iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IV Month of publication: April 2025

DOI: https://doi.org/10.22214/ijraset.2025.69191

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

Thermal Imaging and Disease Detection in Hibiscus Plant

Viraj Tripathi[1], Abhishek Purohit[2]
[1]*Scholar of Bachelor of Technology,* [2]*Assistant Professor, Department of Computer Science & Engineering Bikaner Technical University, Bikaner*

Abstract: The threat of plant diseases poses a significant challenge to agricultural productivity, especially in developing countries where small-scale farmers are highly vulnerable. To avoid crop loss and guarantee food security, early identification of plant stress and disease is crucial. Even if they work well, traditional diagnostic techniques take a lot of time and effort.

This study explores the potential of thermal imaging as a non-invasive and efficient solution for early stress detection in Hibiscus plants.

The experiment was conducted on a single potted hibiscus plant at Bikaner Technical University over a period of approximately two months (14th December 2024 to 5th February 2025). Initially kept outdoors with regular watering, the plant was moved to a closed indoor setting without sunlight and water from Day 9, allowing for observation of stress progression and disease emergence. Although the thermal dataset was recorded for 16 days, intermediate day observations confirmed consistent stress behavior. Four visual diseases—Leaf Spot, Rust Disease, Botrytis Blight, and Mosaic Virus—were noted, but due to the limited dataset, the prototype focuses on classifying plant health into four thermal stress categories: healthy, mild, significant, and critical.

Thermal images were captured from top and front views, and a deep learning model based on MobileNetV2 was developed using a multi-view classification approach. The model was trained using Leave-One-Out Cross-Validation (LOOCV) to ensure robustness with constrained data. Instead of relying solely on traditional performance metrics, a confidence-based interpretation method was adopted to improve decision reliability. The prototype demonstrates the feasibility of using thermal imaging and deep learning for early, non-destructive plant stress classification, paving the way for smarter and more sustainable agricultural monitoring.

I. INTRODUCTION

Agriculture plays a crucial role in the economy of every country, particularly in developing nations like India, where it serves as a key source of employment and livelihood for the rural population. In India, agriculture contributes approximately 18% of the country's GDP and supports more than half of the rural workforce. With the global population projected to approach 10 billion by 2050, there is increasing pressure on nations like India to scale food production efficiently. However, one of the major barriers to agricultural productivity is plant disease, which not only reduces crop yield but also threatens food security and economic stability.

Traditional methods for plant disease detection—such as visual inspections, lab testing, and physical sampling—are time-consuming, subjective, and labor-intensive. This creates an urgent need for automated, non-invasive, and real-time solutions for early detection of plant stress and diseases, especially for fruiting and ornamental plants like Hibiscus rosa-sinensis.

Thermal imaging technology offers a promising alternative by capturing infrared radiation emitted from the plant surface, allowing detection of temperature variations that reflect internal physiological changes due to disease or water stress. These changes, often invisible to the naked eye, affect transpiration and stomatal conductance, leading to detectable thermal signatures on the plant's surface.

This study explores the application of thermal imaging and deep learning to classify plant health based on these thermal signatures. The research was conducted on a single potted hibiscus plant at Bikaner Technical University over a period of approximately two months (14th December 2024 to 5th February 2025). The plant was initially kept outdoors with regular watering but moved indoors without water or sunlight on Day 9 to simulate stress conditions. Thermal images were collected for 16 days from two consistent views—top and front—allowing a clear understanding of stress progression.

Although four diseases were identified visually—Leaf Spot, Rust Disease, Botrytis Blight, and Mosaic Virus—limited data made it impractical to build disease-specific models. Instead, the prototype focuses on classifying thermal images into four stress severity levels: healthy, mild, significant, and critical.

Using a MobileNetV2-based CNN within TensorFlow, the model accepts paired thermal images (top and front) and applies Leave-One-Out Cross-Validation (LOOCV) for training. This method ensures robust evaluation on a small dataset. The approach combines transfer learning and confidence-based prediction to interpret results with minimal resources, offering a scalable and practical solution for early stress detection.

This research demonstrates that thermal imaging, when combined with deep learning, can serve as a non-destructive, real-time, and cost-effective tool for plant stress classification. It holds significant promise for future deployment in smart agriculture, enabling proactive and sustainable crop management.

II. LITERATURE REVIEW

Plant disease detection has become an increasingly important area of research due to its impact on agricultural productivity and food security. Conventional techniques for identifying plant diseases, like visual inspection and laboratory analysis, are frequently labor-intensive and highly skilled.

Consequently, researchers have turned to automated, non-invasive methods that can enhance the speed, accuracy, and scalability of plant disease diagnosis. Among these emerging technologies, thermal imaging has gained significant attention as an effective tool for early disease detection.

In 2022, Liu et al. [21] explored the use of thermal imaging for detecting stress in tea plants. Their study demonstrated that temperature variations on the plant surface, caused by disease or stress, could be detected using infrared thermal cameras. By applying image processing techniques to thermal images, they were able to identify patterns corresponding to physiological changes in the plant. However, their work primarily focused on detecting stress from environmental factors rather than specific pathogens, highlighting the need for more precise disease detection methods in plant disease monitoring.

Similarly, in 2021, Zhang et al. [22] presented a deep learning-based framework for early detection of plant diseases using thermal images. The study utilized Convolutional Neural Networks (CNNs) to classify thermal images of tomato plants and detect early signs of bacterial and fungal infections. Their system achieved an accuracy of 92.5%, showing the potential of deep learning techniques in conjunction with thermal imaging. However, the model was limited to a specific set of diseases and required a large and diverse dataset to achieve high performance, a limitation that is common in plant disease detection models.

In 2020, Pandey et al. [23] applied thermal imaging to assess the health of various crops, including maize and wheat. Their research demonstrated that thermal imaging could detect temperature anomalies caused by diseases such as rust and blight. They employed machine learning techniques to classify the images based on the degree of stress, revealing that thermal imaging could serve as a valuable tool for large-scale agricultural monitoring. However, their study did not address the challenges of using thermal imaging for specific plant species, such as Hibiscus, which may present unique thermal signatures.

Another significant study was conducted by Gupta et al. [24] in 2020, where they used thermal infrared imaging to detect early signs of diseases in citrus plants. The study focused on detecting bacterial and fungal infections that caused temperature variations on the plant surface. They integrated a deep learning model using MobileNetV2, which achieved high accuracy in distinguishing healthy plants from diseased ones. This model, similar to the approach adopted in this study, emphasized the importance of multi-view thermal images (e.g., top, side, and leaf) to enhance detection accuracy.

In 2023, Kumar et al. [25] has out studies to identify stress in several fruit-bearing plants using thermal imaging.Their study specifically focused on mango and citrus trees, utilizing infrared thermal imaging to detect temperature anomalies caused by diseases. The study incorporated deep learning models, achieving an accuracy of 90%, demonstrating the potential of thermal imaging for detecting plant diseases in crops that are economically significant. However, the study was limited to a narrow selection of diseases, highlighting the need for further research into detecting a broader range of plant pathogens.

