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Utilizing Vision Transformer-Based Analysis of Fecal Images for Poultry Disease Diagnosis

Baljinder Kaur[1], Manik Rakhra[2]
[1,2]*School of Computer Science & Engineering, Lovely Professional University, Phagwara - Punjab 144401, India*

Abstract:- In the poultry business, being able to detect and manage diseases as early as possible is crucial for ensuring productivity and minimizing economic losses. While large poultry farms can afford to have veterinary doctors on staff, small and medium scale farmers do not have access to specialized diagnostics. This shortcoming highlights the need for efficient technologies that allow for timely intervention and disease management. Our research proposes novel methodology for accurate and rapid disease diagnosis in poultry using deep learning. Our diagnostic model employs advanced deep learning and image processing techniques for automated poultry disease detection. The analysis of fecal images was done using a variety of convolutional neural networks (CNNs) GoogleNet, ResNet18, ShuffleNet, SqueezeNet and Vision Transformer with a maximal test accuracy of 97.62%. The dataset used contained more than 500,000 images and incorporated many real-life problems such as background noise, noise in the image, and different lighting intensities. The model proposed in this paper successfully detects Coccidiosis, Newcastle Disease, Salmonella and other poultry disorders from fecal images. This research provides a linkage between advanced AI-based diagnostic tools and poultry farmers' needs to improve disease management, biosecurity and sustainability in the poultry industry. The Poultry Pathology Visual Dataset, used in this project, can be accessed by anyone at Kaggle (kaggle.com).

Keywords*: Poultry disease detection, Vision Transformer, deep learning, fecal image analysis, convolutional neural networks, automated diagnosis, biosecurity, AI in agriculture, disease classification, poultry health management.*

1. Introduction

The poultry industry is expected to expand significantly in the coming years, market estimates predicting it will surpass $375 billion by 2030, in order to satisfy the growing global need for superior animal protein. This sector accounts for around $250 billion of the global GDP and provides job opportunities for about 1.6 million people. Over the next years, the financial inflow is also expected to increase significantly, up to a potential of $8.32 billion, with $4.16 already allocated.

This growth, however, faces a significant challenge due to a persistent threat of disease outbreaks in poultry farming which negatively impact productivity and economic value. Diseases like Coccidiosis, Salmonella, and Newcastle disease are much more commonplace and require efficient detection methods. In the past [1], diagnosing any of these diseases required micrometric evaluation of faces in a modern laboratory setting which is too costly and logistically impossible for farmers. Thus, our research aims to develop an automated robust disease identification solution using deep learning image processing techniques which would allow for addressing these limitations. The poultry sector is receiving technological transformation in disease monitoring and welfare, as well as it poultry products yields. The application of AI and ML models in the industry creates avenues for more active disease managerial approaches, increasing economic advantage as well as food safety standards. Moreover, the use of real time data systems allows for predictive disease modeling which enables early interventions that most benefit both the health and sustainability of the entire flock.

Precision invisible disease diagnostics as well as the integration of sensor networks, UAVs, and automated monitoring systems greatly improve poultry business decision making. Such technologies allow real-time data collection that serves various purposes, including optimal feed wherein the poultry enterprise will be most productive while resource usage is at minimum. These intelligent systems are driven by the ever growing need to achieve economic sustainability that supports productivity, resource conservation [2], and environmental sustainability targets. The goal of the research is to integrate traditional poultry farming practices with new computer technologies to increase the industry's ability to withstand changes in the long term. The outcome is a sustainability and technology driven poultry industry.

2. Related Work

The industry has made great progress in investigating the diagnostic sensitivity of fecal and cecal cultures as methods for detecting Campylobacter. A new study analysed datasets obtained from 1600 poultry flocks using two new statistical approaches, revealing crucial details regarding the limitations with sensitivity of fecal cultures. This had direct consequences on the programmatic structure of surveillance systems. However, the improvement of sensitivity in cecal cultures led to the Campylobacter-infected flocks suffering from diagnostic misclassification, indicating the need for more refined analytical methods.

