Jurnal teknika

(Jurnal Fakultas Teknik Universitas Islam Lamongan)

Tersedia Online http://www.jurnalteknik.unisla.ac.id/index.php/teknika/index
Volume 18, No.1, Tahun 2026 - ISSN: 2085-0859- EISSN : 2620-4770

Performance Improvement of CNN Algorithm with Data Augmentation for Tobacco Leaf Disease Classification

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ABSTRACT

Digital image processing of tobacco leaves is an important approach in early and accurate detection of plant diseases, particularly for high-economic-value agricultural commodities. This research proposes a multi-strategy data augmentation approach to improve the accuracy of tobacco leaf disease classification using Convolutional Neural Networks (CNN). Three augmentation techniques were applied: traditional augmentation, mixed-sample augmentation, and model-based augmentation on three CNN architectures (MobileNetV2, EfficientNetB0, and VGG16). The dataset consists of 400 tobacco leaf images with five disease classes collected from Wonosobo Regency. Experiments were conducted with two data splitting scenarios: 70:30 and 80:20. Results show that the application of multi-strategy augmentation successfully improved classification accuracy up to 81.25% on MobileNetV2 with an 80:20 ratio, representing a 20% increase compared to the model without augmentation. Additionally, the augmentation technique effectively reduced overfitting by decreasing the gap between training and validation accuracy from 0.5-0.7 to 0.1-0.2.

Keywords: Data Augmentation, CNN, Tobacco Leaf Disease, Classification

ABSTRAK

Pengolahan citra digital daun tembakau merupakan pendekatan penting dalam deteksi dini dan akurat penyakit tanaman, khususnya untuk komoditas pertanian bernilai ekonomi tinggi. Penelitian ini mengusulkan pendekatan augmentasi data multi-strategi untuk meningkatkan akurasi klasifikasi penyakit daun tembakau menggunakan Convolutional Neural Networks (CNN). Tiga teknik augmentasi diterapkan: augmentasi tradisional, augmentasi sampel campuran, dan augmentasi berbasis model pada tiga arsitektur CNN (MobileNetV2, EfficientNetB0, dan VGG16). Dataset terdiri dari 400 citra daun tembakau dengan lima kelas penyakit yang dikumpulkan dari Kabupaten Wonosobo. Eksperimen dilakukan dengan dua skenario pembagian data: 70:30 dan 80:20. Hasil menunjukkan bahwa penerapan augmentasi multi-strategi berhasil meningkatkan akurasi klasifikasi hingga 81,25% pada MobileNetV2 dengan rasio 80:20, yang mewakili peningkatan 20% dibandingkan dengan model tanpa augmentasi. Selain itu, teknik augmentasi secara efektif mengurangi overfitting dengan menurunkan selisih antara akurasi pelatihan dan validasi dari 0,5-0,7 menjadi 0,1-0,2.

Kata kunci: Augmentasi Data, CNN, Penyakit Daun Tembakau, Klasifikasi

Naskah diterima 26 Februari 2026; Revisi 01 Maret 2026; Diterima 09 Maret 2026. Tanggal Publikasi 01 Maret 2026

DOI: 10.30736/jt.v18i1.1639, Hal 79 - 82

DOI: 10.30736/jt.v18i1.1639
ISSN: 2085-0859, E-ISSN: 2620-4770

1. INTRODUCTION

The development of digital image processing technology has fundamentally changed various fields, including the contemporary agricultural sector that is transforming towards a precision agriculture paradigm. The implementation of artificial intelligence-based plant pest and disease identification https://claude.ai/chat/ddd2823c-07ef-4d1d-a435-aef7bdbd990d Page 1 of 14 Revised Journal - Performance Improvement of CNN Algorithm 08/10/25 13.56 systems not only improves diagnostic efficiency but also opens transformative opportunities in sustainable agricultural management (Taslim et al., 2021). Tobacco (*Nicotiana tabacum*) is a strategic agricultural commodity with significant economic value in global trade, but is susceptible to various complex pathogens that can cause massive production losses (Dorner, 2021). The biological characteristics of tobacco that are sensitive to changes in environmental conditions and multiple pathogen attacks make it an ideal candidate for the application of automated detection technologies.