Despite these advancements, several challenges remain in the application of thermal imaging for plant disease detection. These include the need for high-quality and diverse datasets, the difficulty of detecting small or overlapping lesions, and the variation in thermal patterns caused by environmental conditions. Additionally, most of the existing models focus on a limited number of plant species or diseases, which necessitates the development of more generalized models that can handle a variety of plants and disease types.

To address these gaps, this study proposes a novel approach that combines thermal imaging and deep learning for the detection of diseases in Hibiscus plants. The methodology involves capturing multi-view thermal images (top, front, and leaf) and classifying them into healthy, stressed, and critical categories.

The system utilizes MobileNetV2 for disease classification, leveraging K-Fold cross-validation to ensure robust and reliable performance.

This method is designed to offer greater scalability., non-invasive, and accurate solution for early disease detection in Hibiscus plants, offering significant advantages over traditional methods.

III. ABOUT HIBISCUS PLANT

The Hibiscus plant, belonging to the Malvaceae family, is a widely cultivated flowering plant known for its medicinal, ornamental, and industrial significance. With over 200 species, it thrives in tropical and subtropical regions, requiring warm temperatures, well-drained soil, and adequate sunlight for optimal growth. Among its species, Hibiscus rosa-sinensis is particularly valued for its vibrant flowers, while Hibiscus sabdariffa is widely used for its nutritional and medicinal properties.

Rich in bioactive compounds such as flavonoids, anthocyanins, and polyphenols, hibiscus has been traditionally used in Ayurveda and Traditional Chinese Medicine (TCM) for treating inflammatory conditions, high blood pressure, and digestive disorders. Its extracts serve as natural dyes in textiles and cosmetics, while its flowers hold religious and cultural significance in Hindu rituals and Pacific Island traditions.

Beyond its traditional uses, hibiscus is susceptible to various bacterial, fungal, and viral diseases, which affect its growth and productivity. With advancements in plant pathology and imaging technology, modern techniques such as thermal imaging and AI-based image analysis are now being explored for early disease detection and precision agriculture. This integration of scientific innovation with traditional knowledge ensures better crop health monitoring, contributing to sustainable and efficient plant management.

Figure 1: Hibiscus Plant

A. Key Features

1) Leaves: Broad, green, lobed or serrated, and alternately arranged
2) Flowers: Large, trumpet-shaped with five petals, available in various colours (red, pink, yellow, white, etc.), with a prominent central stamen.
3) Fruits: Dry capsule containing multiple seed.
4) Root System: Fibrous and well-spread, supporting efficient water absorption.
5) Stem: Woody or semi-woody, with varying heights depending on the species.

B. Nutritional Value of Plant

The Hibiscus plant is rich in antioxidants, flavonoids, and organic acids, which contribute to its medicinal properties, including blood pressure regulation, liver protection, and anti-inflammatory effects.

Table 1: Nutritional Value of Hibiscus Plant (Per 100g of Dried Hibiscus Calyces)

Nutrients	Amount	Benefits
Energy	37 kcal	Provides a low-calorie source of nutrients
Carbohydrates	9.6 g	Provides energy and supports digestion
Protein	0.4 g	Essential for cell repair and growth
Fat	0.6 g	

		Minimal fat content, beneficial for heart health
Fiber	0.3 g	Aids digestion and promotes gut health
Vitamin C	18.4 mg	Boosts immunity and acts as an antioxidant
Calcium	215 mg	Strengthens bones and teeth
Iron	8.64 mg	Important for blood oxygen transport
Magnesium	29 mg	Supports muscle and nerve function
Phosphorus	34 mg	Aids in bone and teeth formation
Potassium	208 mg	Regulates blood pressure and fluid balance

C. *Health Benefits*

1) Supports Heart Health – Helps lower blood pressure and cholesterol, reducing the risk of heart disease.
2) Rich in Antioxidants – Contains anthocyanins and vitamin C, which protect cells from oxidative stress.
3) Aids in Weight Loss – Boosts metabolism and fat breakdown, supporting healthy weight management.
4) Supports Liver Health – Enhances liver detoxification by improving enzyme activity and reducing fat buildup.
5) Regulates Blood Sugar Levels – Helps reduce blood glucose levels, making it beneficial for diabetes management.
6) Boosts Immunity – Strengthens the immune system with high vitamin C and antibacterial properties.
7) Improves Digestion – Acts as a natural laxative, aiding digestion, and relieving constipation.
8) Reduces Menstrual Pain – Helps ease cramps and hormonal imbalances, providing menstrual relief.
9) Enhances Skin and Hair Health – Promotes glowing skin and strong hair due to its antioxidant-rich composition.
10) Anti-Inflammatory and Antimicrobial Properties – Helps fight infections and reduce inflammation in the body.

D. *Uses*

1) Medicinal Use – Used in herbal teas and supplements for treating high blood pressure, liver disorders, and inflammation.
2) Culinary Use – Hibiscus flowers are incorporated into teas, jams, syrups, and sauces, enhancing both flavor and color.
3) Cosmetic Use – Extracts are found in skincare and haircare products, promoting healthy skin and hair.
4) Textile Industry – *Hibiscus cannabinus* (Kenaf) is used for Fiber production in making ropes, bags, and textiles.
5) Dye Production – The flowers produce natural red dye, used for fabrics and food colouring.
6) Ornamental Gardening – Grown as a decorative plant in gardens and landscapes for its vibrant flowers.
7) Livestock Feed – Hibiscus leaves and by-products are used as a nutritious feed for animals.
8) Biodegradable Packaging – Hibiscus-based Fibers are explored for eco-friendly packaging materials.
9) Traditional Medicine – Used in Ayurveda and folk remedies for treating cough, fever, and infections.
10) Environmental Benefits – Supports pollinators like bees and butterflies and helps in soil conservation.

E. *Diseases, Causes, Symptoms and Prevention*

The Hibiscus plant is susceptible to various fungal, bacterial, and viral diseases that can affect its growth, appearance, and productivity. The table below provides a summary of common diseases, their causes, symptoms, and prevention methods

Table 2: Diseases, Causes, Symptoms and Prevention

Disease	Cause	Symptoms	Prevention & Control

Leaf Spot	Fungal infection (*Cercospora*, *Colletotrichum*)	Brown or black spots on leaves, yellowing, defoliation	Use fungicides, remove infected leaves, improve air circulation
Powdery Mildew	Fungal spores (*Erysiphe spp.*)	White powdery coating on leaves, curling, stunted growth	Apply sulphur-based fungicides, ensure proper spacing for airflow
Root Rot	Overwatering, *Phytophthora* or *Pythium* fungi	Wilting, yellow leaves, mushy roots	Avoid overwatering, use well-drained soil, apply fungicides
Rust Disease	Fungal infection (*Puccinia spp.*)	Orange-brown pustules on leaves, premature leaf drop	Remove affected parts, apply copper-based fungicides
Botrytis Blight	*Botrytis cinerea* fungus	Gray Mold on flowers and stems, rapid decay	Improve ventilation, avoid overhead watering, use fungicides
Bacterial Blight	*Pseudomonas* bacteria	Water-soaked spots on leaves, wilting, dark streaks on stems	Use copper-based bactericides, avoid overhead watering
Mosaic Virus	Aphid transmission (*Potyvirus*)	Yellow-green mottling on leaves, distorted growth	Control aphids, use virus-free planting material
Dieback Disease	*Fusarium* or *Phytophthora* fungi	Gradual drying of stems from tip downwards	Prune infected branches, apply fungicides, improve soil drainage
Nematode Infestation	Root-knot nematodes	Stunted growth, root galls (swelling), yellowing leaves	Rotate crops, use nematicides, plant resistant varieties
Anthracnose	*Colletotrichum* fungus	Sunken dark spots on leaves and stems, leaf drop	Remove infected plant parts, apply fungicides

