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Estimation Model of Nutritional Content Based on Broiler Feed Images Using Convolutional Neural Network and Random Forest

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Abstract.
Purpose: This research aims to develop an intelligent model to estimate the nutritional content of broiler chicken feed based on feed images to assist farmers in selecting the best broiler feed and quickly verifying its quality to meet requirements.
Methods: The methodology of this research includes literature study, data collection, data preprocessing, image classification, model evaluation, integration of CNN and random forest models, and estimation of nutritional content based on feed images. We collected 99 samples of broiler chicken feed from online stores in various regions of Indonesia, particularly Java. Next, we took pictures with a smartphone and analyzed the nutritional content using near-infrared spectroscopy. Preprocess the data by enhancing the dataset (color space and data augmentation). We use Convolutional Neural Network (CNN) for the classification of broiler feed images. The performance of the CNN model is evaluated using a confusion matrix. We integrate CNN and Random Forest Regressor (RFR) to estimate nutritional content from the features of broiler feed images.
Result: The performance evaluation shows that the CNN (VGG-16) model is 0.9744% accurate and the RFR model has the highest R2 value of 0.8018. The benefits of this research include faster, more efficient, and automated feed quality measurement compared to traditional methods; maintaining feed quality standards; and avoiding health risks for livestock.
Novelty: This research introduces an intelligent model to estimates the nutritional content of broiler feed images by integrating a CNN model with an RFR.

Keywords: Broiler chicken feed, CNN, NIR, Nutritional content estimation, VGG-16
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INTRODUCTION

Broiler chicken feed is one of the key factors in the success of poultry production [1]. Feed quality directly affects broiler chickens' growth, health, and productivity [2]. Based on data from the Directorate General of Livestock and Animal Health, Ministry of Agriculture of Indonesia 2023 [3], proper feed consumption can increase the weight of chickens by 10–15% in a short period. As shown in Figure 1, feed is the most important component in broiler chicken farming, accounting for about 70% of the total production costs [4]. Therefore, selecting and formulating the proper feed are crucial to achieving excellent results in poultry farming [5]. However, the challenge in managing feed is finding the best nutritional content according to the chickens' needs, so it is important to get an accurate estimate of the feed's nutritional content [6], [7].

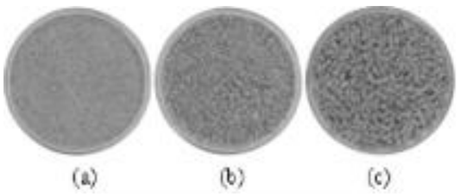

Figure 1. Forms of broiler chicken feed: (a) mash, (b) crumble, and (c) pellets

Conventional methods for nutritional analysis require specialized expertise and complex, time-consuming procedures [8]. Therefore, technology-based methods such as image processing and analysis with machine

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learning algorithms are needed [9]. In 2022, Mutya [10] and Novita [11] used the K-Nearest Neighbour (KNN) method to figure out how much lignin was in feed. The first one was 0.7212 and the second one was 0.7455. These findings may be better if the right algorithms were used for the image and their performance was improved.

This study proposes a Convolutional Neural Network (CNN) and Random Forest Regressor (RFR) model to determine the best feed for broiler chickens by looking at the images [12]. CNN is used because it can automatically extract key features from images using convolutional layers, which makes it very effective and accurate at classifying images [13]. Meanwhile, RFR offers advantages in handling the complexity and variability of data resulting from CNN feature extraction [14], facilitating more robust regression modelling and reducing the risk of overfitting. Therefore, the combination of these two algorithms is highly effective for processing and analysing image data comprehensively. The purpose of this study is to use basic image-capturing tools and the rapid near-infrared (NIR) analysis method [15] to generate better and more accurate estimations. This work combines the CNN model with RFR [16] to make feed nutrition estimates more accurate. Additionally, this research contributes to advancing technology in livestock farming, especially in feed management [17]. Using feed images, it is expected that the model created can be widely applied in Indonesia's broiler chicken farming industry, especially on the island of Java, which is the centre of broiler chicken production [18].

METHODS

The flowchart of the steps in this research is shown in Figure 2. The first step in this research is to study knowledge about this research topic through related articles. The research references were related to image technology, machine learning, and feed nutritional content.

