# Image Classification of Common Flowers In The Philippines Using Modified EfficientNetV2S

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## ABSTRACT

This study explores the application of Modified EfficientNetV2S for classifying ten common Philippine flower types, addressing challenges in biodiversity conservation and botanical education. Using a dataset of 1,000 images split into training (800), validation (200), and test (100) sets, the model achieved a validation accuracy of 94% and a test accuracy of 88%. Among the ten classes, Gumamela and Rafflesia demonstrated perfect precision, recall, and F1 scores in the validation set, while minor misclassifications were observed, particularly for Sampaguita. Data augmentation techniques, including rotation and zooming, enhanced model generalization was applied. The EfficientNetV2S architecture, fine-tuned with a dropout rate of 0.5 and optimized with Adam (learning rate = 0.001), demonstrated superior performance over other pre-trained models such as ResNet50 and VGG16. This study provides a scalable solution for local flora classification and highlights the potential for future enhancements, including dataset expansion and integration of real-time image classification capabilities.

### CCS Concepts

Computing methodologies→Machine learning→Machine learning approaches→Neural networks

### Keywords

Image Classification, Common Flower Types, EfficientNetV2S, Flower In The Philippines, Deep Learning, CNN.

### Introduction

Flower classification is an essential job in computer vision, with numerous applications in botany, agriculture, environmental conservation, and education. Accurate identification of flower species is vital for understanding plant biodiversity, assisting ecological study, and facilitating agriculture activities. However, the work remains difficult due to the large range of flower varieties, which frequently share similar colors, forms, and textures. These visual similarities make it difficult to discriminate between species using traditional methods, prompting the development of improved and automated categorization algorithms.

Image-based flower classification has gained recognition in recent years, owing to the growing demand for fast and adaptable systems that are capable of processing huge quantities of flower photos. A large number of existing algorithms separate flower varieties by extracting visual information from photos and applying classification techniques. While these techniques have created a solid foundation, they still have limits in terms of accuracy, generality, and adaptation to varied datasets.

In the context of Southeast Asia, including the Philippines, there is a growing body of research focusing on regional flora due to its ecological importance and biodiversity. Studies such as Nguyen et al. (2020) developed models for classifying Vietnamese medicinal plants using mobile applications. Similarly, in Malaysia and Indonesia, researchers have begun building local plant datasets to improve classification systems specific to their native species. The Philippines is home to a rich variety of endemic and native flowers, such as the Sampaguita, Waling-Waling, and Gumamela. However, there is limited literature focusing on automated classification systems for these species. Most existing applications rely on general plant recognition APIs that may not perform well on Philippine-specific flora due to dataset limitations. This gap presents a significant opportunity to build localized image classification models that better reflect the country's biodiversity and support educational, ecological, and agricultural initiatives.

In image classification, choosing a reasonable and pertinent number of classes is essential to guaranteeing the viability and precision of model training, particularly in settings with limited resources. Earlier research, including that conducted by Andrew Zisserman and Maria-Elena Nilsback. (2008) have shown that important insights on model performance, feature extraction, and classification accuracy may be obtained even from limited-class flower datasets, such as the Oxford 17 Category Flower Dataset. Likewise, Sikiru, A. B., Egena, S. A., Kilani, M. A., Azeez, M. E., Adam, M. N., & Abdullahi, A. (2024) highlighted that in early-stage classification studies, class relevance and data quality are more important than quantity. This study focuses on ten flower types, which are Anthurium, Bougainvillea, Dama de Noche, Gumamela, Rafflesia, Rosal, Sampaguita, Santan, Waling-waling, and Ylang-ylang, all of which are either native to or commonly cultivated in the Philippines. These flowers were selected due to their cultural significance, ecological importance, and relative availability of images for training purposes. According to Pantazis, Omiros & Brostow, Gabriel & Jones, Kate & Aodha, Oisin. (2021), using locally relevant flora not only improves model relevance for real-world applications such as biodiversity monitoring and educational tools, but also enhances dataset integrity by reducing ambiguity in class labeling. Focusing on these flowers helps us understand species that are not just important for their botanical features but also for their cultural and visual value in the Philippines.