In addition, a new approach was developed for the diagnosis of poultry diseases of a new class by using the system for analysing chicken carcasses with high speed real time hyperspectral imaging. This system provided new levels of flexibility in automated inspection through pathogen scanning, quality control sorting, and systemic disease screening. Furthermore, the development of an imaging system for the detection of fecal contamination [3] made it easier to implement in poultry processing plants. At the same time, efforts have been made towards combining computing science with epidemiology in poultry. One study used SVM based learning algorithms to interpret epidemiological observational datasets from broiler farms. The algorithms successfully determined risk factors for hock burn. These novel insights produced by machine learned models, in comparison to conventional logistic regression predictive models, highlight its capability to enhance poultry welfare worldwide. Furthermore, another study incorporated posture recognition with digital image processing to automatically diagnose diseases in poultry. The algorithm used behavioural changes to quickly classify the health status of broilers [4], which enabled early warnings for outbreaks of disease. The SVM model with polynomial kernel function outperformed other methods and continues to illustrate the use of computation in monitoring poultry health.

An approach using depth cameras and video surveillance to monitor behaviour in broilers was developed. This approach enabled feature extraction through two-dimensional posture descriptors. The objective of this study was to establish predictive features for infection to develop classification models to test them against. The model standing out from the rest was the Radial Basis Function Support Vector Machine (RBF-SVM) [5]. It gave non-invasive real-time monitoring of disease warning signs in broiler trainer models. In terms of poultry management this marks a significant advance in improving disease detection monitoring, and health monitoring protocols.

In parallel [6], did develop a sophisticated algorithm aimed at optimizing the use of various indicators in assessing poultry health and facilitating the automation of detection of sick birds. This model combines big data analytics and IoT, enabling monitoring and detection of poultry health anomalies during farming in a precise and timely manner. With respect to chicken illness identification, they have also refined the architectural configuration of the ResNet residual network and came up with an enhanced ResNet-FPN model. This framework's scalability allows for its application in disease recognition across a wide range of livestock, making it suitable for precision animal health management.

Using these technologies [7], looked into the use of various CNN models, including baseline CNN, VGG16, InceptionV3, MobileNetV2, and Xception, to improve detection of diseases in poultry. The application of models based on deep learning for disease identification is a game-changing development for precision livestock farming as it enhances the accuracy of diagnosis and speeds up the implementation of automated poultry health monitoring systems.

The field of poultry disease detection has recently made progress in incorporating new technologies for precise and timely diagnosis of diseases. One of the strategies uses cellphone-captured fecal images with deep learning models that classify the samples into four categories: healthy, salmonella, coccidiosis, or Newcastle Disease

(NCD) [8]. In this work, eight CNNs were individually trained and then combined four of the optimized models in a novel ensemble learning method to increase the predictive power of the models. Moreover, the scientists sought an opportunity to replace tedious and error-prone manual adaptive-diagnostic procedures with AI-assisted systems. This system utilizes [9] the YOLO-V3 object detection model to identify regions of interest (ROIs) in the fecal pictures, then applies ResNet50 to classify the sample into certain predetermined health states. To adequately train and test the models, fecal images that were already labeled were obtained from a public data repository [10]. The dataset contained 10,500 images in total.

In addition, another study analysis employed an extensive dataset of 14,618 labelled fecal sample images retrieved from poultry farms situated in Southwestern Nigeria. This data set formed the basis of machine learning applications intended for health anomaly detection and farm management optimization. Evaluations proved that classification of deep learning was better achieved than with conventional models ICD Inception [11-13] V3, ResNet50 and VGG16, thus confirming the ability to use even more advanced methods for real world disease detection. Another group of researchers investigated the application of AI and computer vision for non-invasive poultry health diagnostics and focused on fecal morphology abnormalities detection.

