SPEKTRA: Jurnal Fisika dan Aplikasinya
Volume 10, Issue 1, April 2025
Homepage: doi.org/10.21009/SPEKTRA

DOI: doi.org/10.21009/SPEKTRA.101.02

Stem-base Rot Disease Detection in Oil Palm using RGB (Red, Green, Blue) and OCN (Orange, Cyan, NIR) Image Fusion Method Based on ResNet50

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Received: 15 November 2024
Revised: 9 December 2024
Accepted: 30 December 2024
Online: 12 February 2025
Published: 30 April 2025

SPEKTRA: Jurnal Fisika dan Aplikasinya
p-ISSN: 2541-3384
e-ISSN: 2541-3392

ABSTRACT

Current image acquisition and processing methods still need to be improved to effectively detect oil palm diseases. A precise and fast method to detect stem base rot disease in oil palm trees can be developed using drone technology and image processing approaches. An OCN (Orange, Cyan, NIR) camera is added to a standard drone and equipped with an RGB (Red, Green, Blue) camera. Combining the two cameras is proposed to generate multispectral imagery using an image fusion method called early fusion. A Multispectral Convolution Neural Network (MCNN) is also introduced to detect stem base rot disease by analysing the leaf patterns of oil palms. Healthy and unhealthy leaf samples were collected from oil palm plantations in Bogor. The images that have passed the image processing stage with the fusion method become inputs for modelling to identify stem base rot disease in oil palm. The results of the research using the multispectral image fusion method (RGB and OCN) based on the ResNet50 architecture can be used to identify stem base rot disease in oil palm effectively, as evidenced by the training and validation accuracy of 97.75% and 96.48%.

Keywords: basal stem rot, image fusion, CNN

INTRODUCTION

Basal stem rot, a disease of oil palm caused by the pathogen Ganoderma sp, is a major disease of oil palm, especially in Indonesia. Control measures carried out manually are still not effective, as they still focus on extending the life of oil palm plants [1], [2], [3]. The role of using DJI Air 2S Drone technology can provide a better and more effective observation method, especially for monitoring oil palm conditions [4], [5], [6]. This drone is equipped with two cameras (RGB and OCN). RGB (Red, Green, Blue) and OCN (Orange, Cyan, NIR) have advantages and disadvantages that complement each other's information. The RGB camera has a better resolution than the OCN camera and also produces colour images while the OCN camera can monitor and detect the condition of oil palm trees affected by disease, especially basal stem rot. Previous research has identified oil palm diseases by utilising certain wavelengths that can detect oil palm diseases, a method previously used by many researchers [7], [8], [9], [10], [11]. The utilisation of RGB and OCN images can be used to detect or identify stem base rot disease, thus requiring appropriate image acquisition and processing methods to combine information from RGB and OCN images.

One of the appropriate image data processing techniques is image fusion, which is a technique of combining two or more different image data sets (in terms of resolution, recording system, and wavelength) to produce a new image that has more accurate information. Image fusion techniques have been widely used by previous researchers [12], [13], [14], [15], [16]. The use of image fusion methods to detect oil palm diseases is still not optimally utilised, especially for basal stem rot disease. The fusion of two cameras is proposed to generate multispectral images with an early fusion technique. A Multispectral Convolution Neural Network (MCNN) was also introduced to detect basal stem rot disease by analysing the leaf patterns of oil palms. Healthy and unhealthy leaf samples were collected from oil palm plantations in Bogor. The proposed method is expected to have better performance than previous studies in identifying oil palm diseases. This research will use the multispectral image fusion method (RGB and OCN) based on ResNet50 architecture to identify oil palm diseases, as well supported by previous research [17], [18], [19], [20]. The purpose of this research is to identify oil palm diseases using a multispectral image fusion method based on a Convolution Neural Network (CNN) using ResNet50 architecture [21], [22], [23], [24], [25]. The data used are RGB and multispectral image data (OCN) of oil palm trees.

METHOD

The data used in this study are images of oil palm leaves taken using a drone equipped with RGB and OCN cameras, as shown in FIGURE 1, at a height of 30 m, with a total of 950 photos, located at PT Perkebunan Nusantara VIII, Cikasungka Oil Palm Plantation, Bogor.

