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Deep Learning Based Poultry Diseases Diagnosis

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Abstract: Poultry farming is critical for global food security, yet it faces significant challenges in disease diagnosis, leading to economic losses and public health risks. Traditional methods are often time-consuming and inaccurate. Recently, deep learning (DL) techniques have emerged as powerful tools for disease diagnosis. This paper reviews the application of DL methods in poultry disease diagnosis. First, we discuss various poultry diseases, emphasizing early and accurate diagnosis. Next, we explore deep learning concepts, highlighting its ability to learn complex patterns from large datasets. We survey state-of-the-art deep learning architectures like convolutional neural networks (CNNs) optimized for poultry disease diagnosis. We address challenges such as dataset availability, model interpretability, and generalization to diverse conditions. Finally, we outline future research directions, including transfer learning and multi-modal data fusion, to enhance poultry disease diagnosis and mitigate its impact on global food security.

Keywords: Poultry, Disease diagnosis, Deep Learning, Dataset, Preprocessing, Convolutional Neural Networks (CNNs), Image classification, transfer learning, fine tuning, accuracy.

I. INTRODUCTION

Poultry farming is crucial for providing the animal protein needed to feed our growing global population. However, the industry encounters ongoing hurdles, with disease outbreaks posing a major threat to flock health and productivity. Detecting and diagnosing diseases accurately and promptly is vital for managing them effectively, preventing widespread outbreaks, and ensuring the overall well-being of poultry.

In the past few years, the rise of deep learning technologies has brought about exciting opportunities to revolutionize how we detect and handle poultry diseases. Deep learning, which is a branch of artificial intelligence, is making significant strides and has already demonstrated its potential in diverse areas such as medical diagnosis and image interpretation. Using deep learning for diagnosing poultry diseases is a novel and potentially game-changing method.

In our country, farmers rear different kinds of birds, with chickens making up a whopping 96% of the total livestock population. However, chicken production encounters considerable challenges, including unpredictable markets, restricted access to essential resources, inadequate support from extension services, and the looming threat of diseases such as Newcastle disease, Coccidiosis, and Salmonella.

Salmonella bacteria spread among birds mainly through contact with feces, a process known as the fecal-oral route. Chickens can also encounter Salmonella from sources like manure piles, carcasses, barn dust, and rodents like rats and mice. Young chickens, especially those less than two weeks old, are particularly vulnerable to diseases and death caused by Salmonella. Signs of infection can vary and may include weakness, decreased appetite, and stunted growth.

Coccidiosis, caused by parasites called Eimeria, affects the intestinal tracts of poultry and is a leading cause of protozoan-related deaths among chickens. This disease poses a significant threat to both the productivity and overall health of chickens, posing a major concern for the global poultry industry. Outbreaks occur when young chicks ingest large quantities of sporulated oocysts. Symptoms include reduced food intake, bloody diarrhea, and weight loss. Overall, coccidiosis leads to diarrhea, weight loss, and decreased production in poultry due to parasitic protozoa affecting their intestinal tract.

Newcastle disease, caused by a paramyxovirus, is a highly contagious illness that affects birds. It spreads through contact with droppings and secretions from the nose, mouth, and eyes of infected birds. The main way it spreads is through direct contact between healthy birds and bodily fluids of infected ones. This disease is often transmitted through contact with birds already carrying the virus, who may shed it in their feces, leading to contamination in the environment. Transmission can occur through exposure to feces and respiratory secretions, or via contaminated food, water, equipment, and even human contact.

Deep learning techniques, particularly in computer vision and image classification, have gained attention for their ability to outperform traditional machine learning methods. In this study, a Convolutional Neural Network (CNN) is used for several reasons: it allows for multi-layer processing, optimization of extracted features, and operates quickly while requiring fewer computational resources. Deep Convolutional Neural Networks (DCNNs) enable computers to

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automatically learn from data, including feature extraction, representation, classification, localization, and recognition. This technology has been applied to early disease detection in animals.
Our research aims to showcase how deep learning models excel not only in pinpointing poultry diseases accurately but also in forecasting potential outbreaks and offering valuable insights into disease development. Additionally, we will explore how these models can be practically applied in poultry farming, including real-time monitoring and automated diagnosis. Such applications can greatly aid both poultry farmers and veterinarians in managing health issues effectively.

