Informatics in Medicine Unlocked 28 (2022) 100837

Contents lists available at ScienceDirect

Informatics in Medicine Unlocked

journal homepage: www.elsevier.com/locate/imu

Automated masks generation for coffee and apple leaf infected with single or multiple diseases-based color analysis approaches

Reem Ibrahim Hasan [a,b,*], Suhaila Mohd Yusuf [a], Mohd Shafry Mohd Rahim [a], Laith Alzubaidi [c,d,**]

[a] School of Computing, Faculty of Engineering, Universiti Teknologi Malaysia, Skudai, Johor, 81310, Malaysia
[b] Al-Nidhal Campus, University of Information Technology & Communications, Baghdad, 00964, Iraq
[c] Faculty of Science & Engineering, Queensland University of Technology, Brisbane, QLD, 4000, Australia
[d] School of Engineering, Architecture and Information Technology, The University of Queensland, Brisbane, QLD, 4000, Australia

ARTICLE INFO

Keywords:
Overlapped plant diseases
Semantic segmentation
Color processes analysis

ABSTRACT

Identification of plant disease is affected by many factors. The scarcity of rare or mild symptoms, the sensitivity of segmentation is influenced by light and shadow of images capturing conditions, and symptoms characteristics are represented by multiple lesions of varied colours on the same leaf at different stages of infection. Traditional approaches face several problems: contrast handling leads to mild symptoms being undetected and deals with edges results in curved surfaces and veins being considered new regions of interest. Thresholding of segmentation restricts it to a specific range of values, which prevents it from dealing with an entire area (healthy, injured, or noise). Deep learning approaches also face problems of dealing with imbalanced datasets. The existence of overlapped symptoms on the same leaf sample is rare. Most deep models detect a single type of lesion at a single time. Masks with a single type of infection are used for training these models that lead to misclassification. Manual annotation of symptoms is considered time-consuming. Therefore, the proposed framework in this study is an attempt to overcome certain drawbacks of traditional segmentation approaches to generate masks for deep disease classification models. The main objective is to label datasets based on a semi-automated segmentation of leaves and disordered regions. There is no need to manage contrast or apply filters that keep lesion characteristics unchanged. As a result, every pixel in the predetermined lesions is selected accurately. The approach is applied to three different datasets with single and multiple infections. The obtained overall precision is 90%. The average intersection over the union of the injured regions is 0.83. The brown and the dark brown lesions are more accurately segmented than the yellow lesions.

1. Introduction

In agricultural production, plant diseases are the primary cause of economic losses worldwide. Diseases have a crucial impact on both the quality and yield of crops. The detection of mild lesions and the taxonomy of rare symptoms are considered current limitations due to the difficulty of providing experts to diagnose diseases in vast fields.

Previous studies have proposed methodologies to detect two main types of fungi on coffee leaves. Lesions show significant variation in shape, size, texture, and region of interest (ROI) color. It is not easy to collect samples that combine all these variations. Adopting new information has been considered sensible for most existing supervised or unsupervised approaches, but they fail to handle data under natural conditions [1,2]. There was a need for pre-processes, such as the resizing of images and conversion of them to greyscale [3], or taking color information from three channels, i.e., red, green, and blue [4], or segmenting lesions according to handcrafted approaches [5]. Due to the irregular shape of lesions, a previous study used a grey-level co-occurrence matrix and a local binary pattern that provided texture characteristics of the infected regions [6] but considered a solution only for certain circumstances.

Under natural conditions, a leaf has a curved surface, rather than being flat. The leaf shape can be changed due to biotic or abiotic factors. For example, with the progress of a disease life cycle, the leaf edge may

* Corresponding author. School of Computing, Faculty of Engineering, Universiti Teknologi Malaysia, Skudai, Johor, 81310, Malaysia.
** Corresponding author. Faculty of Science & Engineering, Queensland University of Technology, Brisbane, QLD, 4000, Australia.
E-mail addresses: ihreem@graduate.utm.my (R.I. Hasan), laith.alzubaidi@hdr.qut.edu.au (L. Alzubaidi).

https://doi.org/10.1016/j.imu.2021.100837
Received 4 December 2021; Received in revised form 25 December 2021; Accepted 25 December 2021
Available online 29 December 2021

Table 1
The samples of individual leaves with multiple infections.

Diseases	No. of samples
Miners and *Phoma*	1
Rust and *Phoma*	2
Brown spot and *Cercospora*	7
Miners and *Cercospora*	15
Miners and rust	112
Rust and *Cercospora*	166
Total	303

be directed upwards [7] or the leaf may become folded. They cause a contrast between regions. Therefore, noise or lack of consistency in image samples affects the detection of mild symptoms. Sometimes, noise may be misclassified and regarded as an infection. In some cases, histogram equalization leads to contrast stretching. It increases brightness [8] and makes mild symptoms challenging to be detected.