(a)

(b)

FIGURE 1. (a) The RGB and (b) OCN images

The vehicle used is a DJI Air 2S Drone with a maximum flight time of 31 minutes equipped with RGB and OCN cameras with a 20 megapixel image resolution (5472 x 3648 px) and (4000 x 3000 px). The RGB and OCN camera has six bands: red (red/R) with a wavelength of 660 nm, green (green/G) with a wavelength of 550 nm, blue (blue/B) with a wavelength of 475 nm, orange (orange/O) with a wavelength of 615 nm, cyan with a wavelength of 490 nm, and near infrared (NIR) with a wavelength of 850 nm (Survey3W Camera – Orange + Cyan + NIR (OCN, NDVI) - MAPIR CAMERA). Before starting the flight mission, the OCN camera is first calibrated using the T3-R125 Target Reflectance Calibration because it does not yet have a light sensor, ensuring it is always calibrated according to the conditions under which the image is taken. The system design and acquisition of RGB and OCN images are shown in FIGURE 2.

The next process adjusts the position of the RGB and OCN cameras to face downward so that the camera can take an image of the top of the oil palm tree. Next, the time for taking or recording with the RGB and OCN cameras is set, and automatic settings for recording images are configured according to a predetermined time is the morning around 10.00 WIB. When recording images, each camera sends data to the server in real time, containing RGB images, OCN images, and image capture locations. The recorded image captured by the RGB camera has a resolution of 5472 x 3648 pixels, and that of the OCN camera is 4000 x 300 pixels, with wavelengths (Red: 660 nm Green: 550 nm Blue: 475 nm NIR: 850 nm Orange: 615 nm Cyan: 490 nm). RGB and OCN images are then processed by image registration first, to adjust the position and scale of both images. The image that has been registered will be segmented to produce a region of interest (ROI) using MATLAB software. The results of image segmentation, which already have an ROI according to the desired area, namely healthy and unhealthy oil palms, will be combined using the image fusion method, specifically early fusion, which produces a new image that has six channels: Red, Green, Blue, Orange, Cyan, and NIR, with size of (4000 x 3000 x 6). This image will then be used as input for the classification model that has been built and trained using the Python programming language. In the final stage, two outputs will be generated, indicating healthy and unhealthy oil palms.

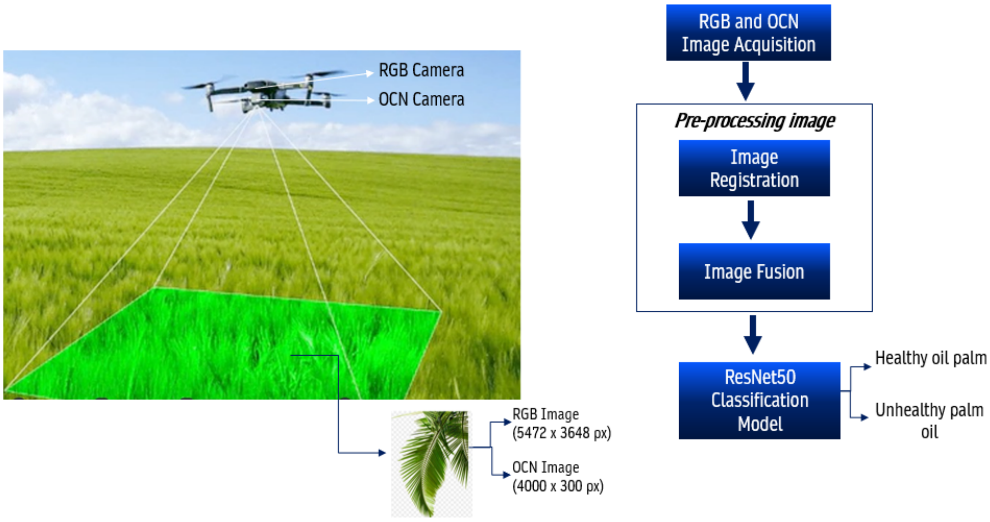


FIGURE 2. System design and acquisition of the RGB and OCN images

Image registration is an image processing technique used to align or equalize the position and orientation of different images. The image registration process is shown in FIGURE 3. The RGB image is used as the referenced image, and the OCN image is used as the target image. The selection of the OCN image as a reference is because it has a smaller resolution size than RGB image. In this process, the RGB image will be registered and adjusted to the OCN image. The original RGB image has a resolution of 5472 x 3648 pixels and the OCN image has a resolution of 4000 x 300 pixels. The initial stage of the image registration process involves converting the colour of the RGB and OCN images into ash scale to make it easier to find suitable features. The second stage of feature detection uses the SURF (Speeded Up Robust Feature) algorithm to find important points in the image that can be used for feature matching. The third stage extracts feature descriptors from the detected points to focus the image and locate features that match the two images. The fourth stage performs feature descriptor matching of the two images by finding matching points between the two images and storing them, then the fifth stage performs geometric transformation estimation to transform and adjust the RGB image with OCN and remove outliers.

