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http://publisher.uthm.edu.my/ojs/index.php/emait
e-ISSN : 2773-5540

Emerging Advances in Integrated Technology

Computational Approaches Based On Image Processing for Automated Disease Identification On Chili Leaf Images: A Review

Nuramin Fitri Aminuddin[1], Ariffuddin Joret[2], Shamsul Aizam Zulkifli[3], Herdawatie Abdul Kadir[4], Marlia Morsin[5], Zarina Tukiran[2*]

[1]Faculty of Electrical and Electronic Engineering,
Universiti Tun Hussein Onn Malaysia, 86400, Batu Pahat, Johor, MALAYSIA

[2]Internet of Things Focus Group (IoT FG),
Universiti Tun Hussein Onn Malaysia, 86400, Batu Pahat, Johor, MALAYSIA

[3]Power Electronics, Drives and Machines (PEDM),
Universiti Tun Hussein Onn Malaysia, 86400, Batu Pahat, Johor, MALAYSIA

[4]Groups of Robotics Engineering and Technology (GREAT),
Universiti Tun Hussein Onn Malaysia, 86400, Batu Pahat, Johor, MALAYSIA

[5]Microelectronics & Nanotechnology - Shamsuddin Research Centre (MiNT-SRC),
Universiti Tun Hussein Onn Malaysia, 86400, Batu Pahat, Johor, MALAYSIA

*Corresponding Author

DOI: https://doi.org/10.30880/emait.2022.03.02.002
Received 27 September 2022; Accepted 22 December 2022; Available online 31 December 2022

Abstract: Chili, an important crop whose fruit is used as a spice, is significantly hampered by the existence of chili diseases. While these diseases pose a significant concern to farmers since they impair the supply of spices to the market, they can be managed and monitored to lessen their impact. Therefore, identifying chili diseases using a pertinent approach is of enormous importance. Over the years, the growth of computational approaches based on image processing has found its application in automated disease identification, leading to the availability of a reliable monitoring tool that produces promising findings for the chili. Numerous research papers on identifying chili diseases using the approaches have been published. Still, to the best knowledge of the author, there has not been a proper attempt to analyze these papers to describe the many steps of diagnosis, including pre-processing, segmentation, extraction of features, as well as identification techniques. Thus, a total of 50 research paper publications on the identification of chili diseases, with publication dates spanning from 2013 to 2021, are reviewed in this paper. Through the findings in this paper, it becomes feasible to comprehend the development trend for the application of computational approaches based on image processing in the identification of chili diseases, as well as the challenges and future directions that require attention from the present research community.

Keywords: Chili disease, chili leaf, computational approaches, image processing

1. Introduction

From the Solanaceae family, chili (Capsicum sp.) is a significant crop native to Central and South America [1]. It is a laborious crop to grow and is widely farmed in equatorial America and tropical Asia. The crop has a high degree of genetic variation, and its fruit is edible and most often used as a spice in cooking [2]. The crop can be broken down into

**Corresponding author: zarin@uthm.edu.my*

three categories: bell chili, sweet chili, and hot chili, respectively. Most familiar chili varieties are thought to fit into one of the following categories or a hybrid. The chili hybrids are popular among farmers owing to their great fruit-yielding capabilities, which include a rise in fruit weight and a large number of fruits per crop, homogeneous size of fruit, and highly appealing fruit [3]. Many nutrients are found in the fruit, including phosphorus, potassium, fiber, vitamin C, and antioxidants, including flavonoids like lutein, cryptoxanthin, zeaxanthin, α-carotene, β-carotene and Vitamin-A.

Crop diseases brought on by bacterial, fungal, viral infections, and insect infestations have been a severe problem for farmers since they can significantly affect crop fruit yield, both in terms of quantity and quality, which has a direct influence on the nation economy [4]. The physiological processes of the crop are altered when a disease is present, and the emergence of disease signs can be seen on the crop leaves, fruits, stems, flowers, and roots. According to reports, 60 to 70% of disease signs can be found on crop leaves alone [5].

On the other hand, the manual procedures of identifying and evaluating crop diseases are challenging, even for workers with the necessary qualifications [4]. These manual procedures are carried out using either laboratory detection methods, biomarker-based detection methods, or imaging methods. Molecular methods such as Deoxyribonucleic Acid (barcoding, microarray, probe-based), Ribonucleic acid (sequencing-based, reverse transcriptase) and protein (immunosorbent assay, western blot) as well as serological methods are among the examples of laboratory detection methods [6]. Correspondingly, methods for detecting diseases using biomarkers include spectroscopic methods and crop metabolic and gaseous monitoring [7]. In contrast, imaging methods to detect crop diseases have included fluorescence imaging, multispectral imaging, thermal imaging, visible imaging and hyperspectral imaging [8]. Despite the availability of these methods, there is a need for automated disease identification for the crops to minimize the job difficulty [9].

Over the years, the growth of computational approaches based on image processing has found its application in automated disease identification, leading to the availability of a reliable monitoring tool that produces promising findings. Several reviews have been conducted to investigate the computational approaches based on image processing to identifying crop diseases. A review in [10] offers an analysis and discussion on using expert systems in agricultural crop diagnostics. The emphasis of this review is on an expert system that can analyze the signs of a variety of crop diseases, such as those that affect tomato, wheat and rice and provide recommendations for potential treatments to the farmers. On the other hand, the review in [11] presents a discussion on the application of image processing to identify diseases that affect citrus automatically. The review also presents numerous diverse aspects of image processing that can be used to diagnose crop diseases. Correspondingly, the review in [12] discusses predicting and identifying crop diseases, monitoring agricultural output and productivity, monitoring pests, and monitoring irrigation systems for smart agriculture. In contrast, the review in [13] examines numerous artificial intelligence applications for the automated processes of a variety of agricultural activities, including crop disease monitoring, weed management, pesticide control, storage management and management of water and irrigation. Meanwhile, the authors in [14] give a review on the application of deep learning and machine learning technologies to detect crop diseases caused by pests. The review also includes an overview of various machine learning and deep learning methods, as well as a comparison of the benefits and drawbacks associated with each of these methods. On the other hand, the authors in [15] give an overview of the expert system that can be used to address disease issues in the agricultural sector. The authors focus specifically on the functions of fuzzy logic for early disease detection and prediction at the farm. Likewise, the authors in [16] have written and published a review on the function that neural network methods play in identifying crop diseases. The review concentrates mainly on deep learning architecture and handcrafted feature extraction techniques that have been employed for the identification of crop diseases. In addition, the review also highlights the significance of gathering big datasets with high variability, transfer learning, data augmentation, and the display of deep learning activation maps in the process of increasing identification accuracy.