The application of filters can facilitate handling of a particular type of lesion. The top-hat filter can enhance yellow spots; it makes them appear yellowish, thus rendering them detectable. Brown spots become darker or black, indicating another disease (for example, miner spots are dark brown while Phoma spots are even darker). This process changes the characteristics of spots by changing the intensities of the concerned area and enabling the detection of a single infection at a time [9–11]. Blurry filters like block-matching and 3D (BM3D) filters [12] may soften the noise effects, but they dissolve the edges of lesions, making them undetectable.

On the other hand, manual labelling (background, healthy regions, and infected regions), or manual generation of symptom datasets, is considered time-consuming [13,14]. Any error at this level may affect the training process [15] unless experts perform the annotations.

Segmentation is employed to separate leaves from the surrounding environment [16–20]. Segmentation is also employed to separate regions of infection from healthy areas on leaves. In both cases, the number of clusters is unfixable. Therefore, there is a need to dynamically determine the number of clusters. In automatic segmentation, such as K-means clustering, finding the best centroids for each cluster to determine suitable centroid locations consumes time [21].

Other segmentation techniques, like Otsu's thresholding, do not detect mild symptoms. A system has been proposed to separately detect rust and leaf miners on coffee leaves [22]. It applied Otsu's thresholding for segmentation preceded by color analysis depending on the YCbCr colour space. However, the author cited anomalies concerning some misclassified cases of illuminated regions and identified them as infection. Edge detection [23] and contouring operations [24] consider the veins and curved surfaces of the leaf as new regions of interest. The modified color processing (MCP) approach, which depends on three transformation channels (red, green, and blue), has been demonstrated as effective in detecting all color gradients via the three channels [25].

Lighting condition is the factor that prevents detecting the ROI [26] when leaves are exposed to shady and light conditions unless additional procedures are performed to enhance the regions of infection or segment them. These processes handle lighting effects by, for example, random noise extraction [27] and contrast handling approaches with morphological operations [28]. The complicated background factor affects semantic segmentation. A dense scale-invariant feature transform (DSIFT) algorithm was suggested to extract unrelated features [29]. It generated a sliding window that combined the ROI. However, it was challenging to distinguish between similar pathological characteristics of some symptoms at different stages of infection. Some lesions were nearly identical to the soil color [30] in the background. One of the common problems was the annotated images if they had a single lesion [31]. Therefore, overlapped lesions led to misclassification. Other studies have proposed modified architectures that accommodate classes in a target dataset, which is considered challenging [32].

Imbalanced dataset is another critical factor. Many models have been applied for semantic segmentation of leaves with complicated surroundings [33]. The dominant regions in each sample of the target dataset were the healthy regions and the background. The lack of injured regions prevented the models from identifying them more accurately than the other regions. This paper is aimed to investigate the orientations of methods for overlapping plant disease detection. The study undertakes the following:

- Investigates the ROI enhancement and detection techniques.

