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DEEP LEARNING BASED DETECTION OF LAYING HEN HEALTH STATUS FROM EXCRETA IMAGES USING MOBILENETV2

Muhammad Nidhomun Ni'am[1], Sri Widiastuti[2], Wildan Deni Fahrezi[3], Thoriqul Irfah Al-Huda[2], Abdul Karim Muqofi[4], Rizal Aji Mustofa[1], Arib Zainul Muafi[1]
[1] Program Studi Produksi Ternak, Universitas Muhammadiyah Karanganyar, Karanganyar*
[2] Program Studi Magister Ilmu Peternakan, Universitas Gadjah Mada, Yogyakarta
[3] Program Studi Teknik Komputer, Universitas Muhammadiyah Karanganyar, Karanganyar
[4] Program Studi Peternakan, Universitas Muhammadiyah Karanganyar, Karanganyar
Corresponding e-mail: muhammadnidhomun@gmail.com

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Abstract

Early and accurate disease detection is a critical challenge in modern poultry farming. This study aimed to develop and evaluate a deep learning-based classification system using MobileNetV2 Convolutional Neural Network (CNN) architecture for automated detection of poultry diseases from excreta images only, and to validate model predictions against laboratory microbiological analyses. A total dataset of 8,087 labeled excreta images was compiled across four health categories: Healthy, Salmonella, Coccidiosis, and Newcastle Disease, and subsequently split into training (6,471) and validation (1,616) subsets at an 80:20 ratio. The MobileNetV2 model was trained over eight epochs with data augmentation strategies and evaluated using precision, recall, F1-score, accuracy, and confusion matrix analysis. The model achieved an overall accuracy of 91%, with the highest per-class F1-score for Coccidiosis (0.97) and the lowest for Newcastle Disease (0.75). The CNN MobileNetV2 architecture demonstrates strong potential for real-time, non-invasive poultry disease monitoring.
Keywords: *Convolutional Neural Network, Excreta Images, MobileNetV2, Poultry Diseases*

Deteksi Status Kesehatan Ayam Petelur Berbasis *Deep Learning* Dari Citra Ekskreta Menggunakan MobileNetV2

Abstrak

Deteksi dini penyakit secara akurat merupakan tantangan kritis dalam peternakan unggas modern. Penelitian ini bertujuan untuk mengembangkan dan mengevaluasi sistem klasifikasi berbasis deep learning menggunakan arsitektur Convolutional Neural Network (CNN) MobileNetV2 untuk deteksi otomatis penyakit unggas dari citra ekskreta saja, serta memvalidasi prediksi model terhadap hasil analisis laboratorium mikrobiologi. Total dataset sebanyak 8.087 citra ekskreta berlabel dikompilasi dalam empat kategori kesehatan: Sehat, Salmonella, Koksidiosis, dan Newcastle Disease, yang kemudian dibagi menjadi subset pelatihan (6.471 citra) dan validasi (1.616 citra) dengan rasio 80:20. Model MobileNetV2 dilatih selama delapan epoch dengan strategi augmentasi data dan dievaluasi menggunakan presisi, recall, F1-score, akurasi, dan analisis confusion matrix. Hasil model mencapai akurasi keseluruhan sebesar 91%, dengan F1-score tertinggi untuk kelas Koksidiosis (0,97) dan terendah untuk Newcastle Disease (0,75). Arsitektur CNN MobileNetV2 menunjukkan potensi kuat untuk pemantauan kesehatan unggas secara real-time dan non-invasif.
Kata Kunci: *Citra Eksreta, Convolutional Neural Network, MobileNetV2, Penyakit Unggas*

1. Introduction

The global poultry sector faces mounting production pressures driven by rising worldwide demand for animal protein. Within this context, the management of infectious diseases in laying hens represents one of the most operationally critical challenges, given its direct consequences on flock morbidity, mortality, and overall production efficiency. Diseases such as Salmonellosis, Coccidiosis, and Newcastle Disease have been widely reported to cause substantial economic losses across commercial poultry operations globally (Okinda et al., 2020; Yang et al., 2024).