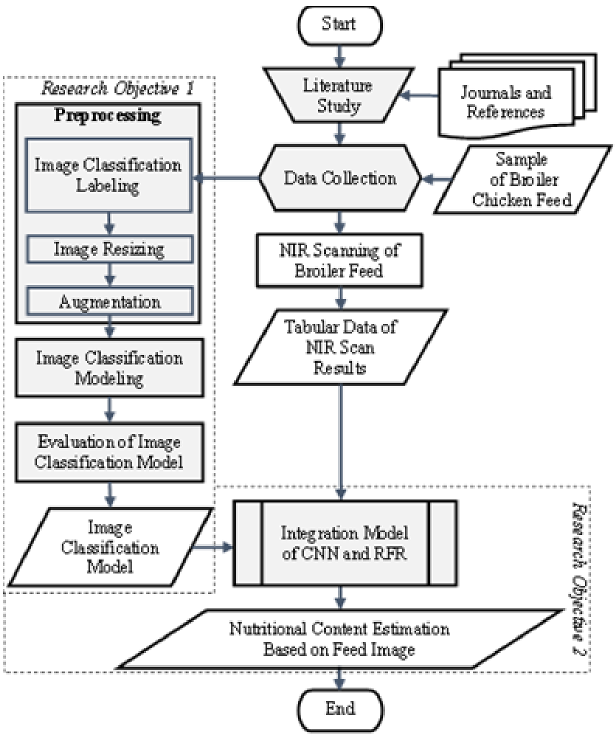

Figure 2. Research steps

The second step in the research was to get 99 samples of broiler chicken feed from online retailers and e-commerce sites in different parts of Indonesia, especially Java. Broiler feed consists of three categories, including pre-starter for use from 1 to 7 days old, starter for use from 8 to 21 days old, and finisher for use from 22 days old until harvest, with 33 samples each [19]. The study was placed at the Logistic Analysis Laboratory Indonesia Netherland (ALIN), which is part of the Department of Nutrition Science and Feed Technology at IPB University. Data collection from each feed sample was done by taking pictures using a smartphone camera (Oppo F5) as shown in Figure 3 under the same lighting conditions (10" 8W ring light) [20].

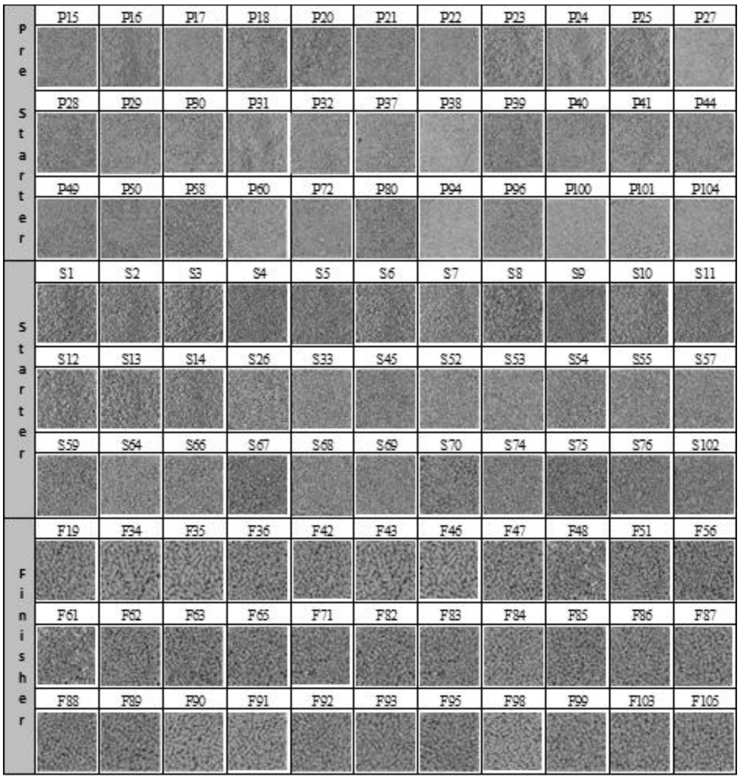

Figure 3. Image dataset of broiler chicken feed

We also scanned each feed sample using a BUCHI NIR-Flex N-500 instrument, as shown in Figure 4. The near-infrared approach is known for showing what nutrients are present in food quickly and precisely [21]. The information from this near-infrared analysis will be used to build a nutritional value estimation model for the feed images [22].

