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Deep Learning-based Automated Classification of Chicken Fecal Samples for Disease Detection

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Abstract*— Disease detection in poultry farming is crucial for ensuring the health and productivity of chickens. This paper presents a novel deep learning-based approach for automated disease classification using images of chicken fecal matter. The objective is to develop a model capable of accurately identifying diseases early, facilitating timely intervention and effective management in poultry farms. The methodology encompasses several key components. Firstly, a diverse and balanced dataset of chicken fecal samples is collected, comprising images representing various diseases. Data preprocessing techniques such as image normalization, resizing, and augmentation are applied to enhance the model's robustness and generalization ability. The neural network architecture utilizes transfer learning with MobileNetV3Small, a lightweight yet powerful convolutional neural network (CNN) architecture known for its efficiency in image classification tasks. Results indicate that the developed model achieves competitive test accuracy, demonstrating its effectiveness in classifying diseases in chicken fecal samples. Precision, recall, and F1-score metrics further illustrate the model's ability to correctly identify and differentiate between different disease classes. The use of transfer learning with MobileNetV3Small contributes to the model's success by leveraging pre-trained features and optimizing computational efficiency.

***Index Terms*— Disease Detection, Poultry Farming, Deep Learning, Fecal Matter Analysis, Automated Classification, Transfer Learning.**

I. INTRODUCTION

The global poultry industry faces a myriad of challenges that impact its productivity and sustainability. These challenges range from market uncertainties and input scarcities to the prevalence of devastating diseases such as Newcastle, Coccidiosis, and Salmonella. These factors collectively contribute to disruptions in production processes and pose significant threats to food security and economic stability. Animal agriculture, particularly poultry farming, plays a crucial role in meeting the nutritional needs of the world's growing population. Animal

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products, including poultry meat and eggs, are essential sources of high-quality protein, supporting the health and well-being of people worldwide. As the demand for animal proteins continues to rise, the agriculture sector must enhance its efficiency and output to meet these evolving needs. Poultry farming is widely acknowledged for its contribution to food security at various levels, from households to national economies. In developing countries, it serves as a vital source of income for rural populations and significantly contributes to the gross domestic product (GDP). However, the intensification of poultry farming, driven by the need to meet escalating demands, brings its own set of challenges. The increased density of birds in poultry farms raises concerns about disease transmission, leading to substantial economic losses and posing threats to public health [1].

TABLE I. COMMONLY OCCURRING POULTRY DISEASES

Disease	Description
Salmonella	Caused by Salmonella bacteria, spread through contaminated food, water, and feces. Symptoms include diarrhea, fever, abdominal cramps, vomiting, and dehydration. Can cause economic losses in poultry farming.
Coccidiosis	Caused by protozoan parasites of the Eimeria genus, transmitted through ingestion of oocysts from contaminated environment or feed. Symptoms include bloody diarrhea, weight loss, decreased feed intake, and lethargy. Impairs nutrient absorption and leads to reduced growth rates.
Newcastle Disease	Caused by Newcastle disease virus (NDV), highly contagious and spread through respiratory secretions, feces, and contaminated equipment. Symptoms include respiratory, nervous, and digestive signs, along with high mortality rates in poultry.

