The 12th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications
7-9 September, 2023, Dortmund, Germany

Detection of Chicken Diseases from Fecal Images with the Pre-Trained Places365-GoogLeNet Model

Ilkay Cinar
Department of Computer Engineering, Selcuk University, Konya, Türkiye
ilkay.cinar@selcuk.edu.tr, ORCID: 0000-0003-0611-3316

Abstract—**A variety of chicken diseases pose significant challenges to chicken farmers worldwide, posing a threat to the safety of food and potentially resulting in economic losses. In this study, we propose the utilization of the pre-trained deep learning model, Places365-GoogLeNet, for the detection of chicken diseases from chicken fecal images, including Healthy, Coccidiosis, Salmonella, and New Castle Disease. By leveraging the powerful image analysis capabilities of deep learning, our approach achieves a remarkable classification accuracy of 98.91%. This accuracy surpasses the results reported in related studies in the literature. Moreover, our findings highlight the potential of artificial intelligence and machine learning techniques, particularly in the agricultural sector, for automated disease detection. The presented results not only contribute to early disease diagnosis and prompt intervention in poultry farming but also pave the way for future research to develop more advanced methods and utilize larger and diverse datasets to enhance the model's generalization ability.**

Keywords— automatic disease detection, chicken diseases, deep learning, fecal images, GoogleNet

I. INTRODUCTION

Poultry, globally recognized as a valuable source of protein, plays a crucial role in human nutrition. Especially chicken meat and eggs are considered significant contributors to the human diet. To meet the growing demand for poultry products, many countries have to increase their poultry production. Poultry farming also holds great importance in terms of food and nutrition security. Eggs are recognized as an economical source of protein and nutrients, particularly in developing countries where they contribute to addressing protein deficiency and ensuring local food security. Meanwhile, chicken meat, being affordable and nutritious, helps improve nutrition security. Furthermore, poultry farming is a vital sector supporting socio-economic development in developing countries. It offers opportunities for farmers to generate income and supports rural economies. Additionally, it has the potential to create employment, contributing to the overall welfare of society and reducing poverty in rural areas. Based on all these sages, it is possible to say that chicken farming is an important part of food production worldwide. However, diseases in chickens can adversely affect production efficiency and profitability. Therefore, early diagnosis and accurate identification methods play a critical role in helping farm owners combat these diseases [1, 2].

Traditionally, the diagnosis and identification of chicken diseases have been carried out by expert veterinarians. However, this process is often time-consuming and experts are not available everywhere. Therefore, the use of artificial intelligence and machine learning techniques to provide an automatic and quick diagnosis method is increasingly being researched [1, 3].

In recent years, advances in the field of computer vision and image analysis have made it possible to use images for the detection of diseases. Specifically, images obtained from chicken fecal can contain valuable information for the diagnosis of diseases. Chicken fecal can carry symptoms of many diseases due to the pathogens and biological components they contain [1, 4].

In this study, we are investigating the use of deep learning methods for detecting chicken diseases using images of chicken fecal. Deep learning refers to a subdivision of machine learning in which deep neural networks are utilized to automatically acquire intricate data representations and structures. With the images obtained from chicken fecal, it is aimed to classify diseases using deep learning algorithms and thus to diagnose them early.

II. RELATED WORKS

The studies carried out in the literature using artificial intelligence techniques to detect chicken diseases from fecal images are summarized below.

Quach et al. (2020) used deep learning models VGG16 and ResNet50 in their study for the automatic detection of diseased chickens from fecal images. They reported that they achieved the highest classification accuracy in detecting 4 different diseases (Infectious Laryngotracheitis, Newcastle, Marek, and Healthy) with the VGG16 model [5].

Mbelwa, Machuve, and Mbelwa (2021), in their study, classified chicken fecal images into 3 different disease classes (Healthy, Coccidiosis, and Salmonella) using deep learning. They reported in the study results that they achieved the highest classification accuracy of 93.67% with the Xception model [6].

Akbudak (2022) utilized deep learning models for disease detection from chicken fecal images. He reported achieving the highest validation accuracy with the Xception model in classification processes conducted using 8 different deep-learning models for the classification of 4 different disease groups (Healthy, Salmonella, New Castle Disease, and Coccidiosis) [7].

Degu and Simegn (2023) utilized deep learning models in their study on the detection and classification of poultry diseases. They used the ResNet50 model for the classification processes of diseases evaluated in 4 different classes (Healthy, Salmonella, New Castle Disease, and Coccidiosis) and reported a classification success of 98.7% [8].

