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Chicken Disease Classification Based on Inception V3 Algorithm for Data Imbalance

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Abstract: In order to supply the world's protein needs, one of the most crucial industries is the poultry business. The problem that often occurs in chicken farms is disease, and this can have a significant impact on the farm. The availability of large enough amounts of data makes it possible to carry out the process of monitoring chicken diseases using deep learning technology for the classification of chicken diseases. With the availability of large enough data, the dataset has a variety of features that cause problems with data clutter. To overcome the problem of data conflict, an oversampling technique is used to increase the sample data from the minority class so that it has the same value as the other majority classes, and the Inception-V3 algorithm is used to classify chicken diseases based on fecal images. The total number of data used was 8067, which were broken down into the following four categories: Healthy, Salmonella, Coccidiosis, and Newcastle disease. Data balancing was done using oversampling to get the total data to 10500 before the evaluation process was started. The data was distributed by splitting it by 80% of the data will be used for training, 10% for data validation, and 10% for testing. The results of the test, which employed Inception V3 without oversampling, produced the highest possible score of 94.05%.

Keywords: Data Imbalance, Oversampling, Chicken Disease, Classification, Inception V3

INTRODUCTION

One of the crucial agricultural areas in Indonesia is the poultry industry. Apart from being a source of animal protein that is easy to obtain, chickens are also one of the animals most commonly kept by the public. Poultry farming is a sector that has enormous market prospects in Indonesia and is easy to develop and maintain in small to large quantities (Setiadi et al., 2020). However, in the process of rearing chickens, it only sometimes runs smoothly. There are several obstacles that chicken farmers must face, and one of them is a disease. The emergence of chicken diseases can be influenced by a lack of biosecurity, low vaccination coverage, and poor poultry management, many chickens are not prosperous, and an absence of veterinary intervention on the farm (Van Limbergen et al., 2020). Cholera, worm infestation, salmonella, coccidiosis, and Newcastle disease are the most common chicken diseases often found on farms (Asfaw et al., 2019).

From the observations, many people still carry out the process of maintaining and caring for traditional chicken farms. This problem makes farmers only know the initial symptoms of sick chickens without knowing the source of the disease they are suffering. A lack of knowledge of the symptoms and diseases that occur in chickens can cause the spread of the disease to become more widespread, causing death in chickens and providing significant economic losses for farmers (Nuvey et al., 2023). Therefore, a more precise and reliable disease diagnosis in chickens is needed to make it easier for farmers to diagnose a disease. (Hadi Nasyuha, 2020).

With the increasing advances in computer vision technology in the field of artificial intelligence to detect an object, it has generated interest in several industrial fields, especially in the medical field, to be functioned to help diagnose diseases. Convolutional Neural Network (CNN), one of many algorithms used in computer vision, is one of these technologies. A multi-layer perceptron method known as the Convolutional Neural Network (CNN) was created specifically to recognize a two-dimensional object or image. (Primartha, 2021). Convolutional Neural Networks have a number of benefits over traditional methods, including the elimination of the need for manual segmentation and image feature extraction, as well as the ability to recognize patterns that are difficult for the human eye to detect by learning from large amounts of data. (Liz et al., 2023). That way CNN can be used in the process of classifying chicken diseases.

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The availability of a huge amount of data makes it possible to carry out the process of classifying diseases that occur in chickens using deep learning technology so that it becomes a new technological breakthrough (Astill et al., 2018). With the availability of large amounts of data can provide various forms of data with varying amounts.

However, in classification, several class members usually have an unequal number. When the distribution of the data is uneven and the number of the minority class is lower than that of the dominant class, there is a class imbalance (Ustyannie & Suprapto, 2020). This condition causes the classification process to be wrong and tends to ignore the minority class compared to the majority class (Kaope & Pristyanto, 2023). As a result, the majority class will have a much higher forecast accuracy number than the minority class. This can affect how well the classification process performs. One of the key issues with machine learning has been noted to be the issue of data imbalance. Consequently, numerous strategies have been created to address this issue. (Qiang & Xindong, 2006). The way to overcome data imbalance is to apply the sampling method (Ramadhanti et al., 2020). In order to overcome the problem of dataset imbalance, processing must be carried out so that the dataset becomes balanced. The approach used in this study is to apply oversampling with the expectation that it can potentially improve the classification process's performance. Therefore, researchers will use the InceptionV3 algorithm model by applying oversampling for the process of classifying chicken diseases based on fecal images.