Conventional disease surveillance in poultry predominantly relies on two approaches: clinical observation by farm personnel and laboratory-based diagnostic testing. While laboratory diagnostics offer high specificity, they are inherently retrospective, time consuming, and costly, thereby limiting the capacity for timely intervention during early-stage infection. Conversely, manual visual inspection is susceptible to inter-observer variability and is impractical at the population densities typical of industrial poultry operations (Supriyanto et al., 2023). These limitations underscore the urgent need for automated, objective, and computationally efficient early detection systems.

Recent advances in computer vision and deep learning present a compelling opportunity to address these challenges. Convolutional Neural Networks (CNN) have demonstrated strong performance across a range of image classification tasks in precision agriculture, including broiler body segmentation (Akhtari et al., 2026), lameness detection (Triyanto et al., 2024), and excreta image classification for poultry disease prediction (Gawas & Gawas, 2026; Nakrosis et al., 2023). Among the available architectures, MobileNetV2 stands out as a particularly suitable candidate for resource-constrained deployment environments. Its inverted residual block structure and depthwise separable convolutions enable competitive classification accuracy at substantially reduced computational cost (Donthi et al., 2024), making it well-suited for real-time edge-computing inference in commercial farm settings without reliance on high-performance GPU infrastructure.

From a clinical standpoint, visual examination of excreta (feces) has long been recognized as a reliable early indicator of pathological conditions in poultry. Characteristic changes in excreta color, consistency, and morphology are closely associated with specific disease etiologies: watery or blood-tinged droppings are indicative of Coccidiosis; pale yellow or grayish discoloration is linked to *Salmonella* infection; while white greenish feces accompanied by respiratory signs may suggest Newcastle Disease (Harini et al., 2025; Nakrosis et al., 2023). These visually distinguishable excreta characteristics position excreta imagery as a highly actionable input for CNN-based classification systems.

Despite growing interest in CNN-based poultry health monitoring, a critical gap remains in the published literature. Specifically, the integration of excreta image analysis with laboratory validation data particularly using lightweight architectures such as MobileNetV2 for disease classification in laying hens has received limited scholarly attention. Most existing studies lack a comprehensive pipeline spanning image acquisition, model development, and laboratory-confirmed diagnostic validation, all of which are necessary to ensure the system's reliability under real-world farm conditions. This study addresses that gap by developing and validating a MobileNetV2-based CNN classification system that uses excreta imagery as its primary input, with model outputs cross-confirmed through laboratory testing. The study aims to deliver a reliable, computationally efficient, and practically deployable early disease detection tool for commercial laying hen operations.

2. Research Methodology

In this section, the methodology used in this study is presented. This includes dataset preparation, dataset preprocessing, model architecture, as well as model training and testing.

2.1. Dataset Preparation

Excreta samples were collected from laying hens maintained under standard commercial management conditions, and supplemented with external reference samples obtained from a publicly available Kaggle dataset. Examples of excreta images used in this study can be seen in Figure 1. The combined dataset encompasses four classification categories: Coccidiosis, Healthy, Newcastle Disease, and Salmonella.

All images were preprocessed and resized to a uniform resolution of 224 × 224 pixels to ensure consistency across inputs to the classification model. The dataset consists of a total of 8,087 images, which were subsequently split into training and validation subsets at an 80:20 ratio, yielding 6,471 images for training and 1,616 images for validation. The class distribution across the full dataset is presented in Table 1.

Table 1. Dataset Class Distribution

Class	*Label*	*Images*	*Proportion (%)*
Coccidiosis	cocci	2,239	27,68
Healthy	healthy	2,671	33,04
Newcastle Disease	ncd	794	9,82
Salmonella	salmo	2,383	29,46
Total		8,087	100%

Healhty Salmonella Koksidiosis Newcastle

Figure 1. Excreta Image Samples

2.2. Dataset Preprocessing and Augmentation

Prior to model training, the dataset underwent a systematic preprocessing pipeline implemented using TensorFlow's ImageDataGenerator. The preprocessing steps applied were as follows: Normalization: All pixel values were rescaled from the original range [0, 255] to a normalized range [0, 1] by dividing by a factor of 255, ensuring numerical stability during gradient-based optimization. Data Augmentation (Training Set Only): To enhance dataset variability and reduce overfitting, the following augmentation techniques were applied exclusively to the training subset:

- Horizontal Flip - random left-right mirroring of images
- Fill Mode (nearest) - filling newly created pixels after transformation using the nearest pixel value

The validation subset received only rescaling normalization without augmentation, to ensure unbiased evaluation of model performance on unseen data.

