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Poultry Disease Identification In Fecal Images Using Vision Transformer

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Abstract

Early diagnosis and control of diseases assume critical importance in the poultry farming industry. While the large sized scale poultry farms may be able to afford in-house veterinary support, the small and medium-sized operations may not be able to have theirown diagnosis services, making it all the more critical for such farms to make use of the emerging technologies to assist them in the early diagnosis and control of their poultry farms. Prompt and accurate identification of poultry diseases without delay assumes paramount importance, as the delays can be devastating, resulting in significant economic losses. To confront this pressing issue, our research presents a novel and highly practical method with the use of Deep learning models. We harness the capabilities of Deep learning and image analysis to facilitate quick diagnosis of diseases. The paper has attempted to analyze the fecal images and train a range of models such as GoogleNet, Resenet18, ShuffleNet, SqueezeNet, and Vision Transform, achieving a peak test accuracy of 97.62%. Towards this, the study has made use of an extensive dataset of over half a million images and in the process accounted for the challenging environmental conditions such as dust on cameras and lower quality of images. The model can automatically identify common poultry diseases such as Coccidiosis, New Castle Disease, and Salmonella through the analysis of fecal images. The study is an attempt to bridge the gap between technological advancements and the day-to-day requirements in disease detection requirements of the poultry farming community, which may in turn support the poultry industry in better sustainability, economics, and enhanced welfare of the birds. The dataset used in this study has been made available Poultry Pathology Visual Dataset (kaggle.com).

Keywords: Poultry Disease Diagnosis; Automated Disease Identification; GoogleNet; Resenet18; ShuffleNet; SqueezeNet; Vision Transform

Introduction

The poultry industry stands as a cornerstone in meeting the burgeoning global demand for accessible and nourishing animal protein. This sector is experiencing remarkable growth, projected to reach a staggering market size of around $375,412.5 million by 2030. Notably, this industry provides gainful employment for approximately 1.6 million individuals, contributing significantly—almost $250 billion—to the GDP. The substantial investment of around $4.16 billion has already been infused, with forecasts suggesting a doubling of this figure within the next decade.

Amidst this growth, a pressing concern within the industry is the prevalence of diseases that afflict poultry. These include widespread ailments such as Coccidiosis, Salmonella, Newcastle disease, Tick fever, fowl cholera, tuberculosis, and rickets, among others. Our study focuses on the development of a methodology specifically geared toward detecting the presence of Coccidiosis, Salmonella, and Newcastle disease in poultry.

Traditionally, disease assessment in poultry involved the laborious and costly process of analyzing fecal samples under a microscope in laboratory settings—a practice that often posed financial challenges for farmers. Leveraging cutting-edge technologies such as deep learning and image processing, we aim to propose a practical solution that seamlessly integrates technology into the poultry industry.

The recent wave of technological advancements has ushered in significant transformations across various industries, including poultry farming. These novel technologies not only facilitate disease identification but also streamline bird care, bolster their health, and enhance the overall production of poultry products. By harnessing technology's potential, the poultry sector can effectively address its challenges, curtail operational costs, and deliver safer and superior chicken and eggs to consumers.

Our research endeavors to contribute to the creation of a more sustainable and robust poultry industry by amalgamating technological innovation with traditional practices, ensuring not only improved disease detection but also bolstering the industry's resilience and sustainability in the face of evolving challenges.

Moreover, the integration of advanced technological solutions within the poultry sector extends beyond disease detection and enhanced production. These innovations pave the way for data-driven decision-making, facilitating predictive analytics to anticipate disease outbreaks, optimize feed formulations, and fine-tune environmental conditions for optimal bird health. Implementing precision agriculture techniques aided by sensors, drones, and smart monitoring systems further empowers farmers to create tailored, efficient strategies. By embracing these technological advancements, the industry not only secures its economic viability but also aligns with global sustainability goals by minimizing resource wastage and maximizing output efficiency, thus fostering a more environmentally conscious approach to poultry farming.