LITERATURE REVIEW

The application of deep learning in the classification of chicken diseases itself uses data sources from fecal images, but not all of this data is the same or balanced. In conducting research related to helping chicken diseases using CNN, the researcher first reviews the literature related to research that has been carried out by previous researchers as a reference in developing the research that will be carried out. Research (Machuve et al., 2022) applies transfer learning to classify chicken diseases into four classes consisting of New Castle, Salmonella, Healthy, and Coccidiosis. In this study, the amount of data was unbalanced, with the New Castle class having the lowest number among the other classes. The proposed method was able to detect types of chicken diseases with a fairly high f1-score where each class had a value above 85%. Another study by (Kholil et al., 2022) using CNN in the classification of chicken diseases also had an unbalanced amount of data, where one class had the least amount of data compared to the other classes. This research produces predictions for each class with an average f1-score for each class of 95.52%.

Research conducted by (Widyawati & Gunawan, 2022) used the YOLOv5 algorithm in the classification of chicken diseases, which were divided into two classes, namely healthy and unhealthy. This study resulted in an accuracy value of 89.2% in diagnosing chicken diseases. Another study by (Zhang & Chen, 2020) carried out a diagonal process of chicken health based on images using the CNN deep learning architecture, namely ResNet. Based on the network, ResNet researchers developed the network, resulting in a ResNet-FPN model designed to increase the level of accuracy and adapt to different recognition environments. The experimental results show that the accuracy rate of the model is as high as 93.7%. Another study conducted by (Mbelwa et al., 2021) conducted research to identify the most common diseases affecting chickens using the assistance of artificial intelligence and computer vision-based machine learning in analyzing images. This research proposes deep learning based on convolutional Neural Networks (CNN) to diagnose chicken diseases based on fecal images into three classes, namely coccidiosis, health, and salmonella. Researchers propose several models based on CNN architecture in the process of classifying chicken diseases, such as VGG 16, Resnet 50, MobileNet, XceptionNet, and the CNN basic model. Based on the experimental results, the XceptionNet model shows the highest level of accuracy compared to other architectural models, with an accuracy value of 94% in identifying chicken diseases.

METHOD

This study uses the inceptionV3 model to classify chicken manure images by using oversampling in data processing. In developing a model for the faecal image classification process in determining chicken disease, there are several steps, including data collection, data preprocessing, training and testing of deep learning models, and the analysis process. This research has a flow or stages that can be seen in Figure 1.

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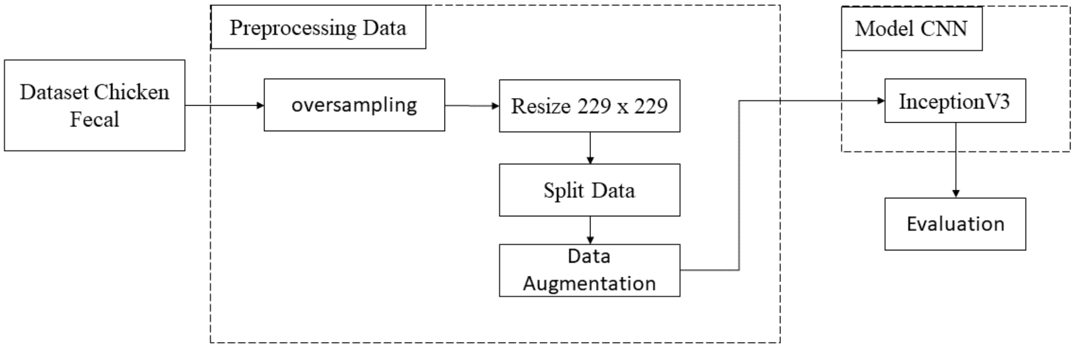

Figure 1. Research Workflow

a. Dataset

The chicken feces image dataset used was obtained from (Machuve et al., 2021) with a total of 8067 data. There are four classes and varying amounts in the dataset, including Healthy 2404 (30%), Salmonella 2625 (32.5%), Coccidiosis 2476 (30.7), and Newcastle disease 562 (6.96%). Figure 2 is an example of the dataset used. The data was collected in the regions of Arusha and Kilimanjaro in Tanzania between September 2020 and February 2021.

