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Pattern Based Leaves Disease Classification Using AI

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Abstract- Artificial Intelligence (AI) is an overarching domain that integrates a variety of techniques, tools, and systems designed to enable machines to learn from data and perform predictive or decision-making tasks. Within this domain, computer vision stands out as a pivotal subfield, offering substantial contributions across multiple sectors, including agriculture. The integration of AI and computer vision has given rise to smart farming an advanced form of agriculture where traditional cultivation practices are optimized through intelligent technologies to enhance productivity, precision, and resource efficiency. A prominent application of computer vision in agriculture is the detection and classification of plant diseases through image classification and object detection techniques. These methods facilitate the automated identification of infected plant leaves by analyzing visual indicators such as lesions, spots, and discolorations. In this context, a specialized approach termed the Single Sample Computer Vision Recognition Algorithm (SSCVRA) has been employed to detect disease symptoms in eggplant leaves. The model was trained and validated using a dataset comprising 20,000 images, achieving an impressive classification accuracy of 99.47%. SSCVRA conducts disease identification by extracting and matching relevant image features, focusing on such parameters of color, shape, texture and comparing with consecutive region area of the leaf. The algorithm is capable of distinguishing among multiple plant diseases, including Powdery Mildew, Bacterial Leaf Spot, and Early Blight. Visualization outputs further support diagnosis by providing quantitative metrics on image similarity and disease likelihood based on color-based image analysis.

Keywords- Computer vision, Machine Learning, Smart Farming, Classification, precision farming.

I. Introduction

Computer vision has emerged as a transformative technology in modern agriculture, significantly enhancing vision-based capabilities to support precision farming practices. One of its key applications is in the automated diagnosis of plant diseases through the use of digital imaging devices. By capturing and analyzing images of crops, computer vision systems can accurately detect and classify various plant diseases. Convolution neural networks (CNNs) have made great progress in aspects such as image recognition [17] and given their importance in the field of deep learning [10]–[15], they have become a central focus of research and allows researchers to identify infected plants at an early stage and implement targeted control measures, thereby improving crop health, reducing losses, and enhancing overall farm productivity. The rapid advancement in plant disease identification has been significantly driven by the integration of the Internet, digital imaging technologies, and artificial intelligence (AI) applications [1]. In response to the challenges posed by the growing global population, precision agriculture has emerged as a crucial solution, aiming to enhance agricultural productivity through the adoption of cutting-edge technologies. To safeguard crop health, it is imperative that farmers remain updated with real-time weather forecasts and respond proactively to environmental and disease-related threats [2]. Common manifestations of plant diseases. i.e. leaf spots, discoloration (yellow, black, white), mold growth, fungal infections, and pest infestations—serve as key

Areas of focus in precision agriculture applications [3][4]. Traditionally, farmers rely on visual inspection for disease detection. While this method is essential for preliminary assessment and continuous monitoring, it lacks the accuracy needed for early and large-scale disease identification. The complexity of monitoring plant health across extensive agricultural lands necessitates the use of automated image processing tools. Researchers advocate the use of OpenCV, a powerful open-source computer vision library capable of processing unstructured image data effectively. Digital images consist of pixel matrices represented in RGB color space, where red, green and blue values range from 0 to 255. Variations in these color intensities enable the detection of different color patterns, shapes, and spot characteristics on plant leaves, which are crucial for disease identification. Analyzing the RGB distribution and associated features helps in assessing the health status of leaves, enabling precise disease diagnosis at various stages [5].

II. Base Manuscripts

Simplification of thresholding technique

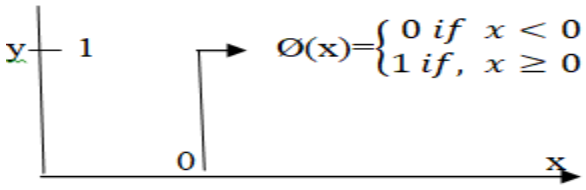


Fig 1 Threshold function

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t images and 20 images testing, that has perform the given data points belongs to based on some decision rule and derived from the data[8].

