A Preliminary Study on Germinated Oil Palm Seeds Quality Classification with Convolutional Neural Networks

Iman Yi Liao, Brandon Soo Khye Shen
School of Computer Science, University of Nottingham Malaysia
iman.liao, hcybs1@nottingham.edu.my

Zi Yan Chen[1], Mohammad Fakhry Jelani[2], Choo Kien Wong[1], Wei Chee Wong[1]
[1]Advanced Agriecological Research Sdn. Bhd., [2]Applied Agricultural Resources Sdn. Bhd., Malaysia
chenzy, m.fakhry, chookienwg, wongwc@aarsb.com.my

Malaysia and Indonesia produce 85% of palm oil in the world [8]. In Malaysia, the yearly requirement of oil palm planting materials is conservatively estimated to be 50 million [12]. To dispatch high quality seeds, traditional oil palm seed production is laborious and prone to human error. Recently, techniques that extract phenotypic traits of seeds from images automatically are gaining great interest in the seed industry as an alternative method for seed quality assessment [4], among which only a few are reported for germinated seeds [2, 10]. Whilst both detecting and classifying individual seeds are challenging, we focus on the latter in the present study by arranging and capturing germinated oil palm seed images such that the individual seeds can be easily detected. The conventional seed phenotyping platforms extract traits such as colour, morphological (e.g. area, perimeter, extend, and solidity), and textural (e.g. contrast, correlation, energy, and homogeneity) features from the segmented seed images for phenotypic analyses [1, 5]. Those traits are based on quantified manual criteria and are restrictive due to human bias. On the other hand, the use of state-of-the-art Convolutional Neural Networks (CNNs) has demonstrated superior performance over traditional methods in classifying Crambe seed quality based on X-ray images [3] and differentiating corn species [5]. The advantage of using CNNs is to let a model to learn the features that are discriminant for a classification task but with large amount of labelled data [13]. One of the main criterion for manual quality inspection of germinated oil palm seeds is to examine the sprouts, however, with no published quantified measures. It thus motivates us to explore the ways to combine non-quantified human domain knowledge with CNN to classify the quality of a germinated oil palm seed.

Germinated Oil Palm Seed Dataset We collected three batches of germinated oil palm seeds, each consisting of 215, 90, and 120 images with 10-11 seeds per image. Both batch-1 and batch-3 were collected using a Sanoto MK40 Photo Light Box. Batch-1 was captured with a compact digital camera Samsung NX2000 fixed 40 cm away from the light box, whereas batch-3 with a digital compact camera Canon IXUS 285 HS fixed 26 cm above a tabletop. Batch-2 was collected under similar condition as that of Batch-3 expect that the source of light was emitted from Phillips Lifemax TLD 36W/54-765 fluorescent bulb under the normal room light condition. At all times the camera was set at auto-focus. Some sample images from batch-1, batch-2 and batch-3 datasets are shown in Figure 1.

Figure 1. Sample images of dataset batch-1 good (1st row), bad (2nd row), batch-2 (3rd row), and batch-3 (4th row). Red and green bounding boxes are annotations for good and bad seeds respectively. The images are manually cropped for tighter view.

Method Figure 1 demonstrate a relatively easier case for individual seed segmentation than those with cluttered background. Classical image processing techniques such as thresholding, edge enhancement, and morphological operations have been used to segment individual seeds from the background [7, 14, 9]. In this study, we propose a 3-part segmentation method primarily based on morphological operations. The combined mask is used for segmentation whilst a part component is used to guide the integration of non-quantified domain knowledge in the quality

Model	Batch-1 annot.	Batch-1 seg.	Batch-2 annot.	Batch-3 annot.
Baseline-1	0.9047±0.0202	0.8090±0.0440	0.6184±0.0370	0.5582±0.0159
Baseline-2	0.9574±0.0125	**0.9465±0.0202**	0.6202±0.0404	0.5817±0.0368
Baseline-3	**0.9676±0.0076**	0.9388±0.0164	0.6680±0.0268	0.6109±0.0216
AG-edge	0.9674±0.0055	0.9369±0.0112	**0.6891±0.0443**	**0.6192±0.0139**
AG-combined	0.9671±0.0048	0.9393±0.0139	0.6769±0.0327	0.6169±0.0136

Table 1. Testing accuracies of 5 models (3 baseline and 2 attention models) on batch-1 testing, batch-1 segmented seeds, batch-2, and batch-3 dataset.

