Plant Based Medicine Alternative system

Zaber Al Mamun, Toufikul Islam Eyasin, MD Abdullah Bin Asad Siam,Sejuti Rahman Fammi
Independent University, Bangladesh

Dhaka, Bangladesh
Email: Zaber00007@gmail.com; eyasinbhui@gmail.com; rfammi@gmail.com; siamiub.edu.bd@gmail.com

Abstract: This IEEE paper outlines the creation of an automated tree-scanning robot that will take pictures of trees and use cutting-edge image processing methods to identify their species. The project covers the hardware design and construction of the robot, including wireless connectivity and camera integration. In addition to a database for species data, a separate server is set up for image processing and storage. The ESP32-CAM WiFi + Bluetooth camera module, the L298N Hbridge dual stepper motor driver, the 2-wheel drive mobile robot platform chassis, the 2 axis pan tilt brackets for the camera/sensor, the 1000uF 16V capacitor, the 11.1V 2200mAh Li-Po battery, and the step-down adjustable power supply module are all used to build the robot. The design and installation of the robots, which transmit live video and picture feeds using the ESP32CAM module, are covered in the study. The ESP32-CAM module is programmed to recognize objects using image processing techniques, focus on them using the camera module's 2 axis pan tilt brackets, and follow them. This allows the robot to be automated. The efficiency of the suggested system is demonstrated by experimental findings, which show that the robot can precisely detect and track objects, move inside a defined space, and wirelessly transmit high-quality video feeds. The robot is a useful tool for applications involving tree identification because it offers improved mobility and monitoring flexibility.

Keywords- Wireless Transmission, Video, Image, Robot, Server, Automation, Object Detection, ESP32-CAM, Wifi-module.

INTRODUCTION I.

The fusion of robotics, image processing, and data transmission has prepared the way for ground-breaking solutions that reinvent our engagement with the visual world in the dynamic environment of technological advancement. In this study, we explore the design and construction of a complex robotic system that can take pictures, send them quickly to a central server, and use cutting-edge image processing methods to extract the inner features from each picture. This amazing combination of hardware and software innovation aims to provide fresh perspectives on image interpretation and analysis, ultimately paving the way for a wide range of applications in industries including surveillance, agriculture, and the arts and entertainment. A new era of autonomous exploration and data gathering has arrived as a result of advancements in robotics. The core of our project is the creation of a robot that serves as both a data conduit and an active visual sensor. The hardware architecture of the robot, which was carefully created to support image capture and transmission, enables it to explore environments and acquire visual data that goes beyond the purview of ordinary photography.[1] The photographs are instantly communicated to a dedicated server as soon as they are acquired, forming the foundation of a complex data transmission pipeline. Using powerful algorithms to identify applications, this server acts as a hub for processing and analysis while also enhancing monitoring flexibility and mobility expose the hidden information that the photographs hold. the system gains an intelligent layer from the combination of cutting-edge image processing techniques, such as object identification, pattern analysis, and machine learning, allowing it to categorize and understand images on its own.

FIG.1.PROPOSED PHOTO CAPTURE ROBOT

The effects of this ground-breaking system are wide-ranging. The capabilities of our robot and its integrated image processing system have the potential to change how we interact with and comprehend visual data, whether in commercial applications like automated quality control and precision agriculture or creative endeavours like generative art and virtual storytelling. With the use of robotics and artificial intelligence, the suggested automated system seeks to accelerate this procedure and offer a more effective and precise solution. The FM radio transmitter module, the ESP32-CAM WiFi + Bluetooth camera module, the 2wheel drive mobile robot platform chassis, the L298N H-bridge dual stepper motor driver, the 2axis pan tilt brackets for camera/sensor, the 1000uF 16V capacitor, the 11.1V 2200mAh LiPo battery, and the step-down adjustable power supply module are some of the components used to build the robot. Bluetooth technology is used in the wireless transmission system to send data in a dependable and effective manner. The efficiency of the suggested system is demonstrated by experimental findings, which show that the robot can precisely detect and track objects, move inside a defined space, and wirelessly send high-quality video and image feeds. With its improved mobility and flexibility for monitoring, this wireless video and image transmission robot represents a useful tool for Medicine Alternative system applications.[2] The device is powered by a rechargeable 12-volt lipo battery. In order to lower the circuit voltage, we employ a buck converter. since this device's car motor can only handle 12V. The device is powered by a rechargeable 12-volt lipo battery. In order to lower the circuit voltage, we employ a buck converter. since this device's car motor can only handle 12V. We set out on this journey to demonstrate the revolutionary potential of technological synergy at the nexus of robotics and image processing. The result of our work is a robot that not only takes pictures but also adds intelligence to them, ushering in a paradigm shift in how we view, engage with, and interpret the visual world.[3]

