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Research Article

Serial Fusion based Hybrid Features Extraction Method for Tomato Plant Leaf Disease Detection

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ABSTRACT

Detecting and classifying leaf diseases at an early stage is crucial. However, many current approaches have struggled to achieve the necessary accuracy due to several challenges. These challenges include dealing with input images that have low contrast, irregularities in leaf spots, minimal color differences between foreground and background, and the need to handle a large number of extracted features. To address these issues, we have explored feature extraction techniques based on color, shape, and texture, each with its own advantages and disadvantages. We have conducted experiments on color histograms, color means, color DHV, dominant colors, and obtained results. In shape feature extraction, we have experimented with existing methods such as linear, UNL, Gaussian, grayscale Fourier, area, perimeter, roundness, compactness, and convex hull parameters. The results obtained from color and shape feature extraction methods show that combining multiple features of the image to detect leaf infections provides better accuracy compared to using single feature types. To extract features from the images, we have proposed a hybrid (serial fusion) strategy for color, texture, and shape feature extraction, which achieves the desired accuracy.

Keywords: Pre-processing, Segmentation, Color Features, Shape Features, Texture Features and Feature Extraction

1. INTRODUCTION

An image feature refers to specific information related to a content or object that aids in its unique identification. To characterize an object based on its features, a suitable class marker is assigned. In the context of plant disease detection, it is essential to automatically learn these features. Commonly, shape, texture and color attributes of factory splint Images are used for identifying defects. Selecting the most appropriate attribute and applying an effective feature extraction algorithm pose challenging tasks [1].

Real-time image sets are prepared under various conditions, typically including undesirable components including shadows, noise, ambiguous distortions and intricate backgrounds. At a lower level of abstraction, image pre-processing becomes essential to enhance subsequent processing. The main goal of pre-processing is to mitigate the effect of unwanted features, making the image more appropriate for successive analysis. Operations like cropping and resizing are also employed to reduce system complexity [2]. The choice of pre-processing operations, including color space conversion, histogram equalization, contrast enhancement, cropping and noise removal and smoothing, depends on the nature of learned images. In real-time images, noise is a common issue, making noise reduction an essential step in factory defect discovery. Various techniques like mean filtering, median filtering, Gaussian smoothing and Weiner filtering are utilized for noise elimination [3].

Image segmentation involves the automatic identification of regions of interest (ROI), with the goal of separating lesion areas from healthy regions. The segmented image version enables the differentiation of infected and healthy leaf areas. There are numerous segmentation methods, such as edge detection-based, region-growing-based and thresholding-based ones [4, 5]. The choice of a particular approach depends on the dataset and application requirements. Traditional approaches such as edge-based and threshold-based segmentation are frequently employed in the field of plant disease identification. These methods work well with photos that show virtue-based object dissimilarity because they rely on pattern discontinuities in the images. Nevertheless, noise and many edges in the image might have an impact on edge-based techniques. However, because threshold-based methods rely on the peaks of the histogram, they could miss important three-dimensional information, which could result in color fluctuations in plant leaf photos that are not seen. Furthermore, it becomes crucial to choose the right threshold value because making the wrong decision might lead to subpar segmentation [6].

An essential part of automated disease detection systems that use leaf image data is the disease identification step. Unsupervised approaches do not rely on labelled data for classification, whereas supervised methods require prior knowledge in the form of labelled samples for good and unhealthy leaves. The effectiveness of supervised classifiers is significantly influenced by the calibre and volume of the training set, which frequently yields more accurate results. Unsupervised classifiers, on the other hand, employ naturally occurring patterns to provide labels and might be helpful in situations when labelled data is not available. Semi-supervised learning is sometimes used for classification, using both labelled and unlabeled data. The ultimate classifier's objective is to distinguish between healthy and diseased leaves and accurately diagnose plant infections [7].