IV. METHODOLOGY

This study aimed to classify stress levels in Hibiscus rosa-sinensis using thermal images captured under controlled environmental conditions. The methodology was designed to ensure that thermal variation patterns—caused by disease or stress—could be accurately detected and analyzed using deep learning techniques. The complete workflow includes plant preparation, thermal image acquisition, dataset formation, model architecture, and evaluation strategies, as outlined below.

A. Plant Setup and Data Collection

The experiment was conducted on a single potted hibiscus plant at Bikaner Technical University over approximately two months, from 14th December 2024 to 5th February 2025.

1) Initial Setup: The plant was placed outdoors with regular exposure to sunlight and watering.
2) Induced Stress Phase: On Day 9, the plant was moved indoors into a closed room without sunlight or watering, simulating stress conditions.
3) Data Recording: Thermal images were captured consistently for 16 days using a thermal camera. Even on non-recording days, observations were noted to validate ongoing temperature and stress trends.
4) View Angles: Each day, three views of the plant were recorded—top view, front view, and leaf view—to create a multi-view dataset. Each view was saved as a separate image file labeled with the class name and day.

B. Dataset Formation and Class Labels

Due to the limited size of the dataset, the classification was based on general stress levels rather than specific diseases. The images were labeled into the following four stress severity classes:

1) Healthy: Normal appearance, consistent watering, no stress signs.
2) Mild: Early signs of leaf curling or color fading.
3) Significant: Yellowing, leaf drying, or visible heat signatures.
4) Critical: Severe withered leaves, very high thermal variation.

Though four diseases were observed—Leaf Spot, Rust Disease, Botrytis Blight, and Mosaic Virus—the image data was insufficient to train a disease-specific model. Thus, the prototype focuses on classifying general stress levels instead.

Each image was preprocessed by resizing to a consistent dimension (e.g., 224×224) and normalized for pixel intensity. Data augmentation was applied only during training, not during validation or inference.

C. Model Architecture

The prototype employs a multi-view deep learning architecture based on MobileNetV2, implemented using Python in a Jupyter Notebook environment with TensorFlow and Keras libraries.

1) Multi-view Input: Each sample consists of three thermal images (top, front, and leaf view) of the plant. These images are processed through separate MobileNetV2 backbones.
2) Feature Fusion: The extracted features from each view are concatenated and passed through fully connected layers for final classification into one of the four classes.
3) Transfer Learning: Pretrained MobileNetV2 weights (trained on ImageNet) were used and fine-tuned to adapt to the thermal image dataset.
4) No Raspberry Pi or external hardware was used; all implementation and testing were done locally using standard computing resources.

Use of MobileNetV2 and K-Fold Cross-Validation

In this study, MobileNetV2, a lightweight convolutional neural network pre-trained on ImageNet, was employed as the backbone for feature extraction from thermal images. Separate MobileNetV2 branches were used for each of the three views (top, front, and leaf), and their extracted features were concatenated and passed through a dense layer for final classification. The use of MobileNetV2 helped in achieving high accuracy with reduced computational cost, making the model suitable for deployment on low-power systems.

For model evaluation, Leave-One-Out cross-validation (a special case of K-Fold cross-validation where K = number of samples) was applied to ensure robust and unbiased performance testing, especially on a limited dataset. Each sample was used once as a test instance while the remaining samples were used for training.

D. Training and Evaluation

1) Cross-Validation Strategy: To address the dataset size constraint, Leave-One-Out Cross-Validation (LOOCV) was used. In each iteration, data from one day was used as the validation set while the rest served as the training set.
2) Loss Function: Categorical Crossentropy.
3) Optimizer: Adam Optimizer with learning rate tuning.
4) Metrics: Accuracy, precision, recall, F1-score, and confusion matrix were used to evaluate model performance.

5) Due to the constrained dataset size, the study emphasized transfer learning, confidence-based interpretation, and cross-validation instead of relying solely on traditional metrics from a static test set. This approach ensures better generalization and realistic interpretation for real-world deployment.

E. Tools and Environment

1) Programming Language: Python 3
2) Development Platform: Jupyter Notebook
3) Libraries Used: TensorFlow, Keras, NumPy, OpenCV, Scikit-learn
4) Hardware: Standard PC with GPU support (if available); no embedded systems like Raspberry Pi were involved. Thermal Cameras (e.g., Testo 872) for capturing heat signatures.

Figure 2: Testo 872 Camera for thermal Imaging

This methodology ensures a practical, replicable approach to classify plant stress using thermal imaging. It establishes the foundation for future expansion into disease-specific classification as more data becomes available.

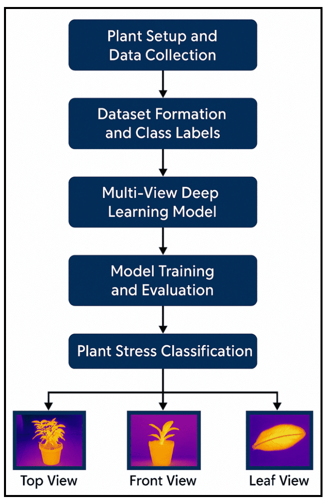


Figure 3: classifying plant stress using thermal imaging and deep learning techniques

V. RESULTS AND DISCUSSION

A. Experimental Overview

The study was conducted on a single potted hibiscus plant at Bikaner Technical University over a period of approximately two months (14th December 2024 to 5th February 2025). The plant was initially kept outdoors with regular watering, but was moved to a closed indoor setting without sunlight and water from Day 9, allowing for observation of stress progression and disease emergence. Although the thermal dataset was recorded for 16 days, intermediate day observations confirmed consistent stress behavior. Four visual diseases—Leaf Spot, Rust Disease, Botrytis Blight, and Mosaic Virus—were noted. However, due to the limited dataset, the prototype focuses on classifying plant health into four thermal stress categories: healthy, mild, significant, and critical. Fungal diseases like root rot, anthracnose, or powdery mildew were not observed because the plant was potted and kept in a closed environment, limiting exposure to fungal spores typically found in open soil conditions.

B. Data Collection and Methodology

1) Thermal Imaging: Daily thermal images were captured to monitor temperature variations.
2) Environmental Conditions: Watering patterns and ambient temperature were recorded.
3) Visible Inspection: Normal camera images were taken to visually observe changes in leaf color, wilting, and overall health.