Limiting the dataset enables better control over class balance and model complexity. As noted by Zhang, Chiyuan & Bengio, Samy & Hardt, Moritz & Recht, Benjamin & Vinyals, Oriol. (2016), a smaller number of well-defined classes allows for more focused feature learning, especially when computational resources or labeled data are limited.

The primary objective of this research is to develop an efficient and accurate flower classification model tailored to the unique and diverse flora of the Philippines. By leveraging different deep learning methodologies, particularly convolutional neural networks (CNNs), the study aims to address the challenges posed by the high degree of visual similarity among flower species. Focusing on ten culturally and ecologically significant flowers native to or commonly cultivated in the Philippines, such as Sampaguita, Waling-waling, and Gumamela, this research seeks to build a localized dataset and classification model. This initiative aspires to bridge the gap in current literature by providing a robust model that supports biodiversity conservation, agricultural advancements, and educational efforts in the region. Additionally, by limiting the dataset to a manageable number of well-defined classes, the study enhances model efficiency and ensures balanced and high-quality training, contributing to the growing body of knowledge on automated image classification systems in Southeast Asia.

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This study utilized a dataset of 1,000 images across 10 common flower types in the Philippines, sourced from free online platforms due to the absence of existing datasets. The dataset was divided into 80% training (800 images), 20% validation (200 images), and a test set of 100 images to evaluate model generalization. Various pre-trained models were trained over 50 epochs with an early stopping patience of 5 to prevent overfitting, and the top 5 models were compared based on validation/test loss, accuracy, confusion matrix, and classification reports. The best-performing model was further optimized through five rounds of modifications to enhance performance, with precision, recall, F1-score, accuracy, training loss, and confusion matrix used as evaluation metrics. Visualizations of results were generated using Matplotlib, ensuring the model's effectiveness in flower classification and its ability to generalize to unseen data.

**Related Studies**

Image Classification has been a pivotal area of research in computer vision, enabling the identification and categorization of objects within images. Flowers, due to their distinct shapes, colors, and textures, serve as an intriguing subject for classification tasks. According to a study by ÇIBUK, Musa & Budak, Ümit & Guo, Yanhui & Ince, M. & Sengur, Abdulkadir. (2019), using deep learning models significantly improves the accuracy of flower classification compared to traditional machine learning approaches. The integration of convolutional neural networks (CNNs), such as AlexNet and VGGNet, demonstrated high efficiency in distinguishing between flower species. Nilsback and Zisserman (2008) also demonstrated that SVMs coupled with color, shape, and texture features can effectively distinguish between flower types. More recent research employs CNNs trained on floral datasets, achieving higher accuracies and enabling real-time classification.

*Philippine Context and Technological Gaps*

In the context of Southeast Asia, including the Philippines, there is a growing body of research focusing on regional flora due to its ecological importance and biodiversity. Studies such as Nguyen et al. (2020) developed models for classifying Vietnamese medicinal plants using mobile applications. Similarly, in Malaysia and Indonesia, researchers have begun building local plant datasets to improve classification systems specific to their native species. The

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*ConvNextTiny*

The usage of deep learning models in image classification has grown significantly due to their greater ability to extract challenging features from visual input. ConvNeXtTiny, a small yet high-performance variation of ConvNeXt, has emerged as an appropriate choice for a wide range of image recognition applications. This review examines two studies that used ConvNeXtTiny in different areas: mosquito gonotrophic stage classification and fire detection, focusing on their methodological approaches and model performance.

Azam et al. (2023) studied the use of ConvNeXtTiny to categorize the gonotrophic stages of mosquitoes using photos acquired from three species at four stages: unfed, fully fed, semi-gravid, and gravid. The impetus originated from the need to streamline a previously manual and expertise-intensive operation. While ConvNeXtTiny was evaluated alongside ResNet50, MobileNetV2, and EfficientNet-B0, it showed lesser classification accuracy (86.75%) than the others. Nonetheless, it stood out for its distinct architecture, which was inspired by a combination of CNNs and Vision Transformers, with a special emphasis on depth-wise convolution for efficiency. Although it did not achieve the highest accuracy, it did give useful insights into the trade-off between model complexity and classification precision.