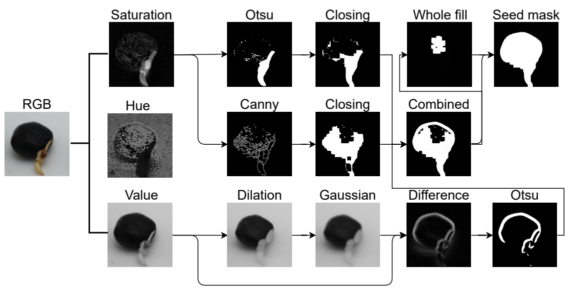

Figure 2. Seed image segmentation.

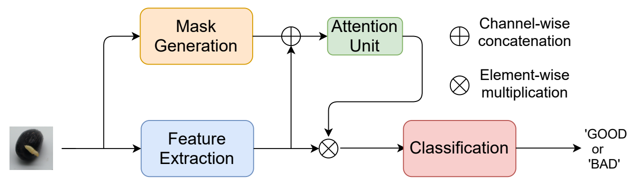

Figure 3. Attention-guided CNN for seed classification. The Attention Unit, Feature Extraction block, and Classification block are learnable. The Mask Generation block is not learnable.

classification process. Thus the representation of the domain knowledge and how it is combined for classification is learned rather than being hard-coded as a human bias.

Figure 2 provides a schematic view of the proposed 3-part seed segmentation. The three parts broadly correspond to the sprouts, main body, and edge map of a germinated oil palm seed. They are combined to produce the whole seed mask for seed segmentation. Either the whole seed mask or a component mask is then used to guide a CNN model to focus on areas that are critical for classifying the quality of germinated oil palm seeds. The architecture of the entire Attention-Guided CNN (AG-CNN) model is shown in Figure 3. As a component mask or whole seed mask may not be accurate, we use an Attention Unit (AU) to learn the area of focus rather than masking out the area outside the input mask. The AU has a U-Net like architecture [11]. The feature extraction and classification modules are respectively the convolutional and linear layers in a baseline CNN model. We explore preliminarily with three simple CNN architectures of 5 layers. Baseline-1 consists of 2 convolutional layers and 3 linear layers, resembling LeNet [6]. Baseline-2 and Baseline-3 both have 3 convolutional layers and 2 linear layers except that the former has much smaller number of convolutional channels and implements drop-out compared to that of the latter.

Results and Discussions We reserved 90 (out of 110) images of good seeds and 85 (out of 105) images of bad seeds in batch-1 for training. Two versions of individual seed images were generated from batch-1 test set, one with larger margin denoted as 'batch-1 annot' and the other with a tighter margin as a result of 3-part segmentation denoted as 'batch-1 seg'. Both batch-2 and batch-3 datasets were kept for testing only. Training images were randomly flipped either vertically or horizontally, each with a probability of 0.5. The training process stops when the validation accuracy does not improve for a number of epochs (e.g., 20 in our experiments). The model with the highest validation accuracy is chosen as the best model for testing. Table 1 shows the testing accuracies of all batches for baseline-1, -2, -3, AG-edge (baseline-3 with edge map as the mask), and AG-combined (basedline-3 with the whole seed mask).

AG-edge and AG-combined performed on par with baseline-3 and better than baseline-1 and baseline-2 on the batch-1 test dataset. Baseline-2 outperformed the other models on 'batch-1 seg', indicating better generalisation probably due to drop-out regularisation. The performances of all five models dropped significantly on batch-2 and batch-3 datasets where AG-edge performed the best followed by AG-combined. It demonstrates that the information guided by segmentation masks has better transferability than the baseline models. All the models performed consistently better on batch-2 than batch-3, despite that batch-3 were collected under a closer hardware condition to batch-1. It may be attributed to the fact that oil palm seeds in batch-3 were placed under a different view to that of batch-1 whereas such difference is not noticeable between batch-2 and batch-1. It suggests that a viewing angle to a seed, particularly sprout, may cause difficulty in differentiating some good seeds from the bad ones. Mult-view images or 3D imaging techniques may be explored in the future.

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