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Research Article

Particle Size Detection of Palm Kernel Cake from Sieving Based on Images Using Convolutional Neural Network

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Abstract: Palm kernel cake (PKC), a by-product of the palm oil industry, is widely used in animal feed due to its economic value. Its utilization reduces the reliance on costly conventional feed ingredients, reducing production expenses and improving livestock efficiency. However, contamination with palm kernel shells remains a key challenge, as it reduces quality and nutritional value. Identifying PKC particle sizes and addressing inconsistencies caused by contamination is complex, requiring advanced computational solutions. This study focuses on classifying the PKC particle sizes -fine, medium, and coarse - using image processing combined with machine learning. A sieve shaker is applied to separate particles by size distribution, and a classification model is developed with Convolutional Neural Networks (CNN) under a transfer learning framework, which is effective for limited datasets. Six CNN architectures, MobileNet, Xception, InceptionV3, ResNet-152, VGG16, and NasNetMobile, are tested in four-layer configurations to identify the optimal setup. The results show that the proposed approach can classify PKC particle sizes with high accuracy. Among the models tested, MobileNet provides the best performance, achieving 0.99 accuracy and 0.98 F1 score in the second variation experiment. These findings present a practical and cost-effective method for assessing the quality of PKC, supporting scalable applications in feed production. This approach not only improves the accuracy of the evaluation, but also contributes to efficiency and sustainability in the livestock industry.

Keywords: Convolutional Neural Network (CNN), Machine Learning, Particle size detection, Palm Kernel Cake

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1 Introduction

Palm Kernel Cake (PKC), a byproduct of the palm oil industry, has considerable economic importance, particularly as a component in animal feed [1]. PKC is rich in nutrients such as protein and fat [2]. Its abundant availability makes it a potential economical alternative feed ingredient [3]. Using PKC as animal feed can reduce the dependence on more expensive conventional feed materials, potentially reducing production costs and increasing efficiency in the livestock industry.

Despite its many benefits, PKC faces a significant issue: shell contamination. Palm shells mixed into PKC can diminish the product's quality and nutritional value of the product [3]. The particle size of the PKC shells is generally coarse, which affects their nutritional value and suitability for animal feed. Larger particles may increase the calcium content in eggshells when used as a dietary supplement, but could also affect the feeding intake depending on their proportion in the diet [3]. Therefore, methods are needed to identify and reduce shell contaminants in PKC. One solution that can be implemented is a physical treatment to separate the shells from the palm kernel cake [4]. PKC is shown in Figure 1.

Figure 1: Palm Kernel Cake

In addition to the contamination problem, the particle size of PKC also plays an essential role in its use as animal feed [1]. The correct particle size affects the digestion and absorption of nutrients in livestock. Therefore, detecting and classifying the PKC particle sizes is essential. The particle sizes of PKC are fine, medium and coarse [5]. Detecting and classifying these particle sizes will help quickly indicate the quality and efficient use of PKC in animal feed. Fine particles are recommended for poultry and medium for ruminants, while coarse particles are not recommended unless they are further grinding to improve suitability. Relevant research related to PKC quality identification has used a Near Infrared (NIR) approach to calibrate the chemical quality of PKC [6]. However, this approach is still limited to general quality aspects and has not explicitly addressed particle size detection. In this context, machine learning technology, particularly Convolutional Neural Networks (CNN), offers excellent potential for detecting and classifying PKC particle sizes based on images [7,8]. CNN has proven to be effective in object recognition [9] and image classification [10]. Accurate detection of PKC particle sizes is crucial to ensure the quality of the resulting animal feed.

This study aims to implement a CNN model to detect and classify PKC particle sizes based on images. This technology is expected to identify and classify the PKC particle sizes as fine, medium, and coarse. This approach can significantly contribute to simplifying the identification of roughness levels of PKC as an economical and sustainable alternative ingredient for animal feed. With this research, we hope to pave the way and provide practical and efficient solutions to the challenges faced by the palm oil and livestock industries.

Additionally, our contribution is to develop a PKC quality detection model using CNN by testing different layer configurations to enhance model performance and achieve an optimal configuration. We also optimize the training process to improve model stability and convergence. Parameter adjustments are made to find the best performing settings. So far, this study is the first to apply multiple CNN architectures with layered configuration comparison to classify the particle size of PKC based solely on visual image data, without chemical or spectral analysis. This study offers an inexpensive and scalable solution for monitoring feed quality.

2 Research Method

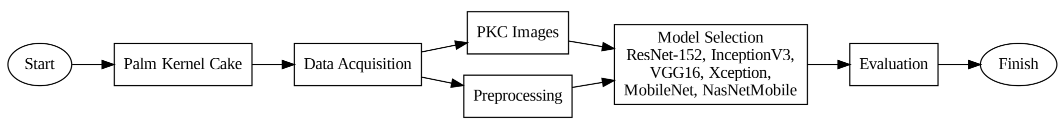

Figure 2: Research workflow.

The PKC particle size detection method is conducted using PKC images. The image data from these particles are then processed using machine learning algorithms to estimate the particle size. There are four stages in the research methodology: the data collection stage, the preprocessing stage, the modeling stage, and the evaluation stage, as shown in Figure 2. The workflow, illustrated in Figure 2, begins with the collected data that undergo preprocessing. Then, in the modeling stage, we use several CNN algorithm architectures which are compared to find the maximum accuracy value in the evaluation stage.

2.1 Data Collection

The PKC used in this research was obtained from several factories. The PKC samples were shaken using a sieve shaker with mesh sizes ranging from 4, 8, 16, 30, 50, to 100 and placed in containers [5]. The sieve shaker used comes from the Bogor Agricultural University (IPB) Feed Industry Lab, as shown in Figure 3. The device utilizes vibrations that facilitate the material to pass through the sieve. In addition to leveling the surface of the screened material, vibrations also direct the unscreened material. The PKC samples processed with the shaker were photographed using a smartphone camera in a white box with additional lighting.

Figure 4 shows several PKC samples that have been shaken using a sieve shaker with mesh sizes ranging from 4, 8, 16, 30, 50, to 100. According to [5], Mesh 4 has a hole size of approximately 4.76 mm. It is used to separate more extensive materials. Mesh 8 has a hole size of about 2.36 mm. This sieve is used for medium-sized materials. Mesh 16 has a hole size of approximately 1.19 mm. It is suitable for separating finer particles. Mesh 30 has a hole size of around 0.595 mm. It is used for smaller particles. Mesh 50 has a hole size of

Figure 3: Sieve shaker.

about 0.297 mm. This sieve captures relatively fine particles. Mesh 100 has a hole size of approximately 0.149 mm. It is used to separate excellent particles.

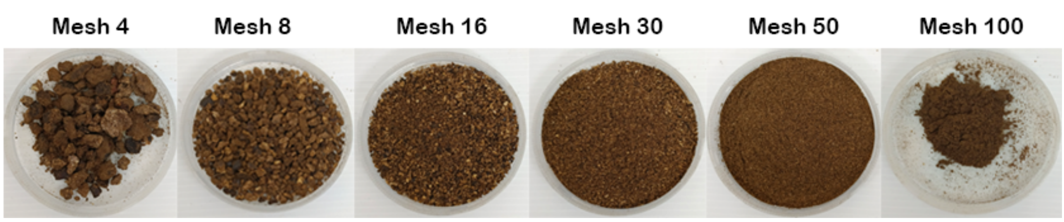

Figure 4: PKC sample after the shaker.

2.2 Preprocessing

At this stage, the captured images are classified as fine, medium, and coarse [3]. Mesh sizes 4 to 16 indicate the coarse category, mesh size 30 means medium category, and mesh sizes 80 to 100 indicate the fine category [4]. The cropping and resizing images are used to adjust the images for training and testing datasets or when performing image classification [11, 12]. Cropping images helps reduce noise and improve image quality [13]. Resizing changes all images to a consistent size, making them more accessible for the model to process [14]. The images were then sliced and resized to 224×224 pixels.

2.3 Augmentation

During the object classification training phase, CNN requires a large amount of data. Therefore, augmentation techniques are used to expand the existing dataset to improve accuracy.

In this study, augmentation was performed using techniques such as horizontal flip, vertical flip [15,16], rotation by 90º, rotation by -90º, rotation by 180º, and zoom range of 0.2 [17].

2.4 Modelling

The training process was conducted using a dataset of 3,640 images distributed in three distinct classes. Of these images, 80% were used for training and 20% for validation. This study used six architectures and compared them to identify the model with the best performance. The architectures used were MobileNet, Xception, InceptionV3, ResNet-152, VGG16, and NasNetMobile. As an initial step in our research and to improve the efficiency of developing the PKC detection model using pre-trained models on large datasets [18,19], these architectures offer advantages such as computational efficiency [20], feature extraction capabilities [21–24] and have undergone extensive feature learning [25]. These reasons make the chosen architectures suitable for testing new data more optimally, with the expectation of improving the accuracy of image classification with limited resources [24,26]. The parameters of the trained models can be seen in Table 1 Several variations of the layers used are detailed in Table 2.

Table 1: Model training parameters

Parameters	**Type**
Number of Epochs	10
Batch Size	32
Optimizer	Adam
Lost Function	Categorical, cross-entropy
Matrics	Accuracy

As shown in Table 1, the training process used specific parameters, including the optimizer and the size of the batch. Furthermore, Table 2 outlines the different layer configurations tested in this study.

2.5 Evaluation

The proposed model must be evaluated to determine its reliability in classifying the sizes of PKC particles. In this study, the evaluated metrics calculated are accuracy, precision, recall, and F1 Score, as shown by the formulas in Eqs. (1), (2), (3), and (4) [27–29].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Table 2: Layer variation

Variation	Layers
1	1. Flatten 2. Dense (256) 3. Dropout (0.5) 4. Dense(3)
2	1. GlobalAveragePooling2D 2. Dense (256) 3. Dropout (0.5) 4. Dense(3)
3	1. Maxpooling2D (2x2) 2. Flatten 3. Dense (256) 4. Dropout (0.5) 5. Dense (3)
4	1. Maxpooling2D (2x2) 2. Maxpooling2D (2x2) 3. Flatten 4. Dense (256) 5. Dropout (0.5) 6. Dense (3)

True Positive (TP) refers to the count of actual palm kernel cake images that are accurately extracted. True Negative (TN) represents the number of actual palm kernel cake images that are incorrectly classified. False Positive (FP) denotes the number of incorrect palm kernel cake images mistakenly identified as correct. The false negative (FN) indicates the number of incorrect palm kernel cake images that are inaccurately classified.

3 Result

The testing was carried out by comparing several CNN architectures. The test results for each layer variation of each architecture are explained in this section. Table 3 shows the performance comparison for six architectures with four-layer variations. Figure 5 displays the performance comparison for each architecture, highlighting the best layer variation. In layer variation 1, Xception achieved the best accuracy in all metrics, with a value of 0.96 and the best precision. However, it performed poorly in the recall, although it still outperformed InceptionV3, ResNet-152, and NasNetMobile in the recall for variation 1. Similarly, the F1 Score for Xception was lower than that of VGG16 and Xception. The lowest accuracy was obtained by the NasNetMobile architecture, with a value of 0.91. The results are summarized in Table 3.

In the second variation, MobileNet achieved the best values in all metrics: 0.99 for accuracy, 0.99 for precision, 0.97 for recall, and 0.98 for the F1 Score. Xception obtained the worst accuracy performance with a value of 0.94, and the lowest precision was recorded by InceptionV3 and ResNet-152, with a value of 0.95. Compared to variation 1, all metrics

Table 3: Transfer learning architecture performance

Architecture	Variation	Accuracy	Precision	Recall	F1 Score
Mobilenet	1	0.95	0.96	0.84	0.88
	2	0.99	0.99	0.97	0.98
	3	0.98	0.97	0.95	0.96
	4	0.96	0.96	0.91	0.93
Xception	1	0.96	0.96	0.90	0.92
	2	0.94	0.96	0.90	0.92
	3	0.93	0.94	0.84	0.87
	4	0.94	0.94	0.84	0.87
Inceptionv3	1	0.92	0.94	0.82	0.85
	2	0.95	0.95	0.92	0.94
	3	0.94	0.93	0.87	0.89
	4	0.92	0.92	0.87	0.89
Resnet-152	1	0.92	0.92	0.82	0.85
	2	0.96	0.95	0.91	0.92
	3	0.94	0.92	0.84	0.86
	4	0.93	0.92	0.84	0.87
VGG16	1	0.95	0.96	0.91	0.93
	2	0.97	0.97	0.91	0.93
	3	0.95	0.94	0.89	0.91
	4	0.95	0.95	0.90	0.92
NasnetMobile	1	0.91	0.90	0.82	0.84
	2	0.94	0.94	0.89	0.91
	3	0.95	0.93	0.90	0.91
	4	0.93	0.95	0.82	0.85

improved in variation 2, except for Xception, which experienced a decrease in accuracy by 0.2.

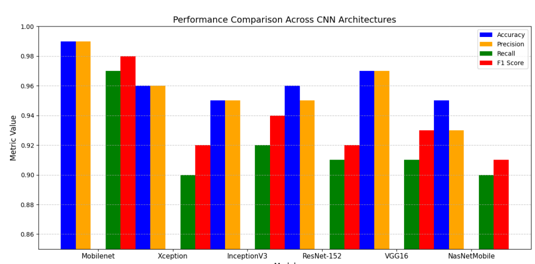

Figure 5: Performance comparison across CNN architectures.