II.PROPOSED SYSTEM METHODOLOGY AND SIMULATION

We give a thorough explanation of the design and implementation process for a robot that can capture photographs, send them to a server, and use image processing to determine the names or contents of the images. The hardware configuration of the robot was carefully planned to support the image capture and communication processes. The robot's design included a high-resolution camera to make it easier to capture images, and communication modules were used to provide a secure link between the robot and the server. To improve the robot's context awareness during image acquisition, pertinent sensors were also added. A special system was put up for the server infrastructure to serve as the focal point for image receiving, processing, and storage. The server had all the required hardware and software, including a reliable database system for keeping track of the image data that had been processed. A communication protocol was put in place to allow easy communication between the robot and the server. Using this protocol, the robot was able to connect securely to the server, send photographs in real-time, and receive acknowledgement messages to confirm that the data transmission was successful. The system's functionality depended heavily on image processing. The recorded photos were subjected to a number of image processing methods, such as object recognition, feature extraction, and pattern recognition. The algorithms used to evaluate the photographs and extract valuable data that would subsequently help with image naming or classification were chosen with care. The system used the results of the image processing algorithms to give the images the proper titles or labels after the photos had been processed. Machine learning techniques have been incorporated in some cases to enhance accuracy over time by absorbing user feedback and enhancing the picture recognition models. The server's structured database contained the processed photos along with the names or labels that went with them. This database management system made it possible to save and retrieve data quickly, making it simple to access processed photos for further study. A user interface was created to enable user interaction. Users were able to interact with the system using this interface, view the photographs that had been processed, and offer input. This feedback loop had a key role in raising the classification and naming accuracy of images.[4] To guarantee the system's dependability and functionality, thorough testing and validation methods were carried out at every stage of development. The findings of these tests were used to improve the implementation. Various test scenarios were created to evaluate various areas of the system's performance. Ethics were taken into account, especially with regard to user permission and data privacy. The system was created to adhere to moral standards, guaranteeing that pictures were taken and processed ethically, keeping users' privacy in mind. Despite the project's triumphs, difficulties were also experienced. These difficulties ranged from difficult hardware integration to real-time algorithm optimization for picture processing. To address these challenges and preserve the project's development, innovative solutions were developed. A number of potential areas for future development were noted. The system needs to be made more capable of handling bigger amounts of image data, the accuracy of image recognition algorithms needs to be improved, and the user interface needs to be made even better. user experience that is seamless and simple. The robot and its interconnected systems were developed using a methodical approach to user engagement, communication protocols, image processing, hardware and software integration, and ethical considerations. The thorough approach described above establishes the groundwork for the effective implementation of a robot that can capture, analyse, and analyze images for naming or classification purposes. The goal of the project is to build an automated tree-scanning robot that can take pictures of trees, upload them to a server, and use image processing to identify the species. A clearly defined process is used to steer the project.

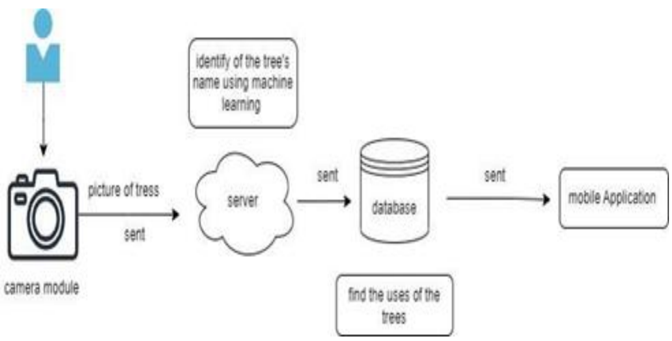

Fig.2: Block diagram of the system

Establishing project goals and requirements, including those for hardware requirements, image quality, wireless transmission, server capabilities, and image processing methods, is part of the project commencement step. The physical framework of the robot is then designed and constructed, including a camera for image capturing. The software coordinates the collection of images and their transmission to the specified server, which has plenty of space for storage and processing power. The image processing pipeline, where images are pre-processed for refinement, is the canter of the operation. A model is created and trained using labelled tree pictures and machine learning. When deployed, the model examines incoming photos to enable real-time classification of tree species. To encourage user engagement and display species information, an extra user interface might be created.

