Indonesian Journal of Data and Science

Volume 6 Issue 3
ISSN 2715-9936
https://doi.org/10.56705/ijodas.v6i3.355

Research Article

Transfer Learning with VGG-16 for Image Classification of Endemic Papuan Orchids

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Received 28 November 2025; Accepted 30 December 2025; Published 31 December 2025

Abstract:
This study applies a transfer-learning approach using the VGG16 architecture to classify three Papuan endemic orchid species—Dendrobium spectabile, Dendrobium lineale, and Dendrobium mirbelianum. A total of 810 field-photographed images were collected, followed by preprocessing and data augmentation to enhance data diversity. The VGG16 model pretrained on ImageNet was used as a fixed feature extractor by freezing its convolutional layers and removing the fully connected layers, while a custom classification head was added to distinguish among the three species. Experimental results demonstrated a validation accuracy of 94.44% and a macro-average F1-score of 0.94, confirming the robustness of the model under limited-data conditions. These findings suggest that transfer learning using VGG16 can effectively support orchid species recognition and serve as a foundation for developing AI-based biodiversity monitoring and conservation systems in Indonesia.

Keywords: Papuan endemic orchids, Classification, Convolutional Neural Network, Transfer Learning, VGG16.

1. Introduction:

Endemic plant species occur naturally and exclusively within specific geographic regions, showing strong adaptation to their native environments, yet their limited distribution makes them highly vulnerable to habitat disturbances [1], [2]. Among these endemic groups, orchids (*Orchidaceae*) represent one of the most diverse and ecologically significant plant families. Papua is recognized as one of the richest regions for orchid biodiversity, hosting approximately 2,869 species, most of which are believed to be endemic to the island [3]. Despite this richness, scientific exploration and documentation of orchids in Indonesian Papua remain limited, resulting in many species that are poorly known or even undocumented. Moreover, habitat loss due to regional development, deforestation, and environmental degradation increasingly threatens these native orchids, emphasizing the urgency of conservation and comprehensive taxonomic studies [3]. Recent advances in plant phenotyping using convolutional neural networks (CNNs) have demonstrated that such models can successfully handle complex plant image classification tasks under variable conditions [4].

The VGG16 architecture was selected because of its proven capability in flower image classification tasks, where its hierarchical convolutional structure efficiently captures complex color and texture variations among floral species. A recent international study (2022) demonstrated that an enhanced version of VGG16 (E-VGG16) achieved high accuracy in flower classification, highlighting its robustness and suitability for fine-grained visual recognition tasks [5]. This evidence supports the use of VGG16 for Papuan orchid datasets, which share similar fine morphological variations and color diversity as other flower species. Given these strengths, VGG16 is expected to generalize well even under limited data conditions, providing a robust baseline before exploring more recent architectures.

This research aims to implement a pretrained VGG16 model using ImageNet weights for the classification of Papuan endemic orchid species without applying any fine-tuning or additional optimization. It also seeks to evaluate the model's performance under limited dataset conditions and to assess its effectiveness through standard metrics such as accuracy, precision, recall, and F1-score, establishing a baseline for orchid species classification [1].

The main research question is: *Can transfer learning using the VGG16 architecture effectively classify Papuan endemic orchid species under limited dataset conditions?* The alternative hypothesis (H_1) states that transfer learning with VGG16 will significantly improve classification performance compared to training from scratch, due to the pretrained model's hierarchical feature extraction capability. The null hypothesis (H_0) assumes that transfer learning with VGG16 will not produce significant classification improvement under data limitations.

The scope of this study focuses on image-based classification of several Papuan endemic orchid species, primarily through visual features such as floral structures. The procedures include data collection, preprocessing, augmentation, application of transfer learning using VGG16, and performance evaluation based on standard metrics. Field validation (e.g., *in situ* botanical confirmation) and molecular analyses are excluded; thus, taxonomic certainty depends solely on image-based classification. The limited dataset size constrains model generalization, and only one architecture (VGG16) is explored without comparison to more recent models such as EfficientNet or Vision Transformers [6].

This research contributes by evaluating the pretrained VGG16 model (using ImageNet weights without fine-tuning or internal optimization) to test its capability in classifying Papuan endemic orchid species under limited dataset conditions, and by establishing baseline performance using accuracy, precision, recall, and F1-score. These findings align with prior studies indicating that pretrained VGG16 models can achieve competitive results even without fine-tuning [7].

