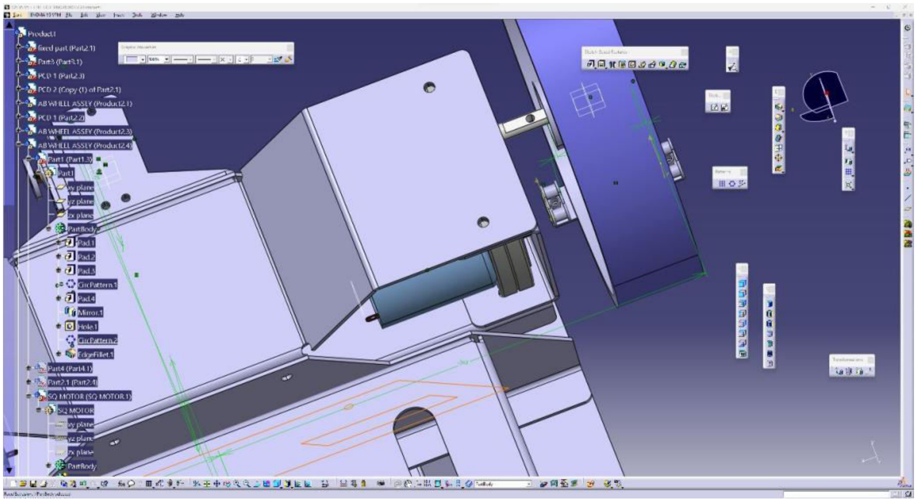
Gray-co-matrix function can be used to create the GLCM (Gray level co-occurrence matrix). Gray comatrix function calculates how often the relationship between the pixel value i occurs with respect to the pixel value j. The pixel to its immediate right and by default the spatial relationship is defined as the pixel of interest Even though the spatial relation between the two pixels is verified. Each element in the GLCM is nothing but the sum of the number of times that the pixel value i occurs with relation to the pixel value j.in the input image.

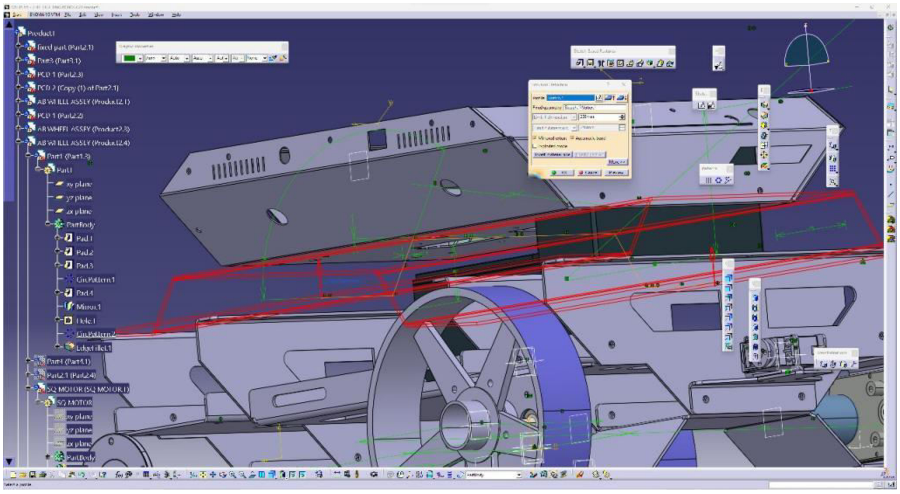
For the full dynamic range of an image the processing required to calculate a GLCM is prohibitive. The input image was scaled by the gray matrix. By default, to reduce the intensity values from 256 to 8 in Grayscale image gray comatrix use scaling. Using the number of levels and the gray limits parameters of the gray comatrix function the number of gray levels and the scaling of the intensity values in the GLCM can be controlled. The properties about the spatial distribution of the Gray level in the texture image can be revealed by the Gray level co-occurrence matrix.

