# EmotiPot: A Machine-Learning Enhanced Smart Plant System with Visual Diagnosis, Trend-Based Assisted Mobility, and Affective Feedback for Urban Plant Care

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## ABSTRACT

Many plant owners struggle to maintain healthy plant growth because they rely on manual observation and inconsistent care. Problems such as unnoticed leaf discoloration, wilting, poor light placement, and lack of personalized guidance may lead to plant stress and delayed intervention. To address these concerns, this study developed the EmotiPot system, a smart plant pot integrated with an Android mobile application for real-time plant monitoring and care support. The system combines a MobileNetV2-based Convolutional Neural Network (CNN) for image classification, sensor-based monitoring, content-based filtering for personalized care recommendations, and a sliding-window trend-based method for assisted mobility. The CNN model was trained using 7,830 plant images classified into six categories: blackspots, cancer, greening, healthy, not plant, and wilting. The study followed a developmental research design using the Agile Scrum approach in building and testing the system. Results from the updated model showed a validation accuracy of 93.17%, indicating that the CNN was effective in classifying plant conditions. The system also successfully interpreted soil moisture and light readings, generated suitable care recommendations based on active thresholds, and supported manual and automatic movement toward better light conditions with ultrasonic-based obstacle detection. Overall, the EmotiPot system was able to meet its intended functions and showed potential as a practical and intelligent tool for supporting plant care through real-time monitoring, diagnosis, and guided decision-making.

**Keywords:** EmotiPot, Plant Health Monitoring, Convolutional Neural Network (CNN), Internet of Things (IoT), Smart Plant Care

## INTRODUCTION

In recent years, technological innovations have continued to transform the way everyday tasks are managed and improved through automation, intelligent monitoring, and data-driven decision-making. The growing use of artificial intelligence, Internet of Things (IoT), and mobile technologies has opened new opportunities for developing systems that can assist individuals in monitoring conditions, interpreting real-time data, and responding more effectively to changing environments. These developments are not only visible in industrial and commercial applications but are also becoming increasingly relevant in small-scale and personal settings such as home gardening and plant care. As more people become interested in keeping plants indoors and outdoors, the need for practical, accessible, and responsive plant care systems also continues to increase.

Many plant owners today enjoy caring for plants because it brings life to their spaces and creates a more pleasant and relaxing environment. However, maintaining healthy plant growth is not always easy. Whether plants are placed indoors or outdoors, owners often depend on manual observation and routine checking to assess their condition. This becomes difficult for individuals with busy schedules, limited experience in gardening, or inconsistent care habits. Important signs of plant stress such as leaf discoloration, wilting, insufficient light exposure, or poor soil condition may not be noticed immediately. As a result, plant health problems may worsen before the owner is able to take proper action.

Traditional plant care methods usually rely on guesswork and do not provide a clear way to detect early signs of stress or determine whether the plant is receiving enough moisture and light. In many indoor settings such as apartments, dormitories, and study spaces, plant placement is often limited, which makes it harder to provide ideal growing conditions. Because of this, plant owners may struggle to make timely and informed decisions regarding watering, light exposure, and other care practices. These limitations highlight the need for a smart plant care system that goes beyond simple observation by combining visual diagnosis, environmental monitoring, and adaptive recommendations.

To address these concerns, this study developed the EmotiPot system, a smart plant pot integrated with an Android mobile application for real-time plant monitoring and care support. The system combines image-based diagnosis, sensor-based monitoring, recommendation generation, and assisted mobility to help users better understand their plant's condition. It uses a Convolutional Neural Network (CNN) to classify captured plant images into six classes: healthy, greening, cancer, blackspots, wilting, and not plant.

After the diagnosis, the application suggests threshold values for moisture and sunlight based on the latest plant condition. The user may choose to use these suggested thresholds or manually override them by selecting custom values inside the application. The system then reads the current soil moisture and light data from the sensors and uses these inputs together with the diagnosis result and selected thresholds to generate personalized care recommendations. These recommendations are produced through a content-based filtering approach, which compares the plant's current condition with stored recommendation features and presents the most suitable suggestions based on the plant's needs. In this way, the system does not only show sensor readings but also helps the user understand what actions may be needed to support healthier plant growth.

The system also includes both manual and automatic movement features. In manual mode, the user can control the movement of the EmotiPot through the arrow buttons in the mobile application. In auto mode, the system checks recent light readings and compares them with the selected sunlight threshold to decide whether the EmotiPot should move toward a brighter area or remain in place. During movement, the ultrasonic sensor is used to detect nearby obstacles and help support safe navigation. Through these features, EmotiPot provides a more practical and adaptive approach to plant care by combining plant diagnosis, environmental monitoring, intelligent recommendations, and assisted mobility in one system.

