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Plant Leaf Disease Detection Using Integrated Color and Texture Features

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ABSTRACT

In the realm of precision agriculture, a pivotal challenge lies in the detection, identification, and grading of crop diseases. This multifaceted task necessitates the involvement of expert human resources and time-sensitive actions aimed at mitigating the risks of production losses and the rapid spread of diseases. The effectiveness of the majority of developed systems in this domain hinges on the quality of image features and disease segmentation accuracy. This paper presents a comprehensive research endeavor in the domain of Content-Based Image Retrieval (CBIR), specifically tailored to detect and classify leaf diseases. The proposed system integrates both color and texture features to underpin its functionality, providing a robust framework for accurate disease detection. By leveraging advanced image processing techniques, the system enhances the precision of disease identification, which is crucial for timely and effective intervention in agricultural practices. To evaluate the system's performance, maize leaves afflicted by rust and blight serve as prime candidates for testing. These diseases were chosen due to their prevalence and significant impact on crop yield. The experimental results demonstrate that the developed system consistently excels in its disease detection and identification tasks, boasting an impressive efficiency rate of 98.33%. This high level of accuracy underscores the potential of the system to be a valuable tool in precision agriculture, aiding farmers and agricultural experts in maintaining healthy crops and optimizing production. The integration of color and texture features not only improves the detection accuracy but also provides a comprehensive understanding of the disease characteristics. This dual-feature approach ensures that the system can distinguish between different types of diseases with high precision, making it a versatile solution for various agricultural applications. The findings of this research highlight the importance of advanced image analysis techniques in enhancing the capabilities of disease detection systems, paving the way for more efficient and effective agricultural practices.

INTRODUCTION

Agricultural growth plays a pivotal role in the economies of countries primarily reliant on agro-based industries. The quality and yield of crops are profoundly influenced by factors such as weather patterns and the prevalence of crop diseases. Notably, research by Kannan (2014) underscores the global impact of these diseases. In the context of India, the statistics are no less concerning, with crop loss estimates of 25% in rice and maize. The economic implications of such losses are substantial, with farmers expending millions of dollars annually to combat crop diseases.

The key strategy for enhancing crop yields lies in the early detection of diseases through vigilant crop monitoring and timely interventions. A study by Prasann Kumar (2012) revealed a survey conducted by the International Crops Research Institute indicates that 93% of Indian farmers heavily depend on pesticides to manage crop diseases and pests, with pesticide application occurring anywhere from 1 to 15 times before harvesting. Unfortunately, this overreliance on pesticides translates into significant losses, ranging from 11% to 40%. Beyond the economic repercussions, the extensive use of pesticides introduces several adverse consequences, including disruptions in the food chain, the potential for secondary pest infestations, heightened human health risks, and the possibility of acute or long-term health issues. Early disease diagnosis not only opens doors to timely remediation but also serves as a fundamental strategy for controlling disease propagation through various trajectories, including time, wind, water, birds, and insects. This approach facilitates the implementation of protective measures, including the application of pesticides, and biological control agents, and the adoption of Integrated Pest Management (IPM) practices.

The process of disease diagnosis in plants is a complex one, typically relying on experts with a profound understanding of plants and their associated diseases. These experts possess the ability to recognize diseases, estimate the extent of damage through visual observation, and recommend suitable treatment options. However, this traditional approach has inherent limitations, marked by subjectivity and relatively low throughput. To address these shortcomings, electronic or computer-based expert systems have emerged as viable alternatives. These systems can encapsulate the knowledge and experience of expert farmers or agricultural advisors, effectively constituting what is termed an "Expert System," as stated by Patil & Kumar (2017).

Electronic expert systems rely on image pattern recognition and understanding to identify and diagnose plant diseases and pests. Developing precise and sophisticated image pattern algorithms is essential for their accuracy. These systems compare input images of diseased plants with stored images to make informed decisions, similar to how human experts use their knowledge and experience. Content-Based Image Retrieval (CBIR) systems work with the same principles as human experts and hence can be employed in electronic expert systems to analyse image content, such as color, shape, and texture, and quickly retrieve similar images. As a result, electronic expert systems are a successful approach for assisting users in diagnosing plant diseases when their knowledge is limited.

The impetus for this research is drawn from the aforementioned considerations. The current investigation aims to conduct a comprehensive exploration of computer vision and image processing algorithms specifically tailored for disease detection based on the principle of image retrieval. These algorithms will be employed for the analysis of plant leaf images, primarily in color, to identify plant diseases and improve both diagnostic accuracy and throughput.

RELATED WORK

The realm of plant disease detection has witnessed substantial growth with the adoption of diverse techniques and methodologies that draw from fields such as Image Processing, Artificial Neural Networks (ANN), genetic algorithms, and wireless technology. These technologies have played a pivotal role in the development of systems capable of not only detecting but also classifying plant diseases, thus facilitating expedited disease diagnosis. Several notable research studies have significantly contributed to this area.

Naik et al. (2014) introduced a plant disease diagnosis system. In their research, they utilized pomegranate leaves with foliar disease spots for experimentation. The acquired images underwent resizing and noise reduction through the application of the Gaussian Low Pass filter. The segmented diseased images using K-means clustering were thresholded to extract Regions of Interest (ROIs), with Haar wavelet used for feature extraction. A Mamdani-type fuzzy classifier was then employed, taking these features as input to classify the disease.

Singh et al. (2015) developed an image-processing-based method for the classification of rice diseases. In their approach, leaf images exhibiting diseased blasts were subjected to noise removal through pre-processing. Further processing involved the application of the Wiener filter and adaptive histogram equalization. The use of K-means clustering facilitated image segmentation, while texture features like entropy and standard deviation were extracted. These features were subsequently utilized for classification through a Support Vector Machine (SVM) classifier. The authors acknowledged the potential for enhancing both segmentation and classification by exploring alternative classifiers.

Karmokar et al. (2015) developed a neural network-based approach for the recognition of diseases in tea leaves. The images of tea leaves afflicted by five distinct diseases were subjected to appropriate pre-processing steps involving cropping and resizing. The process included thresholding for the segmentation of diseased leaf portions and feature extraction. These features were harnessed for training neural networks. The authors reported an accuracy rate of 91% in their developed recognizer and highlighted the possibility of creating a real-time leaf disease recognition system using mobile platforms.