In contrast, Khan et al. (2023) offered an improved ConvNeXtTiny-based architecture for real-world fire detection. This version of ConvNeXtTiny was fine-tuned utilizing methods from the Swin Transformer, such as inverted bottlenecks, depth-wise convolutions, and sophisticated downsampling, which considerably increased its efficacy. Unlike Azam et al., who used the default ConvNeXtTiny structure, Khan et al. added optimization algorithms customized to real-time application demands. Their model performed remarkably well, including 99.91% accuracy on test datasets, and had low latency with high frames-per-second (FPS) inference, making it suited for deployment in limited situations such as IoT devices.

These two research demonstrate different objectives in using ConvNeXtTiny. While Azam et al. prioritized biological categorization and model explainability using approaches such as Grad-CAM and t-SNE, Khan et al. concentrated on system optimization and real-time performance. The former revealed ConvNeXtTiny's promise in visual differentiation tasks despite its moderate accuracy, while the later demonstrated its practical scalability through architectural modifications.

*EfficientNetV2*

Recent advances in computer vision have greatly improved automated corrosion detection, with deep learning models, notably Convolutional Neural Networks (CNNs), displaying high efficacy. Among them, EfficientNetV2 has emerged as a viable architecture because to its scalable structure and strong performance across a variety of image classification tasks. Several research have examined its potential in corrosion picture analysis, using different methods to balance classification accuracy, computing efficiency, and model complexity.

Bashir and Duhu enhanced corrosion picture classification by using a hybrid architecture that included EfficientNetV2-B4 with a Long Short-Term Memory (LSTM) network. In their method, EfficientNetV2-B4 serves as a feature extractor, collecting spatial properties of pictures, while the LSTM component models temporal relationships, allowing the system to account for the development or sequencing of corrosion patterns. Data augmentation techniques, such as flipping and rotation, were used to improve the model's generalization. Their findings indicated that the combined CNN-RNN architecture outperformed models utilizing CNNs or RNNs alone, highlighting the importance of combining spatial and temporal feature learning.

Wu, Wang, Li, and Ma developed a more simplified approach, using EfficientNetV2-B0 as a stand-alone classifier. This model was modified using machine learning on a corrosion picture dataset without the use of any sequential modeling components. Their technique prioritized training efficiency while minimizing computational overhead, making it ideal for real-time applications and contexts with limited processing power. Similar to the prior study, data augmentation was used to improve model resilience. Despite its simplified design, the model demonstrated competitive classification accuracy and speedy convergence during training.

These experiments demonstrate the flexibility of the EfficientNetV2 architecture for corrosion detection. Bashir and Duhu's approach stresses accuracy through a more complicated hybrid model that incorporates both spatial and temporal data, whereas Wu et al. 's technique concentrates on lightweight deployment and speed via a solely CNN-based structure. Deep learning has changed how we categorize images by teaching computers to understand picture details directly from the original image data. Unlike older methods that needed people to manually create features, deep convolutional neural networks (CNNs) find important visual patterns on their own. They focus on parts like edges, textures, and complex shapes by using layers that include steps like convolution, pooling, and nonlinear activations. When sorting flower types common in the Philippines, deep learning models use large sets of labeled images. These images often include flowers like Jasminum sambac, Hibiscus rosa-sinensis, and Vanda sanderiana. The models learn small differences, such as petal shapes, color variations, and flower structures, to distinguish one species from another. Furthermore, transfer learning aids in improving model performance. This approach involves taking a CNN that was pre-trained on a big dataset, like ImageNet, and refining it for a specific flower dataset. This makes the model more effective and faster, even if there are not many labeled flower images, allowing for the easy creation of accurate tools for sorting flowers.