**Significance of the Study**

The following are the individuals who will benefit from this study, as it introduces an innovative way to care for plants through smart technology:

1. Environment advocates. The EmotiPot supports the global movement toward green living by encouraging indoor and outdoor gardening and responsible technology use. With its low-power components and focus on promoting healthy plant growth, the system aligns with goals of biodiversity conservation, air quality improvement, and smart home integration advancing sustainability efforts at the micro level.
2. For Families. EmotiPot adds a touch of life and emotional connection to home environments. The use of visual emotional responses from the plant system encourages children and parents alike to engage in plant care as a shared experience. It can foster responsibility in young family members while also creating a more relaxing, natural atmosphere indoors.
3. For farmers. EmotiPot provides a practical and efficient solution for monitoring the health of their plants and crops. The system focuses on essential environmental factors such as soil moisture, temperature, and light intensity (lux) to help ensure optimal growing conditions. By providing real-time data and analysis, EmotiPot allows farmers to make informed decisions and take timely actions to maintain healthy crops. Its smart features aim to reduce manual monitoring efforts, improve productivity, and make farm management easier and more reliable, especially for those managing wide or multiple areas of cultivation.
4. Future researchers. This study lays the groundwork for future innovations in smart agriculture and emotion-aware systems. EmotiPot's integration of machine learning for plant stress detection, predictive navigation, and affective interfaces offers a rich starting point for extending intelligent feedback mechanisms in other IoT systems. Researchers can use this foundation to explore deeper learning models, expand sensor arrays, or develop adaptive learning systems for other plant species and use cases.

5. For students. EmotiPot serves as a powerful tool for environmental education and science learning. By combining agriculture, IoT, and artificial intelligence, it introduces students to interdisciplinary STEM concepts. The visual feedback system makes it easier to teach plant health, sustainability, and digital innovation, making EmotiPot a practical learning resource for modern classrooms promoting hands-on, eco-conscious education.

**Scope and Delimitation**

This study focuses on the development of EmotiPot, a smart plant pot integrated with an Android mobile application for plant monitoring and care support. The system uses a CNN model to classify captured plant images into six classes: healthy, greening, cancer, blackspots, wilting, and not plant. It also uses a soil moisture sensor and an LDR sensor to monitor environmental conditions, while an ultrasonic sensor is used to help support safer movement during navigation. The mobile application allows users to capture plant images, view sensor readings, select or override threshold values, receive care recommendations, and control the movement of the EmotiPot. The system also includes a trend-based auto navigation feature that helps the EmotiPot move toward brighter areas when light conditions remain below the selected threshold.

Although the EmotiPot system was able to perform its intended functions, the study still has several limitations that should be acknowledged. First, the system was designed only for a single plant setup and was tested under controlled conditions. Because of this, the findings may not fully represent how the system would perform in more complex real-world environments where lighting conditions, surface texture, plant appearance, and physical obstructions may vary. The mobility feature is also limited to simple assisted movement on flat and manageable surfaces and does not include advanced navigation methods such as path planning, localization, or mapping.

Second, the visual diagnosis feature is limited by the dataset used in training the CNN model. Although the model achieved strong validation accuracy, some misclassifications were still observed between visually similar classes. The model mainly depends on visible leaf appearance, which means that lighting variation, image angle, background noise, and image quality may affect the prediction result. In addition, the labels used in the study such as greening, cancer, blackspots, and wilting were treated as operational image classes for the prototype and may not fully represent laboratory-confirmed plant disease categories. Because of this, the diagnosis result should be interpreted as system-based classification output rather than a complete botanical diagnosis.

Third, the recommendation module is limited to the available rule set and stored recommendation features used in the content-based filtering approach. The system does not yet perform plant species recognition, which means the recommendations are generated only from the diagnosis result, current sensor readings, and selected threshold values. This limits the ability of the system to provide more species-specific and context-aware guidance. In the same way, the communication design of the system is limited to Bluetooth, which supports only short-range local connection and does not provide remote monitoring, cloud storage, or long-distance access.

Despite these limitations, the study shows that EmotiPot has strong potential as a practical smart plant care support system. For future improvements, the researchers may use a larger and more balanced image dataset with clearer class definitions and additional image preprocessing or augmentation techniques to further improve CNN performance. Future studies may also include more detailed evaluation metrics such as precision, recall, and F1-score for each class, together with broader testing under different environmental conditions.

In terms of system development, future versions of EmotiPot may include plant species recognition, automated watering support, Wi-Fi or cloud connectivity, and a more advanced mobile dashboard for long-term plant monitoring. The movement module may also be improved by adding stronger navigation logic, better obstacle handling, and wider environmental adaptation. In addition, user testing with actual plant owners may help evaluate the usability, usefulness, and real-world effectiveness of the system. These improvements may further strengthen the reliability, flexibility, and practical value of EmotiPot for both indoor and outdoor plant care.

# METHODOLOGY

This study used a developmental research design to develop and evaluate the EmotiPot system, a smart plant pot integrated with an Android mobile application for plant monitoring and care support. The study followed the Agile Scrum approach so the system could be designed, tested, and improved in smaller stages. The EmotiPot system combines image-based diagnosis, real-time sensor monitoring, recommendation generation, and assisted mobility. It uses a Convolutional Neural Network (CNN) for plant image classification, a content-based filtering approach for plant care recommendations, and a sliding-window trend-based binary classification method for automatic movement toward better light conditions. The system also uses Bluetooth communication between the Android application and the ESP32 for real-time local data exchange.