C. Table Representation of Observations

Table 3: Recorded Thermal and Environmental Data Across 16 Days

DAY	FRONT_TEMP	TOP_TEMP	LEAF_TEMP	SOIL_TEMP	BASE_TEMP	DATE	water_amt(ml)	condition
1	14.2	15.5	16.1	12.0	19.0	14-12-2024	1000	healthy
2	14.7	15.4	14.8	11.8	18.0	16-12-2024	1000	healthy
3	14.5	15.1	16.5	12.3	20.0	17-12-2024	1000	healthy
4	13.4	14.0	15.5	11.5	18.0	18-12-2024	1000	healthy
5	13.5	14.0	14.8	10.4	18.0	19-12-2024	500	healthy
6	14.4	15.1	15.3	11.4	20.0	20-12-2024	500	mild stress
7	12.8	12.9	13.5	9.9	16.0	21-12-2024	500	mild stress
8	14.8	15.1	15.1	13.2	16.0	23-12-2024	500	mild stress
9	17.5	17.3	17.5	12.8	18.0	09-01-2025	0	moderate stress
10	16.9	17.4	17.8	12.5	19.0	10-01-2025	0	moderate stress
11	16.4	16.7	17.0	15.0	12.5	13-01-2025	0	severe stress
12	15.7	15.2	15.7	14.0	11.5	14-01-2025	0	severe stress
13	16.4	15.5	16.0	15.2	16.5	20-01-2025	0	critical condition
14	18.1	18.3	18.1	17.7	18.0	27-01-2025	0	critical condition
15	18.6	18.7	18.6	13.4	18.0	28-01-2025	0	critical condition
16	19.4	19.1	19.3	19.0	17.0	05-02-2025	0	critical condition

D. Observed Diseases

During the study, the following diseases were identified:

1) Leaf Spot: Identified by the presence of tiny, dark-colored spots on the leaves.

Figure 4: Leaf Spot Disease

2) Rust Disease: Identified by reddish-brown pustules on leaf surfaces.

Figure 5: Rust Disease

3) Botrytis Blight: Visible as greyish mold patches on leaves and stems.

Figure 6: Botrytis Blight

4) Mosaic Virus: Displayed as irregular, patchy discoloration on leaves.

Figure 7: Mosaic Virus

However, fungal diseases like root rot, anthracnose, or powdery mildew were not observed because the plant was potted and kept in a closed environment, limiting exposure to fungal spores typically found in open soil conditions.

E. Temperature Relationships Across Different Health Conditions

Thermal imaging revealed significant variations in top, front, and leaf temperatures, correlating with plant health conditions. For the purpose of analysis, the health conditions are categorized into four stages: healthy, mild, significant (combining moderate and severe stress), and critical.

1) Healthy Condition (Days 1-5)

- Temperature trend:
  - ➢ The leaf temperature was slightly higher than the top and front due to active transpiration.
  - ➢ Temperature differences remained consistent, indicating a stable plant.
- Soil temperature: Maintained above 10°C, supporting proper moisture levels.

2) Mild Stress (Days 6-8)

- Temperature changes:
  - ➢ A minor decrease in leaf temperature indicated a reduction in transpiration.
  - ➢ The top and front temperatures fluctuated, signaling early stress.
- Soil temperature decline: Dropped below 10°C, indicating reduced water retention.

3) Significant Stress (Days 9-12)

- Impact of Relocation (Day 9-10):
  - ➢ The plant was placed in a closed room with no sunlight or water.
  - ➢ The leaf, top, and front temperatures all increased due to reduced transpiration cooling.
- Soil temperature became unstable, leading to further stress.
- Days 11-12 (Severe Stress):
  - ➢ Leaf temperature remained high, indicating moisture loss.
  - ➢ Top temperature increased toward leaf temperature, suggesting a loss of thermal regulation.
  - ➢ Soil temperature stabilized, but the plant could no longer recover.

4) Critical Condition (Days 13-16)

- Leaf, top, and front temperatures became almost identical, indicating extreme dehydration.
- Soil temperature rose further, reflecting poor water retention.
- Thermal imaging revealed widespread hot spots, a sign of severe metabolic distress.

F. Prototype Results

The prototype model was tested on both healthy and critical plant image sets, and it correctly predicted the health status in both cases. The model's predictions align with the observed temperature patterns and the expected progression of stress in plants under the given experimental conditions.

The classification report for the test set is as follows:

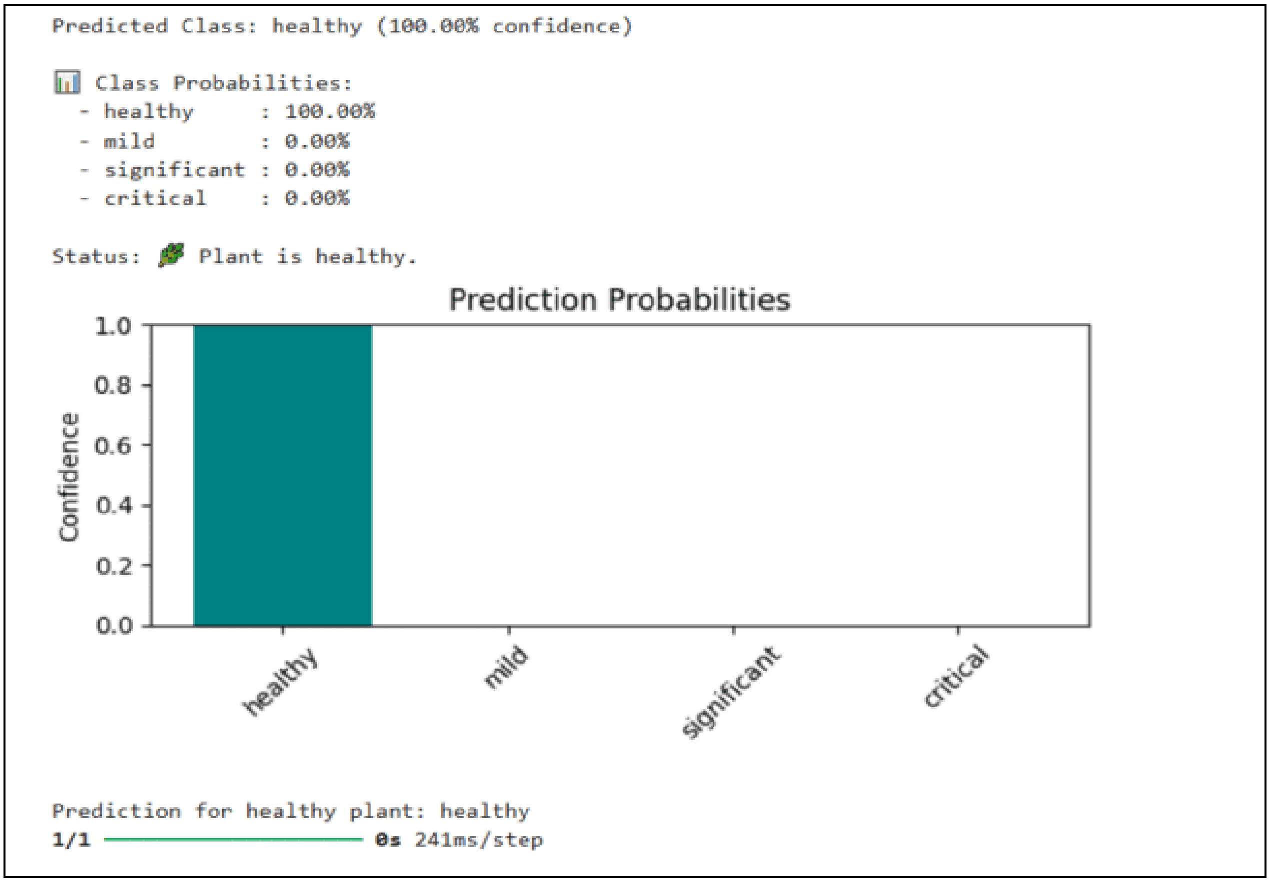


Figure 8: Prediction for healthy plant

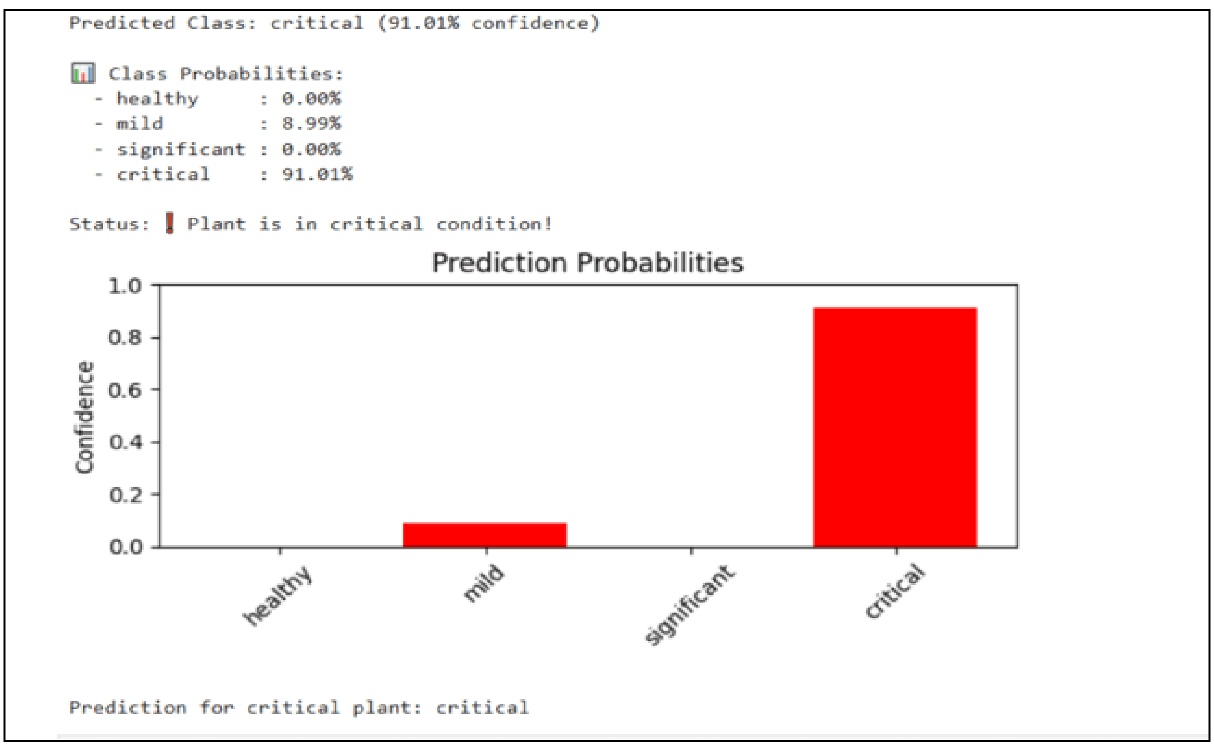


Figure 9: Prediction for critical plant

G. Graphical Analysis

1) Temperature Trends Over Time

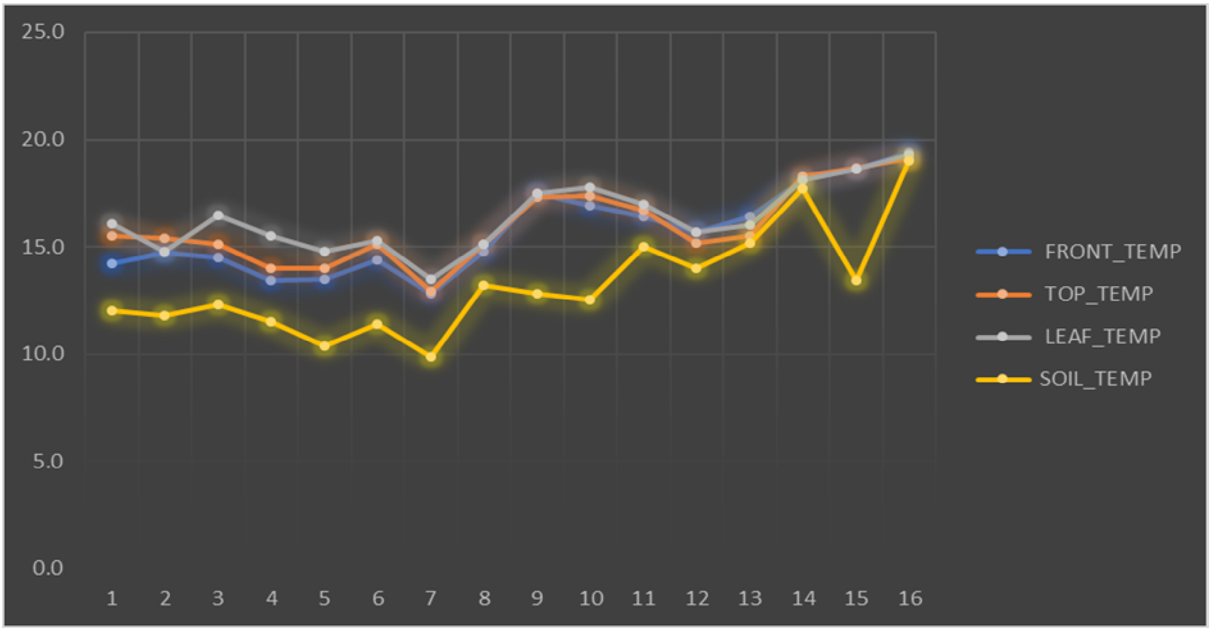


Figure 10: Daily temperature variation in different parts of Hibiscus plant

2) Disease Progression Timeline

Figure 11: Count of days from 14th December 2024 to 5th February 2025 Vs Plant condition