The remainder of this article is structured as follows: Section 1 introduces the research background and objectives; Section 2 describes the methodology, including dataset preparation, model implementation, and evaluation metrics; Section 3 presents and discusses the experimental results; and Section 4 concludes the study with implications and future research recommendations.

2. Method:

This study employs an experimental quantitative research design to assess the performance of a transfer learning–based deep learning model for orchid image classification. The objective is to evaluate the performance of a transfer learning–based VGG16 model to classify three endemic orchid species from Papua. The methodological workflow includes data collection, preprocessing, augmentation, model training, and evaluation, as illustrated in **Figure 1**, which presents the research flow of the proposed method. The process begins with dataset collection from orchid specimens, followed by image preprocessing and augmentation to improve data diversity. Subsequently, model training is performed using the VGG16 transfer learning architecture, and performance is evaluated through standard metrics.

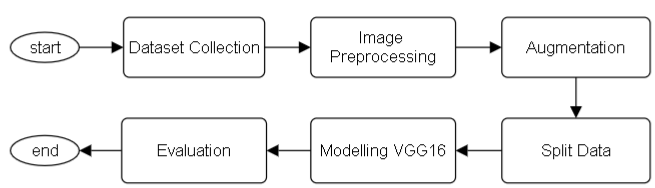

Figure 1. Research flow of the proposed method

Deep learning is a subfield of machine learning that mimics the structure and function of the human brain through artificial neural networks. These networks consist of interconnected neurons that process and learn from large amounts of unstructured data. Through repeated training, deep learning models can automatically extract important features without manual preprocessing [8]. Transfer Learning (TL) is a machine learning technique that reuses pre-trained models to solve new but related problems. Instead of training a model from scratch, TL leverages previously learned features to improve accuracy and reduce computational cost [9]. This approach is widely adopted in Convolutional

Neural Networks (CNNs), where architectures such as VGG16 are adapted for image classification tasks. CNNs are effective in plant image classification due to their ability to capture spatial and textural patterns, including petal morphology and color gradients. The performance of CNN-based models depends heavily on dataset quality and diversity, while transfer learning enhances accuracy by leveraging pretrained knowledge. The VGG16 architecture, consisting of 16 convolutional and fully connected layers, demonstrates strong performance in plant image classification. Its use of 3×3 convolutional filters allows it to capture fine-grained and hierarchical visual features crucial for distinguishing orchid species [10]. Recent studies have confirmed that VGG16 remains one of the most robust transfer learning backbones for limited plant datasets due to its stable gradient propagation and balanced computational efficiency [11].

This study utilized primary data collected directly from orchid plants in Papua. The three orchid species used were *Dendrobium spectabile*, *Dendrobium lineale*, and *Dendrobium mirbelianum*. A total of 810 images were captured, consisting of 270 images per class, categorized based on color and texture. The dataset was divided into 80% for training and 20% for validation to maintain data balance and ensure reliable performance evaluation. Images were captured under natural lighting conditions to preserve the true color and morphological details of the flowers. The images were selected based on clarity, focus, and visibility of floral structures. Blurred or incomplete images were excluded to maintain data quality. To enhance dataset representativeness, image acquisition was performed from multiple angles to capture intra-class variation [12]. Additionally, several studies have demonstrated that smartphone-based image capture can provide high-quality, cost-effective, and flexible data collection for plant classification and phenotyping research, particularly in field conditions [13].

Table 1. Distribution of Papua Endemic Orchid Dataset by Class

Class	Number of Images
Dendrobium spectabile (Anggrek Kribo)	270
Dendrobium mirbelianum (Anggrek Emas)	270
Dendrobium lineale (Anggrek Kelinci)	270
Total	**810**

Figure 2. Sample images from the dataset: (A) *Dendrobium spectabile*, (B) *Dendrobium mirbelianum*, (C) *Dendrobium lineale*.