The data used in the study came from four main sources: plant image data for CNN training, soil moisture readings, LDR light readings, and ultrasonic distance readings for obstacle detection. The mobile application was used as the main interface where users can capture plant images, view sensor readings, choose suggested thresholds or manually override them, receive care recommendations, and control the movement of the EmotiPot. The system was tested in a controlled setting to evaluate how well each feature worked based on the intended functions of the prototype.

## System Overview

The EmotiPot system was designed as a smart plant care platform that combines hardware and software components into one working prototype. The hardware side includes the ESP32 microcontroller, soil moisture sensor, LDR sensor, ultrasonic sensor, motor driver, and mobility components. The software side includes the Android mobile application and the CNN model used for plant image classification.

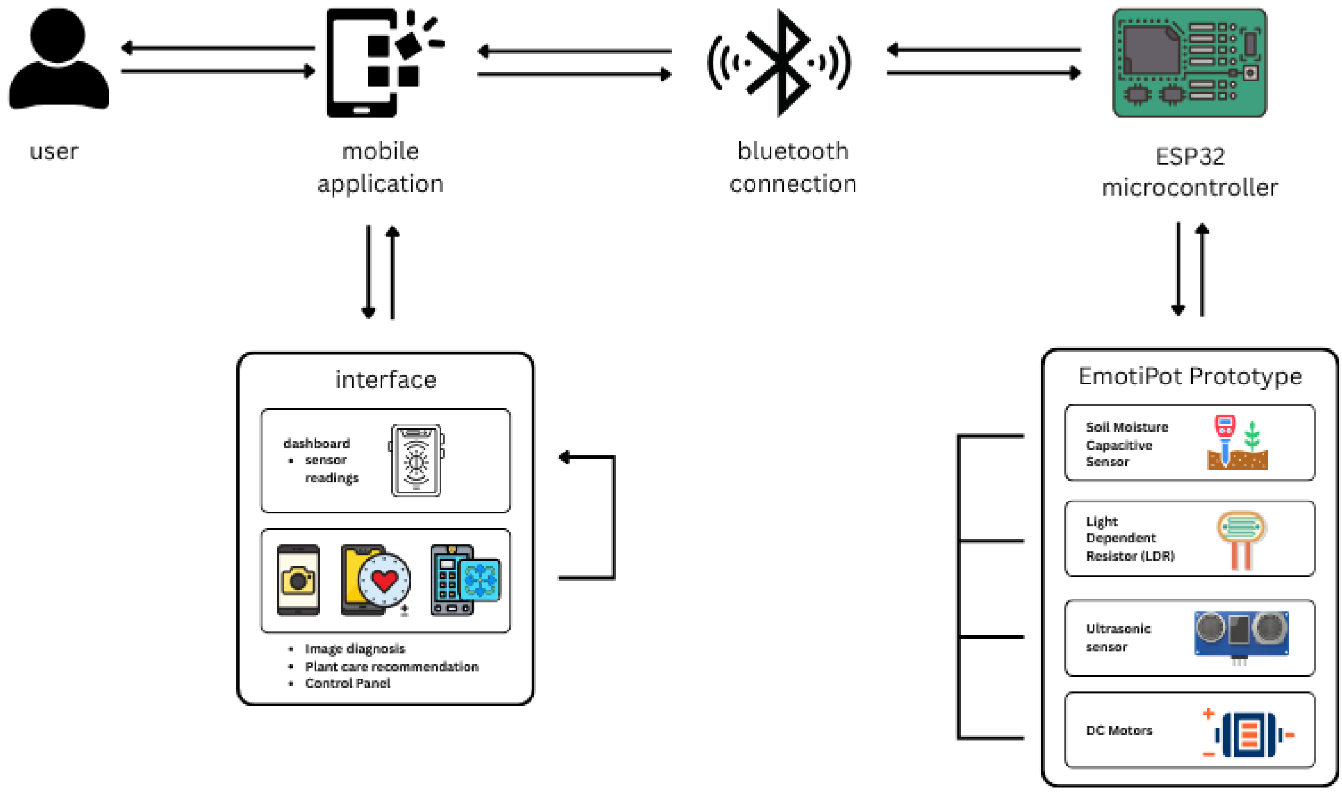


**Figure 1. System Architecture**

The mobile application serves as the main user interface of the system. Through the application, the user can capture plant images, view sensor readings, choose suggested threshold values or manually override them, receive plant care recommendations, and control the movement of the EmotiPot. When the device is paired, the application exchanges data with ESP32 through Bluetooth. The ESP32 collects the sensor readings, receives movement commands, and executes the motor responses of the EmotiPot. The diagnosis result produced by the

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CNN, together with the current sensor readings and the active thresholds selected in the application, becomes the basis for recommendation generation and assisted movement decisions.