Healthy Salmonella Coccidiosis NewCastle

Figure 2. Chicken Disease Dataset

b. Preprocessing Data

The step where data is organized and prepared for usage is known as data preparation. Several operations will be carried out at this step, including data balance through oversampling, resizing, data splitting, and data augmentation. Data preprocessing is carried out to improve data quality so that the data obtained can be used optimally in the classification process (Fan et al., 2021). In overcoming the problems that have been mentioned, namely the imbalance of the dataset owned can cause the quality of the classification to decrease, one of the data balancing strategies, namely oversampling, must be used to balance the data. The oversampling technique itself aims to increase the sample from the minority class so that it has the same value as the other majority class by duplicating the minority class sample randomly (He et al., 2018). This process will produce 10,500 images in all classes with the same number of examples. After the data balancing process is carried out, the image size will be changed to 229x229 pixels. The dataset will be divided into training data (80%), testing data (10%), and validation data (10%). The next set of enhancements include vertical flip, rotation range, and zoom range.

c. Model CNN

Determining the algorithm model to utilize comes after the data pretreatment phase. The CNN InceptionV3 architectural model was employed in this investigation. (Szegedy et al., 2016). To disperse label information over the network, the 42-layer InceptionV3 model uses factorized 7 x 7 convolutions, label smoothing, and additional classifiers. Convolution, average pooling, max pooling, concatenations, dropouts, and fully linked layers are the symmetric and asymmetries building pieces that make up the architectural model. Next, the activation input seen in Figure 3 is subjected to batch normalization, which is often used to normalize the entire model.

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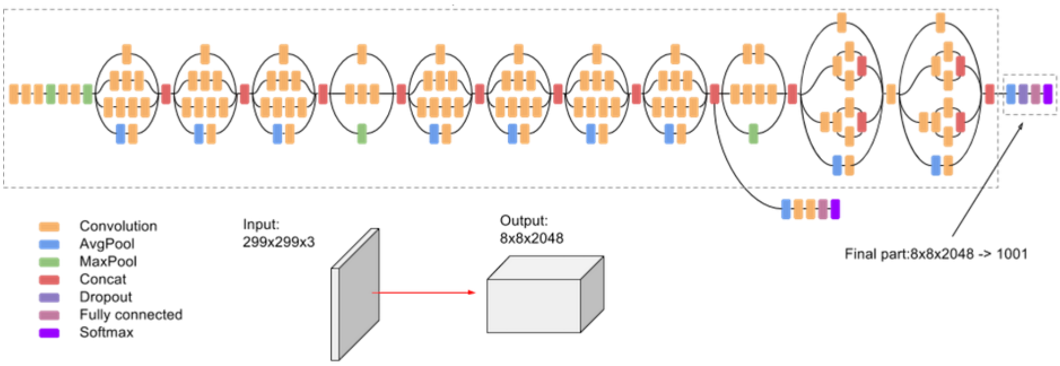

Figure 3. InceptionV3 Architecture

d. Evaluation

The evaluation stage involves measuring and evaluating the model's level of performance, as well as whether the calculation results support the experiment or are in conflict with it. Using a confusion matrix based on TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative), the algorithm model's performance level will be calculated to obtain accuracy (1), recall (2), precision (3), and F1-Score (4).

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

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

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

$$\text{F1 Score} = \frac{2\ x\ (recall\ x\ precision)}{(recall\ +precision)} \text{ x } 100\% \qquad (4)$$

RESULT

The research was conducted using a dataset of chicken feces images with a total of 8067 images the dataset itself has four classes, including Healthy 2404, Salmonella 2625, Coccidiosis 2476, and Newcastle disease 562. It can be seen from the four classes that the data is unbalanced, so an oversampling process is carried out to balance the minority class so that it is the same as the majority class. After the data balancing process is carried out, 10,500 data points are produced, with 2,625 in each class. The research process uses the InceptionV3 algorithm model for the classification process by dividing the managed 80% of the data are used for training, 10% are used for testing, and 10% are used for validation. In the first experiment, the researcher conducted a classification test without carrying out the data balancing process for the dataset, and in the second experiment, the researcher used a technique to balance the dataset. Table 1 displays the experiment's outcomes.

