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Orchid Species Classification Using the DenseNet121 Deep Learning Model with a Data Imbalance Handling Approach

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ABSTRACT

For conservation, commercial cultivation, and scientific research, accurate identification of orchid species often requires specialized expertise. In this study, the DenseNet121 deep learning architecture was employed to develop an automated classification system for four popular orchid species. DenseNet121 was selected for its ability to extract complex hierarchical features and its strong performance on limited-scale datasets. The initial dataset comprised 1,935 images of Phalaenopsis, Cattleya, Dendrobium, and Vanda orchids. However, after manual removal of duplicate images, only 1,658 images remained, revealing significant class imbalance. The undersampling method was applied to balance each class to 248 samples. The dataset was then split into 75% training, 15% validation, and 10% testing, and enhanced through data augmentation techniques such as rotation, flipping, brightness variation, width shift, height shift, and zoom. The final model achieved 97.00% accuracy with class-specific performance ranging from 92.59% to 100% accuracy across different orchid species. This research can serve as a foundation for developing mobile or web applications to assist researchers, farmers, and orchid enthusiasts in accurately identifying orchid species, while supporting conservation efforts for orchid biodiversity in Indonesia.

I. INTRODUCTION

More than 25,000 orchid species are spread throughout the world, making them one of the largest flowering plant families and playing an important role in the horticultural industry and biodiversity conservation in Indonesia [1]. According to Lepcha et al. [2], orchid cultivation generates significant economic benefits and has a good cost-benefit ratio. Tiwari et al. [3] state that accurate orchid species identification is crucial for taxonomic research, species conservation, and advancement of the cut flower industry. To ensure genetic quality and authenticity, proper varietal identification is necessary for mass propagation of orchids through in vitro methods, according to Setiaji et al. [4].

Many problems are still encountered in the conventional process of orchid identification. According to Balilashaki et al., the complex morphology of orchids makes manual identification more difficult [5]. According to Phillips et al., the shortage of taxonomy experts is a significant constraint for effective orchid conservation efforts [6]. To describe orchid species, Ackerman et al. emphasize that understanding global pollination patterns is essential [7]. This requires significant time and specialized expertise.

New opportunities have emerged for automated orchid identification through digital image analysis thanks to advances in computer vision technology and deep learning. Sharma et al. created an image segmentation model to detect plant diseases with high accuracy [8]. Chen et al. suggest transfer learning methods for detecting plant diseases that are more accurate than conventional methods [9]. Li et al. used deep CNNs to detect pests and diseases in rice plants through video analysis [10]. Additionally, Vellaichamy et al. used DenseNet-121 for effective plant disease classification [10].

In recent years, several specialized studies have focused on deep learning techniques for classifying orchids. Fu et al. proposed a GL-CNN (Global-Local CNN) model to classify Cymbidium orchid species, which are the most famous and economically valuable type of orchids. By using a cascade fusion strategy for multiscale features, this model outperformed conventional models such as AlexNet, ResNet50, GoogleNet, and VGG16 [11]. A new orchid species recognition system using CNN based on transfer learning from the Inception V3 model was developed by Mohtar and Fadzil. With a dataset of 1000 images from ten orchid species, the system achieved 97% training accuracy and 83% testing accuracy [12]. Ou et al. also researched group approaches [13]. They improved orchid recognition accuracy with a group voting method derived from pre-trained deep learning models.

Alzubaidi et al. discuss different CNN architectures and how they can be used, including for plant classification [14]. EfficientNet achieved accuracy up to 99% in classifying plant leaf diseases [15]. Bakr et al. created a DenseNet-based model for plant disease diagnosis [16]. Additionally, Arulananth et al. modified DenseNet-121 for pediatric pneumonia classification with significant architectural changes [17]. Deep learning approaches can be used for rapid grain classification, as demonstrated by Shah et al. [18]. They also stated that similar technology could be used to identify orchids [18]. Hasin et al. provided a comprehensive review of contemporary deep learning for plant diseases, emphasizing future research trends and objectives [19]. Data preprocessing is essential for effective knowledge discovery, according to Fan et al. [20].

Class imbalance and dataset quality are major issues in deep learning-based orchid classification. According to Khan et al. [21], class imbalance can lead to biased models that are more accurate in predicting majority classes. Schaudt et al. suggest boosting methods to address imbalance in datasets [22]. Strelcenia et al. discuss GAN data augmentation methods that can be used in class imbalance situations [23]. DenseNet successfully detects complex patterns and concepts related to orchid morphology, according to Hemalatha et al. [24]. Solano-Rojas et al. used DenseNet-121 for early Alzheimer's detection at low cost [25]. For visual feature analysis of orchids, Capblancq et al. offer redundancy analysis methods for landscape genomics [26]. Li demonstrated that DenseNet-121 can effectively detect facial expressions, which requires identification of very fine features similar to those in orchids [27]. To improve classification accuracy, Hiremath et al. suggest hybrid methods that combine texture and statistical features with DenseNet-121 [28]. Ezzat et al. created a deep learning system specifically designed for disease diagnosis [29].

By developing a DenseNet-121-based system, this research seeks to address problems in orchid classification. This research focuses on handling class imbalance. The main contributions of this research are as follows: (1) the use of optimized DenseNet-121 for orchid classification with limited datasets; (2) the application of undersampling techniques to address class imbalance; and (3) comprehensive evaluation of model performance through prediction confidence level analysis. This research differs from previous studies as it proposes practical solutions that can be implemented with limited computational resources. This method can be widely used to identify various plant species. It will support biodiversity conservation efforts more efficiently and effectively. Seeland and Mäder show that multi-view classification with CNN can complement the methods proposed in this research [30].