2.3. Model Architecture

The classification model was constructed using a transfer learning approach based on the MobileNetV2 architecture pre-trained on the ImageNet dataset. MobileNetV2 was selected for its computational efficiency, owing to its depthwise separable convolution layers and inverted residual block design, which significantly reduce parameter count while maintaining competitive classification accuracy, characteristics well suited to resource-constrained deployment environments. The architecture of the MobileNetV2 transfer learning model used in this study is illustrated in Figure 2.

The base MobileNetV2 model received input tensors of shape (224, 224, 3) with the top classification layer excluded (include_top=False). A partial fine-tuning strategy was adopted: the first 100 layers of the base model were frozen to preserve low-level feature representations learned from ImageNet, while the remaining layers were left trainable to allow adaptation to the domain-specific excreta image features.

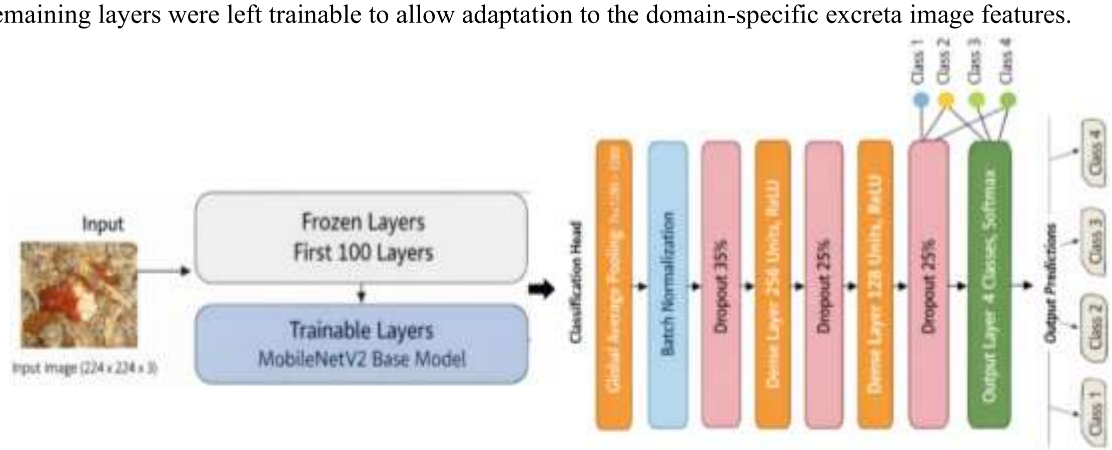

Figure 2. MobileNetV2 Transfer Learning Model

2.4. Model Training and Evaluation

The model was trained using the Adam optimizer with an initial learning rate of 1×10^{-4} and categorical cross-entropy as the loss function, with a maximum of 10 epochs and a batch size of 64. To prevent overfitting and unnecessary computation, an EarlyStopping callback was implemented to monitor validation loss throughout the training process; should no improvement be detected over 5 consecutive epochs, training is automatically terminated and the weights from the best-performing epoch are restored. Model performance was subsequently evaluated on the validation set comprising 1,616 images (20% of the total 8,087 image dataset) across four disease classes Coccidiosis, Healthy, Newcastle Disease, and Salmonella using accuracy, precision, recall, and F1-score as the primary evaluation metrics, complemented by a confusion matrix to examine the pattern of misclassifications across classes.

