

Detecting Coccidiosis in Poultry Using the Yolov8 and Yolov9 Frameworks

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ABSTRACT

The object detection can be done using popular algorithm named YOLO. The paper aims at introducing various model size of YOLOv8 and YOLOv9 which are considered to be the best object detection models by considering the veterinary application of Coccidiosis disease detection. Chicken poultry farming has been one of the vital sources of GDP for many counties and states making it one of the most supported economic activities by farmers. However, many chickens suffer from coccidiosis which is the disease caused by *Eimeria* parasites that invades the intestines. Though not easy, it's important to detect coccidiosis in poultry for keeping the flocks healthy while minimizing any economic detriment that can be suffered. This investigation seeks to detect coccidiosis-affected chickens through the most common symptom of coccidiosis, diarrhea. To this end, the research provides comparison of existing system with experimental results using YOLOv8 and YOLOv9, a deep learning model that has been well tested for its efficiency particularly in real time object detection and classification applications. Being a member of the YOLO suite of models, YOLOv8 or YOLOv9 is able to locate specific signs of coccidiosis allowing it to quickly intervene. Thanks to the speedy processing rate of this model, it would be appropriate when used for large scale poultry farms as infections can be contained at a very initial stage. The drawbacks of previous techniques lead to the development of these models. This work gives a clear differentiation of these models along with experimental results. Overall understanding of these models helps reader to understand the capability of these models.

Keywords: YOLO-You Only Look Once, PGI-programmable gradient information, GELAN-Generalized Efficient Layer Aggregation Network, IoU-Intersection over Union

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1. INTRODUCTION

Simply, chicken poultry farming is merely poultry farming, which is the raising of domesticated fowl, primarily for chickens themselves, for meat, egg and many more[1]. This industry is also a backbone of global agriculture, providing affordable protein for millions of people and hugely contributing to the economy of many countries[2].

Coccidiosis is a common parasitic disease affecting poultry, particularly chickens[2]. Caused by protozoan parasites of the genus *Eimeria*, coccidiosis mainly infects

the intestines of chickens and can lead to severe health consequences, including reduced growth, diminished egg production, and in extreme cases, high mortality rates. Infection takes place through the consumption of sporulated oocysts which are present in feed, water, and litter, making it difficult to control in areas with a heavily populated poultry environment[2]. Symptoms in chickens involve diarrhea, which is frequently bloody (as in figure 1), anorexia, somnolence, and weight loss; these have a tendency of causing losses in economic terms through reduction of productivity and treatment costs[2].

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Figure 1: Image of coccidiosis from chicken diarrhea

Basic coccidiosis in chickens is difficult to diagnose because it mostly recurs in large-scale poultry operations where it becomes important to detect diseases at its onset to prevent another outbreak and avoid some losses[3]. Traditional laboratory-based microscopic method consumes lot of time and also experienced staff is necessary to carry out the task. The signs that the infected chickens might show are usually non-specific, like diarrhoea and reduced feed intake, thus often overshadowing other diseases and delaying or missing diagnosis[2]. Also, the nature of a subclinical infection, whereby birds are normally infected but with minimal outward signs complicates the detection process even more[2].

Introduction of updated deep learning models have led to the use of automated diagnostic tools, like YOLOv8 and YOLOv9, which are the object detection algorithm, in addressing these challenges. The models can rapidly and accurately detect specific visual signs related to coccidiosis, thus leading to timely intervention that is more conducive to efficient management of the disease in poultry establishments[4].

Given the critical influence that coccidiosis imposes on poultry health as well as farm productivity, it is imperative

to have potent, real-time detection methods which can streamline diagnoses while offering appropriate intervention. This paper therefore proposes the pros and cons of the powerful object detection models YOLOv8 and YOLOv9 with respect to the identification of coccidiosis poultry symptoms with great accuracy and speed. Therefore, integrating this technology helps poultry farms to develop better practices of disease management and reduces economic losses and healthier flocks, thus promoting a more sustainable poultry industry.

In the present scenario object detection has gained the high popularity due to the introduction of deep learning algorithms[5]. For real time object detection and classification one of the mostly used algorithm is YOLO. The main reason why YOLO models gained popularity is because it exhibits impressive accuracy and speed. It looks at the object identification as a single regression problem[6]. Over the past few years YOLO has seen drastic improvements in object detection by releasing various models. Each model had updated features which helped researchers to improve the object detection in the best way possible.