Related works

Given the extensive history of research in this field, [7] contributed significantly by introducing innovative methods to assess the sensitivity and specificity of fecal and cecal culture techniques for Campylobacter detection. Their study applied two distinct statistical models to data from 1600 poultry flocks. The findings illuminated the limitations of fecal culture's sensitivity, influencing monitoring program design. Even with improved cecal culture sensitivity, misclassifications in Campylobacter-afflicted flocks underscore the need for precise diagnostic methods.

Additionally, [13] presented another pioneering approach for poultry disease detection, centered on a real-time line-scan hyperspectral imaging system for chicken carcass examination. This innovation laid the foundation for versatile chicken inspection systems with functions including quality sorting and systemic disease diagnosis, along with a commercial imaging platform for fecal detection.

Furthermore, research teams continue to explore various methodologies within this field. [11] delved into the potential of machine learning, specifically employing support vector machine (SVM) techniques in their study to analyze observational epidemiological data related to broiler chicks. The SVM method was utilized to identify characteristics associated with hock burn in commercial broiler farms, revealing fresh insights when compared to conventional multivariable logistic regression. This innovative use of machine learning holds promise for significantly enhancing the health and well-being of broiler chickens on a global scale.

In a similar vein, [6] aimed to enhance poultry disease diagnosis through posture analysis. They examined the postures of ill and healthy broilers using machine learning and digital image processing. The algorithm swiftly determined broiler health, providing early outbreak warnings with high accuracy. The SVM model with the POLY kernel function showed the most promising results, contributing to the evolving poultry disease management landscape.

In a similar manner, [12] introduced an approach that utilized depth cameras and video surveillance to observe broilers. This allowed for the extraction of feature variables based on 2D posture form descriptors. By analyzing these variables, the study aimed to identify early indicators of infection, resulting in the creation of classifiers. Notably, the Support Vector Machine (RBF-SVM) model outperformed other models, offering non-intrusive, ongoing monitoring with the ability to forecast illness onset in broiler hens, thus providing critical early warning signs. The system, as the research indicates, holds the potential to benefit both broiler and poultry farmers by accurately identifying and predicting infections in broiler chicks.

In a similar vein, [10] proposed an algorithm designed to enhance poultry health monitoring and automate the detection of unwell chickens. Their approach leverages big data and the Internet of Things, allowing for the tracking and identification of ill hens in poultry breeding operations. Through the refinement of the ResNet residual network's network topology, they crafted an enhanced ResNet-FPN illness chicken recognition model. This technological advancement is adaptable, with the potential to be extended for the detection and diagnosis of illnesses in a wide range of poultry and livestock, offering a comprehensive solution to livestock health management challenges.

Continuing with innovative methods in poultry disease management, [2] explored the application of various Convolutional Neural Network (CNN) architectures, including a baseline CNN, VGG16, InceptionV3, MobileNetV2, and Xception. Each of these models contributed to the ongoing pursuit of more effective poultry disease detection. The utilization of advanced CNN architectures marks a promising and versatile approach to improving disease diagnosis and management within the poultry industry.

In the quest for more effective poultry disease detection, another notable method was proposed, leveraging modern technology for early detection. This approach, as presented by [4], centers around the utilization of smartphone-captured fecal images. In this innovative study, a total of eight convolutional neural networks (CNNs) were fine-tuned to classify fecal images into one of four categories: healthy, salmonella, coccidiosis, or Newcastle Disease (NCD). To further enhance the performance, an ensemble architecture was developed, comprising four selected networks stacked together as base models. Furthermore, [1] put forward a method that addresses the labor-intensive, time-consuming, and error-prone nature of traditional manual disease detection methods in poultry. Their system is designed to analyze photos of chicken feces using deep learning techniques. The suggested system employs the YOLO-V3 object detection algorithm and the ResNet50 image classification model to divide the region of interest (ROI) in fecal images into four distinct categories: health, coccidiosis, salmonella, and Newcastle disease. To train the models effectively, a dataset comprising 10,500 photos of chicken feces, sourced from an open database, was utilized.