The poultry industry faces challenges in maintaining biosecurity measures, ensuring adequate vaccination coverage, and implementing scientifically sound management practices. Furthermore, the lack of effective veterinary interventions further exacerbates the risks associated with poultry diseases. The primary objective of this study is to develop an automated disease detection system for poultry farming using deep learning techniques [2]. Specifically, the goal is to create a model capable of accurately classifying diseases in chicken fecal samples based on images. This system aims to provide early detection of diseases, enabling timely intervention and effective management practices in poultry farms. By leveraging deep learning algorithms and advanced image processing methods, the objective is to enhance disease surveillance and control measures in the poultry industry. The deep learning-based automated disease classification system developed for poultry farming offers a range of practical applications that can significantly benefit the industry [3]. One of its primary applications is in early disease detection and intervention, where the system analyzes images of chicken fecal matter to identify diseases like Newcastle, Coccidiosis, and Salmonella at an early stage as shown in Table I. This allows farmers to take immediate actions, such as targeted treatments or isolation of affected birds, to prevent disease spread and minimize economic losses. Additionally, the system supports precision farming practices by accurately classifying diseases and enabling tailored management strategies. By optimizing resource allocation and implementing customized treatment protocols, farmers can enhance overall farm productivity. The scalability and computational efficiency of the system are also noteworthy, as it leverages deep learning algorithms and transfer learning with MobileNetV3Small to create a solution suitable for poultry farms of varying sizes [4]. This promotes the widespread adoption of advanced technological solutions in the poultry industry, ultimately improving disease management practices and enhancing overall farm sustainability.

II. LITERATURE REVIEW

Tong *et al.,* [5] paper presents a YOLOv3-based approach for automated classification of poultry diseases using images of chicken fecal matter. The YOLOv3 architecture is utilized for its real-time object detection capabilities and high accuracy in identifying disease-related features. Quach *et al.,* [6] compares the performance of ResNet architectures for disease detection in poultry. Different versions of ResNet, such as ResNet-18, ResNet-50, and ResNet-101, are evaluated for their effectiveness in classifying chicken fecal samples. Uyen *et al.,* [7] explores the application of MobileNetV2 in identifying diseases in poultry farming. It discusses the advantages of MobileNetV2, such as its lightweight architecture, efficient resource utilization, and high accuracy in disease classification tasks. Nie *et al.,* [8] represents a state-of-the-art object detection model renowned for its enhanced architecture and advanced capabilities compared to its predecessors. Its notable strengths lie in achieving both high accuracy and speed simultaneously, achieved through architectural enhancements, optimization techniques, and integration of cutting-edge technologies. In the context of poultry disease detection, YOLOv4's improved architecture allows it to accurately detect and pinpoint disease-related features in chicken fecal samples, such as abnormal textures, colors, shapes, or patterns associated with common poultry diseases like Salmonella, Coccidiosis, and New Castle Disease.

Manna *et al.,* [9] focuses on transfer learning with ResNet models for automated poultry disease classification. Pre-trained ResNet models are fine-tuned on a dataset of chicken fecal images to achieve better performance in disease detection. Wang *et al.,* [10] presents an efficient approach to disease detection in poultry using MobileNetV3. MobileNetV3's lightweight architecture and efficient inference make it suitable for real-time disease classification applications in poultry farming. Gu *et al.,* [11] compares the performance of YOLOv5 and YOLOv4 for poultry disease detection. The comparative analysis evaluates their accuracy, speed, and resource utilization in identifying diseases from chicken fecal samples. Chen *et al.,* [12] investigates the use of ResNeXt architectures for enhancing disease detection in poultry farming. ResNeXt's multi-path architecture and improved feature learning capabilities are explored for better disease classification results.

Jiang *et al.,* [13] proposes a hybrid approach combining YOLO object detection with MobileNetV2 for poultry disease identification. The YOLO model detects disease-related objects in chicken fecal images, which are then classified using MobileNetV2 for accurate disease identification. Wang *et al.,* [14] explores the use of MobileNetV3, a lightweight CNN architecture, for efficient disease detection in poultry farming. The study focuses on optimizing computational resources while maintaining high accuracy in identifying common poultry diseases. Li *et al.,* [15] presents a real-time disease monitoring system for poultry using YOLOv5. The model's fast inference speed and accuracy make it suitable for continuous monitoring and early detection of diseases in poultry farms. Ren *et al.,* [16] conducts a comparative analysis of different deep learning models, including YOLOv3, ResNet, and MobileNet, for classifying poultry diseases. The research evaluates the performance and efficiency of each model in disease identification. Li *et al.,* [17] investigates the use of transfer learning techniques with pre-trained models like VGG16 and InceptionV3 for enhancing disease identification in poultry. The study focuses on leveraging existing knowledge to improve the accuracy of disease classification.