The general comparisons of YOLO versions are described in the figure below[7].

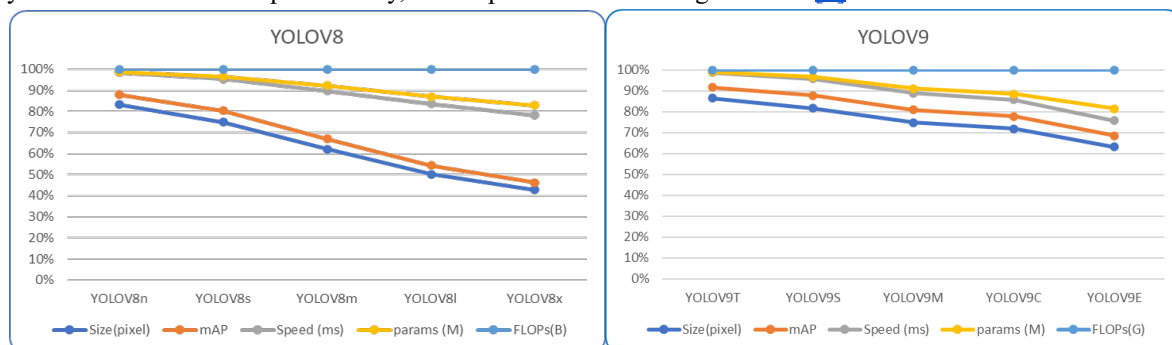


Figure 2: Graphical representation YOLOv8 and YOLOv9 based on standard parameters.

The most recent versions employed for object detection at the moment are YOLOv8 and YOLOv9. The typical result that the corresponding algorithm can create is shown in figure 2. However, this outcome could change depending on the work accomplished. This algorithm can be implemented in veterinary applications to enhance biosecurity, welfare assessment, productivity management, and health surveillance. Detecting coccidiosis using fecal images is one such use.

RELATED STUDY

Deep learning has continuously revised in field of computer vision and medical image analysis by providing outstanding result for disease detection. The Convolutional Neural Networks (CNNs) acts as backbone of most deep learning models due its capacity for hierarchical feature extraction. LeCun et al. (1998) demonstrated the power of CNNs for image recognition tasks, which laid the foundation for modern deep learning

applications in healthcare diagnostics [8]. As a result of superior performance in disease detection, CNN-based models have been widely used in machine learning techniques.

The You Only Look Once considered as one of the fastest and most trustable object identification frameworks. Redmon et al. (2016) introduced the original YOLO algorithm, enabling real-time object detection with a single neural network pass [8]. Subsequent versions, including YOLOv3 and YOLOv5, enhanced detection speed and accuracy, especially for small and complex objects[9]. These improvements have encouraged researchers to adopt YOLO frameworks for real-time disease detection, including tasks in veterinary science where timely interventions are crucial.

YOLOv8, the latest advancement in the YOLO family developed by Ultralytics, has introduced significant enhancements in model architecture, training strategies, and anchor-free detection mechanisms. It use a decoupled head structure for categorising and localization tasks, improving the precision of detection in cluttered backgrounds. YOLOv8 is powerful and simple, so widely used for applications like poultry disease detection where real-time performance on limited hardware is necessary [10]. Its improved feature aggregation also ensures better handling of small lesions or localized infections, which are common challenges in coccidiosis diagnosis.

In recent studies, YOLO-based models have been successfully employed for medical and agricultural imaging tasks. For example, Rakhlin et al. (2018) applied a modified YOLO architecture for breast cancer histology image classification, demonstrating the versatility of YOLO frameworks beyond general object detection . Similarly, researchers working in the agricultural sector have leveraged YOLO variants for identifying plant diseases[11], livestock health monitoring, and even pest detection, proving its potential in biological and veterinary fields. These findings underline the suitability of YOLOv8 for the proposed coccidiosis detection system, aiming for high accuracy and real-time usability.

The poultry industry is also significant in the advancement of world economic development, mainly in socioeconomic growth, supplying the best quality protein and vital nutrients to populations globally [12]. Since agriculture supports economic development, the poultry sector satisfies a large part of meat and egg intake around the world [2]. Worldwide growth in affluence and population has boosted demand for food, hence propelling many countries to increase poultry production. However, the world is expected to have 8.6 billion inhabitants by 2030, making it heavily challenging to provide enough supply of meat products [1]. The study has proven that the demand of meat and egg will be increasing by forty percent in 2050 [13].