In a different implementation, a proof-of-concept system for automated chicken health diagnostics using deep learning based image classification was developed. Normal poultry farm activity is characterized by web based control systems for data storage, image processing servers, and mobile applications for real time data collection [14]. This approach was shown to be practical, but other form factors need to be developed to achieve complete satisfactory results. Another endeavor sought to improve classification accuracy through the application of a mixed attention model on the ResNeXt50 architecture [15] that enhanced the model's capacity to detect disease patterns in avian excreta. This research had a parallel productivity where a computer aided detection system of disease in poultry was developed that placed emphasis on the urgency of diagnosis. This work helped to apply Artificial Intelligence in a more comprehensive way [16] to separate the healthy from the sick based on droppings to showcase the possibilities that intelligent systems can offer in poultry farming [17]. These studies will show that the implementation of artificial intelligence technology and deep learning in the development of avian disease diagnostic systems is revolutionary in its approaches and focus on accuracy and speed of diagnosis and treatment. On the other hand, most studies elaborate on challenges pertaining to environmental conditions, for instance, noise disturbances and image decaying are affecting too, but not on Kent's research. We seek to answer this question by applying image enhancement techniques supple to automatic classification for robustness against degrading imaging conditions [18].

3. Proposed System and Methodology

In order to achieve precise identification of poultry ailments, our approach combines sophisticated techniques of image preprocessing, which include Gaussian blurring and average blurring, contrast enhancement, and geometric transformations like flipping. These techniques increase the variance of the dataset by capturing real-world distortions caused by the elements and environmental factors such as rain, dust, and the gradual malfunctioning of the sensor. These factors contribute noise in the image framework, which may obstruct deep learning models from conclusively diagnosing the disease on an uncontrolled farmland setting.

Moreover, the nurture wear and tear or mechanical damage on the imaging tools can change the angles from which the images are captured, resulting in lesser accuracy during classification. To combat these setbacks, systematic alterations of the image set are performed, resulting in obtaining a dataset of more than five hundred thousand samples [19] rather than using the original collection. This greatly assists in model generalization and greatly increases the power of the system. Afterward, the data set is sent for stratified splitting for the training, validation, and testing subsets in an iterative manner throughout the entire model training process. In order to classify the four distinct groups of healthy, coccidiosis, salmonella, and Newcastle disease, the framework makes use of GoogLeNet, ResNet18, ShuffleNetV2, SqueezeNet, and Vision Transformer deep neural network architectures to perform feature discrimination. The selection of optimal architectures is particularly focused on edge-deployable automation agriculture intelligence, so they have to resource efficient.

This step fine-tunes the hyper parameters in order to model the performance validation results on independent data sets, which was the model performance assessment step in the previous stage. This cyclic processing step improves the precision of the model's inference, allowing it to meet the needs of changing real-life agricultural situations enabling reliable and accurate classification of poultry diseases.