2. RELATED WORK

The process of feature extraction in infection management and control becomes increasingly intricate due to the visual resemblance in symptomatology across various conditions within a single culture or across different cultures. Thus, the selection of an appropriate feature extraction method and the identification of relevant attributes for a specific application emerge as critical and demanding tasks [9]. The following highlights significant research endeavors in the domain of plant/leaf disease detection utilizing diverse feature extraction techniques, all of which relate to our proposed work. A comprehensive survey of the literature pertaining to different feature extraction methods for plant/leaf disease detection has been conducted.

Sharad et al. introduced an automated apple disease detection and recognition system, combining machine learning and computer vision based on leaf symptoms. Their innovative approach fuses proposed Discrete Wavelet Transform (DWT) and color histogram features, achieving an impressive accuracy of 98.63% for detecting and recognizing apple leaf diseases [10]. Pravin Kumar et al. presented an approach involving pre-processing of plant leaf images, followed by the segmentation of diseased sections through Background subtraction using the Particle Swarm Optimisation (PSO)-based Fuzzy C-Means Segmentation (PSO-FCM) and the Gaussian Mixture Model (GMM) [11]. Ahmad Almadhor et al. introduced a framework utilizing color difference image segmentation to isolate disease-infected zones. The Bagged Tree classifier achieved the most accurate recognition results using RGB, HSV and LBP features, attaining a 99% accuracy in distinguishing between healthy fruit and four guava fruit disorders (canker, mummification, dot and rust) [12]. Abayomi et al. discussed an innovative technique involving to create synthetic images for data augmentation in image classification applications, image color histogram modification is used. This approach led to a significant increase in classification accuracy for low-quality images, improving from 3% to 15% compared to a baseline neural network. An impressive 99.7% accuracy was maintained for the original high-quality images [13]. R. Karthickmanoj et al. proposed an effective plant disease diagnosis system designed for smart agriculture is created using a pixel replacement-based segmentation procedure and a twofold feature extraction strategy. The framework achieved an average detection accuracy of 92.325% and classification accuracy was utilized to assess the framework's performance [14]. YuanqiuLuo et al. highlighted the relatively weak disease characteristic significance of apple leaves in complex surroundings and the high fine-grain differences among various apple leaf diseases. They noticed that traditional feature extraction techniques might obliterate discriminatory data. The classification accuracy on the pre-processed dataset increased to 94.99% from the original dataset's 94.24% [15]. Khan and Narvekar have proposed a methodology based on a combination of super pixel and color balancing. Results reveal that the suggested strategy is successful at classifying diseases despite a cluttered background, with a precision of 93.12% on the entire dataset using cross-validation. [16].

3. METHODOLOGY

We have the general process of highlighted a critical aspect of feature extraction in classification tasks in Figure 1. Feature extraction plays a fundamental role in converting raw data, such as images, text or numerical data, into a more meaningful and concise representation that captures relevant patterns for classification. This transformation aims to reduce within-class variations and enhance between-class differences ultimately improving the performance and efficiency of classification algorithms [8].