Another approach, as in [3], utilized a dataset with images of both healthy and unhealthy chicken feces samples from farms in South-West Nigeria. This dataset, comprising 14,618 labeled photos, which supports the development of machine-learning models for identifying poultry farm abnormalities and computer vision applications. The ultimate aim is to provide comprehensive tools for poultry farm management. Deep learning techniques, as demonstrated in [5], proved effective in classifying poultry diseases based on fecal images. The model outperformed advanced alternatives, like Inception V3, ResNet50, and VGG16, showing promise for early and accurate poultry disease diagnosis. similarly, [8] explored AI and computer vision for non-invasive poultry health examinations by classifying chicken droppings based on visual anomalies.

A similar method of using deep learning image categorization based on fecal pictures, [9] a proof-of-concept chicken health assessment system was created. When it came to distinguishing between birds that were healthy and those that had Newcastle disease, salmonella, and coccidiosis. It included a website for data administration, a computer server for picture categorization, and a mobile application for on-site image collection. The method showed that on-site poultry health evaluation was feasible, but further work is needed to maximize its potential. An almost identical method was proposed by [14] where a deep learning investigation on the automated diagnosis of illnesses associated with chicken faeces was conducted. To improve the model's perception and capacity for learning, the researchers suggest incorporating a mixed attention mechanism into the ResNeXt50 network model. The technique supports disease diagnosis in chicken breeding because it successfully uses infected birds' excrement to identify them.

A comparable approach, as detailed in [15], focuses on utilizing computer vision and deep learning in poultry farming to detect and address avian diseases. The paper addresses the importance of early detection and the adoption of AI-assisted technology to enhance poultry system efficiency. The primary focus of the study is the examination of bird droppings to determine their health status, with an emphasis on the precision of the deep learning model in distinguishing between healthy and unhealthy excrement.

Collectively, these approaches presented in the related works section highlights the growing significance of technology, particularly computer vision and deep learning, in the domain of poultry disease detection and management. These methods prioritize early detection, precision, and efficiency, offering valuable tools to poultry farmers. As we delve into our research, we aim to address this research gap by considering environmental factors like image noise and low or degraded image quality, which have been unaddressed in these studies.

Methodology

Our approach to identifying poultry diseases prioritizes precision and effectiveness. Initially, we employ various image enhancement techniques—like Gaussian blur, average blur, flips, and contrast adjustments—to diversify our image collection. This step is crucial as it mirrors the real-life degradation of camera image quality over time, simulating scenarios where camera sensors in farmlands endure harsh weather conditions like rain, wind, and storms. These conditions challenge the deep learning model's ability to predict diseases accurately, especially when the images contain noise due to weather-induced factors such as dust or rain droplets on the camera sensor.

Moreover, the wear and tear caused by weather or mishandling can affect the camera's components, hindering the capture of images at necessary angles and positions for precise predictions. Hence, employing image augmentation methods becomes imperative to address these real-time challenges. Augmenting the image data has allowed us to generate slightly over half a million images from the original dataset, playing a pivotal role in subsequent steps of our methodology.

To ensure robust model training, we've shuffled the dataset and divided it into training, testing, and validation sets. This segmentation facilitates ongoing verification at each stage of model training, ensuring the resulting model's reliability.

Following this data preparation, we utilize various deep neural network models—such as Googlenet, Resnet18, ShifflenetV2, Squeezenet, and the Vision Transformer—to decode patterns within the images and classify them into distinct groups: healthy, coccidiosis, salmonella, and Newcastle. Our goal is to identify the most effective model for categorizing these classes, particularly those suitable for edge computing systems in real-time farmland applications.