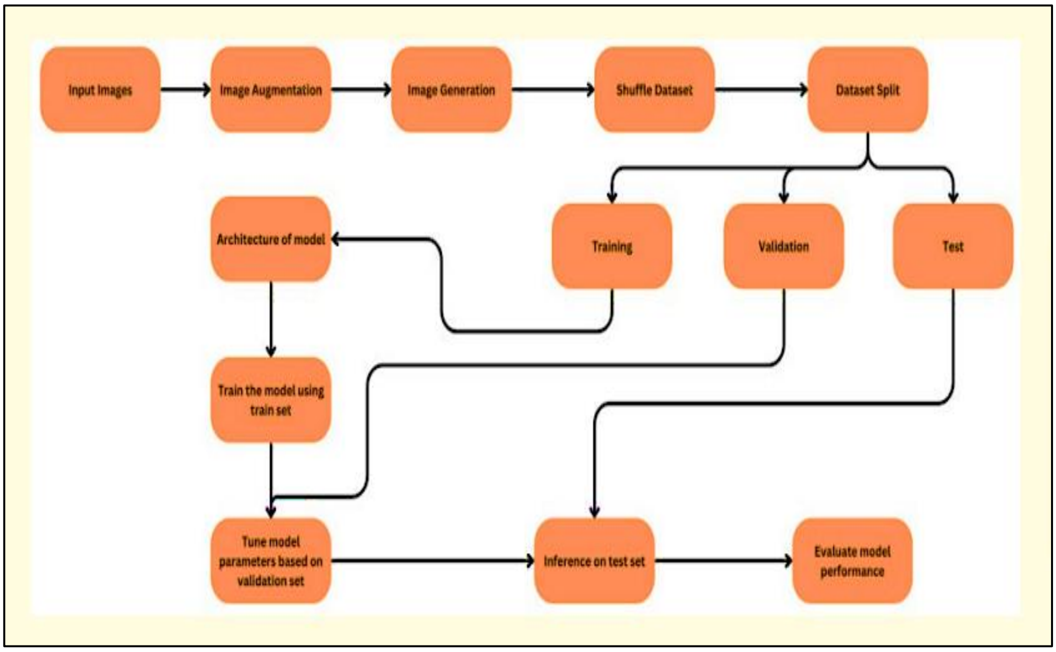

Fig. 1.1 To illustration workflow of Proposed Model.

1.3.1 Description of Dataset

To address the insufficiencies our initial dataset had in representing the four classes of healthy, coccidiosis, Newcastle disease and salmonella, we incorporated newer techniques of image augmentation into our work. These methods were aimed at replicating the gradual reduction in camera image quality that real world devices display over time as they move out of focus. Our augmentation procedure applied the use of diverse transformations such as horizontal and vertical flips, sharpening and inversion, grayscale and contrast adaptive adjustments and blurring methods using Gaussian, median, and average blur. The modification techniques utilized enabled us to create a dataset that exceeded the actual distorting real world images. In doing so, we augmented an estimated 500 thousand images that now makes the project a greater volume and variety to work with. All images in the original dataset were kept at a resolution of 224×224 pixels, so that a set standard could be achieved. In Figure 2, some of the preprocessing steps are shown, and representative samples are shown from the augmented dataset to prove that our augmentation techniques worked. In this case, data augmentation is required in order to make the dataset more robust, which is critical to the building of high-fidelity and deep-leaning models that are resilient to changes.

Within the narrow scope of poultry disease detection, the data has to be of the highest quality to ensure diagnostic accuracy. By modelling actual conditions systematically, our work helps shift from an ideal high resolution image capture setting to a more realistic one, which improves deep learning-based diagnostic system's accuracy and generalizability. This study demonstrates the continuing importance of data augmentation in advancing theoretical and practice-based work.

1.3.2 Image Generating and Image Augmentation

This augmentation uses a diverse set of image transformations, including horizontal and vertical flipping, cropping, padding, affine transformations, super pixel generation, and a variety of blurring techniques including Gaussian, average, and median blur. Additional augmentations performed on the image include sharpening, embossing, noise manipulations (simple noise alpha, additive Gaussian noise, frequency noise alpha), bit-wise pixel manipulations (inversion, addition, multiplication, linear contrast adjustment), and altering the colour space through hue-saturation modulation and conversion to grayscale. Moreover, elastic transformations, piecewise affine transformations, and perspective transformations are geometric distortions that introduce spatial variations in the image.

Gaussian blur is Preprocessing, widely used to smooth image details by reducing noise from the high-frequency parts of the signal through Gaussian function weighting at the pixel distribution area. Average blur modifies each pixel into a blur pixel designated as the average of a region surrounding it. Flipping of an image adds or removes spatial details in an image by mirroring the image about the x or y axis. The process of grayscale conversion focuses on an image's intensity, and it assists in transforming images for use in diverse analysis contexts. These augmentation strategies helped create a new dataset that tries to simulate real-life deterioration that happens in images taken by a camera. The augmentation strategy increased the dataset size to about 500,000 images, keeping all images at a constant height and width of 224 × 224 pixels which helps to make the model withstand differences in image quality during training.