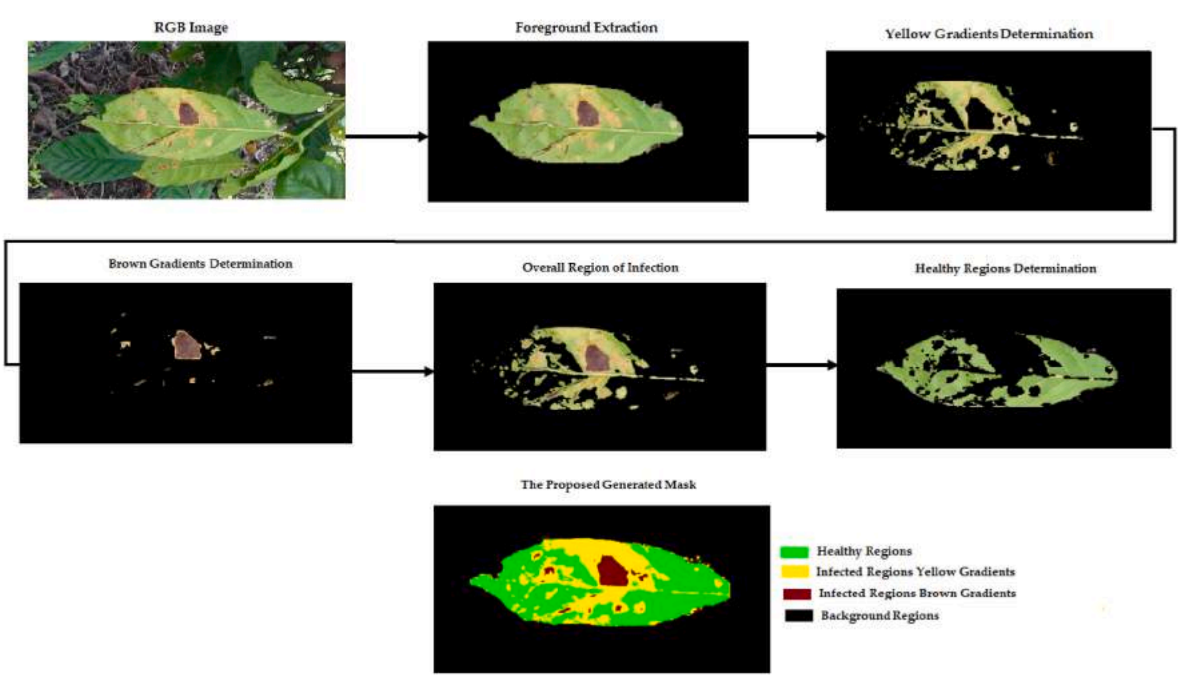

Fig. 1. The proposed framework for lesion extraction.

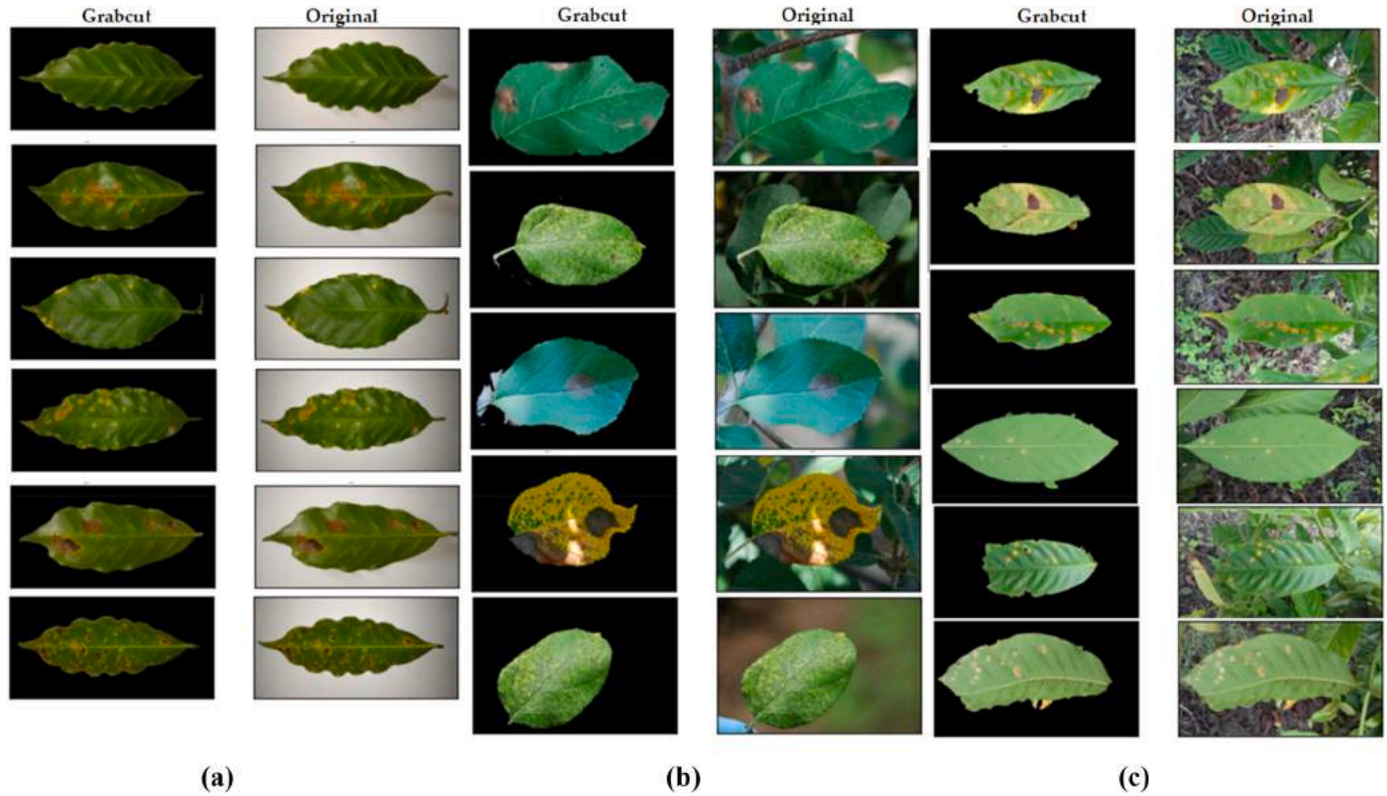

Fig. 2. Different samples of leaf segmentation where (a) represents images taken in lab conditions of the coffee dataset, (b) apple dataset and (c) RoCoLe dataset images taken with complicated background.