Convolutional Neural Networks, also known as CNNs, are highly effective for sorting images of plants. They excel at this task because they can recognize image parts that have been repositioned or altered and are capable of understanding intricate patterns. A CNN uses distinctive filters to scan images and generate maps focusing on significant features, like the edge of a Plumeria flower petal or the flower cluster in an Ixora coccinea. Additional layers in the network then simplify these maps, enabling the CNN to manage varying lighting conditions, different angles, and cluttered backgrounds which are often seen in nature photos. In the Philippines, recent studies highlight how well CNNs function for recognizing ornamental plants. One such study demonstrated that CNNs could accurately classify different flower varieties developed by DOST, a leading scientific body. Moreover, another study confirmed that CNNs perform remarkably well in identifying various plant species across different categories. In our project, we utilize CNN designs specifically crafted to detect the unique features of ten Philippine flowers. The aim is to develop a dependable and versatile system capable of automatically identifying flowers.

Recent research have demonstrated the effectiveness of EfficientNet topologies in plant categorization tasks. Sandhya Devi, Vijay Kumar, and Sivakumar used the EfficientNetV2 framework to recognize plant diseases and pests by combining transfer learning with a gradual learning technique. They used three datasets—Cassava, PlantVillage, and IP102—with class numbers of 5, 38, and 102, accordingly. To overcome confusion among similar-looking leaf diseases, they used Mixup to improve data for tomato disease classes. Their model demonstrated great accuracy across datasets (99.5%, 97.5%, and 80.1%), outperforming InceptionV3 and Vision Transformer in terms of accuracy, training time, and predictability.

Xiao Zuowen, on the contrary, utilized the EfficientNetB7 model with DropPath regularization to classify flowers. This approach removes network routes at random throughout training, which improves generalization and reduces overfitting. Using a dataset of 104 flower kinds, the model obtained flawless classification accuracy, with precision, recall, and F1 scores all around 0.95. The study covered thorough model architecture, learning rate scheduling, and validation performance but did not compare it to alternative designs.

While both research made efficient use of EfficientNet models, the uses and scopes were different. EfficientNetV2 demonstrated exceptional performance for big, diverse, and unbalanced datasets, particularly in commercial situations including various crops and pests. In contrast, EfficientNetB7 produced impressive results for a single, well-structured dataset including high-resolution photos. Together, these results demonstrate that EfficientNet variations may be tailored to particular classification issues, with V2 being more adaptable and B7 excelling at certain tasks.

**Methodology**

This study aims to classify ten common flowers in the Philippines—Anthurium, Bougainvillea, Dama de Noche, Gumamela, Rafflesia, Rosal, Sampaguita, Santan, Waling-waling, and Ylang-ylang—using various pre-trained models and selecting the best-performing model.

A dataset of 1,000 images will be compiled, containing 100 images per flower class. These images will be sourced from various free online sources, as no pre-existing datasets were available at the time of this study. The dataset will be organized into subfolders by class. A test set of 100 images (10 images for each class) will be created to measure the generalization performance of the model.

The dataset will be split into 80% training (800 images; 80 for every class) and 20% validation (200 images; 20 for every class). Images will be preprocessed through normalization of pixel values. Data augmentation techniques—including horizontal flipping, rotation, and zooming—will be applied to increase dataset variability and reduce overfitting.

The hyperparameters for training various pre-trained models will be set to 50 epochs and a patience of 5. This number of epochs is expected to be sufficient to train a small dataset across multiple pre-trained models, with early stopping if no improvement occurs across 5 consecutive epochs. Other parameters will be kept at their default values..

Each pre-trained model will be trained and evaluated. Metrics including accuracy, loss, confusion matrix, and classification reports (precision, recall, and F1-score) will be recorded. The top five models will be selected based on validation performance.

The model with the highest validation performance will be further modified to improve the performance. Five modified versions will be created by adjusting configurations such as fine-tuning selected layers, modifying dropout rates, and adding regularization. Each version will be trained and validated, and the best-performing version will be selected based on performance metrics.