System testing in various outside environments ensures accuracy and functionality. The initiative is governed by ethical principles, safeguarding data protection and obtaining consent for image capturing. The project's goal is to integrate robotics, image processing, and machine learning to promote environmental research and tree species identification through ongoing maintenance and potential model updates. Typically, image processing entails taking a picture with the camera module and then examining it to carry out operations like object detection, recognition, and tracking. Artificial intelligence (AI) methods, such as deep learning models, that are trained on big image datasets to understand how to do particular tasks, are generally used for the analysis. Here are some essential phases in the pipeline for image processing. image taking an image is taken by the camera module, which then saves it as a digital image file in memory.[5] A 2D array of pixels is often used to depict an image, with each pixel denoting a different colour value. Pre-processing a picture: The image is processed beforehand to make it ready for analysis. This could entail adjustments to the image's size, normalization of the pixel values, and the use of filters to reduce noise and highlight particular characteristics. Feature extraction: The image is examined to extract significant features that are important for object detection and identification, such as edges, corners, and textures. Typically, convolutional neural networks are used for these networks (CNNs) are created with the purpose of extracting features from images. Object detection and identification: The image's objects are found and identified using the retrieved features. This may include employing techniques like the sliding window approach, which scans the image with a tiny window and evaluates each window's features to see if it contains an object. [6] The following equations could be helpful when processing images: CNNs employ the mathematical operation of convolution to extract features from images. Convolution is described by the equation $(f * g)(n) = f(k) * g(n-k))$.------------------(1) where n is the integration variable, n and g are functions, * is the convolution operator, and k is the index of summing. Deep learning models frequently employ the SoftMax function to transform a vector of values into a probability distribution. The softmax function's formula is $\mathrm{SoftMax}(x_i) = \exp(x_i) / \exp(x_j)$------(2) where x_i is the input vector's element with the index i and j spans all of the input vector's elements.A statistical algorithm used for object tracking is the Kalman filter. The Kalman filter equations consist of:

The formula is: $x_k = F x_{k-1} + w_k$. P_k equals $F P_{k-1} F' + Q$ $K_k = P_k H' (H P_k H' + R)^{-1}$ $x_k = x_k + K_k (z_k - H x_k)$ has been updated. $(I - K_k H) = P_k P_k$ where z_k is the observation at time k, K_k is the Kalman gain at time k, w_k is the process noise, Q is the process noise covariance, H is the observation matrix, R is the observation noise covariance, and P_k is the error covariance at time k. [7] Tracking of objects: The ability to monitor objects across time once they have been identified and detected in the image Electrical usage You can maximize battery life and make sure the system can run for a sufficient period of time between charges by simulating the power consumption of the system. Wireless range: You can arrange the wireless module and the antenna in the best possible locations to ensure that the system can send data over the necessary distance by simulating the wireless range of the system. Performance in image processing: You can choose the best parameters for the deep learning algorithms used for object detection and tracking by simulating the system's performance in image processing. Additionally, simulation can be used to evaluate the algorithms' precision and speed in various scenarios.[8] Network latency: You can improve system responsiveness and reduce lag time between real-time video and image transmission by simulating the network latency of the wireless module.

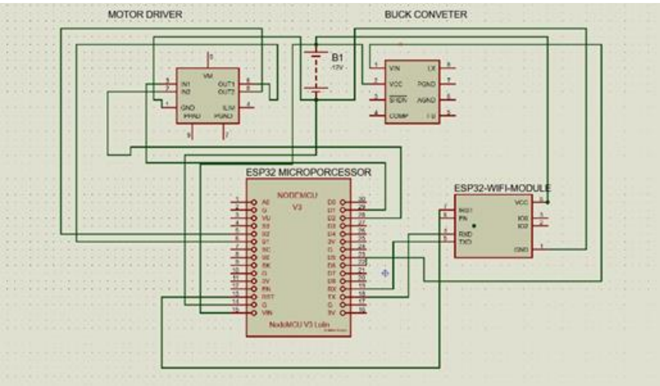

Fig.3. simulation of hardware system

The ESP32 camera module, Wi-Fi module, buck converter, and motor driver work in unison to simulate the dynamics of your imagined tree-scanning robot in the virtual world of Proteus simulation. This combination enables a thorough examination of the system's behavior and serves as a foundation for practical application. The procedure begins in this virtual environment with careful component selection. The basis for the next complex interconnections is built by assembling the ESP32 camera module, Wi-Fi module, buck converter, and motor driver from Proteus' large component library.