Ahmad et al. (2015) proposed an algorithm rooted in Artificial Bee Colony (ABC) for leaf lesion classification. In the filtration phase, healthy and dying leaf images were filtered out from three categories of leaf images (healthy, unhealthy, and dying). Recognition and detection algorithms were designed leveraging Artificial Bee Colony, Fuzzy Logic, Otsu's thresholding, and geometric formulas. The algorithm's performance was evaluated using leaf images with varying lesion severities and compared against Otsu, Canny, Robert, and Sobel algorithms, yielding an average accuracy of 96.83%.

Another approach, reliant on thresholding, was adopted for disease spot detection on plant leaves by Revathy & Chennakesavan (2015). The approach encompassed the conversion of diseased color leaf images from the RGB color space to other color spaces, including Gray, HSV, YCbCr, YIQ, and CIELAB. The median filter was utilized for noise removal and image smoothing. Disease spot segmentation was realized through Otsu's thresholding and histogram-based methods, specifically focusing on a particular channel from various color spaces. The research revealed that the 'I' component of YIQ and the 'A' component of CIELAB color spaces exhibited enhanced disease spot detection capabilities in comparison to other color models.

Notably, the aforementioned research efforts have presented diverse methods in the detection and classification of various leaf diseases. These methodologies primarily rely on image processing and ANN, often necessitating significant training time. In light of these observations, there is a notable scarcity of research leveraging Content-Based Image Retrieval systems, which offer promising potential for disease detection. CBIR systems, mirroring the working principles of human agricultural experts, hold the potential to address multifaceted challenges in plant disease detection and classification while enhancing accuracy.

MATERIALS AND METHODS

In the conventional tactics within plant science, plant scientists typically rely on visual observation and their expertise to subjectively assess leaf damage without the aid of photographic documentation. This approach suffers from inherent limitations, characterized by subjectivity and low throughput. This research endeavors to introduce an innovative disease detection and classification system based on Content-Based Image Retrieval, as illustrated in Fig. 1.

Any CBIR system comprises two fundamental steps: Feature Extraction and Feature Matching. In the Feature Extraction step, image characteristics, including color and texture, are extracted and subsequently stored within a dedicated Feature Database. Upon presentation of a query image, its feature vector is extracted and subsequently compared with the feature vectors archived in the database during the ensuing feature-matching phase. The retrieval of similar images hinges on the relative value of the comparison threshold. The ultimate determination of leaf health status is contingent on the precision of the retrieved images.

The cornerstone of CBIR's effectiveness lies in the robustness and relevance of the image features used. An assortment of image features, encompassing color, shape, and texture, can be systematically extracted and applied in CBIR systems. The system presented in this research is specifically tailored to exploit color and texture features, optimizing its performance for the given application.

Color Feature

The human visual system is naturally attuned to color images, exhibiting a heightened sensitivity compared to grayscale images. This inherent quality has led to the widespread utilization of color features as the predominant image feature in retrieval processes. In their study, Singh & Hemachandran (2012) noted that color features are notably straightforward to extract, robust against variations in background conditions, and self-sufficient. The choice of a color space or model is a critical aspect of color image processing, significantly influencing the outcomes. Within any color space, color features can be extracted using diverse techniques, including methods such as color histograms as used by Choras (2007), Suhasini et al. (2009), correlograms, moments by Huang et al. (2010), Maheswary & Srivastav (2008), Shih & Chen (2002), and color structure descriptors, among others.

Human perception is inherently more responsive to luminance than chrominance. In this context, the YCbCr color space capitalizes on this attribute to achieve an effective representation of images. YCbCr color space uncouples the luminance and chrominance of an image, offering advantages over conventional color spaces like RGB and HSV, as found by Patil & Kumar (2017). The transformation from RGB space to YCbCr space is accomplished using the following equations used by Phatale et al. (2020)

$$Y = 0.299(R - G) + G + 0.114(B - G) \quad ...(1)$$

$$Cb = 0.564(B - Y) \quad ...(2)$$

$$Cr = 0.713(R - Y) \quad ...(3)$$

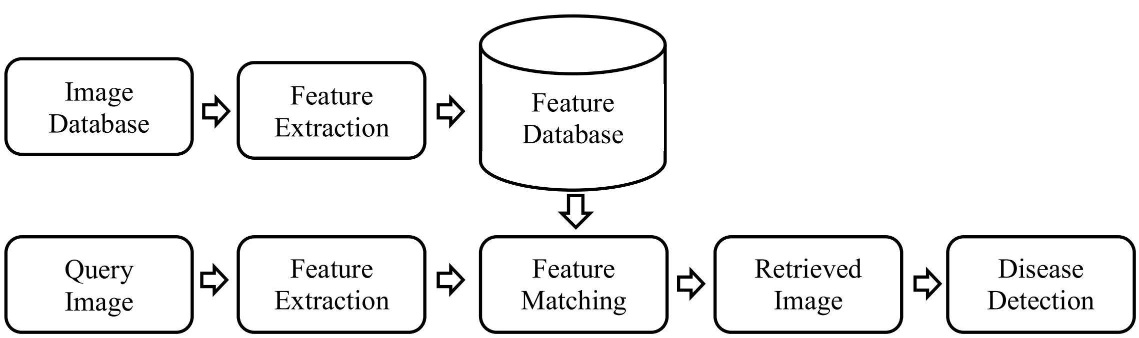


Fig. 1: Block diagram of CBIR system for disease detection.

Among the diverse color features enumerated earlier, the Histogram stands out as an easily computed attribute, displaying robustness against minor image variations. Comparing the histograms of two images employing appropriate similarity measures establishes a solid foundation for the classification or recognition of objects. The Histogram, in this context, is defined as a graphical representation illustrating the distribution of image pixel counts across various light intensities within an image. An image histogram is a discrete function, as stated in equation (4) by Gonzalez & Woods (2008).

$$P(r_k) = \frac{n_k}{N} \quad ...(4)$$

Where,

r_k is the kth gray level, N is the total number of pixels in the image, is the number of pixels in the image with that gray level,

Texture Feature

The definition of image texture is inherently elusive, as it encompasses recurring patterns of variations in intensity and color, manifesting as complex visual patterns. These encompass sub-patterns that are associated with the perception of attributes such as lightness, uniformity, density, roughness, regularity, linearity, and frequency. These attributes are intricately linked to image brightness and color, as specified in research by Grigorescu et. al. (2002). Textures are a rich source of visual information, rendering texture feature extraction a pivotal function in a myriad of image processing applications, including but not limited to medical imaging, face recognition, and Content-Based Image Retrieval (CBIR).