1.3.3 Architecture of Model

GoogleNet architecture has shown better performance than VGG models in classifying diseases in chickens because of the sophisticated inception mechanism embedded within it. This model allows for parallel and efficient feature extraction which greatly improves the efficiency of the system. The model's speed in visual data processing is especially useful in situations where diseases need to be diagnosed quickly and accurately, which makes it possible to assess the health of poultry in a timely manner. In addition, a comparative analysis with Vision Transformer (ViT) model is also planned because ViT applies a specific attention mechanism in spatial pattern recognition, which gives it a different perspective regarding feature learning and classification of diseases.

1. GoogleNet: GoogleNet, which is also called as Inception, is a deep CNN for image classification and object detection purposes. Its design is competitive because it has multiple inception modules, allowing for enhanced computational operations. Moreover, GoogleNet has an auxiliary classifier that helps in training. It offers 22 deep layers which allow the network to perform feature extraction on complex tasks efficiently [20]. This type of

architecture is good at dealing with advanced visual data because it enables fast object recognition and localization in images.

2. ResNet 18: ResNet18 was developed to serve as an image classifier, as well as for other vision related tasks. This convolutional neural network (CNN) comprises of 18 layers and makes use of a ResNet characteristic called residual learning to make training easier. The model is particularly recognized for its ability to capture important [21] features of images with low computing power, and because of this, it is highly proficient in image classification and related tasks while requiring less training. This makes ResNet18 suitable for applications that are sensitive to time as they need quick convergence with high performance. With the ability to extract features efficiently, it becomes the most preferred model in scenarios that require fast and accurate results in computer vision problems.

3. ShuffleNetV2: ShufflenetV2 is a state-of-the-art deep learning architecture for convolutional neural networks (CNNs) that focuses on image classification and other vision tasks in mobile and embedded systems. Its main difference from other CNNs is its compact and computationally efficient design, which enables devices [22] with low memory capacity to perform inference tasks effectively. Its efficiency makes the architecture highly suitable for edge computing applications where real-time processing is essential, and energy consumption needs to be minimized. It delivers high accuracy and dependable performance, underscoring its significance in environments where compactness, efficiency, and reliability matter, such as in edge computing.

4. SqueezeNet: SqueezeNet is designed specifically for object detection and image classification with deep learning in a highly optimized way that is proficient in handling large volumes of data. Differentiating itself from others, this architecture boasts a highly compact model design that reduces the number of required parameters [23], which in turn increases the speed of processing while not compromising on accuracy. Compared to traditional Convolutional Neural Networks (CNNs), SqueezeNet offers a more resource efficient alternative while remaining competitively effective. One of the main characteristics of SqueezeNet is its effectiveness in resource-constrained environments, especially on edge devices. This makes it a promising candidate for real-time applications that need low power consumption and fast inference. Therefore, SqueezeNet is an excellent candidate for scenarios in which AI models need to be deployed operationally fast and, in an energy efficient context.

5. Vision Transform Model: The Vision Transformer (ViT) indicates Deep learning with a shift of gears through the integration and adoption of the transformer model to image data through the lens of Natural Language Processing (NLP). This novel method has been very successful in a variety of computer vision applications including image classification, object recognition, and image segmentation. Compared to other Convolutional Neural Networks (CNN), ViT excels in feature recognition. This is done by obtaining an optimal tradeoff with respect to the resources used, and speed at which computations are done, proving to be a perfect fit in resource constrained settings. On the other hand, while ViT is excellent in the performance, it tends to take a much longer time to train the model to reach an achievable performance level due to the need for finely capturing details in the data. This balance between speed and accuracy is one of the most significant challenges in computer vision. In the end, analyzing images and texts makes ViT a great candidate, definitively showing that even with complexity deep learning tasks, efficiency and accuracy can be achieved simultaneously.