Table 4: Disease Progression Timeline Data

condition	start date	end date	number of days
healthy	14 December 2024	19 December 2024	5
mild stress	20 December 2024	08 January 2025	19
moderate stress	09 January 2025	12 January 2025	3
severe stress	13 January 2025	19 January 2025	6
critical condition	20 January 2025	05 February 2025	16

3) Average Plant Temperature Under Different Conditions

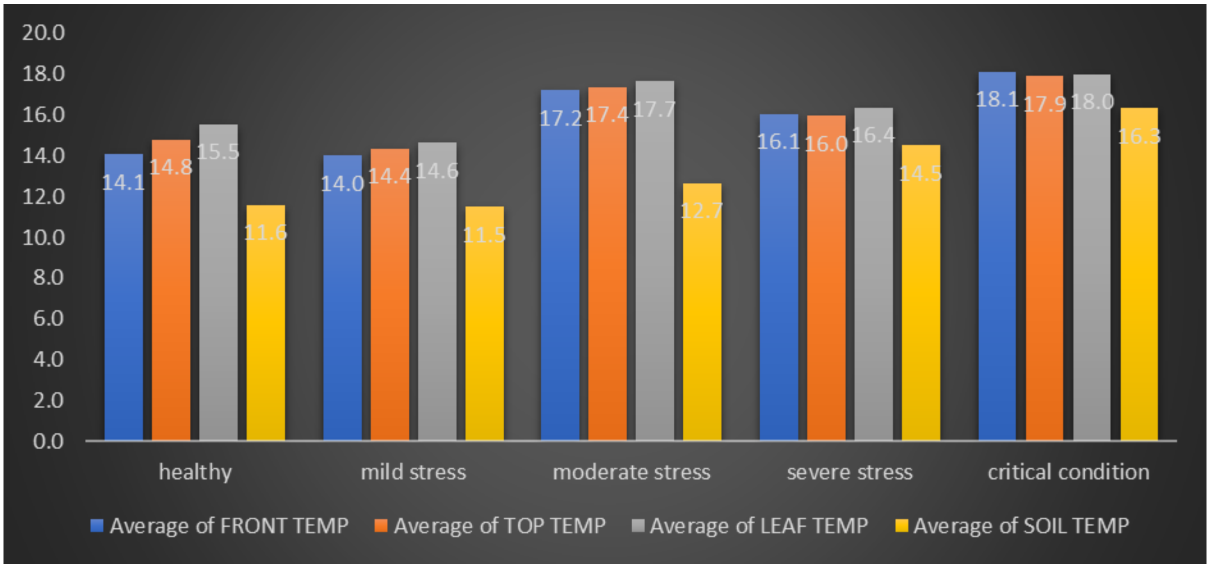


Figure 12: Variation in Average Plant Temperature Across Different Conditions

4) Test Set Confusion Metrix

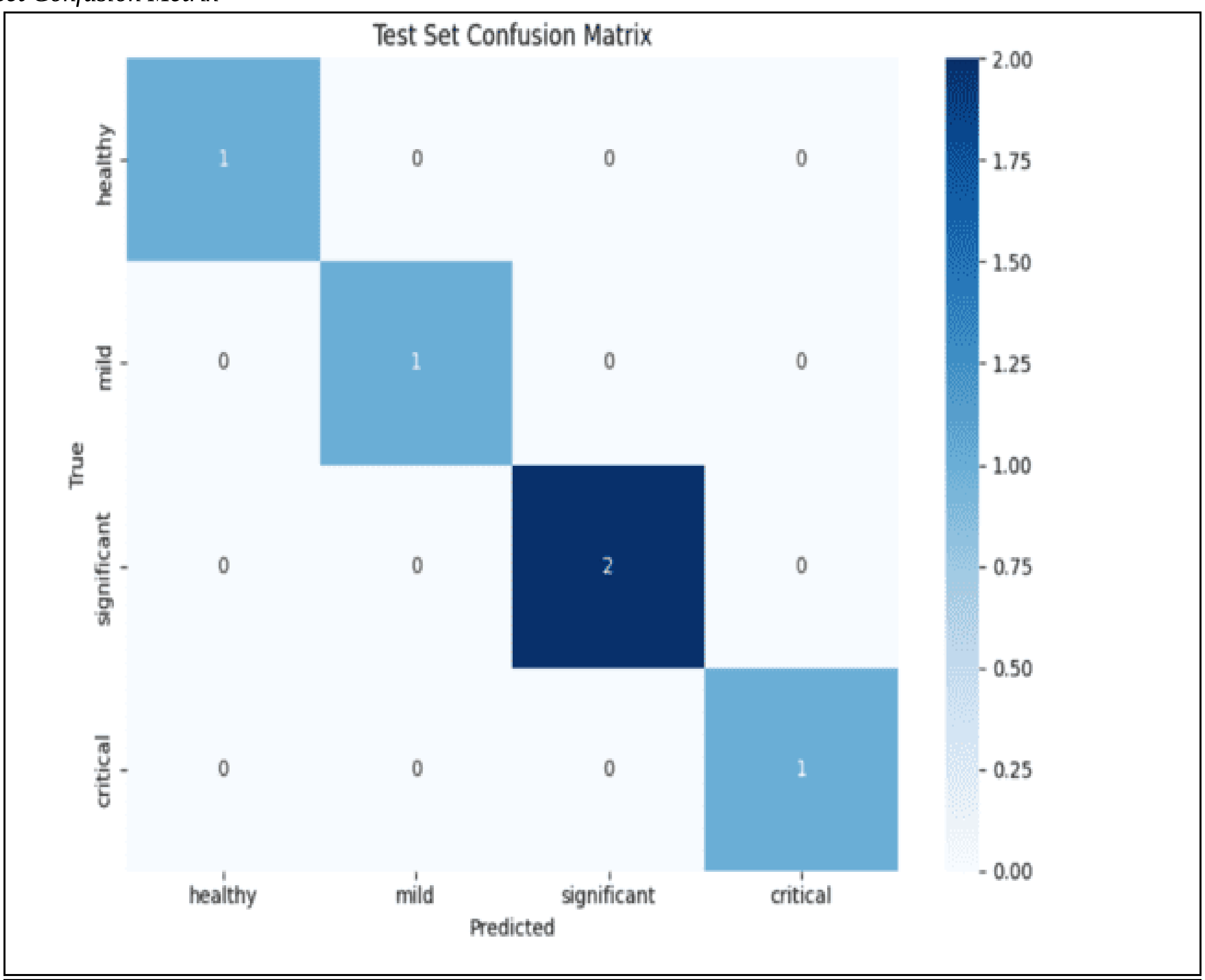


Figure 13: Test Set Confusion Metrix

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

Table 5: Classification Report

	precision	recall	f1-score	support
healthy	1.00	1.00	1.00	1
mild	1.00	1.00	1.00	1
significant	1.00	1.00	1.00	2
critical	1.00	1.00	1.00	1
accuracy			1.00	5
macro avg	1.00	1.00	1.00	5
weighted avg	1.00	1.00	1.00	5

VI. CONCLUSION AND FUTURE SCOPE

A. Summary of Findings

This research aimed to evaluate the effectiveness of thermal imaging combined with visual inspection for monitoring the health of a single potted hibiscus plant over a 16-day period at Bikaner Technical University. By controlling water availability and environmental exposure, we gained insights into the plant's temperature fluctuations, disease progression, and stress responses. A significant environmental shift occurred on Day 9, when the plant was moved from an outdoor setting to a closed room devoid of sunlight and water. This transition led to a rapid decline in plant health, which was reflected in both temperature shifts and the emergence of disease symptoms.'