Table 2
Results of the proposed method applied to the existing disease overlap cases in coffee dataset.

Overlapping symptoms	IOU Infected Region	IOU Healthy Region
Miners and *Phoma*	0.9	0.9
Rust and *Phoma*	0.9	0.9
Cercospora and *Phoma*	0.9	0.9
Miners and *Cercospora*	0.9	0.9
Rust and miners	0.9	0.9
Rust and *Cercospora*	0.9	0.9

- Proposes a framework for mask generation of a target dataset based on semantic segmentation of single and multiple symptoms.
- Generates clusters dynamically based on the existing lesions on a single leaf. The results are compared to the traditional approaches.

2. Materials and proposed framework

2.1. Dataset of samples

Three datasets are used for this study. The coffee dataset [34] includes 1685 samples of arabica coffee leaves with principal stresses (rust, leaf miner damage, *Phoma*, and *Cercospora*). Images are taken in the lab with a whiteboard background. Some samples contain overlapping symptoms. Table 1 shows the co-occurrence of these disorders. They appear at different stages of their life cycles.

The RoCoLe dataset [35] contains 1560 image samples of Robusta coffee leaves. It combines healthy and infected samples (red spider mite and rust) at different levels. Each sample contains a single symptom. Samples were taken in a field with different weather conditions and complicated backgrounds.

The apple dataset [36] contains 3735 healthy and diseased leaf samples. Two types of diseases are presented: Marssonina blotch and Alternaria leaf. A single leaf contains a symptom. Images are taken in different natural conditions from different angles, with solid and complicated backgrounds.

2.2. Proposed framework

Semantic segmentation techniques determine the ROI by detecting their directions and analyzing textural similarities. Therefore, the magnitude of the color gradient of these regions has a crucial role in all these techniques. A cut graph approach is used to isolate the foreground. A modified color analysis process is implemented to extract single and overlapped symptoms. The proposed framework is illustrated in Fig. 1. Each process is detailed in the subsequent subsections.

2.2.1. Leaf segmentation

One of the pixel labelling solutions of graph-cut is the GrabCut [37]. This is a method used for segmenting target objects from a complex environment. It depends mainly on a Gaussian mixture model (GMM). It is applied once on the foreground region and once on the background region. A Gaussian distribution is utilized for each cluster. According to the author, five clusters for each region are taken into considerations. It is a suitable number of clusters for complex environments. The GrabCut is also based on the min-cut, which provides segmentation for a leaf. Extracting the leaf from its surrounding background needs two nodes to be determined manually. The nodes represent starting and ending points of the leaf graph in the image. Fig. 2 below, shows the applied method to the three datasets.