**Convolutional Neural Network (CNN)**

For the diagnosis feature, the study used a MobileNetV2-based Convolutional Neural Network. The dataset used in the updated system build was assembled and labeled by the researchers into six operational classes: healthy, greening, cancer, blackspots, wilting, and not plant. These class names were retained as the working labels of the dataset and of the mobile diagnosis module so that the application outputs would remain consistent. The healthy class represents leaves without visible signs of stress, while the other plant classes represent visible conditions used by the prototype to distinguish abnormal leaf appearance. The not plant class was included so the system could reject invalid image inputs.

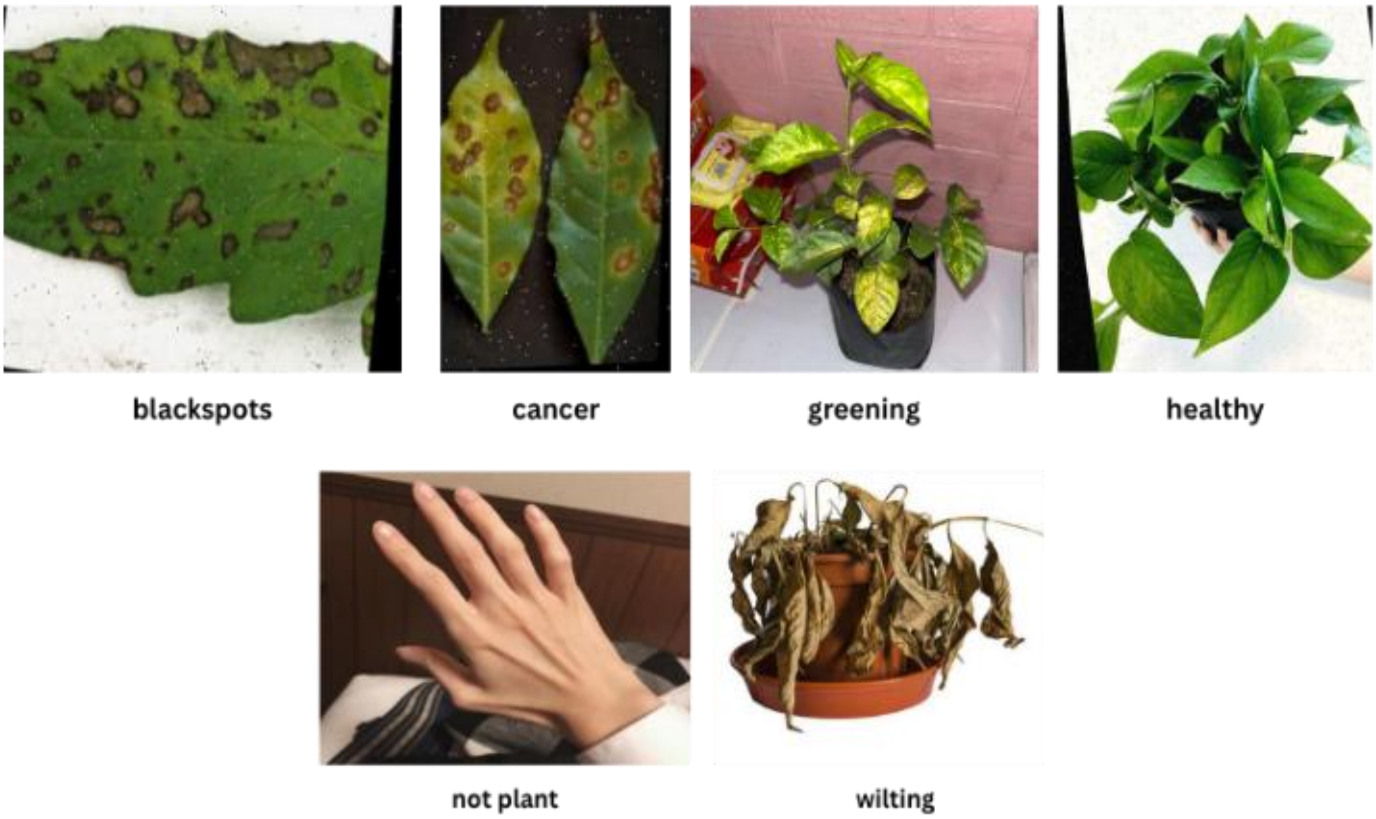


Figure 2. Sample Plant Image Classes

**Table 1. Dataset Distributions Used To Train The CNN**

| Class | Number of images | Means |
|---|---|---|
| Healthy | 3,720 | Largest plant class and strongest visual baseline |
| Greening | 605 | Operational label retained from the dataset |
| Cancer | 790 | Operational label retained from the dataset |
| Blackspots | 705 | Represents spotted leaf conditions |
| Wilting | 55 | Smallest class; most underrepresented |
| Not plant | 1,955 | Used to reject invalid image inputs |

The class distribution shows that the dataset was imbalanced. Healthy and not plant contained the largest number of samples, while wilting contained only 55 images. This imbalance helps explain why the model showed its strongest behavior in clearer and more frequent classes and why some visually similar unhealthy classes remained harder to separate.