This heightened poultry production elevates the likelihood of birds coming into direct contact with their excreta and a moist environment, which are ideal for oocysts survival

and transfer to healthy flocks [14]. The most common and severe poultry disease, It imposes severe economic losses at a Global. Symptoms of this infection include growth retardation, poor feed conversion efficiency, and death in severe cases. More importantly, coccidian parasites tend to depress the immunity level of the flock, leading to increased vulnerability to secondary diseases [15]. The prominent poultry diseases usually features symptoms such as ruffled feathers, lethargy, panting, watery or bloody diarrhea, drooling, coughing, swelling of the head and eyes and decreased egg production. These symptoms help in determining the health status of the poultry through vocalizations, body temperature, feces, and daily behaviors [2]. A protozoan intracellular parasite of the Eimeria species is Coccidiosis, infects chickens. The reason that the disease significantly impacts poultry production is that among the symptoms associated with diarrhea, ruffled feathers reduced appetite, weight loss along with impaired nutrient absorption through gastrointestinal wall damage [8].

Coccidiosis are identified by the images captured and are widely utilized analysis and detection across various fields [16].

With computing and algorithms having become so cheap, modern technologies have been a must for keeping track of super farms to increase productivity [17]. Advanced technological systems are more paramount in poultry healthcare management especially since poultry-based meat and eggs are very essential among the global human protein [3]. Reduction of losses in poultry cases due to diseases is promoted by real monitoring or early detection cases. This will ensure productive production as the poultry business. Generally, early detection and alerting systems would ensure consistent monitoring, thereby isolating sick birds before an outbreak could set in to control the disease from spreading further.

Early research on disease diagnosis and classification was done decades ago. In general, traditional practices of machine learning were adopted. For example, the studies used SVM and Decision Tree techniques in analysing data regarding Clostridium perfringens-infected chicken vocal sounds, which had been obtained from audio recording from healthy and diseased birds[18].

A forecast by [19] reveals that it is anticipated that broiler chickens will often be affected by hock burn, which is a swelling of the skin around the hock. Data was gathered from farms over 36 months, dependencies have been analysed, and classifiers have been trained to deliver an accuracy of 78%. In addition, avian pox in chickens was detected using SVM by [20].

It must be competent to self-train and automated evaluate image data using standard deep learning technology. It may enhance evaluation and oversight of the poultry farming sector, especially in early identification of diseased poultry. AI and advanced learning will be integrated into standard data analysis for analysis, forecasting, and alerting of unusual circumstances, hence

preventing the transmission of poultry diseases and guaranteeing high levels of biosecurity. Thus, the use of big data presents an excellent chance to develop tools that will maximize economic performance on farms, minimize the negative impact on the environment and boost health and well-being among livestock and humans. [21].

At recent times, research studies were released demonstrating the effectiveness of methods based on machine learning to identify common poultry illnesses [22]. Some of them are the emergence of computerized poultry digestive disease detection using deep learning Convolutional Neural Network models including Faster R-CNN and YOLO-V3 to categorize finely detailed atypical poultry droppings image data as either normal or abnormal. The YOLO-V3 version demonstrated a standard recall of 88.7% and average mean precision of 84.3% on the testing dataset, whereas Faster R-CNN achieved recall of 94.1% and mean average precision of 93.3%. Thus, the results of this research are focused on an automated, contactless, model for identifying unusual feces in poultry that are not diagnosed with digestive condition [23]. In contrast, the answer for such system should be effective in the early identification of the poultry diseases.

A different researcher demonstrated a tracking system for broiler poultry based on standard machine vision [24]. Utilizing 2D pose shape description and corresponding mobility features, a set of characteristic variables was extracted. Two sets of classification algorithms were created. One with just posture shape descriptors and the other with all characteristic variables. The SVM with radial basis kernel operation performed better than other approaches with an accuracy level of 0.975. The proposed system provides continuous and non-invasive warning and prediction of disease occurrence. Nevertheless, validation must be performed by using multiple types of pathogens and chicken varieties.