Table 1. Comparison of Accuracy and Loss

Technique	Training		Validation	
	Accuracy	Loss	Accuracy	Loss
InceptionV3 without oversampling	95.64%	19.24%	94.84 %	23.12%
InceptionV3 using oversampling	94.35%	16.71%	93.71%	18.53%

In the experiment, there was a distinction between the data that had undergone the balancing process and the data that had not. The most accurate datasets are those without data balance, with a training accuracy of 95.64 % and a validation accuracy of 94.4 %. The disparity between the accuracy and loss values on the training data and validation data without performing the data balancing procedure is graphically shown in Figure 4. The experimental process using the oversampling method is shown in Figure 5.

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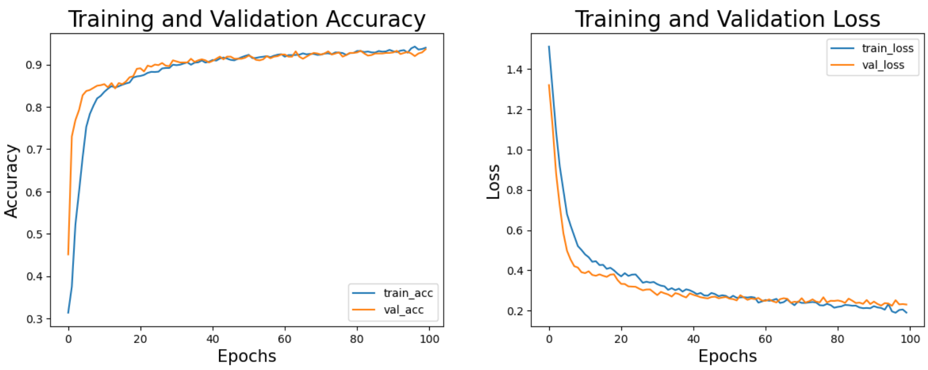

Figure 4. Accuracy and Loss without oversampling

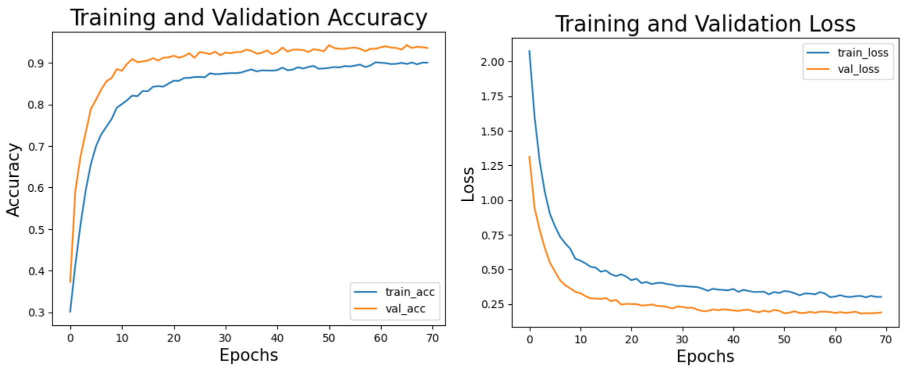

Figure 5. Accuracy and Loss using oversampling

Data testing is the following stage after the data training procedure has been completed in order to determine how far to go in determining the performance level of each scenario. Each data point is now subjected to data testing, which generates values for f1-score, precision, accuracy, and recall. The confusion matrix in Figures 6 and 7 is then used to represent these findings.