Related work

Researchers have used the digital image processing approach, that will go through with the step on reading and displaying an Image, convert to grayscale, blurring, detect the edge, Thresholding operations are applied on Fig 2 Cadamba leaf have train and test on different plant leaves with Threshold segmentation technique [7].



Fig 2 Cadamba leaf

Image can broke down in pixels that can be store in Array matrix as the following Fig 3 in discussed that will produce the BGR (blue green and red) format matrix image pixels code, Convolution neural network layer takes RGB images BGR pixels code as input feature and send them as output to another layer for further processing, after received the input, the layer reads pixels as values to produce feature maps [9].

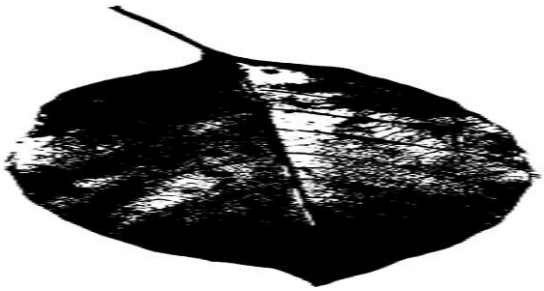


Fig 3 Threshold Cadamba leaf

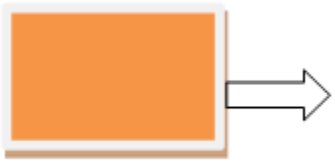


Fig 4 Image to Array

As Fig 4 Image to Array data has stored in matrices of input feature, hidden layer and output maps in 2D and 3D channels where information are bind with strides and pooling features. Hidden is a part of feature detector that can be filtered by the kernel [10].

Pre- processing and Segmentation

Image pre- processing is performed with the color balancing technique that is useful to resize the image and smoothening [8]. Segmentation: Color based segmentation that is blue green red to Hue, Saturation, and Value, as the available RGB model is helpful to handle the disease part. The pixels for the infected part of the leaf has been match the 0 intensity of black [9].

Feature Extraction

Leaf spot symptoms on plants manifest as lesions with diverse morphologies, including circular, oval, square and irregular shapes. These lesions often display varying degrees of color intensity and blurred boundaries, reflecting different stages and types of infection. The heterogeneity in shape, size, and color patterns serves as key indicators for accurate identification and classification of the underlying plant pathogens. Principal Component Analysis is a statistical approach, reduce the dimensionality reduction for deep feature that is easier to filter fresh and rotten plant's leaves & fruits. Fig 5, 6,7,8,9 are the sample of input features [11]. and Region of Interest are advanced concept used in image analysis and pattern recognition techniques are employed to systematically characterize these infected regions and enhance disease diagnosis accuracy through ROI, i.e.

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Rectangularity = $\frac{Area\ of\ the\ Leaf\ (A)}{Area\ of\ Minimum\ Enclosing\ Rectangle\ (AMER)}$ ... (i)

Where A = Area of the object (e.g., a leaf)

AMER is known as Area of the Minimum Enclosing Rectangle are also called Minimum Bounding Rectangle [12]. Roundness & compactness is a computer vision feature that is optimize in shape analysis, object detection, segmentation and feature extraction, it is easier to measure the compactness with the parameters of perimeter and shape of the infected particles that is discussed with the equation of (ii) and (iii). Compactness=$\frac{4\times\pi\times A}{P^2}$ …equation (ii) Where A = Area of the leaf shape, P = Perimeter of the leaf shape and π = 3.1416 is processed in eq (ii) & Roundness= 4×A / (π×l^2) …equation (iii) here A = Area of the shape & l = Major axis length (sometimes maximum diameter of the shape) [13]. Contrast refers to the visual properties. Such as highlights, shadows, texture (rough and smooth) and color differences (like black and white), that make an object distinguishable from its background. These differences help define the object's shape and size, making it easier to recognize.