The paper is organized into three main sections. Section II details the materials and methodologies used for disease detection. Section III discusses the findings and engages in subsequent discussions. Lastly, Section IV concludes the study, providing conclusions and suggesting areas for future research.

II. EXPERIMENTAL SETUP

The programming language chosen for this project is Python. Deep learning frameworks, namely TensorFlow and Keras, were utilized, along with image processing libraries such as OpenCV and Albumentations. Model evaluation was performed using a confusion matrix. Visual Studio Code served as the Python Integrated Development Environment (IDE) for coding purposes. In terms of hardware requirements, a modern multicore processor like Intel Core i5 or higher was recommended to handle deep learning computations efficiently. A minimum of 8 GB of RAM was deemed necessary for data processing and model training, and sufficient SSD storage was essential for storing images, datasets, and models.

III. DATASET

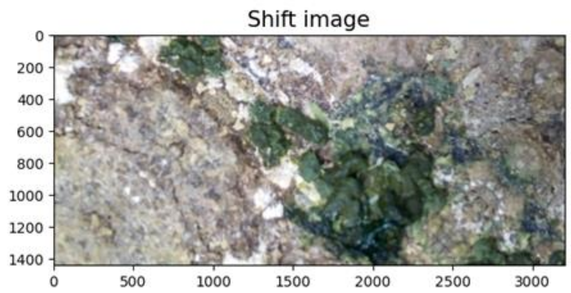
For this project, we gathered fecal images from inoculation sites in January 2024. We utilized various phone cameras with differing resolutions, resulting in images saved in Joint Photographic Experts Group (JPG) format. These images were then categorized into three class labels: Health images, Coccidiosis images, and Salmonella images. Through meticulous curation, we acquired a dataset that precisely met our requirements for diverse images. Subsequently, the images were divided into three sets: 60% for training, 20% for testing, and 20% for validation purposes.

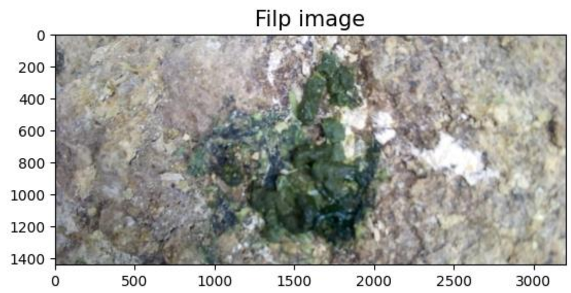
IV. PRE-PROCESSING

Deep Learning belongs to a category of machine learning methods. Unlike traditional machine learning, Deep Learning streamlines the need for extensive data pre-processing. These algorithms excel at handling unstructured data such as text and images, and they streamline feature extraction, reducing the reliance on human expertise. Deep Learning is particularly effective in tackling image classification tasks because it autonomously learns from the features present in the images.

Data preprocessing is a crucial step in readying raw data for machine learning models. Initially, essential modules are imported, incorporating libraries like Albumentations for image augmentation. Following this, the data undergoes segmentation into training, testing, and validation sets. For a given dataset containing classes such as cocci, Salmo, healthy, and ncd, these classes are defined, and corresponding images are gathered. Subsequently, the data is partitioned into training, testing, and validation sets based on predetermined proportions. For example, within the cocci class, 60% of the images are allocated for training, 20% for testing, and 20% for validation.

To enrich the training dataset, image augmentation techniques are implemented, involving actions like flipping and shifting images to introduce more variability. Following preprocessing, the training dataset comprises 1261 images for the cocci class, 2925 images for the ncd class, 1234 images for the healthy class, and 1365 images for the Salmo class. These images encompass the original image along with horizontally flipped, shifted, and noised images.