Before training, all images were resized to 224 x 224 pixels to match the required input size of MobileNetV2. The updated training workflow used an 80/20 split, with 6,264 images used for training and

**Table 2. Evaluation Summary Report**

| Training and Evaluation Item | Value |
|---|---|
| Model backbone | MobileNetV2 |
| Image input size | 224 x 224 |
| Training epochs | 20 |
| Batch size | 32 |
| Optimizer | Adam |
| Loss function | Sparse categorical crossentropy |
| Training accuracy | Approximately 97.25% |
| Validation accuracy | 93.17% |
| Post-conversion deployment | TFLite model showed comparable performance |

The training logs showed that both training and validation loss decreased across epochs while accuracy increased, which indicates effective learning and acceptable generalization in the updated training run. The validation output was further reviewed through a confusion matrix and the converted TFLite model was evaluated separately to confirm that the model remained usable after on-device optimization.

## Content-Based Filtering Implementation

For the recommendation feature, the study used a content-based filtering approach. The recommendation module analyzes four main inputs: the diagnosis result from the CNN, the current soil moisture reading, the current light reading, and the active threshold values selected in the mobile application. After the diagnosis step, the application may suggest threshold values for moisture and sunlight, but the user may also manually override these values. These active values serve as the reference for evaluating whether the plant's current readings already require care action.

Before recommendation matching is performed, the system first converts the raw sensor values into interpretable forms. The soil moisture sensor is read by the ESP32 through a 12-bit Analog-to-Digital Converter with a range of 0 to 4095. Because higher raw values indicate drier soil, the system applies inverted linear normalization using the formula Moisture% = 100 - ((Raw / 4095) x 100). The resulting moisture percentage is then categorized into low, medium, or high moisture status. The LDR sensor readings are also interpreted into low, medium, and high light categories so the application can compare the present light level with the selected threshold more clearly.

Once the input values are processed, the module compares the diagnosis result, moisture status, light status, and threshold condition with stored recommendation rules. Each recommendation entry contains a condition pattern and a corresponding plant-care action. Recommendations with the highest similarity are ranked and shown to the user together with a short explanation of why they matched the current condition of the plant.

## Sliding-Window Trend-Based Assisted Mobility

To support movement toward better light conditions, the study implemented a sliding-window trend-based decision rule. The LDR sensor continuously sends light readings to the ESP32, and the system stores the most recent readings in a fixed history array. Each new reading replaces the oldest value in the current window so the system can observe whether the light is improving or not.

The movement decision is based on two conditions. First, the current light reading must still be below the user-selected threshold. Second, the recent trend must show that the light is not improving. If both conditions are met, the environment is classified as unfavorable and the system triggers the assisted movement routine. The EmotiPot then moves in short and controlled bursts, sometimes alternating between spinning and linear motion, so it can search nearby directions for better light without moving continuously.

For safe operation, the ultrasonic sensor checks nearby obstacles during movement. If an object is detected within an unsafe distance, the system stops unsafe forward movement and re-evaluates the environment. The application also includes manual controls, which allow the user to move the EmotiPot directly when needed.

## RESULTS AND DISCUSSIONS

This chapter presents the results of the EmotiPot system after the development and testing of its major features. The purpose of this chapter is to show how well each module of the system performed based on the intended objectives of the study. The discussion is organized according to the three main functions of the system: image-based diagnosis, personalized recommendation generation, and trend-based assisted movement.

### Results

### CNN Image Classification Results

The results of the CNN model showed that the diagnosis feature was able to classify plant images effectively. The updated training run used 7,830 total images, with 6,264 used for training and 1,566 used for validation. The final training accuracy reached approximately 97.25%, while the validation accuracy reached 93.17%. The training and validation loss also decreased over the 20 epochs, which indicates that the model learned the visual features of the target classes and remained stable enough for integration into the EmotiPot diagnosis module.

The confusion matrix analysis strengthened the evaluation by showing how the model behaved at the class level. The healthy and not plant classes showed the strongest classification behavior, which suggests that the model was able to recognize clearer and more frequent categories with high reliability. Some misclassifications still occurred between visually similar unhealthy classes such as blackspots and cancer, or between greening and wilting, which is consistent with the overlap in their visible features and with the smaller number of examples available for some classes