Suthagar et al. (2023) used pre-trained DenseNet, MobileNet, and Inception deep learning models for the detection of chicken diseases. In their study, they classified fecal images belonging to 4 different disease classes (Healthy, Coccidiosis, Salmonella, and New Castle Disease) and stated that the highest classification success belonged to the DenseNet [9].

Zhou et al. (2023) used deep learning models to detect abnormalities in chicken fecal. In their study evaluating 3 different fecal abnormalities (abnormal shape, abnormal water, abnormal color), they reported reaching the highest classification accuracy with the ResNet50 model [10].

When reviewing the studies found in the literature, it is observed that there are a few studies that use artificial intelligence techniques to detect chicken diseases from fecal images. When these few studies are examined, it is seen that deep learning models, which are frequently used in the literature, are used in the diagnosis of disease. Although the Places365-GoogLeNet model used in this study was developed on scene recognition, it has been tried to show that it can also be used in different areas.

III. MATERIAL AND METHODS

In this section, a comprehensive explanation of the dataset, CNNs, transfer learning, cross-validation, confusion matrix, and performance metrics is provided. Additionally, a graphical representation of the study can be found in "Fig. 1", illustrating the visual depiction of the research.

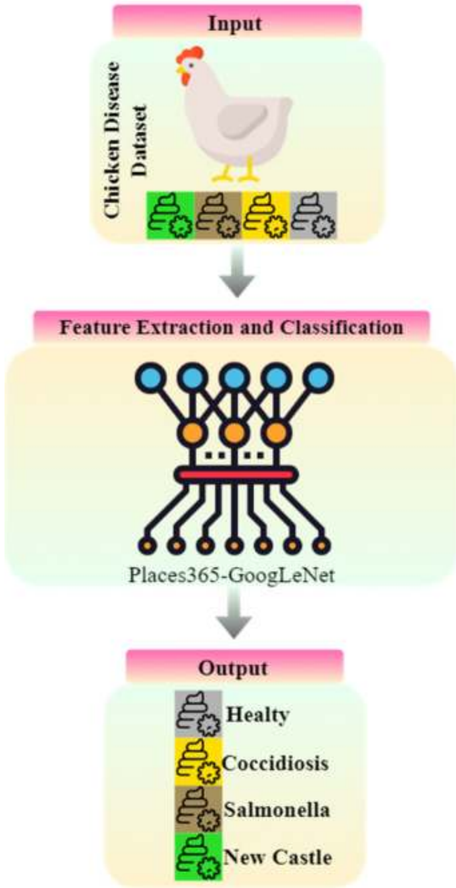

Figure 1. Graphical representation of the study

A. Dataset Details

The data used in the study was obtained from 'kaggle.com'. The dataset is accessible from link 'https://www.kaggle.com/datasets/allandclive/chicken-disease-1'. The dataset consists of 4 classes: Healthy, Coccidiosis, Salmonella, and New Castle Disease. There are a total of 8067 images in the dataset with dimensions of 224 by 224 pixels. The total number of images for each class is given in "Fig. 2", and examples of images for each class are given in "Fig. 3".