Although these published reviews provide a considerable amount of reporting, an attempt has not been made to properly discuss the systematical diagnosis steps in the computational approaches themselves. The disease identification process is stated to be essentially consistent with the utilized computational approaches [9]. The process starts with collecting crop leaf images using sensors such as cameras and then continues via four diagnosis steps to obtain the results, which include pre-processing, segmentation, extraction of features, and identification techniques. It is also important to note that wwhen it comes to developing a system for diagnosing crop diseases that can be used in actual cultivation environments, there are still several challenges that need to be addressed. Additionally, it is important to highlight that there has only been a limited amount of reporting on crop diseases driven by biotic factors. Hence, this review aims to systematically analyze the steps of diagnosis in applying computational approaches based on image processing for the chili diseases driven by biotic factors, as well as examine its challenges and future directions. Fig. 1 presents the literature review selection procedure for identifying chili disease using the computational approaches.

The remainder of the paper is structured as follows: section 2 provides a taxonomy of diverse chili diseases. In Section 3, a comprehensive systematic review of the computational approaches for identifying chili leaf diseases is presented. Section 4 discusses the challenges faced in the chili disease identification system. The future directions of chili disease identification system are presented in section 5. The review is finally summarized and concluded in Section 6.

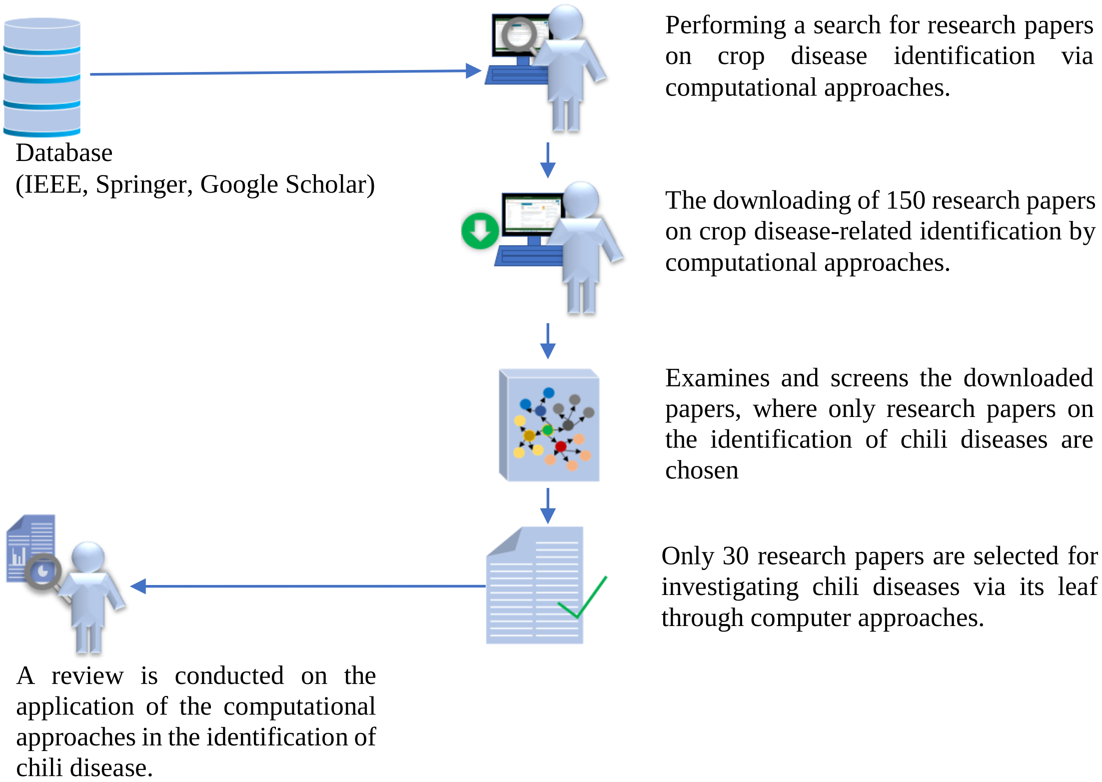

Fig. 1 - Flow diagram of the review selection process

2. Taxonomy of Chili Diseases

Most research has found verifiable evidence of the increased severity and prevalence of biotic-related crop diseases as a cause of crop yield reduction. According to [17], biotic-related crop disease is caused mainly by the impacts of living forms within the environment. Fig. 2 shows the living forms that play a significant role in inducing crop diseases. These diseases are highly contagious and proven mainly by the symptom of exterior spots on the crops, which makes them easily recognizable. The biotic-related crop disease can affect crop production by making the crop yield unfit for use due to its detrimental influence on the growth of crops. A summary of the chili diseases linked with the biotic factors is presented in Table 1.

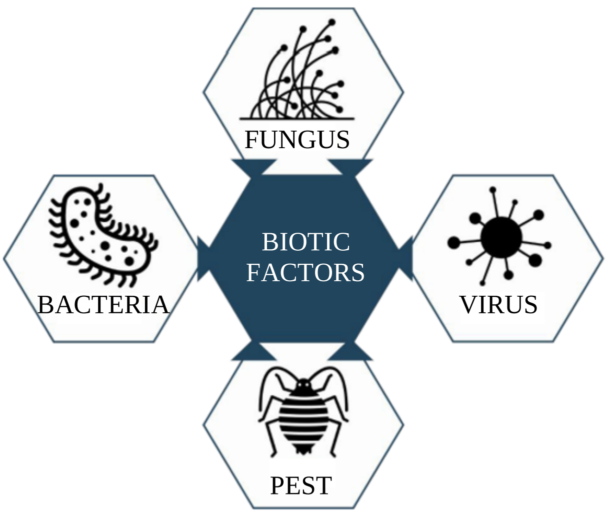

Fig. 2 - Biotic factors in chili diseases

2.1 Fungal-Caused Chili Disease

A pathogenic fungus takes nutrients directly from host crop tissues via its cell walls. Insects and other invertebrates quickly distribute their spores, allowing the fungus to infest the crop. Chili diseases caused by the fungus such as powdery mildew, fusarium wilt, Cercospora leaf spot, verticillium wilt, damping off, phytophthora blight, Rhizoctonia root rot, and anthracnose are worthy causes of chili fruit yield losses and lower chili fruit yield quality.

