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Poultry disease classification using EfficientNetV2-L and MobileNetV2 based on fecal images

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Abstract

The timely identification of poultry diseases is essential for maintaining high livestock yields and curbing the transmission of infections, which directly supports global food security. The integration of multi-layered neural architectures has advanced this diagnostic process, offering an innovative approach to automated health monitoring through enhanced classification accuracy. By employing Convolutional Neural Networks (CNNs), the extraction of discriminative features from fecal images is automated, providing a scalable and robust approach to sustainable agriculture. This study proposes poultry disease classification using two CNN architectures, EfficientNetV2-L and MobileNetV2, trained under three scenarios: baseline, class weights, and Focal Loss. Using a dataset of 6,812 chicken fecal images, the experimental results demonstrate that applying Focal Loss significantly improves performance across all metrics. The EfficientNetV2-L model with Focal Loss achieved superior results, with 99.51% accuracy, 99.57% precision, 99.51% recall, and 99.52% F1-score. Meanwhile, MobileNetV2 performed reasonably well with a faster training time, making it suitable for resource-constrained environments. These findings indicate that combining Focal Loss with efficient CNN architectures enhances the classification of imbalanced datasets and provides a promising technological solution for real-time poultry disease detection systems.

1. Introduction

Poultry diseases represent a primary catalyst for declining productivity within the livestock industry, particularly in developing nations such as Indonesia. The prevalence of intensive poultry farming has facilitated the rapid transmission of infectious pathogens, including Coccidiosis, Salmonellosis, and Newcastle Disease, resulting in high mortality rates and substantial economic disruption [1]. Early diagnostic is imperative to curb infection spread and maintain sustainable production cycles. However, conventional diagnostic frameworks remain heavily reliant on manual observation or laboratory procedures, which are often prohibitively expensive, time-consuming, and dependent on expert interpretation [2].

Modern AI-driven methodologies have advanced image-based diagnostics across both healthcare and veterinary sciences. Specifically, Convolutional Neural Networks (CNNs) have demonstrated high proficiency in automated feature extraction, object recognition, and complex image classification [3], [4], [5], [6], [7]. The efficacy of CNN frameworks is well documented in the automated detection of agricultural diseases, leveraging visual data from diverse biological sources ranging from plant organs to animal excretions [8], [9], [10], [11], [12]. Various CNN architectures, such as VGGNet, AlexNet, ResNet, Inception, DenseNet, and MobileNet, have achieved state-of-the-art performance in diverse recognition tasks [13], [14], [15]. Among these, MobileNetV2 and EfficientNetV2 are distinguished by their relatively low computational overhead and reduced parameter counts, rendering them suitable for embedded or real-time deployment [16], [17]. While EfficientNetV2-L utilizes progressive training and fused-MBConv modules to optimize the balance between throughput and accuracy [17], MobileNetV2 prioritizes resource efficiency through linear bottlenecks and inverted residual blocks, maintaining predictive power despite reduced complexity [18].

Recent literature has explored the application of CNNs for poultry disease detection specifically through fecal images. Degu and Simegn [19] developed a smartphone-based CNN system that achieved over 95% accuracy, while Mustopa et al. [20] successfully classified fecal images to distinguish between healthy and diseased poultry with 97% accuracy. Despite these robust performances, a significant challenge in poultry disease classification persists: class imbalance. In many datasets, certain disease categories contain significantly fewer samples than healthy classes, causing models to become biased toward the majority class. This bias results in poor sensitivity for minority classes, which are often the most critical in real-world outbreak scenarios [21], [22]. Proposed mitigation strategies for this issue include oversampling, class weighting, and adaptive loss functions such as Focal Loss [23], [24], [25]. Focal Loss, in particular, adaptively down-weights the contribution of easy-to-classify samples to concentrate the learning process on challenging or minority cases [26].

To address the limitations imposed by class imbalance, this study proposes an integrated classification framework utilizing Focal Loss in conjunction with the EfficientNetV2-L and MobileNetV2 architectures. Unlike data-level resampling or ensemble methods, Focal Loss offers a more efficient and direct mechanism for addressing imbalance within the loss function during training without altering the original data distribution.

The primary contributions of this work are as follows:

1. Implementation of an optimized poultry disease classification approach using EfficientNetV2-L and MobileNetV2 based on fecal images.
2. An empirical evaluation of the effectiveness of Focal Loss in mitigating class imbalance compared to baseline and class-weighting strategies.
3. A comprehensive performance analysis focusing on accuracy, precision, recall, and F1-score, alongside an assessment of computational efficiency for potential real-time implementation.

The remainder of this paper is organized as follows: Section 2 details the methodological framework, including data preparation and training strategies; Section 3 presents the experimental results and comparative discussion; and Section 4 concludes with the key findings and future research directions.

2. Research Method

2.1 Method

This study employed two Convolutional Neural Network (CNN) models, namely EfficientNetV2-L and MobileNetV2, to classify poultry diseases based on fecal images. Both models in this study were trained directly on the poultry feces dataset under three experimental scenarios: Baseline, Class Weights, and Focal Loss. Each scenario aimed to analyze the model's capabilities in handling class imbalance and improving classification performance. The research process included data preprocessing, model design, training, evaluation using accuracy, precision, recall, and F1-score metrics, and result analysis. The overall methodological flow is shown in Figure 1.

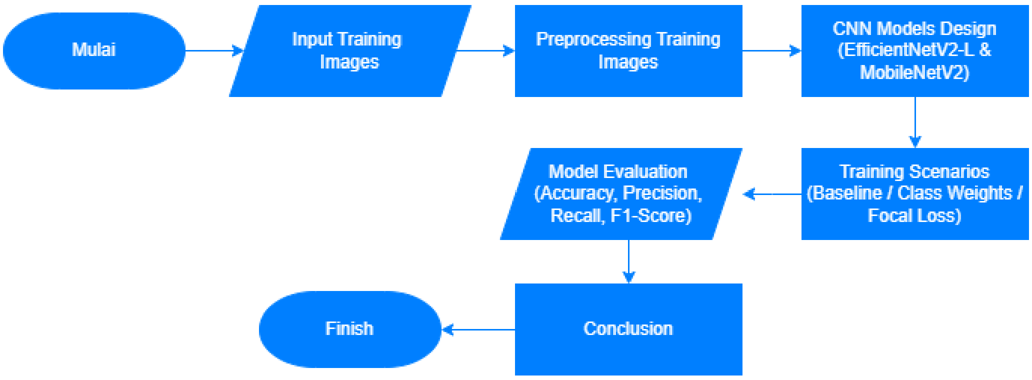

Figure 1. Research Method

2.2 Dataset

Data for this research were retrieved from the Poultry Diseases Detection Dataset available on Kaggle [27]. The dataset contains four categories of chicken fecal images, namely Coccidiosis, Salmonella, Newcastle Disease, and Healthy with a total of 6,812 samples. All images are in RGB format with varying lighting conditions, orientations, and backgrounds. All images were resized to a resolution of 224 pixels to align with the input specifications of the CNN models. Subsequently, the dataset was partitioned into three distinct groups, consisting of 70% for model training, 15% for validation, and the remaining 15% for testing, to balance the need for sufficient training data with an adequate test sample size for stable estimation [28].

Prior to model training, all pixel intensity values were normalized by dividing them by 255, resulting in values within the range of 0 to 1 to accelerate model convergence and prevent gradient explosion [29]. This normalization step reduced computational cost and accelerated convergence during model optimization. To improve generalization and prevent overfitting, data augmentation was also performed on the training set. The applied augmentation techniques included image rotation of up to 30°, zooming up to a scale of 0.3, horizontal flipping, random translation in both width and height directions with a range of 0.3, and a shear transformation of 0.3. These variations were introduced to ensure that the model could recognize features under diverse environmental conditions, such as differences in lighting and backgrounds. A recent study highlights that augmentation significantly improves classification accuracy in limited or imbalanced image datasets, particularly in agricultural and medical domains [30]. Sample images from the dataset are presented in Figure 2.

Figure 2. Random Image Samples: (1) Coccidiosis, (2) Salmonella, (3) NewCastle Disease, (4) Healthy

2.3 Design of the CNN Model

Two prominent architectures, EfficientNetV2-L and MobileNetV2, were selected for the CNN model design based on their well-documented reliability and performance in image classification tasks. These architectures were adopted for their superior performance-to-efficiency ratio, making them suitable for the automated recognition of poultry diseases from fecal samples. Figure 3 illustrates the overall CNN architecture used in this study.

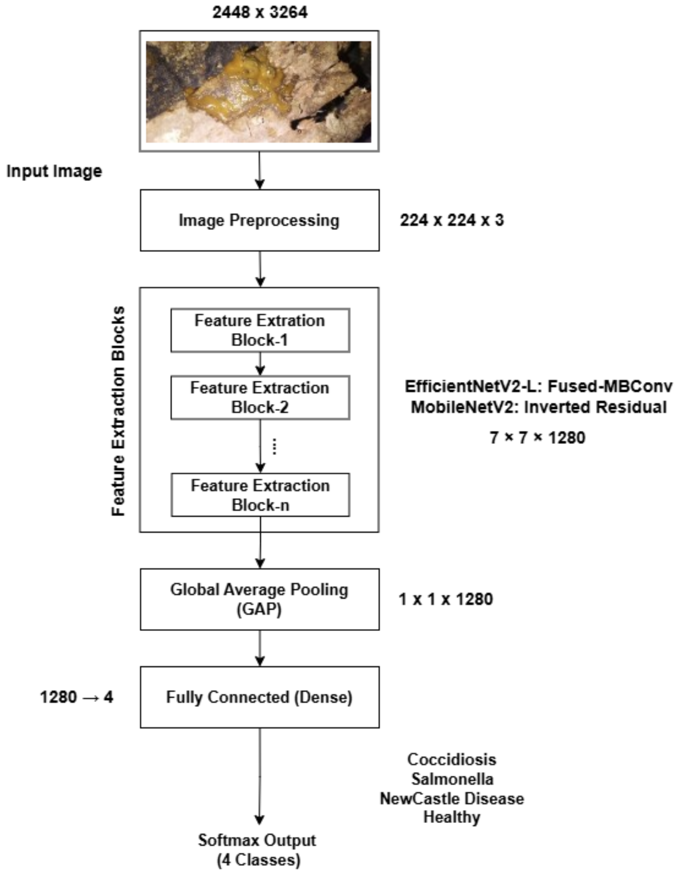

Figure 3. CNN Model Architecture for Poultry Disease Classification using EfficientNetV2-L and MobileNetV2

EfficientNetV2-L introduces a combination of fused-MBConv and progressive learning strategies to accelerate training and enhance feature extraction at higher resolutions. This architecture scales depth, width, and input resolution in a compound manner, enabling improved performance with fewer parameters [17].

MobileNetV2 is characterized by its lightweight structural design, which effectively balances model compactness with robust representational capabilities for use in resource-constrained environments [31]. This lightweight structure is highly efficient for mobile and real-time implementations, making it advantageous for potential deployment in field environments.

Both CNN architectures share a similar overall structure consisting of three main components:

1. Feature extraction: Feature extraction is performed using convolutional layers and batch normalization to capture spatial and textural information from input images [32].
2. Global Average Pooling (GAP): GAP reduces feature dimensionality while helping prevent overfitting by aggregating global spatial information from feature maps [33].
3. Classification Layer: A fully connected layer followed by a Softmax activation function is used to produce probability outputs for each class: Coccidiosis, Salmonella, Newcastle Disease, and Healthy [34].

2.4 Experimental Environment

The experiments were conducted using Google Colab Pro on a system configured with an Intel(R) Core (TM) i5-1035G1 with 8 CPUs at 1.00 GHz, 8 GB of RAM, and Tesla T4 GPU with 12.7 GB of available memory. The platform used Python with TensorFlow and Keras libraries as the primary deep learning frameworks.

2.5 Training Scenarios

To evaluate the impact of class-imbalance handling techniques, this study implemented three training scenarios using the same dataset and model architectures. The first scenario, referred to as Baseline, trained both models without applying any loss adjustment or class-balancing mechanism. The second scenario, Class Weights, introduced weighting factors into the loss function based on the inverse frequency of each class in the training dataset. This method increased the influence of minority classes during optimization. The third scenario employed the Focal Loss function. This loss function dynamically reduced the contribution of easily classified samples while emphasizing harder-to-classify or minority-class examples. By combining Focal Loss with efficient CNN architectures, the models were expected to learn more effectively from difficult samples and achieve balanced classification performance across all disease categories. The training scenarios are presented in Table 1.

Table 1. Training Scenarios

Scenario	Model	Hyperparameter			
		Optimizer	Learning Rate	Batch Size	Epochs
Baseline	MobileNetV2	Adam	0.001	32	20
	EfficientNetV2-L	Adam	0.001	32	20
Class Weights	MobileNetV2	Adam	0.001	32	20
	EfficientNetV2-L	Adam	0.001	32	20
Focal Loss	MobileNetV2	Adam	0.001	32	20
	EfficientNetV2-L	Adam	0.001	32	20

2.6 Evaluation Framework

The predictive performance of the CNN architectures was quantified using a set of evaluation metrics, specifically accuracy, precision, recall, and F1-score. These metrics were computed based on the distribution of True Positives, True Negatives, False Positives, and False Negatives within the test dataset. Accuracy, precision, recall, and F1-score were calculated using Equations 1, 2, 3, and 4, respectively.

$$Accuracy = \frac{TruePositives + TrueNegatives}{TruePositives + TrueNegatives + FalsePositives + FalseNegatives} \tag{1}$$

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{2}$$

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{3}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

3. Results and Discussion

3.1 Baseline Performance Analysis (Scenario 1)

In the initial experimental phase, both CNN architectures were evaluated without class-balancing techniques or loss function modifications to establish a performance baseline. EfficientNetV2-L consistently outperformed MobileNetV2 across all evaluated metrics, achieving higher accuracy, precision, recall, and F1-score. This performance advantage can be attributed to its deeper architecture and fused-MBConv structure, which enables more robust representation of the spatial and textural variations present in fecal images.

While EfficientNetV2-L demonstrated nearlyoptimal results, MobileNetV2 yielded relatively lower performance on the imbalanced dataset. Both models exhibited specific limitations in handling minority classes, as evidenced by the misclassifications shown in the confusion matrices.

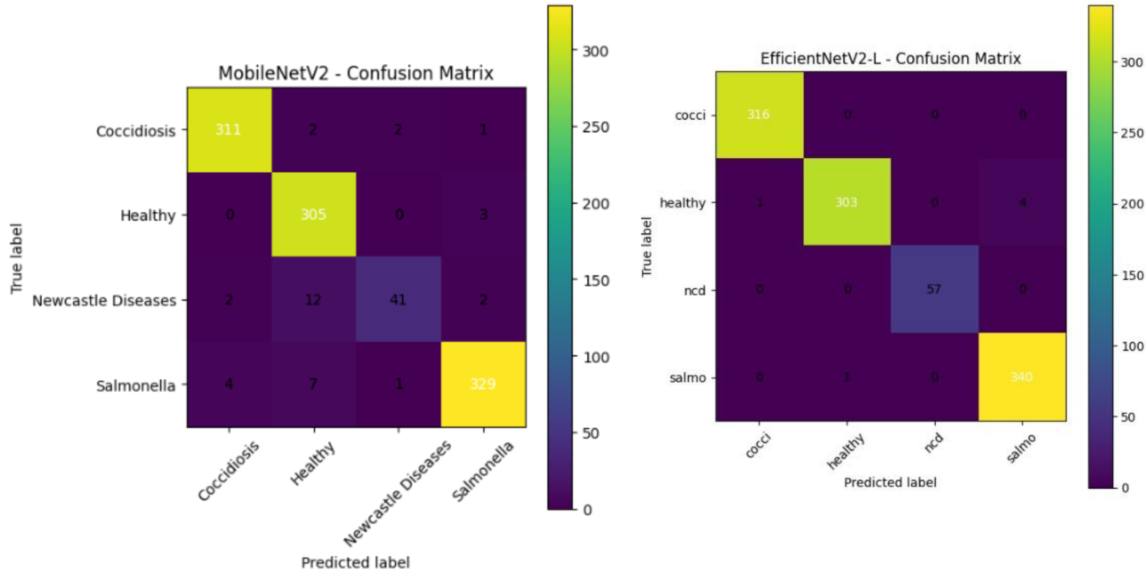

Figure 4. Confusion Matrix of MobileNetV2 and EfficientNetV2-L in the Baseline Scenario

Based on the confusion matrices in Figure 4, the majority of misclassifications occurred within the Newcastle Disease class. This pattern indicates that this specific class possesses more complex visual features compared with the others, suggesting that the models struggle to distinguish subtle differences between similar disease patterns when no optimization techniques are applied.

3.2 Performance Under Class-Weights Optimization (Scenario 2)

The second experimental phase integrated a class-weighting strategy to mitigate dataset imbalance. By increasing the penalty for misclassifications of minority classes within the loss function, the models were encouraged to learn features from underrepresented samples. Under this configuration, EfficientNetV2-L maintained high performance, while MobileNetV2 demonstrated relatively stable performance.

A comparative analysis between this scenario and the initial baseline indicated a marginal reduction in overall classification accuracy for both CNN architectures, with MobileNetV2 achieving 96.38% and EfficientNetV2-L achieving 98.86%. This decline can occurr when class weighting is applied because the mechanism encourages the models to place greater emphasis to underrepresented classes, potentially at the expense of overall accuracy. Consequently, although overall accuracy decreased slightly, the models became more sensitive to minority classes.

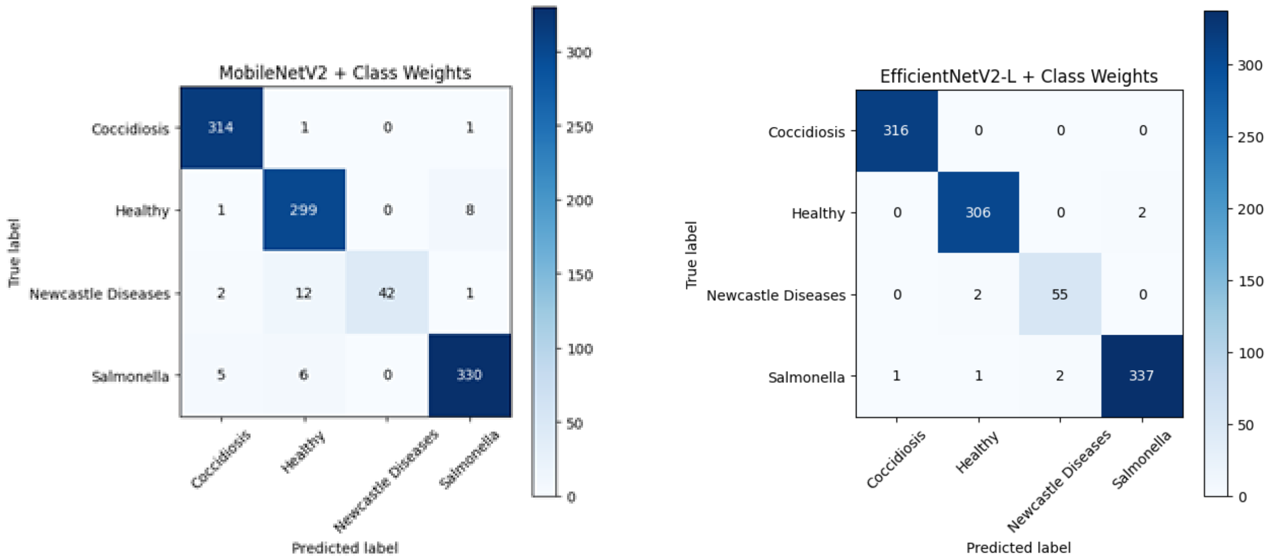

Figure 5. Confusion Matrices of MobileNetV2 and EfficientNetV2-L in the Class Weights Scenario

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As shown in Figure 5, the application of class weights reduced the bias toward the majority class. Compared to the baseline scenario, the number of correctly classified samples in minority classes—specifically Newcastle Disease—increased, indicating a more balanced prediction distribution. However, minor misclassifications persisted between visually similar classes, suggesting that although class weighting redistributed the learning focus, it did not fully resolve the challenge of distinguishing complex patterns in the imbalanced dataset.

3.3 Performance Assessment with Focal Loss Optimization (Scenario 3)

In the final experimental stage, the Focal Loss function was integrated to enhance the models' sensitivity to underrepresented and challenging samples. By assigning a focusing parameter ($\gamma = 2$), the training process effectively down-weighted the contribution of easily classified instances, prioritizing the learning of more difficult data patterns. This configuration yielded the strongest results in the study, with both architectures converging within 20 epochs. EfficientNetV2-L achieved an accuracy of 99.51% and an F1-score of 99.52%, while MobileNetV2 demonstrated a steady improvement, reaching an accuracy of 97.55%.

The implementation of Focal Loss resulted in a noticeable performance improvement compared with the previous two scenarios, particularly in recall and F1-score, indicating enhanced sensitivity toward minority classes. These results suggest that Focal Loss effectively addressed class imbalance by focusing the learning process on hard-to-classify samples. EfficientNetV2-L's superior performance can be attributed to its deeper architecture and capacity to extract complex features from fecal images. While MobileNetV2 was more computationally efficient, its slightly lower performance compared to EfficientNetV2-L suggested limitations in capturing highly complex patterns.

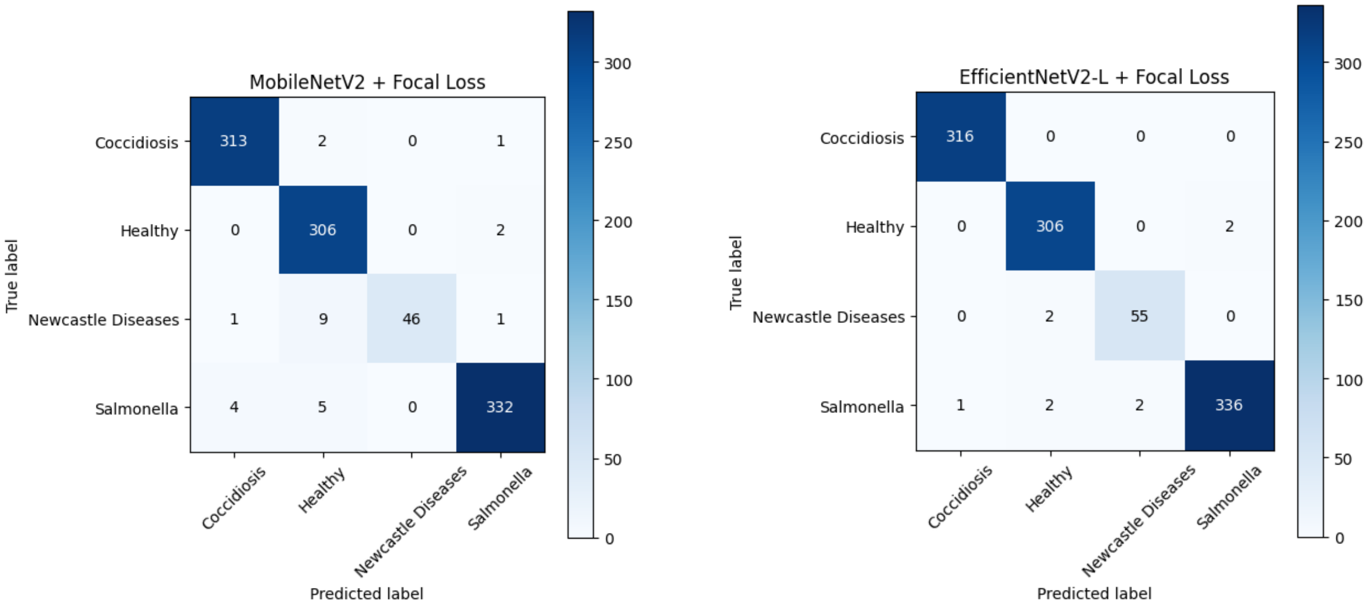

Figure 6. Confusion Matrices of MobileNetV2 and EfficientNetV2-L in the Focal Loss Scenario

Based on Figure 6, the confusion matrices demonstrated a significant reduction in misclassification across all classes. The model achieved high precision for minority classes, specifically Newcastle Disease and Salmonella, which previously exhibited higher error rates in the baseline and class-weights scenarios. The use of Focal Loss effectively directed the learning process toward challenging instances, promoting more consistent classification. This was further supported by the confusion matrices, where the strong diagonal dominance reflected the model's success in distinguishing the characteristics of each disease class.

3.4 Research Analysis and Limitations

The overall performance comparison of both CNN architectures under all training scenarios is summarized in Table 2. The table shows that applying Class Weights and Focal Loss significantly improved the model performance compared to the Baseline configuration. The highest accuracy was achieved by the EfficientNetV2-L model using Focal Loss, reaching 99.51%, followed by MobileNetV2 with 97.55%.

Table 2. Performance of CNN Models in All Scenarios

Models	Scenario	Evaluation Metrics (%)				Epoch Stop
		Accuracy	Precision	Recall	F1-Score	
MobileNetV2	Baseline	96.48	96.50	96.48	96.38	18

MobileNetV2	Class Weights	96.38	96.45	96.38	96.29	18
MobileNetV2	Focal Loss	**97.55**	**97.62**	**97.55**	**97.51**	20
EfficientNetV2-L	Baseline	99.41	99.42	99.41	99.41	20
EfficientNetV2-L	Class Weights	98.86	98.85	98.86	98.85	20
EfficientNetV2-L	Focal Loss	**99.51**	**99.57**	**99.51**	**99.52**	20

From the comparison, it can be observed that the use of adaptive loss functions improved both architectures' ability to classify minority classes. The Focal Loss method yielded the highest gains in accuracy, precision, recall, and F1-score, demonstrating its effectiveness in handling imbalanced datasets. Although EfficientNetV2-L achieved superior accuracy, it required longer computational time compared to MobileNetV2, which converged faster with fewer parameters. Therefore, the choice between the two models depends on the target application: EfficientNetV2-L is suitable for high-accuracy systems, while MobileNetV2 is more practical for real-time or embedded deployment. The training and validation accuracy and loss for all scenarios are presented in Figure 7.

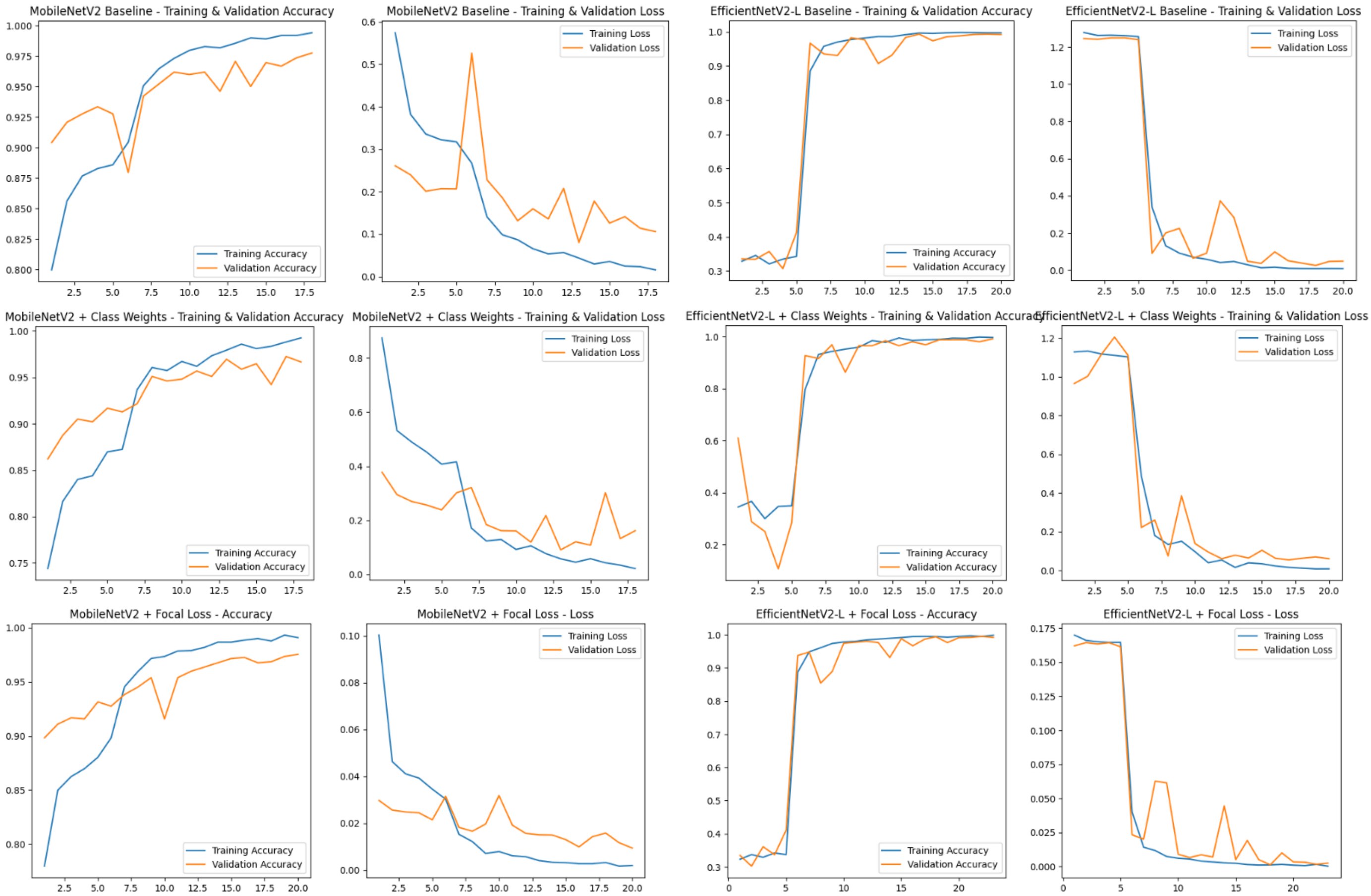

Figure 7. Accuracy and Loss Curves of EfficientNetV2-L and MobileNetV2 Under All Scenarios

Despite the high classification performance, this study still has some limitations. The dataset only covers four poultry disease classes, which may not represent all possible field conditions. Additionally, image variations such as lighting, texture, and camera quality could influence prediction accuracy in real-world applications. Future research may expand the dataset, integrate more disease types, and explore hybrid or ensemble CNN architectures to further improve robustness.

To further validate the effectiveness of the proposed method, a comparison with previous studies was conducted. Degu and Simegn [19] developed a CNN-based approach for poultry disease detection and achieved an accuracy of over 95%. Similarly, Mustopa et al. [20] reported an accuracy of approximately 97% using CNN architectures for fecal image classification. In comparison, the proposed method in this research demonstrated superior accuracy of 99.51% using EfficientNetV2-L with Focal Loss. This result demonstrates a considerable advancement over prior techniques, indicating that the integration of Focal Loss is effective in addressing class imbalance and enhancing classification performance. This improvement suggests that the integration of Focal Loss plays a crucial role in addressing class imbalance, which was not explicitly handled in previous studies.

While prior investigations typically utilized a single model, this study implemented a multi-faceted evaluation involving dual architectures and a trio of training scenarios to better understand model dynamics under various imbalance-handling techniques.

The evidence suggests that the proposed system delivers both heightened precision and robust performance under imbalanced conditions, establishing it as a highly feasible candidate for practical poultry health monitoring. Analysis of the confusion matrices provides a detailed view of class-specific performance, indicating that the Focal Loss method effectively bridges the gap between majority and minority class learning. There is a clear trade-off between the high-resource requirements of EfficientNetV2-L and the rapid, low-cost inference of MobileNetV2; the former is optimized for accuracy, while the latter is better suited for real-time applications. Future developments aim to incorporate cross-validation and Grad-CAM methodologies to bolster the model's interpretability and statistical reliability.

4. Conclusion

Implementing Class Weights and Focal Loss significantly improved the performance of the pre-trained CNN models used in this study. Based on the experimental results, the EfficientNetV2-L model with Focal Loss achieved the highest accuracy of 99.51%, precision of 99.57%, recall of 99.51%, and F1-score of 99.52%, outperforming other configurations. Meanwhile, the MobileNetV2 model also demonstrated competitive results with faster computational time, making it more efficient for real-time implementation.

These findings indicate that the use of adaptive loss functions, particularly Focal Loss, can effectively handle class imbalance in image-based poultry disease classification. Future work can explore extending the dataset with more disease variations, optimizing model architectures for lightweight deployment, and integrating real-time detection through IoT or mobile platform applications.

Notation

Model performance is quantified using four primary notations. True Positives and True Negatives correspond to successful predictions for the respective classes. In contrast, False Positives involve the misclassification of negative data, whereas False Negatives occur when positive instances are inaccurately labeled as negative.

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