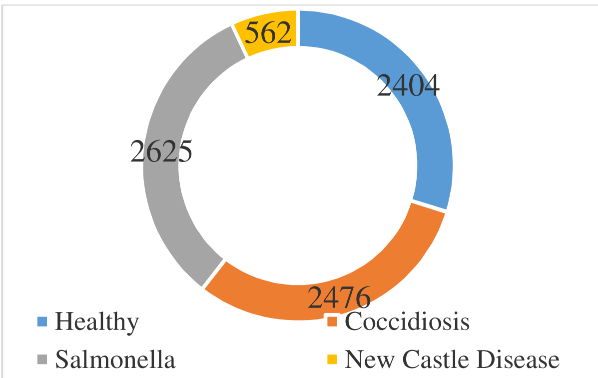

Figure 2. The total number of images for each class

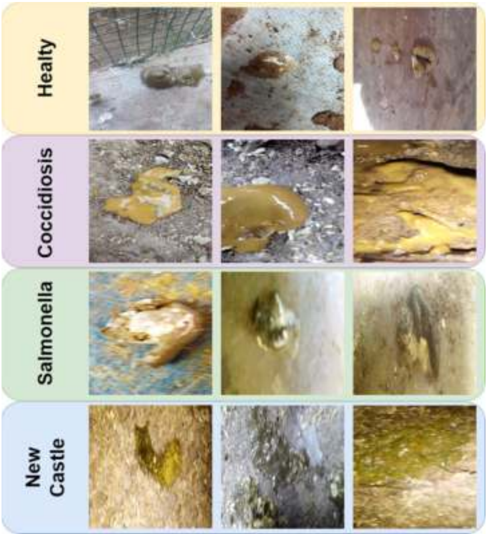

Figure 3. Examples of images for each class

B. Convolutional Neural Networks (CNN) and Transfer Learning

CNNs are a specific kind of artificial neural network primarily designed to handle and process data that exhibits a grid-like structure, such as images and videos, commonly used in tasks related to image and video processing. CNNs detect features by applying a series of filters to an input data (usually an image). These filters are used in convolutional layers to particularly identify low-level features, such as edges and color blocks. These low-level features are then transformed into higher-level features, such as shapes and objects. These features are later utilized by fully connected layers to generate an output relevant to the task at hand (for example, determining the class of an image in an image classification task) [11-13].

Transfer learning is a machine learning technique that involves leveraging a pre-trained model, usually a neural network, and adapting it to tackle a new problem that is closely related. This can save significant time and computational resources compared to training a new model from scratch. CNNs have been particularly successful in transfer learning, especially in computer vision tasks [13-15].

The key idea behind transfer learning is that the lower layers of a CNN learn general features, such as edges, corners, and textures, which are common across different tasks. Higher layers, on the other hand, learn more specific features and concepts relevant to the original task. When applying transfer learning, the lower layers are usually kept fixed, and the higher layers are fine-tuned or replaced with new layers specific to the new task [11, 13, 16].

The transfer learning technique has been widely accepted and applied to a broad range of computer vision tasks, including image classification, object detection, and segmentation. It has proven to be a highly valuable technique in leveraging pre-trained models to enhance performance and expedite training in these domains. This approach has proven to be highly beneficial, as it can substantially enhance performance and decrease the time required for training [13, 16].

1) Places365-GoogLeNet

Places365-GoogLeNet is a GoogLeNet model trained on Places365, a large-scale scene recognition dataset. GoogLeNet is a convolutional neural network model that aims to make CNNs deeper and broader using an architecture called Inception [17-19]. Some of the features of the Places365-GoogLeNet model are:

- GoogLeNet uses Inception modules, which perform multiple convolution and pooling operations in parallel and combine the results. This structure helps capture features from a wider area and increases the computational efficiency of the model.
- The GoogLeNet model is deep and broad, which increases learning capacity and allows for the recognition of more complex features and scenes.
- By using 1x1 convolutions, GoogLeNet reduces the number of parameters, thus reducing the memory and computational needs of the model.
- During training, the GoogLeNet model uses auxiliary classifiers to speed up the learning process and achieve better local minimums depending on its depth.

The model has 144 layers and 170 connections. The model architecture is given in “Fig. 4”.

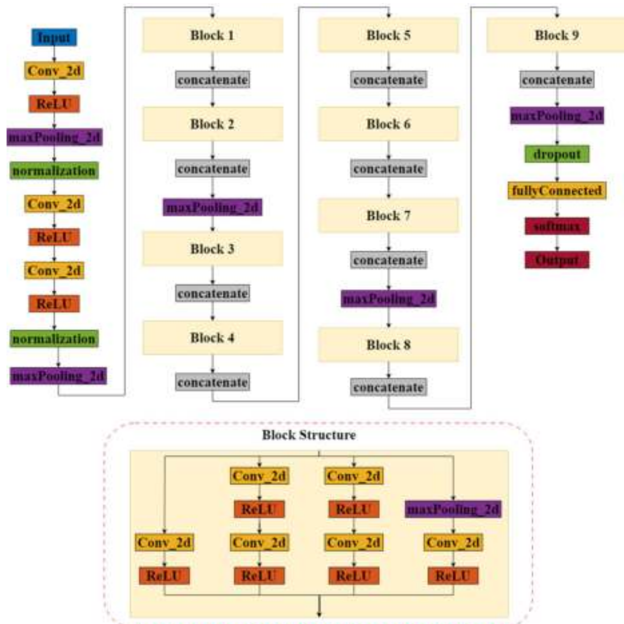

Figure 4. Model architecture

C. Cross-Validation

Cross-validation is a statistical method used to assess a model's ability to generalize. The main purpose is to understand how well the model can generalize to new, unseen data. This is especially important for identifying and preventing overfitting issues with the model [20, 21]. Cross-validation typically includes the following steps:

- Partitioning a dataset into equal-sized subsets is known as 'k'.
- Models are trained with 'k-1' subsets, while test subsets are reserved for testing.
- This process is iteratively repeated until each subset has been utilized as a test set exactly once, forming a complete cycle.
- During each cycle, the performance of the model is evaluated and recorded.
- Once all cycles are finished, the overall performance of the model is usually computed by taking the average of the recorded measurements.

In this study, as shown in "Fig. 5", 10-fold cross-validation was used.

Figure 5. 10-fold cross-validation

D. Confusion Matrix

To determine whether a classification model is accurate, confusion matrices demonstrate how real and predicted classes correlate. It provides a comprehensive view of the model's predictions, allowing for the evaluation of accuracy and other performance metrics [22]. The study includes a confusion matrix for a four-class classification task, which is depicted in "Fig. 6".

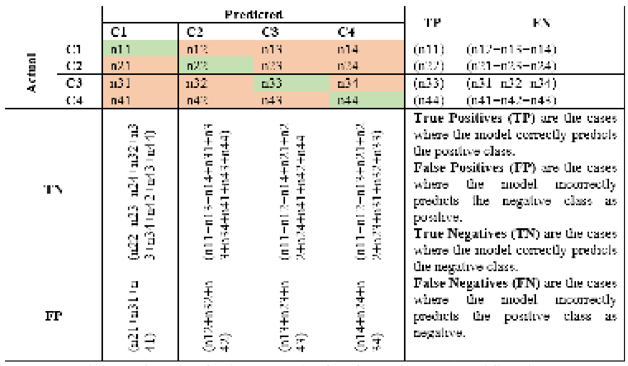

Figure 6. Confusion matrix for four-class classification

E. Performance Metrics

Descriptions of the performance metrics Accuracy, F1-Score, Precision, and Recall which are used in determining the weak points of a model and how accurate results it gives, are given in Table I [22].

TABLE I. PERFORMANCE METRICS

Metrics	Explanations and Formulas
Accuracy	The total number of examples accurately predicted is divided by the overall number of examples to determine accuracy. $Accuracy = \frac{(TP + TN)}{(TP + FP + FN + TN)}\ x\ 100$
Precision	It is basically expressing how much we can trust that a predicted positive instance is truly positive. $Precision = \frac{TP}{TP + FP}$
Recall	It expresses the ability to find all the positive instances. $Recall = \frac{TP}{TP + FN}$
F1-Score	The overall performance of the model is often assessed using the harmonic mean of precision and recall. $F1 - Score = \frac{2\ x\ (Precision\ x\ Recall)}{(Precision +\ Recall)}$

F. Experimental Setup

Before training the model, various training trials were carried out by considering different parameters and values. The optimum classification accuracy obtained in this study was achieved with the training options given in Table II.

TABLE II. TRAINING OPTIONS

Parameters	Values
Solver	sgdm
Learning Rate	0.0001
Validation Frequency	5
Max. Epochs	8
Mini Batch Size	11
L2 Regularization	0.0001
Gradient Threshold Method	l2norm
Learn Rate Drop Factor	0.1
Learn Rate Drop Period	10

In the study, 'sgdm' was chosen as the Solver. This optimization algorithm accelerates the gradient descent by using momentum and provides a faster local minimum. The Learning Rate is set at 0.0001. The learning rate controls the step size in updating the weights. A slow learning rate allows the weights to be updated more slowly and a more stable training process can be achieved. Validation Frequency value is set as 5. The performance of the model is evaluated on a validation set every 5 epochs. This is used to check if the model is overfitting during training. Maximum Epochs value is set to 8. Epoch represents a one-time pass of the entire training dataset. The 8 epochs chosen depending on the capacity of the device used in the training mean that the model passes over the training dataset 8 times in total. Again, depending on the capacity of the device used, the Mini Batch Size value was determined as 11. The mini-batch corresponds to small parts of the training dataset. Each mini-batch is used to update the weights. The mini-batch size of 11 means that 11 samples are used for each update. L2 Regularization value is set as 0.0001. L2 regularization is a regularization method used to control the size of weights and reduce overfitting. The regulation parameter 0.0001 encourages small weights.

