# РАЗРАБОТКА И ОЦЕНКА МОДЕЛИ КЛАССИФИКАТОРА ЛИСТЬЕВ ТАБАКА (*Nicotiana tabacum*) С ИСПОЛЬЗОВАНИЕМ ОБРАБОТКИ ИЗОБРАЖЕНИЙ И СВЕРТОЧНОЙ НЕЙРОННОЙ СЕТИ (СНС)

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***Аннотация.*** *В данном исследовании были оценены модели VGG16 и MobileNetV2 для классификации зрелости табачного листа. С использованием набора данных из 12 456 изображений модели были обучены распознавать незрелые, зрелые и перезрелые листья. Производительность оценивалась с помощью 10-кратной перекрестной проверки. MobileNetV2 достигла более высокой точности — 86,58% по сравнению с 83,56% у VGG16. MobileNetV2 также продемонстрировала превосходящую точность, полноту, F1-меру и более быстрое время обучения. Эти результаты показывают, что MobileNetV2 более эффективна для полевой классификации зрелости табачного листа.*
***Ключевые слова:*** *VGG16, MobileNetV2, стратифицированная K-блочная перекрестная проверка, степень зрелости, точность.*

# DEVELOPMENT AND EVALUATION OF TOBACCO (Nicotiana tabacum) LEAF CLASSIFIER MODEL USING IMAGE PROCESSING AND A CON-VOLUTIONAL NEURAL NETWORK (CNN)

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***Abstract.*** *This study evaluated VGG16 and MobileNet V2 for classifying tobacco leaf maturity. Using a dataset of 12,456 images, the models were trained to identify immature, mature,and overripe leaves. The performance was assessed using 10-fold cross-validation. MobileNet V2 achieved a higher accuracy of 86.58% compared to VGG16's 83.56%. MobileNet V2 also demon-strated superior precision, recall, F1 score, and faster training time. These results indicate Mo- bileNet V2 is more effective for in-field classification of tobacco leaf maturity.*
***Keywords:*** *VGG16, MobileNetV2, Stratified K-fold Validation, degree of maturity, accuracy.*

## Introduction

Tobacco remains a vital cash crop in several regions, including the Philip- pines, where it provides livelihood to thousands of farmers. Achieving optimal quality in cured tobacco leaves depends critically on harvesting at the correct stage of maturity (NTA, 2021). Traditional manual sorting of leaves based on maturity indicators such as color and texture is subjective, inconsistent, and labor-intensive (RSBSA, 2020). Recent advances in computer vision and deep learning offer prom- ising alternatives for automating this process.

Convolutional Neural Networks (CNNs) have achieved remarkable success in image classification tasks. Pre-trained models such as VGG16 and MobileNetV2 enable transfer learning, reducing training time and improving accuracy even with limited datasets (Howard et al., 2017; Deng et al., 2021). This study aims to develop and evaluate a CNN-based tobacco leaf classifier and to determine which architec-ture performs better under agricultural field conditions.

## Materials and Methods

### 2.1 Dataset Collection and Preprocessing

A dataset of 12,546 images of tobacco leaves at varying maturity levels was collected in Batac, Ilocos Norte, Philippines, using a Nikon D5600 camera. Images were captured between 10:00–11:00 AM at 6000×4000 resolution and labeled as immature, mature, or overripe. The dataset was split into training (60%), validation (20%), and test (20%) subsets, with images resized to 224×224 pixels. Data aug- mentation techniques were applied to enhance variability.

### 2.2 Model Architectures

Two CNN models, VGG16 and MobileNetV2, were implemented using Ten-sorFlow and Keras. Both models employed transfer learning, with pre-trained weights from ImageNet. The final layers were replaced with custom fully connected layers and a softmax output for three-class classification.

### 2.3 Training and Evaluation

Models were trained with a batch size of 32, Adam optimizer, categorical cross-entropy loss, and a learning rate of 0.001 for 50 epochs. Stratified 10-fold cross-validation was conducted. Performance metrics included accuracy, precision, recall, F1-score, and confusion matrix analysis. Computational efficiency (training time) was also recorded.