Among the multitude of texture feature extractors, Gabor filters, as described by et al. (2004), and Local Binary Pattern (LBP), as described by Vatamanu et al. (2015), emerge as particularly significant for this research. The human visual system exhibits characteristics associated with image decomposition, wherein an image formed on the retina is deconstructed into several filtered images. Each of these filtered images conveys variations in intensity within specific ranges of frequencies and orientations. Gabor filters are adept at simulating these characteristics, as they are orientation-sensitive.

LBP effectively describes local structures within an image and is computationally efficient while demonstrating resilience to illumination variations. Consequently, LBP finds applications in various image processing tasks, encompassing the analysis of biomedical images, facial images, aerial imagery, and image and video retrieval, as listed by Ahonen et al. (2006), among others. Senechal et al. (2011) found that the fusion of Gabor and LBP, denoted as Local Gabor Binary Pattern (LGBP), further enhances the effectiveness of texture feature extraction.

In the proposed experimentation, a modified version of LGBP, referred to as Local Gray Gabor Pattern (LGGP), is developed to extract texture features as researched by Patil & Kumar (2016). It extracts texture features from diseased leaves that exhibit pronounced textural characteristics owing to the manifestation of disease symptoms. The procedure employed for the extraction of LGGP features from the image is elucidated in the flowchart depicted in Fig. 2.

To derive LGGP values from LBP and LGBP images, the mathematical computation described in equation (5) is employed. This computation involves the comparison of each pixel within the LBP and LGBP images using a (3x3) neighborhood, as outlined in equation (5).

$$LGGP(x,y) = \begin{cases} LBP(x,y) & if\ LBP(x,y) = LGBP(x,y) \\ 1 & if\ [A \cup B] have\ more\ number\ of\ 1's than\ number\ of\ 0's \\ 0 & otherwise \end{cases} \quad ...(5)$$

Where A and B represent adjacent neighbors of LBP(x,y) and LGBP(x,y), respectively.

Proposed Method

In the proposed methodology, features extracted from both the color and texture of an image, in the form of the YCbCr histogram and the LGGP histogram, are extracted and subsequently stored in a feature database. Upon presentation of a query image, its features are extracted using a method similar to the feature extraction process applied to the database images. To measure similarity, correlations between the color histograms and correlations between the LGGP texture histograms are utilized. Fig. 3 illustrates the CBIR System employing the YCbCr Histogram and LGGP Histogram.

The algorithm utilized for the development of CBIR, incorporating a combination of the YCbCr histogram and LGGP histogram, is presented as follows.

Algorithm: CBIR using YCbCr histogram and LGGP histogram

Step 1: The RGB leaf image is provided as input for the query.

Step 2: Transform the RGB image into the YCbCr image.

Step 3: Calculate the histogram of each plane, i.e., Y, Cb, and Cr- plane.

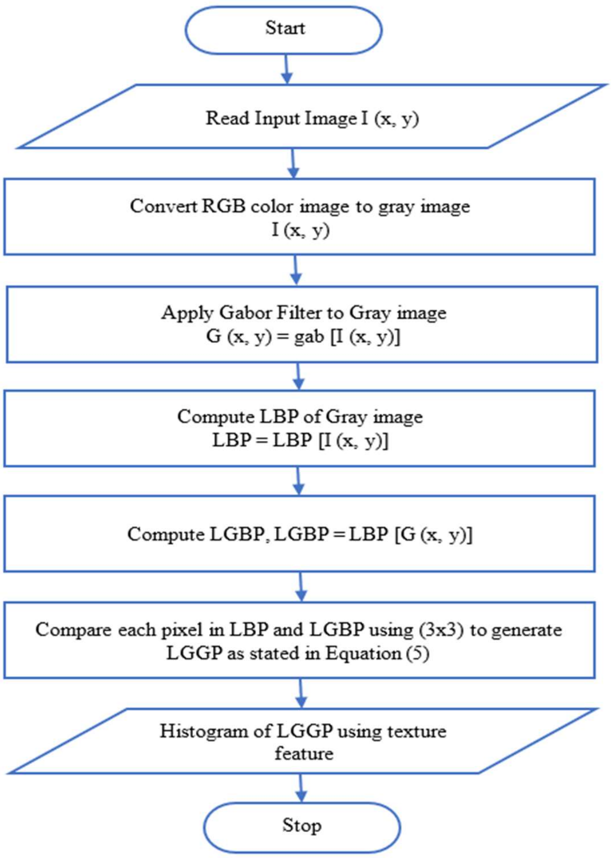


Fig. 2: Flowchart for extracting LGGP features.

Step 4: Combine the histograms of Y, Cb, and Cr components to generate a query color histogram, denoted as HQ.

Step 5: Convert the input image to a gray image

Step 6: Compute LGGP histogram (LQ).

Step 7: Extract the YCbCr histogram (H_D) and LGGP histogram (L_D) of database images from the feature database.

Step 8: Formulate a final feature vector for retrieval by uniting the correlation of H_Q and $H_{D,}$ and L_Q and L_D

Step 9: Determine the mean value of the feature vector obtained in Step 8 for all database images.

Step 10: Organize mean values in descending order and retrieve images that are similar.

Step 11: Based on the top N retrieval results, the disease of the query image is deduced to match that of the maximum-retrieved image.