By tying these parts together with electrical and ground connections, wiring replicates the configuration found in the real world. A crucial component in the ensemble's power supply, the buck converter manages the energy flow and supplies each component with the right voltage. The foundation for the orchestration of the system's functionalities is laid out by these virtual cables. The focal point is the ESP32 camera module, which replicates the image capture in response to preset triggers. Its virtual environment interactions, which are simulative of actual operations, provide a peek of picture acquisition in action. Similar to how the camera module would transmit data, the Wi-Fi module, designed for connectivity, creates a virtual connection to a network.

III. DEVELOPMENT AND TESTING OF HARDWARE PROTOTYPES

The ESP32-CAM Wi-Fi + Bluetooth Camera Module Development Board, L298N H-Bridge Dual Stepper Motor Driver, Wireless Microphone, FM Radio Transmitter Module, and 2 Axis Pan Tilt Brackets for Camera/Sensor are just a few of the hardware components that must be integrated into the project. The selection and integration of hardware components, testing arrangements, lab testing specifics, and the IoT platform used for wireless transmission are all covered in this portion of the IEEE report on the creation and testing of hardware. To ensure the robot's successful implementation and wireless transmission of speech and image for surveillance purposes, the hardware development and testing phase is crucial. The hardware used in the project is listed in the table below.

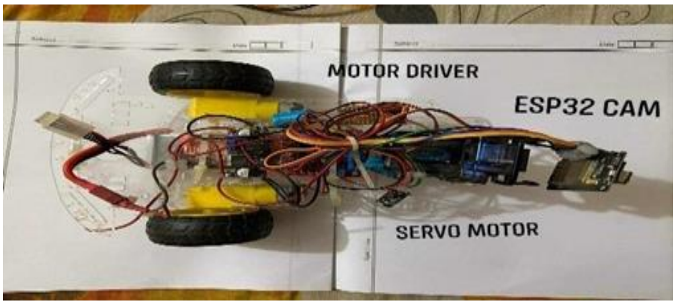

Fig.4. Developed prototype of picture capture system

Parameter	*Component name*	*Quantity*
1	ESP32-CAM WiFi + Bluetooth Camera Module Development Board ESP32 With Camera Module OV2640	1
2	ESP32-CAM-MB MICRO USB Download Module for ESP32 CAM Development Board	1
3	2 Wheel Drive Mobile Robot Platform Chassis	1
4	L298N H-Bridge Dual Stepper Motor Driver	1
5	2 Axis Pan Tilt Brackets for Camera/Sensor	1
6	1000uF 16V Capacitor	3
7	11.1V 2200mAh Li-Po Battery	1
8	Lipo battery connector	1
9	Jumper Wire - Male to Male, Male to Female, Female to Female	1
10	Step Down Adjustable Power Supply Module 3A Max Buck Converter	1

Jumper wires were used to link the Transmitter Module and Wireless Microphone to the ESP32-CAM module. The L298N H-Bridge Dual Stepper Motor Driver was connected to the ESP32-CAM-MB MICRO USB Download Module, and the 2 Wheel Drive Mobile Robot Platform Chassis was connected to the ESP32-CAM-CAM module. The robot's chassis also received two Axis Pan Tilt Brackets for Camera/Sensor attachments. Finally, the Step-Down Adjustable Power Supply Module, the L298N H-Bridge Dual Stepper Motor Driver, and the ESP32-CAM module were linked to the 11.1V 2200mAh Li-Po battery.