Even though the previous work on detecting poultry diseases is promising, our proposed method has filled up several gaps in the previous research. Past research work like those done using Faster R-CNN and YOLO-V3 focus only on the detection of droppings or specific abnormal behaviours of the poultry birds [25]. In most cases, it does not provide early and overall detection of diseases like coccidiosis. Further, although such methods achieved high

accuracy, they were not real-time applicable for large poultry farms. Our approach with YOLOv8 achieves 98% accuracy while having rapid detection ability, critical for timely intervention. Past systems have also been bounded by the fact that such systems needed validation of the breed and environmental conditions [26,27]; our method has been built to be flexible across the different breeds of chicken and farm environments. Lastly, although prior work has presented non-intrusive monitoring systems, the earlier work is more concentrated on either behavioural or image-based detection, but in this paper, both were combined to provide a holistic non-intrusive method. Hence, our proposed approach fills this gap and presents a focused, scalable, and efficient method for early coccidiosis detection in poultry.

METHODOLOGY

This research presents a proposes a method of recognizing coccidiosis in poultry species using YOLOv8 and YOLOv9. YOLOv8 and YOLOv9 represent modern algorithms for deep learning known for their outstanding accuracy and quickness in real-time object detection tasks. The goal of this method is to identify early indications of coccidiosis in chickens based on the examination of visual data, with particular emphasis on the identification of abnormalities that correspond to the disease. The suggested approach is compared with other popular algorithms in the area of poultry disease detection such as a faster R-CNN, RESNET50, and traditional machine learning techniques such as Support Vector Machine (SVM) and Decision Trees, respectively [28,29]. Each of these algorithms has its strengths and limitations when applied to disease detection in poultry. This comparison highlights the advantages of YOLOv8 and YOLOv9 over existing methods in detecting coccidiosis in poultry.

A. Dataset:

In this study, we introduce a method for identifying coccidiosis in poultry using YOLOv8 and YOLOv9, it uses effecient deep learning algorithm recognized for its high speed and accurate in object detection. The aim of these approach is to spot early signs of coccidiosis in chickens by analyzing visual data, with a particular emphasis on identifying abnormalities linked to the disease. To train and evaluate these models, we utilize a custom dataset that includes fecal images of healthy and infected chickens from various farms[30].

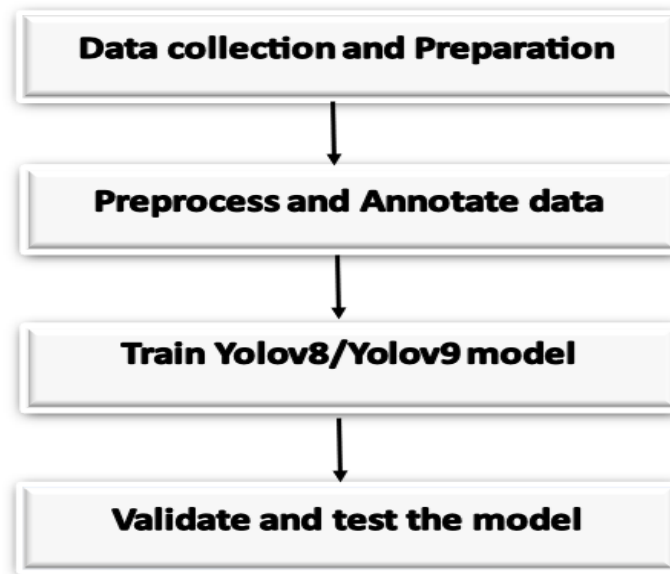


Figure 3: Flow chart of proposed method

Overall, the following is an elaborate step-by-step framework for the coccidiosis detection process leveraging the YOLOv8 and YOLOv9 algorithms as in figure 3. Both of these algorithms follow the same steps and use the same dataset.

B. Proposed Method

Data Collection and Preparation

In order to come up with an efficient model for the detection of coccidiosis, the first step involves collecting as many related coccidiosis images as possible. Collections include both coccidia infected samples and their non-infected versions. Thus, this should encompass images taken under different geographical locations, source light intensity levels, and even optical powers in use (If microscope images are incorporated). Ensure that there are infected and healthy samples for the model to learn coccidiosis pattern recognition without mixing up such image patterns with other inconsequential elements in the samples. Such differences will assist the model to perform adequately in its practical applications irrespective of the changes in conditions.

The data collection utilized in this study was gathered from Kaggle, which a popular internet portal. Its extensive dataset collection is primarily utilized for machine learning projects.