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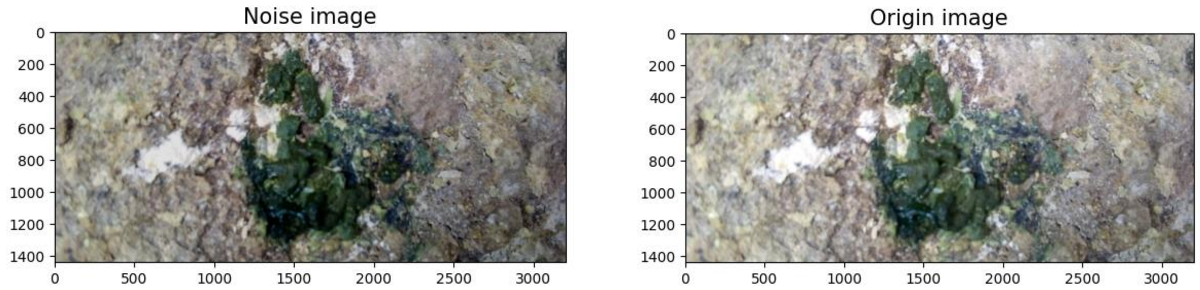

V. PROPOSED MODEL

This research utilizes various architectural models tailored for image classification tasks, including VGG, ResNet, XceptionNet, and MobileNet. The terms "VGG 16" and "VGG 19" refer to the number of weighted layers within each network. These networks consist of blocks with consecutive convolution layers using 3x3 size filters, resulting in a large parameter count and requiring significant training time. A study introduced a Transfer Learning (TL) approach for image recognition, leveraging the VGG 16 architecture.In transfer learning, the knowledge from a pre-trained machine learning model is applied to a different but related problem. For instance, if a simple classifier is trained to predict whether an image contains a watch, the knowledge gained during its training can be utilized to recognize other objects, such as clocks.

VGG, an acronym for Visual Geometry Group, was developed by Karen Simonyan and Andrew Zisserman at Oxford University. It achieved notable success, securing second place in the ILSVRC-2014 competition with a classification performance of 92.7%. The VGG model emphasizes layer depth, employing small 3x3 convolutional filters to handle large-scale images. VGG16, with 16 layers (13 convolutional and 3 fully connected), is named accordingly. It starts with 64 filters in the first block and doubles until reaching 512. The model concludes with two fully connected layers, each with 4096 neurons, and an output layer of 1000 neurons corresponding to ImageNet categories. Despite its computational cost, VGG16 is favored for transfer learning in image classification due to its straightforward pre-processing.

A Convolutional Neural Network (CNN) is tailored for image analysis and recognition tasks, learning patterns autonomously from labeled data points, often in the millions. While CNNs demand high-performance processors like GPUs or NPUs, reducing training epochs can mitigate computational demands while maintaining accuracy.

MobileNet, optimized for mobile and embedded vision applications, prioritizes efficiency and low latency. Its architecture, featuring depthwise separable convolutions, reduces parameters significantly compared to traditional CNNs. This design enables the creation of lightweight deep neural networks suited for resource-constrained environments. MobileNet typically consists of 28 layers, structured around depthwise and pointwise convolution components, facilitating compact and efficient deep neural network development for mobile and embedded vision tasks.

VI. RESULTS AND DISCUSSIONS

In setting up a Convolutional Neural Network (CNN), the initial step involves importing all CNN models. Following this, a function is crafted to visualize the loss function and accuracy score graph. Verifying the availability of GPU is essential to harness its computational capabilities. The image dataset undergoes preprocessing, where parameters such as image size are configured to streamline model complexity. Typically, smaller input image sizes are preferred to alleviate the model's computational burden. Specific parameters like batch size (set to 50) and image height and width (both 128) are specified. Additionally, pixel values are rescaled to further reduce image dimensions before inputting into the model.

Once training, testing, and validation datasets are set up, sample images are examined both before and after rescaling. Subsequently, CNN model training commences, beginning with the compilation of the model. The input layer filters images through matrix dot products to identify objects. Hidden layers aid in abstracting image features, enhancing the model's ability to handle slight variations in object positions. The resulting 2-dimensional arrays are then flattened into a single continuous linear vector.