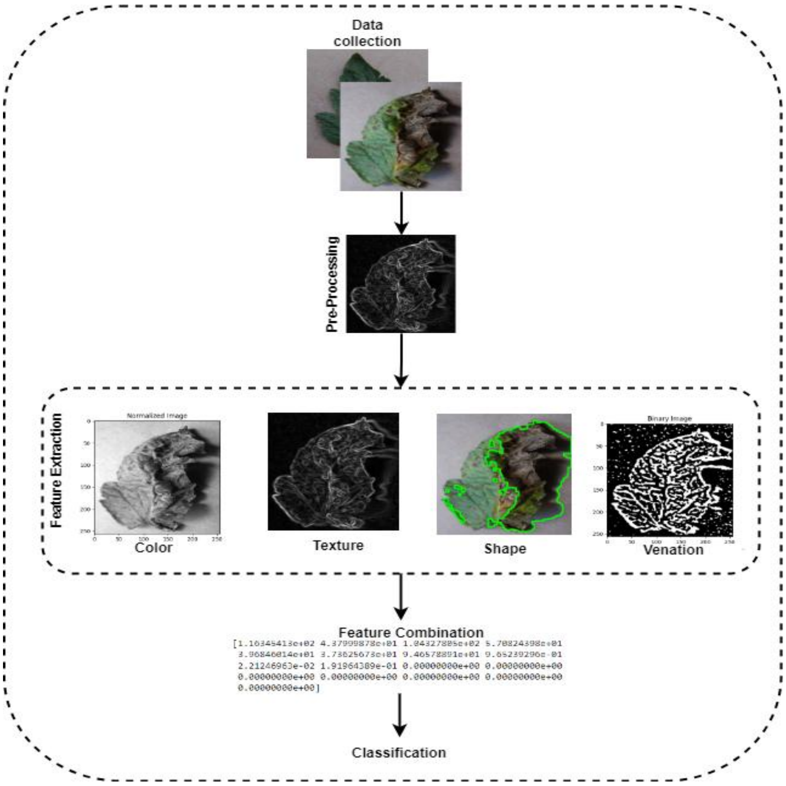

Figure 1. Critical Aspect of Feature Extraction in Classification Tasks.

Features of a leaf

As vital parts of plants, leaves show a variability of appearances that help with identification, labeling and environmental knowledge. Here are some typical characteristics of a leaf:

Leaf shape: Leaves can be oval, simple, elongated and palm shape. It is important to note that leaves are a key characteristic that can be used to identify different plant species.

Margin: It denotes to the edge of the leaf blade. It can be flat, notched, lobed or saw-toothed and it differs among plant type.

Venation: The organization of veins on a leaf is known as venation. For monocot it is parallel or for dicots it is reticulate.

Arrangement: The arrangement of the leaves on the stem might take the form of a rosette, whorled, opposite or alternate arrangement.

Structure: Leaves contain of three main parts: the edge, the petiole and stipules.

Color: Leaf color differs mid plant classes, with shades of green presence the most collective due to chlorophyll's presence. Some leaves may have distinct colors like red, purple, yellow or variegations.

Texture: Dissimilar textures of a leaves such as smooth, rough, hairy or waxy, which can be important for identification.

Apex: The tip of the leaf blade can be sharp, round or tapering.

Base: The base of the leaf edge can be balanced or unbalanced.

Size: Leaves come in several dimensions, reaching from tiny, needle-like leaves to large, broad ones.

Orientation: Certain leaves are concerned with flat, while others are held vertically or have a comfortable angle.

Venation Pattern: In reticulate venation, the arrangement of secondary veins can be palmate (radiating from a single point) or pinnate (running parallel to the midrib).

Surface: The leaf surface might have a waxy cuticle, be hairy, glossy, or matte.

Persistence: There are two types of leaves: evergreen (persisting all year round) and deciduous (shedding seasonally).

Complexity: Simple leaves just have one leaf blade, whereas complex leaves are made up of many leaflets. These characteristics offer important information for classifying, identifying, and comprehending the ecological roles of plants. These traits are frequently used by ecologists and botanists to distinguish between different plant species and investigate how they have adapted to various settings [17]–[18].

Texture Features Extraction

It is a defining feature of a particular visual region, especially when a small patch inside it has significant tone fluctuations. It basically depicts the color schemes and spatial patterns seen in the picture. Texture perception is affected by a number of factors, including light, contrast, separation, and direction. Numerous metrics, including as entropy, contrast, skewness, variance, and homogeneity, may be used to quantify the texture of an image. A useful method for illustrating the correlations between pixel intensities in photographs is the Grey Level Co-occurrence Matrix (GLCM), which works particularly well for texture analysis. While Gabor Filters may recover texture information at different sizes and orientations, Local Binary Patterns (LBP) are better at capturing local texture patterns [19]. Figures 2, 3, and 4 show the LBP, GLCM, and Gabor feature extraction.