Automated detection systems integrate image acquisition, visual processing, segmentation algorithms, feature extraction, and machine learning methodologies. These automated diagnostic systems provide agricultural practitioners with plant pathology identification solutions with optimal levels of accuracy and temporal efficiency. Automation of detection systems is essential to accelerate plant diagnosis (Zamani et al., 2022).

Convolutional Neural Network (CNN) has been proven effective for image recognition. However, it requires a large and diverse dataset to achieve optimal performance (Swasono et al., 2019). To overcome this limitation, data augmentation techniques are applied to increase the variety of training data while expanding the range of features that the model can learn (Pailus et al., 2022).

Previous research by (Mohith Kumar et al., 2022) developed a custom CNN model for tobacco plant disease detection with a real-time dataset of 660 images through data augmentation. The model successfully achieved 80% accuracy on validation data and 74% on test data. However, this study faced a significant overfitting problem after achieving 80% accuracy, so training was stopped to prevent further performance degradation.

Based on these issues, this study explores the optimization of CNN for tobacco leaf disease classification through analyzing the synergistic effect between data augmentation techniques and dataset sharing ratio. The dataset used consists of 400 images with five classes from the agricultural area of Wonosobo Regency, selected based on high disease prevalence and diverse environmental conditions. Comparisons were made on three CNN architectures (MobileNetV2, EfficientNetB0, VGG16) proven accuracy and efficiency in image classification tasks but also for their potential compatibility with mobile deployment in future agricultural applications with the implementation of multi-strategy augmentation to overcome the challenges of limited datasets. This study identifies the optimal training data volume and analyzes the effectiveness of 70:30 and 80:20 dataset splits in reducing overfitting. Performance assessment uses train-test split and accuracy metrics, precision, recall, F1-score to provide practical guidance on the selection of the optimal augmentation strategy.

2. METHODE

This research adopts a quantitative experimental approach by comparing the performance of CNN models in two scenarios: before and after the application of data augmentation. The research stages include dataset preparation, baseline model training, implementation of augmentation techniques and evaluation using standard confusion matrix.

2.1 Data Collection

The dataset consists of 400 tobacco leaf images categorized into five disease classifications: TMV (*Tobacco Mosaic Virus*), *Bacterial Brown Spot*, *Leaf Spot*, *Sunscald* and Healthy. The data labeling process was performed to ensure uniform distribution to support robust analysis.

Table 1. Dataset

No.	Classification	Number
1	TMV	80
2	Bacterial Brown Spot	80
3	Leaf Spot	80
4	Sunscald	80
5	Healthy	80
Total		400

The dataset covers the spectrum of pathological conditions of tobacco plants from healthy to various disease manifestations. TMV induces a mosaic pattern on leaves and triggers *glutathione upregulation* as a defense mechanism (Guo & Wong, 2020). Brown Spot caused by *Pectobacterium carotovorum subsp. carotovorum* causes brown lesions with a wet texture and yellow halo (Perfileva et al., 2025). Leaf Spot due to *Spodoptera litura* caterpillar damage creates circular perforations with a diameter of 1 cm (Harlita, 2021). Sunscald is physiological damage caused by high-intensity solar radiation at low humidity (D Blancard (INRAe), n.d.), while Healthy conditions indicate optimal plants without pathological symptoms.

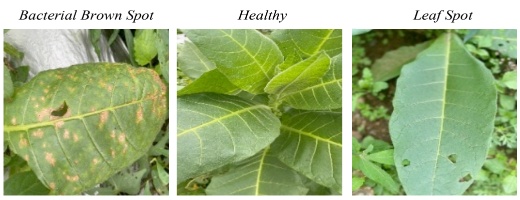

Figure 1. Data Labeling

DOI: 10.30736/jt.v18i1.1639
ISSN: 2085-0859, E-ISSN: 2620-4770

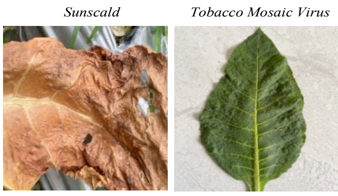

Figure 2. (continuation)

2.2 Data Preprocessing

It is an important step to prepare data before model training which includes three main stages (Joshi & Patel, 2021). First, data cleaning is performed to clean the data from noise, outliers and invalid values to improve the quality of the dataset. Second, data normalization is applied as a technique to standardize the data to a certain scale to accelerate model training by changing the pixel values to the range [0,1]. Thirdly, model input preprocessing is performed to prepare the data before being input to the model by resizing the image to a dimension of 224×224 pixels according to the input requirements of the CNN architecture used.