The final selected model's performance will be generated and visualized, including plots of training and validation losses, as well as the confusion matrix. The model will be evaluated on the test set and its performance will be generated and visualized in the same method. Matplotlib library will be used to visualize performance metrics and confusion matrices.

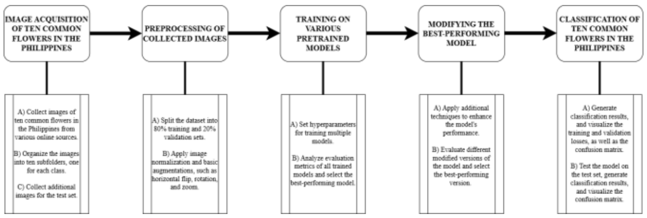


Figure 1. Workflow of the Research Methodology

**Results and Discussions**

The dataset were trained in various deep learning models and selected the top 5 models that performed better than the rest. As shown in Table 1. The lowest performing is InceptionV3 of all metrics and will not be chosen. Despite ResNet50 and VGG16 achieving moderate validation accuracy of 86% and 87% respectively, their performance in the prepared test set is low having accuracy of 67% and 73% which tells that these models didn't generalize to unfamiliar or unseen data. While ConvNextTiny shows unbelievably high validation accuracy might be due to the validation set has high similarity to training set and having a 9.5% drop of accuracy when it comes to test accuracy despite it having a high sky validation accuracy suggest that the model memorized the validation set instead of generalizing from it which is a sign of overfitting.

The considered model was EfficientNetV2S due to it having a believable validation accuracy of 93% and an acceptable test accuracy of 83% which can be improved with modifications. It shows more realistic and generalized performance without the risk of overfitting. EfficientNetV2S is the chosen best performing model in the allocated dataset.

Table 1. Top 5 Performing Models

| Pretrained Model | Validation Loss | Validation Accuracy | Test Loss | Test Accuracy | Epoch Stopped |
|---|---|---|---|---|---|
| ResNet50 | .5065 | 86% | 2.4443 | 67% | 20 |
| VGG16 | .3571 | 87% | 1.0425 | 73% | 7 |
| EfficientNet V2S | .2036 | 93% | .6743 | 83% | 10 |
| InceptionV3 | 1.1886 | 71% | 1.6931 | 62% | 14 |
| ConvNextTiny | .0462 | 99.5% | .3232 | 90% | 34 |

After various modifications were trained using EfficientNetV2S, applying these techniques resulted in the best out of five modified versions. Table 2 shows the techniques that were applied.

Table 2. Techniques Applied

| Features | Modified EfficientNetV2S |
|---|---|
| Augmentations | HorizontalFlip, Rotation, Zoom, Width/Height Shift, Shear |
| Optimizer | Adam (lr=0.001) |
| Callbacks | EarlyStopping (5), ReduceLROnPlateau (3) |
| Base Output Layer | GlobalAvgPooling → Dense(10, softmax) |
| Dropout Layer | Dropout (0.5) |

As shown in Table 3, the model early stopped at epoch 36 and achieved a validation accuracy of 94% which improved by 1% with a validation loss of 0.2172 that tells the model improved while maintaining the predictions close to the ground truth. After it was tested into the test set it achieved 88% accuracy which improved by a significant 5% than before the modifications and a loss of 0.4965.

Table 3. Performance Result

| Performance Result | Modified EfficientNetV2S |
|---|---|
| Validation Loss | .2172 |
| Validation Accuracy | 94% |
| Test Loss | .4965 |
| Test Accuracy | 88% |
| Epoch Stopped | 36 |

In Figure 2, the training accuracy steadily increases across epochs and the validation accuracy with minor spikes. It shows that the model learned in correctly classifying closer to the ground truth.