Accurate image classification is fundamental for precisely identifying poultry diseases based on these underlying patterns, assigning them to the respective four classes mentioned earlier.

Moving to the final phase, rigorous testing and evaluation of the trained models are conducted against predefined criteria. This stage involves separate test and validation sets, and based on the results, we fine-tune the model's hyperparameters. This meticulous process ensures optimal performance of the trained model when presented with any image, enabling accurate predictions and classifications in real-world scenarios.

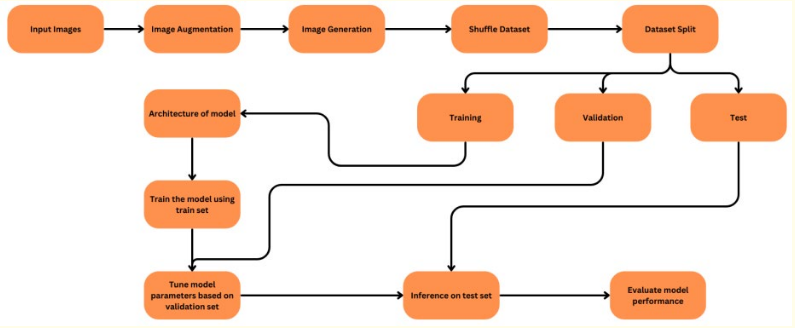

Figure 1: Workflow of the proposed model.

Figure 1 visually outlines the sequential steps employed to achieve the desired outcomes in poultry disease detection.

Data

The initial dataset we initially had access to consisted of images, which it did not meet the specific requirements for each of the four distinct classes: healthy, coccidiosis, Newcastle disease, and salmonella. To address this limitation, we undertook a careful process to enhance our data, employing a variety of image augmentation techniques aimed at faithfully simulating the gradual degradation in image quality that naturally occurs with real-world cameras over time.

Our image augmentation methods included techniques such as image flipping, sharpening, inverting, grayscale conversion, fine-tuning of linear contrast, as well as the application of Gaussian blur, median blur, and average blur, among others. The strategic use of these techniques allowed us to generate a substantial quantity of images that authentically replicated the kind of image quality degradation one might encounter in practical scenarios. The implementation of these image augmentation methods resulted in the generation of slightly over half a million images, significantly enriching our dataset.

In its original form, the dataset maintained a uniform image size, with all images standardized at 224x224 pixels. Figure 2 visually exemplifies the outcome of the image augmentation techniques, providing sample images from our expanded dataset. This importance of our research underscores the paramount importance of data argumentation, emphasizing its pivotal role in enhancing the quality and diversity of the dataset.

These enhancements are crucial in driving the progress of more precise and resilient deep-learning models. Specifically within the specialized arena of poultry disease detection, the quality of data assumes a fundamental role in ensuring trustworthy diagnostic outcomes. Our diligent method effectively closes the gap between highquality images and real-world situations, thus significantly contributing to the advancement of more reliabl and precise disease detection techniques. This underscores the sustained importance and relevance of data augmentation in both scientific investigations and practical use cases [21].

Figure 2: Sample image from dataset.

Image augmentation and Image generation

The image processing pip line that is used to achieve the required results is as follows horizontal flip, vertical flip, crop, pad, affine transform, superpixels, Gaussian blur, average blur, median blur, sharpen, emboss, simple noise alpha, additive Gaussian noise, invert, add, add to hue and saturation, frequency noise alpha, multiply, linear contrast, grayscale, elastic transformation, piece wise affine, perspective transform are the methods that are used perform image argumentation on the input data set. Gaussian blur is an image argumentation method that reduces the noise and smooths the details in an image and this is one of the most common image processing operations used in image processing. This uses used Gaussian function to pixel values of an image hence the name of Gaussian blur. Average or mean blur is an image processing method which used to perform the same operation as Gaussian blur but replaces each pixel value with the average value of its neighboring pixel. Median blur is an image processing method that is used to reduce noise and preserve the edge and important features of an image. Image flip is an image processing method used to perform a flip on a given image horizontally by a certain angle value. The grayscale converts a given image input into its grayscale value.

