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# IMPROVING RESNET-50 PERFORMANCE FOR CHICKEN DISEASE CLASSIFICATION BASED ON DUNG IMAGES

**Yudikha Andalantama*[1)], Tonny Hidayat[2)], Agus Purwanto[3)]**
1. Universitas AMIKOM Yogyakarta, Indonesia
2. Universitas AMIKOM Yogyakarta, Indonesia
3. Universitas AMIKOM Yogyakarta, Indonesia

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* Corresponding author.
Corresponding Author
E-mail address:
kayudi34@students.amikom.ac.id

**ABSTRACT**
This study examines the application of the ResNet-50 model for categorizing chicken illnesses. The dataset utilized comprises 8,876 samples, which are classified into four main categories: healthy feces, Salmonella, Coccidiosis, and Newcastle disease. The dataset consists of 2,057 samples classified as healthy feces, 2,276 samples classified as Salmonella, 2,103 samples classified as Coccidiosis, and 2,440 samples classified as Newcastle disease. The implementation of the ResNet-50 model for analysis showcases outstanding performance, with a classification accuracy of 99.25%. This result affirms the model's exceptional ability to precisely identify poultry illnesses. The results of this study highlight the effectiveness of ResNet-50 in performing complex classification tasks and also provide a basis for future improvements. Considering the exceptional results, there are other aspects that can be improved upon to attain optimal performance. By integrating modern hyperparameter tuning approaches and incorporating diverse supplementary data, the model's generalization is expected to be improved, leading to higher accuracy in many real-world settings. Moreover, this will expand the practical applications of the approach in the veterinary and poultry sectors. This study greatly contributes to the diagnosis of diseases in poultry, relying on the findings obtained. It enables the potential for further progress that can improve the effectiveness of disease detection and prevention.

## I. INTRODUCTION

ONE of the important agricultural areas in Indonesia is the poultry business. Chickens are not only a readily available source of animal protein, but they are also among the most often raised animals by the community. Agriculture in Indonesia has a significant market potential and may be easily cultivated and sustained on a small scale while producing huge quantities [1]. Nevertheless, when it comes to raising hens, the procedure only proceeds seamlessly on certain occasions. Chicken growers encounter multiple challenges, one of which is the presence of diseases. Chicken infections can arise due to factors such as inadequate biosecurity measures, insufficient vaccination rates, subpar poultry management practices, a high prevalence of unhealthy chickens, and a lack of veterinary intervention on the farm [2]. Cholera, worm infestation, salmonella, coccidiosis, and Newcastle disease are prevalent poultry diseases frequently encountered on farms [3].

Based on surveillance, a significant number of individuals continue to engage in the practice of breeding and tending to conventional chickens on agricultural lands. This issue restricts farmers to simply being aware of the initial indications of ill hens, while being unaware of the specific origin of the disease afflicting them. Inadequate understanding of the signs and diseases prevalent in hens can lead to a broader dissemination of the disease, resulting in chicken mortality and substantial economic repercussions for farmers [4]. Thus, there is a requirement for a more accurate and dependable method of diagnosing chicken diseases in order to facilitate disease identification for farmers.

The poultry industry in Indonesia, particularly in rearing indigenous chickens, has considerable market potential. However, it encounters substantial obstacles due to widespread diseases such as cholera, salmonella, coccidiosis, and Newcastle disease. These diseases can significantly affect the economic operations of farmers. Hence, expeditious development of precise and dependable diagnostic techniques is imperative. Convolutional Neural Networks (CNN) have found extensive use in item detection and illness diagnosis, particularly in poultry, exhibiting exceptional efficacy in recognizing significant characteristics from images. Data preparation, selection of CNN architectures such as VGG, Resnet, or Inception, and evaluation using measures like accuracy are typical stages in related research [4].

The datasets frequently comprise photographs of hens exhibiting diverse health states, characterized by different sizes and characteristics, significantly impacting the model's performance. The research findings indicate that Convolutional Neural Networks (CNN) can deliver a notable degree of precision in identifying chicken diseases. Several studies have reported accuracy rates ranging from 95% to 96% when employing advanced architectures like Resnet and Inception V3 [5]. Nevertheless, variations in architecture, dataset quality, and preprocessing methods significantly impact the ultimate outcomes, underscoring the need for data extraction and processing enhancements to enable broader and more pragmatic applications in the domain.

The rapid progress of computer vision technology in the realm of artificial intelligence for object detection has generated significant interest in several industrial sectors, particularly the medical profession, where it can be utilized to aid in disease diagnosis. The Convolutional Neural Network (CNN) is a computer vision technique that is widely utilized in the field. The Convolutional Neural Network (CNN) is a specialized approach, known as the multi-layer perceptron, that is created exclusively for the recognition of two-dimensional objects or images [6]. Convolutional Neural Networks offer numerous advantages compared to conventional approaches, such as eliminating the requirement for manual segmentation and feature extraction of images, and the capability to identify patterns that are challenging for human perception by learning from extensive datasets [7]. Therefore, CNN can be utilized for the purpose of classifying chicken diseases.

Early detection of poultry diseases is critical in the poultry sector, particularly in emerging nations such as Indonesia. Convolutional Neural Networks (CNN) exceptional accuracy in identifying poultry diseases is attributed to their capacity to identify intricate patterns in images [7]. A key benefit of CNNs is their capacity to handle extensive and varied datasets, enabling more accurate illness detection than conventional approaches [8]. Nevertheless, CNN also has drawbacks, including the requirement for substantial computational resources and protracted training durations. The performance of CNNs is crucially influenced by the quality and balance of the dataset [9]. However, conventional approaches like visual inspection and basic algorithms continue to be widely used because of their straightforwardness and efficiency in implementation, particularly in settings with limited resources. Even with reduced precision, these techniques are straightforward and do not require substantial data quantities [9].

The abundance of data enables the utilization of deep learning technology to classify diseases in hens, hence serving as a novel technological advancement. The abundance of data can offer diverse types of information with variable quantities. However, in categorization, it is common for certain classes to have unequal numbers of members. When there is an uneven distribution of data and the number of minority classes is smaller than the dominant class, a mischievous class arises. This circumstance leads to misclassification and a tendency to overlook the minority class in favor of the majority class [10]. Consequently, the majority of the class will likely have a significantly higher predicted accuracy rate compared to the minority class. This can impact the efficacy of the classification procedure. One of the primary challenges in machine learning is the issue of biased data. Consequently, multiple techniques have been devised to address this issue [11].

The study conducted by [12] successfully devised a method based on Convolutional Neural Network (CNN) to classify poultry diseases using image processing. The methodology achieved a test accuracy of 93.23%. Nevertheless, there remains a chance to enhance the model's performance by implementing more advanced data augmentation approaches. This strategy is anticipated to enhance the representation of each disease class in the dataset, hence addressing the issue of class imbalance and, ultimately, augmenting the accuracy and efficacy of the model in detecting different poultry diseases. The objective of this study is to enhance the efficiency of Convolutional Neural Networks (CNN) and ResNet-50 in accurately categorizing chicken diseases by analyzing images of droppings. The identification of diseases in chickens is a crucial component of livestock production that has a significant impact on the productivity and well-being of the animal. An accurate measure of chicken well-being is alterations in excrement, which can indicate different health issues such as bacterial infections, parasites, or digestive abnormalities [13].

The distinguishing feature of this work is the novel methodology of identifying chicken diseases using faecal image analysis, a non-invasive and very effective technique. In contrast to conventional approaches that typically involve laborious and costly physical or laboratory evaluations [14], this work uses ResNet-50 to detect intricate patterns in photos of chicken excrement. The ResNet-50 model was selected due to its ability to identify intricate patterns, enabling accurate disease diagnosis [14]. Furthermore, this work incorporates refining techniques like SURF (Speeded Robust Features) to enhance the precision of disease categorization [14]. In order to address the issue of data imbalance, this work employs a sampling technique, which is a crucial method to enhance the accuracy of the model in contexts of imbalanced data [15]. Prior investigations have demonstrated that Inception V3 may attain exceptional accuracy (94.05%) without oversampling. However, this method is only sometimes ideal for all scenarios [16]. Using the ResNet-50 model and novel data processing techniques, this work presents a more effective and precise approach for diagnosing chicken diseases compared to traditional methods.

The present study presents substantial advantages to the poultry sector by providing a prompt, precise, and non-intrusive diagnostic instrument. Through the use of faecal image analysis and convolutional neural network (CNN) models like ResNet-50, farmers can identify diseases at an earlier stage, enabling quicker and more efficient diagnostic interventions. This can decrease chicken mortality rates, enhance production, and mitigate medical expenses and financial losses resulting from diseases. Furthermore, this non-intrusive approach alleviates the strain on animals, enhancing their overall welfare. Implementing this technology enables farmers to enhance operational efficiency and animal health while mitigating the economic consequences of poultry diseases. Due to its broad applicability, this technology has the potential to completely transform the diagnostic process for diseases in the poultry industry worldwide.

## II. RESEARCH METHODS

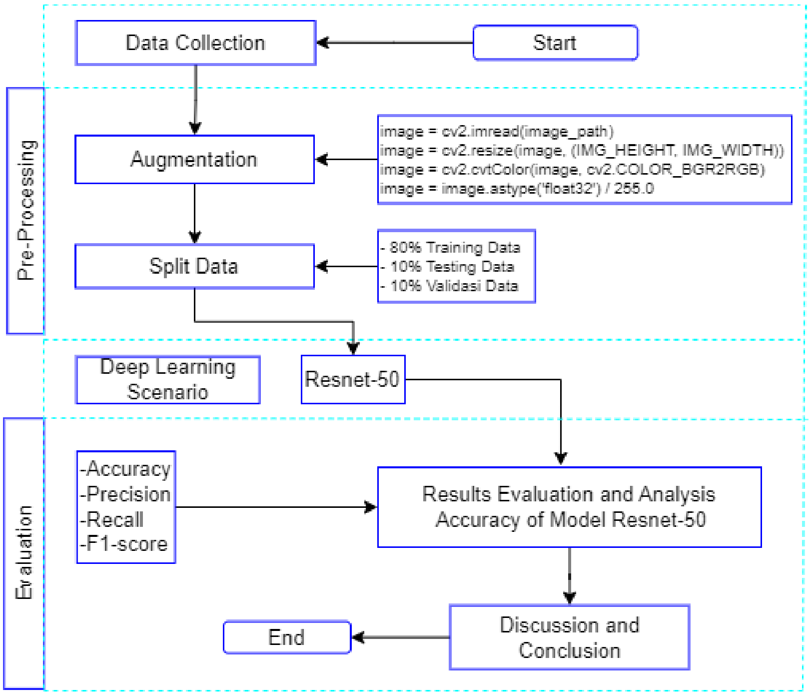


Fig. 1. Research flow

Figure 1 depicts the research flowchart during the process stage, specifically the collecting of data in the form of photos related to the categorization of chicken diseases. These images undergo a pre-processing step, which involves data augmentation to enhance the quantity and variety of training data. Every image is downsized to a certain resolution, and its color scheme is altered and standardized to maintain uniformity during the model's training process. After processing, the data is partitioned into subsets for the purposes of training, testing, and validation. This is done to guarantee the integrity and precision of the outcomes. The ResNet-50 model is employed in the primary stage to categorize chicken diseases. It utilizes the residual block architecture to effectively manage deep networks and prevent gradient degradation. Model performance evaluation employs parameters such as accuracy, precision, recall, and F1-Score, which are calculated using the confusion matrix. The evaluation results are extensively examined in the discussion to ascertain the effectiveness of the model and draw conclusions. The focus is mostly on identifying potential enhancements and providing ideas for future study. The study concludes by presenting the primary findings and discussing their practical relevance.

### *A. Dataset Collection*

The dataset included in this investigation is the Chicken Disease Image Classification dataset, consisting of 8876 data points categorized into four classes: Healthy feces (2057), Salmonella (2276), Coccidiosis (2103), and Newcastle disease (2440) [17]. Figure 2 displays a dataset obtained from the Arusha and Kilimanjaro areas of Tanzania. The dataset covers the time period from September 2020 to February 2021 and offers detailed information about the socio-economic and environmental changes in the region.

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Fig. 2. Chicken Disease Dataset

### *B. Data Preprocessing*

This study implemented data augmentation techniques, including scaling the images to dimensions of 224x224 pixels, switching the color scheme from BGR to RGB, and normalizing the pixel intensities to a range of 0 to 1. This procedure generates images that are prepared for subsequent analysis and machine learning, guaranteeing uniformity and optimization of model performance to ensure the model is resilient to variations and conditions in the dataset. The augmented data was partitioned into three sets: 80% for training, 10% for testing, and 10% for validation. The model can undergo training, testing, and validation using a well-balanced and diverse distribution of data.

### *C. Deep Learning Scenario*

ResNet-50 is composed of 50 layers, which incorporate residual blocks, a crucial advancement that enables the model to avoid the issue of vanishing gradients that often occurs in extremely deep networks [18]. Residual blocks utilize shortcut connections to immediately pass the output of a layer to deeper layers, resulting in enhanced stability and learning efficiency. Figure 3 displays the architectural configuration of ResNet-50.

The ResNet-50 architecture is comprised of several levels of convolutional layers that are interconnected using residual blocks. The model typically commences with a solitary convolutional layer and max pooling, succeeded by four primary stages, each comprising several residual blocks. The initial phase comprises of 3 residual blocks, the subsequent phase comprises of 4 blocks, the following phase comprises of 6 blocks, and the last phase comprises of 3 blocks. Each residual block comprises three convolutional layers with filters that progressively increase in depth. Following each block, the output is directly added to the original input using shortcut connections [18]. After the main stage, a global average pooling layer is used to decrease the spatial dimension before being passed to the fully connected layer for the purpose of final classification. ResNet-50 successfully addresses the problem of accuracy decline commonly observed in extremely deep neural networks and demonstrates exceptional generalization capabilities across different categorization tasks. This model demonstrates exceptional performance on extensive datasets like ImageNet and is particularly effective for transfer learning on smaller datasets [18]. ResNet-50 has emerged as the preferred model in numerous investigations due to its ideal balance of depth and performance. This model is extensively utilized in object detection and image segmentation tasks and is frequently employed as a foundational component in more intricate deep-learning frameworks.

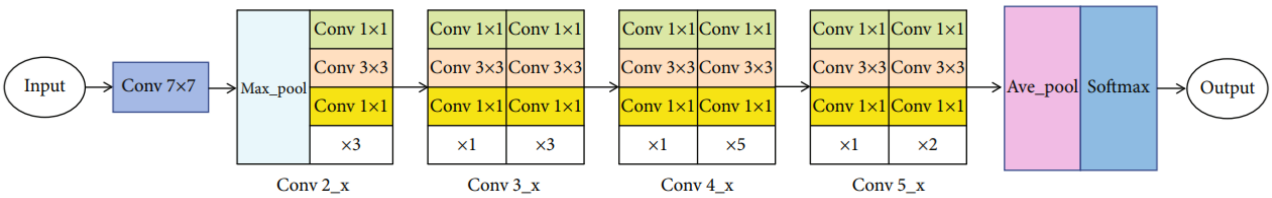


Fig. 3. ResNet-50 Network Structure

### *D. Model Evaluation*

The objective of doing research utilizing evaluation models such as accuracy, precision, recall, and F1 score is to thoroughly evaluate the performance of classification models in data processing [17]. Precision is a measure of the percentage of accurate predictions out of all forecasts made. However, when dealing with imbalanced data, this statistic should be more representative. Accuracy is of utmost importance when the consequences of false positive predictions are large, making precision a critical factor to consider. Recall quantifies the model's capacity to correctly identify all instances that should be categorized as positive, which is particularly crucial in scenarios when false negatives carry significant consequences. The F1 score, calculated as the harmonic mean of precision and recall, provides a more suitable equilibrium between the two metrics, particularly when addressing data class imbalance. By combining these measures, a comprehensive and all-encompassing understanding of the model's skills and constraints in carrying out classification tasks is obtained [17].

The evaluation phase is centered around quantifying and evaluating the performance of the model, and determining if the results align with the experimental hypothesis or reveal any inconsistencies. The approach involves utilizing a confusion matrix that includes True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) to compute model performance metrics such as accuracy (1), recall (2), precision (3), and F1-Score (4). This evaluation offers comprehensive insights into the efficacy of the model within the stated task's environment.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \text{ x } 100\% \quad (1)$$

$$Recall = \frac{TP}{(TP+FN)} \text{ x } 100\% \quad (2)$$

$$Precision = \frac{TP}{(TP+FP)} \text{ x } 100\% \quad (3)$$

$$F1\ Score = \frac{2\ x\ (recall\ x\ precixion)}{(recall\ x\ precixion)} \text{ x } 100\% \quad (4)$$

## III. Result and Discussion

The study utilized a dataset consisting of 8876 photos of chicken feces. The dataset consists of four classes: Healthy faeces data (2057 samples), Salmonella (2276 samples), Coccidiosis (2103 samples), and Newcastle Disease (2440 samples). The study used the Resnet-50 algorithm model to classify the managed data. Specifically, 80% of the data is allocated for training, 10% for testing, and 10% for validation. The experiment findings are displayed in Table I.

TABLE I
Comparison of Accuracy and Loss

| Technique | Training | | Validation | |
|---|---|---|---|---|
| | Accuracy | Loss | Accuracy | Loss |
| Model Resnet-50 | 99.97% | 00.35% | 98.54% | 03.78% |

Table II investigation unveiled substantial disparities between datasets that had undergone the balancing process and those that had yet to. Curiously, the dataset that was not balanced had the highest performance, with a training accuracy of 99.97% and a validation accuracy of 98.54%. The results of this study highlight the significance of the data balancing procedure on the ultimate model outcomes and emphasize the need to select the appropriate method in data set transformation. An investigation undertaken by [12] effectively developed a Convolutional Neural Network (CNN) approach for the classification of poultry diseases through image processing. The chosen methodology attained a test accuracy rate of 93.23%. Nevertheless, there is still potential to enhance the performance of the model by including more sophisticated methods of data augmentation. The implementation of this approach is expected to enhance the representation of every disease category in the dataset, therefore resolving the issue of class imbalance and, ultimately, augmenting the precision and effectiveness of the model in identifying different poultry diseases. The aim of this work was to enhance the effectiveness of Convolutional Neural Networks (CNN) and ResNet-50 in precisely classifying chicken diseases through the analysis of fecal photograms. Diagnostic testing for diseases in chickens is a crucial aspect of livestock farming that greatly affects animal productivity and well-being. Chicken welfare can be accurately assessed by observing alterations in faecal matter, which can serve as an indicator of many health issues such bacterial infections, parasites, or digestive disorders [13].

Figure 4 visually demonstrates the disparity in accuracy and loss values between the training and validation data on the unbalanced dataset. This offers valuable insights into how data balancing affects the performance of the model. These findings emphasize the impact of the data balancing procedure on the final model outcomes and underscore the significance of selecting the appropriate approach in dataset processing. Comparative Analysis: Evaluate the efficacy of your Convolutional Neural Network (CNN) model by comparing it with conventional methods or other CNN models documented in prior research. A sensitivity analysis was performed during the model testing phase to assess the impact of parameter adaptations on the model's performance, including batch size, learning rate, and number of epochs. The resultant graph displays the patterns of accuracy and loss obtained during the training and validation phases. According to the study results, the model had the highest accuracy of

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0.9854 during the 24th epoch, while the lowest loss of 0.0378 was seen at the 50th epoch. The findings suggest that the model has effectively attained a harmonious equilibrium between precision and generality while exhibiting little overfitting. A further assessment was carried out using a confusion matrix to evaluate the model's overall performance in data classification. The demonstrated ability of the model to accurately classify data suggests that the parameters chosen during the training process are optimum. This study's results emphasise the need for precise parameter selection in developing machine learning models and demonstrate the approach's efficacy.

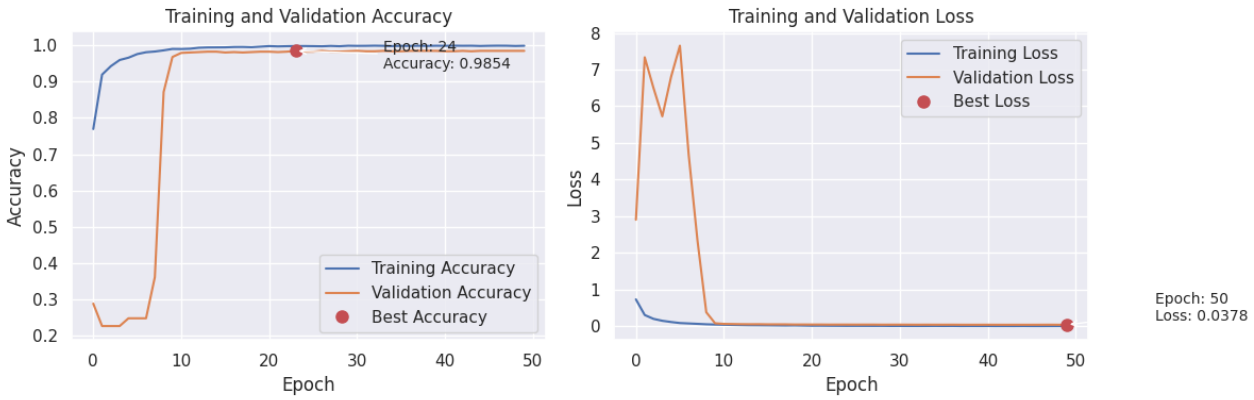


Fig. 4. Accuracy and Loss ResNet-50

The data testing phase is an essential stage that follows the completion of the training process. Its purpose is to assess the model's performance in various tested scenarios. During this step, every data point undergoes thorough testing to assess important performance measures such as F1-score, precision, accuracy, and recall. The outcomes of this examination are depicted using a confusion matrix, as illustrated in Figure 5, which offers an intricate portrayal of the model's accuracy in accurately categorizing data.

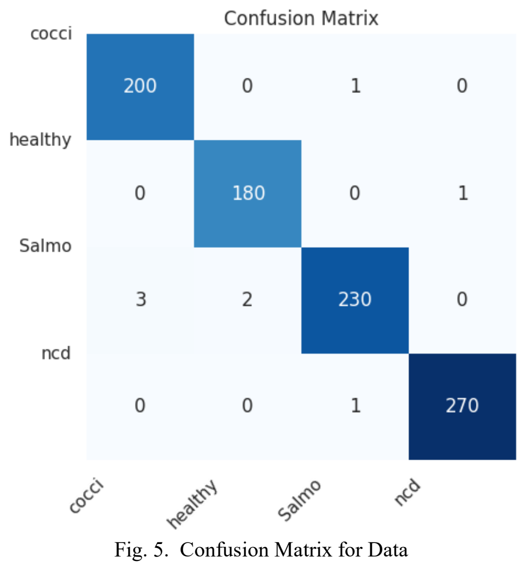


Fig. 5. Confusion Matrix for Data

According to the confusion matrix in Figure 5, a total of 880 chicken feces image data were accurately classified. This includes 200 data points for Coccidiosis, 180 data points for Healthy, 270 data points for New Castle Disease, and 230 data points for Salmonella. The sparse data employed in this work may impact the efficacy of the created model for classifying chicken faeces images. The confusion matrix reveals that while the model achieves a high level of accuracy in classifying a total of 880 data points, there are signs of inconsistent representation between the different classes. The classes "Coccidiosis" and "New Castle Disease" contain a more extensive dataset compared to the "Healthy" class, which comprises only 180 samples. This imbalance can introduce bias into the model, resulting in a tendency for the model to exhibit higher accuracy in classifying the more dominant class and lower effectiveness in identifying classes with lower representation. This constraint is necessary as it can affect the model's generalization, particularly in practical scenarios where class distributions exhibit more significant variability. One might implement techniques such as data balance or class weighting to surmount this challenge and enhance the model's capacity to identify all classes uniformly, leading to more resilient and generalizable performance.

TABLE II
RESNET-50 MODEL PERFORMANCE RESULTS

| Technique | Class | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|---|
| Model Resnet-50 | Coccidiosis | 99.25% | 99.50% | 99.50% | 98.61% |
| | Healthy | | 97.25% | 97.79% | 98.61% |
| | New Castle Disease | | 99.25% | 98.15% | 98.61% |
| | Salmonella | | 98.31% | 99.14% | 98.61% |

In this study, Table II presents the performance of the ResNet-50 model in classifying chicken diseases. The accuracy, precision, recall, and F1-score evaluation findings are pretty remarkable. With an overall accuracy of 99.25%, the model demonstrates its remarkable capacity to recognize chicken conditions precisely. In terms of precision, which quantifies the ratio of accurate optimistic predictions to all positive predictions generated by the model, Coccidiosis achieved the highest Score of 99.50%. Evidence indicates that the model exhibits a high level of accuracy in detecting instances of Coccidiosis since nearly all predictions categorized as Coccidiosis correspond to the actual diagnosis of the condition. By contrast, the Healthy category has a precision of 97.25%, suggesting that the model demonstrates high accuracy in detecting healthy hens. However, its performance could be better in the Coccidiosis category.

The Recall metric quantifies the model's capacity to identify and include all positive instances in the dataset accurately. The model had exceptional performance in the Salmonella category, with a recall rate of 99.14%. Consequently, the model demonstrates a high level of efficacy in identifying nearly all instances of Salmonella within the dataset, leading to a minimal number of overlooked Salmonella cases. Furthermore, the model had a high recall rate for Coccidiosis and Newcastle disease, suggesting its ability to accurately detect most diseases, albeit without overlooking some instances. Moreover, the F1 Score, a composite measure of precision and recall, offers insight into the equilibrium between the two metrics. The Coccidiosis category attained the highest F1 Score of 98.61%, demonstrating that the model exhibits high precision and recall for this category while maintaining a favourable equilibrium between the two statistics. The F1-score values for the remaining categories also demonstrate strong consistency, with minimal variance, suggesting accurate model performance across categories.

In general, these findings emphasize the efficacy of the ResNet-50 model in categorizing different forms of chicken diseases. The model demonstrates robust and reliable performance, particularly in accurately detecting Coccidiosis and Salmonella with exceptional precision and recall. While the model demonstrated promising outcomes for all criteria, there are signs that the categories in which the model exhibited the highest performance include Coccidiosis and Salmonella. The ResNet-50 model has exceptional accuracy and robust metrics, making it a dependable and effective diagnostic tool for poultry disease diagnosis applications.

## IV. CONCLUSION

This study entailed the examination of 8,876 data samples categorized into four classes: healthy faeces (Healthy) with 2,057 samples, Salmonella with 2,276 samples, Coccidiosis with 2,103 samples, and Newcastle disease with 2,440 samples. The ResNet-50 model utilized in this investigation demonstrated exceptional performance, with a peak accuracy of 99.25%. The results unequivocally validate the efficacy of ResNet-50 in accurately diagnosing diverse poultry illnesses with exceptional precision. Nevertheless, there are ample prospects for further study to enhance the model's performance. One possible strategy to correct the imbalance of data between classes is to utilize alternative data balancing strategies, such as oversampling or undersampling. Furthermore, delving into various model topologies, such as EfficientNet or DenseNet, might yield novel perspectives and potential enhancements in accuracy. Enhancing the generalization and accuracy of the model in real-world scenarios can be achieved by incorporating new parameters, such as advanced hyperparameter tuning techniques or integrating diverse supplementary data.

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