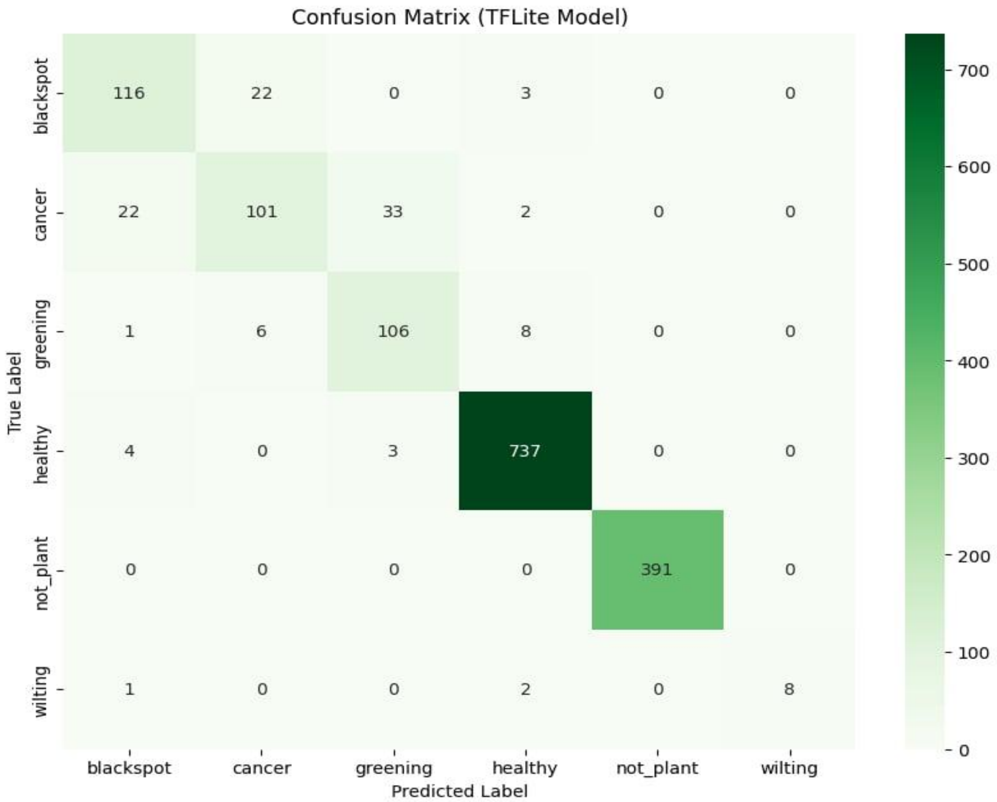


**Figure 3. Confusion Matrix**

Based on the confusion matrix, the model performed best on the healthy and not plant classes. The healthy class recorded 737 correct predictions, while the not plant class recorded 391 correct predictions. The blackspots, cancer, and greening classes also produced many correct predictions, although some misclassifications occurred between visually similar unhealthy classes. The wilting class recorded fewer samples but was still identified correctly in most cases. These results show that the CNN model was effective enough to support the diagnosis feature of the EmotiPot application.

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**Table 3. Precision, Recall, F1-Score, and Support**

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Blackspot | 0.81 | 0.78 | 0.79 | 149 |
| Cancer | 0.76 | 0.62 | 0.68 | 170 |
| Greening | 0.75 | 0.88 | 0.81 | 121 |
| Healthy | 0.98 | 0.97 | 0.98 | 758 |
| Not Plant | 1.00 | 1.00 | 1.00 | 391 |
| Wilting | 0.25 | 0.73 | 0.37 | 11 |
| **Accuracy** | | | **0.91** | **1600** |
| **Macro Average** | **0.76** | **0.83** | **0.77** | **1600** |
| **Weighted Average** | **0.92** | **0.91** | **0.92** | **1600** |

Table 3 presents the class-wise evaluation metrics of the MobileNetV2-based CNN model used in the EmotiPot system. Based on the updated results, the model showed strong performance in classifying the healthy and not plant classes, which obtained the highest precision, recall, and F1-score values. The blackspots and greening classes also showed acceptable performance, while the cancer and wilting classes were more difficult to distinguish due to visual similarity and fewer samples. Overall, the results support that the CNN model was effective enough to classify the six plant image classes and to support the diagnosis feature of the EmotiPot application. The training summary also showed that the model achieved 97.25% training accuracy and 93.17% validation accuracy after 20 epochs, which further supports the reliability of the developed diagnosis module.

**Recommendation Results**

The recommendation feature was able to interpret soil moisture and light readings and generate plant-care suggestions based on the diagnosis result and the active threshold values. During testing, the sensor readings responded to changes in the environment and were displayed correctly in the application. The soil moisture values were successfully converted into percentage form, while the light readings from the LDR sensor were interpreted into low, medium, and high light categories.

The application also performed well in displaying suggested threshold values after diagnosis while still allowing the user to manually override them. This made the recommendation feature more flexible because the user could either follow the suggested threshold values or set preferred values according to the desired plant condition. The recommendation module therefore did not rely on the diagnosis result alone. Instead, it combined the visible leaf condition with the current environmental readings and the active thresholds.