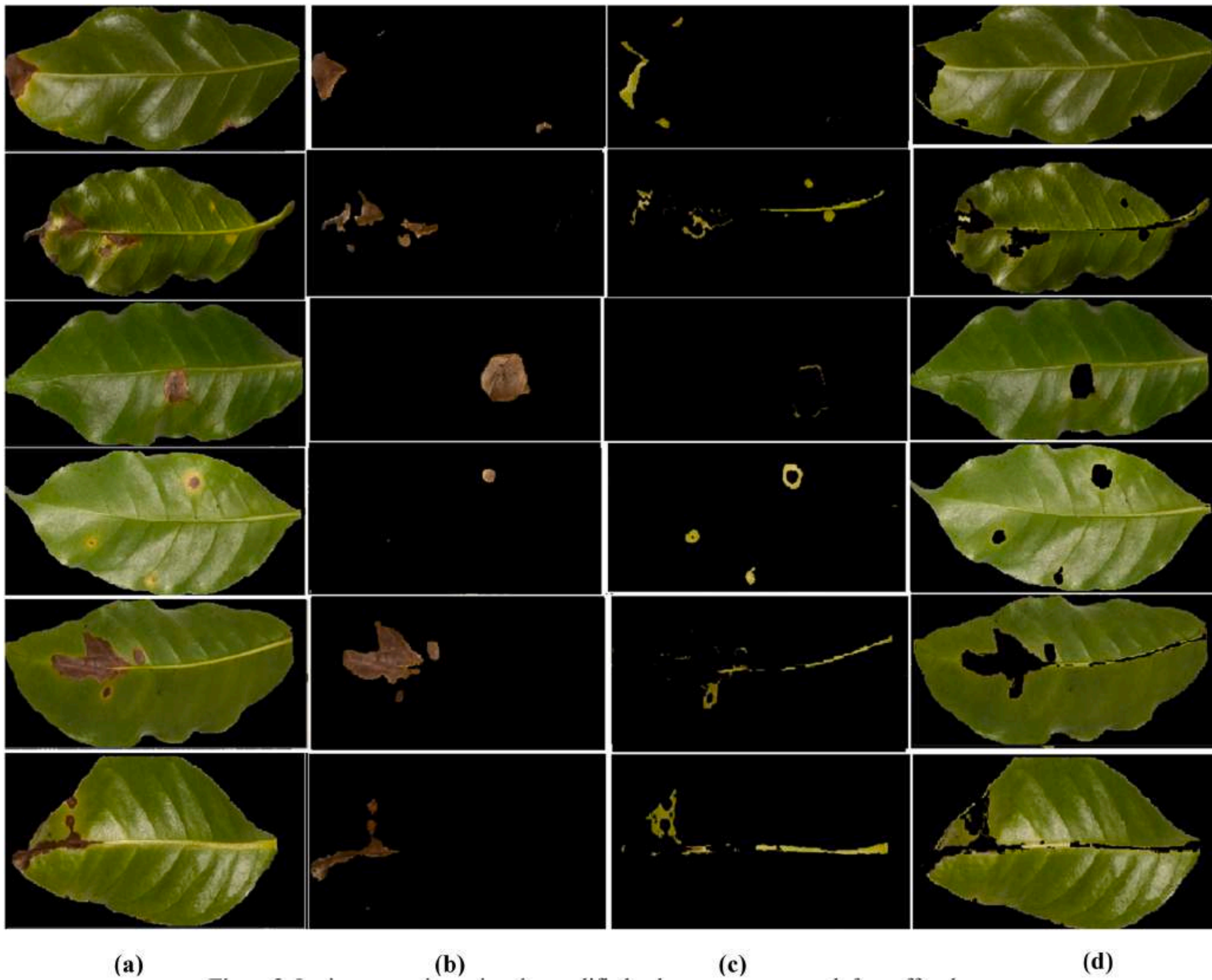

Fig. 3. Lesion extraction using the modified color process approach for coffee dataset: (a) represents the extracted leaf, (b) represents the brown lesions, (c) yellow lesions, and (d) healthy regions. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

2.2.2. *ROI determination and extraction*

Generally, lesions are contoured by determining pixel intensities in the horizontal and vertical directions. In some cases, the veins and the curved surfaces are contoured (curved surfaces refer to the damage of symptoms or molecular causes). Consequently, a modified color processing detection (MCPD) approach is adopted to select every pixel in the scattered lesions. The image is converted to three channels (red, green, and blue). The red and green pixel values (RPV and GPV) are subtracted from the greyscale image value (GIV) as follows:

$$\text{Modified red pixels (MRP)} = \text{RPV} - \text{GIV} \tag{1}$$

$$\text{Modified green pixels (MGP)} = \text{GPV} - \text{GIV} \tag{2}$$

The MRP is accurately returned yellow pixel intensity, while the MGP is returned brown pixel intensity. However, some light spots could not be detected via the MRP or the MGP. Therefore, the MRP is altered as follows:

$$\text{Red pixel (RP)} = \text{MRP} - \frac{GPV}{2} + \frac{BPV}{2} \tag{3}$$

$$AMRP = \begin{cases} 0, \; else \\ p(i,j), \; RP(i,j) \geq \; thresholding \end{cases} \tag{4}$$

P(i,j) represents the current pixel. The threshold value is greater than the mean of the most repeated values in the red pixel array.

3. Results and discussion

We compared the chosen segmentation method with other traditional image processing methods that are made in similar conditions (solid or natural background with individual leaf samples). The experiment is conducted using Intel(R) Core(TM) i7-4710HQ CPU, 8G memory and Windows 10 Pro operating system. The Anaconda platform is used with python programming language.

3.1. *Quantative results*

The appearance of specific symptoms together led to choosing an approach that enables us to obtain the gradients of the ROI separately. This approach is applied to three different datasets. The number of segments is generated dynamically according to the existing lesions in a leaf. Two measures are used to evaluate the segmentation process. The intersection over union (IOU) is applied to determine whether every pixel in the detected ROI is correctly selected and matches the true ROI on the original leaf. A precision (PRC) measure is used to evaluate the