2.3 Data Augmentation

This research applies three types of data augmentation to enrich the variety of datasets. Traditional augmentation uses geometric transformation (±35° rotation, 20-30% shift, 10% shear, 70-130% zoom) and photometry. 70-130%) and photometric (flip, brightness 90-110%, channel shift ±5). The stage is specifically designed to preserve the pathological features of tobacco leaves while preventing overfitting (Alomar et al., 2023).

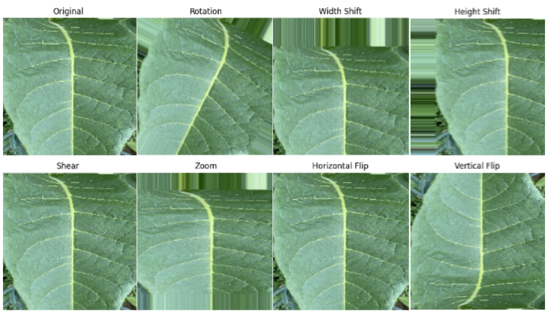

Figure 3. Traditional Augmentation

Mixed sample auugmented applies the *CutMix* technique that combines images through region swapping (Yun et al., 2019) and *MixUp* that uses a linear combination of images and labels (Carratino et al., 2022) to generate synthetic samples that help the model distinguish diseases with similar visual characteristics.

Figure 4. Mixed Sample Augmented

Model-based augmentation uses Conditional Generative Adversarial Nets (CGAN) consisting of a Generator (G) to create synthetic images from noise vectors and class labels, and a Discriminator (D) to discriminate between the original and synthetic images, with the entire process conditioned on the class labels to ensure the relevance of the generated images to the target disease category (Álvarez et al., 2020).

MixUp

$$\begin{aligned} &\lambda \sim Beta(\alpha,\alpha) \\ &x' = \lambda x\_i + (1-\lambda)x\_j \\ &y' = \lambda y\_i + (1-\lambda)y\_j \end{aligned} \tag{1}$$

λ: The mixing value of the Beta distribution.
x_i, x_j: Input image.
y_i, y_j: One-hot labels.

CutMix

$$\begin{aligned} &M \sim BinaryMask(B\_x, B\_y) \\ &x' = M \odot x\_i + (1-M) \odot x\_j \\ &y' = \lambda y\_i + (1-\lambda)y\_j \end{aligned} \tag{2}$$

M: Binary mask.
⊙:Element-wise multiplication (*Hadamard product*).

CGAN

$$\begin{aligned} &G(z,y) \rightarrow x\_fake \\ &D(x,y) \rightarrow [0,1] \\ &min\_G\, max\_D\, V(D,G) = E\_\{x,y \\ &\qquad \sim p\_data\}[log\, D(x|y)] + E\_\{z \\ &\qquad \sim p\_z\}[log(1-D(G(z|y)))] \end{aligned} \tag{3}$$

x: Input image (real or synthetic).
y: Class label as condition.
z: Noise vector.
*x*fake:The resulting synthetic image.
*p*data:Original data distribution.
pz:Noise distribution.
*p*label:Distribution of class labels.

2.5 Justification of CNN Architecture Method

CNN was chosen as the main architecture due to its ability to effectively process tobacco leaf images through three key components: convolution layer for feature extraction, pooling for dimension reduction and fully connected for classification (Hassan et al., 2021). This research implements three model architectures namely MobileNetV2 which is a

DOI: 10.30736/jt.v18i1.1639
ISSN: 2085-0859, E-ISSN: 2620-4770

lightweight CNN architecture with optimized depthwise separable convolution and residual connections that processes 224×224 pixel images through 16 MBConv blocks with Global Average Pooling and ReLU-softmax activation (Dong et al., 2020).