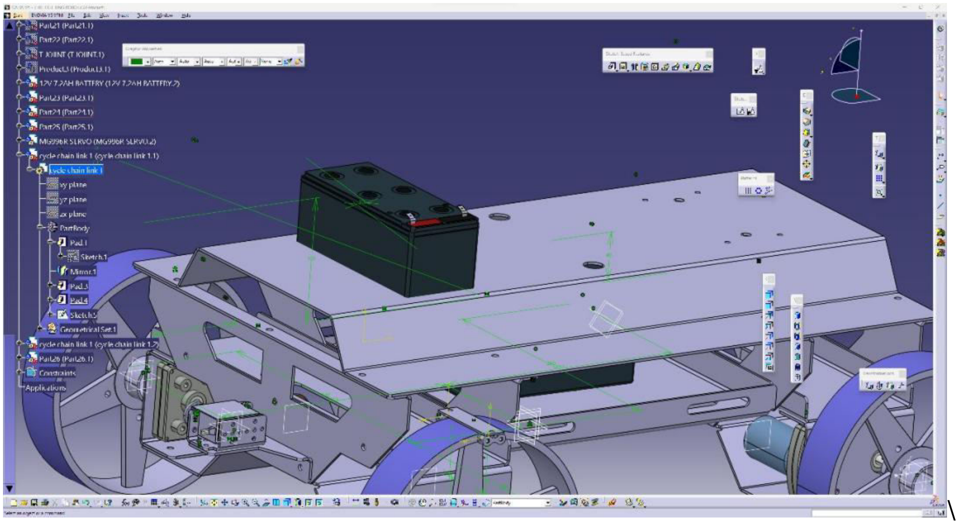
4. RESULTS AND DISCUSSION

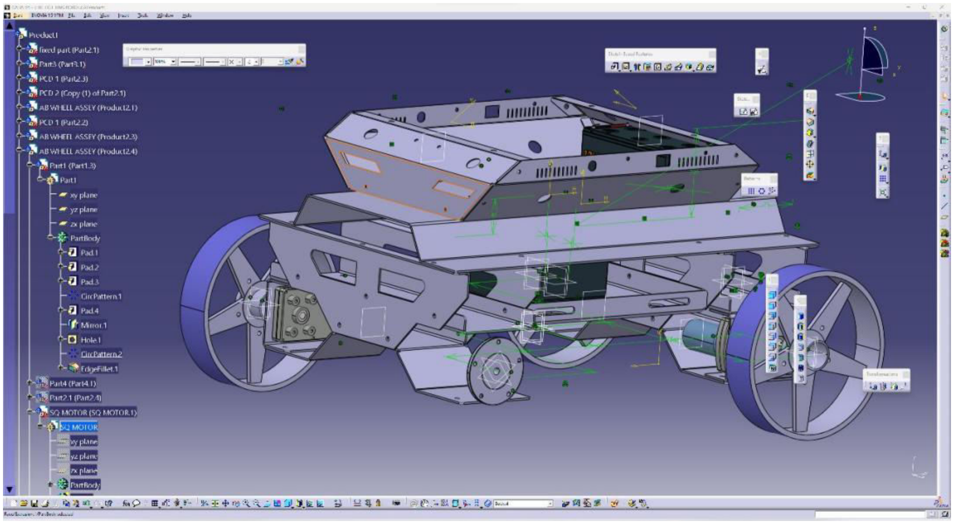
4.1 3D-Design Modelling

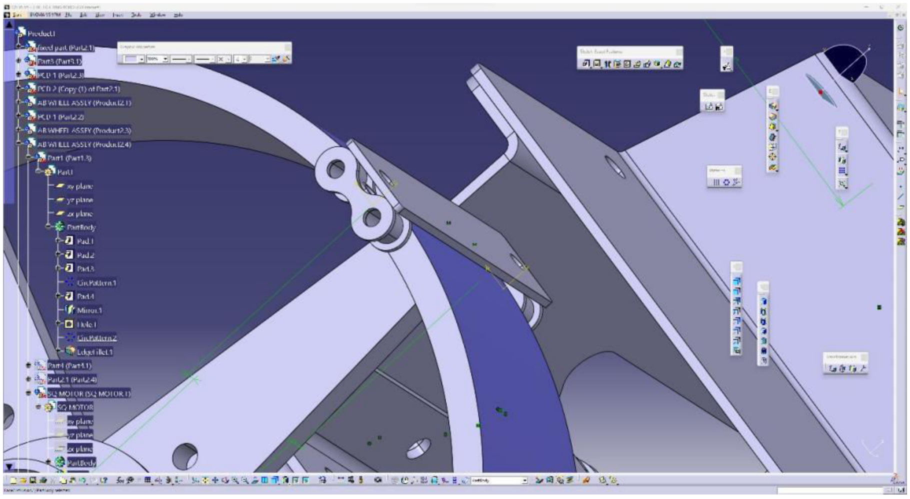


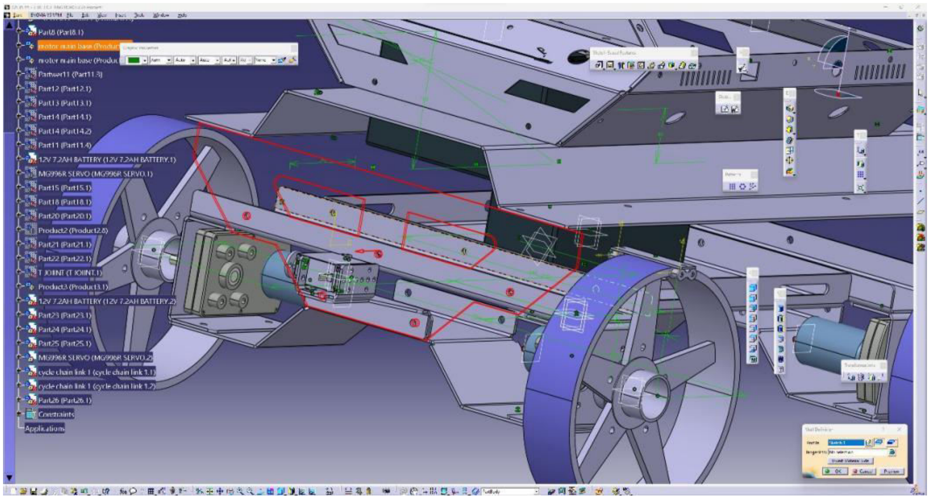