Cercospora spp., the fungus responsible for this disease, produced spot symptoms such as approximately circular lesions. The lesions are initially yellowish but quickly become translucent or grey only a few days following infection, followed by a dark brown colour with a red border. Around the red border, a translucent to the yellowish ring may form. Typically, diseased lesions dry up and drop off the leaf, producing visible holes. The infected leaf turns yellow and drops off the chili [18].

Leveillula Taurica fungus creates a white and powdered fungal growth that dominates the bottom of the leaf surface, whereas the top leaf surface of the infected leaf is discoloured brown or yellow. In rare instances, sporulation can occur on the top leaf surface. Gradually, the margins of the diseased leaf roll upward, revealing the fungus. The infected leaf then falls off the chili prematurely, revealing the chili fruit to light and potentially creating sunscald [19].

Fusarium oxysporum f.sp.capsici fungus is responsible for the elimination of veinlets as well as leaf chlorosis. The lower leaf is successively becoming yellow, and the afflicted leaflets can wilt and dies within a few days. The symptoms persist in subsequent leaves. At a later date, the vascular system becomes brown. The chili gets dwarfed and dies afterwards [20].

Phytophthora capsici causes leaf spots by directly penetrating the fungus into the leaf. The spots are first relatively small and uneven before becoming circular. As time progresses, the spots get more prominent, take on a lighter brown colour, and sometimes fracture around the spots. During high humidity, infected spots can be surrounded by a white growth resembling a fungus. In addition, rapid leaf blighting will also occur [21].

The fungus known as Verticillium dahliae lives in the soil and can directly infect chili roots. It travels via the root cortex to the xylem tissue, which is responsible for transporting water throughout the crop. The fungus causes the xylem to get blocked, which results in the yellowing of the leaf and the eventual fall of the leaf. The chili can wither due to water stress since the fungus can eventually clog the xylem [22].

The seedling disease, sometimes referred to as damping off, can be brought on by a number of different species of fungus, including Pythium spp., Fusarium spp., and Sclerotinia spp. When these fungi attack chili seeds or early seedlings, a condition known as damping off can result. The majority of the time, these fungi prevent the seeds from germinating. There are two different ways that these seedlings are harmed: either the roots can rot, which can cause the seedling to wilt and die rapidly, or the seedling can be attacked on the stem right at the ground line, which can cause the seedling to collapse [23].

The Rhizoctonia solani fungus infects the lower stems of chili, which are located closer to the ground. While the taproot decays, the fungus travels down and up the stem, causing the vascular tissue to be discoloured and producing a lesion at the soil line that is brownish-red in colour. Once a crop has been infected, its vitality is severely diminished, and the quality of the fruit yield suffers as a result [24].

The Colletotrichum spp. is a fungus that lives on infected chili seeds, chili detritus, and other hosts outside the crops. The fungus infects young fruit, but the symptoms mostly do not manifest themselves until the fruit is fully developed and has finished going through all of its colour changes. The symptoms first manifest themselves as a series of tiny lesions that quickly grow. The fully developed lesions can vary in colour from a dark reddish brown to a brownish black. As the infection develops, spores ranging in colour from brown to scarlet might become visible inside the lesions, either strewn about or arranged in concentric rings [25].

2.2 Virus-Caused Chili Disease

Viruses are crop pathogens that interact with the defence barriers of crops. The viruses can either integrate into the crop genome and remain dormant or actively multiply and regulate the host biosynthetic processes. Crop viruses produce severe emergent crop diseases, causing global and regional economic losses. Chili Leaf Curl Virus (ChiLCV), Chili Veinal Mottle Virus (ChiMV), Alfalfa Mosaic Virus (AMV), and Beet Curly Top Virus (BCTV) are some viruses found in chili.

Whitefly transmitted Geminivirus causes ChiLCV disease to the chili. Some of the first indications are yellow vein engraving as well as the deformation of an immature leaf. As the infection spreads, signs of mosaic, chlorosis, and mottling appear, and the distortion becomes more apparent. The growth of infected chili is slowed, and the fruit is abnormally small in size, mottled, and deformed [26].

Aphid transmitted Potyvirus causes ChiVMV disease to the chili. This virus causes the symptoms to show as a deformed leaf that gets highly puckered, as well as bright and dark areas mostly on foliage that give the chili a mottled look. Other symptoms include a loss in crop fruit yield. In addition to this, the fruit is disproportionately small. The disease overall impact is shown in the form of slowed chili growth and decreased fruit output [27].

Aphid-transmitted Bacilliform virus causes AMV disease in the chili. This virus causes symptoms that include mosaic, stunting, yellowing, and spotting of the leaf of the crop. Other symptoms include the crop exhibiting some degree of leaf withering. The fruit has the potential to be undersized and misshapen [28].

Leafhopper transmitted Geminivirus causes BCTV disease to the chili. Infected chili seedlings can display symptoms such as curling, yellowing, and twisting of the leaf due to the virus. Infection in seedlings almost always leads to mortality. When chili is affected, the first sign to appear is stunting of the crop growth. As the disease advances, the symptoms include the veins on the leaf becoming more visible and the leaf curling, puckering, and twisting. The leaf eventually matures into a brittle and rigid state. The chili that has been affected can eventually lose its roots. In addition, infected chili with the disease is severely stunted and yields very little fruit [29].

2.3 Pest Injury-Caused Chili Disease

Pest insects, which feed on the contents of individual crop cells, can cause some agricultural damage. Pests that feed on chili include nematodes, mites, thrips, and aphids.

Feeding of nematode Meloidogyne incognita on the chili results in the creation of galls, mainly on the root system. This condition is referred to as root-knot. The presence of the nematode in the root tissue, where it feeds and lives, causes the formation of these knots. Damage caused to infected chili includes the difficulty of nutrients and water to pass up through the knots, which causes the crop to typically be stunted, wilt, and have fewer little leaves that are either yellowish or light green. The infected chili also produces fewer fruits or fruits of a worse quality [30].

The feeding of the mite Polyphagotarsonemus latus causes the chili leaf to curl and crinkle downward, resulting in the appearance of upturned spoon-shaped leaves as well as pods with a chlorotic surface. In addition, the development of the crop is hindered, and there is a widespread occurrence of fruit scarring and decreased fruit size [31].

When thrips, Scirtothrips dorsalis feed on chili leaf; the leaves acquire patches that range in colour from light brown to silvery and are speckled with black excrement. In severe situations, there is a complete disfigurement of the leaf, followed by early defoliation of the crop [32].