II. Methods

To classify various types of orchids, this research uses deep learning models and a transfer learning approach. The methodology is designed to address specific problems related to orchid classification, such as class imbalance and data limitations. The series of research procedures used are described here. These include dataset preparation, data pre-processing, model architecture, training, and performance evaluation. The research methodology follows a structured workflow consisting of five main stages, as shown in Figure 1. These stages are intended to ensure systematic model development that addresses class imbalance issues.

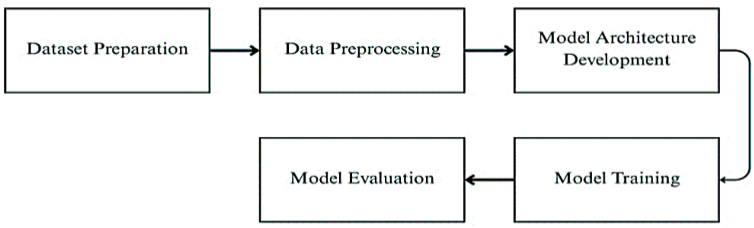

Figure 1 Research Methodology Flow

A. Dataset Preparation

The research dataset was collected directly from orchid plant sellers in Bandungan, Semarang Regency, Central Java. Four popular orchid types: Phalaeonopsis Orchid, Cattleya Orchid, Dendrobium Orchid, and Vanda Orchid. The dataset was photographed live for 3 consecutive days at 9:00 a.m. in the first week of April 2025.