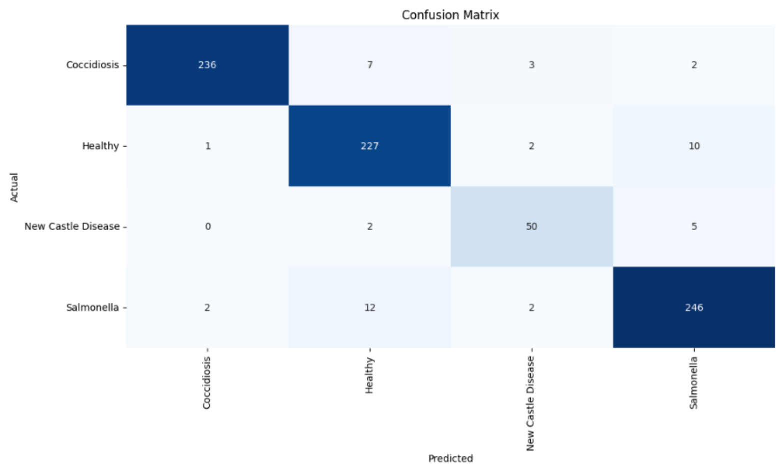

Figure 6 Confusion Matrix for data without oversampling

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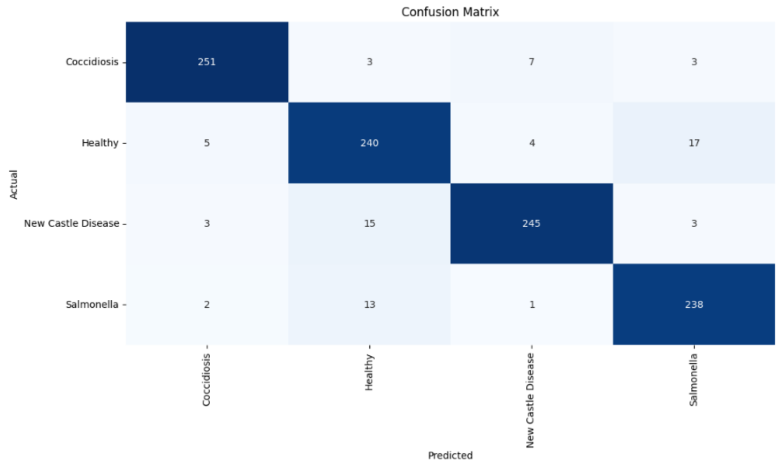

Figure 7 Confusion Matrix for data oversampling

According to the results of the confusion matrix in figure 6, there are 759 correctly identified chicken feces image data, including 236 Coccidiosis, 227 Healthy, 50 New Castle Disease, and 246 Salmonella data. In contrast, it is known that 974 chicken feces image data in figure 7 are correctly identified, including 251 Coccidiosis, 240 Healthy, 5245 New Castle Disease, and 238 Salmonella data.

DISCUSSIONS

The first experiment was carried out using a dataset without a balancing process, which had a total of 8067 data points; the second experiment was carried out by balancing the data with an oversampling technique, which had a total of 10500 data points. Based on the experimental results on the training data above, it can be seen that in figure 5, both the training data and the validation data are overfit. Table 2 displays the outcomes of the measurements made using the InceptionV3 algorithm model for precision accuracy, recall, and F1-score values.. Experiments without using the oversampling technique produced an accuracy of 94.05%, and experiments using the oversampling technique produced an accuracy value of 92.78%. There is a significant difference in the New Castle Disease class, where this class has the least amount of data compared to the other classes. These results show that by oversampling to balance the data, it produces higher precision, recall, and F1-score values than Compared with unbalanced data, however, the coccidiosis, healthy, and salmonella classes in the oversampled data have lower precision, recall, and F1-score values compared to unbalanced data.

Table 2. Without oversampling and without using oversampling to handle unbalanced data, the inceptionV3 method performs prediction.

Technique	Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
InceptionV3 without oversampling	Coccidiosis	94.05	98.74	95.16	96.92
	Healthy		91.54	94.58	93.03
	New Castle Disease		87.72	87.72	87.72
	Salmonella		93.54	93.89	93.71
InceptionV3 using oversampling	Coccidiosis	92.78	96.17	95.08	95.62
	Healthy		88.56	90.23	89.39
	New Castle Disease		95.33	92.11	92.43
	Salmonella		91.19	93.7	92.34

However, bear in mind that the results of this study only apply to the same dataset and the conditions of the parameters. Additional study can be carried out by experimenting with various designs or by adding more factors in order to improve accuracy with the same or different datasets.

CONCLUSION

This study uses two scenarios: in the first experiment, it uses a dataset without carrying out a data balancing process, where the data has a total of 8067; in the second experiment, it uses a dataset that has been oversampled to balance the minority class in the data so that it has the same number as the majority class, with the number of

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each class being 2625. From the evaluation results, the highest accuracy was 94.05% using Inception V3 without oversampling. because there are differences in the amount of data that are too great, making data balancing techniques actually ineffective. For further research, this can be done using other balancing techniques to increase accuracy, try other architectures, or add other parameters.

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