Pests such as Myzus persicae aphids cause fading and distortion of the chili leaf that are afflicted with them. In addition, the crop has limited shoot growth, resulting in necrotic patches on the leaf. Honeydew is a sticky, sweet fluid that is secreted by aphids. This honeydew supports the formation of sooty mould on the crop [33].

2.4 Bacterial-Caused Chili Disease

Bacteria can be found in every environment: soil, water, food, people, animals, and crops. Almost all crop pathogenic bacteria grow as parasites in the host crop, as epiphytes on the crop surface, especially buds, and partially in crop waste or soil. Chili diseases caused by bacteria include bacterial wilt, bacterial spot, bacterial canker, and bacterial soft rot.

Ralstonia solanacearum bacterium infects roots of chili and causes wilting of the crop. The chili that has been infected can wilt gradually, and its leaf can become yellow. The lower stems of the afflicted crop acquire a dark browning at the vascular locations, which often spreads into the pith and cortical tissues. Once the stems of the crop that is affected are cut and put in water, milky-white streams of bacteria pour from the cut ends of the stems [34].

The bacterium known as Xanthomonas campestris pv. vesicatoria makes its way into the chili stem and leaf by either wounds or stomata. On the stem and leaf, the bacteria are responsible for the emergence of water-soaked lesions that range from circular patches to irregular patches. As time passes, the patches have a purplish-grey colour with a black core and are encircled with a yellow halo just a few millimeters wide. The infections have a greater propensity to manifest themselves in the lower canopy, where the infected leaf first develops a ragged appearance before ultimately turning brown and falling off the crop. Defoliation of the crop can occur as a consequence of severe infections. The infection also causes significant loss of blossoms, and the emergence of roughly spherical, scabby and black lesions can be seen on the fruit where the disease is present [35].

The bacteria Clavibacter michiganensis subsp. michiganensis creates tiny blisters or swollen white patches on the chili stem and leaf. Later, the leaf has spots with its centers turning necrotic, dark, and surrounded by a white halo. There are also lesions on the stem with a gritty look and extend to produce cankers. Initially, the bacteria cause symptoms on chili fruit to emerge as tiny, spherical, slightly elevated bumps. As they get larger, these bumps can have a brown centre and a white halo. As the infection progresses, there is progressive leaf wilting followed by crop death [36].

Lesions on the chili produced by insects or hail can allow the soil-borne bacteria Pectobacterium carotovorum to enter the crop. The bacteria penetrate the crop at the end of the stem, which then causes the surrounding tissue to become more pliable, ultimately converting into a mass of liquid. On the other side, infected chili fruit has a tendency to shrivel up and hang off of the crop like a water-filled bag. When the fruit contents begin to leak out, the fruit outer peel begins to dry up and remains attached to the crop [37].

Table 1 - Chili diseases related to biotic factors

Biotic Factor	Disease	Pathogens	Symptoms	Crop part affected	Refs.
Fungal	Cercospora leaf spot	Cercospora spp. (Cercospora capsici, Cercospora unonidicola)	The leaf has small brown spots that are round and have a light grey centre and dark edges.	Leaf, stem	[18]
Fungal	Powdery mildew	Leveillula taurica	Leaf develops chlorotic patches and blotches, then fall off.	Leaf	[19]
Fungal	Fusarium wilt	Fusarium oxysporum f.sp.capsici	The disease causes chlorosis in the leaf, darkening of the veins, and chili degradation.	Leaf	[20]
	Phytophthora blight	Phytophthora capsica	The infected leaf has small dark green spots that grow and turn white.	Leaf, stem and fruit	[21]
	Verticillium wilt	Verticillium dahliae	Stunting, leaf withering, and discolouration of the chili vascular system.	Whole chili	[22]
	Seedling disease /damping off	Pythium spp. Fusarium spp. Sclerotinia spp.	Seedling mortality and fruit yield decrease.	Roots and crown of chili	[23]
	Rhizoctonia root rot	Rhizoctonia solani	The wilting of leaf and chili degradation.	Base of the stem and root	[24]
	Anthracnose/ Fruit rot	Colletotrichum spp.(Colletotrichum truncatum capsici, Colletotrichum Gleosporoides, Colletotrichum acutatum)	Lesions with concentric rings that have been submerged in water and sunken.	Leaf, stem, and fruit	[25]
Virus	ChiLCV	Whitefly transmitted Geminivirus	Leaf yellowing and decreased chili growth.	Leaf, stem	[26]
	ChiVMV	Aphid transmitted Potyvirus	Misshaped leaves and dark spots on the foliage. The fruit is small and misshapen.	Leaf, fruit	[27]
	AMV	Aphid transmitted Bacilliform virus	Shoestring leaf and leaf spots are seen. Fruit can be small in size.	Leaf, fruit	[28]
	BCTV	Leafhopper transmitted Geminivirus	Stunted growth and yellowed chili leaf.	Whole chili	[29]
Pest	Nematodes feeding injury	Meloidogyne Incognita	Stunted chili growth, low fruit yield and yellowish leaf.	Whole chili	[30]
	Mites feeding injury	Polyphagotarsonemus Latus	Inverted spoon-shaped leaves and fruit scaring are common.	Leaf, fruit	[31]

	Thrips feeding injury	Scirtothrips dorsalis	Infested leaf develops light brown to silvery spots and fruit scaring.	Leaf, fruit	[32]
	Aphids feeding injury	Myzus persicae sulzer	Distorted leaf, and fruit scaring.	Leaf, fruit	[33]
Bacteria	Bacterial wilt	Ralstonia solanacearum	The roots and lower part of the stem turn brown, which causes chili degradation.	Root, stem	[34]
	Bacterial spot	Xanthomonas Campestris pv. Vesicatoria	Water-soaked lesions on leaves that turn brown, patches on fruits and stems.	Leaf, stem, and fruit	[35]
	Bacterial canker	Clavibacter michiganensis subsp. michiganensis	The light brown colour of lesions on the leaf and stems of the chili.	Leaf, stem	[36]
	Bacterial soft rot	Pectobacterium carotovorum	Softening of fruit tissues.	Fruit	[37]

3. Computational Approaches for Automated Disease Detection On Chili

The use of the computational approaches based on image processing plays a crucial part in the automated identification of chili diseases, which helps to contribute to disease monitoring that ultimately gives rise to the chili growth and quality of chili fruits. In most cases, a computerized system based on image processing is composed of four diagnosis phases, including pre-processing, segmentation, extraction of features, and identification. All of these phases include the chili leaf as an input. Fig. 3 displays the structure for identifying chili disease using computational approaches based on image processing.