RESULTS AND DISCUSSION

Database

The leaves of Maize, one of the most widely distributed crops globally, have been selected as candidates for testing the developed methods. Maize is renowned for its richness in carbohydrates, proteins, iron, vitamin B, and minerals, rendering it a valuable resource for the production of a diverse range of food and non-food products, including

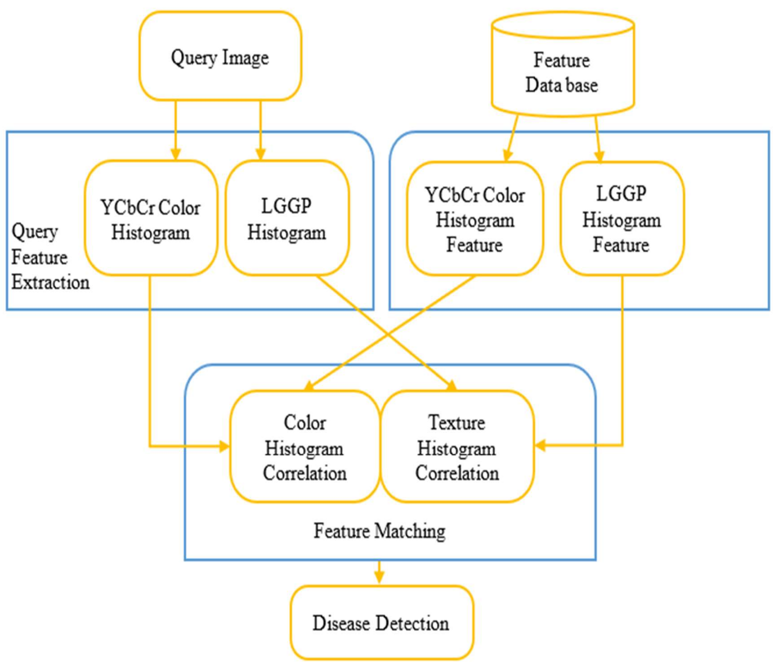


Fig. 3: CBIR System using YCbCr Histogram and LGGP Histogram.

cornmeal, oil, starch, and ethanol. With over 70 countries engaged in maize production, India secures the fifth position globally in maize production, as reported by Corn (2008).

To facilitate experimentation, a maize database has been curated, incorporating samples of diseased leaves affected by maize rust, leaf blight, and healthy leaves. These samples have been collected from fields located in the Sangli and Kolhapur districts of the state of Maharashtra, India, as well as from internet sources. For training purposes, 100 images of each disease type and healthy condition are utilized, along with an additional set of 365 images designated for testing.

Performance Parameters

Precision measures exactness according to equation (6), while recall assesses completeness as per equation (7), which is employed to evaluate the performance of the developed system. The % of retrieval precision is called retrieval efficiency defined by Wang & Qin (2009).

$$\text{Precision(p)} = \frac{N_{rr}}{N_{tr}} \quad \text{...(6)}$$

$$\text{Recall(r)} = \frac{N_{rr}}{N_{tri}} \quad \text{...(7)}$$

Where, N_{rr}: number of relevant images retrieved, N_{tr}: total number of images retrieved and

N_{tri}: total number of relevant images.

The efficiency of disease detection is calculated using equation (8) as the ratio of correctly detected diseased leaf images to the total number of leaf images tested during experimentation.

$$\text{Disease Detection Efficiency (e)} = \frac{Ic}{It}\ \text{x100} \quad \text{...(8)}$$

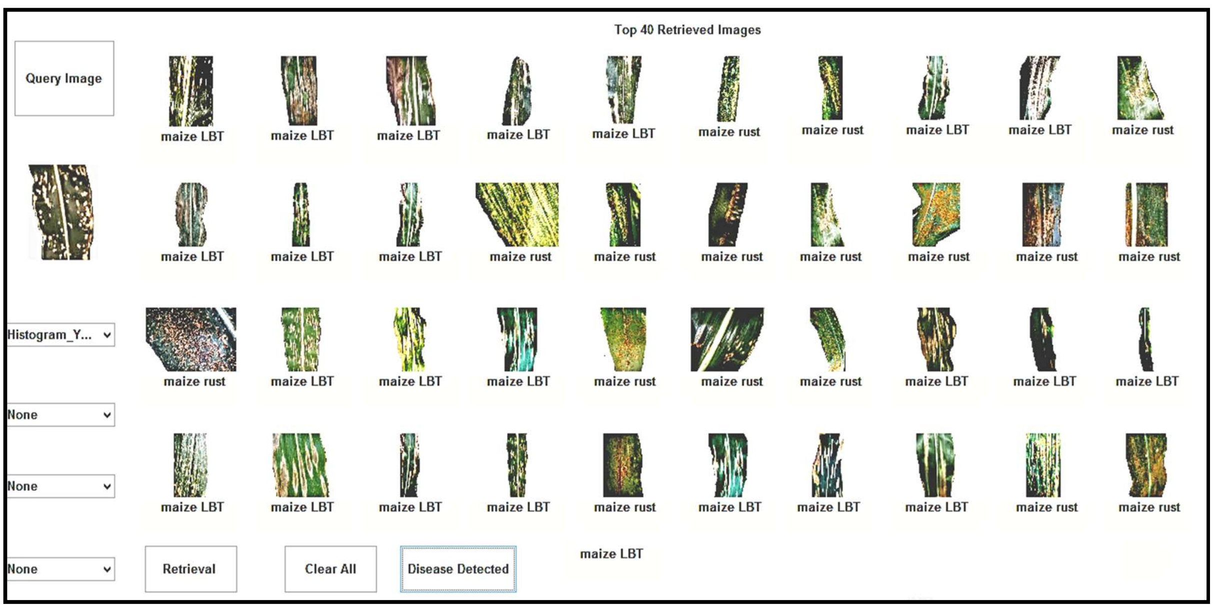
Where *Ic* is the number of correctly detected images, and it is the total number of tested images.

Sample Result of the Developed System

To assess the effectiveness of the developed system, it is essential to carry out a thorough examination of the CBIR system, analyzing individual features such as the YCbCr color histogram and the LGGP histogram separately. The evaluation concentrates on the top 40 retrieved images, with disease detection determinations relying on the precision of the top 10 images.

