

# Detection of palm oil bud rot employing artificial vision

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**Abstract.** This paper describes the development of a system capable of capturing, processing, and analysing images of palm oil plantations in order to detect and identify bud rot disease. The process begins with the capturing of images using the DJI Phantom 4 UAV, which is first configured for a flight plan of the desired area and altitude. The resulting images are processed by photogrammetry software to create orthomosaics. The developed algorithm uses the grayscale of the generated orthomosaic and identifies the palms affected by bud rot. This is accomplished using the sliding-window method, by which smaller samples of the image are used and evaluated independently. Each sample is then extracted with a ULBP feature vector that numerically represents the texture of the image and is classified by means of a previously trained logistic regression model, allowing the recognition of positive cases of the disease. Possible positive cases are further distinguished using the non-maximum suppression algorithm. The system was tested with different images than the images used for training and for establishing the set point. As a result, the system showed a 92% precision and a 96% of sensitivity for bud rot disease detection. These results are satisfactory in terms of detecting bud rot disease using a low-cost system.

## 1. Introduction

Colombia is the largest producer of palm oil in Latin America and the fourth largest in the world. As such, palm oil is one of Colombia's principal and most valuable agricultural products. The principal threats to Colombia's palm oil industry are exposure to pests and disease. The most common disease is bud rot [1][2]. Bud rot can decrease the production of a given field from 8% to 29% [3], which results in millions of dollars lost annually. At this time, the oil palm industry in Colombia has a great opportunity to contribute to the development of the country. Therefore, it is important that significant investments be made in technologies that ensure plant health and increase yield, i.e., that improve overall crop quality and enhance sustainability of the industry [4]. Traditionally, disease detection, especially of bud rot, has been the responsibility of trained personnel who manually inspect all areas of a plantation for the diseased crop and then write this information on paper charts. To inspect an entire crop using this method can require months. This method is not only inefficient and unnecessarily time consuming, but it is also labor intensive, uneconomical, and prone to error. The process is so time-consuming that it is likely that the crop will change during the inspection process, rendering the results even less useful. Currently, some oil palm farmers use photos taken by small airplanes to show the health of the palm with respect to bud rot, observing the diameter of the crown [5], but this inspection method is prohibitively expensive due to the cost of flight time. For this reason, unmanned aerial vehicles (UAVs)



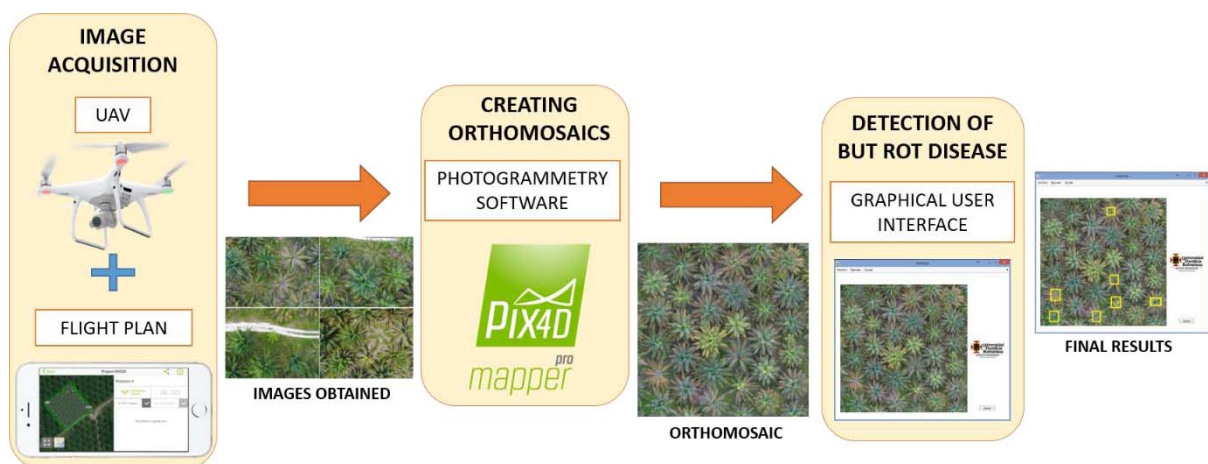
have gained prominence in the monitoring of oil palm plantations. This new technology offers a wide variety of equipment designed to fly and capture aerial images over large areas at a reasonably low cost, with resolutions varying depending on the properties of the onboard cameras, altitude and flight autonomy [6].