Based on the operation performed above on the data set we were able to generate images to simulate a real situation of camera quality degradation. The total amount of data that we have generated using the above is a little over half a million images where the image size is kept constant at 224x224.

Model architecture

We then move to the GoogleNet architecture, which is well known for its notable performance advantage over VGG models, for the classification of poultry diseases. GoogleNet's novel inception design, which enables quick and parallelized feature extraction, is credited with this increased performance.

In circumstances when prompt and accurate disease identification is essential, this accelerated processing capability proves to be quite valuable in guaranteeing fast assessments of poultry health. We also want to investigate a comparison with the Vision Transformer model, which shows a more intentional process of pattern learning.

GoogleNet

Googlenet, also known as "Inception" within the domain of deep Convolutional Neural Network (CNN) architectures, is made to perform image classification and object detection tasks. Distinguishing itself through its distinctive architectural design, Googlenet seamlessly integrates multiple inception models, amplifying its capability through the incorporation of an auxiliary classifier intended to elevate the training process. One impressive thing about Googlenet is that it's really deep, like having 22 layers in its architecture.

Googlenet is great at handling complex tasks, like telling what's in a picture and finding objects in it. Its multilayer approach enables us to perform complex computations on data such as images so that we can extract relevant features as per the required feature [16].

ResNet18

Resnet18 is a unique version of the ResNet (Residual network) architecture, designed for tasks like image classification and various vision-related jobs. It's a deep Convolutional Neural Network (CNN) built with 18 layers, following the ResNet tradition known for its smart utilization of residual learning.

What makes the Resnet18 model distinctive is its remarkable ability to efficiently capture essential features, enabling effective image classification and various vision-based tasks with fewer training epochs. This exceptional trait positions it as a valuable asset for applications that require faster learning and robust performance. The efficiency of the Resnet model in feature extraction expedites the learning process, making it an excellent choice for scenarios where time-efficient and reliable results are crucial. This quality enhances its reputation as a preferred tool for image-centric and vision-focused applications [17].

ShuffleNetV2

ShufflenetV2 is a significant deep Convolutional Neural Network (CNN) model designed for image classification and various vision-related tasks, with a special focus on edge computing scenarios, including mobile and embedded devices. What truly sets this model apart is its compact and efficient design, which stands in contrast to the traditional CNN-based architectural structures. This compactness enables it to perform inferences with remarkable efficiency, even on devices with limited memory and computational resources.

The compact nature of ShufflenetV2 makes it exceptionally suitable for smaller, resource-constrained devices, where its strengths truly come to the forefront. This characteristic establishes it as the preferred option for a variety of edge computing applications, ensuring not only rapid, real-time data processing but also the efficien utilization of energy resources. All of this is accomplished while consistently providing accurate and reliable results. This quality encapsulates the lasting desirability and importance of ShufflenetV2 in the domain of edge computing, where efficiency, compactness, and reliability hold significant value [18].

SqueezeNet

Squeezenet stands as a carefully designed neural network architecture in deep learning, particularly used in tasks related to object detection and image classification. What sets it apart is its efficiency, making it a more approachable model choice for those aiming to attain competitive accuracy in data processing while managing computational resources and parameter usage. This focus on efficiency provides a unique advantage compared to traditional Convolutional Neural Network (CNN) architectures.

An additional aspect that distinguishes Squeezenet is its resource-efficient design, which not only lessens computational requirements but also broadens its applicability to deploy trained models on edge computing devices. This built-in adaptability to edge computing scenarios plays a pivotal role, ensuring its appropriateness for applications where quick, energy-efficient processing is of crucial importance. Basically, Squeezenet stands as a valuable tool well-suited for real-time, on-device inference, making it an attractive choice for various applications where both speed and prudent energy consumption are of paramount significance [19].