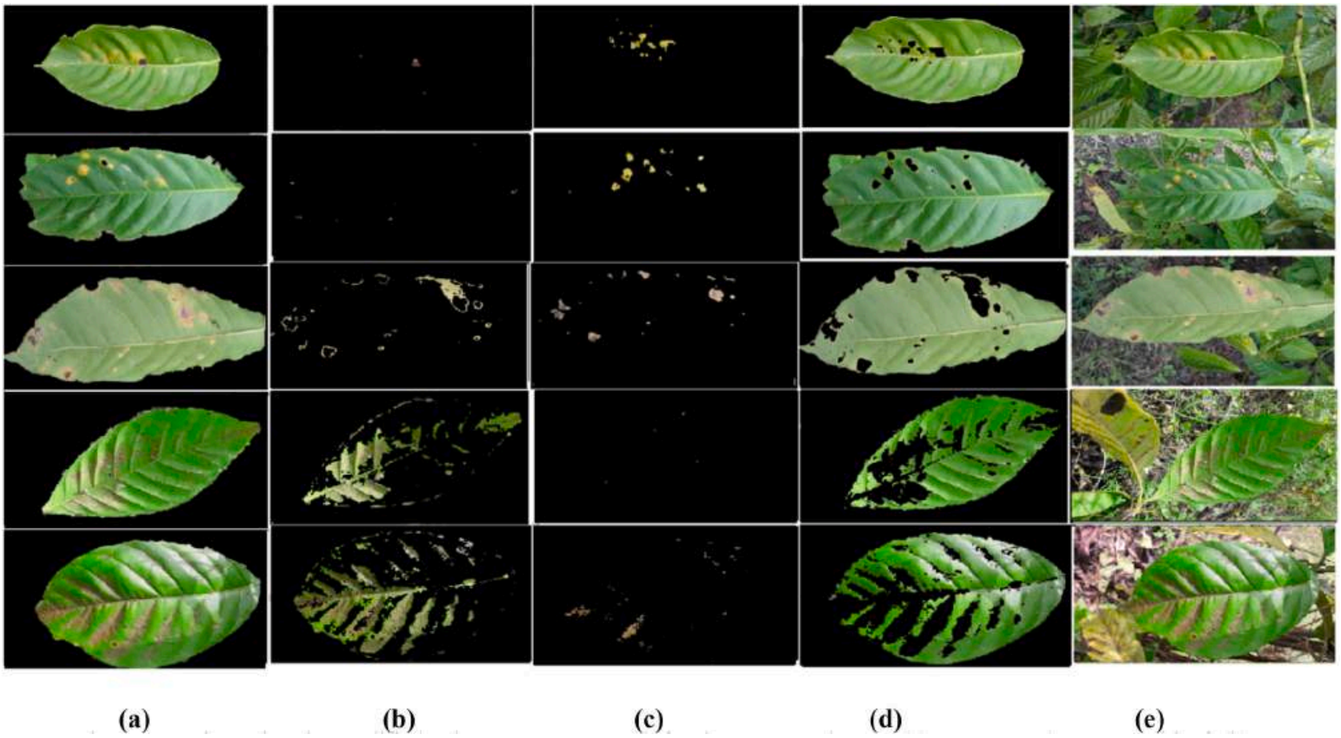

Fig. 4. Lesions extraction using the modified color process approach for the RoCoLe dataset. (a) represents the extracted leaf, (b) represents the yellow lesions, (c) brown lesions, (d) healthy regions, and (e) is the original image. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Results of the proposed method applied to the existing disease overlap cases in the coffee data set.

Symptoms	IOU symptom	IOU healthy region
Rust	0.9	0.9
Rust	0.9	0.68
Rust	0.8	0.9
Red mite	0.9	0.8
Red mite	0.9	0.9

segmented regions compared to the ground truth.

$$\mathrm{IOU} = \frac{\mathrm{Area\ \ of\ \ Intersection}}{\mathit{Area\ of\ Union}} \tag{5}$$

$$\mathrm{PRC} = \frac{\mathrm{Match\ \ (Segmented\ \ Regions\ \ , Ground\ \ Truth)}}{\mathrm{Segmented\ \ Regions}} \tag{6}$$

For the coffee dataset, the samples are taken with lab conditions. In the leaf segmentation stage, the obtained accuracy is 95%. All images are fixed with one position, which facilitates the detection of the leaf using a GrabCut approach (the terminal nodes that separate foreground from the background are set for all the samples). The evaluation measures are applied for the infected area in the lesion extraction stage, as shown in Table 2. The best IOU (0.9) is obtained for lesions and leaves. It is used for all existing lesions on an individual leaf. The overall precision obtained was 95%. Fig. 3 clarifies how yellow and brown lesions are extracted.

For the RoCoLe dataset, the samples are taken with natural conditions; all of the images are captured in the same direction, which facilitates the segmentation of the leaves using the GrabCut approach. The terminal nodes have almost the same position as the coffee dataset. Some background conflicts are shown in Fig. 2 (c) and 4 (a). The continuities of joint nodes in the background are overlapped with leaf nodes. These cases are adjusted manually. The obtained leaf segmentation precision is 75%. The lesion extraction depends mainly on the cut graph and whether it has a complete representation for the leaf. Only in this case, the proposed method can segment all lesions successfully. The best IOU (0.9) is obtained for brown lesions, while the healthy regions have some conflicts with the close overlapped leaves. Fig. 4 clarifies how yellow and brown lesions are extracted. Table 3 explains the results of these samples.