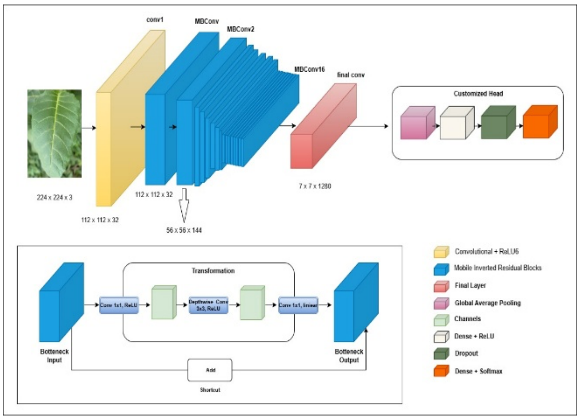

Figure 5. MobileNetV2

EfficientNetB0 optimizes network scale in a balanced way for maximum efficiency by processing images through seven MBConv blocks that transform the dimensions to 7×7×160, followed by Global Average Pooling and a fully connected layer with Swish and Dropout activations (Atila et al., 2021).

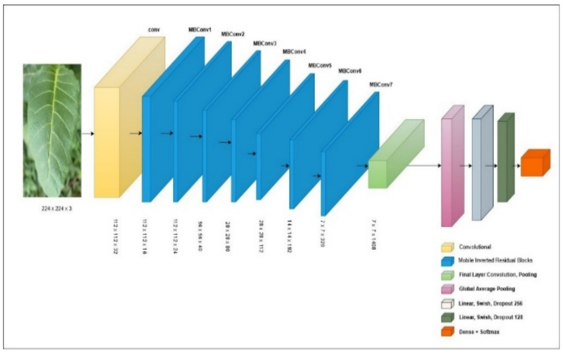

Figure 6. EfficientNetB0

VGG16 as a classic CNN architecture uses an iterative convolution stack for hierarchical feature extraction with five convolution blocks (3×3 kernel + ReLU) and max pooling for progressive feature extraction, and three fully connected layers for final classification (Sujatha et al., 2021).

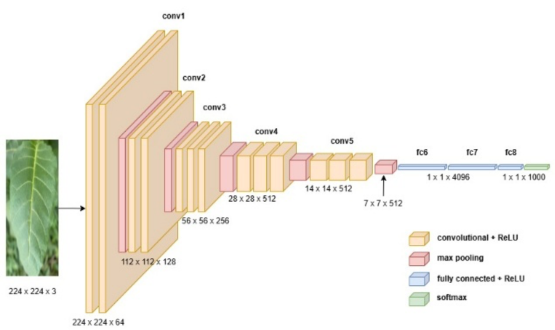

Figure 7. VGG16

2.6 Parameter Option

This research uses different optimizers for each model with careful hyperparameter selection. The Adam optimizer is applied for MobileNetV2 and EfficientNetB0 with an initial learning rate of 0.001 that decays exponentially to 0.00001. Adam parameters include Beta1 of 0.9 for exponential decay rate of first moment estimates, Beta2 of 0.999 for second moment estimates, and Epsilon of 1e-07 for numerical stability. Adam was chosen for its ability to adaptively adjust the learning rate for each parameter, making it suitable for architectures with varying layer sensitivities. The adaptive learning rate is particularly beneficial for EfficientNetB0's compound scaling approach.

VGG16 uses SGD (Stochastic Gradient Descent) with momentum as a comparison to optimize model training. The initial learning rate is 0.001 with step decay (multiplied by 0.1 every 30 epochs), momentum of 0.9, and Nesterov momentum enabled (Irfan et al., 2022). VGG16's simpler architecture benefits from SGD's consistent update direction. Momentum helps accelerate convergence and overcome local minima.

Batch size of 32 was selected based on GPU memory constraints (8GB VRAM) and to provide stable gradient estimates. Larger batches (64) led to memory overflow, while smaller batches (16) resulted in noisy gradients and slower convergence. A maximum of 200 epochs were applied with an early stopping mechanism that stopped training if validation loss did not improve within 15 epochs. This prevents overfitting by terminating training when validation loss plateaus and ensures the model with optimal generalization is retained. Additional regularization includes Dropout of 0.1-0.5 in fully connected layers to prevent co-adaptation of neurons and L2 regularization with weight decay of 0.0001 to penalize large weights and improve generalization.

2.7 Model Evaluation

The dataset is randomly divided into training and validation subsets with a ratio of 70:30 and 80:20. The training set is used to build the model while the validation set serves as independent data to test the generalization ability of the model (Bichri et al., 2024). Confusion matrix is used as a fundamental evaluation tool in classification that compares model predictions with ground truth to calculate four main evaluation metrics (Powers, 2020):

a. $$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

b. $$Precision = \frac{TP}{TP+FP} \quad (5)$$

c. $$Recall = \frac{TP}{TP+FN} \quad (6)$$

d. $$F1-Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (7)$$

DOI: 10.30736/jt.v18i1.1639
ISSN: 2085-0859, E-ISSN: 2620-4770

Where True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) represent the number of correct and incorrect predictions for positive and negative classes, respectively.

3 DISCUSSION

3.1 Model Training

1) Train Split Data 70:30

Experimental results show a comprehensive evaluation of three deep learning architectures at 70:30 data ratio. MobileNetV2 has the highest performance with 65% accuracy using augmentation, undergoing three-phase learning of archetype recognition (epoch 1-15), memorization-generalization trade-off (epoch 15-30), to overfitting with gap loss 0.5-0.6 without augmentation which reduces to moderate overfitting with augmentation (epoch 30±). EfficientNetB0 underwent a dramatic transformation from underfitting without augmentation (56.67% accuracy, weak convergence epoch 20-25, extreme volatility) to optimal generalization with augmentation (62.5% accuracy, minimal gap loss 0.1-0.2, healthy parallel loss curves). VGG16 showed consistent overfitting characteristics with fast convergence of 10-15 epochs followed by divergence, resulting in 61.67% accuracy without augmentation (strong overfitting, gap loss 0.4→0.7) and 62.5% with augmentation (moderate overfitting, gap ~15%).

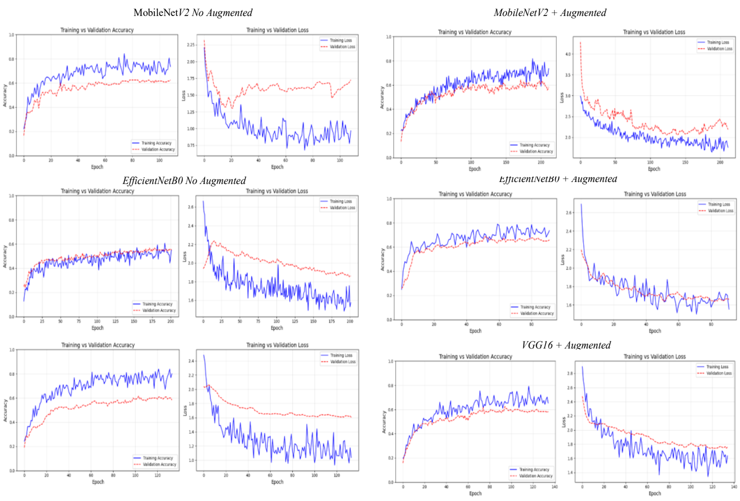

Figure 8. Train-Split Data Ratio 70:30

2) Train Split Data 80:20

At an 80:20 data ratio, MobileNetV2 showed the most dramatic transformation with accuracy jumping from 61.25% without augmentation to 81.25% with augmentation (a 20% increase). Strong overfitting conditions (loss gap of 0.5-0.6) changed to minimal overfitting with a gap of ~10%, where training and validation accuracy moved in parallel throughout epochs. EfficientNetB0 experienced significant improvement from underfitting conditions without augmentation (65% accuracy) to very good generalization with augmentation (80% accuracy, minimal overfitting with ±10% gap). VGG16 continued to show overfitting vulnerability but with improvement from 56.25% to 66.25%.

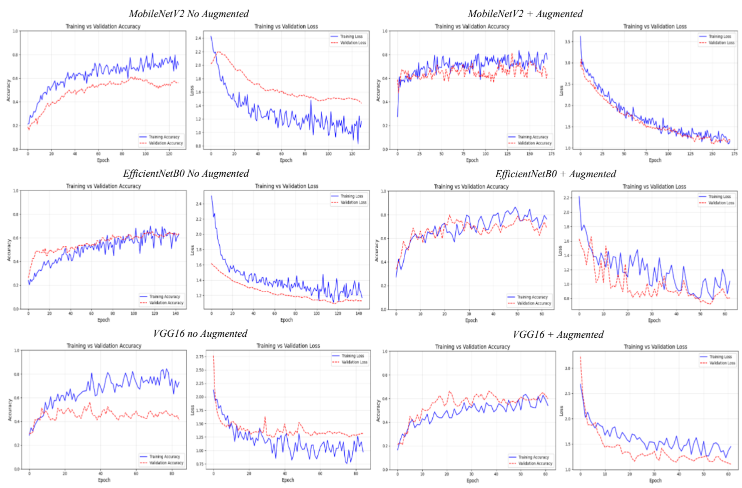

Figure 9. Train-Split Data Ratio 80:20

DOI: 10.30736/jt.v18i1.1639
ISSN: 2085-0859, E-ISSN: 2620-4770

The application of data augmentation proved effective in reducing overfitting in all models. The gap between training and validation accuracy decreased from 0.5-0.7 (without augmentation) to 0.1-0.2 (with augmentation). A more stable and convergent learning curve indicates an increase in the generalization ability of the model, resulting in the following accuracy table:

Table 2. Model Training Results

Model	70:30		80:20	
	Augmentation		Augmentation	
	No	Yes	No	Yes
Mobile NetV2	62.5%	65%	61.25%	**81.25%**
EfficientNetB0	56.67%	62.5%	65%	80%
VGG16	61.67%	62.5%	56.25%	66.25%

The superior performance of MobileNetV2 at 80:20 ratio compared to 70:30 can be explained through several architectural and data-related factors. The 80:20 split provides 320 training samples compared to 280 samples in the 70:30 split. This additional 40 images (14.3% increase) proves critical for MobileNetV2's depthwise separable convolution architecture. Each additional sample contributes more effectively to learning discriminative features in the inverted residual blocks. The lightweight architecture of MobileNetV2 requires sufficient data diversity to fully train its efficient bottleneck structures.

MobileNetV2's inverted residual structure with linear bottlenecks is specifically designed for efficient learning from limited data. At 80:20 ratio, the increased training data allows the network to better optimize the expansion layers (1×1 convolutions) that increase channel dimensionality, more effectively train depthwise convolutions for spatial feature extraction, and properly tune projection layers that reduce dimensionality back to efficient representations. In contrast, at 70:30 ratio, insufficient training samples cause these bottleneck structures to underfit, preventing the model from learning optimal feature representations.

The smaller validation set in the 80:20 configuration (80 samples compared to 120 samples in the 70:30 split) contributes to reduced variance in the validation metrics. With 16 samples per class, the model receives more consistent and representative feedback during the training process. This condition enables the adaptive learning mechanism of MobileNetV2 to converge more effectively toward optimal weight configurations, minimizing the influence of noisy validation signals. Furthermore, the lightweight nature of the MobileNetV2 architecture exhibits a stronger synergistic effect with data augmentation techniques under the 80:20 ratio. The increased amount of training data (320 samples) combined with augmentation strategies—such as traditional augmentation, MixUp, CutMix, and CGAN-facilitates the construction of a more diverse and comprehensive feature space.

In contrast, VGG16 and EfficientNetB0 demonstrate relatively smaller performance improvements under the same data split. VGG16 shows an increase in accuracy from 61.67% to 66.25% (a gain of 4.58%), which can be attributed to its deeper and more parameter-heavy structure that requires a larger dataset to mitigate overfitting. Meanwhile, EfficientNetB0 achieves an accuracy of 80%, reflecting a moderate improvement (15% gain) compared to MobileNetV2's 20% gain. Despite its efficient compound scaling, EfficientNetB0 still maintains higher architectural complexity. The parameter efficiency of MobileNetV2 allows it to optimize learning from the 80:20 training configuration while minimizing the risk of overfitting.

3.2 Model Evaluation Results

1) Confusion Matrix 70:30

Based on the performance analysis of the classification model with 70:30 data split, MobileNetV2 showed the best performance with 65% accuracy after data augmentation (increased from 62.5%), followed by EfficientNetB0 which experienced the most significant improvement (5.83% points) and VGG16 which was the most stable. Per-class analysis showed that TMV and Sunscald were easy to detect with high F1-score (89.80% and 85.71%), while Bacterial Brown Spot was the most difficult class with low recall (≤50%) across all models. The Healthy class shows a decrease in performance when using augmentation, creating a trade-off that requires different strategies per class.