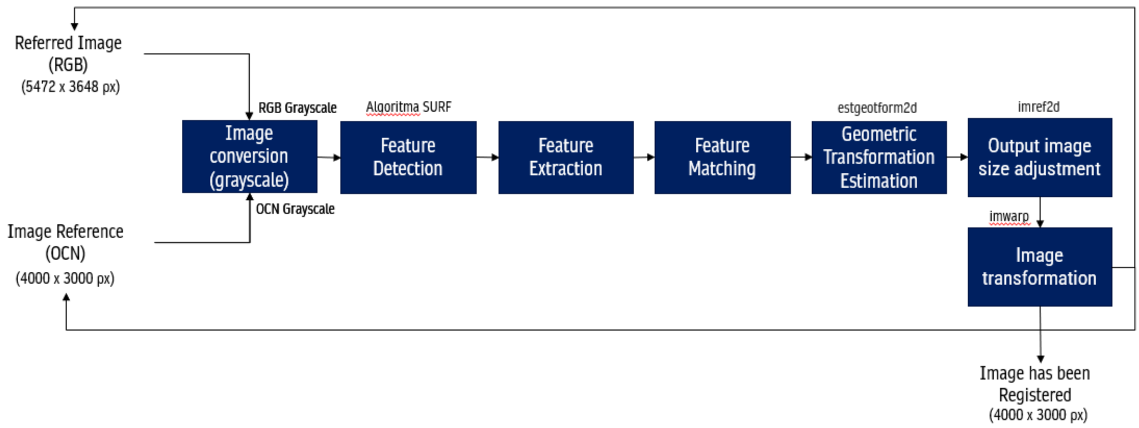


FIGURE 3. Image registration plan

(a) (b)

FIGURE 4. (a) The registered RGB image and (b) the referenced OCN image

The sixth stage applies the results of the geometric transformation to the RGB image so that it matches the OCN image and adjusts the scale of the two images to ensure they have the same size, resulting in an RGB image that has been registered and matches the OCN image with a size of 4000 x 3000 pixels. The resulting registered image is shown in FIGURE 4.

Furthermore, the segmentation process on the RGB image of the oil palm that has been registered aims to produce the desired oil palm image regions, namely healthy and unhealthy areas. In the research, the oil palm image segmentation process focuses on the leaves, with ROI (region of interest) selection still performed manually. The ROI size used is 200 x 200 pixels, determined using MATLAB software. The selection of ROI size is adjusted to the RGB image data that has been registered and provides the information needed as input for modelling. The RGB image of the oil palm that has been registered aims to produce the desired regions of interest so that it can be used in the image fusion stage using the appropriate method. RGB and OCN image data that have been segmented then proceed to the image fusion method stage to combine RGB and OCN images that already have the same dimensions. Before combining images, normalisation is typically performed; however, at this stage, normalisation is not needed because the bit values of RGB and OCN images are the same. The image fusion process, shown in FIGURE 5, will produce an image that contains information on oil palm disease. The fused image has 6 channels, namely Red, Green, Blue, Orange, Cyan, and NIR with a size of (4000 x 3000 x 6).

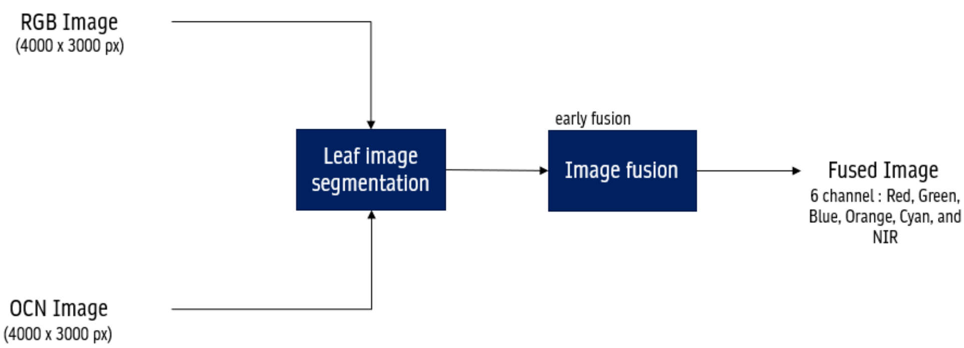


FIGURE 5. Image fusion design

TABLE 1. Dataset construction result

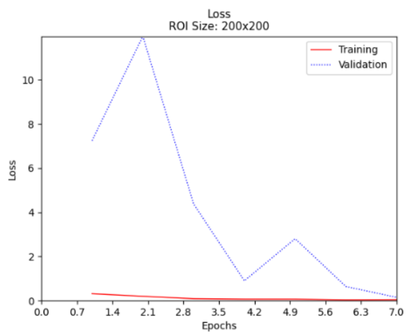
Variable	Amount	Percentage
Training	666	60%
Testing	142	20%
Validation	142	20%