Figure 4. BUCHI NIR-Flex N-500 [23]

We cleaned the images to ensure consistency before modelling. We also pre-processed the data to help the model learn better [24]. The images are labelled with the types of broiler feed: pre-starter, starter, and finisher [19]. The next step is to create a data table like Table 1 that shows the nutritional value of broiler feed based on near-infrared scanning. Nutritional values include dry matter, moisture content, crude protein, crude fat, crude fibre, and ash. So that the CNN algorithm can extract image features well, we resize the image to 224x224 pixels [25].

Table 2. Feed nutrition content dataset

Code	Class	Dry Ingredients	Water content	Crude Protein	Crude Fat	Crude Fiber	Ash
S1	Starter	91,34	8,66	20,96	8,00	4,84	6,57
S2	Starter	91,44	8,56	19,59	7,79	4,97	4,32
S3	Starter	91,34	8,66	20,96	8,00	4,84	6,57
S4	Starter	90,54	9,46	21,47	7,65	3,92	6,37
S5	Starter	89,38	10,62	22,05	4,79	4,93	7,65
S6	Starter	91,44	8,56	19,59	7,79	4,97	4,32
S7	Starter	89,51	10,49	21,35	4,93	3,62	6,92
S8	Starter	91,77	8,23	9,92	6,20	6,31	1,77
S9	Starter	90,54	9,46	21,47	7,65	3,92	6,37
S10	Starter	90,22	9,78	21,66	8,19	4,39	7,02
S11	Starter	89,38	10,62	22,05	4,79	4,93	7,65
S12	Starter	93,40	6,60	4,41	5,65	15,7	19,28
S13	Starter	90,40	9,60	16,29	6,84	7,58	4,64

S14	Starter	90,40	9,60	20,07	8,04	4,13	4,44
P15	Pre Starter	90,69	9,31	14,96	6,25	7,26	7,90
P16	Pre Starter	89,00	10,34	21,33	5,25	3,00	5,30
P17	Pre Starter	87,72	12,28	20,35	5,02	2,93	6,63
P18	Pre Starter	89,81	10,19	23,43	6,20	3,79	5,64
F19	Finisher	87,69	12,31	19,70	6,58	4,53	5,84
P20	Pre Starter	89,85	10,15	20,27	6,93	4,13	6,60
P21	Pre Starter	90,69	9,31	14,96	6,25	7,26	7,90

The third step is preprocessing; we changed the images into several colour spaces, such as RGB, grayscale, HSV, and L*a*b*, to add more images to the dataset [26], [27]. The modification brought the total number of images in the collection to 396. We split the dataset into three groups: 70% (277 images) for training, 10% (39 images) for validation, and 20% (80 images) for testing [28]. Adding new data are important to prevent the CNN model from overfitting. Rotating, flipping, and adjusting the contrast are some techniques to add to data [29]. The purpose of adding data variations is to handle a small amount of data [30].

The fourth step is modelling use CNN architecture. We use three CNN architectures to train the model: LeNet-5 [31], AlexNet [32], and VGG-16 [33]. LeNet-5 is a well-performing CNN architecture for basic image classification. On the other hand, AlexNet has worked well with bigger and more complicated datasets. VGG-16 has a deeper and more complex convolutional architecture that allows for better feature extraction [34]. The second model uses RFR and the chosen CNN architecture to nutritional value estimation of broiler chicken feed images. The model utilizes two interrelated data types: the flattened CNN layer, packaged (frozen) with the nutritional content table data. Each model was trained using feed image data.

The fifth step, model evaluation, uses a confusion matrix to measure the performance of each CNN architecture or to verify the results of the data training process. The model was evaluated using various evaluation metrics, such as accuracy in equation (1), precision in equation (2), recall in equation (3), and F1-score in equation (4) for each class [25], [35]. The higher the accuracy value, the better the performance of the CNN model in image classification.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

$$\text{F1} - \text{Score} = 2 \times \frac{(\text{Precision}\times\text{Recall})}{(\text{Precision+Recall})} \tag{4}$$

Where:
TP is true positive, which is the number of positive data classified correctly.
TN is true negative, which is the number of negative data classified correctly.
FP is false positive, which is the number of positive data that are incorrectly classified.
FN is false negative, which is the number of negative data that are classified incorrectly.