The experiments were conducted using Google Colaboratory (Colab), a cloud-based computational platform supporting GPU acceleration (NVIDIA Tesla T4). The research utilized Python 3.10 with the TensorFlow 2.x (Keras API) framework for model development and training. Supporting libraries included NumPy (for numerical operations), Matplotlib and Seaborn (for visualization), and Scikit-learn (for evaluation metrics). The dataset was stored in Google Drive and accessed directly from Colab for reproducibility. Image preprocessing and augmentation were implemented through Keras utilities with random flipping, rotation, translation, shearing, and zooming. All images were normalized to the [0, 1] range. The VGG16 architecture from TensorFlow Applications was employed with *include_top=False* to act as a feature extractor. The base convolutional layers were frozen, while a custom classifier — Flatten → Dense → Softmax — was trained for multi-class orchid classification. This approach follows the feature extraction strategy, where the convolutional base of a pre-trained model is reused to leverage learned visual representations from large-scale datasets such as ImageNet, thus reducing computational cost and minimizing overfitting when working with limited data [14].

Orchid images were collected through field observation in the natural habitats of Papua using an iPhone 11 camera. Each image was examined for sharpness and completeness of the floral display. Blurred, partially cropped, or unclear images were eliminated. The remaining images were then categorized by species and manually verified to ensure dataset quality and consistency. To improve visual clarity and emphasize the main subject, the background of each image was slightly blurred during preprocessing. This step helped reduce background noise and enhance feature visibility for the orchid structures [15].

Model evaluation was conducted to assess the performance and generalization capability of the transfer learning–based VGG16 architecture in classifying orchid species. The evaluation used accuracy, precision, recall, and F1-score [16]. Accuracy quantified the overall correctness of predictions, precision and recall measured class-wise identification, and F1-score provided a harmonic mean for balanced assessment—a confusion matrix visualized misclassification patterns [17]. To obtain a more comprehensive performance assessment, Receiver Operating Characteristic (ROC) and Area Under Curve (AUC) values were computed per class, while training and validation loss curves were analyzed to detect potential overfitting [18].

In addition, the performance of this model is evaluated in reference to the comparative study *Efficiency in Orchid Species Classification: A Transfer Learning-Based Approach* [19], which achieved approximately 96% accuracy using a transfer learning framework for orchid species recognition. This prior research serves as a baseline benchmark, reinforcing the relevance of using VGG16 as a robust architecture for limited-data orchid classification.

3. Result and Discussion:

Result

The experimental results demonstrate the effectiveness of the transfer learning–based VGG16 architecture in classifying three endemic orchid species from Papua: *Dendrobium spectabile*, *Dendrobium lineale*, and *Dendrobium mirbelianum*. During training over 50 epochs, the model showed steady convergence—training accuracy increased to 84.78%, while validation accuracy reached 94.44%, indicating a well-generalized learning process. The training and validation loss curves exhibited a consistent downward trend, confirming stable gradient updates and the absence of overfitting.

In comparison, a recent study employing a transfer learning–based ResNet34 architecture for orchid species classification utilized a substantially larger dataset comprising 12,227 images of 12 orchid classes obtained through network and field photography. Their framework involved analyzing inter-dataset relationships and fine-tuning frozen convolutional layers to optimize training efficiency, achieving a classification accuracy of 96.16% and demonstrating reduced training time and overfitting risk [19].

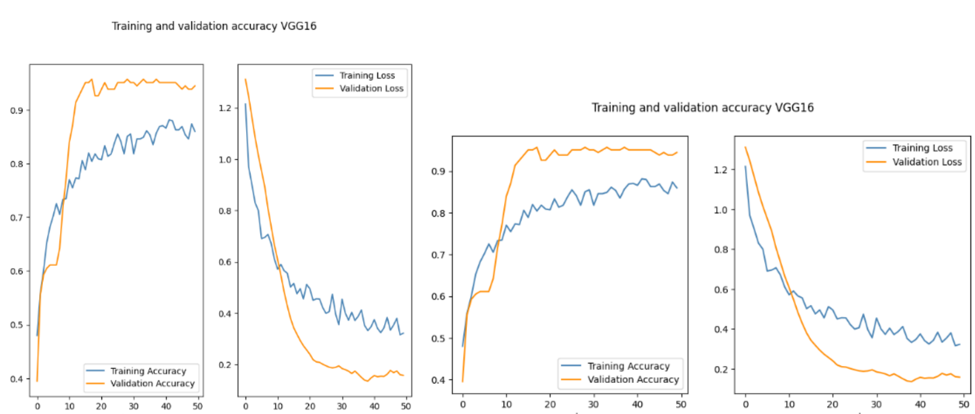

Figure 3. Training and validation accuracy and loss curves for VGG16-based orchid classification

Figure 3 illustrates the training–validation accuracy and loss curves throughout the learning process, showing that both curves reached a stable plateau after approximately 40 epochs. This visualization emphasizes that the model effectively reduced both bias and variance components of error during optimization.