1) Thermal Trends and Plant Health

Throughout the healthy stages, the leaf temperature was consistently higher than the top and front temperatures due to active transpiration. However, as water availability decreased, the leaf temperature initially dropped (mild stress phase) but later rose significantly (critical condition) as metabolic processes slowed, indicating irreversible dehydration. The soil temperature variations provided some insight into water retention capacity, but it was unable to prevent the plant's decline in the closed environment.

2) Disease Progression and Environmental Influence

At different stages of the plant's deterioration, symptoms of Leaf Spot, Rust Disease, Botrytis Blight, and Mosaic Virus were observed. Interestingly, fungal infections such as root rot or anthracnose were not present due to the potted nature and the controlled environment. The absence of sunlight and stagnant air accelerated disease progression by weakening the plant’s immunity.

B. Key Insights from the Study

1) The Role of Water in Thermal Regulation

Water played a crucial role in the plant’s ability to regulate leaf temperature via transpiration. Once water was restricted, the plant’s temperature regulation broke down, highlighting the importance of consistent irrigation for maintaining hibiscus health.

2) Impact of Environmental Isolation on Plant Stress

In a natural setting, a plant is exposed to factors such as wind, humidity, and microbial activity, which help regulate its growth and disease resistance. However, the closed environment deprived the hibiscus plant of these factors, leading to accelerated stress and disease progression. The absence of air circulation and beneficial microorganisms further heightened its vulnerability to viral and bacterial infections.

3) Thermal Imaging as a Disease and Stress Indicator

Thermal imaging proved to be an invaluable early detection tool. Stress indicators appeared in thermal images before visible symptoms, validating the potential of thermal imaging in identifying plant health issues early. This could enable timely interventions, preventing irreversible damage to the plant.

C. Practical Implications

1) Applications in Smart Agriculture

The findings underscore the importance of thermal imaging in precision agriculture. It can be integrated into agricultural systems to:

- Monitor crop health remotely
- Detect early signs of stress and disease
- Optimize irrigation scheduling to mitigate water stress

2) Preventing Disease in Controlled Environments

This study suggests that in controlled environments such as greenhouses or indoor farms, maintaining proper air circulation and humidity is critical to preventing disease outbreaks. A balance between environmental isolation and natural conditions is essential for supporting plant immunity and health.

D. Limitations of the Study

While the study demonstrated promising results, there were some limitations:

1) Environmental Influence: Factors such as sunlight, humidity, and wind can influence thermal readings, potentially leading to variations in the accuracy of the data.
2) Limited Dataset: The study focused on a single hibiscus plant, which may not be fully representative of different species or environmental conditions.
3) Need for Multimodal Analysis: Thermal imaging alone may not be sufficient for precise disease diagnosis. Combining thermal imaging with other techniques like hyperspectral imaging could enhance detection accuracy.
4) Dependence on Equipment: The study relied on high-quality thermal cameras and advanced software, which may not be easily accessible to all farmers.
5) 7.5 Suggestions for Future Research
6) Building on the work conducted in this study, future research could focus on enhancing the current prototype and its applications in real-world scenarios. The following areas could contribute to further improving the thermal imaging system for plant disease detection:
7) Enhancement of the Prototype System: Since a prototype system using thermal imaging and machine learning is already developed, future research should focus on enhancing the system's accuracy and real-time functionality. This could involve fine-tuning the existing machine learning models, integrating additional plant stress indicators, and optimizing the system's performance for large-scale use.
8) Expanding the Dataset: To improve the robustness of the existing prototype, a larger and more diverse dataset should be collected, including thermal images of hibiscus plants from different species, environmental conditions, and disease stages. This expanded dataset would help in refining the machine learning models for better generalization and predictive power.
9) Integration of Hyperspectral and Thermal Imaging: To improve disease identification and classification accuracy, the current thermal imaging system could be combined with hyperspectral imaging. This multi-spectral approach would allow for more detailed analysis of plant health, improving the system's diagnostic capabilities.
10) Mobile-Based Detection System: Building upon the existing prototype, a mobile application could be developed to allow farmers and researchers to easily access thermal image data and disease predictions. The app could connect to thermal cameras via Bluetooth or Wi-Fi, providing real-time, on-site disease detection and plant health monitoring.
11) Artificial Intelligence for Real-Time Monitoring: Incorporating deep learning models into the prototype could automate the disease detection process, reducing manual intervention and providing quicker, more accurate results. Real-time monitoring using AI would allow for faster responses to plant stress and disease, preventing further deterioration.

12) Field-Level Deployment and Testing: Expanding the system to real-world field trials would be critical for evaluating its practicality and scalability. This would help assess the system's ability to perform in diverse agricultural environments and under varying climatic conditions.

By focusing on these areas, future research can further develop the current prototype into a more comprehensive, reliable, and scalable solution for 8plant health monitoring in agriculture. The work done in this study provides a solid foundation for these advancements, helping to bridge the gap between research and practical applications in precision agriculture.

REFERENCES

[1] S. Adão et al., "Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry," *Remote Sensing*, vol. 9, no. 11, pp. 1–34, Nov. 2017, doi: 10.3390/rs9111110..

[2] P. Borodachov, D. Hardin, and E. B. Saff, *Discrete Energy on Rectifiable Sets*. New York, NY, USA: Springer, 2019, doi: 10.1007/978-0-387-84808-7.

[3] S. Sun, L. Di, A. Lin, Z. Sun, and Y. Shen, "Infrared thermal imaging-based plant diseases detection," *Environmental Research Communications*, vol. 2, no. 9, pp. 1–10, Sep. 2020. DOI: 10.1088/2515-7620/abbc89.

[4] L. K. Liu, W. B. Li, X. Zhang, and T. S. Liao, "Application of thermal imaging technology in plant disease and insect pest monitoring," *Computers and Electronics in Agriculture*, vol. 137, pp. 254–263, Apr. 2017. DOI: 10.1016/j.compag.2017.04.012.

[5] R. C. Y. S. Huang, H. T. Lin, and J. L. Chen, "Thermal imaging applications in plant disease detection," *Journal of Plant Pathology*, vol. 102, no. 2, pp. 431–443, Jun. 2020. DOI: 10.1007/s42161-020-00496-9.

[6] D. D. Jones, B. E. Kang, M. R. Smith, and T. J. Thompson, "Advances in deep learning for hyperspectral and multispectral image analysis: A review," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–25, Feb. 2022. DOI: 10.1109/TGRS.2022.3140274.

