Computer Vision and Machine Learning based Segmentation for Fungus Determination in Areca Plates

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Abstract. Areca sheaths are bio-degradable materials used for manufacturing dinnerware. However ensuring quality during and after production is essential particularly in detecting fungus. This work proposes a deep learning approach for fungal detection utilizing the annotations generated by unsupervised learning focusing on areca plates. Images are captured using Raspberry Pi camera setup. Computer Vision techniques are applied to pre-process the images and remove misleading features like sheath veins. The fungal pixels are clustered using DBSCAN clustering and convex hulls are drawn around those pixels. Pixel-wise clustering is computationally intensive. While unsupervised learning is effective, the latency is 4224 ms with standard deviation 0.9851. To address this, these convex hull annotations are then converted to segmentation masks which are used to train a supervised U-Net segmentation model aimed at automated fungal detection. Supervised learning The model's performance is then evaluated by Intersection over Union and Dice coefficient metrics showing stable results. The latency for supervised learning is 83 ms with standard deviation 0.445. The reduced variation and latency shows that this supervised learning method is a better choice for fungal segmentation in areca plates. This method can be used for quality assessment in pre-manufacturing for sheaths and post manufacturing for plates.

Keywords: Areca Plates · DBSCAN · U-Net.

1 Introduction

Areca sheaths are a variant of palm leaves used to manufacture dinnerware. As these sheaths are biodegradable, there has been an increase in demand for dinnerware made out of areca sheaths over plastics. However, quality control during manufacturing and post manufacturing is essential. The manufacturers face several challenges in their manufacturing process. One of those challenges is presence of fungus in the sheaths before production and in the plates after production. This might lead to products with reduced quality and rejects. As a pre-processing step before manufacturing, the sheaths are taken from the trees, soaked in water and dried overnight for manufacturing. When moisture persists in the sheath for a very long time, it leads to fungus formation. This challenge prevents manufacturers from providing good quality products. Each sheath is manually checked by the worker before manufacturing for fungus and the same process is repeated for the finished product. As this is a manual process, there are chances of errors due to lack of well trained personnel or operator fatigue. An alternative to the manual process is the use of computer vision and machine learning techniques to automate the inspection and classification process. This work aims to address this challenge with unsupervised learning and supervised machine learning techniques. After pre-processing the images with computer vision techniques, pixel-wise clustering is done using DBSCAN clustering and convex hulls are drawn around the clusters. These convex hull markings are used as annotations for training a supervised U-Net segmentation model. The dataset consists of areca plates. In this paper, we propose a fungus detection method for areca plates using image processing techniques, combining DBSCAN-based pixel-wise clustering with supervised learning for fungal region segmentation in areca plates. This can be applied to segment fungus in sheath too.

2 Related Works

There is limited research available on fungal detection in areca plates and sheaths. Most of the works focus on arecanuts and fruits using image processing with machine learning techniques for classification, disease detection, and quality assessment. For example, classification of rot, split and rot-split arecanut images using CNN has been reported [3]. Another work describes detecting and classifying the quality of arecanuts using arecanut images. The defect arecanut image was segmented by the detection line method. Six shape characteristics such as the length of the main axis, the length of the secondary axis, the number of axes, the area, the perimeter, and how compact the arecanut image is; three color characteristics, like the average gray level of an areca nut image in the R, G, and B color channels; and the area of defects were used to classify the areca nuts. A back-propagation neural network classifier was employed to sort the quality of arecanuts. The methodology achieved an accuracy of 90.9% [2]. Likewise, there are a few remarkable works in classifying illness in arecanuts. But all the works are carried out on arecanut images and not areca sheath or plate images to detect fungus. The works on areca sheaths or plates are scarce. One notable work on detecting fungus was carried out using microbial contaminants associated with areca plates [5]. However this research is completely based on microbiology. While research on fungal detection in areca sheaths and plates is scarce, image processing on the other hand addresses this gap. One notable approach for segregating the pixels is using pixel-wise clustering. There are works done in pixel-wise clustering using K-means [1], another notable work proposed an algorithm called Ant Colony–Fuzzy C-means Hybrid Algorithm (AFHA) for pixel-wise clustering [9]. Entangled random forest for pixel-wise clustering of images where the pixels are classified into soil, residue, living plants and stones has been reported [6]. Another paper about pixel-wise clustering proposed a method with K-Means clustering and DBSCAN to detect and isolate hotspot areas in PV modules for the images captured by infrared [4]. Supervised learning is well-suited when the annotated data is available. Although supervised learning for labeled datasets for arecanuts has shown great results, in the case of fungal segmentation, an architecture such as U-Net [7] is well suited as it does pixel-wise classification and generates masks for fungal infected areas. While U-Net's benchmark in image segmentation in the field of bio-medical is high [8], this model can be utilized for this problem statement too. While supervised approaches like U-Net require annotated datasets for training, combining them with unsupervised methods like DBSCAN can help in pre-labeling or validating fungal regions, reducing the manual effort of annotation. To the best of our knowledge, no prior research has explored the use of DBSCAN clustering for generating pixel-wise annotations to train supervised models for fungal detection in areca plates.