Vision Transform Model

The Vision Transformer model (ViT) signifies a substantial stride forward in the landscape of deep learning, leveraging the transformative potential of transformer architecture to delve into the realm of image data processing. While transformers initially etched their reputation in the realm of natural language processing (NLP), their adaptability extends seamlessly into the domain of computer vision, where ViT has asserted its prowess in tackling multifaceted tasks. These encompass but are not limited to image classification, object detection, and the intricate art of image segmentation.

One remarkable advantage of ViT over traditional Convolutional Neural Network (CNN)-based models lies in its exceptional ability to uncover hidden features within input data. This capability is defined by a finely tuned balance between computational efficiency and time economy. In situations where speed and resource optimization are highly valued, ViT emerges as an attractive option. However, the field of image processing comes with its own advantages and disadvantages.

It's important to understand that ViT's rapid efficiency may require a more extensive learning process. Its ability to extract intricate data patterns may take some extra time to comprehend the subtleties of the data. This balance between efficiency and accuracy is crucial in image processing techniques. In conclusion, ViT is a significant step forward in deep learning, offering a flexible solution for handling both text and image data. Its contribution highlights the intricate interplay between efficiency and precision, emphasizing the delicate balance needed for effective image-processing tasks [20].

Positional Encoding

Positional encoding is crucial in Vision Transformers (ViT) to incorporate spatial information into the input image patches. The positional encoding formula for a given position pos and dimension 2i is defined as:

$$\mathrm{PE}_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{\mathrm{model}}}}\right)$$

Similarly, the positional encoding for position *pos* and dimension 2*i* + 1 is given by:

$$\mathrm{PE}_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{\mathrm{model}}}}\right)$$

Here, $\mathrm{PE}_{(pos,2i)}$ and $\mathrm{PE}_{(pos,2i+1)}$ represent the positional encodings for different dimensions at a specific position in the input. d_{model} denotes the dimension of the model, and the use of sine and cosine functions in positional encoding allows the model to differentiate between positions effectively.

Multi-head Self-Attention

The multi-head self-attention mechanism calculates attention weights represented as A using queries Q, keys K, and values V:

$$\mathbf{A} = \mathrm{softmax}\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)\mathbf{V}$$

Here, Q, K, and V represent the query, key, and value matrices, respectively. d_k denotes the dimension of the keys. The softmax function normalizes the attention scores across different keys for each query, and the resulting attention weights A are used to weigh the values V.

Feedforward Network

The feedforward network in ViT consists of two linear transformations followed by a ReLU activation function:

$$FFN(x) = ReLU(xW_1 + b_1)W_2 + b_2$$

Here, FFN(x) represents the output of the feedforward network for input x. W_1 and W_2 are weight matrices, and b_1 and b_2 are bias vectors. The ReLU function introduces non-linearity after the first linear transformation.

Results

The outcomes derived from our extensive evaluation of different methodologies, encompassing GoogleNet, Resnet18, ShuffleNet, SqueezeNet, and the Vision Transformer model, are exhaustively documented in the tabular format represented in Table 1 below. This tabulated data provides a comprehensive view of the performance metrics associated with each model, facilitating a detailed understanding of their respective capabilities.

Of particular note is the exemplary performance of the Vision Transformer architecture, which achieved an outstanding overall test accuracy of 97.62% the other model test accuracy is as follows GoogleNet achieved a test accuracy of 95.52% Resent18 achieved a test accuracy of 95.02% ShuffleNet achieved a test accuracy of 95.22% and SqueezeNet achieved a test accuracy of 90.97%. Considering the amount of parameters that need to be trained for each model makes a difference in the time and speed at which the model is trained as we can see in the below table 1 the amount of parameters present for each model. This exceptional level of accuracy underscores the Vision Transformer's effectiveness in the context of poultry disease detection. Similar patterns can be seen with other model parameters such as F1-score, Precision, and Recall. It is, however, imperative to acknowledge that achieving this elevated accuracy comes at the expense of a more extended training duration.