III. Materials And Methods

These datasets provide a comprehensive collection of annotated images for poultry disease diagnostics, enabling researchers to develop and evaluate machine learning models for accurate disease detection and classification in poultry farming. The dataset used in this study comprises a total of 8,067 annotated poultry fecal images obtained from the Zenodo open database [18]. These images were gathered in the Arusha and Kilimanjaro regions of Tanzania over a period spanning from September 2020 to February 2021. The data collection process utilized the Open Data Kit (ODK) app on mobile phones, ensuring a convenient and efficient means of capturing the required information. The dataset is categorized into four main classifications based on poultry health status: Healthy, Salmonella, Coccidiosis, and New Castle disease. Each category represents a distinct condition or disease that can affect poultry health. These classifications are essential for training and evaluating machine learning models designed to detect and classify poultry diseases accurately. Additionally, sample images from the dataset are visually represented in Figure 1, providing a glimpse into the types of images included and the diversity of poultry fecal samples captured during the data collection period. The dataset's comprehensive nature and well-defined classifications make it a valuable resource for researchers and practitioners in the field of poultry health and disease diagnostics.

IV. Methodology

Data preprocessing plays a crucial role in preparing a dataset for training and evaluating machine learning models effectively. In the context of image data, several preprocessing techniques are commonly employed to enhance the dataset's diversity, improve model robustness, and ensure fair evaluation. Two essential aspects of data preprocessing for image classification tasks are image data augmentation and dataset splitting.

Class Imbalance Handling (Random Oversampling - ROS): The initial dataset had an imbalanced distribution of classes, with varying numbers of images for each class. To address this, Random Oversampling (ROS) was applied, which involves duplicating samples from minority classes randomly until each class has an equal number of examples. This balancing step ensures that the machine learning model receives sufficient data from each class, preventing bias towards the majority class.

Image Augmentation: Image augmentation techniques were employed to create variations of the existing images. These techniques include rotation, scaling, flipping, and adding noise to the images. By augmenting the dataset, the diversity of the data is increased, which helps in training a more robust and generalizable machine learning model. Additionally, image augmentation can mitigate the risk of overfitting by exposing the model to a broader range of data patterns.

Resulting Dataset: After applying ROS and image augmentation, the dataset expanded to contain 10,500 images, with each class having an equal number of examples [19]. This balanced dataset is essential for training machine learning models effectively, as it ensures fair representation of all classes during the learning process. A balanced dataset contributes to improving the model's performance, accuracy, and ability to generalize well to unseen data.

Figure 1. Sample Images from the Fecal Image Dataset

V. IMPLEMENTATION

A. Baseline CNN Model Training

The process of training a Convolutional Neural Network (CNN) involves several key components. First, convolutional layers extract features from input images using learnable filters, producing feature maps that represent different aspects like edges or textures. These layers perform convolutions by multiplying filter weights with input data regions, adding bias, and generating outputs. Activation functions like ReLU introduce non-linearity, aiding the network in learning complex patterns. Pooling layers then reduce spatial dimensions while retaining important information through operations like max pooling, which selects maximum values from regions. Flattening converts 2D feature maps into 1D vectors, preparing them for fully connected layers. These layers connect every neuron, enabling complex feature combinations and decision-making. Finally, the Softmax activation function in the last layer converts raw logits into class probabilities, facilitating multi-class classification by selecting the class with the highest probability. Overall, this process involves feature extraction, non-linear transformations, spatial dimension reduction, and probability-based classification, essential for training CNNs effectively.