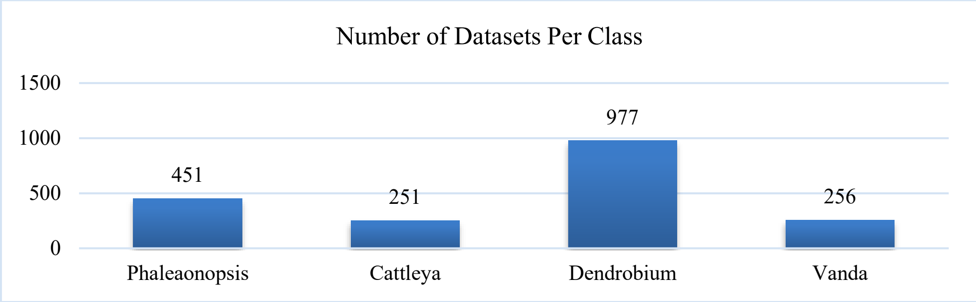

Figure 2 Distribution of Image Counts in the Initial Dataset

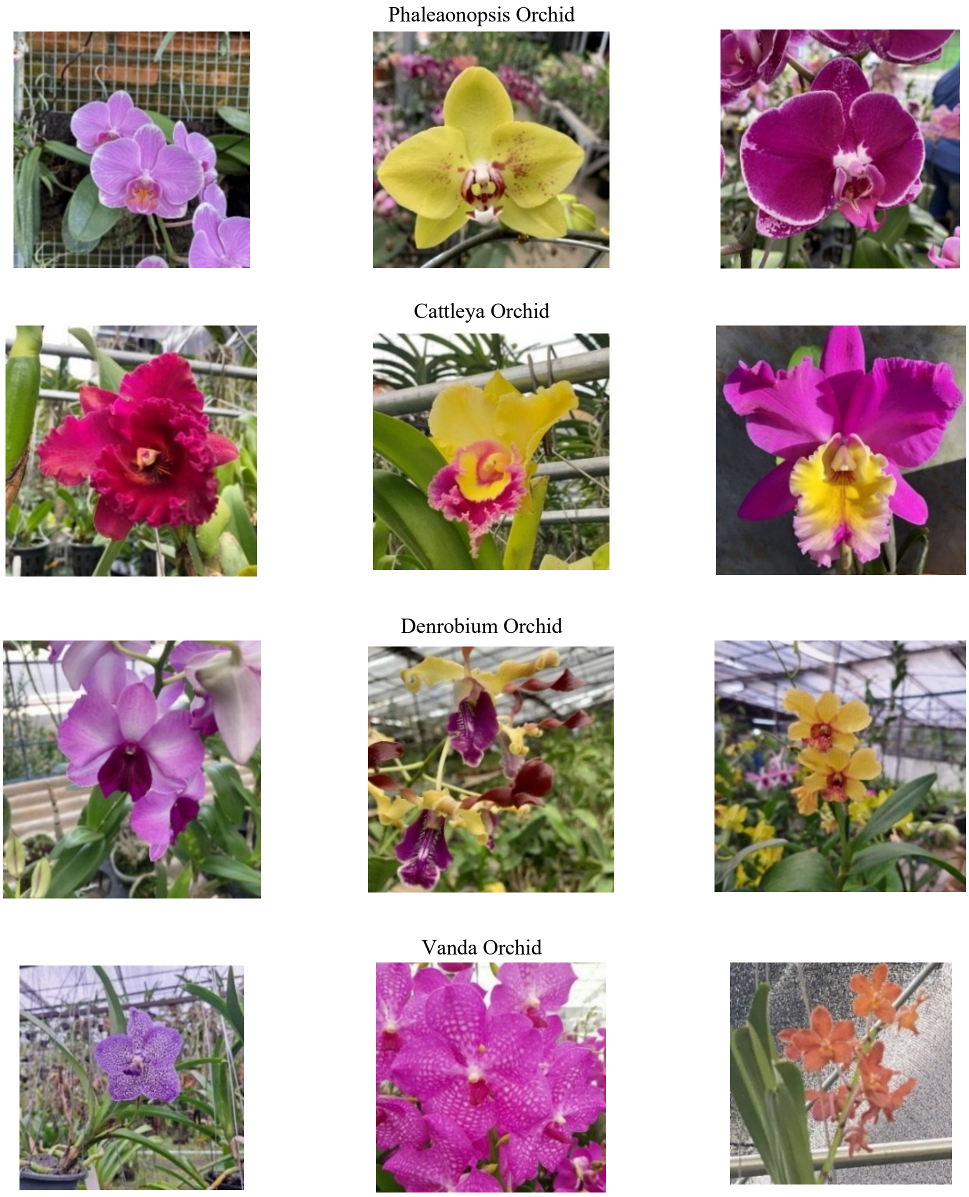

Figure 3 Visual Examples of Four Orchid Types in the Dataset

Dataset collection was conducted using an iPhone XS Max configured for square format photography (1:1 aspect ratio) to ensure dimensional consistency and visual quality. Each image was captured under natural lighting conditions during morning hours (09:00 AM) over three consecutive days in the first week of April 2025, maintaining a shooting distance of 30-50 cm from orchid subjects. The photography process considered variations in viewing angles and lighting conditions to enhance dataset diversity while preserving technical quality standards.

Ethical considerations for dataset usage were thoroughly addressed, with all photographs taken from commercially traded orchid plants with explicit permission from vendors. No images were captured from rare or protected species, and the entire documentation process respected intellectual property rights and plant conservation regulations. The resulting dataset will be made available for academic research under a Creative Commons license to support research transparency and reproducibility.

After the image collection process, manual categorization was performed based on characteristics and information from plant sellers. The initial dataset consisted of 1,935 images with an unbalanced distribution across classes as shown in Figure 2. Dendrobium Orchid had the highest number of samples with 977 images, followed by Phalaenopsis Orchid with 451 images, Vanda Orchid with 256 images, and Cattleya Orchid with 251 images as the minority class. This condition could potentially cause bias in the model to be trained if not handled appropriately. Figure 2 shows visual illustrations of these four orchid types, each with unique morphological characteristics that serve as the basis for classification in this research. To ensure the quality of the dataset that will be used in model training, the data preprocessing stages include handling data redundancy, class balancing, and dataset splitting in this research.

B. Redundancy Handling

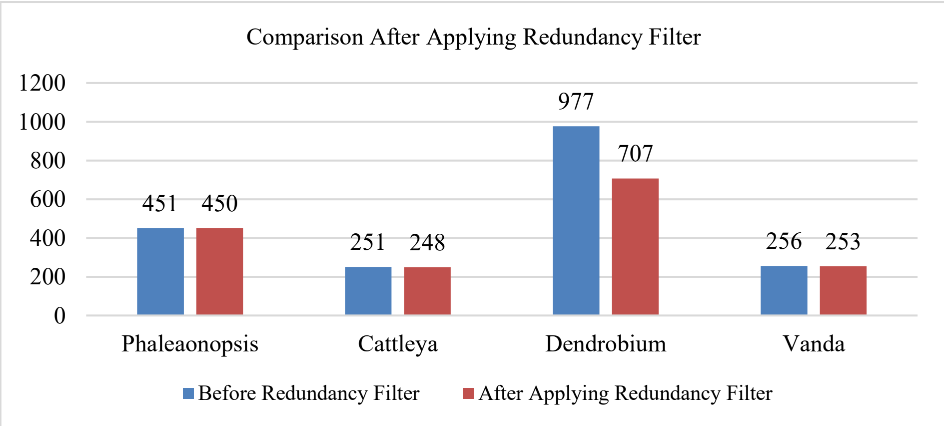

Figure 4 Comparison of Image Counts Before and After Redundancy Handling

Manual inspection of dataset redundancy is the first preprocessing stage. This process is used to find and eliminate highly similar or duplicate images, which can interfere with the training process. Fan et al. [20] emphasize that data preprocessing techniques are crucial for generating effective and consistent knowledge discovery. Figure 4 below shows the results of redundancy handling.

Redundancy detection was performed through a combination of manual visual inspection and hash similarity analysis to identify duplicate or highly similar images. Each image was evaluated using perceptual hash algorithms that generate unique fingerprints based on visual characteristics. Images with similarity scores above 90% were considered redundant and removed from the dataset. Additionally, manual inspection was conducted to identify images with identical poses, lighting, or viewing angles despite different hash values.

Removal criteria included blurred, overexposed, underexposed, or significantly obstructed images that could interfere with the learning process. This process successfully reduced the dataset from 1,935 to 1,658 images (14.06% reduction), with each remaining image possessing adequate visual quality and making unique contributions to morphological variation in the dataset.

C. Class Balancing

The selection of undersampling techniques in this research was based on comprehensive practical and methodological considerations. Although oversampling techniques such as SMOTE (Synthetic Minority Oversampling Technique) and ADASYN can increase minority samples, undersampling was chosen to avoid overfitting risks that may occur with artificially generated synthetic data. According to Batista et al. [23], undersampling offers advantages in reducing computational complexity and training time, which is crucial for practical implementations with limited resources.