For the apple dataset, the samples are taken with natural conditions. The images are captured from different views, as in Fig. 6. The variety of shapes and colours of healthy regions made leaf segmentation complicated. Leaves are assembled according to their similar shape and sights. The terminal nodes are manually chosen for each type. The obtained leaf segmentation precision is 75%. The best results are shown in Fig. 5, while the effects of lesion segmentation are clarified in Table 4.

3.2. *Comparisions and limitations*

Several traditional segmentation approaches are compared to the chosen method. These approaches were performed for an individual leaf and one type of symptom (Table 5). Several evaluation measures are used to verify whether every true-positive pixel in the segmented ROI has been selected accurately.

The histogram equalization and K-means method [9] cannot detect some spots at early stages. Spots are selected as ROI. The applied equalization technique increased the false-positive pixels due to the effect of the direct light. In contrast, the method detected other symptoms more accurately.

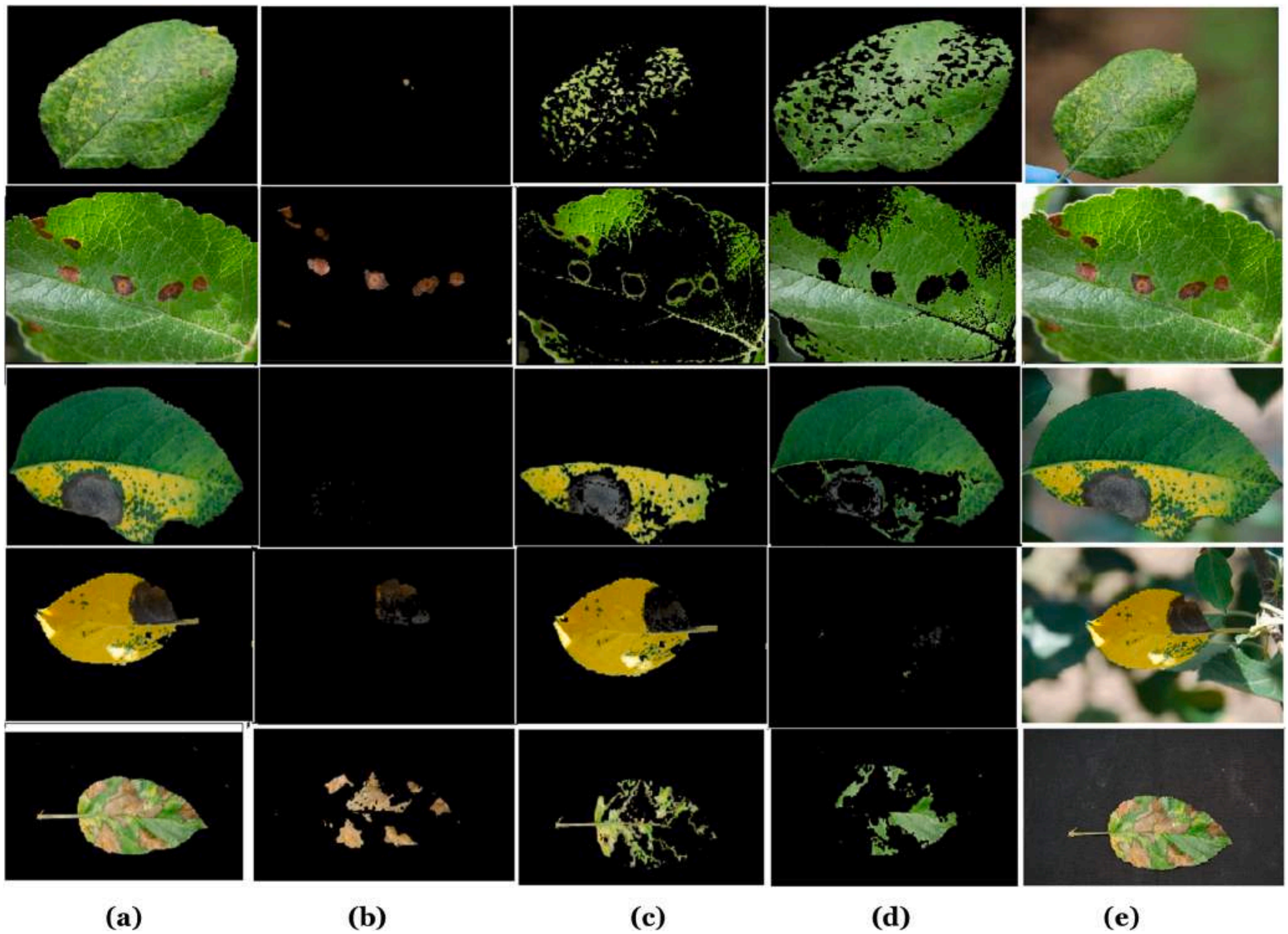

Fig. 5. Lesion extraction using the modified color process approach for apple dataset. (a) represents the extracted leaf, (b) represents the brown lesions, (c) brown lesions, (d) healthy regions, and (e) is the original image. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Fig. 6. Samples of apple dataset.