Combining techniques of computer vision and machine learning with the images taken by UAVs have been implemented successfully to create a lower-cost, less labor-intensive way to identify pests in *Begonia Semperflorens* crops [7], as well as to count the palms in oil palm plantations [8]. This technique could be applied further in the detection and classification of diseases in the leaves of a variety of native plants found in Tamil Nadu [9].

The purpose of this paper is to fully outline the development of a system capable of detecting and identifying bud rot disease in a timely, efficient manner that will overall benefit production. Images are first captured by UAVs and then processed with photogrammetry software into a more usable format. These orthomosaics can be analysed by a logistic regression model that can detect specific areas of bud rot disease among the palms.

## 2. Palm oil bud rot disease detection system

This system is based essentially on three stages. These stages are outlined as a block diagram in figure 1. The first stage is the acquisition of images using the DJI Phantom 4 UAV, followed by the creation of orthomosaics that will later be processed with an algorithm for detection of bud rot disease.



**Figure 1.** Block diagram of the general structure of the system

### 2.1. Image acquisition

Image acquisition is the first and one of the most important stages of the detection process as it significantly influences the subsequent stages. Without proper imaging, errors may result during the creation of the orthomosaic, thus preventing adequate detection of bud rot disease. The images are obtained with the Phantom 4 UAV, which uses a mobile application to create a flight plan at a programmed altitude, with a manually specified overlap. The flight plan controls the points where the images are captured. These images are acquired with the maximum frontal and lateral overlap, which is 90% at a height of 25 m. This overlap makes it possible to compensate for the perspective error caused by low-altitude flight. Figure 2 shows some of the images obtained in this stage. Low-altitude flight

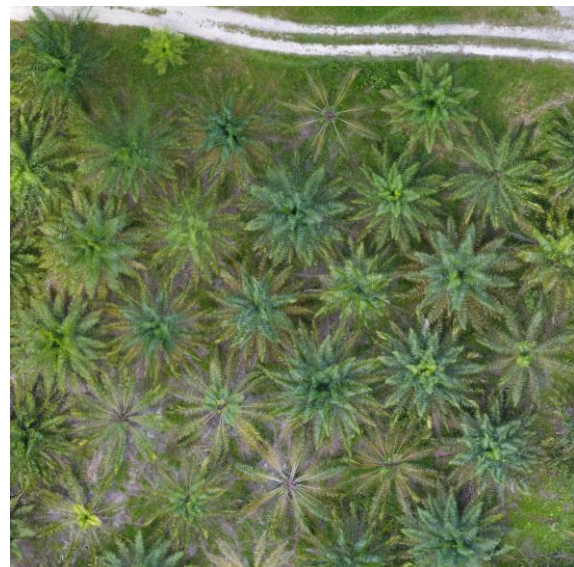
allows analysts to photograph the most relevant part of the palm at a quality sufficient for the detection of the bud rot disease.

## 2.2. Creating orthomosaics

The images resulting from the first stage are initially processed by the Pix4Dmapper photogrammetry software [10], via which all images are related and all geometric errors are corrected so that every point in the terrain is observable from a perpendicular perspective, as shown by the orthomosaic in figure 3. This process is performed automatically by finding thousands of common key points between the different images.