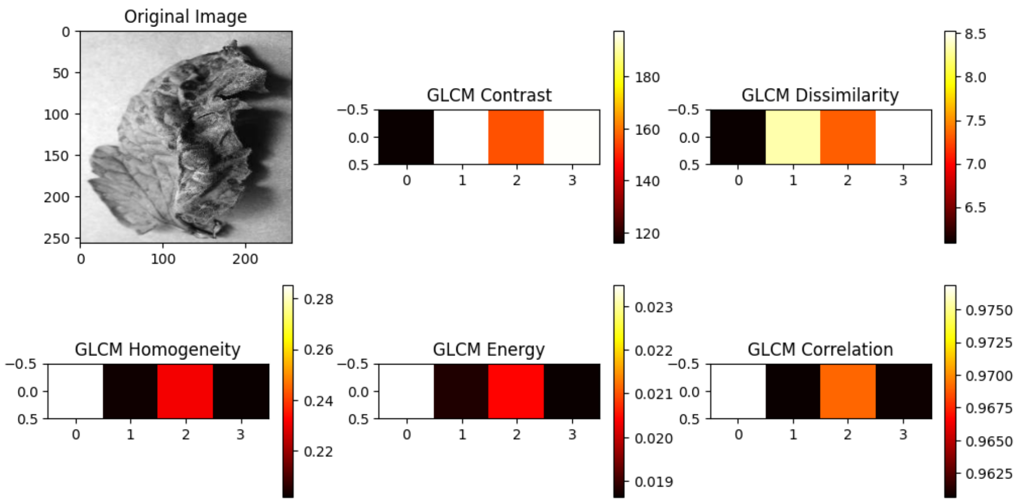

Figure 2. GLCM Feature Extraction.

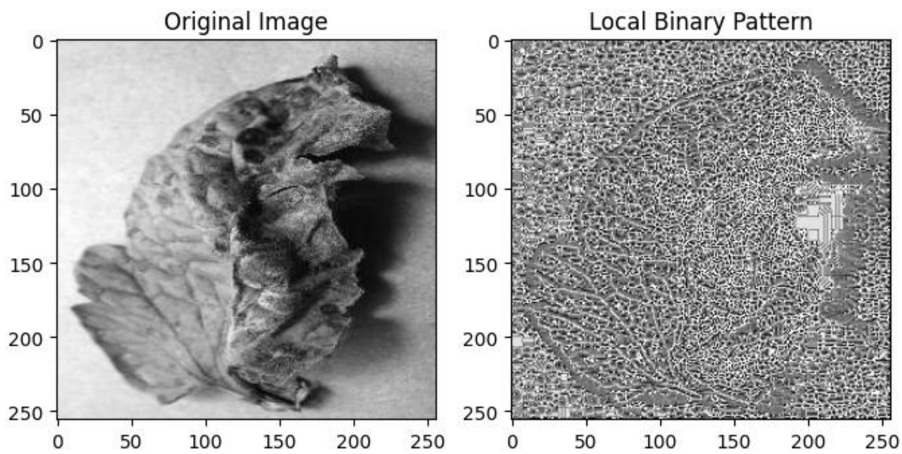

Figure 3. LBP Feature Extraction.