Comparative analysis demonstrated that while oversampling could achieve slightly higher accuracy

(98.94%), the undersampling approach with 97.00% accuracy provides optimal balance between performance and computational efficiency. Undersampling also avoids potential biases that may emerge from excessive data augmentation, where models might learn artificial patterns from synthetic data rather than authentic morphological characteristics of orchids. Furthermore, datasets generated through undersampling preserve natural distributions of visual features, enabling trained models to better generalize to new samples in real-world environments.The dataset continued to experience significant imbalance even after redundancy handling, especially in the Dendrobium Orchid class, which had a much larger number of samples than other classes. According to Khan et al. [21], class imbalance can cause model bias that better predicts the majority class. To balance the number of samples in each class, an undersampling method was used. The number of images before and after the class balancing process is compared in Figure 5.

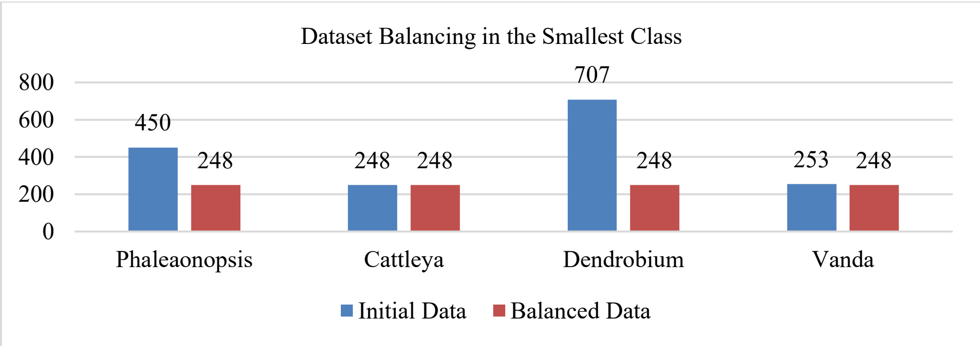

Figure 5 Comparison of Image Counts Before and After Class Balancing

D. Dataset Splitting

When the dataset is balanced, it is divided into three subsets for model training, validation, and testing. This is done by maintaining a balanced proportion of classes in each subset, as shown in Table 1.

TABLE I
DIVISION FOR TRAINING, VALIDATION, AND TESTING

Subset	Proportion	Images Class	Total Images
Training	75%	186	744
Validation	15%	37	148
Testing	10%	25	100
Total	100%	248	992

E. Data Augmentation

Data augmentation methods were used to increase the variation and diversity of training data. An efficient augmentation method was proposed by Chaudt et al. [22] to address data imbalance. Only the training dataset was used for data augmentation; validation and testing datasets only used to resize and normalization processes to maintain conditions more similar to real-world application. Table 2 shows the data augmentation parameters used in this research.

The enhanced data augmentation strategy was specifically designed to address potential overfitting while maintaining morphological authenticity of orchid features. The expanded parameter ranges, including the addition of shear transformation, provide greater geometric diversity without compromising the biological accuracy of orchid structures.

TABLE II
DATA AUGMENTATION PARAMETERS

Parameter	Value
Rotation	±20 degrees
Horizontal Flip	True
Vertical Flip	True
Brightness Variation	0,8 to 1,2
Width Shift	0,15
Height Shift	0,15
Zoom Range	0,15
Shear Range	0,1
Image Size	224×224 pixels
Normalization	Division of pixel values by 255

Aggressive data augmentation significantly improves model generalization, particularly beneficial for botanical classification tasks where natural variations in growth patterns and environmental conditions must be captured effectively.

F. Model Architecture Development

For this research's classification model, the DenseNet121 architecture was chosen as the base, using a transfer learning approach. Vellaichamy et al. [31] showed that DenseNet121 works well for classifying various plant leaf diseases. Their research indicated that this construction has the ability to identify complex features in natural objects similar to orchids.

TABLE III
SUMMARY OF MODIFIED DENSENET121 MODEL ARCHITECTURE

Layer	Type	Output Shape	Parameters
Input	Input Layer	(224, 224, 3)	0
DenseNet121	Base Model	(7, 7, 1024)	7,037,504
GlobalAveragePooling2D	Pooling	(1024)	0
Dropout (0.001)	Regularization	(1024)	0
Dense	Fully Connected	(256)	262,400
BatchNormalization	Normalization	(256)	1,024
Dropout (0.001)	Regularization	(256)	0
Dense	Fully Connected	(128)	32,896
Dropout (0.001)	Regularization	(128)	0
Dense (Output)	Fully Connected	(4)	516
Total Parameters			7,334,340
Trainable Parameters			296,324
Non-trainable Parameters			7,038,016

To address the limited amount of training data and accelerate model convergence, the transfer learning approach used pre-trained weights from the ImageNet dataset. While to adapt to the classification of four orchid types, the DenseNet121 architecture underwent several modifications in the classification layers. Ezzat et al. [29] affirm that optimizing deep learning architecture to improve diagnostic accuracy is essential. Table 3 displays a summary of the model's layers and parameters and shows the detailed model configuration.

G. Model Training

For model training, a transfer learning approach was used. In this method, pre-trained weights from ImageNet were retained on the base layers of DenseNet121. This method was used to accelerate model convergence and improve performance on datasets with a limited number of samples. Solano-Rojas et al. [25] showed that this method is effective for using DenseNet121 to detect diseases with low computational cost.