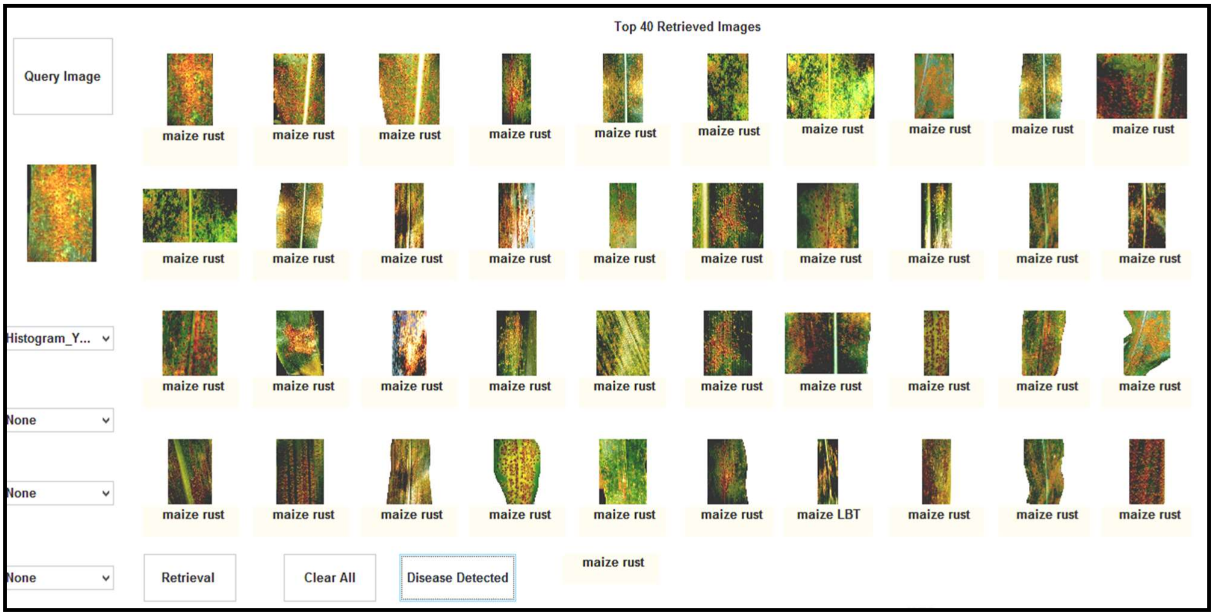
When using the YCbCr color histogram as a standalone feature, the approach involves utilizing three image planes: Y (Luminance), Cr, and Cb (Chrominance). The histogram of the query image is calculated for each of these planes and then compared with the histograms stored in the feature database using correlation analysis. Subsequently, based on the correlation values between the query image and all the images in the database, the top 40 similar images are retrieved for performance analysis, as illustrated in Fig. 4.

For instance, in the case of a query about maize leaf blight, Fig. 4(a) demonstrates that the YCbCr histogram



(a) Leaf Blight

Figure Cont....



(b) Leaf Rust

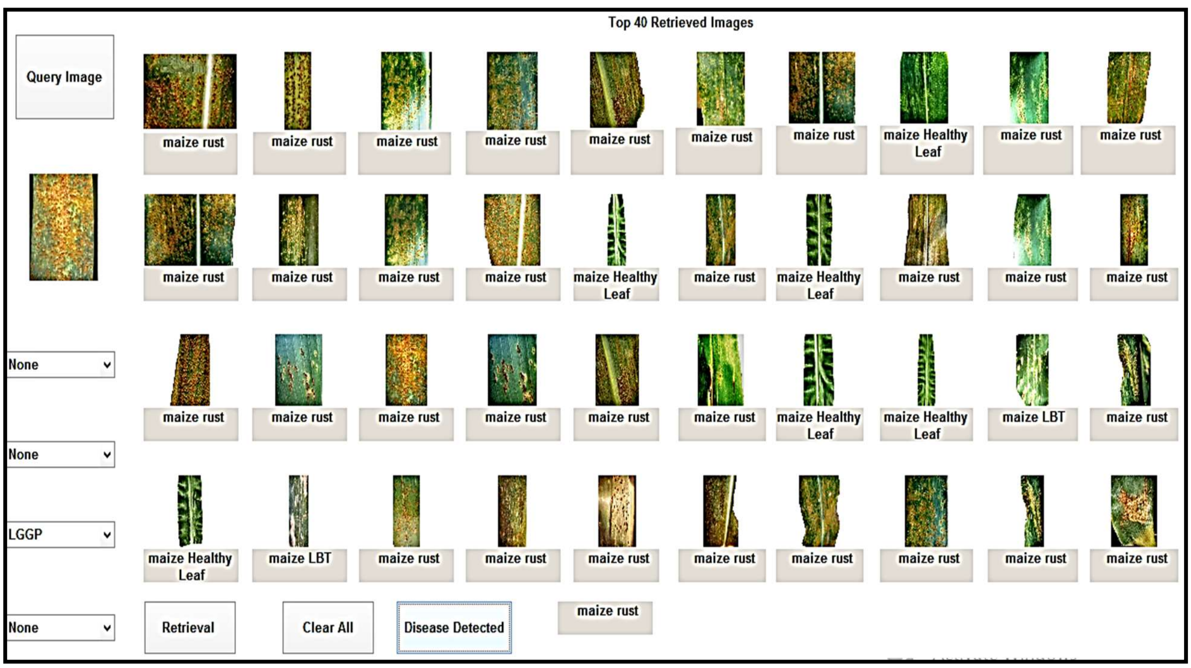
(c) Healthy Leaf

Fig. 4: CBIR for maize leaf using YCbCr histogram.

method yields a precision of 70% within the top 10 retrieved images, leading to accurate disease detection. Similarly, when dealing with maize rust, as depicted in Fig. 4(b), a precision of 100% is achieved within the top 10 retrievals, resulting in precise disease detection. Even in the case of a healthy leaf query, a precision of 80% is maintained within the top 10 retrievals, as illustrated in Fig. 4(c). These findings underscore the system's ability to effectively and accurately detect diseases in plant leaves using the CBIR approach, particularly when employing the YCbCr color histogram feature.