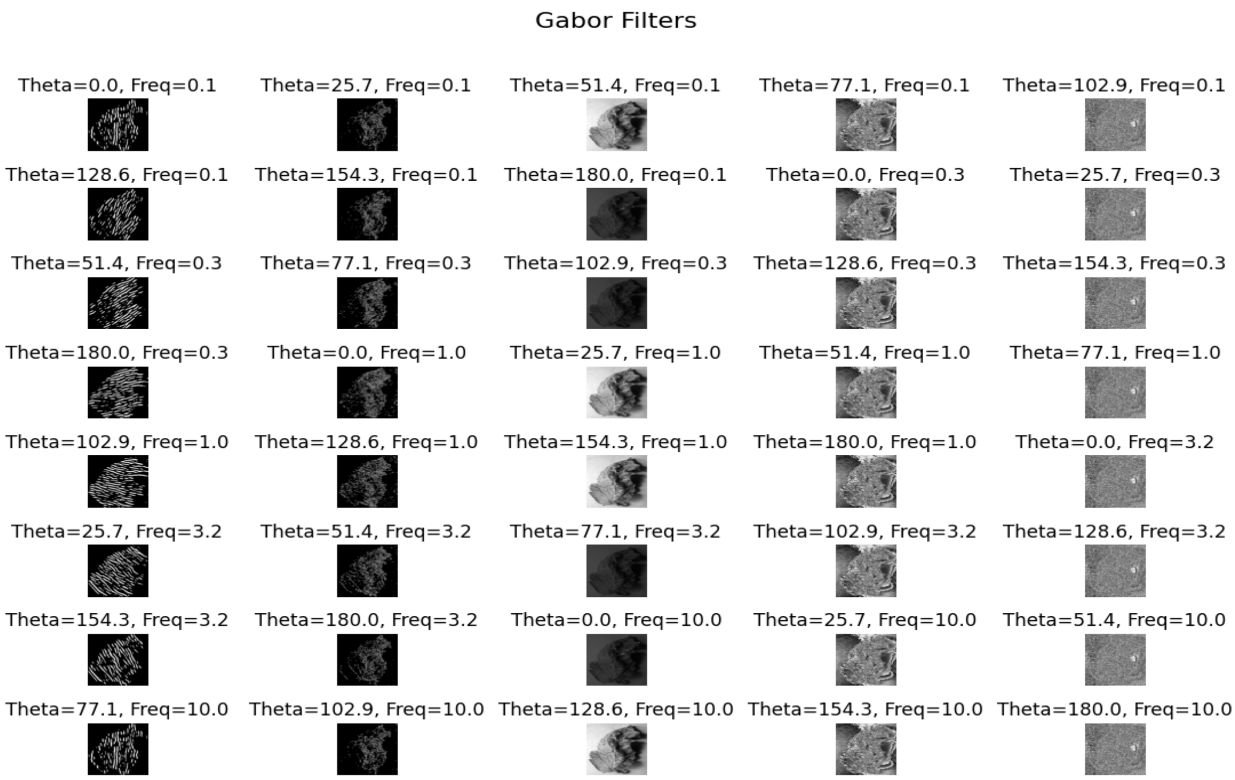

Figure 4. Gabor Feature Extraction.

Color Feature Extraction

It illustrates the chromatic and physical properties of colors by showing how various wavelengths cause sensors to react. These characteristics show resilience to complicated backgrounds and maintain their invariance to changes in scale and orientation. They provide photometric information on the color channels' optical density, lighting, shadow, and shadiness. Color moments offer significant statistical information about color channels, whereas color histograms skillfully depict the distribution of color inside pictures. As an alternative, color descriptors use textures or color gradients in the photos to extract information [19].

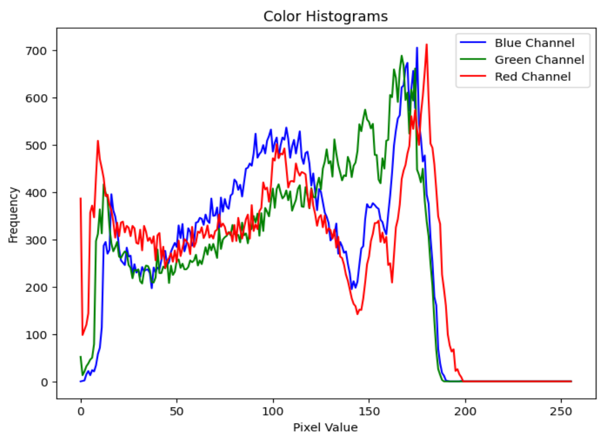

Figure 5. Color Histograms.