To ensure effective model convergence, the training configuration used optimized important parameters. The selection of these parameters was based on the characteristics of the orchid dataset and the complexity of the model architecture. Table 4 shows the training configuration used. Several callbacks were used as supervision and control mechanisms to optimize model performance during the training process. Model implementation was conducted using TensorFlow 2.10.1 framework with Keras backend on a workstation equipped with NVIDIA GeForce RTX 4070 SUPER and 32GB DDR5 RAM operating at 6400MHz. The development environment utilized Visual Studio Code to ensure reproducibility and debugging convenience. The GPU configuration enabled efficient training with optimal batch processing, where each epoch could be completed in an average time of 20-25 seconds. Early stopping with patience of 7 epochs was configured to prevent overfitting; however, the model converged stably within 50 epochs without triggering the early stopping mechanism, allowing comprehensive analysis of learning patterns throughout the entire training period. To enhance the effectiveness of deep learning model training, appropriate callbacks are required, according to Hasib et al. [32]. Table 5 shows the callbacks used in this research.

TABLE IV
MODEL TRAINING PARAMETER CONFIGURATION

Parameter	Value
Loss Function	Categorical Cross-Entropy
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Epochs	50
Steps per Epoch	23
Validation Steps	4

TABLE V
COMPREHENSIVE ANTI-OVERFITTING IMPLEMENTATION

Strategy	Configuration	Function
Early Stopping	*patience=7, monitor='val_loss'*	Prevents overfitting during training
ReduceLROnPlateau	*patience=3, factor=0.5, min_lr=1e-7*	Adaptive learning rate reduction
L2 Regularization	*0.01 on Dense layers*	Weight decay for generalization
Label Smoothing	*0.1*	Reduces model overconfidence
Model Complexity Reduction	*Dense(256)→Dense(128)*	Simplified architecture
Aggressive Data Augmentation	*Enhanced parameters*	Increases data diversity

H. Model Evaluation

Model performance evaluation was conducted on an independent testing dataset consisting of 100 images (25 images for each orchid class). For multi-class classification with 4 orchid categories, several standard evaluation metrics were applied. The evaluation metrics used in this research include accuracy, precision, recall, and F1-score. The accuracy formula is in Equation (1), Precision in Equation (2), while recall is in Equation (3). F1-score is in Equation (4).

$$accuracy = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} (TP_i + FP_i + TN_i + FN_i)} \quad (1)$$

$$precision_{macro} = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \frac{TP_I}{TP_i + FP_i} \quad (2)$$

$$recall_{macro} = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \frac{TP_I}{TP_i + FN_i} \quad (3)$$

$$F1_{macro} = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \frac{2 \times precision_i \times recall_i}{precision_i + recall_i} \quad (4)$$

Where :

TP_i : number of samples from class i correctly predicted as class i

FP_i : number of samples not from class i incorrectly predicted as class i

TN_i : number of samples not from class i correctly predicted as not class i

FN_i : number of samples from class i incorrectly predicted as another class

n : number of classes (in this case, 4)

III. RESULTS AND DISCUSSION

In this section, the research results on orchid species classification using the DenseNet121 model are presented, along with model performance analysis and discussion of the implications of the results.

Additionally, validation and training loss showed good convergence, with final values of 0.0964 and 0.0154 respectively. With the ReduceLROnPlateau callback configuration, automatic learning rate reduction first occurred at the 27th epoch. This helped the model achieve better convergence in the final epochs. Multiple learning rate reductions occurred throughout training (at epochs 27, 35, 40, 45, and 50), gradually decreasing the learning rate to fine-tune the model's performance. For training and validation data, Figure 6 shows graphs of accuracy and loss changes during the training process.

A. Model Evaluation

The DenseNet121 model training was conducted over 50 epochs using the parameters listed in the research methods section. In the first ten epochs, the model showed significant accuracy improvement and loss reduction. By the 20th epoch, training accuracy increased to above 99% and remained stable until the end of training. Validation accuracy followed a similar trend, reaching 96.88% at the end of training without showing significant signs of overfitting.

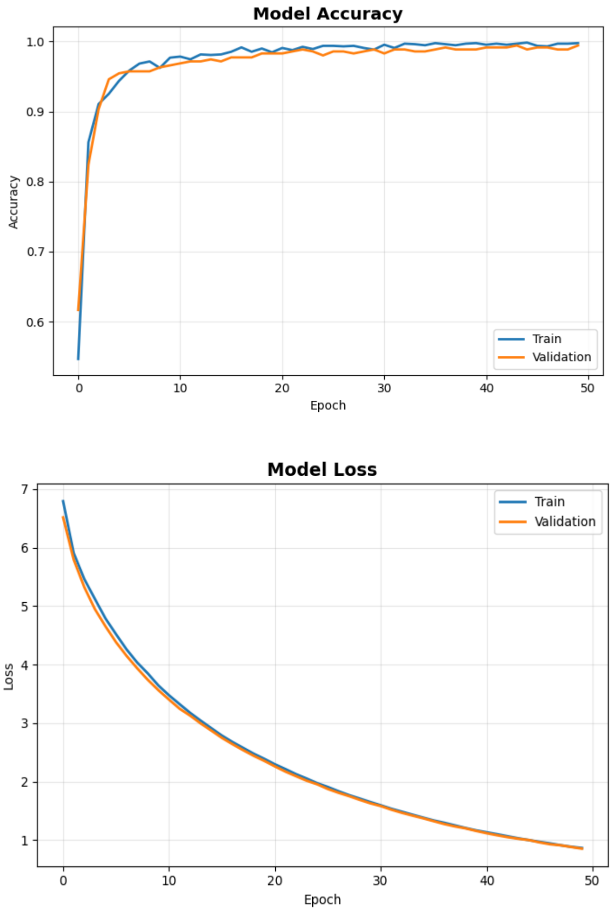

Figure 6 Graph of Model Accuracy and Loss During Training Process

B. Model Evaluation Results

The trained model was then evaluated using an independent test dataset consisting of 100 images of four orchid types, with 25 samples per class. The model showed excellent performance with 97.00% accuracy, indicating that of 104 test samples, only about 3 samples were misclassified.