Table 2. Performance metrics of the transfer learning–based VGG16 model for classifying three endemic orchid species from Papua.

	Precision	Recall	F1-Score	Support
Anggrek Kribo	1.00	0.94	0.97	54
Anggrek Emas	0.90	0.96	0.93	54
Anggrek Kelinci	0.94	0.93	0.93	54
Macro avg	0.95	0.94	0.94	162
Weighted avg	0.95	0.94	0.94	162

Table 2 presents the detailed class-wise performance of the model based on four evaluation metrics—accuracy, precision, recall, and F1-score. Additionally, **Figure 4** shows the confusion matrix that visually represents the model's ability to distinguish among the three-orchid species with minimal misclassification.

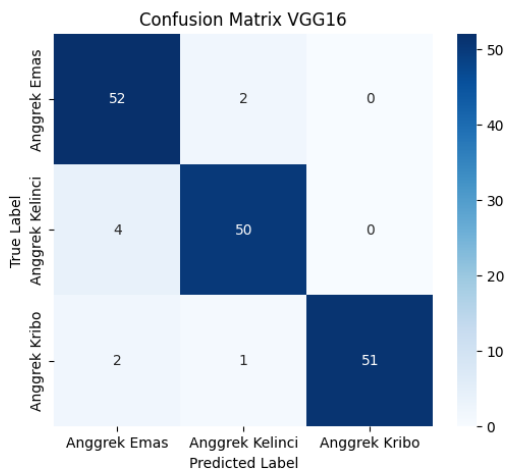

Figure 4. Confusion matrix illustrating classification performance for the three-orchid species.

The macro-average F1-score of 0.94 indicates that the model maintained balanced predictive performance across all classes. The high precision and recall scores, especially for *Dendrobium spectabile* (precision = 1.00, recall = 0.94), reflect that the model effectively captures the discriminative morphological characteristics of the species. The confusion matrix also confirmed that misclassification primarily occurred between visually similar classes, which is common in plant image recognition tasks due to overlapping visual traits such as color and petal curvature. This pattern is consistent with recent research in plant species identification, where VGG16-based transfer learning models demonstrated strong capability in distinguishing subtle morphological similarities across different plant classes [20].

The most significant finding is that the transfer learning approach using VGG16 achieved high classification accuracy despite the limited dataset size. This demonstrates that pre-trained convolutional layers from ImageNet can effectively extract discriminative visual features for orchid classification without requiring additional fine-tuning or architectural modifications. Similar results were observed in studies using VGG16 as a fixed feature extractor for plant leaf recognition, where the model successfully identified species under data-constrained conditions [21]. These findings confirm that transfer learning remains a dependable strategy for biodiversity image analysis, particularly when dataset availability is limited.

Discussion

The results confirm that transfer learning using VGG16 effectively enhances classification accuracy for small and domain-specific datasets, such as Papuan orchid images. This finding is consistent with previous studies reporting that pre-trained CNN models significantly improve plant classification performance when training data is limited [1]. The high accuracy and balanced F1-score demonstrate that the model could capture essential visual cues — including petal structure, venation, and chromatic texture — despite environmental variations in the dataset. The combination of data augmentation and batch normalization contributed to model stability and prevented overfitting, as also reported in recent studies on plant species recognition [22]. Moreover, a 2024 study by Li et al. demonstrated that CNN models with transfer learning and adaptive normalization layers yield superior stability compared to classical architectures such as AlexNet and InceptionV3 [23].