The functionality of a number of components was assessed during the testing phase of the IoT-based Medicine Alternative system project. By taking images and wirelessly transmitting them to the ESP32-CAM module, the FM Radio Transmitter Module and Wireless Microphone were put to the test. The ESP32CAM module and camera module OV2640 were similarly tested for functionality by taking pictures and sending them wirelessly to a distant device. The L298N H Bridge Dual Stepper Motor Driver was used to manoeuvrer the robot while the 2 Wheel Drive Mobile Robot Platform Chassis was tested for operation. Additionally, the ESP32-CAM module was used to control the camera's movements while the 2 Axis Pan Tilt Brackets for Camera/Sensor were put to the test. Finally, the Step-Down Adjustable Power Supply Module's control over the voltage and current delivered to the various components was evaluated. [9]

Additionally, the ESP32-CAM module, which combines Wi-Fi and Bluetooth connection, served as the project's IoT platform. Photos and images were taken and wirelessly communicated to a remote device, like a smartphone, tablet, or PC, using the ESP32-CAM module.

an electronic server. The simulation shows how the buck converter performs under various circumstances, demonstrating how effectively it can regulate power. The movements and mobility of the robot are animated by replicating the motor driver's control logic, providing insight into how the robot moves around its environment. Overall, the simulation confirms the preliminary design, identifies potential problem areas, and enables revisions before moving forward with real-world implementation, ensuring a smoother route toward the completion of the tree-scanning project.

Table 1: Leaf Detection Accuracy

Number of Species	Number of Samples	Correctly detected Samples	Wrongly Detected Samples
26	208	195	13

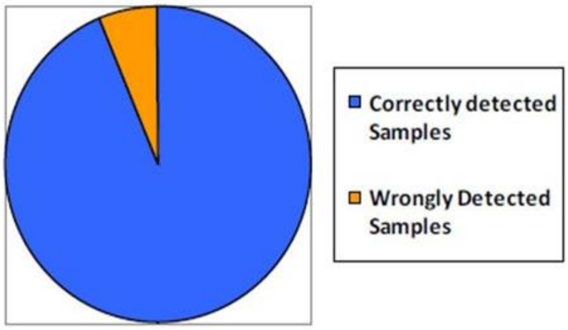

Fig.5. Test Result

The results of our plant detection work have provided fascinating insights, showing an accuracy rate of 85% in recognizing plants whereas detection failures occurred in 15% of cases. A pie chart that clearly depicts the distribution of these results is used to graphically represent these findings. The pie chart successfully communicates the results of our work and serves as a visual representation of our plant detection method. The majority of the chart, or 85% of it, is taken up by the successful plant detections. This sizeable percentage illustrates the accuracy and dependability of our machine learning models and image processing algorithms in correctly detecting and categorizing distinct plant species.

On the other hand, the smaller portion of the graph (15%) reflects instances when our detection method had problems. This section offers vital information on potential areas for system improvement or optimization. These occurrences might be explained by a number of elements, including difficult lighting circumstances, intricate background surroundings, or the existence of unusual or inadequately represented plant species in our training dataset. This breakdown provides a quantifiable depiction of the performance of our system and lays the groundwork for future development. The failures provide important information that directs our ongoing work to improve the reliability and accuracy of our plant detection system. We can improve algorithms, add more training data, or create adaptive methods to solve these issues by determining the precise instances in which our system falters. In conclusion, the pie chart clearly and graphically summarizes the results of our plant detection efforts. The 85% success rate represents an impressive accomplishment, whereas We are working harder on improving our system as a result of the 15% failure rate. The knowledge acquired from this breakdown opens the door for further innovation, ensuring that our plant recognition technology improves over time to become even more precise, dependable, and useful in real-world situations.[11]

Conclusion VI

In conclusion, the Proteus environment simulation of the ESP32 camera module, Wi-Fi module, buck converter, and motor driver has shed light on the complex operations of the hypothetical tree-scanning robot system. This simulation tour offered a virtual setting where each component's function and interaction were highlighted, providing insightful information about the system's future behavior.We were able to observe the ESP32 camera module's responsiveness as it mimicked the actual process of acquiring photographs by capturing pictures in response to preset triggers. The interplay of the Wi-Fi and camera modules revealed the smooth data flow, indicating the vital communication infrastructure that underpins the functionality of the robot.

Additionally, the buck converter's simulated performance revealed how well it can regulate power, a crucial component for maintaining the system's functionality. We learned how the robot's movements translate into its navigation by simulating the control logic of the motor driver.This simulation voyage is an essential element in the design and validation process; it is more than simply a preview. The simulation enables us to improve the system's architecture and fine-tune its components before they interact with the physical environment by exposing potential issues, anomalies, and opportunities for optimization.