6. Method of Positional Encoding: In Vision Transformers (ViTs), encoding spatial relationships between image patches is critical, so positional encoding is very important. To get more technical, the formula for positional encoding at position pos and dimension 2i employs sinusoidal functions of sine and cosine to extract specific information of each individual position. This makes the model effective at differentiating among various spatial locations arising from the positional context of each patch in the sequence input.

7. Model of Multi-Head Self Attention Model: The multi-head self-attention mechanism calculates attention coefficients A with the aid of the query matrix Q, key K , and value matrix V. The dimension of the key vectors is indicated by dkdk. The SoftMax operation serves to scale the attention values associated with each key to unit sum for every query. Each of these normalized attention weights A are used to scale and sum the relevant value vectors V.

8. Model of Feed Forward Network: In the Vision Transformer (ViT), the feedforward network (FFN) consists of two sequential linear layers, which are separated by a ReLU activation function. The FFN(x) denotes the output produced for a given input x, and where W1 and W2 are the weight matrices and b1 and b2 are the bias vectors. The subsequent application of the ReLU activation function after the first linear transformation introduces additional nonlinearity which increases the expressiveness of the network.

4. Result and Discussions

In detail analysis of the frameworks GoogleNet, ResNet18, ShuffleNet, SqueezeNet and the Vision Transformer, is made in Table 1 along with the performance measures of each model which is formulated in detail in the table. This data amalgamates their strengths in one place making it easier to assess their metrics in depth. Most importantly, the Vision Transformer model surpasses everyone with the highest mark, which is an astonishing 97.62% test accuracy. On the other hand, GoogleNet had a score of 95.52%, ResNet18, 95.02%, and ShuffeNet with SqueezeNet scoring 95.22% and 90.97% respectively. Also, in the diagram is shown the number of parameters of each model because of which training time and training speed is affected directly. Even though the training period is increasingly longer in comparison to the rest, the Vision Transformer exhibits exceptional accuracy in poultry disease classification which makes it worthwhile in the end. F1-score, Precision, and Recall work best in conjunction, although in unison these three factors render extreme value, making vision transformer eradicating poultry disease classification cost obsolete.

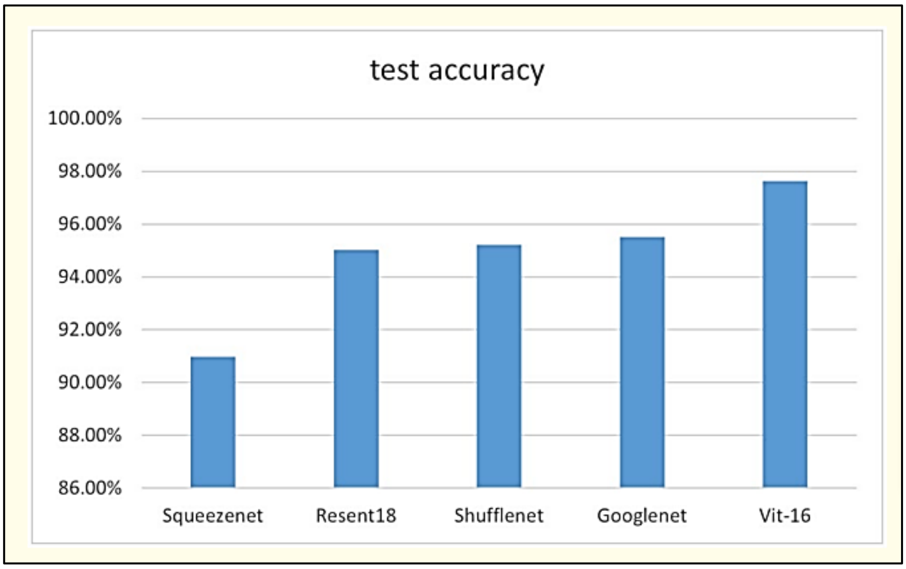

Fig. 1.3 To illustration of plotting Test Accuracy.