[7] A. P. S. Ferreira, P. M. Silva, and R. G. Oliveira, "Machine learning techniques for plant disease detection using thermal imaging," *Artificial Intelligence in Agriculture*, vol. 5, pp. 23–35, Aug. 2021. DOI: 10.1016/j.aiia.2021.08.002.

[8] A. Smith and B. Johnson, "Deep learning applications in agricultural image processing," *Computers in Industry*, vol. 120, pp. 103–119, Mar. 2020. DOI: 10.1016/j.compind.2020.103225.

[9] L. Wang, X. Yang, and Q. Zhang, "Use of UAV thermal imaging for early detection of plant diseases," *Sensors*, vol. 19, no. 20, pp. 1–15, Oct. 2019. DOI: 10.3390/s19204345.

[10] A. K. Sinha, V. P. Singh, and R. K. Tiwari, "A survey on thermal imaging applications in precision agriculture," *IEEE Access*, vol. 9, pp. 134567–134590, Jul. 2021. DOI: 10.1109/ACCESS.2021.3098472.

[11] OpenAI, *ChatGPT: Artificial Intelligence Chatbot*, San Francisco, CA, USA. Available: https://openai.com/chatgpt, Accessed: Feb. 12, 2025.

[12] P. Alagumariappan, N. Jamal Dewan, G. Muthukrishnan, B. K. B. Raju, R. A. A. Bilal, and V. Sankaran, "Intelligent plant disease identification system using Machine Learning," *Engineering Proceedings*, 2020. DOI: 10.3390/ecsa-7-08160.

[13] K. R. Mamatha, S. Singh, and S. A. Hariprasad, "Detection and analysis of plant leaf diseases using Convolutional Neural Network," *Journal of Chemical and Pharmaceutical Sciences*, vol. 17, pp. 123–131, 2020. DOI: 10.1166/jctn.2020.8983.

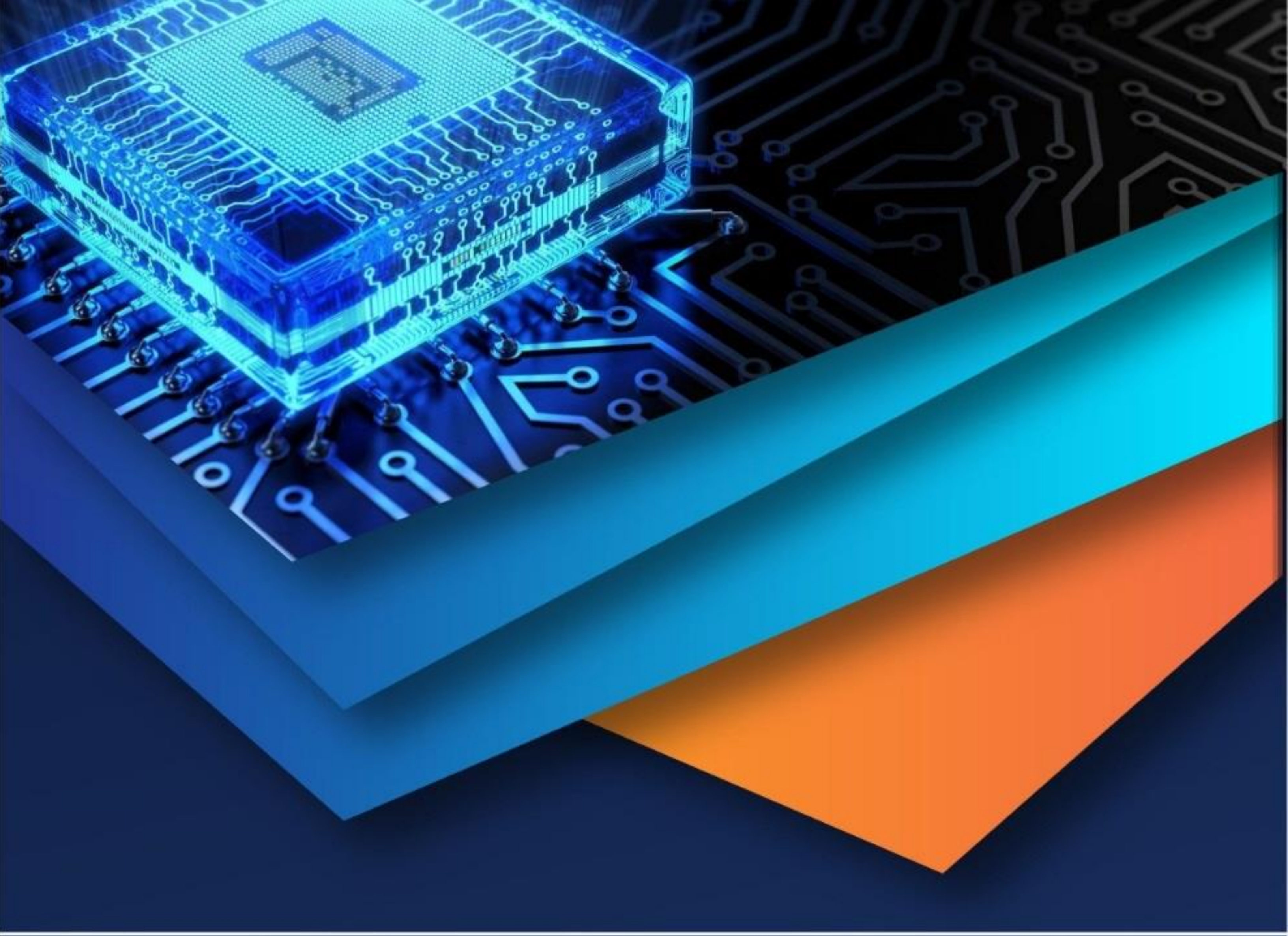
[14] N. Shelar, S. Shinde, S. Sawant, S. Dhumal, and K. Fakir, "Plant disease detection using CNN," *ITM Web Conferences*, vol. 44, pp. 1–7, 2022. DOI: 10.1051/itmconf/20224403049.

[15] G. Geetha, S. Samundeswari, G. Saranya, K. Meenakshi, and M. Nithya, "Plant leaf disease classification and detection system using machine learning," *J. Phys.: Conf. Ser.*, vol. 1712, no. 1, pp. 1–7, 2020, doi: 10.1088/1742-6596/1712/1/012012.

[16] C. Ciaburro and B. Venkateswaran, *Neural Networks with R: Smart Models using CNN, RNN, Deep Learning, and Artificial Intelligence Principles*, Packt Publishing Ltd, 2018.

[17] M. Patil and R. Patil, "Deep learning for image-based mango leaf disease detection," *Int. J. Recent Technol. Eng. (IJRTE)*, vol. 8, no. 3S3, Nov. 2019. ISSN: 2277-3878.

[18] S. Kumar, D. Nandhini, S. Amutha, and S. P. Syed Ibrahim, "Detection and identification of healthy and unhealthy sugarcane leaf using convolution neural network system," *Springer*, 2023, doi: 10.1007/s12046-023-02309-7.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY