Automated Classification of Monthong, Chanee, and Kan Yao Durians Using VGG16 Convolutional Neural Network

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Abstract

Durians are a vital agricultural product in Thailand, contributing significantly to the country's economy and exports. However, distinguishing between durian varieties, such as Monthong, Chanee, and Kan Yao, remains a challenge due to their similar external characteristics, leading to consumer confusion. This study employs a convolutional neural network (CNN) approach using VGG16 to classify these durian varieties along with a non-durian category. A dataset of durian images was preprocessed with resizing and augmentation techniques to enhance model performance. The model was trained and validated over 20 epochs, with accuracy and loss metrics recorded to assess learning progression. Results indicate that the VGG16 model achieved a training accuracy of approximately 92% but struggled with generalization, with a validation accuracy stabilizing around 60%. The overall test accuracy of the model was 67.3%, reflecting a moderate level of classification effectiveness. The confusion matrix revealed that while Monthong and Chanee were classified with relatively high accuracy, Kan Yao exhibited frequent misclassification, likely due to visual similarities with other varieties. Despite these challenges, the study demonstrates the potential of CNN-based classification for durians, suggesting that additional dataset expansion and model fine-tuning could improve performance. This approach offers a potential time-saving and cost-effective solution for durian classification, reducing reliance on manual inspection and promoting consistency in quality assessment.

Keywords: *durian classification, deep learning, artificial intelligence, convolutional neural network*

1. Introduction

Durians hold significant importance in business and exports, particularly in Southeast Asia, where they are often referred to as the "king of fruits". Thailand, Malaysia, and Indonesia are the leading producers and exporters of durians, with Thailand alone accounting for 82% of global shipments. The fruit's distinctive aroma and taste have also led to its integration into various culinary products, further expanding its market potential. The global demand for durian is primarily driven by the species *Durio zibethinus*, which is highly sought after in Southeast Asia and increasingly in international markets, particularly in China. Within this species, the Malaysian Musang King (Mao Shan Wang) and the Thai Monthong are particularly popular (Thorogood et al., 2022).

Thailand's durian industry remains a dominant force in global exports, with a total export value of 2,980.40 million USD from January to June 2024. The majority of these exports consist of fresh durian (2,790.48 million USD) and frozen durian (189.92 million USD), with China serving as the largest market, accounting for 97.43% of exports. Other key markets include Hong Kong and South Korea. Thailand's leading durian varieties, including Monthong, Chanee, and Kan Yao, are cultivated primarily in Chanthaburi, Rayong, Chumphon, and Trat provinces. The country's competitive edge lies in its sweet, fragrant, firm, and smooth-textured durians, alongside strong quality control standards (Department of International Trade Promotion, 2024).

Monthong, meaning "golden pillow", is the most well-known and widely exported variety. It has a large, elongated shape with a tapered end, and its flesh is golden-yellow, soft, creamy, and mildly fragrant, making it suitable for those who are not accustomed to the strong durian aroma. Kan Yao, or "long stalk"' is a medium-sized, round durian with an indistinct locule structure. It has a smooth, sweet flavor with minimal fiber and is highly sought after for its consistent yield and balanced taste. Chanee, often recognized by its distinct bulging middle and tapered ends, produces dense, thick flesh with an intense aroma and rich, buttery flavor. Due to its strong fragrance and firm texture, Chanee is commonly used for processing into durian-based products and desserts (Department of International Trade Promotion, 2024).

However, distinguishing between durian varieties remains a significant challenge, as some varieties share similar external characteristics (Siew et al., 2018). Consumers unfamiliar with durian varieties may experience confusion and difficulty correctly identifying them, leading to uncertainty in their purchasing decisions. This issue is not limited to domestic consumers but also affects international tourists, who may lack knowledge about different durian types. As a result, misidentification can lead to unsatisfactory consumer experiences, potentially impacting the perception of Thai durians in global markets. Addressing this issue through improved labeling, education, and digital tools could enhance consumer confidence and strengthen Thailand's position as a leader in the durian industry.

AI, image processing technologies, and deep learning offer promising solutions for overcoming these identification challenges. In particular, convolutional neural networks (CNNs) have proven highly effective in detecting subtle distinctions in various fields, such as medical imaging and agricultural classification (Gill et al., 2024). Compared to traditional machine learning approaches, CNNs automatically extract relevant features, making them superior for complex image classification tasks (Teo et al., 2024). CNN models have been successfully applied to classify durian varieties such as Musang King, Black Thorn, and D24, using preprocessing techniques like image resizing and dataset augmentation to enhance accuracy. In their study, VGG-16 and Xception models were used for classification, achieving accuracy rates of 56.64% and 92%, respectively (Diana et al., 2025). Lim and Chuah (2018) developed a CNN model to classify durian cultivars based on bottom-view images. Their study utilized a dataset of 800 labeled durian images, achieving an initial accuracy of 82.50%, which slightly dropped to 81.25% when non-durian images were included. In addition, Khazri and Kutty utilized image processing techniques, including Gaussian and Median filters and Canny edge detection, to classify durians into defect and non-defect categories, achieving accuracy rates of 87% and 75%, respectively (Khazri et al., 2024).

While CNN-based models have demonstrated high accuracy in durian grading systems, no studies have specifically focused on classifying the three main Thai durian varieties Monthong, Chanee, and Kan Yao. This study aims to fill that gap by leveraging CNNs to improve durian classification, thereby enhancing consumer experience and supporting Thailand's durian market competitiveness. Therefore, this study aims to address the classification challenges by leveraging deep learning to develop an automated identification model for Thailand's three most exported durian varieties. Despite existing efforts in durian classification, there is a research gap regarding models that focus specifically on these Thai cultivars, and this study seeks to fill that void. The main contribution of this study is the development and evaluation of a CNN-based model that specifically targets the classification of Thailand's top three durian varieties, providing a foundation for future applications in agricultural automation and mobile consumer tools.

2. Objectives

1) To develop a Convolutional Neural Network (CNN)-based approach using VGG16 to classify Monthong, Chanee, and Kan Yao durians along with a non-durian category.
2) To evaluate the performance of the VGG16 model in durian classification based on the model's accuracy, loss, and generalization ability using training, validation, and test datasets.

3. Materials and Methods

The VGG-16 model has been effectively applied to fruit classification tasks, including the classification of durian ripeness and other fruit-related characteristics. For example, it was utilized for classifying the ripeness levels of Monthong durians, achieving a notable accuracy of 94.50%, which was among the top-performing models in their comparison of various deep learning architectures (Sukkasem et al., 2024). This demonstrates its capability in handling complex fruit classification tasks, such as distinguishing between different ripeness levels. Additionally, VGG-16 achieved a 97% accuracy across more than 20 fruit types after only six training epochs (Geng, 2024). Furthermore, VGG-16 was applied to classify crown density and foliage transparency in broadleaf trees, including durian, achieving an accuracy of 86.60%

for durian trees, which highlights the model's versatility in different classification contexts (Octarina et al., 2023). These studies collectively illustrate VGG-16's robustness and adaptability in fruit classification tasks, including its application to durian, whether for ripeness or other characteristics, making it a valuable tool in agricultural and industrial applications.

The VGG16 model was selected due to its proven reliability, ease of fine-tuning, and availability of pre-trained weights that allow for efficient feature extraction, especially with limited training data. While other models such as ResNet and EfficientNet offer deeper architectures, preliminary trials revealed that VGG16 provided the most consistent performance with this dataset. The decision to exclude other CNNs was based on computational constraints and the objective of developing an interpretable and adaptable model for practical use.

The dataset used in this study consists of images categorised into four classes: Chanee, Monthong, Kan Yao, and a non-durian category. These images were stored in separate directories for training, validation, and testing. The dataset was collected from various sources to ensure diversity in lighting conditions, angles, and backgrounds. The images were manually labelled and organised into structured folders corresponding to each category. The inclusion of the non-durian category helps the model distinguish durian from other objects, improving classification accuracy. To enhance the diversity of the training dataset and improve the model's generalisation ability, data augmentation techniques such as rotation (20 degrees), width and height shifting (0.2), shearing (0.2), zooming (0.2), and horizontal flipping were applied. All images were resized to 224×224 pixels and rescaled to the range [0,1] by normalising pixel values with a factor of 1/255. The dataset consisted of 56 training images, 56 validation images, and 44 test images, distributed evenly across the four categories.

A CNN based on the VGG16 architecture was employed for classification, leveraging a pre-trained VGG16 model initialised with ImageNet weights as a feature extractor, excluding its fully connected layers. The base model was frozen during initial training to retain learnt features from the pre-trained model (Bakasa, & Viriri, 2023). A custom classification head was added, comprising a Flatten layer to convert feature maps into a one-dimensional vector, a dense layer with 256 neurons and ReLU activation for feature learning, followed by an output layer with four neurons corresponding to the three durian types and the non-durian category, using softmax activation for multi-class classification.

The model was compiled using the Adam optimiser with categorical cross-entropy loss and accuracy as the evaluation metric. The training process was conducted for 20 epochs with a batch size 32, utilising the augmented training dataset. The validation dataset was used to monitor performance and prevent overfitting, ensuring the model generalises well to unseen data. During training, the layers of the pre-trained model remained frozen for the initial epochs, after which fine-tuning was performed by unfreezing some of the deeper layers to further adapt feature extraction to the durian classification task. Early stopping was employed to halt training when validation performance plateaued, preventing unnecessary computations and mitigating overfitting (Moreno Escobar et al., 2023).

Throughout training, accuracy and loss metrics were recorded for both training and validation sets. The learning behaviour was analysed by plotting training and validation accuracy/loss curves to visualize improvements and detect overfitting trends. Additionally, the final model's performance was assessed using a separate test dataset, which consisted of unseen images to evaluate real-world classification accuracy. A confusion matrix was generated to analyse class-wise performance and identify misclassification patterns. This helped in understanding which durian types were most commonly misclassified and in optimizing the model further if needed. The combined evaluation using accuracy graphs and the confusion matrix provided a comprehensive assessment of the model's reliability. Finally, the trained model was saved in HDF5 format for future inference and deployment in practical applications, such as automated durian sorting systems or mobile applications for durian recognition.

4. Results and Discussion

The performance of the VGG16-based CNN model in classifying Monthong, Chanee, and Kan Yao durians, along with non-durian images, was evaluated over 20 epochs. Figure 1 illustrates the training and validation accuracy trends, as well as the corresponding loss curves. The training accuracy steadily increased, reaching approximately 92%, while the validation accuracy exhibited fluctuations, stabilizing around 60%. The training loss decreased consistently, indicating effective learning of patterns, while the validation loss demonstrated fluctuations, suggesting potential overfitting. The gap between training and validation accuracy, particularly in later epochs, indicates that the model performed well on the training data but struggled with generalization, highlighting a need for additional tuning, such as regularization or dropout techniques, encouraging the model to generalize better rather than relying too much on specific training examples.

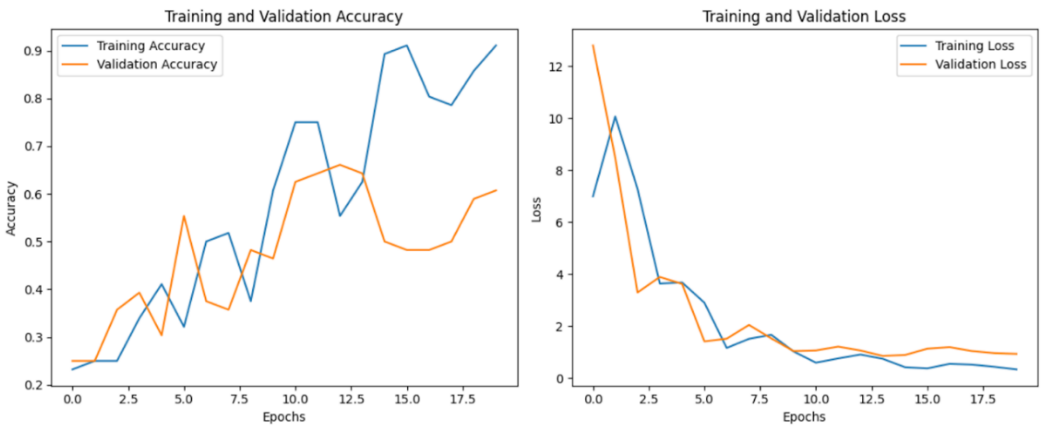

Figure 1 Training and validation accuracy and loss curves for the VGG16 model

The model was trained for 20 epochs; however, convergence remained an issue. Validation accuracy plateaued after approximately the 12th epoch, and further training did not improve generalisation, indicating potential overfitting. The relatively low test accuracy of 67.3% suggests that the current dataset may not provide sufficient diversity, especially for visually similar varieties such as Kan Yao.

To further analyse the model's classification performance, a confusion matrix was generated, as shown in Figure 2. The model achieved high accuracy in classifying Chanee and Monthong durians, correctly identifying 9 out of 11 instances for each class. However, Kan Yao durians were frequently misclassified, with the model predicting them as Monthong or non-durian in several cases. This suggests that Kan Yao durians share visual similarities with other categories, making differentiation more challenging. Meanwhile, the non-durian class performed relatively well, with 8 out of 11 correct classifications, indicating that the model effectively distinguished durians from other objects.

The overall test accuracy of the model was 67.3%, reflecting a moderate level of classification effectiveness. The misclassification patterns observed in the confusion matrix suggest that additional strategies could improve model performance. These include expanding the dataset size, applying more robust augmentation techniques (such as brightness adjustments, rotations, and contrast normalization), and fine-tuning hyperparameters to enhance the model's generalization. Additionally, employing transfer learning from models pre-trained on fruit classification datasets may improve feature extraction and boost accuracy. Despite high training accuracy, the moderate test accuracy highlights the challenge of overfitting and the need for additional data diversity and model regularisation techniques.

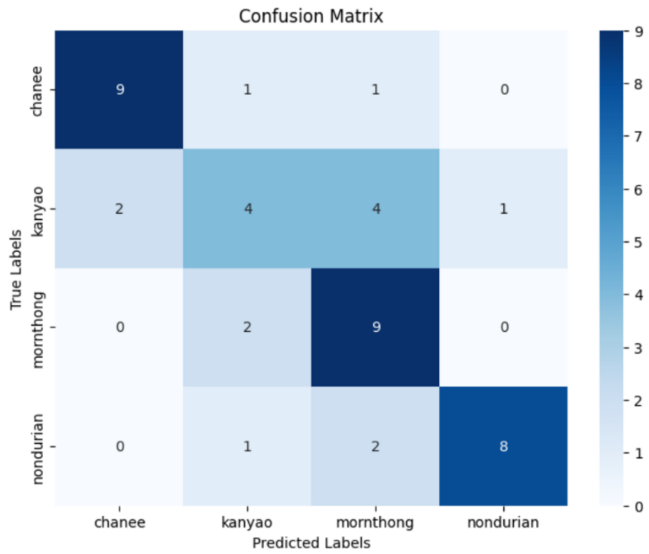

Figure 2 Confusion matrix of the VGG16 model for durian classification

Figure 3 Sample Predictions of VGG16 for Durian Classification

Manual classification of durian varieties is time-consuming, requires expert knowledge, and is prone to human error. By automating this process using CNNs, significant reductions in labour and classification time can be achieved, making this technology beneficial for exporters, quality assurance teams, and even individual sellers. A comparison with Diana et al. (2025), who used VGG16 to classify Musang King, Black Thorn, and D24 durians, provides additional insight into the model's limitations. Their study achieved a classification accuracy of 56.64%, which is lower than the results obtained in this study. However, both sets of results reinforce the notion that VGG16 alone may not be the most optimal CNN model for durian classification. The shared challenge between both studies lies in the subtle visual similarities between durian varieties, which require more refined feature extraction capabilities than VGG16 provides. Although the previous work demonstrated Xception's superior performance in durian classification (56.64% accuracy with VGG16 and 92% with Xception), this study opted for VGG16 due to its simplicity, reliability, and ease of fine-tuning. To further explore this, we also tested the Xception model using the same dataset and training conditions. However, contrary to prior studies, our implementation of Xception only achieved 53% accuracy, performing worse than VGG16. This suggests that while Xception has demonstrated strong classification performance in some studies, its effectiveness may depend on dataset characteristics, preprocessing techniques, or specific hyperparameter tuning. VGG16's structured design, with stacked convolutional layers and max pooling, makes it more interpretable and adaptable, particularly when working with limited datasets. Additionally, its compatibility with pre-trained weights facilitates transfer learning, reducing the need for extensive data collection. Given the subtle visual similarities among durian varieties, a model with strong spatial feature extraction was necessary. Its compatibility with pre-trained ImageNet weights also facilitated transfer learning, reducing data requirements (Howard et al., 2020). While Xception may provide higher accuracy in some cases, VGG16's generalization ability and ease of use make it the preferred choice.

Moreover, while VGG16 served as a solid baseline, the study acknowledges its limitations in distinguishing between subtle features. Further experimentation with attention mechanisms or ensemble models may reveal more robust classifiers. These developments could pave the way for deployment in real-time classification systems for farmers and retailers. Future research should focus on several key areas to enhance durian classification accuracy. Increasing the dataset size with a more diverse range of images under varying lighting conditions, angles, and backgrounds could help improve model generalization and reduce misclassification, particularly for Kan Yao durians (Wang et al., 2023). Implementing advanced augmentation techniques, such as adaptive histogram equalization, GAN-generated synthetic images, or domain-specific feature extraction, could further refine classification performance. Additionally, experimenting with hybrid models that integrate VGG16 with attention mechanisms or transformer-based architectures may enhance feature learning and differentiation between visually similar durian varieties (Zhang et al., 2024). Hyperparameter optimization, including learning rate scheduling and dropout regularization, should be explored to mitigate overfitting and improve validation accuracy. Future studies may also benefit from a comparative analysis of additional CNN architectures, such as EfficientNet or ResNet, to determine their suitability for durian classification. Lastly, integrating mobile-based real-time classification applications could provide practical benefits for consumers and farmers, making durian identification more accessible and efficient in real-world settings.

5. Conclusion

This study demonstrated the feasibility of using VGG16-based convolutional neural networks for classifying three major Thai durian varieties Monthong, Chanee, and Kan Yao along with non-durian images. The key contribution of this work is demonstrating the applicability of VGG16 to the classification of Thai durians, which lays the groundwork for future tools that assist in quality control, reduce labour costs, and enhance consumer trust in durian products. The model achieved a training accuracy of approximately 92%, but its validation accuracy stabilized around 60%, with an overall test accuracy of 67.3%. The confusion matrix revealed that Monthong and Chanee were classified with relatively high accuracy, while Kan Yao was frequently misclassified, likely due to visual similarities with other varieties. A comparative analysis with previous studies showed that VGG16 has been effective in fruit classification, though its performance can be limited when distinguishing visually similar categories. Interestingly, while prior research indicated that Xception outperformed VGG16 in durian classification, our implementation of Xception on the same dataset achieved only 53% accuracy, reinforcing the need for further dataset-specific optimizations. These findings highlight the potential of CNN-based classification for durians while also emphasizing the need for dataset expansion, enhanced augmentation techniques, and hybrid model approaches to improve accuracy. Future research should explore transformer-based architectures, optimized hyperparameters, and real-time classification applications to further refine durian identification, ultimately benefiting consumers and supporting Thailand's durian industry.

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