MobileNet still has the best values for accuracy, precision, recall, and F1 Score in the third variation, just as in variation 2. Xception remains the lowest performer. In variation 3, there is a general decrease in values across all metrics compared to variation 2, although there is an improvement compared to variation 1. The only exception is NasNet, which shows a slight increase in performance in variation three compared to variation 2. In variation 4, MobileNet, InceptionV3, ResNet-152, and NasNetMobile experienced a decrease in performance. However, MobileNet still achieved the best scores among the architectures in variation 4. The results of variation 4 were worse than those of variations 2 and 3, except for Xception, but better compared to variation 1, except for Xception.

From the confusion matrix shown in Figure 6, MobileNet maintains the highest accuracy with minimal misclassification, establishing itself as the best architecture. In contrast, Xception demonstrates the weakest performance, with a high error ratio, particularly in class 2. This aligns with its lower precision, recall, and F1 Score than other models. For NasNet, the improved accuracy in variation three is primarily attributed to a better classification of class 0, although the misclassification in class 2 persists. Meanwhile, ResNet-152 and InceptionV3 show a decrease in variation 4, with increased prediction errors that reduce overall performance.

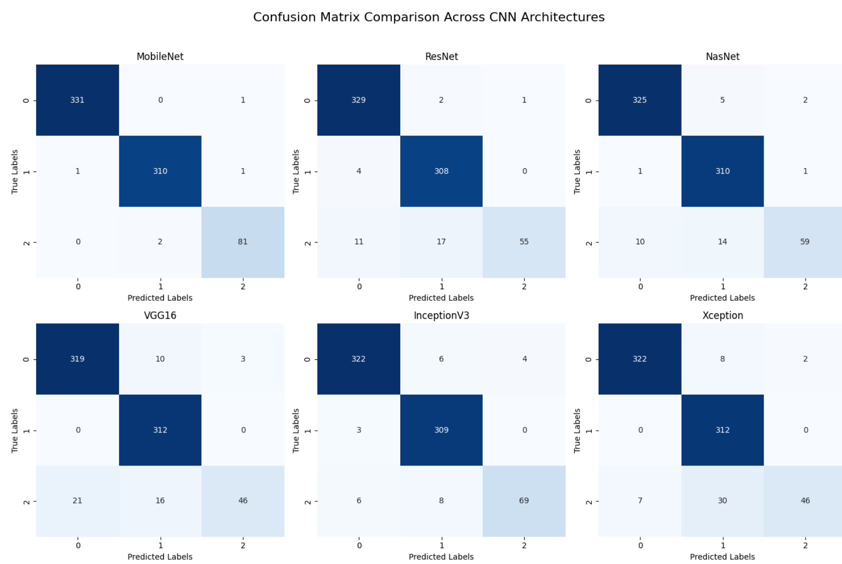

Figure 6: Confusion matrix representation of classification results.

In general, the confusion matrix highlights the classification effectiveness of each architecture, reaffirming MobileNet as the most robust model.

4 Discussion

Figure 7 presents a graphical representation of accuracy trends in various architectures, highlighting their peak performance levels and comparative effectiveness.

The MobileNet model, specifically its second variation, exhibits high and stable accuracy across both training and validation datasets. The validation accuracy marginally exceeds the training accuracy, suggesting effective generalization and minimal overfitting. These findings align with previous research, such as that of [30], which underscores MobileNet's efficiency and robustness in various image classification tasks, particularly in