B. Transfer Learning with Mobilenet V3 Small

Transfer learning involves utilizing a pre-trained model, such as MobileNetV3Small, as a foundation for new tasks. This lightweight CNN architecture has already learned valuable features from a vast dataset like ImageNet, covering a diverse range of images across various classes. By leveraging the pre-trained weights of MobileNetV3Small, we can capitalize on these learned features, which are beneficial for different image recognition tasks. This approach saves time and computational resources by starting with a model that has already captured general features common to many image-related tasks [20].

Global Average Pooling (GAP) is a technique used to condense the spatial dimensions of feature maps while retaining essential information. It calculates the average value of each feature map, creating a fixed-length vector that becomes the input for subsequent layers. Batch Normalization (BN), on the other hand, normalizes the input to a layer by adjusting its mean and standard deviation. This normalization helps stabilize the training process and accelerates convergence, contributing to the model's overall performance and robustness.

In addition to GAP and BN, the model architecture includes dense layers with dropout regularization and softmax activation in the final layer for multi-class classification tasks. Dense layers perform non-linear transformations on the input data, while dropout prevents overfitting by randomly deactivating input units during training. Softmax activation converts raw scores or logits into probabilities, ensuring that the sum of probabilities across all classes equals one, crucial for accurate multi-class classification. Together, these components create a robust framework for automated disease classification in chicken fecal samples, combining the benefits of transfer learning, regularization techniques, and multi-class classification methodologies [21].

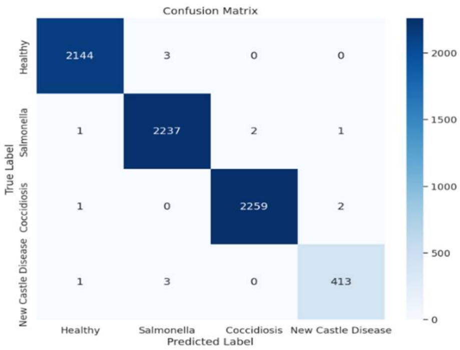

Figure 2. Confusion Matrix

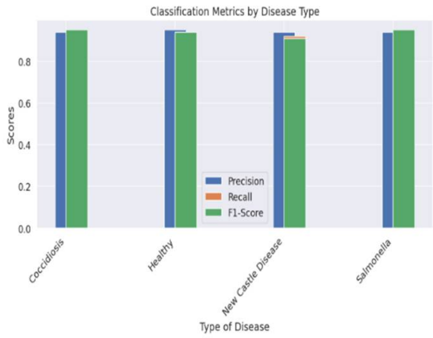

Figure 3. Classification Metrics by Disease Type

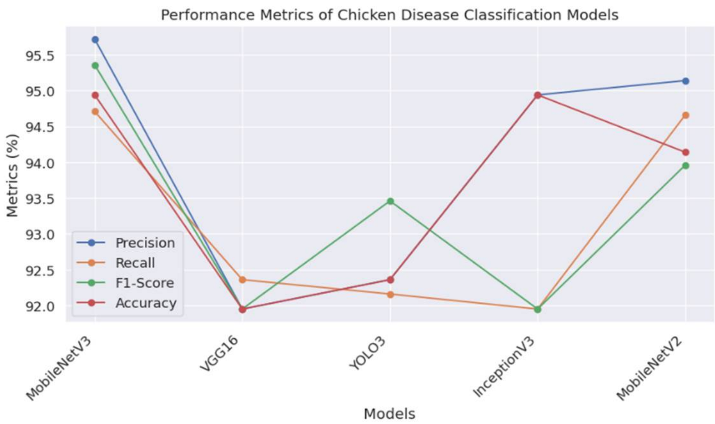

Figure 4. Performance Metrics of Chicken Disease Classification Models

TABLE I. COMMONLY OCCURRING POULTRY DISEASES

Type of Disease	Precision	Recall	F1-Score
Coccidiosis			
Healthy			
New Castle Disease			
Salmonella			