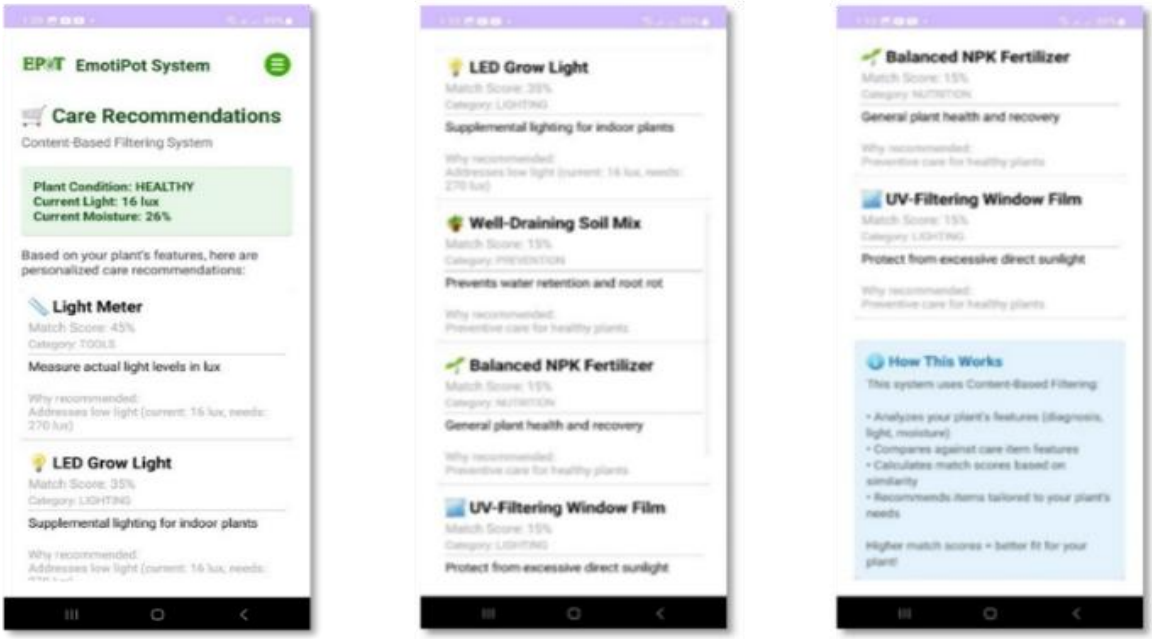


**Figure 4. Recommendation Output Screenshot**

The content-based filtering output showed that the recommendation system was able to rank relevant items according to the plant's current condition.

**Trend-Based Assisted Mobility Results**

The movement feature showed that EmotiPot was able to respond to persistent low-light conditions and support movement toward a brighter area when needed. The sliding-window routine correctly triggered movement only when the current light stayed below the selected threshold and the recent readings did not show improvement. This means the system did not react to a single low reading alone, which helped keep the movement behavior more stable.

When assisted movement was triggered, the prototype moved in short controlled bursts. During testing, the planter alternated between spinning and linear motion, which helped it explore nearby directions and avoid remaining stuck in one path. The ultrasonic sensor also helped support safer movement by preventing unsafe forward motion when obstacles were detected.