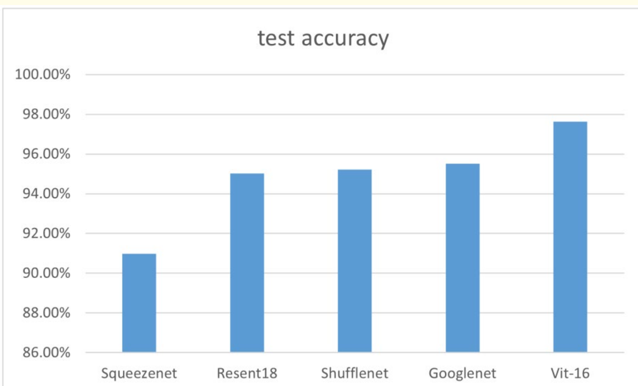

Figure 3: Test accuracy plot.

This prolonged training period is primarily attributed to the Vision Transformer's substantial parameter count, which necessitates a more extensive learning process.

Model name	Val accuracy	Test accuracy	Model parameters	Precision	Recall	F1-score
SqueezeNet	89.58%	90.97%	1,235,496	90.86%	90.96%	90.89%
ShuffleNet	92.34%	95.22%	7,393,996	95.21%	95.22%	95.20%
GoogleNet	93.74%	95.52%	6,624,904	95.51%	95.47%	95.48%
ResNet18	94.70%	95.02%	11,689,512	94.93%	95.01%	94.96%
Vision transform model	97.84%	97.62%	86,567,656	97.58%	97.61%	97.59%

Table 1: Accuracy of the model.

Conclusion and future work

This paper has made use of deep learning architectures to obtain the requisite accuracy for predicting poultry diseases based on the image data. The model has made use of GoogleNet, ResNet, SqueezeNet, ShuffleNet, and the Vision Transformer model, with the latter emerging as the top performer in our analysis as this had a lower learning rate compared to all the other models based on its architecture. Vision Transformer model to take more compute time per epoch and achieve better accuracy from the initial epoch compared to other models' initial epoch accuracy. The model tests the accuracy of Vision Transform, GoogleNet, Resent18, ShuffleNet, and SqueezeNet as follows 97.84%, 95.52%, 95.02%, 95.22%, and 90.97% respectively. The other model parameters such as Precision, Recall, and F1-score for each model are 97.58%, 97.61%, and 97.59% for the Vision Transform model similarly for Resenet18 the model parameters values are 04.93%, 95.01%, 94.96% for Googlenet the model parameters values are 95.51%, 95.47%, 95.48% for ShuffleNet the model parameters values are 95.21%, 95.22%, 95.20% and similarly for SqueezeNet, the model parameters values are 90.86%, 90.96%, 90.89% are achieved with the proposed methodology. So, our approach also extensively utilized various image augmentation techniques to generate images simulating real-world camera image quality degradation.

The primary objective of these endeavors is to offer effective means of detecting and isolating infected poultry. This, in turn, facilitates timely intervention and treatment, thereby averting potential losses for farmers and safeguarding the well-being of the animals in poultry farms, which are vital sources of income. Our research paves the way for several promising avenues in this domain. Firstly, while our study primarily relied on pre-trained models for poultry disease detection, exploring the development and utilization of customized deep-learning architectures tailored specifically for this purpose has the potential to further enhance model performance. Secondly, our future endeavor involves investigating the feasibility of implementing an embedded Internet of Things (IoT) based system for real-time disease detection. Such a system, coupled with on-the-fly analysis, holds the potential to provide immediate insights and drive timely actions based on the results obtained. As an extension to this study, we are inclined to explore the implications of reducing image size on model parameters and computational time, with the objective of ascertaining whether a smaller image size can yield similar results to those achieved by the proposed models while potentially reducing computation time.

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