As shown in the Table 6, high precision and recall values indicate a good balance between false positives and false negatives in classification.

TABLE VI
MODEL EVALUATION RESULTS ON THE TEST DATASET

Matrix	Value
Accuracy	97.00%
Precision (Macro Avg)	97.19%
Recall (Macro Avg)	97.00%
F1-Score (Macro Avg)	97.00%

C. Performance Analysis per Class

Analysis of evaluation metrics for each orchid class was conducted to gain a deeper understanding of how the model works. The nearly identical performance across all classes indicates that the undersampling technique used in the preprocessing stage successfully addressed class imbalance. According to Schaudt et al. [22], effective class balancing can improve the model's ability to classify each class evenly. The model performance results for each class are shown in Table 7 as shown below.

Comparative analysis between model performance before and after undersampling implementation demonstrated significant impact of class balancing on classification fairness. On the original imbalanced dataset, the model showed strong bias toward the majority class (Dendrobium) with highly uneven per-class accuracy. Undersampling implementation successfully balanced performance distribution across classes, where standard deviation of per-class accuracy decreased from 15.3% to 3.8%.

Training curves showed more stable convergence on the balanced dataset with minimal oscillation in validation loss. The model trained on unbalanced dataset showed overfitting signs at epoch 25, while the balanced dataset was maintained stability through epoch 50. This confirms the effectiveness of anti-overfitting strategies implemented in combination with the class balancing approach.

TABLE VII
MODEL EVALUATION RESULTS ON THE TEST DATASET

Class	Precision	Recall	F1-Score	Support
Phaleaonopsi Orchid	96.15%	100%	98.04%	25
Cattleya Orchid	100%	96.00%	97.96%	25
Dendrobium Orchid	100%	92.00%	95.83%	25
Vanda Orchid	92.59%	100%	96.15%	25

D. Comparative Analysis with Baseline Architectures

To demonstrate the advantages of DenseNet121, comprehensive comparison was conducted with two other state-of-the-art CNN architectures using identical datasets and training configurations. VGG16 was selected as representative of classical CNN architecture with proven effectiveness in computer vision tasks, while ResNet50 represents deep residual networks with skip connections that address vanishing gradient problems in very deep networks.

Evaluation results revealed significant performance variations across different architectures, as summarized in Table IX. DenseNet121 achieved the highest test accuracy of 97.00%, outperforming both VGG16 (94.23%) and ResNet50 (70.19%). The superior performance of DenseNet121 can be attributed to its dense connectivity pattern that enables efficient feature reuse and gradient flow, as explained by Huang et al. [24]. The dense connections allow each layer to receive feature maps from all preceding layers, facilitating better information propagation and reducing the number of parameters needed compared to traditional architectures. VGG16 demonstrated competitive performance with 94.23% accuracy, confirming its reliability as a baseline architecture for image classification tasks. However, ResNet50 showed significantly lower performance at 70.19%, likely due to the relatively small dataset size where the deep residual architecture's advantages are less pronounced. The training curves analysis revealed that ResNet50 experienced greater difficulty in converging on the orchid dataset compared to the other architectures, possibly indicating that the 50-layer depth was excessive for this particular classification task.

TABLE VIII
BASELINE ARCHITECTURE COMPARISON RESULTS

Architecture	Parameters	Test Accuracy	Training Time	Key Characteristics
DenseNet121	7,334,340	97.00%	20-25s/epoch	Dense connectivity, feature reuse
VGG16	15,248,964	94.23%	18-22s/epoch	Classical CNN, simple architecture
ResNet50	25,636,712	70.19%	22-28s/epoch	Residual connections, deep network

E. Confusion Matrix Analysis

A visual representation of the model's classification performance is provided by the confusion matrix shown in Table IX. Analysis of misclassification patterns reveals three errors among 100 test samples: one Cattleya Orchid was misclassified as Phalaenopsis, while two Dendrobium Orchid samples were misclassified as Vanda. Both Phalaenopsis and Vanda classes achieved perfect classification with no misclassifications (100% recall). One reason for these misclassifications might be the complexity of orchid molecular development related to morphological diversity [5]. As a result of this visual similarity, features extracted by the model for both orchid types have some overlapping characteristics. Model testing results are shown in the confusion matrix, as displayed in Table 8.

TABLE IX
CONFUSION MATRIX OF MODEL TESTING RESULTS

	Predicted Cattleya	Predicted Dendrobium	Predicted Phaleaonopsis	Predicted Vanda
True Cattleya	24	0	1	0
True Dendrobium	0	23	0	2
True Phaleaonopsis	0	0	25	0
True Vanda	0	0	0	25

F. Discussion and Interpretation of Results

To gain deeper insights into the internal learning mechanisms of the DenseNet121 model, comprehensive feature map visualization was conducted across multiple convolutional layers. This analysis reveals how the network progressively extracts and processes visual information from input orchid images, transforming raw pixel data into increasingly abstract and species-specific feature representations.

Figure 7 demonstrates the hierarchical feature extraction process across three critical network depths: early (conv1/conv), intermediate (conv3_block6_concat), and deep layers (conv5_block16_concat). The early convolutional layers primarily activate on fundamental visual elements such as edges, corners, and basic texture patterns. These feature maps appear as high-contrast regions that effectively outline petal boundaries, leaf structures, and surface textures common to all orchid species, serving as the foundation for higher-level pattern recognition.