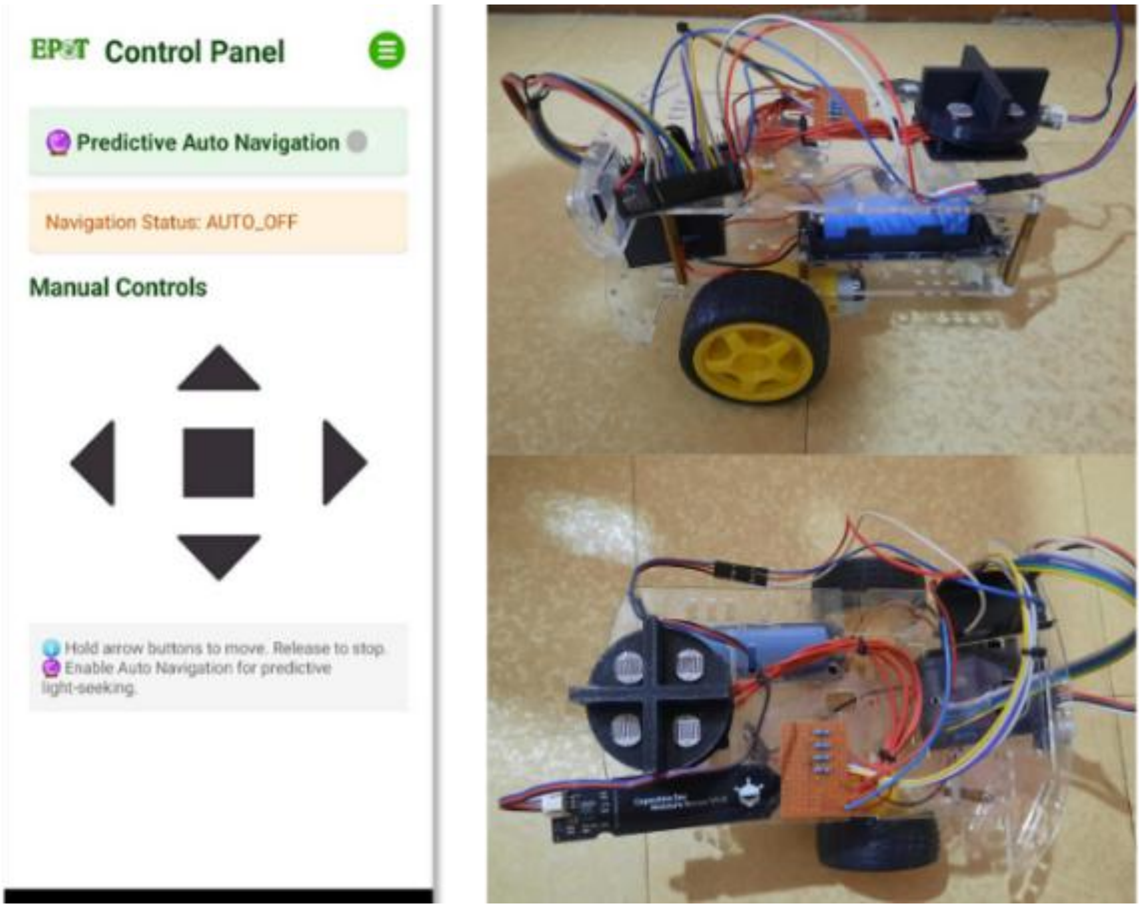


**Figure 5. Navigation Output and Prototype**

The mobile application supported both manual and automatic movement within one connected interface. These results confirm that the movement module was able to support simple light-seeking behavior with safer navigation inside the limits of the prototype.

Overall, the results showed that the EmotiPot system was able to meet the main objectives of the study. These findings show that the EmotiPot prototype has potential as a practical tool for plant monitoring and care support.

## CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the conclusions and recommendations based on the results of the study. It summarizes the main findings that show how the EmotiPot system supports plant monitoring and care through image-based diagnosis, sensor-based monitoring, recommendation generation, and assisted mobility.

## Conclusions

Problem 1: How can the system detect the condition of the plant through image-based diagnosis?

The results show that the EmotiPot system was able to detect plant condition through its CNN-based diagnosis feature. The MobileNetV2-based model was trained using 7,830 plant images divided into six classes: blackspots, cancer, greening, healthy, not plant, and wilting. Based on the updated training results, the model reached a validation accuracy of 93.17%, which shows that it was able to correctly classify most of the validation images. The confusion matrix also showed strong performance, especially in the healthy and not plant classes. These results confirm that the diagnosis module was effective in classifying plant images and can support early identification of plant condition in the mobile application.

Problem 2: How can the system provide personalized plant care recommendations?

The results show that the EmotiPot system was able to provide plant care recommendations by analyzing the diagnosis result together with real-time soil moisture readings, light readings, and active threshold values. Through the content-based filtering approach, the system was able to generate care suggestions that matched the plant's current condition. The application also allowed the user to use suggested threshold values or manually override them, which made the recommendation feature more flexible. These results confirm that the recommendation module was able to support users by translating plant condition and sensor data into clearer and more useful plant care guidance.

Problem 3: How can the system support movement toward better light conditions?

The findings show that the EmotiPot system was able to respond to low-light conditions through its sliding-window trend-based movement feature. The system monitored recent LDR readings and compared them with the selected sunlight threshold. When the light remained below the threshold and the trend showed that the light was not improving, the system correctly triggered movement toward brighter areas. The ultrasonic sensor also helped support safer movement by detecting nearby obstacles. These results confirm that the movement module was able to support simple light-seeking behavior within the limits of the prototype.

In conclusion, the results show that the EmotiPot system was able to meet the main objectives of the study. The system successfully combined image classification, sensor monitoring, recommendation generation, and assisted mobility in one Android-connected prototype. The diagnosis module was effective in classifying plant images, the recommendation module provided suitable plant care suggestions, and the movement module supported light-seeking behavior with safer navigation. Although the system still has limitations such as single-plant monitoring, short-range Bluetooth communication, no plant species recognition, and simple mobility only, the results show that EmotiPot has potential as a practical smart plant care tool for monitoring and supporting plant health.

## Recommendations

Based on the results of the study, the following recommendations are presented:

- It is recommended to expand the CNN dataset by adding more plant images, especially for classes with fewer samples such as wilting, to further improve classification performance and reduce misclassification between visually similar unhealthy classes.

- It is recommended to improve the recommendation module by adding more plant care items, richer plant condition rules, and more detailed explanations so the application can provide more complete guidance to users.

- It is recommended to add plant species recognition in future versions of the system so that the recommendations can become more specific and better matched to the actual plant type.

- It is recommended to improve the movement feature by adding more advanced navigation methods, stronger obstacle handling, and better route control so the system can operate more safely in more complex environments.

- It is recommended to enhance the communication and monitoring features of the system by adding Wi-Fi connectivity, cloud storage, and remote access for longer-range monitoring and control.

- It is recommended to conduct further testing using more plant types, more varied environmental conditions, and longer actual use periods to better evaluate the reliability and practicality of the system.

- It is also recommended that future researchers use the EmotiPot system as a basis for improving smart plant care systems that combine artificial intelligence, IoT, recommendation systems, and mobility features.

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