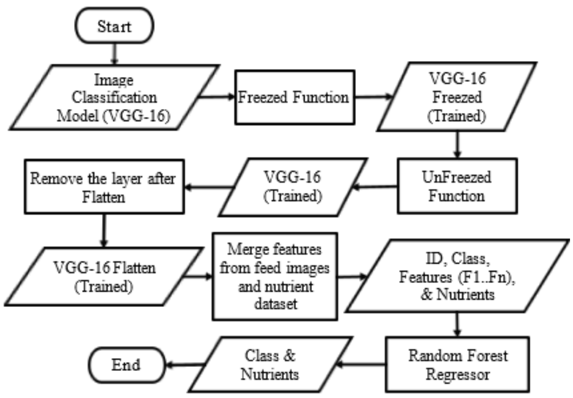

Figure 5. Flowchart of VGG-16 and RFR integration

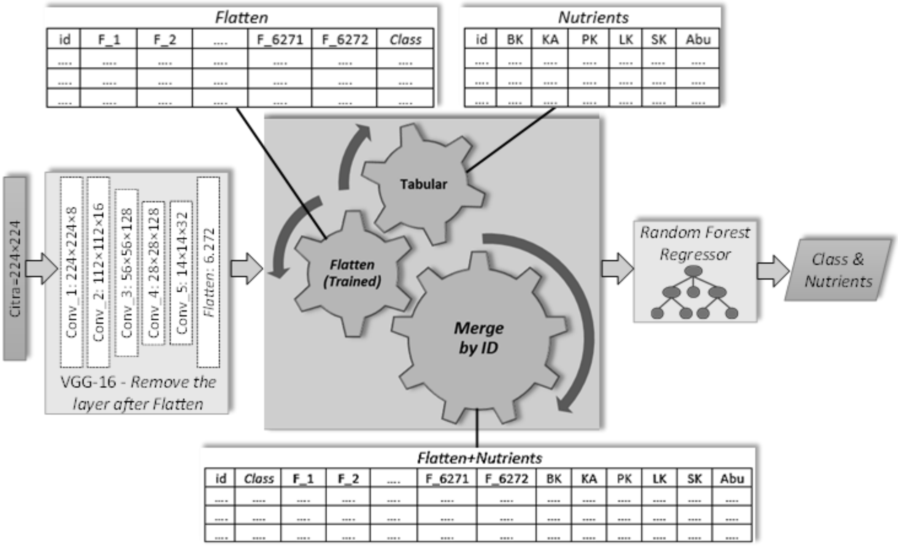

Figure 6. Integrate the VGG-16 architecture with RFR models

The seventh step is to evaluate the model RFR. we measure the accuracy of the predictions compared to the actual values for each nutrient using the R-squared method [36] in equation (5). To find out how much the predicted values differ from the actual values when checking the model, we used methods to measure error, like mean squared error in equation (6), root mean squared error in equation (7), and mean absolute error in equation (8) for each nutrient [37], [38], [39]. Random Forest Regressor allows for clear decision-making, making it easier to understand and interpret the target nutritional values of feed from near-infrared scanning data tables. The image analysis capability of CNN and the prediction speed of RFR help farmers determine the proper feed formulation, there by contributing to improving broiler chicken productivity and health.

$$R^2 = 1 - \frac{\sum_1^n (y-\hat{y})^2}{\sum_1^n (y-\bar{y})^2} \tag{5}$$

$$MSE = \frac{1}{n}\sum_1^n (\hat{y} - y)^2 \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_1^n (\hat{y} - y)^2} \tag{7}$$

$$MAE = \frac{1}{n}\sum_1^n |\hat{y} - y| \tag{8}$$

Where:
n = number of observations
y = observed actual data
$\hat{y}$ = the prediction results from the regression model
$\bar{y}$ = the average of all observation values

RESULTS AND DISCUSSIONS

Selection of optimal CNN architectures (LeNet-5, AlexNet, VGG-16)

This study uses three different CNN architectures to classify images of broiler chicken feed. The implementation uses a Python 3 Google Compute Engine backend (GPU). TensorFlow, NumPy, Pandas, Multiprocessing, OS, and CV2 are the libraries used. Augmentation with a rotation range of 45 degrees, the parameters used are a batch size of 32, 1024 epochs, and L1 and L2 regularization. The results of the experiments on each architecture to determine the best hyperparameters are as follows:

LeNet-5 architecture

The experiment was conducted 254 times using the random search optimizer to obtain the best hyperparameter configuration. The best hyperparameters were obtained in the 144th trial with two convolutional layers, two dense layers, and a learning rate of 0.0001, as shown in Table 2. The model training implementation on the LeNet-5 architecture, as shown in Figure 7, achieved the highest accuracy of 0.9973 and a loss of 0.0223.