3 Methodology

Hardware and Image Detection Setup The arrangement for capturing images in real time employs a Raspberry Pi 5 single-board computer (with a Broadcom BCM2712 2.4GHz quad-core 64-bit Arm Cortex-A76 CPU) to handle processing, as well as a Raspberry Pi Camera Module 3 (featuring a Sony IMX708 sensor with 12 megapixels and a resolution of 4608×2592 pixels). Raspberry Pi OS (32-bit) is the operating system used by the system. The camera module uses libcamera library to handle image acquisition.

Fungus detection As discussed, fungus detection is crucial as it plays a major role in maintaining the quality of the manufactured dinnerware.

Data Pre-processing The captured image is initially pre-processed through the use of computer vision techniques. Gaussian blur is applied to the images to reduce noise in the captured image. A major difficulty in processing the images was that the veins in the plates were also detected as fungi. The veins may be either vertical or horizontal. The Prewitt edge detection technique is employed to eliminate both vertical and horizontal lines to tackle this issue. Vertical and horizontal kernels are applied separately to the image and two different outputs are obtained. After this step, a few observations are made. The image contains either vertical or horizontal lines, as stated previously. Thus, in the kernel applied images, one image displays veins with fungus while the other contains only the fungus. The count of white pixels in each of the images is determined. The image containing more white pixels is not used because it shows veins. The image containing fewer white pixels is converted into a binary format for subsequent processing.

Annotations generation After converting the input images to binary format, pixel-wise clustering is done on the segmented fungal regions using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. DBSCAN is a density-based clustering method that groups similar points into clusters while identifying isolated points as noise. Instead of conventional bounding boxes, convex hulls are drawn around each identified cluster, for efficient enclosure of fungal areas while preserving the maximum healthy region. These clustered fungal regions are then used as annotations to train a supervised learning model for segmentation in further analysis.

Supervised Learning Using the images with convex hulls, corresponding segmentation masks are created and stored with the original. These masks are stored as ground truth for supervised learning. To perform the segmentation, U-Net architecture is chosen for its encoder-decoder architecture and skip connections to make the model capture spatial and fine-grained information. The architecture is implemented with a depth of five levels. Before training, the images and masks are resized to 256×256. Data augmentation included random horizontal flips, vertical flips and rotations to improve the model's generalization. The model is set to a learning rate of 0.002 and a segmentation threshold of 0.4 after trial and error. 300 DBSCAN annotated images and 200 data augmented images, resulting in a total of 500 images were used to train the model. As the task involves binary segmentation, the number of output classes is set to 1, representing the fungal regions. The loss function used is Dice Loss and the optimizer used is Adam's optimizer. The model is trained for 50 epochs to learn the pixel-wise mapping between the input images and their corresponding segmentation masks. Intersection over Union (IoU) and Dice Coefficient metrics are implemented to monitor the progress while training. By combining convex hull-based mask generation and a U-Net model, this method aims to segment fungus for areca sheath plates.

4 Results and Discussions

4.1 Clustering Results

After converting the image to a binary image, DBSCAN clustering is applied for pixel-wise clustering surrounded by convex hulls.An example of clustering result is shown in the Fig. 1.

4.2 Supervised Learning Results

Pixel-wise clustering is computationally intensive. The clustering process required considerable amount of time for each image due to the pixel-wise operations involved. The average processing time is 4224.2761 ms with standard deviation 0.9851 To address this issue, a U-Net model was trained using convex hull