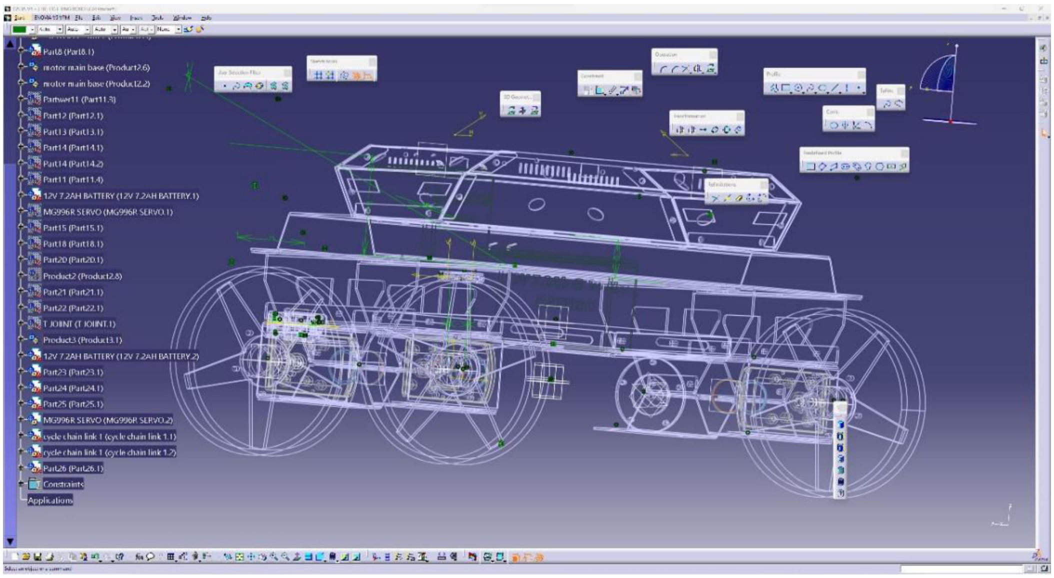


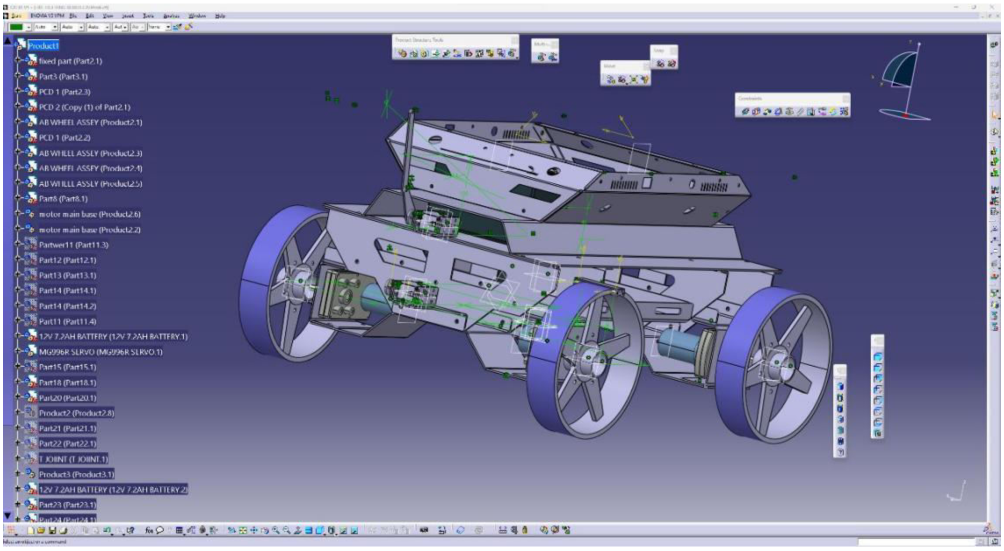


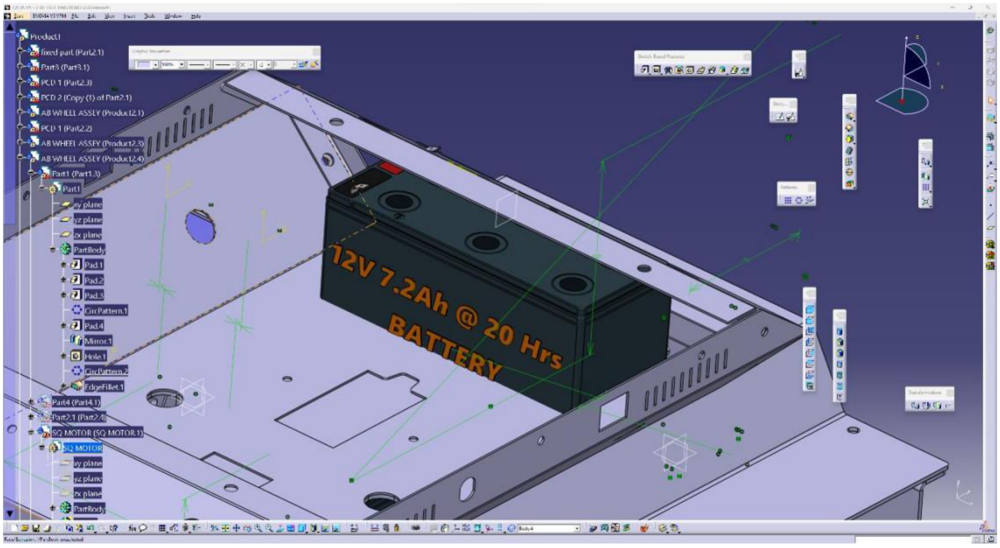












4.2 Software results

Identified Phyto-pathological problems experiments modules are developed using MATLAB R2014a, which runs in the environment Windows7, 8, 10 and 11. Two species of samples are taken for the experiment, whose digital images are obtained by a camera. FIG shows the species type and numbers of leaves images for these species.