Shape Features Extraction

It provides an overview of the graphical properties of objects in pictures, including perimeter borders and forms like triangles, circles, and rectangles. Shape feature extraction adheres to features like scale invariance and statistical independence, Identification, rotation and translation. Disease types, crop species and pathogen types are only a few of the variables that might affect how an infection appears on a plant leaf in an image. Diameter, solidity, eccentricity, centroid, area, extent, major axis length, convex hull and minor axis length are some shape characteristics. These features hold significance across various image analysis tasks. Contour-based descriptors, such as moments and Fourier descriptors effectively analyze object boundaries and shapes. Meanwhile, region-based descriptors encompassing properties like area, perimeter and eccentricity provide valuable shape information crucial for image classification [19].

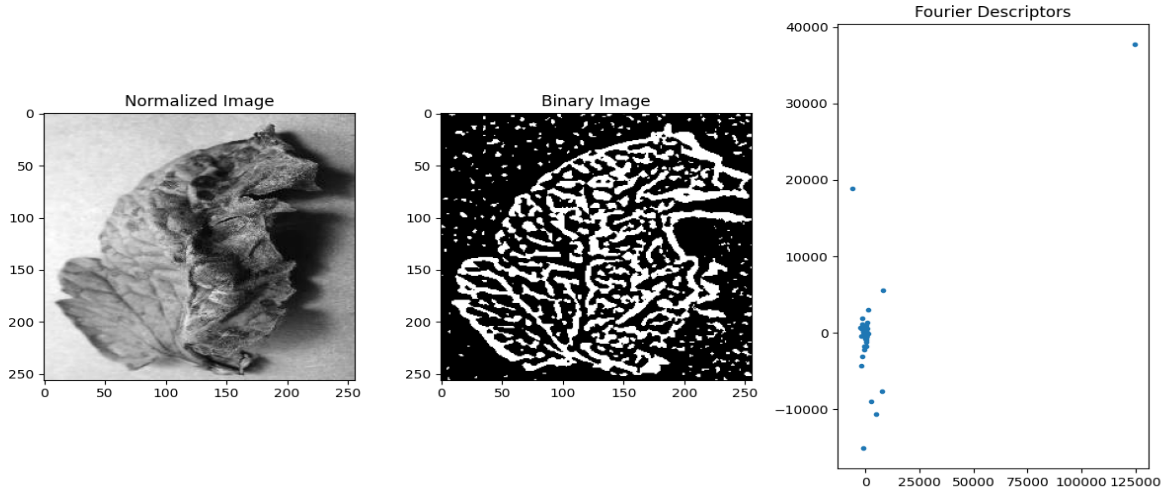

Figure 6. Fourier Descriptor Graphs**.**

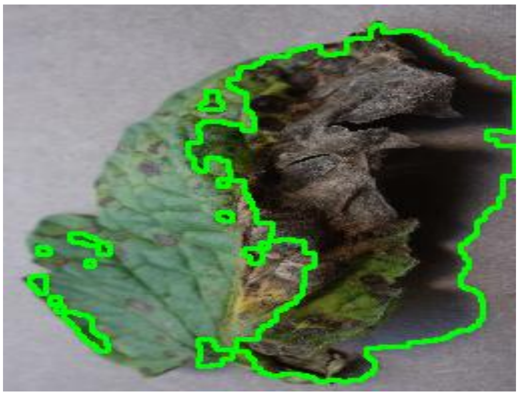

Figure 7. Extracted Damaged Part Shape From Tomato Leaf**.**

4. MOTIVATION FOR HYBRID APPROACH

When all three features are combined, the retrieval outcomes improve significantly. However, individual color and shape remain the most crucial and extensively employed features due to their straightforward extraction process and superior accuracy in contrast to texture. Presently, the realm of deep learning algorithms, including Convolutional Neural Networks (CNNs), autoencoders and deep belief networks, is experiencing substantial advancement, as they possess the ability to autonomously extract features from images [20]-[21]. In comparison to color and shape features, the texture attribute does not contribute significantly to plant disease identification. Leaf image-based plant disease identification follows two approaches: (i) deep learning-based, employing intricate architectures for automated feature learning and (ii) feature-based, extracting manually crafted features like color and shape to train conventional machine learning algorithms. While deep learning approaches yield superior accuracies, they entail greater computational resources, making them unsuitable for memory- and computation-constrained devices such as mobile or handheld devices [22].