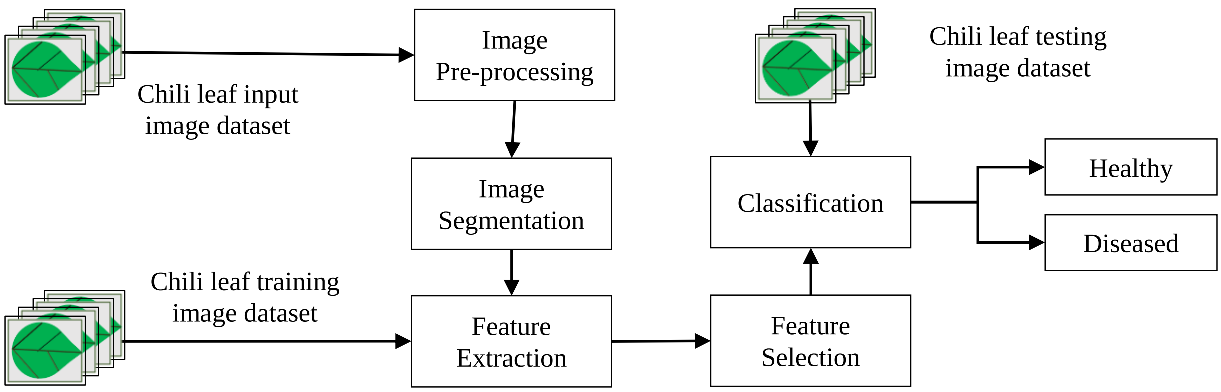

Fig. 3 - General structure of chili disease identification

3.1 Image Pre-Processing

The pre-processing phase is very significant since it aids in improving the quality of the image by getting rid of any unwanted distortions and enhancing certain aspects of the image that is supplied. Since most images are taken directly from the camera used by the farmers, the input leaf images are often comprised of noisy data and poor quality. There are numerous approaches for pre-processing, such as noise removal and image enhancement techniques.

Noise is a recognized undesirable signal that corrupts an image. The most common reason for the emergence of an unwanted signal is the usage of malfunctioning equipment, but more significantly, natural phenomena can intrude on the image and cause image quality deterioration. As a result, noise removal is an important and fundamental stage of image processing [38]. The research of [39] centred on applying a Gaussian filter to remove noise from resized images of chili leaves. Firstly, the colour channel of images is converted from Red, Green, Blue (RGB) to Hue, Saturation, Value (HSV) to make disease identification easier. Last but not least, the colour of the disease characteristics, which include the colour of the border area and the colour of the diseased spot, is derived from the images of the chili leaf. In the research published by [40], the Median filter is used to remove noise from a vast number of images of healthy and diseased chili leaves stored in an image repository. The first thing that is done is to increase the size of the window in the image. The increasing window size is done to provide room for the processing of pixels that are corrupted. After that, the median value is determined by utilizing the corrupted pixels in the calculation. In the last step, the value of the corrupted pixel is changed to the median value, and the procedure is repeated until all corrupted pixels in the window are fixed. The research in [41] uses a Local adaptive filter with 3x3 neighbourhoods to remove the digitization noise in diseased leaf images. In the research by [42], a morphological algorithm is used in conjunction with an area-filling approach to remove noises from leaf images. The morphological algorithm also identifies spot symptoms on the leaf through dilating and eroding. The images are dilated and then eroded to identify the leaf spot disease on the leaf. When images are dilated, the number of iterations has to be carefully selected so that noises on the leaf image are not mistaken for the leaf spot disease. Table 2 presents the performance assessment of noise removal techniques utilized for chili disease identification.

Table 2 - Performance assessment of noise removal techniques

Noise Removal Technique	Image Dataset	Overall System Accuracy Result	Refs.
Gaussian filter	Chili leaf	Disease identification ≤ 98%	[39]
Median filter	Chili leaf	Disease identification ≤ 92%	[40]
Local adapter filter	Chili, melon, and tomato leaves	Disease identification ≤ 91%	[41]
Region filling	Chili, citrus and mandarin leaves	Disease identification in black spot ≤ 92% Disease identification in powdery mildew ≤ 98%	[42]

Image enhancement is one of the pre-processing steps to improving the interpretability of information in images, in this case, providing better input for an automated chili disease identification system. The basis of doing image enhancement is to improve the visual quality of images to the next level and prepare these images to extract the maximum possible disease features [43]. The studies by [44], [45], and [46] start the enhancement of diseased leaf images by increasing the image contrast. After that, a histogram equalization technique is done to the image to determine the colour tone of the leaf. The studies also use a distribution function to distribute the intensities of the images throughout a colour spectrum. The authors in [47] also engage in image enhancement by using the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm to increase the quality of captured leaf images on a farm. The algorithm adjusts multiple histograms, each corresponding to a different image portion. Contrast limiting is then applied to each neighbourhood of pixels, and a transformation function is derived from these neighbourhoods. In the investigation, the difference between the homogeneous and inhomogeneous areas is kept to a minimum to avoid amplifying noise. The research in [48] entails the application of colour space conversion for the development of visual analysis of the leaf images. The initial input of RGB leaf images is converted to CIE L*a*b* (CIELAB) colour space. Colour space modification is then done to determine the light layers and chromaticity of the images. Table 3 presents the performance assessment of image enhancement techniques utilized for chili disease identification.

Table 3 - Performance assessment of image enhancement techniques

Image Enhancement Technique	Image Dataset	Overall System Accuracy Result	Refs.
Image contrast and histogram equalization	Chili leaf	Qualitatively measured	[44]
Image contrast and histogram equalization	Chili, grape, rice, soya bean, wheat, rose, cotton, apple and mango leaves	Disease identification ≤ 98%	[45]
Image contrast and histogram equalization	Chili leaf	Qualitatively measured	[46]
CLAHE algorithm	Chili leaf	Disease identification ≤ 91%	[47]
Colour space conversion	Chili, maize, peanuts, coconut trees, papaya, cotton, tomato and brinjal leaves	Qualitatively measured	[48]

3.2 Image Segmentation

Image segmentation refers to breaking up an image into several parts and then homogenizing each so that the Region of Interest (ROI) can be found within the image [49]. The image processing operations can then run on areas of the image connected with crop elements by identifying the ROI. This section examines the use of thresholding and *k*-means clustering to segment diseased areas of chili leaf.