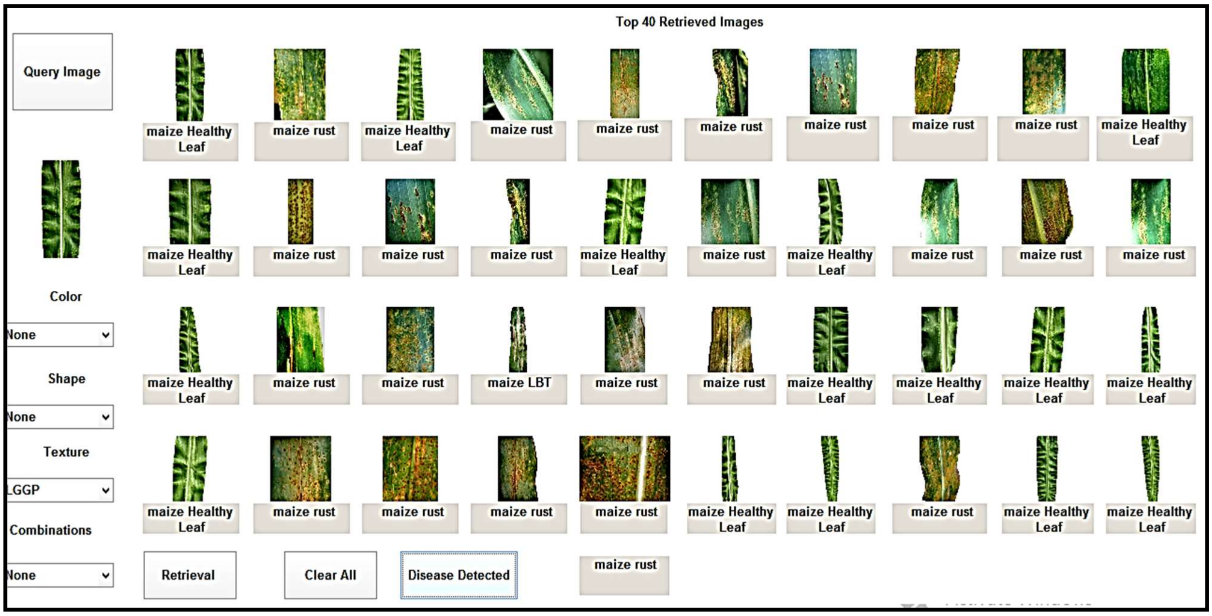
The study assesses the performance of Local Gray Gabor Pattern (LGGP) for disease retrieval and detection, maintaining consistency by comparing LGGP histograms of database and query images using the

(a) Leaf Blight



(b) Leaf Rust

Figure Cont....



(c) Healthy Leaf

Fig. 5: CBIR for maize leaf using LGGP.

methodology outlined in the texture feature. Fig. 5 illustrates the outcomes.

Fig. 5(a) reveals that for the query on leaf blight, most retrieved images correspond to healthy leaves, with relevant images appearing only at the 8th and 9th positions, resulting in a modest precision of 20%. In contrast, Fig. 5(b) displays a remarkable precision of 90% in correctly detecting maize rust disease due to its distinctive textural features, highlighting LGGP's efficacy in texture-based disease detection. This texture-sensitivity feature of LGGP proves invaluable in identifying objects with rich textures across various image recognition and computer vision applications regardless of color. Additionally, Fig. 5(c) demonstrates a 60% precision in correctly identifying healthy leaves.

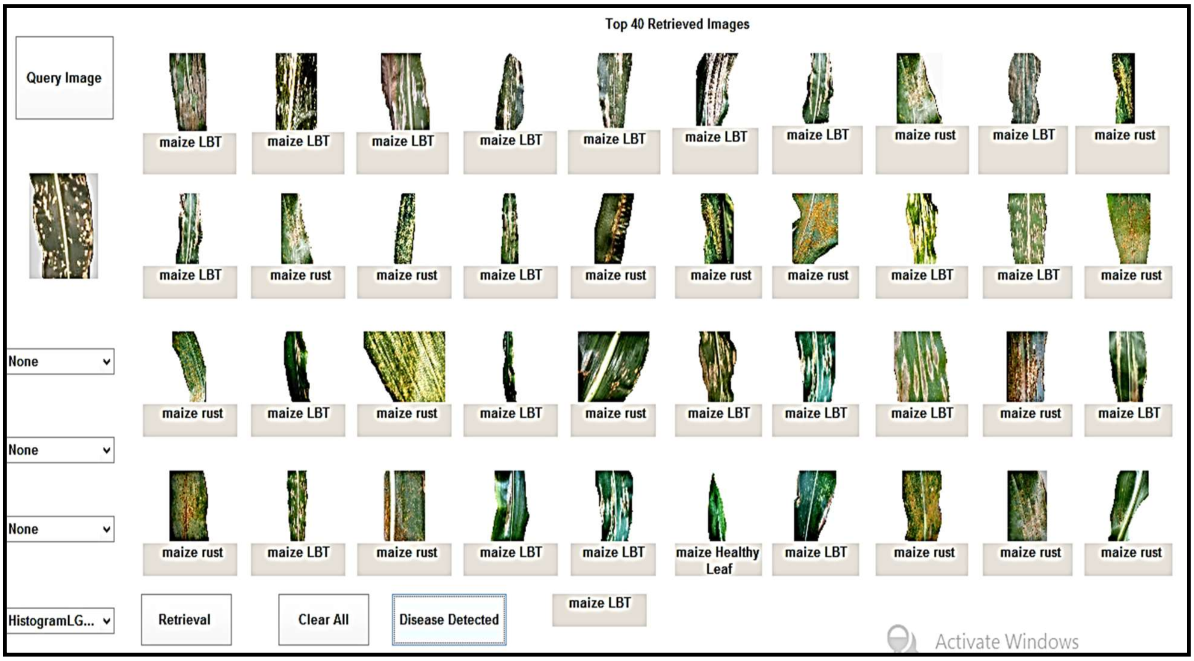
Now, observe the results obtained from the Content-Based Image Retrieval (CBIR) system, integrating both the YCbCr color histogram and the Local Gradient Binary Pattern (LGGP) histogram, as illustrated in Fig. 3. Integration at the classification stage produces better identification results as experimented by Dhole et al. (2023). A feature vector is constructed according to the algorithm outlined in the proposed method, and the findings are presented in Fig. 6.