The extended training duration is mainly due to the large number of parameters in the Vision Transformer, which demands a more prolonged optimization phase to effectively learn the underlying patterns.

Neural Architecture	Validation Performance (%)	Testing Performance (%)	Parameter Count	Classification Precision (%)	Model Sensitivity (Recall) (%)	Harmonic Mean (F1-Score) (%)
SqueezeNet	89.58	90.97	1.23M	90.86	90.96	90.89
ShuffleNet	93.42	95.22	7.39M	95.21	95.22	95.20

GoogleNet	93.74	95.52	6.62M	95.51	95.47	95.48
ResNet18	94.70	95.02	11.68M	94.93	95.01	94.96
Vision Transformer	97.84	97.62	86.57M	97.58	97.61	97.59

Table 1. Comparison Table of Model Accuracy

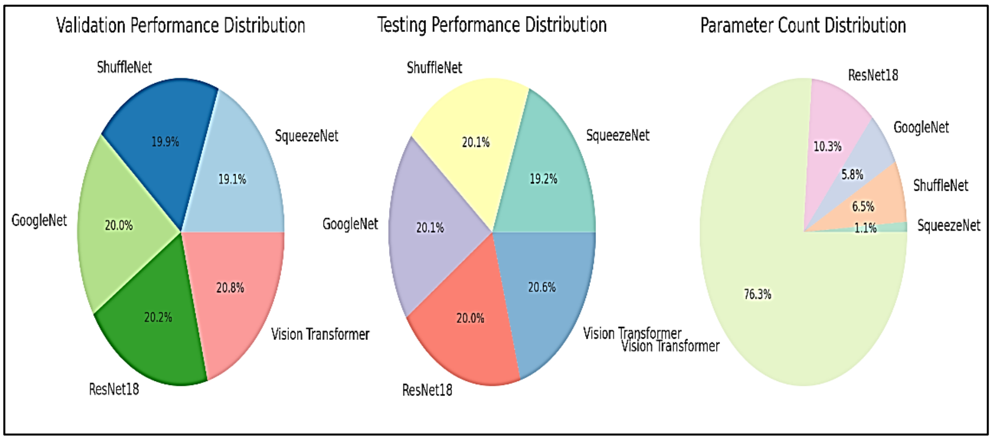

Fig. 1.4 To illustration of plotting Model Accuracy.

5. Conclusions and Future Work

This research utilized deep learning models to effectively predict poultry diseases via image data analysis. Various structures were tested, including GoogleNet, ResNet, SqueezeNet, ShuffleNet, and Vision Transformer, with the latter performing best due to its lower learning rate and higher initial accuracy than other models, even though it consumed more computational power per epoch. The Vision Transformer model achieved 97.84% accuracy in classification. Following closely behind were GoogleNet (95.52%) and ResNet18 (95.02%), while ShuffleNet scored 95.22% and SqueezeNet 90.97%. In the case of Vision Transformer, the scores obtained for the three metrics, Precision, Recall, and F1-score were 97.58%,97.61%, and 97.59%, respectively. Other models performed F1-resNet18 (94.93%, 95.01%, 94.96%), GoogleNet (95.51%, 95.47%, 95.48%), ShuffleNet (95.21%, 95.22%, 95.20%), SqueezeNet (90.86%, 90.96%, 90.89%). Alongside the work, high-level methods of image augmentation were used to imitate real-world camera image quality degradation. The objective of the research is to develop a reliable method useful for the quick detection and segregation of infected poultry to minimize the economic impacts as well as enhance the livestock welfare within the farms. looking forward to, Further research could focus on creating dedicated deep learning architectures for classifying diseases, implementing embedded IoT systems for real-time monitoring diseases, and studying how lowering the image resolution affects the model's performance and computational resources needed while keeping the accuracy at the desired level.

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