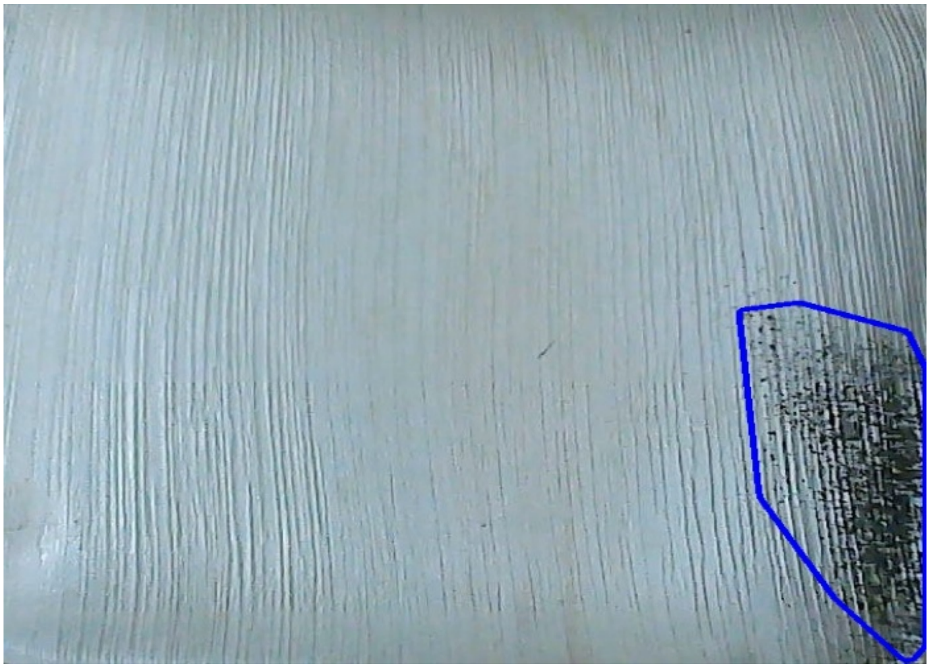

Fig. 1. Pixel-wise clustering using DBSCAN

based masks generated using convex hulls. The model was trained with a depth of 5 levels, a learning rate of 0.002, a threshold of 0.4, and a single class representing the fungal region. The training was conducted over 50 epochs. The average processing time for supervised learning is 83.1446 ms with standard deviation 0.0445. This reduced results shows that supervised learning is a better choice for segmenting fungus in areca plates. The performance of the segmentation model was evaluated using Intersection over Union (IoU) and Dice Coefficient metrics. Fig. 2 shows the IoUs obtained in the training process. The IoU remains stable and the fluctuations are very less implying that the model generalizes well. The obtained dice coefficient is 0.883 implying that the similarity between two sets are good. Sample segmentation is shown in Fig. 3, comparing the predicted masks with the ground truth masks. The predicted masks align with the ground truth, capturing the fungal regions. Additionally, the supervised learning approach reduces processing time compared to pixel-wise DBSCAN clustering, making it more practical for large-scale deployment.

5 Conclusion

In this work, pixel-wise clustering using DBSCAN is implemented on binary images to cluster fungus in areca plates, and convex hulls were drawn around

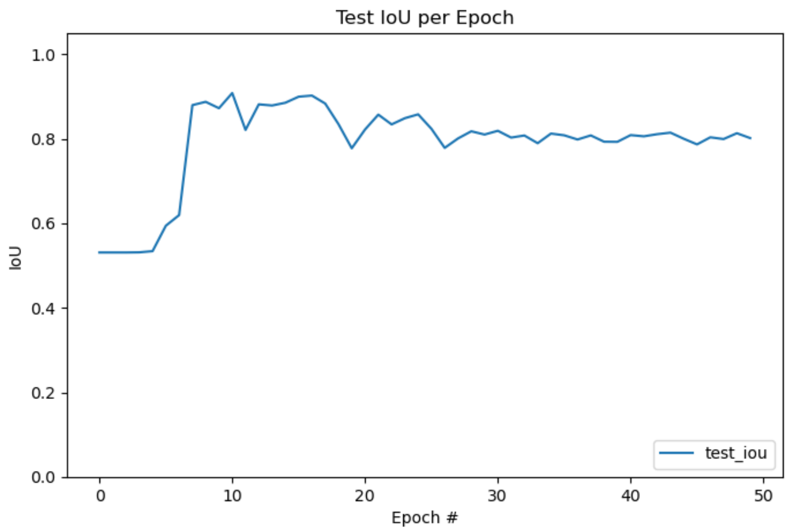

Fig. 2. Test IoU graph

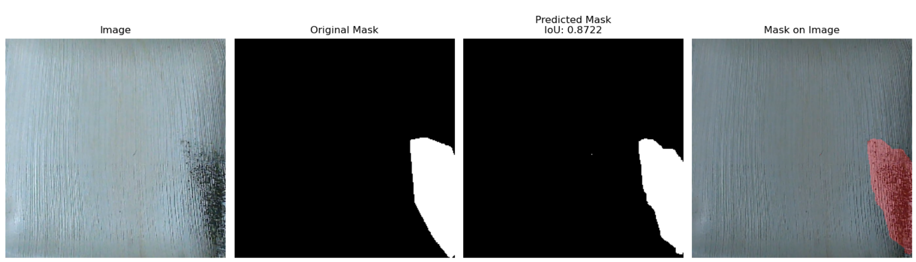

Fig. 3. Sample images with predicted masks

Method	Latency (ms)	Standard Deviation
DBSCAN	4224	0.9851
U-Net	83	0.445

Table 1. Comparison of Average Processing Time and Standard Deviation between DBSCAN and U-Net Methods

Metric	Value
Intersection over Union	0.879
Dice Coefficient	0.883

Table 2. Segmentation Performance Metrics for Fungal Region Detection.

the cluster. These convex hull annotations were then used to generate segmentation masks, which were used to train a U-Net model. The segmentation model achieved stable Intersection over Union (IoU) and Dice Coefficient values, demonstrating good generalization and reliable segmentation performance. This method can be applied to the quality assessment in areca plates after manufacturing or in areca sheaths before manufacturing. The ability to detect fungus on the plates helps the manufacturers post-production.

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