For leaf blight, a precision of 80% within the top 10 retrievals is achieved (Fig. 6(a). This is an improvement compared to the individual YCbCr color histogram method, which retrieved 22 leaf blight images within the top 40 retrievals (Fig. 4(a)). Furthermore, the integrated method outperforms the individual YCbCr histogram (Fig. 4(b)) and LGGP histogram (Fig. 5(b)) methods when dealing with maize rust, delivering 100% precision in both top 10 and top 40 retrievals. As depicted in Fig. 6(c), healthy leaves are correctly identified with a precision of 70%. The performance of this integrated approach surpasses individual texture-based methods (Fig. 5(c) but lags behind the individual color-based performance (Fig. 4(c)), primarily due to leaf blight's retrieval at the 7th position.

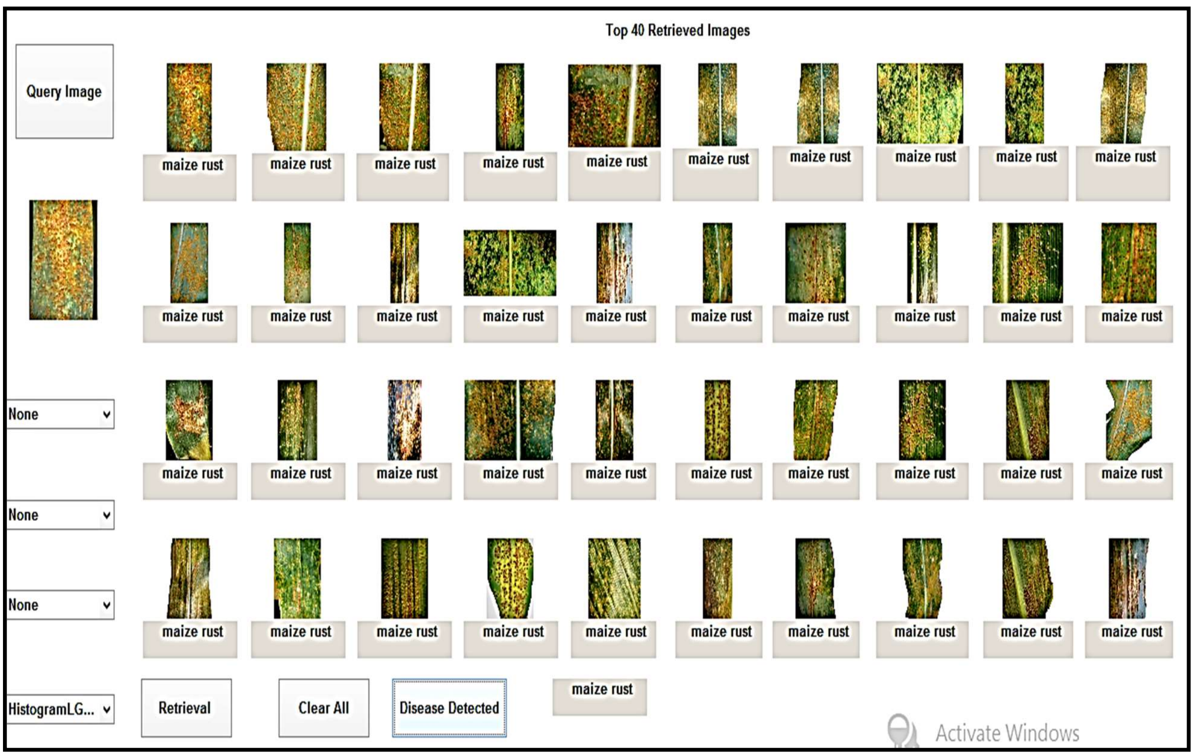
This integrated approach demonstrates significant promise, particularly for scenarios such as maize rust detection.

The experiment is replicated for a set of randomly chosen images. Fig. (7) shows a performance comparison of all tested methods for all candidate maize diseases concerning disease detection precision, recall, and efficiency.

The individual performance of the color histogram exhibits commendable results, with a disease detection efficiency of 96.66%. However, it is essential to acknowledge its limitations that when two distinct images exhibit a similar color distribution, their histograms can be indistinguishable. Consequently, relying solely on histograms cannot guarantee accurate object detection or recognition. Conversely, texture features yield favorable outcomes when images are texture-



(a) Leaf Blight



(b) Leaf Rust

Figure Cont....

(c) Healthy Leaf

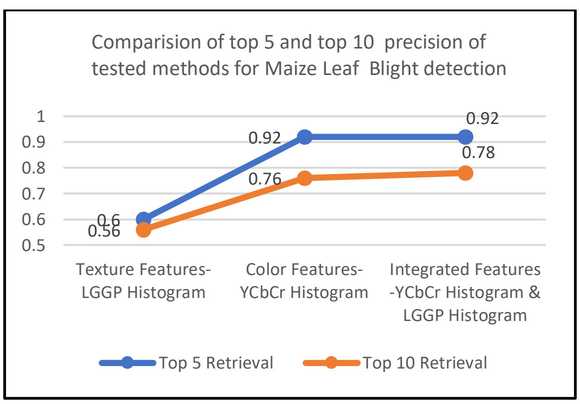
Fig. 6: CBIR for maize leaf using YCbCr histogram and LGGP histogram.

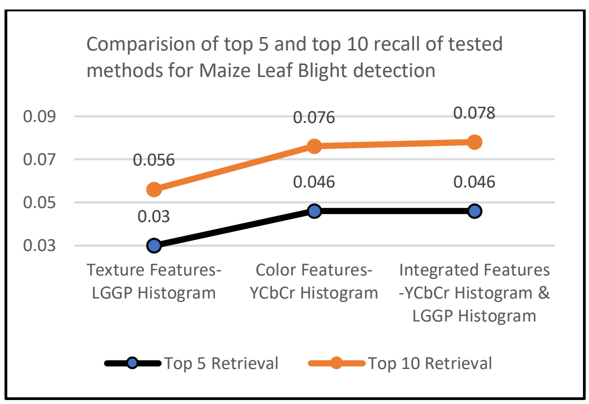
rich, but their individual use results in an average efficiency of 63.33%. Therefore, it is evident that the integration of both color and texture features is pivotal to achieving the highest efficiency, amounting to 98.33%.