Table 2. Parameters of each architecture

No.	Architecture	Convolution Filters	Kernel	Strides	Learning Rate
1	LeNet-5	18×18 and 16×16	5×5	1×1	0.0001
2	AlexNet	24×24, 16×16, 192×192, 384×384, and 64×64	11×11, 5×5, 3×3, 3×3, and 3×3	4×4, 1×1, 1×1, 1×1, and 1×1	0.0001
3	VGG-16	8×8, 16×16, 128×128, 128×128, and 32×32	3×3,	2×2	0.001

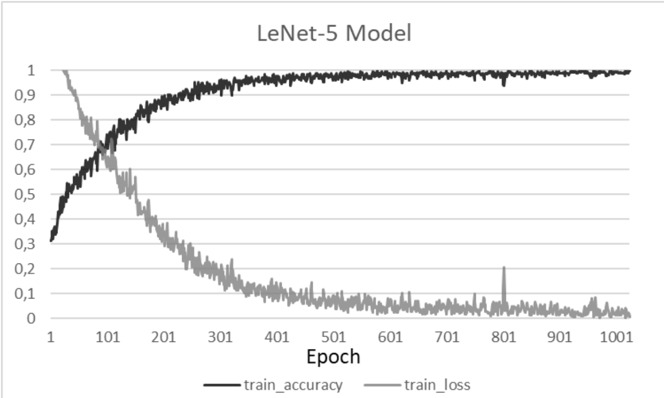

Figure 7. The accuracy and loss graph of the LeNet-5 model

AlexNet architecture

The experiment was conducted 254 times using the random search optimizer to obtain the best hyperparameter configuration. The best hyperparameters were obtained in the 201st trial with five convolutional layers, two dense layers, and a learning rate of 0.0001, as shown in Table 2. The results of the model training implementation on the AlexNet architecture are shown in Figure 8, achieving the highest accuracy of 0.9776 and a loss of 0.1104.

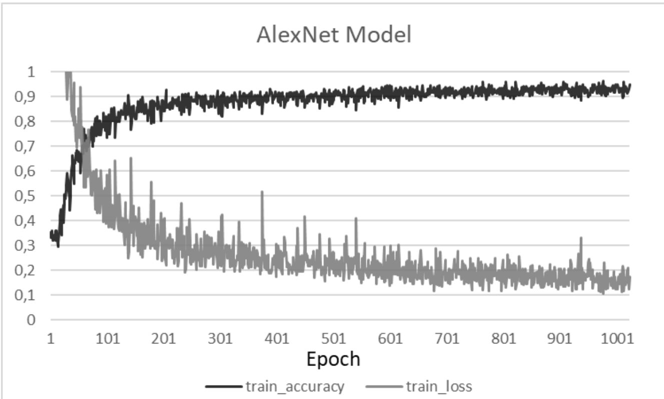

Figure 8. The accuracy and loss graph of the AlexNet model

VGG-16 architecture

The experiment was conducted 248 times using the random search optimizer to obtain the best hyperparameter configuration. The best hyperparameters were obtained in the 135th trial with five convolutional layers, two dense layers, and a learning rate of 0.001, as shown in Table 2. The results of the model training implementation on the VGG-16 architecture are shown in Figure 9, achieving the highest accuracy of 0.9969 and a loss of 0.0034.

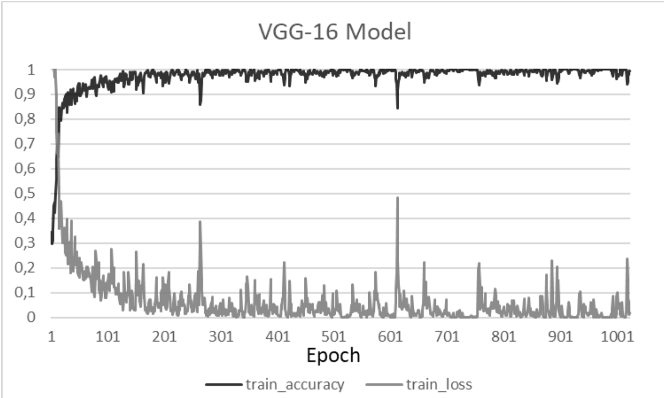

Figure 9. The accuracy and loss graph of the VGG-16 model

The selection of the appropriate CNN architecture significantly influences the estimation results. LeNet-5, although a simpler architecture, cannot capture the complexity of features in feed images well. AlexNet showed improved performance but still fell short compared to VGG-16. The VGG-16 architecture, which has more layers and is more complex, effectively recognizes smaller details in feed images, leading to more precise predictions.