Table 4
Results of the proposed method applied to the existing disease overlap cases in the coffee dataset.

Symptoms	IOU Symptom	IOU healthy region
Marssonia Blotch	**0.9**	0.9
Alternaria Leaf Spot	0.9	0.8
Marssonia Blotch	0.8	0.9
Marssonia Blotch	0.9	0.8
Alternaria Leaf Spot	0.9	0.9

Table 5
Traditional state-of-the-art segmentation methods applied to overlapping symptoms.

Method	IOU	PRC	Entropy	Acc.
Histogram equalization and K-means [9]	0.9	90%	0.3	90%
Adaptive K-means clustering [21]	0.9	90%	0.1	90%
Graph cut and LBP [36]	0.8	85%	0.2	90%
Threshold segmentation with CCV and LBP [37]	0.8	85%	0.2	99%
Proposed method	**0.9**	**90%**	**0.1**	**90%**

Adaptive K-means clustering is an effective method [21] based on compactness and distance separation between classes. However, the number of clusters is inflexible using the k-means approach. The graph-cut and local binary pattern (LBP) method [38] is applied. It suggests segmenting the leaf as foreground using a graph-cut, then extracting features based on the LBP. According to the author, the approach is sensitive to noise, but it does not consider the effect of light. The light is embedded in the ROI.

Leaf segmentation is based on a threshold value to retain only the ROI. This method is based on hue, saturation and value (HSV) color model transformation [39]; specific processes are applied to extract features (color coherence vector [CCV] and LBP). The threshold process is sensitive; under natural conditions, it is difficult to restrict healthy green regions within specific ranges, even with other color representations like longitude, latitude, and altitude (LAB) or HSV. In some cases of healthy leaves, the random noise of lighting effects prevents the recognition of them as healthy.

3.3. Discussion

This method is proposed to generate masks for training disease classification models. The regions of diseases are represented in two colours (yellow and brown). The proposed framework overcomes the following segmentation problems:

- The Gaussian mixture model provides various probability distributions for clusters [40]. Whatever the shape of the leaf is, it enables GrabCut segmentation to detect leaves despite the color gradations that belong to the leaf surface.
- No need to apply any method to highlight lesions. The proposed framework focuses on determining the possible gradients of healthy regions in the target dataset and subtracting them from the leaf.
- Can use it for symptoms dataset generation and masks generation. It can replace the manual annotation used for training a deep classifier.

While the drawbacks concerning leaf and lesion segmentation are:

- In the lesion segmentation stage, the healthy gradients regions may vary according to the selected leaf species. These gradients have to be chosen manually for each dataset. This drawback does not affect the disease detection process. It involves the disease severity estimation. Fig. 7(a) shows a manually made mask sample [34], and (b) shows the segments generated by our proposed method. Some pixels are segmented as a lesion, but no red pixels refer to them in the corresponding mask because the value used for thresholding is greater than the suitable one for this sample.
- In the leaf segmentation stage, terminal nodes are fixed according to the size of the leaf and its position. So, the variety in datasets requires manual intervention.

4. Conclusion

This study proposes a segmentation framework based on a graph-cut method and color analysis processes. The framework is applied to three different datasets where samples include individual and multiple infections. The overall obtained precision is 90%. The best obtained IOU is for spots with brown gradients. Yellow spots can be determined correctly according to the predetermined healthy regions because their slopes are close to the green, especially at the early stages of infection.

In future studies, we propose clustering the overlapped diseases in samples, so that deep classifiers can handle multiple diseases identification separately.

Author contributions

Conceptualization, R.I.H., M.S.M.R., and S.M.Y.; methodology, R.I.H., L.A., M.S.M.R., and S.M.Y.; writing—original draft preparation, R.I.H., and S.M.Y.; writing—review and editing, R.I.H., S.M.Y., and L.A; visualization, R.I.H., S.M.Y., M.S.M.R., and L.A; supervision, S.M.Y.; project administration, S.M.Y., and L.A. All authors have read and agreed to the published version of the manuscript.

Fig. 7. Red spots in (a) represent the true set of ROI while (b) shows the proposed ROI. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Funding

This research received no external funding. Institutional Review Board Statement: Not applicable.

Informed consent statement

Not applicable.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was supported by Esgario, J. G; who provided rare dataset annotated by experts in the field that greatly assisted the research. And made it available online for the academic studies.

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