To prevent overfitting, strategies such as saving checkpoints during training are utilized, with careful consideration given to ensuring the proper saving of checkpoint paths. Following 25 epochs of training, the final accuracy scores are

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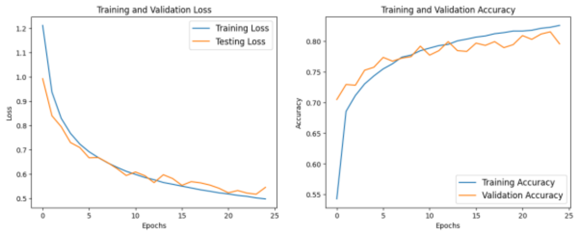
evaluated, revealing training and validation accuracies of 93% and 92%, respectively. The loss function outcomes indicate a training loss of 0.18% and a validation loss of 48% after the same 25 epochs.

In training the VGG16 model with transfer learning, the initial step entails importing the VGG16 model from the Keras API. The input size for the training images is configured to be 224x224 pixels. To implement transfer learning, the parameter 'include_top = False' is added, which omits the default output layer, enabling the addition of custom input data. Default weights for the model are determined, with fixed weights and biases in the hidden layers.

In this process, a custom head and output layer are trained for the VGG16 model. These layers are added, with the output layer configured for multi-class classification using 'activation = "SoftMax"'. Prior to the output layer, a GlobalAveragePooling2D layer is employed as a type of flattening layer. Subsequently, the model summary is inspected to verify its correctness, revealing a total of 14,716,740 parameters in the hidden layers and 2052 trainable parameters in the input and output layers. Checkpoints are saved during training using callbacks to ensure accurate preservation of the model's weights. The training procedure is meticulously executed, and graphs are plotted to monitor for potential overfitting between the training and validation datasets.

Following 25 epochs of training, the final accuracy scores are assessed. The training accuracy is determined to be 83%, while the validation accuracy stands at 80%. Examining the loss function scores after 25 epochs reveals a training loss of 0.50% and a validation loss of 0.55%. It is observed that this model demonstrates lower performance compared to the baseline CNN model.



MobileNet, an open-source computer vision model developed by Google, is specifically designed for training classifiers. It employs depth-wise convolutions to notably decrease the number of parameters in comparison to other networks, thus creating a lightweight deep neural network. MobileNet stands out as TensorFlow's inaugural mobile computer vision model.

When training a model utilizing MobileNet as a foundation, the decision regarding whether to fine-tune before or after introducing MobileNet relies on several factors. These factors include characteristics of the dataset, similarity to the task at hand, and the computational resources available.

Fine-tuning before introducing MobileNet involves adjusting deep learning models such as VGG16, VGG19, and XceptionNet for particular tasks like image classification. Although these models are large and computationally demanding, fine-tuning them on a new dataset can result in high accuracy, particularly if the new dataset shares similarities with the dataset used for pre-training.

After the advent of MobileNet, fine-tuning gained even more significance, particularly for tasks executed on mobile and embedded devices. The lightweight architecture of MobileNet facilitated quicker training and inference on these devices. Fine-tuning MobileNet on a new dataset could still result in achieving high accuracy levels.

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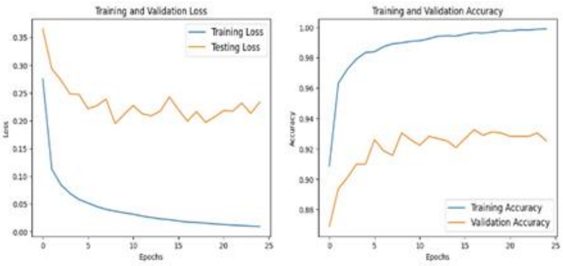
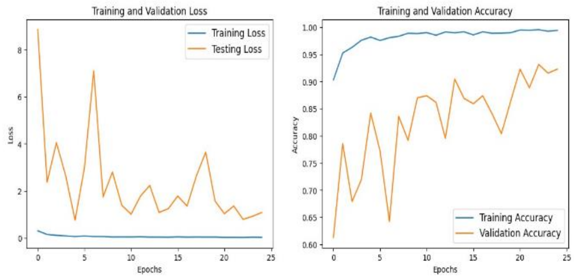


MobileNet model before Fine-tuning



MobileNet model after Fine-tuning

In our project, we discovered that fine-tuning the MobileNet model led to notably higher accuracy levels. Following fine-tuning, we attained an impressive accuracy rate of 98%.