**Figure 2.** Photos obtained with the flight plan



**Figure 3.** Orthomosaic with constant orthogonal projection for every point

## 2.3. Design of detection algorithm of bud rot disease of the oil palm

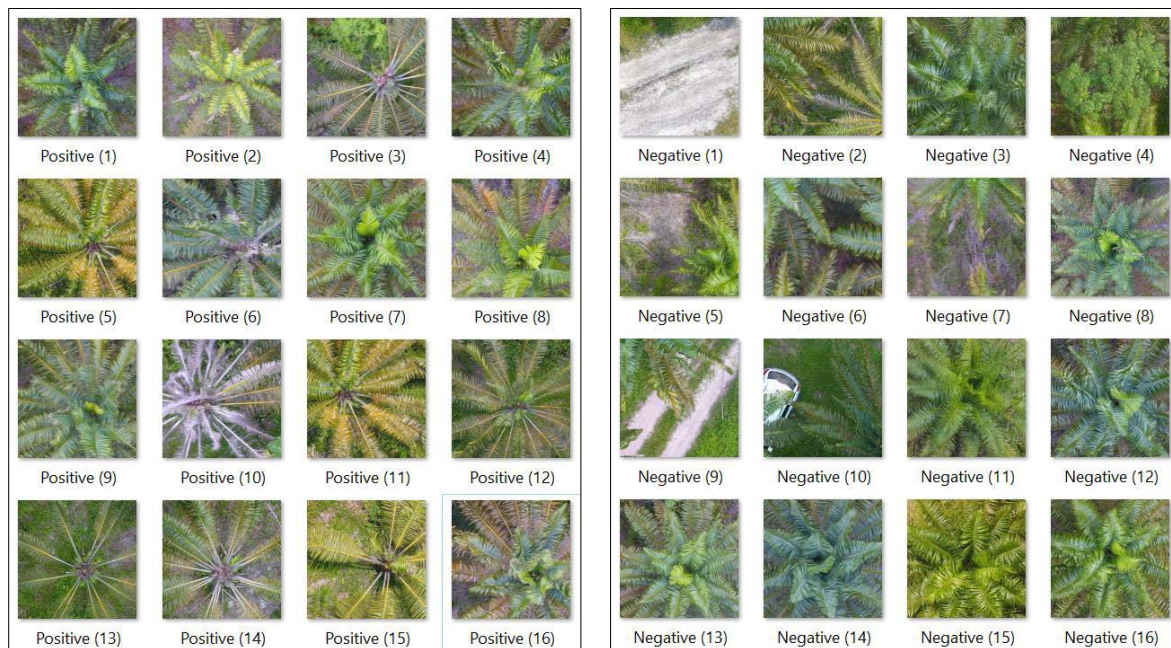
The development and evaluation of the algorithm used 15 orthomosaics, which were divided according to the recommendations of Ng [11] indicating that the database should be divided into three groups: 60% of the images for training, 20% for validation, and the remaining 20% for the evaluation of the model. The final images are completely different from those used in the process of creating the model.

**2.3.1. Training of the logistic regression model.** The system implements a supervised, machine-learning model [12][13][14] [15][16] for the detection of bud rot in diseased palms. This logistic regression model requires a training database classified into two categories: positive samples (diseased palms) and negative samples (healthy palms and backgrounds). A professional technician in oil palm Classification does this separation, focusing especially on differentiating between healthy and diseased palms. This process is performed in all the orthomosaics that were previously processed.

What resulted is a database that includes 450 positive samples and 2700 negative samples, as observed in Figure 4 using 60% training orthomosaics. These RGB samples are then converted to grayscale, followed by the application of a median filter in the spatial domain to reduce “noise”. Every sample has a size of 750x750 pixels, thus ensuring that the center of the palm and its main branches can be observed. Each one is described using U-LBP where each pixel gets a value according to the texture pattern that surrounds it. This descriptor has the quality of being invariant to

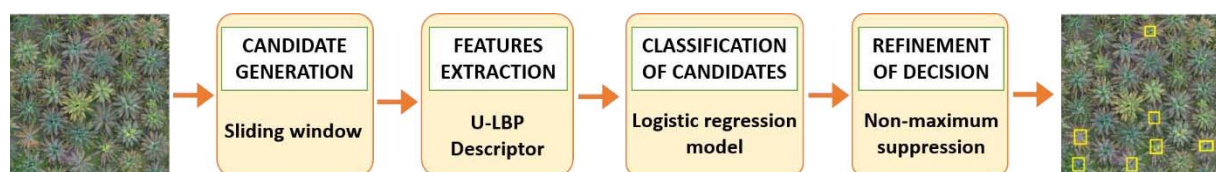


the rotation. As a result, we modified the descriptor to detect the diseased palm in the center of each window. The new descriptor is made by the consecutive union of 9 U-LBP vectors, consisting of 59 patterns each. It is obtained by dividing the sample into 9 equal parts. As a result, we achieved a vector of 531 values per sample. Using these vectors, a matrix is created in which the rows correspond to each training image and the columns to the descriptor (figure 4). Finally, a preliminary logistic regression model is created with reference to the training matrix.