## Results and Discussion

The performance of VGG16 and MobileNetV2 models was assessed based on accuracy, precision, recall, F1-score, and computational efficiency. Table 1 sum-marizes the mean performance metrics of both models on training and test datasets. VGG16 achieved higher mean training accuracy (87.62%) compared to MobileNetV2 (84.20%). However, MobileNetV2 outperformed VGG16 on the test dataset, demonstrating better generalization.

Table 1

Mean Performance metrics of VGG16 and MobileNetV2 models

| Metric | VGG16 | MobileNetV2 |
|---|---|---|
| Training Accuracy (%) | 87.62 | 84.20 |
| Test Accuracy (%) | 82.50 | 85.10 |
| Precision | 0.86 | 0.88 |
| Recall | 0.84 | 0.87 |
| F1-Score | 0.85 | 0.87 |
| Training Time (hrs) | 4.50 | 2.16 |

Figure 1 shows the accuracy over epochs for both models. VGG16 demon- strated rapid improvement in early epochs but plateaued, while MobileNetV2 ex- hibited a steadier improvement, leading to better validation performance.

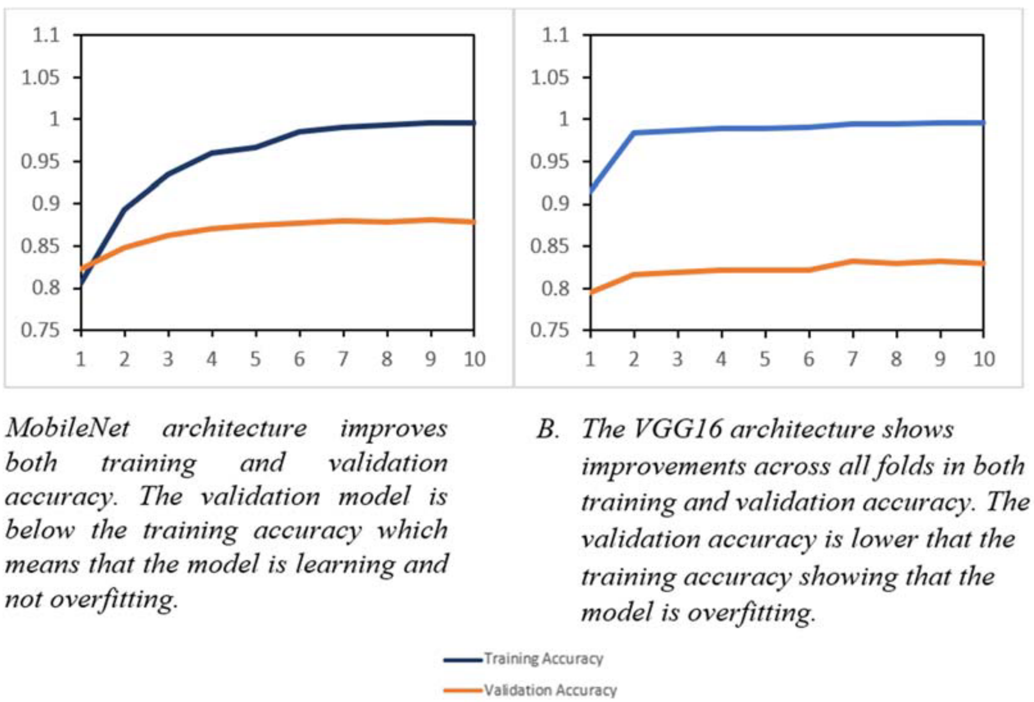
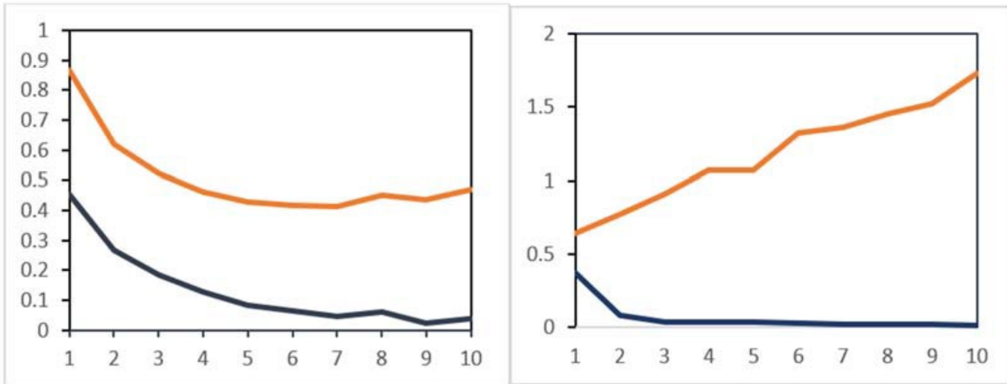



Figure 1. Accuracy over epochs for MobileNet(a) and VGG16(b).