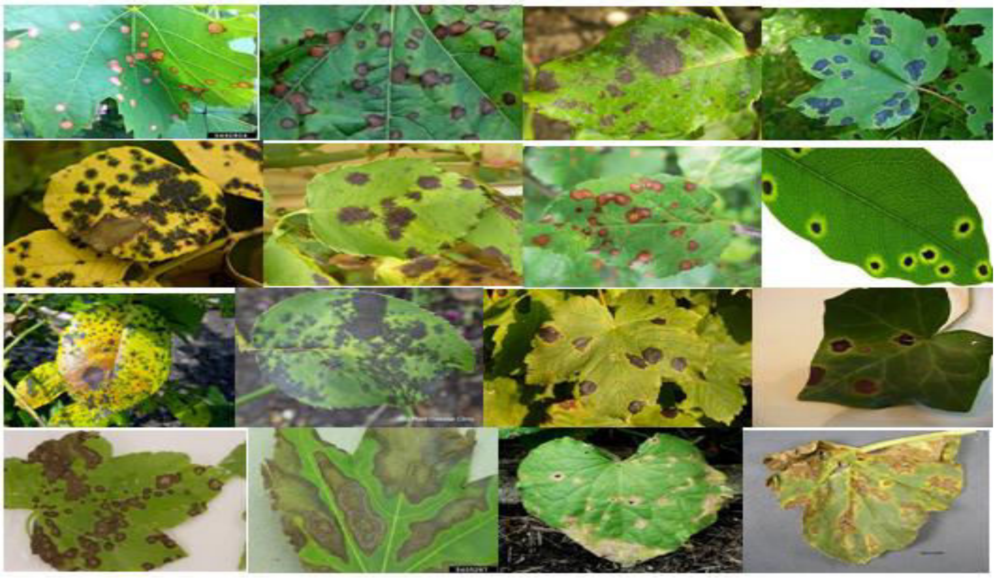


Fig. 4 dataset used for disease identification

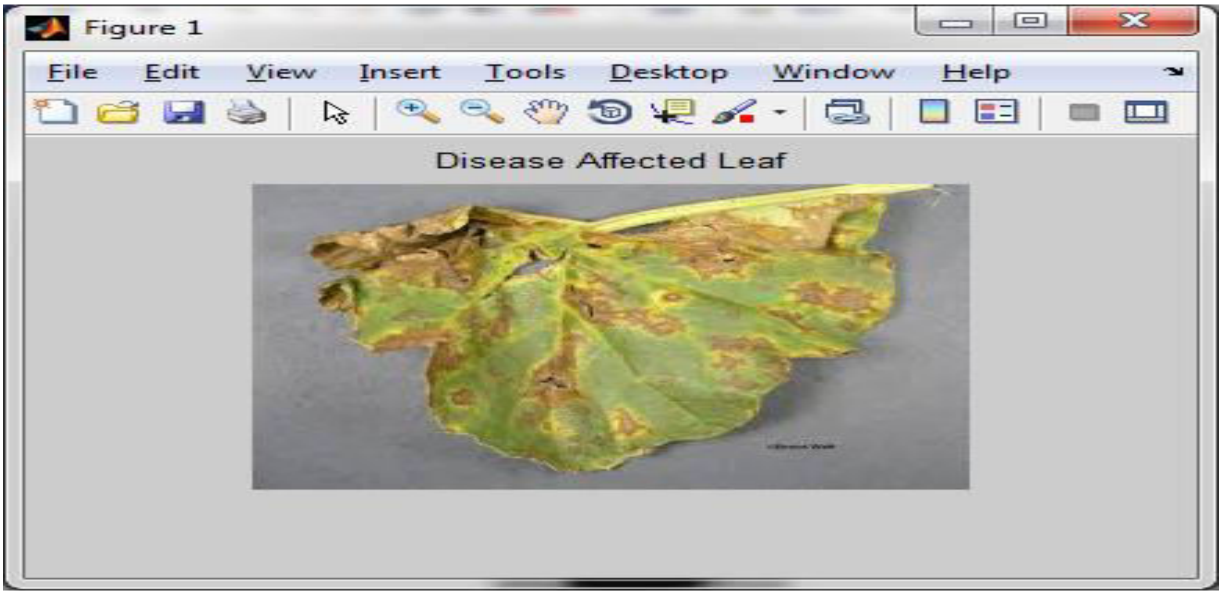


Fig. 5 Disease affected leaf from the dataset

Fig. 6. Cluster indexes after K-means segmentation process

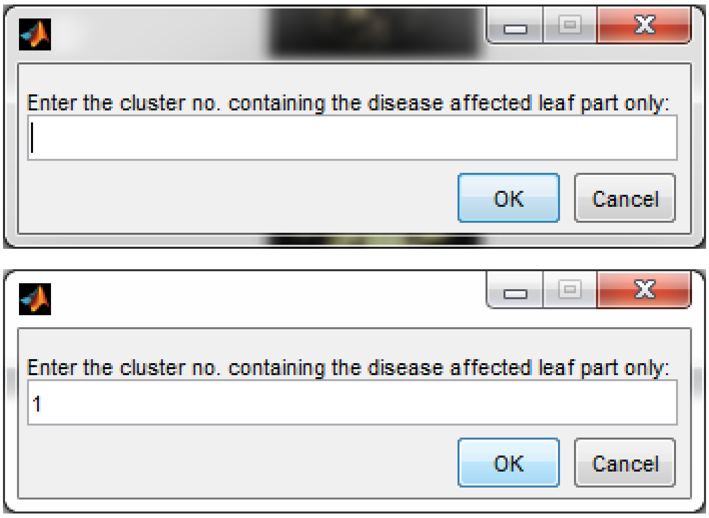


Fig. 7 select the cluster index in which the disease is presented

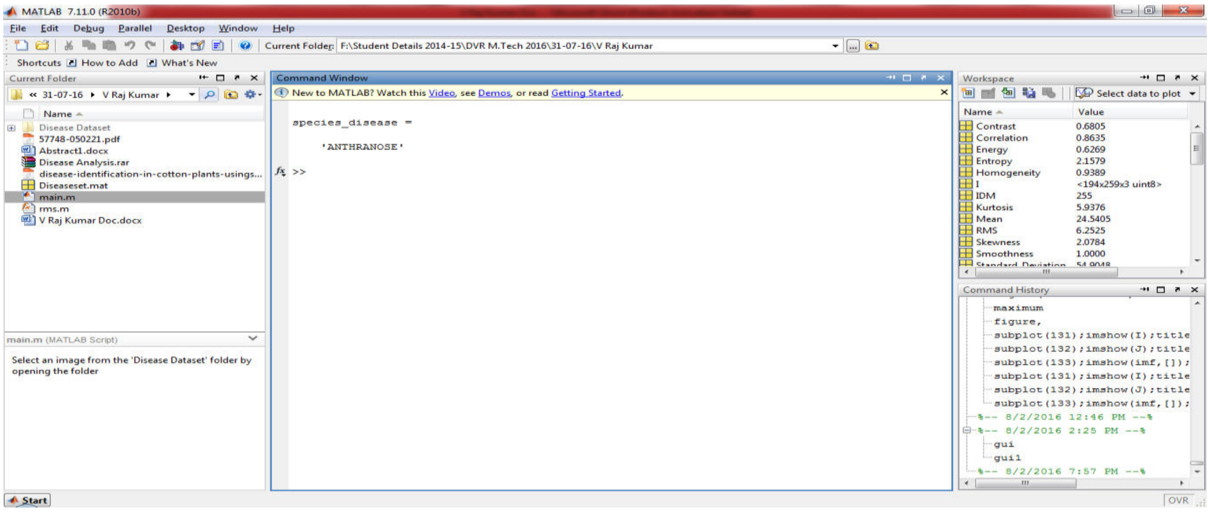


Fig. 8 snapshot of MATLAB environment after the execution of program

5. CONLUSION AND FUTURE SCOPE

In conclusion, the integration of a robotic arm-based soil moisture sensor and a live camera on a rover presents a promising solution for monitoring soil moisture levels and detecting plant diseases in agriculture. By automating these processes, the rover system offers several advantages, including real-time data collection, increased efficiency, and improved crop productivity.

The use of the robotic arm allows the rover to access different areas within the field and accurately measure soil moisture levels, providing valuable information for irrigation and water management. The live camera captures high-resolution images of plants, enabling the detection of diseases, nutrient deficiencies, and other plant health issues at an early stage done using machine learning based SVM. This early detection allows for timely intervention and targeted treatment, reducing crop losses and improving overall yield.

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