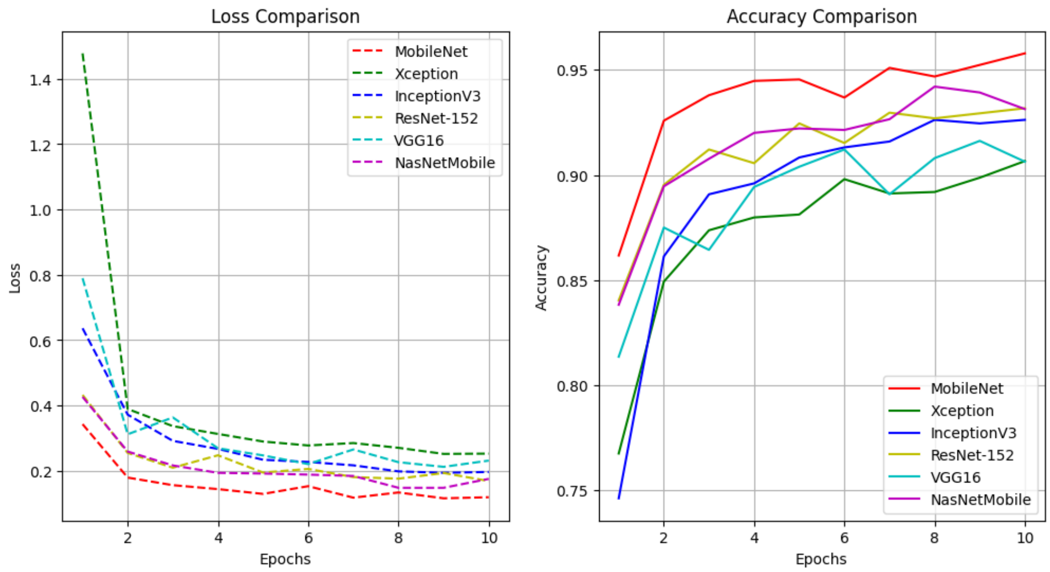

Figure 7: Comparative analysis of CNN architectures: trends in accuracy and loss.

resource-constrained environments. However, its capability in handling fine-grained particle size classification within agricultural applications, such as PKC particle detection, remains inadequately explored, signifying a potential research gap in optimizing MobileNet for precision feed quality monitoring.

Similarly, the Xception architecture demonstrates promising performance, with validation accuracy consistently exceeding training accuracy throughout the model's training process. These results align with previous findings from [21], highlighting the strong generalization capacity of Xception's depthwise separable convolutions. Existing studies have yet to thoroughly investigate the application of Xception in detecting agricultural feed particle size. This necessitates further research to assess its performance across diverse hyperparameter settings, including variations in epoch count or batch sizes. The InceptionV3 model shows steady performance improvement, accompanied by minor fluctuations in validation accuracy. The research by [31] acknowledges the strength of the Inception architecture in processing high-resolution image data, but its potential for PKC particle size classification remains underexplored. Future investigations could further explore the effects of improved image resolution and refined preprocessing techniques to improve classification accuracy.

In contrast, ResNet152 exhibits signs of overfitting, as the validation accuracy initially appears strong but subsequently declines after multiple training epochs. [32]previously highlighted ResNet's capability to manage deep network architectures effectively. However, the observed overfitting raises concerns about the generalizability of the model when applied to complex data sets such as PKC particles. Mitigation strategies, including early stopping mechanisms and regularization techniques, warrant further exploration to enhance ResNet's robustness in this domain.

The NasNetMobile architecture presents challenges due to fluctuations in validation accuracy, a trend consistent with findings from [24]. These findings report that, despite the high computational efficiency of NASNet, substantial fine-tuning is required to achieve stability. These fluctuations suggest the need for advanced optimization strategies, particularly within real-time agricultural feed monitoring systems, where model consistency and processing efficiency are critical.

In general, while experimental results validate the effectiveness of deep learning approaches in the classification of PKC particle size, the review of the literature underscores an existing research gap regarding the specific application of these architectures to agricultural datasets. Future studies should fine-tune these models to accommodate the unique characteristics of PKC while exploring complementary approaches such as transfer learning or hybrid architectures to maximize the performance of agricultural feed quality assessment.

CNN is an advanced method for the classification and detection of the coarse, medium, and fine features of PKC particles. At the same time, NIR is more suitable for analyzing the chemical composition, such as crude protein, fiber, ash, and fat content. With respect to performance and accuracy, CNN exceeds NIR in recognizing particle size patterns, while NIR is more effective in analyzing their chemical content. Although previous studies relied on NIR for chemical prediction, CNN offers distinct advantages in visual identification, which NIR cannot achieve.

5 Conclusion

Based on the results and discussion, the MobileNet architecture with the second variation is the most suitable for detecting PKC particle sizes from images. This method shows great potential for practical applications, such as monitoring feed quality. Furthermore, this research opens opportunities for further development. Given the shell contamination issues associated with PKC, future experiments should focus on detecting shell contaminants. Optimizing the training process by addressing computation time will be crucial to balancing model accuracy and computational efficiency. The model offers a low-cost solution that requires only a camera once it is deployed, and it operates quickly on site to distinguish PKC coarseness levels. However, its limitation lies in its visual-based approach, as it cannot assess proximate quality. Additionally, the model requires fine-tuning when used under different lighting conditions, presenting an opportunity for further development in future studies. Future work could integrate multimodal data, combine image analysis and proximate features, and deploy trained models for live field assessment devices.

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