By assigning a value of intensity known as the threshold, *T*, to each pixel in an image in such a way that a pixel can either be classified as a point in the background or a point in the foreground, thresholding is the simplest method for segmenting an image that can be used to separate an intended object from its background image [50]. Through the use of thresholding, binary images can be generated from grayscale images. The benefits of using a binary image include a reduction in the complexity of the data as well as a simplification of the approach used for detection and classification. The authors in [51] conduct research that focusess on simple thresholding. They do this by establishing a threshold value, *T*, to reduce the amount of disturbance caused by changes in light and the vein of the leaf. The authors in [52] also use a similar thresholding method with the combination of Prewitt filters that are applied on spaces color transformed input leaf images such as Hue, Saturation, Value (HSV), Hue, Saturation, Lightness (HSL) and Hue, Intensity, Saturation (HIS) to determine the magnitude of the disease. On the other hand, the authors in [53] present an automatic thresholding technique called the p-tile technique, which combines double thresholding and hysteric thresholding processes. The double thresholding process converts an input image into a binary image with its edge generated by the Canny edge detector. The pixels in the binary image with a magnitude above the maximum threshold are discarded, and those with a magnitude less than the minimum threshold are discarded. During the step of canny edge detection, the image pixel matrix is convoluted with the Prewitt operator to find the exact edge point. Irrelevant edge points are later discarded through the hysteric thresholding process. Likewise, the authors in [54] investigate the use of the Otsu technique to partition the diseased portion of the leaf. For the technique to perform, it must first calculate a threshold in the grey-level image histograms. The research is based on the hypothesis that the foreground and background pixels each belong to their unique Gaussian distribution with distinct values for both mean and variance. Therefore, the developed method will discover the ridge between two peaks by optimizing the variance between the two classes, and the final point in the grey-level histogram will serve as a cut-off point to segment the image. In contrast, the authors in [55] employ an approach similar to Otsu, but they do it using the Fiji-ImageJ programme to differentiate the portions of the leaf image that are bright green and sections that are dark green. In the research by [56], the authors segment an image of healthy potted leaf seedlings using an optimized thresholding method based on a genetic algorithm. The technique begins with converting the input grayscale image into a 16-bit binary number map. The first eight bits of this map indicate the segmentation threshold T_1, while the remaining eight bits constitute the segmentation threshold T_2. In order to calculate the optimum fitness of each generation of healthy leaf seedlings and segment the leaf area of each seedling, T_1 and T_2 are employed. Table 4 presents the performance assessment of image thresholding techniques utilized for chili disease identification.

Table 4 - Performance assessment of thresholding techniques

Thresholding Technique	Image Dataset	Overall System Accuracy Result	Refs.
Simple thresholding	Chili leaf	Qualitatively measured	[51]
Simple thresholding with Prewitt filter	Chili leaf	Qualitatively measured	[52]
Automatic thresholding (p-tile technique)	Chili leaf	Disease identification ≤ 98%	[53]
Automatic thresholding (Otsu method)	Apple, cherry, chili, blueberry, grape, corn, potato, peach, soybean, raspberry, tomato and raspberry leaves	Disease identification ≤ 82%	[54]
Automatic thresholding (Otsu method)	Chili leaf	Disease identification (R2 value ≤ 0.99)	[55]
Optimal thresholding	Chili leaf	Disease identification ≤ 94%	[56]

A *k*-means clustering approach is an unsupervised form of machine learning used to segment ROI, such as those derived from images of crop leaves. Since it is suited for data sets with enormous quantities of data and high feature dimensions, as well as having a low dependency on the data itself, the *k*-means clustering technique has become one of the most used approaches for segmentation [57]. The authors in [58] entail the usage of k-means clustering on crop leaves with several steps. The first step that has to be done is to divide the images of the leaf into *k* clusters according to how similar they are to one another. Then, the author utilizes the number of clusters, *k* and uses a subtractive clustering algorithm to produce the centre (initial centre values) for *the k*-means algorithm. In the last step, the authors compute the Euclidean distance of the centroid for each pixel in a leaf image. Based on this value, the authors allocate the centre of each pixel to the k-means cluster until it reaches the tolerance level. In contrast, the authors in [59] use *k*-means clustering for segmentation and collecting texture and colour features to determine the severity of the mosaic virus. The *k*-means clustering performed in the research used the Squeclidean method to compute point-to-cluster centroid distances. This led to the calculation of the squared Euclidean distance, and each centroid is determined to be the mean of the included points in that cluster. In order to prevent data overfitting and data under fitting, various clusters are used in an iterative process to determine the optimal number of clusters. An unsupervised *k*-means clustering technique is used in the spectral domain during the research, which is carried out by [60]. The technique is done in order to separate the leaf from the background image. By using the large spectral profile variation between vegetation and its surroundings, cluster analysis can accurately classify the image spectra into two distinct groups. A two-dimensional mask of the leaf surface is produced after the spatial position of each identified spectrum is preserved throughout the process. After that, the contours of the binary mask are recognized with the help of a border following algorithm so that the leaf can be found and any areas that had been incorrectly labelled could be found. The portion of the detected contours that was the biggest is the one that is used to represent the leaf. The portions of the detected contours smaller than the leaf are eliminated as misclassified pixels. After locating the outermost points of the most prominent contours, the mask is then cropped to fit the foreground leaf image, with a 5% buffer added to each dimension. The authors in [61] focus on clustering two-dimensional matrix image data obtained in a mixed cropping field using k-means. The data is divided into clusters to classify the types of crops in the fields before further crop disease detection. Correspondingly, the authors in [62] use *k*-means clustering to separate the diseased region of the leaf, which includes 14 different types of crops, using a dataset of healthy and diseased crop leaves acquired under controlled settings. Meanwhile, the authors in [63] propose using a hybrid clustering algorithm consisting of *k*-means and a genetic algorithm to segment the diseased portion of the leaf image. The proposed algorithm automatically selects the number of clusters from *k*-means through the calculation of the Davies Bouldin Evaluation method. The local minima problem of *the k*-means algorithm is later overcome by providing an optimal solution for selecting initial cluster centroids using the genetic algorithm. Table 5 presents the performance assessment of *k*-means clustering techniques utilized for chili disease identification.