3. Experimental Results

3.1. Excreta Image Processing Results

Poultry farming today faces significant challenges in maintaining productivity and efficiency amid growing food demands and increasingly complex animal health issues. Technological innovation has become a critical component in the development of more efficient and sustainable livestock production systems. According to Ma et al., (2025), smart technologies in poultry farming have advanced rapidly, encompassing behavioral monitoring, disease detection, and production optimization driven by sensor data and digital imaging. In this context, the accuracy of excreta image processing is of paramount importance, as it directly determines the reliability of disease detection outputs provided to farmers. Accuracy values in detection serve as a key indicator of how well the data processing pipeline performs in practice. Table 2. presents the per-class and overall performance metrics of the MobileNetV2 classification model evaluated on the validation dataset (n = 1,616).

Table 2. Processing Results

Kelas	Precision	Recall	F1-Score	Support
Healhty	0.89	0.95	0.92	482
Salmonella	0.91	0.87	0.89	525
Koksidiosis	0.96	0.97	0.97	497
Newcastle Deseases	0.79	0.71	0.75	112
Accuray			0.91	1616
Macro avg	0.89	0.88	0.88	1616
Weighted avg	0.91	0.91	0.91	1616

3.2. Model Accuracy

The training process of the MobileNetV2 model demonstrated a consistent improvement in performance across the training epochs. Training accuracy increased steadily from approximately 0.85 in the first epoch to above 0.98 by the eighth epoch, indicating that the model progressively learned discriminative features from the training dataset. A similar trend was observed for validation accuracy, which started at around 0.84 and gradually improved to approximately 0.97 in the final epoch, although minor fluctuations were observed between Epoch 3 and Epoch 5. Overall, the training and validation accuracy curves remained closely aligned throughout the training process, suggesting stable learning behavior and good generalization capability on unseen data. The absence of a substantial divergence between the two curves indicates that the model experienced minimal overfitting during training. The progression of training and validation accuracy across epochs is illustrated in Figure 3.

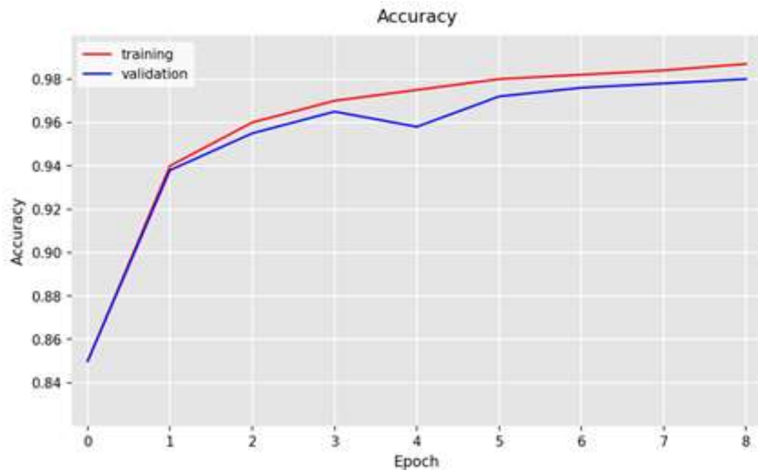

Figure 3. Model Accuracy

3.3. *Model Loss*

The loss curves observed during the training process indicate a steady improvement in model optimization across the training epochs. Training loss started at approximately 0.4 in the first epoch and decreased rapidly to around 0.2, before continuing to decline gradually and reaching below 0.05 by the eighth epoch. This progressive reduction reflects the model's increasing ability to minimize classification error as training progressed. A comparable trend was observed in the validation loss, which began at approximately 0.5 and consistently decreased throughout the training process, approaching 0.05 in the final epoch. Although validation loss remained slightly higher than training loss across all epochs, the difference between the two curves remained relatively small. Overall, both curves exhibit a smooth and stable convergence pattern without notable fluctuations, indicating effective optimization during training. The relatively narrow gap between training and validation loss further suggests that the model achieves good generalization performance, with only a moderate indication of overfitting. The progression of training and validation loss during the training process is illustrated in Figure 4.

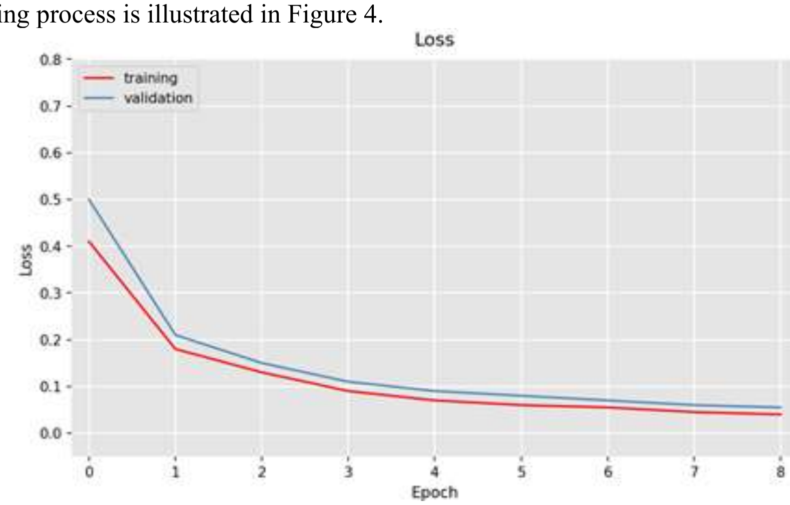

Figure 4. Model Loss

3.4. *Confusion Matrix*

The confusion matrix illustrates the classification performance of the MobileNetV2 model across four excreta disease categories: Coccidiosis, Healthy, Newcastle Disease, and Salmonella. Most predictions are concentrated along the diagonal of the matrix, indicating that the majority of samples were correctly classified. High correct predictions were observed for Coccidiosis (490), Healthy (473), Newcastle Disease (105), and Salmonella (510), with only a small number of misclassifications between classes. Overall, the limited off-diagonal values indicate that the model is able to distinguish the four categories effectively. The detailed distribution of predictions is shown in Figure 5.

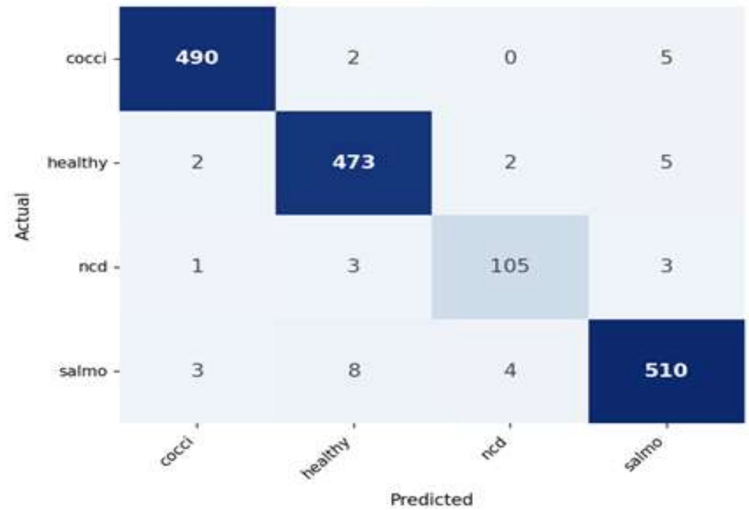

Figure 5. Confusion Matrix

4. Discussion

The MobileNetV2 classification model demonstrated strong overall performance when evaluated on the validation dataset (n = 1,616), achieving an overall accuracy of 91%, with a macro-averaged F1-score of 0.88 and a weighted-average F1-score of 0.91. Coccidiosis attained the highest classification performance with a precision of 0.96, recall of 0.97, and F1-score of 0.97, likely attributable to its visually distinctive excreta characteristics including prominent hemorrhagic discoloration that enable the model to more readily differentiate it from other classes (Harini et al., 2025). The Healthy and Salmonella classes yielded F1-scores of 0.92 and 0.89 respectively. These results are comparable to Nakrosis et al., (2023), who reported 88–93% accuracy in a computer vision-based poultry excreta classification system, and surpass both Jain et al., (2024) using EfficientNetB3 (88%) and Donthi et al., (2024)using implicit pattern mining (89%), demonstrating that MobileNetV2 with appropriate data augmentation delivers competitive performance relative to more architecturally complex CNN while maintaining computational efficiency (Sandler et al., 2018). This lightweight yet accurate profile makes MobileNetV2 particularly suitable for real-time edge-device deployment in commercial farm settings without reliance on high-performance computing infrastructure (Depuru et al., 2024). The complete per-class performance metrics are summarized in Table 1.