5. EXPERIMENTAL SETUP

Extraction of the useful feature from an image is an essential step for object recognition and segmentation because the information in an image is extremely complicated and high dimensional. Image-based Acquisition represents the initial stage, encompassing the gathering of a plant leaf and capturing high-quality images using a camera Images are gathered from the PlantVillage dataset [23]. Different color spaces are utilized to identify the images at the beginning of image analysis. The algorithm for hybrid color and shape feature extraction for tomato plant leaf disease detection is shown in the algorithm 1.

Algorithm 1: FeatureExtraction

Input: An RGB image I of size $H \times W$. Output: A feature vector F of size K.

Step 1: Pre-process Image 1.1 Resize the image to a desired size. 1.2 Denoise the image to reduce noise. 1.3 Convert the image to grayscale: $I_{\text{gray}} = 0.299 \times I_R + 0.587 \times I_G + 0.114 \times I_B$, where I_R, I_G, I_B are the red, green, and blue channels of the image, respectively.

Step 2: Convert Image to Desired Color Space 2.1 Convert the grayscale image to the desired color space (e.g., RGB to HSV).

Step 3: Extract Color Features 3.1 Compute color histograms to capture color distribution: $\text{Hist}(I) = [h_1, h_2, \ldots, h_N)$, where h_i represents the count of pixels with intensity i. 3.2 Compute color moments to capture color characteristics: $\mu_i = \frac{1}{N}\sum_{j=1}^{N} I^i_j$, where μ_i is the i-th color moment and N is the total number of pixels.

Step 4: Normalize the Color Histogram 4.1 Normalize the color histogram to ensure consistent scale across different images: $\text{Hist}_{\text{norm}}(I) = \frac{\text{Hist}(I)}{\|\text{Hist}(I)\|}$.

Step 5: Choose a Threshold 5.1 Choose a threshold value to convert the image to binary: T.

Step 6: Convert the Image to Binary 6.1 Apply the chosen threshold to convert the image to binary: $I_{\text{binary}}(x, y) = \begin{cases} 1, & \text{if } I(x, y) > T \\ 0, & \text{otherwise} \end{cases})$.

Step 7: Extract Fourier Descriptor 7.1 Compute the Fourier descriptor from the binary image to capture shape information: $\text{FD}(I_{\text{binary}})$.

Step 8: Extract shape features. Compute

Step 9: Concatenate Features 8.1 Concatenate the normalized color histogram and the Fourier descriptor to create a fused feature vector $F = [Hist_{norm}(I), FD(I_{binary}), Shape(I_{binary})]$

Step 9: Output 9.1 Output the fused feature vector F.

End Algorithm

The amount of the feature vector F depending on how many bins there are in the in the color histogram as well as number of blocks used to divide the image. The number of bins can be chosen based on the specific application. The Figure 8. below demonstrates the original image alongside the extracted shape features image and the attention image. These graphic representations emphasise areas of interest in the image and offer insights into the feature extraction procedure. Significant outlines and qualities that are crucial for classification and further investigation may be originate and used using this study.