RESULTS AND DISCUSSION

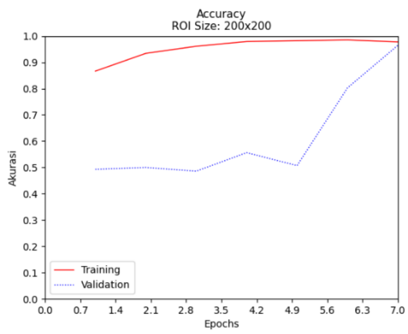
The RGB and OCN images that have been registered then enter the stage of labelling healthy and sick (infected with basal stem rot disease) on each oil palm leaf image with an ROI size of 200 x 200, with a total of 475 healthy and sick images each. The labelled RGB and OCN images will be combined using the image fusion method to enhance information needed to identify disease in oil palm leaves. Images that have been combined using the early fusion method produce leaf image data that has 6 channels, namely Red, Green, Blue, Orange, Cyan, and NIR. The fused oil palm leaf image becomes the input for modelling the architecture of the healthy and unhealthy classification system of oil palm plants based on their leaves. A CNN-based classification architecture is designed using ResNet50. The output of the classification is healthy and unhealthy oil palm plants.

The dataset in this study is divided into three, namely training data, test data, and validation data, with their distribution is shown in TABLE 1. Simulation results that shows the relationship between training loss and validation loss, along with ResNet50 model accuracy, are shown in FIGURE 6.

The performance results of the ResNet50 classification architecture, with an accuracy value of 97.75% for training and 96.48% for validation on the fusion image using ROI of 200 x 200, are shown in FIGURE 7(a). Based on the confusion matrix of the fusion image shown in FIGURE 7(b), it is presented that 71 True Positives (TP) are correctly predicted as unhealthy palm leaves, 70 True Negatives (TN) are correctly predicted as healthy palm leaves, 1 False Positives (FP) are predicted as unhealthy palm leaves that should be predicted as healthy, 0 False Negatives (FN) are predicted as healthy palm leaves that should be predicted as unhealthy.

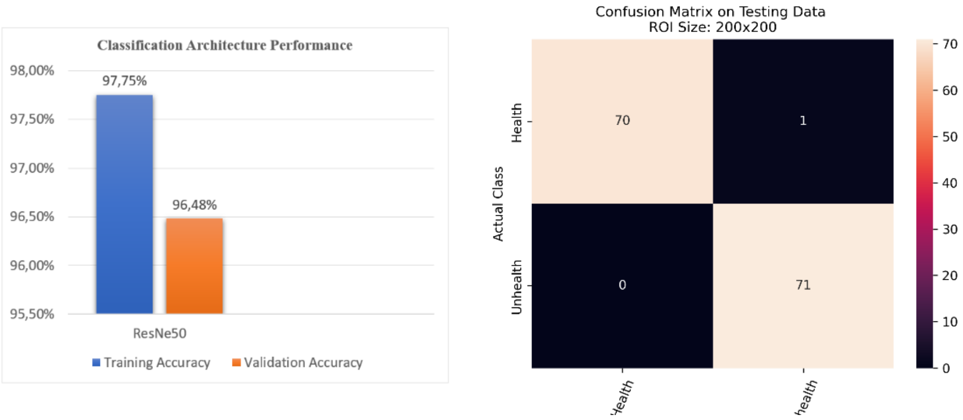


(a)



(b)

FIGURE 6. (a) loss graph and (b) accuracy graph



(a) (b)

FIGURE 7. (a) accuracy and (b) confusion matrix graph

CONCLUSION

The ResNet50 architecture-based image fusion method with an ROI selection of 200 x 200 can be used to detect oil palm disease with training and validation accuracy of 97.75% and 96.48%, respectively, demonstrating its ability to distinguish healthy and unhealthy oil palms, as evidenced by the training and validation accuracy values. The process of tuning parameters such as the number of epochs and learning rate, affects the accuracy of the data. This research still has limitations in providing information on various types of oil palm diseases, indicating that it can still be developed further using additional variations of oil palm disease information.

ACKNOWLEDGMENTS

Thank you to Adhi Harmoko Saputro and Windri Handayani for helping with this research, and PT Perkebunan Nusantara VIII, Cikasungka Oil Palm Plantation, Bogor, for providing data for our research.

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