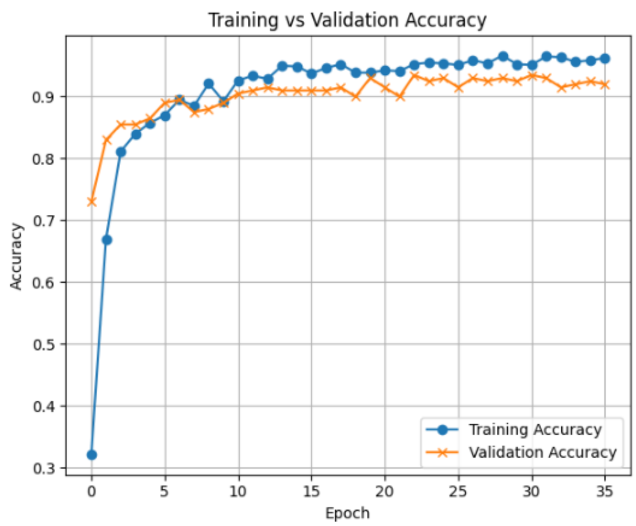


Figure 2. Accuracy Plot Across Epochs

In Figure 3, both training and validation losses steadily decrease across epochs. It shows that the model learns the training data with minimal errors and effectively generalizes to unseen data due to the validation loss decreasing across epochs.

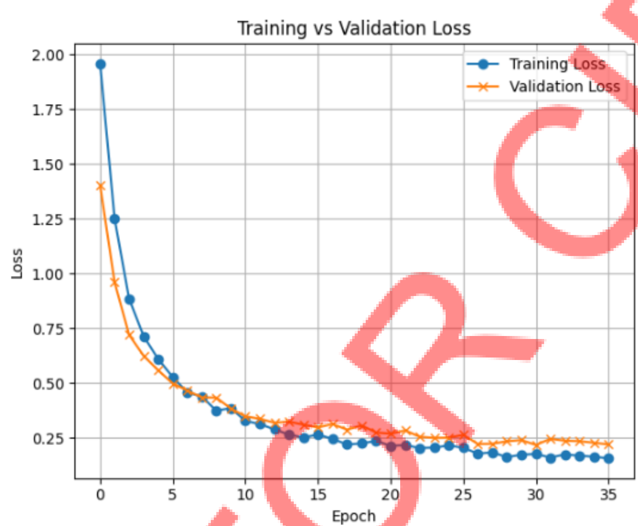


Figure 3. Training And Validation Loss Across Epochs

In Table 4 is the performance metrics of each class which shows the ability of the model in classifying correctly. The evaluation of the model's performance reveals strong overall accuracy of 94%, with Gumamela and Rafflesia achieving perfect precision, recall, and F1-scores. However, other classes displayed slightly lower precision, suggesting that the model occasionally misclassified other flower types as these classes. For example, the lower recall scores for classes like Sampaguita indicate that the model missed some actual instances of this class, resulting in false negatives. The high averages of the model shows that most of the classes were classified correctly with minor confusion between similar-looking flowers.

Table 4. Validation Classification Metrics

| Class | Precision | Recall | F1-score |
|---|---|---|---|
| Anthurium | 1.00 | 0.95 | 0.97 |
| Bougainvillea | 0.87 | 1.00 | 0.93 |
| Dama de noche | 0.83 | 1.00 | 0.91 |
| Gumamela | 1.00 | 1.00 | 1.00 |
| Rafflesia | 1.00 | 1.00 | 1.00 |
| Rosal | 0.86 | 0.95 | 0.90 |
| Sampaguita | 0.94 | 0.80 | 0.86 |
| Santan | 0.95 | 0.90 | 0.92 |
| Waling-waling | 0.95 | 0.90 | 0.92 |
| Ylang-ylang | 1.00 | 0.85 | 0.92 |
| | | | |
| Accuracy | | | 0.94 |
| Macro Avg | 0.94 | 0.93 | 0.93 |
| Weighted Avg | 0.94 | 0.94 | 0.93 |

In Figure 4, it shows the confusion matrix which tells the correct and incorrect classification of the model in the validation set. The classes that were predicted with 100% accuracy were Bougainvillea, Dama de noche, Gumamela, and Rafflesia. While the most misclassified class were Sampaguita which misclassified three times as Dama de noche and once as Rosal. The model shows strong performance with minor misclassification.