Table 5 - Performance assessment of k-means clustering techniques

***K*-means Clustering Technique**	**Image Dataset**	**Overall System Accuracy Result**	**Refs.**
k-means clustering and subtractive clustering	Cassava, maize, tomato, chili, cotton and rice leaves	Qualitatively measured	[58]
k-means clustering	Chili leaf	Disease identification ≤ 57%	[59]
k-means clustering	Chili leaf	Disease identification ≤ 90%	[60]
k-means clustering	Grapes, chili and rice leaves	Qualitatively measured	[61]
k-means clustering	Apple, blueberry, orange, grape, cherry, chili, peach, squash, raspberry, soy, potato, tomato and strawberry leaves	Qualitatively measured	[62]
Genetic algorithm with *k*-means	Tomato and chili leaves	Qualitatively measured	[63]

3.3 Extraction of Features

The process of obtaining valuable information that distinguishes one class from another is known as feature extraction, which is a fundamental stage in constructing disease-based identification techniques. The output of feature extraction is known as a feature vector. In order to construct feature vectors, specific characteristics from the ROI are first extracted. Classifiers subsequently see the target class via the use of these feature vectors [64]. In order to distinguish between healthy and diseased chili leaves, the colour, texture, and morphology aspects of the crop leaf are extracted and analysed.

The Gray Level Co-occurence Matrix (GLCM) is a statistical model for extracting the second level of textural complexity elements from the images [65]. Through the construction of the GLCM, it simulates the regional pixel relationships. This technique is utilized to estimate image properties related to second-order statistics. It does so by considering the relation between two neighbouring pixels in one offset as the second-order texture. The first pixel is referred to as the reference pixel, and the second pixel is referred to as the neighbour pixel. The authors in [66] use GLCM on leaf images, creating an image matrix from the input leaf image and determining how frequently a pixel with a grey level value appears horizontally next to a neighbouring pixel using GLCM. Later, the research extracted three leaf features using the GLCM values, such as smoothness, coarseness and regularity. In research conducted by [67], a disease-infected leaf area is retrieved using GLCM, and the primary five features recovered from the diseased affected area are contrast, correlation, energy, entropy, and homogeneity. Correspondingly, the authors in [68] entail the usage of GLCM on images of infected leaf clusters, where eleven features are extracted, namely mean, standard deviation, entropy, variance, skewness, smoothness, contrast, kurtosis, energy, correlation, homogeneity, Inventive Design Method (IDM) and Root Mean Square (RMS). Likewise, the authors in [69] also engage in an experiment in which GLCM and Haralick texture feature techniques are used in the leaf disease detection of several crops, including apple, cherry, grape, peach, bell pepper and strawberry. Both techniques are utilized to extract a large number of features from the diseased region of the images of the leaf. However, in order to achieve a greater degree of accuracy, only five significant features are chosen for extraction: contrast, correlation, entropy, inverse difference moments, and the colours of red, green, and blue.

On the other hand, Histograms Oriented Gradient (HOG) are common descriptors and employed to extract features of objects following a change within the intensity [70]. The gradient histogram statistical feature is created by decomposing images into a dense array of cells, producing a histogram of oriented gradients for each cell. Finally, the feature is normalized by overlapping the contrast of the local cells. The research of [47] employs six traditional feature-based approaches, one of which is HOG, to extract disease characteristics from chili leaves. More specifically, the HOG counts the instances of gradient orientation in specific regions of the chili leaf image. In the research carried out by [71], the HOG feature descriptor is used to tally the number of instances of gradient orientation in processed images with dimensions of 64 by 128. The gradients are used in the computation of the magnitude and orientations. These gradients are created by patching the whole image into 8 by 8 squares. The next step is to use the min-max technique to normalize the HOG values once they have been computed for each 8 x 8 cell.

In contrast, Local Binary Pattern (LBP) is a feature descriptor that identifies the local properties of an image by making use of the structural and statistical elements of the image [72]. The LBP operates on a per-pixel basis and provides a binary representation of the eight pixels immediately found around the foreground pixel. Afterwards, the LBP creates a summary of all values in the form of a histogram, making it easier to extract a texture feature. In further work that is carried out by [47], LBP is used to extract disease characteristics from chili leaves. The LBP quantified the grayscale intensity variations of disease in the neighbourhood of the foreground pixel. Within the scope of this research, the parameters of the LBP, namely the radius and the number of neighbouring pixels, have been held constant at 3 and 24, respectively.

Correspondingly, Scale-Invariant Feature Transform (SIFT) is an algorithm that identifies and defines local features in crop leaf images [73]. It locates some key points and then generates quantitative information for image classification. The research of [47] uses SIFT to detect key points in chili leaf and computes description features vectors for each key point. The key point descriptor uses a set of 16 histograms aligned in a 4×4 grid, each with eight orientations resulting in 128 elements for each key point.

Additionally, Speeded Up Robust Feature (SURF) is a local feature descriptor that can efficiently detect local features of an image because SURF maintains a constant value regardless of changes in rotation, lighting, scale, three-dimensional transformation and blurring [74]. The research carried out by [47] uses SURF to calculate a total of 64 descriptive feature vectors. The research results show a greater computing speed without sacrificing the feature originality of chili leaf.

Conversely, Oriented Fast and Rotated Brief (ORB) is a local feature detector that utilizes a fast key-point detector in addition to a binary descriptor [75]. In the tests carried out by [47], ORB is used to extract important point characteristics in order to acquire spatial variation in images of chili leaves.

Alternatively, the deep learning technique uses a certain kind of multi-layer neural network design. The ability to extract characteristics from images without the intervention of a customized search algorithm is the primary advantage of deep learning, and Convolutional Neural Network (CNN), in particular, offers this benefit. During training, CNN can automatically learn and eliminate complicated hierarchical features by using various filter types [76]. InceptionV4, Xception, VGG19, VGG16, DenseNet, MobileNet, ResNet50, and InceptionV3, are the eight pre-trained deep learning models utilized in the research by [77]. These models extract the deep features from pest and diseased chili leaf images. The models are trained from the ImageNet data. The dimensions of the deep features that are retrieved are determined by the model that is used for training, and the performance of each model is then evaluated. Meanwhile, the authors in [78] use a faster Region-Based Convolutional Neural Network (R-CNN) in the research in order to construct a base of knowledge system that is capable of automatically identifying chili pests and diseases. The use of a faster R-CNN selects region proposals straight from the CNN feature map in order to highlight the location and size of several affected regions inside the image. During the investigation of the usefulness of deep learning for diagnosing diseases affecting chili leaf, the research in [47] also makes use of the deep learning technique. In order to extract features from the chili leaf image inputs, six deep learning models are used. These models are InceptionV3, ResNet152, DenseNet169, InceptionV3, MobileNet, and DenseNet201. These models are trained using the ImageNet dataset, which consists of over 1.2 million images belonging to 1000 distinct categories. In order to extract features from the chili leaf images that are utilized as input for the research, pre-trained model weights are employed as an initial weight. An analysis and comparison of the performances of these deep learning models take place at the end of the research. The technique highlighted most prominently in the research carried out by [79] involves using CNN to identify images of chili leaf diseases. The VGG model and blocks are used in the research, and the architecture of the model consists of building convolutional layers using small 3x3 filters, which is then followed by a max-pooling layer. Later, a block is formed by combining convolutional layers and pooling layers. The blocks are then repeated when the number of filters in each block is raised with the depth of the network. On the convolutional layers, padding is used to guarantee that the height and breadth dimensions of the output feature maps are identical to those of the input images of the leaf. Correspondingly, the authors in [80] build a system for identifying chilli leaf disease based on deep learning. The research involves collecting real-time data from an agricultural chili field and testing the developed system with many distinct kinds of deep learning models, including VGG16, AlexNet, LeNet, ResNets and VGG19 and ResNets. The performance of each model iteration in the system is evaluated and compared in the research.