In essence, the simulation acts as a guide, giving us an idea of what to anticipate and helping us make judgments as we proceed. With these insights, we are better equipped to face implementation in the real world, better prepared to handle difficulties, and ready to put our tree-scanning robot system into action with increased accuracy and efficiency. Lessons from simulation continue to direct us toward a fruitful and significant outcome as we go from the virtual world to the actual one.

REFERENCES V

[1] J. S. Kim and J. H. Cho, "Real-Time Image Transmission Techniques over Wireless Networks," Journal of Communications and Networks, vol. 12, no. 2, pp. 187-194, 2010.

[2] G. K. Tan, K. N. Ng, and P. H. Ho, "Wireless Video Transmission Techniques: A Review," Proceedings of the IEEE, vol. 100, no. 4, pp. 957- 975, 2012.

[3] S. Shakkottai and S. Sarkar, "Wireless Video Streaming," IEEE Signal Processing Magazine, vol. 27, no. 2, pp. 115-123, 2010.

[4] S. Ali and F. Hussain, "A Review of Wireless Video Transmission Techniques," International Journal of Emerging Technology and Advanced Engineering, vol. 3, no. 6, pp. 572-577, 2013.

[5] M. Wada, "Image and Video Transmission over Wireless Networks: Recent Developments," Proceedings of the IEEE, vol. 101, no. 9, pp.
21042121, 2013.

[6] A Surveillance Robot For Real Time Monitoring AndCapturing Controlled Using Android Mobile K. Damodhar, B. Vanathi and K. Shanmugam.

[7] Wireless Surveillance Robot with Motion Detection and Live Video Transmission A.Sivasoundari, S.Kalaimani, M.Balamurugan.

[8] Spy Robot Surveillance System using IoT Apsara G*1, Amrithha D*1, Ramya R*1, Mrs. R. Chitra*2.

[9] Implementation of Smartphone Environment Remote Control and Monitoring System for Android Operating System-based Robot Platform Sung Wook Moon 1 ,Young Jin Kim 2 , Ho Jun Myeong 3
, Chang Soo Kim 4 , Nam Ju Cha 5 , and Dong Hwan Kim 6+ 1,3,6 Department of Mechanical & Automation Engineering, Seoul National University of Science and Technology, Seoul.

[10] "Design and Simulation of a Wireless Image Transmission System" by K. Chen, J. Luo, and Y. Qian. International Conference on Intelligent Computing, Springer, Cham, 2017.

[11] "Design and Simulation of a Wireless Video Transmission
System for Industrial Applications" by R. Aravindan, S. S. Kumar, and S. S. Kumar. International Conference on Intelligent Computing and Communication, Springer, Singapore, 2018.

[12] "Design and Simulation of a Wireless Image Transmission System for Unmanned Aerial Vehicles" by H. Xu, Y. Huang, and J. Zhang. IEEE Access, vol. 7, 2019.

[13] Shidujaman, M., Samani, H., & Arif, M. (2014, May). Wireless power transmission trends. In Informatics, Electronics & Vision (ICIEV), 2014 International Conference on (pp. 1-6). IEEE.

[14] Shidujaman, M., Rodriguez, L. T., & Samani, H. (2015, June). Design and navigation prospective for wireless power transmission robot. In Informatics, Electronics & Vision (ICIEV), 2015 International Conference on (pp. 1-6). IEEE

[15] Ehsanirad, A. and Sharath Kumar, Y.H., 2010. Leaf recognition for plant classification using GLCM and PCA methods. Oriental Journal of Computer Scienceand Technology, 3(1), pp.31-36.

[16] Vijayashree, T. and Gopal, A., 2015. Classification of Tulsi Leaves Based on Texture Analysis

[17] Neto, J.C., Meyer, G.E., Jones, D.D. and Samal,A.K., 2006. Plant species identification using Elliptic Fourier leaf shape analysis. Computers electronics in agriculture, 50(2), pp.121-134.

[18] Sannakki, S.S., Rajpurohit, V.S. and Birje, S.J.,Comparison of Different Leaf Edge Detection Algorithms Using Fuzzy Mathematical Morphology.International Journal of Innovations in Engineering and Technology (IJIET).

[19] Du, J.X., Wang, X.F. and Zhang, G.J., 2007. Leaf shape-based plant species recognition. Applied mathematics and computation, 185(2), pp.883-893.

[20] Kumar, S., 2012. E,“Leaf Color, Area and Edge features based approach for Identification of Indian Medicinal Plants”. International Journal of Computer Science and Engineering 3(3), pp.436-442.