That is discussed with the equation of (iv) where p(i, j, d, θ) is the normalized co-occurrence probability between gray levels i and j at a certain distance d and direction θ. $(i - j)^2$ that is the measurement of the squared difference between gray levels, which can emphasizes the more heavily differences.

$\text{Contrast} = \sum_i \sum_j (i-j)^2 p(i,j,d,\emptyset)$ …. (iv) [14].

Color uniformity, as defined in equation (v), is an advanced feature that filters out lighting and texture inconsistencies on green leaf or fruit surfaces. It is leveraged to reduce shadows and highlights that could distort feature extraction that is High IDE (indicates complex textures with subtle gray-level transitions) and Low IDE (indicates rough or abrupt textures, where gray levels vary a lot between neighboring pixels).

As we have discussed in previous features equation of (ii), (iii) and (iv) extraction of image in uniformity of color resolutions, disease patterns, lighting and its background, which directly affect model performance. i.e. will normalized the different value of angle, position, pixels distance and gray levels in equation (v).

$\text{Uniformity} = \sum_i \sum_j p(i,j,d,\emptyset)^2) \ldots (v)$

Where p (i, j, d, θ)**:** This is the normalized value of the Gray Level Co-occurrence Matrix at position (i, j):

- i, j: gray levels
- d: pixel distance
- p: position
- θ: angle (e.g., 0°, 45°, 90°, 135°)[15].

Height, width and color channels are the core shape of image, i.e. is break down in input feature with blue, green and red color channels are discussed in Matrix 6.1, converted Input feature from fig 6 to matrix (Array) And deal the Strength of linear relationships between color channels or regions is used as an input feature map (e.g., red and green color correlation), i.e. helpful in CNN for distinguish color distortions over to disease [17]. In this work, we propose a SSCVRA algorithms that is known as Single-Sample Computer Vision Recognition approach, aimed at accurately identifying plant leaf and fruit diseases using only a single image sample.

Proposed SSCVRA Algorithm

Single Sample Computer Vision Recognition (SSCVRA)

Step 1: Import the valid image through camera or secondary storage source.

Step 2: Crop the manually infected particles of the image.

Step 3: Save cropped image temporarily.

Sampled Data:

Step 4: Call the disease identification function.

Step 5: Initialize the color range definition:

- Early Blight: Defined by a yellowish- brown color.
- Powdery Mildew**:** Identified by white powdery spots.
- Bacterial Leaf Spot**:** Recognized by yellow spots.

Step 6: Convert BLUE, Green, Red to Hue Saturation Value.

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Step 7: Apply the masking feature in HSV image as the lower to upper order.

Step 8: Isolates the pixels in the image that match the color of interest.

Step 9: Calculate the percentage of color range for a specific disease exceeds threshold (e.g. 5%).

Step 10: Return the disease function and Identify Early Blight, Powdery Mildew or Bacterial Leaf disease.

If no disease:

Return “Unknown Disease”.

Step 11: Finish.

Lab tested Image to Array here with discussed in Fig 5, Brinjal disease object detected that is visualized with BGR code, and discussing with another sample also.



Fig 5 Brinjal disease object detected

array([[[181, 206, 230],[176, 202, 224],[170, 196, 217],...,[75, 97, 129],[87, 106, 138],[94, 115, 145]],[[175, 199, 219],[171, 197, 215],[171, 197, 215],...,[56, 77, 110],[68, 88, 119],[76, 96, 127]],[[175, 201, 215],[167, 194, 207],[164, 190, 205],...,[50, 69, 104],[59, 76, 110],[63, 80, 112]],...,[[153, 185, 192],[158, 189, 196],[162, 190, 197],...,[148, 189, 192],[146, 190, 192],[146, 189, 193]],[[126, 159, 167],[126, 158, 165],[144, 173, 181],...,[144, 184, 186],[156, 196, 199],[151, 189, 195]],[[154, 185, 195], [148, 179, 188],[147, 178, 187],...,[130, 169, 172],[168, 205, 210],[176, 208, 217]]], dtype=uint8)