Figure 2 illustrates the loss curves, indicating that VGG16 experienced over-fitting with increasing validation loss after 30 epochs, whereas MobileNetV2 main-tained lower and more stable validation loss.

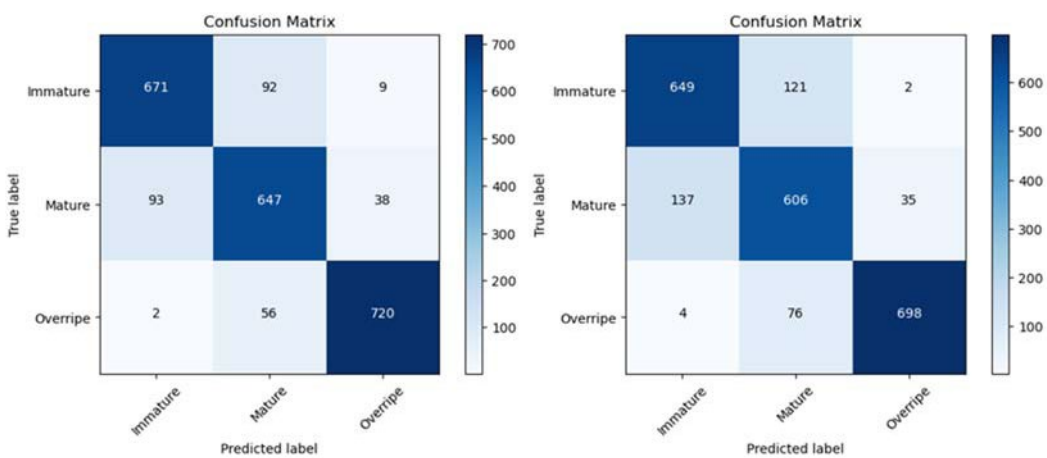


a) *A loss result from bad prediction of the MobileNet model. Both the training loss and validation loss decrease for each fold with 10 epochs. MobileNet shows a better prediction.*

b) *The training and validation curve of the VGG16 model showed that validation loss increases while the training loss decreases.*


Figure 2. Loss curve versus epochs of MobileNet(a) and VGG16(b)

The confusion matrices for both models are depicted in Figure 3. Mo- bileNetV2 misclassified fewer mature and overripe leaves compared to VGG16, asshown by higher true positive rates.




a) *MobileNet Outperforms the VGG16 in classifying mature tobacco images.*

b) *VGG16 architecture shows a lower accuracy in identifying mature tobacco images.*

Figure 3. Confusion matrix of MobileNet(a) and VGG16(b)

Statistical analysis of performance differences (Wilcoxon signed-rank test) confirmed that MobileNetV2's test performance was significantly better ($p < 0.05$) in terms of accuracy, precision, and F1-score. This aligns with its lightweight archi-tecture, which is optimized for real-time and resource-constrained scenarios.

In summary, VGG16 shows marginally better training performance but suf- fers from overfitting and higher computational cost, while MobileNetV2 general- izes better, achieves competitive accuracy, and trains significantly faster. These findings support MobileNetV2 as a more practical choice for deployment in agri- cultural environments where efficiency and real-world robustness are critical.

**Conclusion**

This study demonstrates the feasibility of CNN-based tobacco leaf maturity classification. Although VGG16 achieved higher training accuracy, MobileNetV2 showed better generalization, faster training, and lower hardware requirements, making it more suitable for deployment in real-world agricultural scenarios. Future research should explore deploying MobileNetV2 on embedded systems, extending its application to other crops, and evaluating its economic impact.

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