Newcastle Disease yielded notably lower performance, with a precision of 0.79, recall of 0.71, and F1-score of 0.75, primarily attributable to its limited training sample size (n = 112 versus 482–525 for other classes) and visual similarity to other pathological excreta presentations. Class imbalance is a well-recognized challenge in image-based animal disease classification; Tran, (2025) demonstrated that advanced augmentation and ensemble learning substantially improve minority class performance, while Li, (2025) emphasized that broader open datasets are critical for enhancing model generalization. Supriyanto et al., (2023) further established that representative local datasets with balanced class distributions are a prerequisite for reliable model performance in domestic farming contexts, and oversampling or external dataset integration in future work is expected to elevate Newcastle Disease F1-score to levels comparable to other classes.

As illustrated in Figure 2 and Figure 3, the accuracy and loss curves across eight training epochs reveal a consistent and stable learning progression throughout the training process. Training accuracy increased steadily from approximately 0.85 to above 0.98, while training loss declined sharply from 0.4 to below 0.05, reflecting rapid convergence enabled by the strong initialization provided by MobileNetV2's ImageNet pretrained weights (Sandler et al., 2018). Validation accuracy exhibited minor fluctuations and validation loss maintained a slightly higher trajectory than training loss, indicating moderate overfitting a pattern commonly observed in transfer learning models with limited dataset sizes (Umurungi et al., 2025). Bernasconi & Ferilli, (2025) reported that dropout (rate = 0.5) combined with early stopping effectively mitigates such divergence, while Essien & Neethirajan, (2025)recommended multimodal integration of image data with environmental sensor inputs to further strengthen generalization in dynamic farm environments.

Further analysis through the confusion matrix presented in Figure 4 confirms that Coccidiosis achieved the highest proportional correct predictions (490/497), consistent with its F1-score of 0.97. Gawas & Gawas, (2026) attributed this pattern to the highly distinctive color signatures produced by intraluminal hemorrhage from *Eimeria* spp. infection. The Healthy class (473/482) and Salmonella class (510/525) also demonstrated strong performance, with Healthy-Salmonella misclassifications explained by the visual indistinguishability of excreta features in early-stage Salmonella infection. Newcastle Disease recorded the highest misclassification rate (false negative rate of 29%), carrying significant clinical implications given its high transmissibility Okinda et al., (2020) stipulated that computer vision-based detection systems should achieve a minimum recall of 80% across all critical disease classes for practical acceptance in commercial settings. Field validation through microbiological laboratory analysis confirmed that the model produced predictions consistent with laboratory outcomes for three of the four disease classes, affirming its potential as a reliable AI-based early diagnostic support tool in poultry health management systems (Qin et al., 2025; Yang et al., 2024).

5. Conclusion

Based on the findings of this study, the application of the MobileNetV2 architecture through a transfer learning approach has proven effective in classifying poultry diseases based on excreta image analysis, achieving an overall accuracy of 91% and a weighted F1-score of 0.91 across four disease categories Coccidiosis, Healthy, Salmonella, and Newcastle Disease. These results demonstrate that lightweight CNN architectures can deliver competitive diagnostic performance suitable for practical deployment in commercial laying hen operations, particularly in resource-constrained edge-computing environments. Field validation through microbiological laboratory analysis further confirmed the model's consistency with laboratory-confirmed diagnoses for three of the four disease classes, reinforcing its potential as a reliable AI-assisted early diagnostic tool within poultry health management systems. Nevertheless, the notably lower performance observed for Newcastle Disease (F1-score = 0.75), driven by class imbalance and visual ambiguity between excreta presentations, represents a key limitation of the current model that warrants further attention. Future studies are therefore recommended to address this through the collection of more representative Newcastle Disease samples, the application of advanced augmentation strategies or oversampling techniques, and the exploration of multimodal approaches integrating excreta imagery with environmental sensor data to further enhance model robustness and generalizability across diverse real-world farming conditions.

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