Matrix 6.1 converted Input feature from fig 6 to matrix (Array)

Another brinjal fruit image was tested using the previously discussed algorithm, which successfully identified moderately infected regions within the fruit. As illustrated in Fig. 7, the algorithm was able to detect and highlight the affected areas, demonstrating its ability to distinguish between healthy and diseased tissues. This output further validates the robustness of the model in assessing varying degrees of infection, providing useful insights for early disease detection and targeted treatment in agricultural practices. The moderately infected regions appeared with distinguishable color patterns and texture irregularities, confirming the algorithm's capability in handling real-world scenarios with varying infection severities.



Fig 6 brinjal fruit image

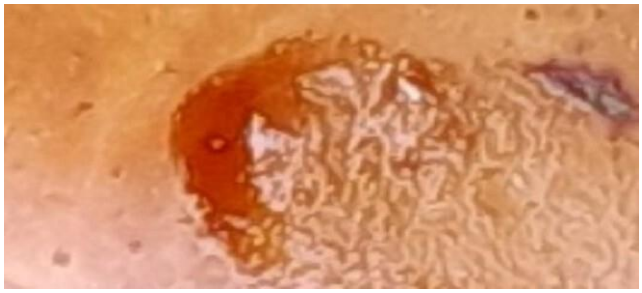


Fig. 7 Response of Fig. 6 brinjal fruit

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Table 1 Result set of Fig. 7

Description of disease	Percentage
Percentage of image matching Powdery Mildew:	53.64%
Percentage of image matching Bacterial Leaf Spot:	0.00%
Early Blight detected with matches of:	79.81%
Percentage of image matching Early Blight:	0.00%
Percentage of image matching Powdery Mildew:	0.00%
Percentage of image matching Bacterial Leaf Spot:	0.00%
Disease identified based on color analysis:	No



Fig 8 Another sample of forest leaf



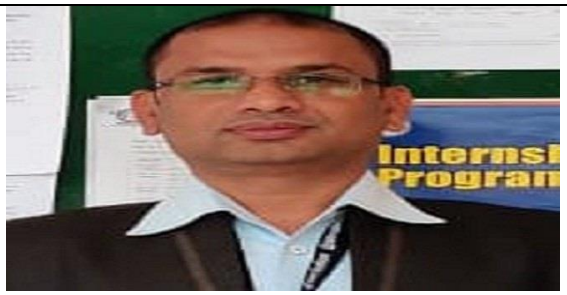
Fig 9 Disease identified cropped image

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Mr. Madan Mohan Mishra is a research scholar in the Department of Computer Application & Information Technology and Science, A K S University, Satna MP, India. He holds over 16 years of teaching and academic experience. His research interests span a broad range of areas in computer science, including pattern recognition, image processing, computer vision, federated learning, electronic design automation (EDA), time series analysis, and convolutional neural networks. Mr. Mishra has been actively involved in academic research and continues to contribute to the advancement of knowledge in emerging domains. He expresses his sincere gratitude to Dr. Pushpendra Kumar Shukla, Principal, VITS Satna, and Dr. Pramod Singh, Associate Professor, Department of Computer Applications, IT and Science, AKS University, Satna, for their continuous support and inspiration in the development of this work.

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III. Conclusions

Many researchers are using computer vision techniques, particularly to analyze plant leaf images for disease detection. This paper presents a method based on OpenCV and RGB color analysis for identifying pattern-based plant diseases. The proposed system not only identifies the disease but also visualizes the results by displaying both the disease name and the percentage of infection detected. This study explores a threshold-based classification approach. i.e., a significant limitation is identified: this method is non-differentiable at the threshold point, resulting in binary outputs, that is evaluated on SSCVRA algorithm applied for single sample testing of plant leaf and fruit also.