Figure 8. Original Image

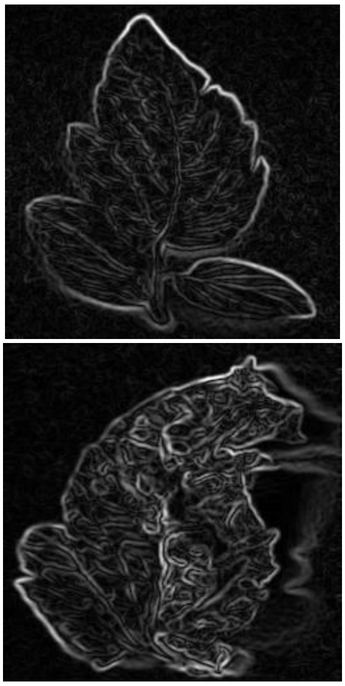

Figure 9. Leaf Segmentation

Figure 10. Attention Map

A geometric representation of an image's color transmission, color histograms deliver light on the color conFigureuration of the image's Red, Green, and Blue (RGB) frequencies. Histograms offer a useful method for comparing and classifying images based on their color content, making them a generic tool for computer vision tasks like object detection and image retrieval. On the other hand, Fourier descriptors are scientific depictions of an object's margins or system that are got using Fourier transformations. These descriptors are helpful for form analysis and classification activities because they provide a small and immutable representation of object contours to translation, rotation, and scale changes. Despite having different uses, Fourier descriptors and color histograms are both essential tools in image analysis that help researchers better understand the content and structure of images in a range of fields. Figure 9 applies both Fourier descriptors and color histograms to demonstrate how they aid in the interpretation and study of images.

Color histograms and Fourier Descriptor features are used to improve image exploration and appreciation by using both color and shape information by joining is our goal. This concatenated feature vector gives an accurate representation of the image content by combining color and form features. Here, Investigations illustration that this technique works well for a range of image analysis bids, such as object detection, classification, and picture retrieval. The concatenated features, color histograms, and Fourier descriptors are shown in Figure 10.

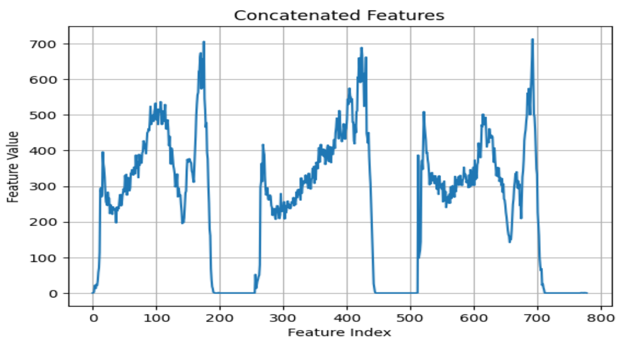

Figure 11. Serial Fusion Color Histograms, Shape Features and Fourier Descriptor Features.

The serial integration of color histograms, shape characteristics, and Fourier descriptor features in tomato leaf disease detection is crucial for improving the pinpointing and dependability of disease identification systems. Color histograms, which are suited to detecting color-related problems like discoloration or lesions, are used to record the distribution of colors in images of leaves. Shape features provide geometric information on leaf morphology, which aids in identifying structural irregularities such as curling or deformations. Fourier descriptor characteristics give a concise and invariant summary of leaf contours, which enables the correct characterization of shape modifications arising from diseases.

6. CONCLUSION

Feature selection and image recognition is the important phase in computer vision which defines the overall accuracy. Low interclass similarity must be ensured to improve intraclass similarity within the specified characteristics. These characteristics establish the foundation for determining the algorithm's accuracy. The leaf picture is the input at this point, and the feature vector with distinguishing characteristics is the output. Three basic features of a leaf are color, texture, and form. Well-established techniques were used to extract features related to color and form. An instantaneous computation of feature extraction techniques allows for an efficient selection according to picture properties (color or grayscale) and complexity. For the purpose of extracting color and form features from tomato plant leaves, we suggest a hybrid (serial fusion) strategy that can improve results over those obtained by a single method. This hybrid approach might improve the accuracy of classification.

Abbreviation

LBP- Local Binary Pattern

DWT- Discrete Wavelet Transform

PSO- Particle Swarm Optimisation

FCM- Fuzzy C-Means

GMM - Gaussian Mixture Model

CNN- Convolutional Neural Networks

GLCM-Grey Level Co-occurrence Matrix

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Ethics Approval

Not Applicable

Conflict of Interest

The authors report there are no competing interests to declare.

Author's Contribution

Puja Dipak Saraf, Jayantrao Bhaurao Patil and Rajnikant Bhagwan Wagh have Contributed equally to the conceptualization, methodology, data analysis and writing of this article.

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