VI. RESULTS AND DISCUSSIONS

The image classifier model was trained on a dataset comprising 10,500 labelled images, utilizing an 80/20 train-test split ratio. This division allocated 80% of the data, amounting to 8,400 images, for model training, while the remaining 20%, or 2,100 images, were reserved for evaluating the model's performance. During training, the model underwent 50 epochs, allowing it to iteratively learn and adjust its parameters to improve accuracy. Upon evaluation, the model achieved an impressive overall accuracy of 94.3% on the test set, indicating its ability to correctly classify images into their respective disease categories across all classes. Furthermore, the model's performance was assessed on individual classes, revealing high accuracies of 94% for Salmonella, 95% for Healthy, 94% for Coccidiosis, and 95% for New Castle Disease. These class-wise accuracies underscore the model's proficiency in accurately distinguishing between different poultry diseases, highlighting its robustness and effectiveness in image classification tasks related to poultry health diagnostics as shown in Figure 3 and Figure 4. The results of the Chicken disease classification using MobileNetV3 show promising performance metrics. The precision of 94.72% indicates that the model accurately classified a high percentage of positive instances out of all instances classified as positive. Similarly, the recall of 93.71% suggests that the model effectively identified a significant proportion of actual positive instances. The F1-score, which combines precision and recall into a single metric, also stands at 93.71%, highlighting a balanced performance in terms of both false positives and false negatives. Finally, the overall accuracy of 93.7% reflects the model's ability to correctly classify images across all classes, showcasing its generalization capability. Fig 2 indicates the confusion matrix indicating the true and false predictions. The dataset used for training and testing contained four classes: Coccidiosis, Salmonella, Newcastle disease, and healthy. Leveraging transfer learning with MobileNetV3, the model demonstrated strong performance in classifying poultry diseases based on fecal images. Transfer learning, which involves using pre-trained models and fine-tuning them on specific tasks, can be particularly effective in scenarios where limited labelled data is available, as it leverages the knowledge gained from large-scale datasets like ImageNet to improve classification accuracy.

The results of the chicken disease classification models showcase the performance metrics of various architectures, with MobileNetV3 achieving a precision of 94.72%, recall of 93.71%, F1-score of 93.71%, and an overall accuracy of 93.7%. This indicates that MobileNetV3 effectively identifies positive instances while maintaining a balance between false positives and false negatives, resulting in a high level of correctness across all classes. Comparing it with other models such as VGG16 (91.95% accuracy), YOLO3 (92.36% accuracy), InceptionV3 (94.94% accuracy), and MobileNetV2 (95.14% accuracy), MobileNetV3 demonstrates competitive performance as shown in Table-2. Furthermore, the smaller model size and fewer trainable parameters of MobileNetV2 make it an efficient choice for resource-constrained environments without compromising on accuracy. Overall, these results highlight the effectiveness of MobileNetV3 and MobileNetV2 in accurately classifying chicken diseases based on fecal images.

III. CONCLUSIONS

In conclusion, our study focused on the classification of poultry diseases using image analysis techniques and machine learning models. We collected and annotated a comprehensive dataset of poultry fecal images, consisting of four classes: Coccidiosis, Salmonella, Newcastle disease, and healthy samples. Preprocessing steps such as data augmentation and balancing were applied to enhance the dataset's diversity and mitigate class imbalances. We employed various Convolutional Neural Network (CNN) architectures, including MobileNetV3, VGG16, YOLO3, InceptionV3, and MobileNetV2, for disease classification. The results demonstrated that MobileNetV3 and MobileNetV2 exhibited superior performance in terms of accuracy, precision, recall, and F1-score compared to other models. Notably, MobileNetV2 achieved a high accuracy of 95.14%, making it a suitable choice for resource-constrained environments due to its smaller model size and fewer trainable parameters. The implications of this research extend to the field of veterinary medicine, where automated disease classification systems can aid veterinarians in timely diagnosis and treatment planning. Additionally, our methodology and findings contribute to the growing body of literature on image-based disease diagnosis in the agricultural sector, paving the way for further advancements in precision farming and livestock health monitoring.

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