The Gradient Threshold Method is designated 'l2norm'. This ensures that gradient values are clipped if they exceed a threshold. The Learn Rate Drop Factor value was set to 0.1. This is a factor used to reduce the learning rate. In each 'Learn Rate Drop Period' step, the learning rate is reduced by multiplying this factor. The Learn Rate Drop Period value is set to 10. This determines the frequency with which the learning rate is reduced.

IV. Experimental Results

In this section, detailed experimental results obtained using the pre-trained deep learning model, Places365-GoogLeNet, are presented.

For the experimental studies, a dataset containing a total of 8067 images across 4 classes was used. The dataset includes images of healthy chicken fecal as well as fecal images of Coccidiosis, Salmonella, and Newcastle Disease.

For model training, the pre-trained deep learning model, Places365-GoogLeNet, was utilized. To classify chicken fecal images, the last fully connected layer of the Places365-GoogLeNet model was removed, and a dataset-specific fully connected layer was added. The training, validation, and loss curves obtained after the model training and evaluation are provided in “Fig. 7”.

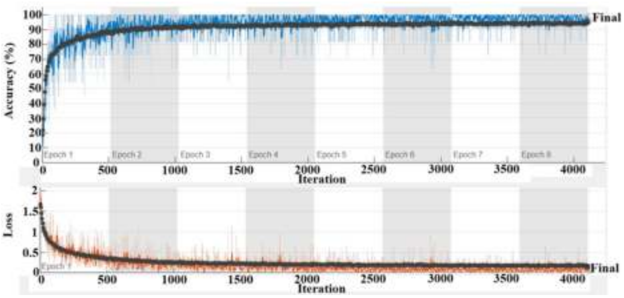

Figure 7. The training, validation, and loss curves

When examining the Loss graph shown in “Fig. 7”, it can be observed that the loss value initially starts at 2.5 and gradually decreases throughout the training process, reaching a level of 0.25. This indicates that the model is adapting to the training data and making improved predictions. A low loss value signifies that the model is better at following the data and making fewer errors. Analyzing the Accuracy graph, it can be seen that the model initially has low predictions, but as the training progresses, the accuracy rate increases significantly, reaching a high accuracy of 98.91%. This demonstrates that the model is better at predicting the data.

The confusion matrix obtained after classification is presented in Table III, while the performance metric values for each class are given in Table IV.

TABLE III. Confusion Matrix

	Coccidiosis	Healthy	New Castle Disease	Salmonella
Coccidiosis	2457	4	5	3
Healthy	9	2382	13	15
New Castle Disease	2	3	536	3
Salmonella	8	15	8	2604
Total	**2476**	**2404**	**562**	**2625**

TABLE IV. Performance Metrics for Each Class

Class	Accuracy	Precision	Recall	F1-Score
Coccidiosis	99.62	1.0	0.99	0.99
Healthy	99.27	0.98	0.99	0.99
New Castle Disease	99.58	0.99	0.95	0.97
Salmonella	99.36	0.99	0.99	0.99

When examining Table III and Table IV, it can be observed that the model achieved high accuracy and performed well in correctly identifying instances of coccidiosis. The precision value of 1.0 suggests that all the instances classified as coccidiosis were indeed correct. The recall value of 0.99 indicates that the model effectively captured a high percentage of the true positive cases for coccidiosis. The F1-Score, which considers both precision and recall, is also high at 0.99, indicating a balanced performance for this class.

The model achieved a high accuracy of 99.27% for classifying healthy instances. The precision of 0.98 suggests that the model correctly classified 98% of the instances as healthy. The recall value of 0.99 indicates that the model captured a high percentage of the actual healthy instances. The F1-Score of 0.99 further indicates a balanced performance for this class.

The model achieved a high accuracy of 99.58% for classifying instances of New Castle Disease. The precision value of 0.99 suggests a high proportion of correct positive predictions for this class. The recall value of 0.95 indicates that the model captured 95% of the true positive instances for New Castle Disease. The F1-Score of 0.97 represents a good balance between precision and recall.

The model achieved a high accuracy of 99.36% for classifying instances of Salmonella. The precision and recall values of 0.99 indicate a high proportion of correct positive predictions and successful capture of true positive instances for Salmonella. The F1-Score of 0.99 represents a balanced performance for this class.