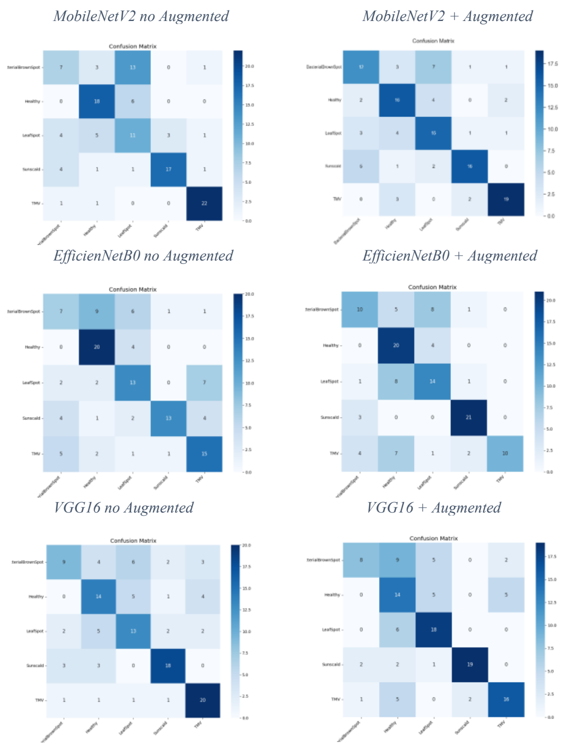

Figure 10. Confusion Matrix Ratio 70:30

DOI: 10.30736/jt.v18i1.1639
ISSN: 2085-0859, E-ISSN: 2620-4770

2) Confusion Matrix 80:20

The performance analysis of the 80:20 ratio model shows a dramatic transformation compared to the 70:30 ratio. MobileNetV2 achieved the highest-accuracy of 81.25% after augmentation (20% point improvement), followed by EfficientNetB0 with 80% (15%) and VGG16 with 66.25% (10%). The Bacterial Brown Spot class, which was previously the biggest challenge, experienced a remarkable F1-score improvement of 81.08% with recall jumping from 62.5% to 93.75% on MobileNetV2. This dramatic improvement can be attributed to the increased training samples allowing better learning of dramatic improvement can be attributed to the increased training samples allowing better learning of subtle brown spot patterns that were previously confused with leaf spot or sunscald damage. Other classes such as TMV and Sunscald maintained good performance with F1-score above 85%. The stability of these classes across different ratios indicates they possess distinctive visual features that are easier for CNN architectures to learn.

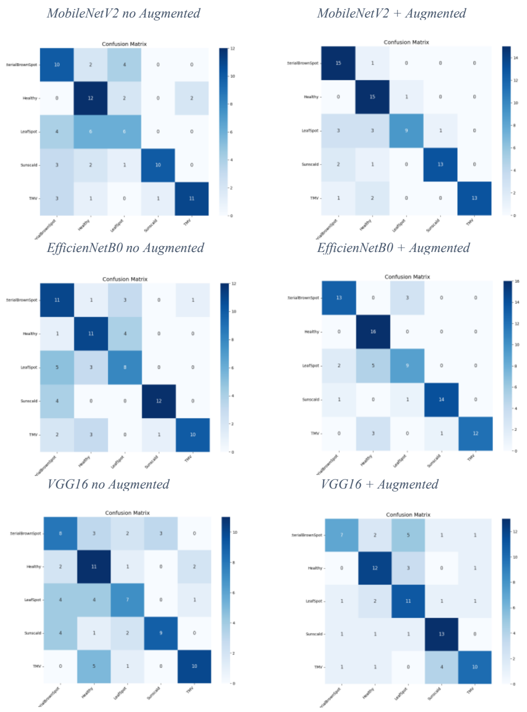

Figure 11. Confusion Matrix Ratio 80:20

From the discussion above, researchers obtained data on the best model per class:

Table 3. Best Model Classification Report

Class	Model (Ratio 70:30)	Precision	Recall	F1-Score	Acc/Class
Bacterial Brown Spot	VGG16 + Aug	72,73%	33,33%	45,71%	84,17%
Healthy	EfficientNetB0 (No Aug)	58,82%	83,33%	68,97%	85%
Leaf Spot	VGG16 + Aug	62,07%	75%	67,92%	85,83%
Sunscald	EfficientNetB0 (No Aug)	86,67%	54,17%	66,67%	89,17%
TMV	MobileNetV2 (No Aug)	88%	91,67%	89,8%	95,83%
Class	**Model (Ratio 80:20)**	**Precision**	**Recall**	**F1-Score**	**Acc/Class**
Bacterial Brown Spot	EfficientNetB0 + Aug	81,25%	81,25%	81,25%	92,5%
Healthy	EfficientNetB0 + Aug	66,67%	100%	80%	90%
Leaf Spot	MobileNetV2 + Aug	90%	56,25%	69,23%	90%
Sunscald	MobileNetV2 + Aug	92,86%	81,25%	86,67%	95%
TMV	MobileNetV2 + Aug	100%	81,25%	89,66%	96,25%

The evaluation results show that the impact of data augmentation varies depending on the model architecture and data sharing ratio, with 80:20 ratio providing superior performance compared to 70:30. At 70:30 ratio, models without augmentation outperformed in certain classes such as EfficientNetB0 with 83.33% recall and 68.97% F1-score for Healthy, and MobileNetV2 with 89.8% F1-score for TMV. This suggests that at lower training data volumes, aggressive augmentation may introduce unnecessary complexity that hinders learning of classes with distinctive features. However, VGG16 with augmentation achieved 72.73% precision but low recall of 33.33% for Bacterial Brown Spot, indicating difficulty in identifying all positive cases of this disease class. At 80:20 ratio, augmentation significantly improved performance with EfficientNetB0 achieving a perfect precision-recall balance of 81.25% for Bacterial Brown Spot and 100% recall for Healthy class, ensuring no diseased plants are misclassified as healthy. MobileNetV2 dominated three classes with 100% precision for TMV and F1-scores ranging from 86.67% to 89.66%, demonstrating excellent disease detection capability. TMV precision increased by 12% although Leaf Spot experienced a trade-off with precision increasing by 22% but recall decreasing by 6.9%, suggesting the model became more conservative in predicting this class. VGG16 showed the lowest augmentation impact with only 10% improvement, while the highest accuracy of 96.25% was achieved by MobileNetV2 for TMV at a ratio of 80:20. The results demonstrate an increase in global accuracy of 15-20% and F1-score of more than 15% for minor classes, successfully overcoming the detection problems of minority classes such as Bacterial Brown Spot.

DOI: 10.30736/jt.v18i1.1639
ISSN: 2085-0859, E-ISSN: 2620-4770

4 CONCLUSION

From the evaluation results, it is evident that multi-strategy data augmentation makes a significant contribution in improving the accuracy of tobacco leaf disease classification using CNN architecture. MobileNetV2 showed the best performance by achieving 81.25% accuracy at 80:20 ratio (improved from 61.25% without augmentation), EfficientNetB0 underwent transformation from underfitting to optimal generalization with 80% accuracy (improved from 65% without augmentation), and VGG16 showed moderate improvement from 56.25% to 66.25%. Comparative analysis of data sharing ratios showed that an 80:20 ratio provided synergistic impact with augmentation compared to the 70:30 ratio, where MobileNetV2 only achieved 65% accuracy with a minimal improvement of 2.5% points at 70:30 ratio, while at 80:20 ratio resulted in a dramatic improvement of 20% points.

The augmentation technique proved effective in overcoming the overfitting problem by reducing the gap between training and validation accuracies from the range of 0.5-0.7 to 0.1-0.2, as well as successfully overcoming the detection challenges of minority classes such as Bacterial Brown Spot which experienced an increase in F1-score to 81.25% on EfficientNetB0 with a ratio of 80:20. The optimal combination of MobileNetV2 with multi-strategy augmentation at a ratio of 80:20 resulted in a tobacco leaf disease detection system ready for practical implementation with 81.25% accuracy and balanced detection capability for all disease classes, providing an effective solution for early detection with limited datasets in the context of precision agriculture. Further research is recommended to focus on the development of adaptive ensemble techniques and real-time system implementation for development on mobile devices in the agricultural field.

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