These results are aligned with earlier investigations that employed transfer learning for orchid and other plant classifications, where VGG-based architectures achieved accuracy above 90% even with limited samples [21]. Compared to conventional machine learning approaches such as SVM or shallow CNNs, the proposed model achieved superior performance while requiring less training time due to the reuse of pre-trained convolutional layers. These findings strengthen the evidence that transfer learning remains an optimal strategy for biodiversity recognition tasks, particularly when dataset collection is constrained [17]. Recent work also suggests that combining transfer learning with Vision Transformer backbones could further improve generalization on complex floral datasets [24].

From a practical perspective, the developed model serves as a foundational prototype for digital biodiversity monitoring systems, supporting conservation efforts and automated identification of Papuan orchid species. A demonstration system was implemented as a web-based prototype using the Flask framework, allowing users to upload orchid images and receive classification results along with confidence scores. **Figure 5** presents the interface of this prototype, which offers an intuitive and accessible demonstration tool for orchid recognition. Although the application has not been fully deployed, similar web-based systems have been increasingly adopted in ecological informatics for species tracking and conservation support.

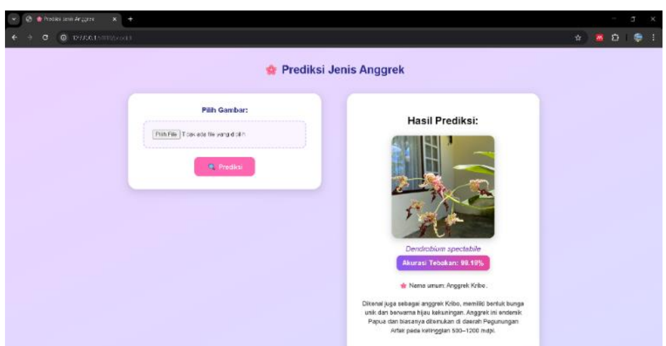

Figure 5. Prototype of the web-based application developed using the Flask framework.

However, this study has certain limitations. The dataset comprised only 810 images from three species, which limits the model's generalization to other orchid taxa or lighting conditions. Furthermore, the current implementation focuses only on RGB-based visual features without integrating spectral or environmental metadata. Future work should incorporate larger datasets and additional species, as well as evaluate the use of newer architectures such as EfficientNetV2 or Vision Transformers (ViT) for improved accuracy and robustness [16]. It would also be valuable to apply explainable AI techniques to interpret the visual patterns used by the model, improving biological interpretability and trustworthiness in ecological applications [25].

Future research should explore the integration of multi-modal data (such as infrared and hyperspectral imaging) to enhance the robustness of orchid identification systems. Incorporating explainable deep learning frameworks may also provide insight into the botanical relevance of learned features, making the system more transparent for researchers and conservationists. Additionally, expanding the study to include mobile deployment on edge devices would enable field biologists to perform real-time species recognition without requiring constant network connectivity.

4. Conclusion:

This study validated the effectiveness of transfer learning using the VGG16 architecture for classifying three Papuan endemic orchid species—*Dendrobium spectabile*, *D. lineale*, and *D. mirbelianum*. The model achieved a validation accuracy of 94.44% and a macro-average F1-score of 0.94, demonstrating that VGG16 successfully captured key visual patterns such as petal morphology and color gradients even with limited data. These findings align with agricultural image analysis research, confirming that transfer learning remains a robust approach under data-scarce conditions [1].

The use of data augmentation and batch normalization ensured stable convergence and balanced classification, supporting the hypothesis that transfer learning combined with regularization can mitigate small-dataset challenges in ecological image classification [26]. This work presents one of the first deep learning–based frameworks for Papuan orchid recognition and offers a methodological foundation for applying CNN-based transfer learning to tropical flora in biodiversity monitoring and digital taxonomy [27].

Despite these strengths, the study is limited by dataset size and species scope. Future work should expand the dataset, include additional environmental variations, and explore advanced architectures such as EfficientNetV2 or Vision Transformers (ViT), as well as lightweight models for mobile, real-time classification [28].

Acknowledgments:

The author would like to express sincere gratitude to Mr. Christian Dwi Suhendra, S.T., M.Cs, and Dr. Ir. Agustina Y. S. Arobaya, M.App.Sc for their invaluable guidance, advice, and continuous encouragement throughout this research. The author also extends appreciation to all friends and colleagues who have provided support, cooperation, and insightful discussions that greatly contributed to the completion of this work.

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