Overall, the model performed well across all classes with high accuracy values and balanced precision, recall, and F1-Score metrics. The average classification accuracy of the Places365-GoogLeNet model is obtained as 98.91%.

These results demonstrate that the pre-trained deep learning model, Places365-GoogLeNet, has a high classification accuracy for disease detection from chicken fecal images.

V. Conclusions

In this study, a pre-trained deep learning model, Places365-GoogLeNet, was used to detect chicken diseases from chicken feces images, including Healthy, Coccidiosis, Salmonella, and New Castle Disease. When the loss and accuracy curves obtained as a result of the training process of the model were examined, it was observed that the loss value decreased and the accuracy rate increased. According to the classification results, it was observed that the model correctly classified the Healthy, Coccidiosis, Salmonella, and New Castle Disease classes with high accuracy values. Precision, recall, and F1-Score metrics for each class also show balanced performance. The results of this study have been compared to similar studies found in the literature, and the comparison is presented in Table V.

TABLE V. Comparison of similar studies in the literature

References	Number of Classes	Number of Images	Data Augmentation	Model	Accuracy (%)
[5]	4	547	No	VGG16	74.10
[6]	3	1590	No	Xception	93.67
[7]	4	15,128	Yes	Xception	88.00
[8]	4	10,500	Yes	ResNet50	98.70
[9]	4	6812	No	DenseNet	97.00
[10]	3	5314	Yes	ResNet50	98.80
This Study	4	8067	No	Places365-GoogLeNet	98.91

When examining Table V, it is evident that the results obtained from this study have achieved higher classification accuracy compared to similar studies found in the literature. The effects of high classification accuracy in such disease detection processes can include:

- Early Diagnosis: The high accuracy rate helps to accurately detect diseases in their early stages. Early diagnosis can prevent the progression of the disease and enable more effective treatment methods to be applied.
- Accurate Treatment: The high accuracy rate ensures accurate identification of the disease, which helps in choosing the right treatment methods. Misdiagnoses or low accuracy rates can lead to incorrect treatments or delays in treatment.
- Efficient Resource Utilization: High accuracy rate allows more efficient use of resources. Accurate diagnoses help prevent unnecessary testing and treatment. This reduces costs and contributes to a more sustainable management of health services.

This study is believed to contribute to the ability of poultry farmers to detect diseases early and intervene rapidly in the treatment process. Furthermore, it highlights the applicability and effectiveness of artificial intelligence and machine learning methods for automated disease detection in the agricultural sector.

The major limitation and potential weakness of this study is the use of a publicly available dataset. The reasons for this can be listed as follows:

- Particularly, utilizing larger and more diverse datasets may enhance the model's generalization ability.
- The quality of the images in the dataset may vary in resolution, lighting conditions and other factors. This may affect the performance of the model and reduce its accuracy.

Despite all this, it is anticipated that this study will provide a solid groundwork for future research endeavours and contribute to the advancement of more sophisticated methods in the domain of chicken disease detection.

In summary, this study has successfully showcased the effectiveness of the pre-trained deep learning model, Places365-GoogLeNet, in achieving a notable level of classification accuracy for the detection of diseases from chicken fecal images.

Acknowledgment

The Scientific Research Coordinator at Selcuk University has provided valuable support to me, and I am grateful for that.

References

[1] P. He, et al., “Research progress in the early warning of chicken diseases by monitoring clinical symptoms,” *Applied Sciences*, vol. 12, issue 11, p. 5601, 2022. DOI: 10.3390/app12115601.

[2] A. Mottet, and G. Tempio, “Global poultry production: current state and future outlook and challenges,” *World's Poultry Science Journal*, vol. 73, issue 2, pp. 245-256, 2017. DOI: 10.1017/S0043933917000071.

[3] J. Vidic, et al., “Advanced biosensors for detection of pathogens related to livestock and poultry,” *Veterinary research*, vol. 48, issue 1, pp. 1-22, 2017. DOI: 10.1186/s13567-017-0418-5.

[4] J. Astill, et al., “Detecting and predicting emerging disease in poultry with the implementation of new technologies and big data: A focus on avian influenza virus,” *Frontiers in Veterinary Science*, vol. 5, pp. 263, 2018. DOI: 10.3389/fvets.2018.00263.