Fig. 8 offers a comparative illustration of disease detection efficiency within the developed CBIR system, evaluated using individual color and texture features, as well as their integrated approach. This visual representation underscores the significant performance improvements achieved through feature integration.

CONCLUSION

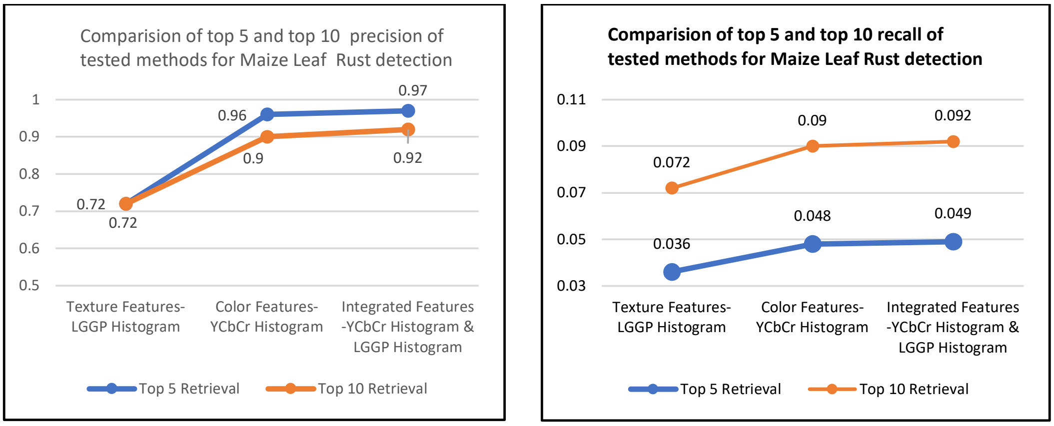
A system is developed to detect and identify plant leaf diseases through the analysis of leaf image features using



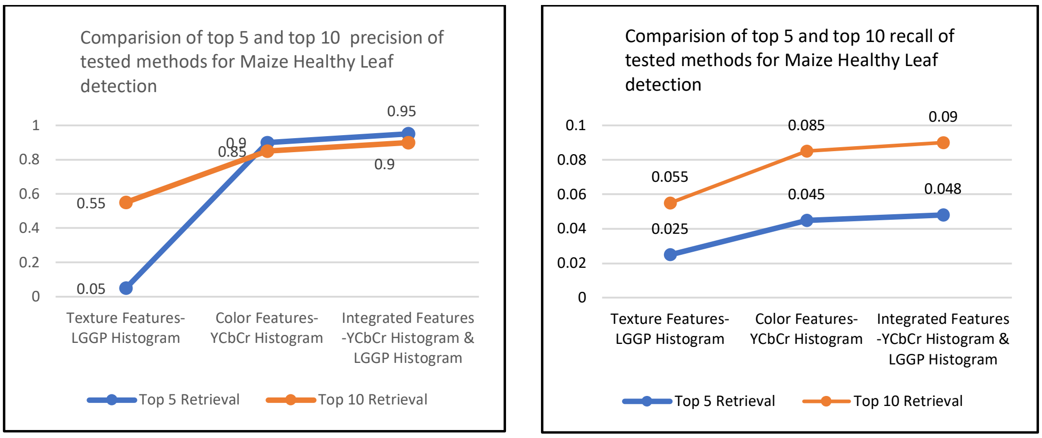


a) Leaf Blight

Figure Cont....



b) Leaf Rust



c) Healthy

Fig. 7: Top 5 and Top 10 average precision and recall for maize leaf disease.

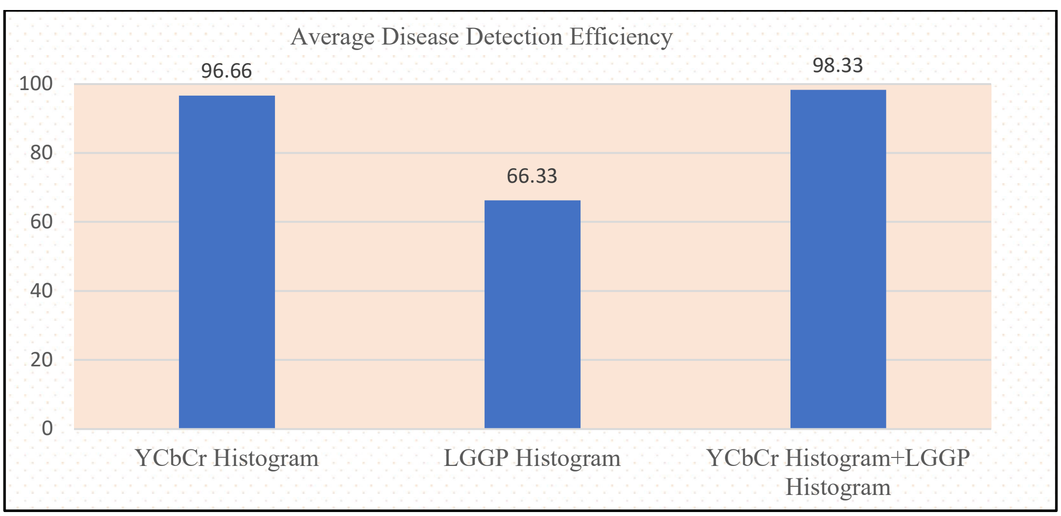


Fig. 8: Disease detection efficiency.

Content-Based Image Retrieval (CBIR). The system's performance is assessed individually using YCbCr color histograms and Local Gradient Binary Pattern (LGGP) texture histograms. To harness the collective power of color and texture features, they are harmoniously integrated to construct a comprehensive feature vector for retrieval purposes. This integration significantly surpasses the individual performance of these two features when considering precision, recall, and the efficiency of disease detection and identification. The integration of features achieves a remarkable disease detection efficiency of 98.33%. To enhance the system's versatility, it can be further evaluated with additional color, texture, and shape features, thus extending its capabilities to detect various diseases across different crop types. This expansion has the potential to bring about the application of CBIR in the realm of precision agriculture.

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