REFERENCES

[1]. M. Wulandari, Basari, and D. Gunawan, "Evaluation of wavelet transform preprocessing with deep learning aimed at palm vein recognition application," AIP Conference Proceedings, vol. 2193, no. 1,p.050005,2019.[Online]. Available:https://aip.scitation.org/doi/abs/10.1063/1.5139378

[2]. Z. Yue, L. Ma, and R. Zhang, "Comparison and validation of deep learning models for the diagnosis of pneumonia," Computational Intelligence and Neuroscience, vol. 2020, 2020.

[3]. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv 1409.1556, 09 2014.

[4]. F. Chollet, "Xception: Deep learning with depthwise separable convolutions," 2017.

[5]. M. T. Almalchy, S. Monadel Sabree ALGayar, and N. Popescu, "Atrial fibrillation automatic diagnosis based on ecg signal using pretrained deep convolution neural network and svm multiclass model," in 2020 13th International Conference on Communications (COMM), 2020, pp. 197–202.

[6]. C. Beretta, F. Stoessel, U. Baier, S. Hellweg, Quantifying food losses and the potential for reduction in Switzerland, Waste Manag. 33 (3) (2013) 764–773, https://doi.org/10.1016/j.wasman.2012.11.007. ISSN 0956-053X.

[7]. C. Mesa-Pineda, J.L. Navarro-Ruíz, S. Lopez-Osorio, ´ J.J. Chaparro-Guti´errez, L. M. Gomez-Osorio, ´ Chicken Coccidiosis: from the parasite lifecycle to control of the disease, Front. Vet. Sci. 21 (8) (2021) 787653, https://doi.org/10.3389/ fvets.2021.787653. PMID: 34993246; PMCID: PMC8724208.

[8]. A. Esteva, K. Chou, S. Yeung, et al., Deep learning-enabled medical computer vision, NPJ Digit. Med. 4 (2021) 5, https://doi.org/10.1038/s41746-020-00376-2.

[9]. X. Zhuang, M. Bi, J. Guo, S. Wu, T. Zhang, Development of an early warning algorithm to detect sick broilers, Comput. Electron. Agric. 144 (2018) 102–113.

[10]. J. Wang, M. Shen, L. Liu, Y. Xu, C. Okinda, Recognition and classification of Broiler droppings based on deep convolutional neural network, J. Sens. 2019 (2019), 3823515, https://doi.org/10.1155/2019/3823515, 10.

[11]. Machuve, Dina, Nwankwo, Ezinne, Lyimo, Emmanuel, Maguo, Evarist, & Munisi, Charles.. Machine Learning Dataset for Poultry Diseases Diagnostics - PCR annotated (Version 3) [Data set] (2021). Zenodo. https://doi.org/10.5281/zenodo. 5801834.

[12]. C. Shorten, T.M. Khoshgoftaar, A survey on image data augmentation for deep learning, J. Big Data 6 (2019) 60, https://doi.org/10.1186/s40537-019-0197-0.

[13]. J. Redmon, A. Farhadi, YOLOv3: an incremental improvement, arXiv:abs/1 804.02767 (2018).

[14]. K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, ar Xiv:/abs/1512.03385 (2015).

[15]. S. Neethirajan, Automated tracking systems for the assessment of farmed poultry, Animals 12 (3) (2022) 232, https://doi.org/10.3390/ani12030232.

[16]. H. Ritchie, P. Rosado and M. Roser, Meat and Dairy Production. Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/meatproduction' [Online Resource]. 2017.