[5] L.-D. Quach, et al., “Identification of chicken diseases using VGGNet and ResNet models,” *Proceedings of the 6th EAI International Conference on Industrial Networks and Intelligent Systems, INISCOM 2020*, Hanoi, Vietnam, August 27–28, 2020, vol. 6. Springer.DOI: 10.1007/978-3-030-63083-6_20.

[6] H. Mbelwa, D. Machuve, and J. Mbelwa, *Deep Convolutional Neural Network for Chicken Diseases Detection*, 2021.

[7] B. S. Akbudak, “Disease detection from chicken feces on a mobile platform using deep learning methods,” *Young Scientist Research*, vol. 6, issue 1, pp. 17-23, 2022.

[8] M. Z. Degu, G. L. Simegn, “Smartphone based detection and classification of poultry diseases from chicken fecal images using deep learning techniques,” *Smart Agricultural Technology*, vol. 4, pp. 100221, 2023. DOI: 10.1016/j.atech.2023.100221.

[9] S. Suthagar, et al., “Faecal image-based chicken disease classification using deep learning techniques,” *Proceedings of the Inventive Computation and Information Technologies: ICICIT'2022*. 2023, pp. 903-917.

[10] M. Zhou, et al., “Detection of abnormal chicken droppings based on improved faster R-CNN,” *International Journal of Agricultural and*

Biological Engineering, vol. 16, issue 1, pp. 243-249, 2023. DOI: 10.25165/j.ijabe.20231601.7732.

[11] Y. S. Taspinar, et al., "Computer vision classification of dry beans (Phaseolus vulgaris L.) based on deep transfer learning techniques," *European Food Research and Technology*, vol. 248, issue 11, pp. 2707-2725, 2022. DOI: 10.1007/s00217-022-04080-1.

[12] M. Jogin, et al., "Feature extraction using convolution neural networks (CNN) and deep learning," *Proceedings of the 2018 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, 2018. DOI: 10.1109/RTEICT42901.2018.9012507.

[13] K. Weiss, T. M. Khoshgoftaar, and D. Wang, "A survey of transfer learning," *Journal of Big Data*, vol. 3, issue 1, pp. 1-40, 2016. DOI: 10.1186/s40537-016-0043-6.

[14] O. Ozaltin, O. Yeniay, and A. Subasi, "Artificial intelligence-based brain hemorrhage detection," *In Accelerating Strategic Changes for Digital Transformation in the Healthcare Industry*, 2023, pp. 179-199. Academic Press. DOI: 10.1016/B978-0-443-15299-3.00008-7.

[15] M. Dogan, et al., "Dry bean cultivars classification using deep CNN features and salp swarm algorithm based extreme learning machine," *Computers and Electronics in Agriculture*, 2023, 204 p. 107575.DOI: 10.1016/j.compag.2022.107575.

[16] Y. Unal, et al., "Application of pre-trained deep convolutional neural networks for coffee beans species detection," *Food Analytical Methods*, vol. 15, issue 12, pp. 3232-3243, 2022. DOI: 10.1007/s12161-022-02362-8.

[17] C. Szegedy, et al., "Going deeper with convolutions," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015.

[18] P. Salavati, and H. M. Mohammadi, "Obstacle detection using GoogleNet," *Proceedings of the 2018 8th IEEE International Conference on Computer and Knowledge Engineering (ICCKE)*, 2018. DOI: 10.1109/ICCKE.2018.8566315.

[19] M. S. AL-Huseiny, and A.S . Sajit, "Transfer learning with GoogLeNet for detection of lung cancer," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 22, issue 2, pp. 1078-1086, 2021. DOI: 10.11591/ijeecs.v22.i2.pp1078-1086.

[20] E. T. Yasin, and M. Koklu, "Classification of organic and recyclable waste based on feature extraction and machine learning algorithms," *Proceedings of the International Conference on Intelligent Systems and New Applications (ICISNA'23)*, Liverpool, United Kingdom, 2023.

[21] O. Ozaltin, M. Koklu, A. Yonar, and O. Yeniay, "Automatically image classification based on a new CNN architecture," *Proceedings of the III International Applied Statistics Conference (UYIK-2022)*, Skopje, N Macedonia, 2022, pp. 22-24.

[22] I. Cinar, Y. S. Taspinar, and M. Koklu, "Development of early stage diabetes prediction model based on stacking approach," *Tehnički Glasnik*, vol. 17, issue 2, pp. 153-159, 2023. DOI: 10.31803/tg-20211119133806.