Model evaluation
This study compares the performance of the classification model with the test data. We evaluate the model performance using a confusion matrix. Figure 10 shows that the VGG-16 model did a good job of classifying feed images, with excellent precision and recall values shown in Table 3. The results indicate that the model can discover and predict the structure of the feed image very accurately.

Table 3. CNN model performance evaluation

CNN Architecture	Accuracy	Precision	Recall	F1-Score
LeNet-5	0.8974	0.8462	0.8462	0.8462
AlexNet	0.8034	0.7051	0.7051	0.7051
VGG-16	0.9744	0.9615	0.9615	0.9615

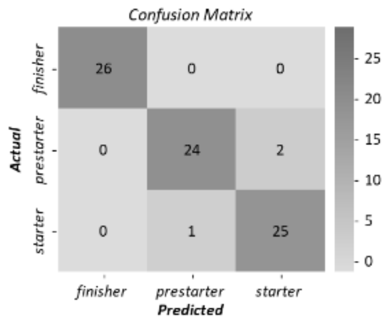

Figure 10. Model performance matrix

The experimental results indicate that the VGG-16 model provides the highest accuracy compared to LeNet-5 and AlexNet. VGG-16 is better than AlexNet and LeNet since it has more layers. VGG-16 can extract more detailed parts of the image and gather more specific information, including essential patterns and textures. The smaller 3x3 convolutional filters makes features more detailed. This gives normalization and regularization methods an edge in generalization (dropout on fully connected layers), which minimizes the risk of overfitting [34]. The use of VGG-16 as a CNN architecture has proven effective in capturing important features from feed images related to nutritional content. According to the performance evaluation using the confusion matrix, this model achieved an accuracy of 0.9744, significantly higher than the previous studies using KNN, which were 0.7212 [10] and 0.7455 [11].

Using CNN (VGG-16) and random forest regressor to figure out the nutritional value
After determining the optimal CNN model, the next step is integrating VGG-16 with the Random Forest Regressor (RFR) algorithm [40]. This approach aims to improve the interpretability and accuracy of the

estimates [41]. The RFR algorithm produces a model for estimating the nutritional content of feed based on extracted image features [42]. Features extracted from the images of broiler chicken feed at the flatten layer of the VGG-16 model, which have been packaged in frozen form, serve as input for RFR to determine the target nutrient content. The first step in the integration process is to unfreeze the VGG-16 model and get rid of all the layers except the flatten layer. The next step is to combine the data in the flatten layer with the tabular nutritional content data based on their IDs. The final step is for RFR to fetch data to estimate the nutritional content based on broiler feed images. The performance of the RFR model, which can predict multi-target nutrient content, is shown in Table 4. These results demonstrate that RFR is a highly effective method for estimating the nutritional content of broiler chicken feed. Although the overall estimation of nutrient content is excellent, the predictions for crude fibber and ash content are still low.

Table 4. Evaluation of RFR model performance

Nutrients	R^2	MSE	RMSE	MAE
Dry Ingredients	0.7976	0.2269	0.4764	0.3080
Water content	0.8018	0.2222	0.4714	0.3021
Crude Protein	0.7782	3.8432	1.9604	1.4339
Crude Fat	0.7948	0.3922	0.6262	0.4317
Crude Fiber	0.7288	1.7977	1.3408	0.9158
Ash	0.6777	6.7794	2.6037	1.5074

CONCLUSION

Based on the experimental results, the integration of CNN (VGG-16) and RFR is able to build a model that can determine how much nutrition is contained in broiler chicken feed. The VGG-16 was the best in classifying images of broiler chicken feed, with an accuracy of 0.9744. We estimate the nutritional content in broiler chicken feed using RFR and VGG-16 feature extraction. This model successfully explained the class and accurately estimated the nutritional value of broiler chicken feed, with an R^2 score of 0.8018. The use of near-infrared technology in feed analysis shows enormous potential for improving efficiency and accuracy in evaluating the quality of broiler chicken feed. This result can be an effective solution for managing broiler chicken feed. To improve the model performance, further research is recommended to develop the model with a larger and more varied dataset and to perform hyperparameters tuning of the RFR. Furthermore, developing an application system that implements this model on farms will increase the productivity and efficiency of broiler chicken production in Indonesia.

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