**Figure 4.** Examples of positive and negative samples from training database

**2.3.2. Software for detection of the bud rot disease in oil palms.** The block diagram in figure 5 illustrates the process to detect bud rot disease in oil palm plantations.



**Figure 5.** Block diagram of the software to detect bud rot disease.

First the candidates for bud rot must be generated. To do so, a sliding window is applied to the entire orthomosaic. These windows must have the same structure as the samples used in the training. For this reason, each candidate is shown in grayscale and is given a median filter for noise reduction. Also, each is sized at 750x750 pixels. The characteristics of each window are then extracted by means of the descriptor U-LBP. These characteristics are evaluated by the logistic regression model, which results in the generation of a “1,” indicating a window containing a palm possibly diseased with bud rot, or a “0,” indicating a healthy palm or mere background. Finally, it is necessary to refine the results because it is possible that the same diseased palm will be detected in more than one window.

The refinement is conducted by means of the non-maximum suppression technique.

#### 2.4. Evaluation

**2.4.1. Evaluation metrics.** In the evaluation of the metrics, three orthomosaics corresponding to 20% of the total are used, as they are different to those used in the training of the model. This is done in order to adjust and refine the final logistic regression model. The first metric evaluated is the decision threshold of the logistic regression model, while the second is the overlap threshold of the non-maximum suppression technique. Sensitivity and precision were used as evaluation parameters. This process resulted in 0.5 for the decision threshold and 0.4 for the NMS threshold, respectively, as the best parameters to adjust the model.

**2.4.2. Results.** Finally, we used the remaining 20% of the orthomosaics for the evaluation of the system—those which were not used in the process of training or adjustment of the system—in order to evaluate and guarantee the performance for new plantation palms. The end result demonstrated a sensitivity of 96%, specificity of 97%, precision of 92% and a Kappa index of 92%, observed through the confusion matrix of figure 6.

|                     |                               | TRUE CONDITION |                               |              |       |
|---------------------|-------------------------------|----------------|-------------------------------|--------------|-------|
|                     |                               | Prediction     | Oil palm with bud rot disease | Healthy palm | Total |
| PREDICTED CONDITION | Oil palm with bud rot disease | 23             | 2                             | 25           |       |
|                     | Healthy palm                  | 1              | 76                            | 77           |       |
|                     | Total                         | 24             | 78                            | 102          |       |
|                     |                               |                | Sensitivity                   | 96%          |       |
|                     |                               |                | Precision                     | 92%          |       |
|                     |                               |                | Kappa                         | 92%          |       |

**Figure 6.** Confusion matrix of system evaluation

### 3. Discussion

The results yielded by this logistic regression model, using parameters of 0.5 for the decision threshold and 0.4 for the NMS threshold and a ULBP descriptor, confirm the model and descriptor originally promised by Mizerque [8].

This classification model obtained can be improved to make it more robust for the detection of bud rot disease in palm oil crops, by varying the parameters of the ULBP characteristic descriptor and comparing them by means of the ROC curves [17] and the method of cross-validation.

### 4. Conclusions

The high quality obtained in the orthomosaic generated by the Pix4Dmapper photogrammetry software allowed the developed classification algorithm to obtain the desired results with a sensitivity of 96% and a precision of 92%. Moreover, it was possible to prove that using UAVs is an economical method

to obtain good quality information from palm oil crops for the purpose of identifying bud rot, thus avoiding the labor-intensive effort of having workers perform periodic visual inspections by traversing the crop.

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