Table 6 presents the performance assessment of feature extraction techniques utilized for chili disease identification.

Table 6 - Performance evaluation of various feature extraction techniques

Feature Extraction Techniques	Image Dataset	Overall System Accuracy Result	Refs.
GLCM with 3 feature extractions	Chili leaf	Qualitatively measured	[66]
GLCM with 5 feature extractions	Chili leaf	Disease identification ≤ 100%	[67]
GLCM with 11 feature extractions	Chili leaf	Qualitatively measured	[68]
GLCM-Haralick with 5 feature extractions	Apple, cherry, grape, peach, chili and strawberry leaves	Disease identification ≤ 98%	[69]
HOG with min-max normalization method	Chili leaf	Disease identification ≤ 89%	[71]
HOG, LBP, SIFT, SURF, ORB, VGG16, ResNet152, InceptionV3, DenseNet169, DenseNet201, MobileNet	Chili leaf	Disease identification ≤ 91%	[47]
ResNet50, VGG16, VGG19, Xception, InceptionV3, MobileNet, InseptionV4, DenseNet	Chili leaf and pests	Disease identification ≤ 88%	[77]
R-CNN	Chili leaf and pests	Qualitatively measured	[78]
VGG model with blocks	Chili leaf	Disease identification ≤ 95%	[79]
LeNet, AlexNet, VGG16, VGG19, and ResNets	Chili leaf	Disease identification ≤ 96%	[80]

3.4 Identification

Techniques based on classifiers are used in order to identify diseased chili leaf images according to the performed feature extraction techniques. This section covers a wide range of techniques based on classifiers, including Support Vector Machine (SVM), Random Forest, and Artificial Neural Networks (ANN), among many others.

SVM is a type of supervised machine learning classifier. Its primary application is a classification based on a hyperplane to determine the optimum decision boundary that can split an n-dimensional space into classes so that a new data point can be projected into the appropriate class. When the SVM makes a choice, the best boundary is created using a hyperplane by selecting points or vectors at the extremes [81]. A Random Forest, on the other hand, is a type of classifier constructed from a number of decision trees picked randomly from the training subset [82]. It compiles the results of the votes cast in the several decision trees to arrive at the predictive class of the object. In contrast, the ANN is composed of structures often stacked and executed parallel to function similarly to a human brain. Synapses are the structures in the ANN that are utilized to model complex behavior and for identification tasks [83]. Research conducted by [47] entails the application of SVM, Random Forest, and ANN as classifiers to identify five different types of chili disease symptoms. These symptoms included spots, mottling mosaic, puckering, yellowish chili leaf and vein bending.

Table 7 summarises the performance assessment of techniques based on classifiers utilized for chili disease identification.

Table 7 - Performance assessment of techniques based on classifiers

Techniques based on classifiers	Image Dataset	Overall System Accuracy Result	Refs.
SVM, Random Forest, ANN	Chili leaf	Disease identification ≤ 91%	[47]

4. Challenges and Future Directions

The social, ecological, and economic damages caused by chili diseases can be severe. Hence, developing an effective approach to aid in the early identification of diseases and improve the quality of chili fruit production must be a top priority for researchers. On the other hand, the computational approaches based on image processing is playing an increasingly important role in identifying chili diseases in their early stages. As a result of this review, the following challenges have been discovered in diagnosing images of chili leaves using the computational approaches based on image processing.

i. Under lighting circumstances that are not consistent, the chili leaf seems to have a darker appearance. As a result of the inconsistent lighting, there is a lack of comprehension of the chili leaf image features.
ii. The chilli leaf images can be shot using a camera of poor quality. As a result, the images can be less prominent in diseased regions where they are required to be identified.
iii. The vast majority of the image processing methods available for extracting features from images of chili leaves currently rely on either the chromatic domain or a single domain. The use of these methods provides information that is partial and incomplete, which can result in incorrect disease identification.
iv. It is more difficult to extract the patterns and features necessary for disease identification due to the irregular forms of the leaf edges and the varied blending orientations of the leaf in the images with dense backgrounds.

Even though some challenges in the approaches need to be addressed, there are also a number of promising directions that can be explored to create a more effective automated chili disease identification system. Firstly, in order to boost both the growth and output of chili fruits, it is required to conduct chili disease surveillance in real-time. The noise present in the chilli leaf images when they are collected in real-time can result in a different interpretation from the identification system. As a result, the effectiveness of the system for identifying chili diseases can be enhanced by improving the use of the pre-processing technique. Secondly, artificial intelligence techniques like neural networks can be customized in chili leaf image segmentation to get the optimum leaf ROI instead of calculating each possible cluster combination. Lastly, the accuracy of chili disease can also be effectively enhanced by providing optimization techniques for feature extraction to increase the selection of better chili leaf features for identification.

5. Conclusions

The identification of crop diseases has been revolutionized throughout time due to the computational approaches based on image processing. Through the revolution, the development of automated disease identification systems that need minimum human intervention to evaluate disease types and stages of severity can now be made feasible. This review has discussed an overall view of the up-to-date computational approaches based on image processing for identifying chili diseases. The following diagnosis steps have been examined, including pre-processing, segmentation, extraction of features, and identification techniques. With the assistance of the review, it is hoped that researchers can be motivated to develop a more effective computational approaches for tackling upcoming chili disease challenges to increase the production of chili fruit for economic and agricultural benefits.

Acknowledgement

This research is supported by Universiti Tun Hussein Onn Malaysia (UTHM) through Tier 1 (vot H916). Special appreciation to the IoT FG and MiNT-SRC, UTHM, for providing related facilities.

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