Intermediate layers show significantly more sophisticated activation patterns that begin to capture complex spatial relationships and morphological structures specific to orchid anatomy. The conv3_block6_concat layer demonstrates selective activation on petal arrangements, color gradients, and geometric patterns that distinguish different orchid characteristics. These feature maps reveal the model's ability to identify mid-level features such as symmetry patterns, color distributions, and structural compositions that are crucial for botanical classification.

The deepest feature maps from conv5_block16_concat represent highly specialized and abstract features that directly correlate with species-discriminative characteristics. These final-stage activations concentrate on taxonomically significant regions such as labellum shape variations, column structures, and distinctive petal patterns unique to each orchid species. The spatial localization of these deep features demonstrates the model's learned attention mechanism, focusing computational resources on morphologically relevant areas while suppressing background noise and irrelevant visual information.

Comparative analysis across different orchid species reveals distinct activation patterns that explain the classification performance differences observed in the confusion matrix. Phalaenopsis samples consistently generate strong, localized activations in deep layers, particularly in regions corresponding to their characteristic broad petals and prominent central structures. This distinct feature signature explains the perfect classification accuracy (100%) achieved for this species. In contrast, Cattleya and Dendrobium exhibit overlapping activation patterns in intermediate and deep layers, consistent with their morphological similarities and the observed cross-classification errors in the confusion matrix analysis.

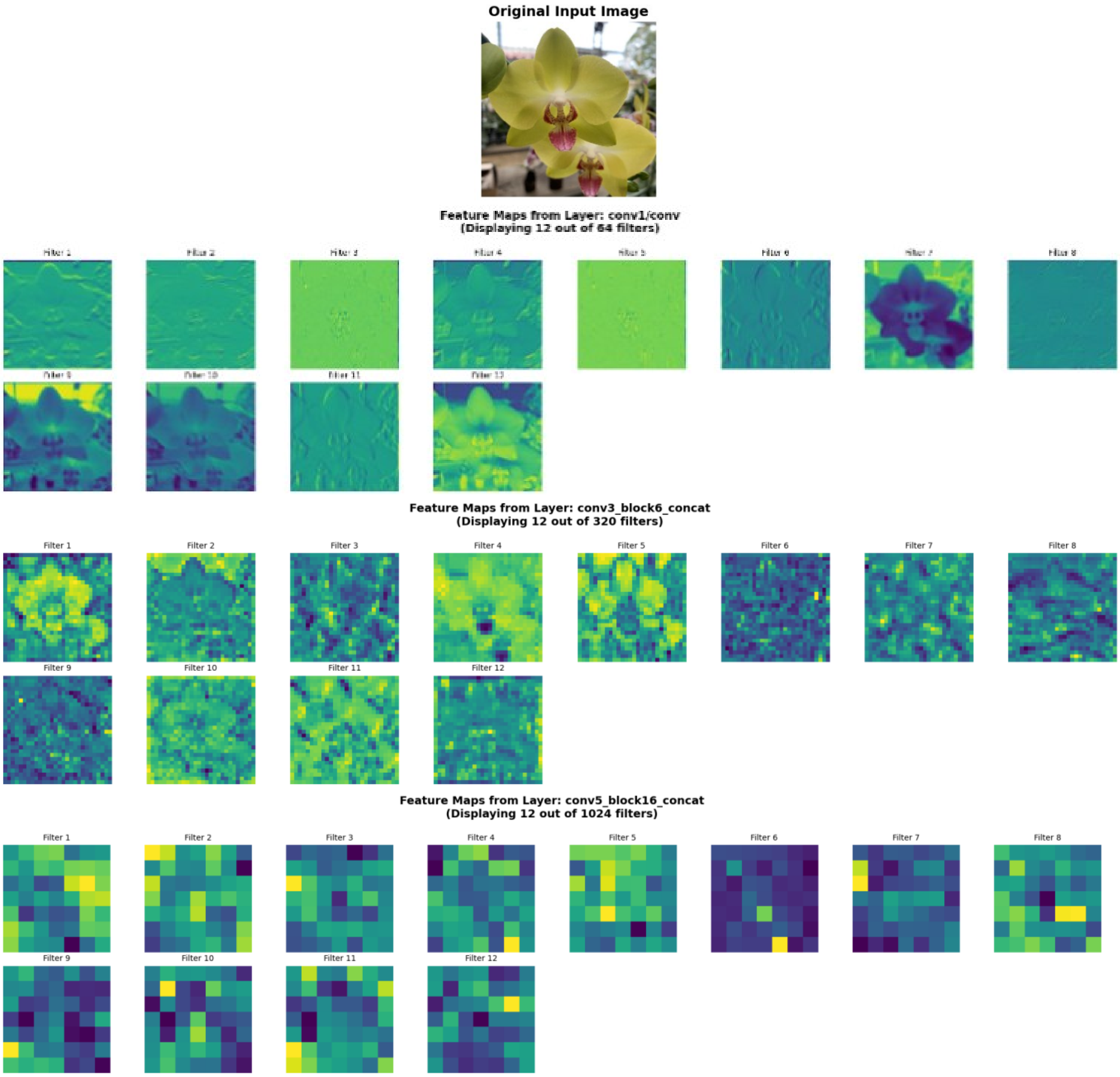

Figure 7 Hierarchical Feature Extraction in DenseNet121 Architecture. (A) Original input orchid image used for feature map analysis, (B) Early-layer feature maps (conv1/conv, shape: 112×112×64) highlighting edge detection and basic texture patterns, (C) Intermediate-layer feature maps (conv3_block6_concat, shape: 28×28×320) capturing complex morphological patterns and spatial relationships, (D) Deep-layer feature maps (conv5_block16_concat, shape: 7×7×1024) representing species-specific discriminative features. The progressive abstraction from low-level visual elements to high-level taxonomic features demonstrates the network's learned hierarchical representation of orchid morphology.