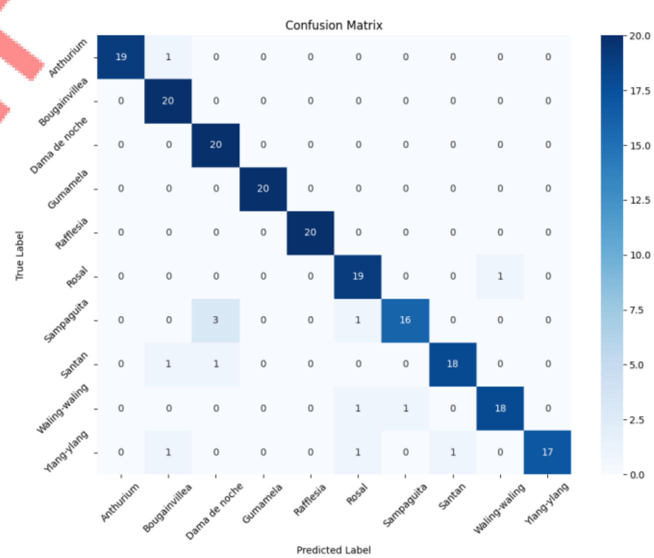


Figure 4. Confusion Matrix

Figure 5 shows the confusion matrix of the model tested in the test set. The classes Gumamela and Sampaguita show these were the most misclassified classes. Gumamela, despite having perfect accuracy at the validation set, doesn't generalize well in the test set and can be due to slight memorizing of the model to the Gumamela class rather than generalizing. Despite having these setbacks, it still shows that most classes were correctly classified.

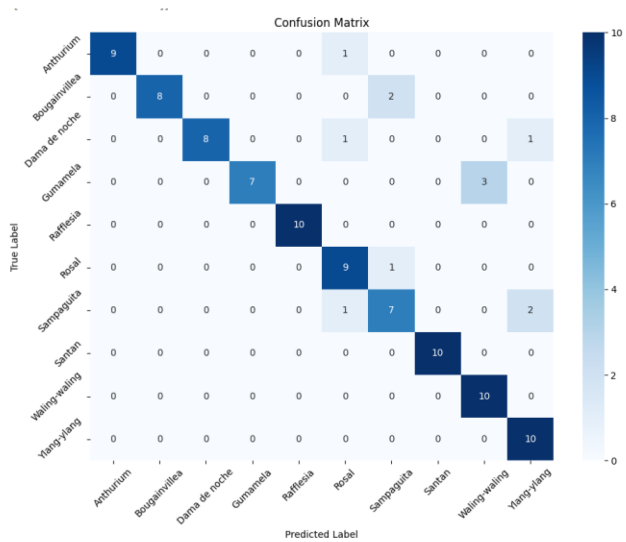


Figure 5. Confusion Matrix on Test Set

**Conclusion**

An image classification model using modified EfficientNetV2S to classify ten common flower types in the Philippines was successfully developed. By applying deep learning techniques, it achieved 94% accuracy during training through an allocated 1,000 image dataset with 100 images each class, and 88% accuracy in the test set demonstrating strong classification capabilities. There are classes that showed near-perfect prediction such as Bougainvillea, Dama de noche, Gumamela, and Rafflesia in validation set but differ than the test set that even though not all classes were near-perfect and can be misclassified, it's a small minor setback. The classification report and confusion matrix shows that most classes achieve values above 0.90. These results confirm the model can be effective in real-world flower classification.

While the model shows high performance, some classes tend to be misclassified especially Sampaguita that perform poorly than the other classes both in validation and test set. The class Gumamela has a possibility of being overfit due to it performing well in validation but poorly in test set. These findings suggest that expanding the dataset, possibly increasing the number of flower types, and testing more models with various deep learning techniques could further improve the accuracy, generalization, and more flower types to be classified. This study can be the steppingstone to future researchers that explore the similar idea and modify it to be real-time classification.

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