References

1. K. Rangarajan and R. Purushothaman, "Disease classification in eggplant using pre-trained VGG16 and MSVM," *Scientific Reports*, vol. 10, no. 1, p. 2322, 2020.
2. P. Krithika and S. Veni, "Leaf disease detection on cucumber leaves using multiclass Support Vector Machine," *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, Chennai, India, 2017, pp. 1276-1281.
3. U. Shruthi, V. Nagaveni and B. K. Raghavendra, "A Review on Machine Learning Classification Techniques for Plant Disease Detection," 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), Coimbatore, India, 2019, pp. 281-284.
4. J. M. Peña, J. Torres-Sánchez, A. Serrano-Pérez, A. I. De Castro, and F. López-Granados, "Quantifying efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected by sensor resolution," *Sensors*, vol. 15, no. 3, pp. 5609–5626, 2015..
5. T. Verma, S. Khattar, H. Joshi, H. Saini, R. Kumar and V. K. Choudhary, "Leaf Disease Detection Using OpenCV And Deep Learning," *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)*, Sonepat, India, 2024, pp. 15-22.
6. C. Tucker and S. Chakraborty, "Quantitative assessment of lesion characteristics and disease severity using digital image processing," *Journal of Phytopathology*, vol. 145, no. 8–9, pp. 257–268, 1997.
7. D.G. Sena Jr and et al,*"Fall armyworm damaged maize plant identification using digital images", Biosyst Eng*. 85 (4) (2003) 449–454.(2003).
8. R. Pydipati, T. F. Burks, and W. S. Lee, "Identification of citrus disease using color texture features and discriminant analysis," *Computers and Electronics in Agriculture*, vol. 52, no. 1–2, pp. 49–59, 2006.
9. H. Rahman, I. Ahmad, P. H. Jon, A. Salam, and M. F. Rabbi, "Automated detection of selected tea leaf diseases in Bangladesh with convolutional neural network," *Scientific Reports*, vol. 14, Art. no. 14097, 2024.
10. Y. Liu, H. Pu, and D.-W. Sun, "Efficient extraction of deep image features using convolutional neural network (CNN) for applications in detecting and analysing complex food matrices," *Trends in Food Science & Technology*, vol. 113, pp. 193-204, 2021.
11. Y. Yuan and X. Chen, "Vegetable and fruit freshness detection based on deep features and principal component analysis," *Current Research in Food Science*, vol. 8, p. 100656, 2024.
12. F. J. Rodríguez, A. García, P. J. Pardo, F. Chávez, and R. M. Luque-Baena, "Study and classification of plum varieties using image analysis and deep learning techniques," *Progress in Artificial Intelligence*, vol. 7, pp. 119–127, 2018.
13. M. B. Bangun, F. Y. Manik, Y. Herdiyeni, and E. N. Herliyana, "Implementation of support vector machine method for identification of Jabon leaf disease based on morphological characteristics," *AIP Conference Proceedings*, vol. 2987, no. 1, p. 020053, 2024.
14. S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, "Plant leaf disease detection using computer vision and machine learning algorithms," Global Transitions Proc., vol. 3, no. 1, pp. 305–310, 2022.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VI, June 2025

15. M. T. Habib, A. Majumder, A. Z. M. Jakaria, M. Akter, M. S. Uddin, and F. Ahmed, “Machine vision based papaya disease recognition,” *J. King Saud Univ. Comput. Inf. Sci.*, vol. 32, no. 3, pp. 300–309, 2020.
16. T. M. Thanjaivadivel, "Leaf disease detection dataset," *Kaggle*, [Online]. Available: https://www.kaggle.com/thanjaivadivelm. [Accessed: Jun. 14, 2025].
17. Y. Shen *et al.*, "Image Recognition Method Based on an Improved Convolutional Neural Network to Detect Impurities in Wheat," in *IEEE Access*, vol. 7, pp. 162206-162218, 2019.