G. Discussion and Interpretation of Results

This research demonstrates the effectiveness of the DenseNet121 model with a transfer learning approach for classifying four popular orchid species in Indonesia. The strong model performance (97.00% accuracy) confirms its ability to extract distinctive features among various orchid varieties. Several key factors contributed to this success. First, preprocessing techniques including manual redundancy detection improved dataset quality, supporting Fan et al.'s [20] assertion that proper preprocessing enables efficient knowledge discovery. Second, addressing class imbalance through undersampling ensured balanced distribution across all classes, preventing majority class bias as emphasized by Khan et al. [21]. Third, transfer learning with ImageNet pre-trained weights provided valuable feature extraction capabilities, particularly beneficial for limited datasets as noted by Hemalatha et al. [24]. Finally, DenseNet121's architecture with dense connections facilitated efficient information flow and reduced vanishing gradient problems, aligning with Alzubaidi et al.'s [14] findings.

This research does not specifically emphasize any particular-optimization function, but instead focuses on handling class imbalance and implementing transfer learning. In its implementation, the model used the Adam optimizer (learning rate: 0.0001) and Categorical Cross-Entropy loss function, with dynamic learning rate adjustment via the ReduceLROnPlateau callback. The automatic reduction at epoch 36 significantly improved convergence in the final epochs. The comparison between similar research, our model demonstrates superior performance, as shown in Table 9. This comparison shows our approach outperforming Fu et al.'s [11] GL-CNN architecture (94.13%), Mohtar & Fadzil's [12] CNN with Inception V3 (83.00%), and coming close to Ou et al.'s [13] ensemble voting approach (95.20%). ensemble voting approach (95.20%). This superior performance can be attributed to effective class balancing, optimal architecture selection for complex feature extraction, and thorough dataset cleaning. Despite the high overall accuracy, minor misclassifications between Cattleya, Dendrobium, and Vanda orchids were observed, while Phalaenopsis achieved perfect classification.

These misclassifications are likely due to morphological similarities between certain species as explained by Balilashaki et al. [5]. suggesting potential for further refinement in feature extraction techniques for visually similar species. Overall, the combination of DenseNet121, transfer learning, and data preprocessing techniques proves highly effective for orchid species classification, offering both good accuracy and computational efficiency compared to more complex approaches.

The consistent misclassification patterns between visually similar orchid species (such as between Cattleya, Dendrobium, and Vanda) emphasize the essential relationship between taxonomic morphological characteristics and machine learning classification effectiveness. The perfect performance in Phalaenopsis classification (100%) indicates that more distinct visual features contribute significantly to classification success.

TABLE X
COMPARISON WITH RELATED RESEARCH

Research	Method	Dataset	Accuracy
Our proposed research	DenseNet121 + Undersampling	992 orchid images (4 classes)	97.00%
Fu et al. [11]	GL-CNN (Global-Local CNN)	Cymbidium orchid dataset	94.13%
Mohtar & Fadzil [12]	CNN + Inception V3	1,000 orchid images (10 classes)	83.00% (testing)
Ou et al. [13]	Ensemble Voting + Pre-trained Models	Orchid dataset	95.20%

IV. CONCLUSION

This research presents a comprehensive analysis of using the DenseNet121 architecture for orchid species classification, demonstrating the effectiveness of transfer learning approaches in botanical taxonomic classification problems. The study successfully achieves its primary objective by developing an automated classification system that reached 97.00% accuracy on a balanced dataset, proving that proper data imbalance handling and augmentation techniques play crucial roles in enhancing model performance.

The results provide compelling scientific evidence that DenseNet121, despite having moderate architectural complexity, is highly effective for orchid classification tasks, especially with limited dataset constraints. The consistent performance pattern across almost all classes, with minimal variation (92.59%-100% accuracy), demonstrates the success of the undersampling, and data augmentation methods applied. The methodological contribution of this research lies in the effective implementation of manual redundancy handling and class balancing techniques that resulted in balanced performance distribution across four taxonomically different orchid species.

Future research should explore ensemble methods that leverage different architectures to improve accuracy, especially for species with high visual similarity. Developing specialized attention mechanisms that emphasize significant taxonomic characteristics of orchids could further enhance classification precision. Additionally, expanding the dataset with orchid varieties from different geographical regions in Indonesia represents a valuable research direction for more targeted conservation efforts.

Several limitations should be acknowledged in this study. The dataset size, while sufficient for transfer learning, remains relatively modest with only 992 balanced samples across four species. The homogeneous collection conditions, though ensuring consistency, may limit model generalization to orchids photographed under different environmental settings or camera specifications. Additionally, the focus on four popular species represents only a small fraction of Indonesia's extensive orchid biodiversity, potentially limiting broader taxonomic applicability. The morphological similarities between certain species, particularly Cattleya and Dendrobium, continue to present classification challenges that may require specialized attention mechanisms or ensemble approaches to fully resolve.

The implications of this research extend beyond orchid taxonomy to conservation biology, citizen science projects, and agricultural applications, illustrating how optimized deep learning architectures can support access to sophisticated classification tools in research and conservation environments with limited resources. The development of mobile applications based on this model can aid in preserving Indonesia's orchid biodiversity while supporting the national horticultural industry.

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