By removing all unclear or erroneous images, 1601 images are taken into account for this purpose. The labelling tool was employed to designate the images. The phrases "coccidiosis," "healthy," and "other" are used for marking. The phrase "coccidiosis" has been used to all of the various types of coccidiosis images. Images of healthy faeces were labeled as such, whereas photos of any other disease were labelled as other.

A thousand pictures were used for studying, 347 for assessment and 254 for verification. The same dataset and dataset splitting are considered for the execution of the YOLOv8 and YOLOv9 algorithms.

Based on the 1000 images used for training the model, 340 images are chickens with coccidiosis, 330 images are healthy chickens, and 330 images are chickens with other diseases.

In 347 test images, we evaluated 116 fecal images of chickens with coccidiosis, 116 fecal images of healthy chickens and 115 fecal images of chickens with different illnesses.

Of the fecal images that were taken into consideration for validation, 86 show coccidiosis, 84 show healthy chickens, and 84 show other diseases. This dataset is incredibly well-suited for immediate use in sickness categorization in poultry using deep learning techniques due to its high level of accuracy and meticulously structured nature, as explained here. Its minimal requirement for sophisticated preprocessing speeds up development cycles and minimizes overhead.

Preprocess and Annotate Data

Being done with the data collection, the next step will be to undergo image preprocessing for homogenization. This always commences with the age-old bane of any model – resizing as per the input requirements of YOLOv8 and YOLOv9 respectively, though in these cases, compression would be considered so that important features are not left out. Thereafter, everybody must annotate the images by drawing boxes or masks around the coccidiosis lesions. Each annotated image should include a clear distinction of areas that are termed as “infected” and “non-infected”. Finally in prepared datasets, they should consist of both training and testing data so as to avoid bias during evaluation of the model’s based on its performance. The

training guides the model how to carry out a task whereas the testing will help us understand the ability of model to perform a trained task.

Conclude YOLOv8/v9 Model Training

To further enhance the YOLOv8/v9 model, it is crucial to make use of the available annotated data to help the model in the identification of coccidiosis infection areas. Let us first outline the key hyperparameters such as batch size (the volume of images handled simultaneously) and epochs (the total number of cycles for the entire training dataset). These parameters alter how the training proceeds such as how fast and accurately the model is able to capture the information. The training process incorporates the training phase where the model performs internal modifications aimed at reducing the rate of error in identifying the correct area infected. Train the model and keep track of loss, a common training metric to evaluate the model's status and re-optimize training parameters if required to enhance output after some training steps have elapsed.

Validate and Test Model

Subsequent to the completion of the training, it is important to perform both validation and testing of the model to guard against overfitting. Performance metrics

are collected using a validation set that is different from the one trained the model on. These include:

Accuracy: The proportion of infected and non-infected regions that were categorised correctly.

$$Accuracy = \frac{True\ Positives(TP) + TrueNegatives(TN)}{Total\ number\ of\ Instances} - (1)$$

Precision: The number of positive detected cases that were actually positive divided by the number of attempted positive detections. This indicates the trust that can be placed in the infection detection system.

$$Precision = \frac{True\ Positives(TP)}{True\ Positives(TP) + False\ Positives(FP)} - (2)$$

Recall: The ability of the model to detect all infected regions, so as to minimize the chances of leaving behind infections.

$$Recall = \frac{True\ Positives}{True\ Positives(TP) + False\ Negatives(FN)} - (3)$$

F1 Score: An average metric calculated for both precision and recall and gives an indication of the ability in making the detections.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} - (4)$$

RESULTS

The empirical findings from comparing the two distinct versions of our postulated algorithm, YOLOv8 and YOLOv9, are shown in this section. Each version's performance is evaluated using a range of measures to show its positive and negative aspects.

A.Outcomes Of Yolov8

An improved ultralytics model for effective object identification is the YOLOv8. This model's computational speed, anchor-free head, and integration of a robust

backbone and neck architecture have made it well-known. Various YOLOv8 subvariants are used for this task. Each YOLOv8 model has pros and cons that make it appropriate for a variety of studies. After testing every subvariants, YOLOv8s proved to be the most effective for detecting and classifying images of chicken feces for utilization in poultry applications.

A customized model is generated after the model's training with fecal images. The ability of this model to identify and categorize fecal images has been verified and tested.



Figure 4: Classification using YOLO V8s custom

In addition to demonstrating how to detect a healthy fecal image, figure 4 also indicates the total proportion of the

object that matches the fecal matter of a healthy chicken based on training.

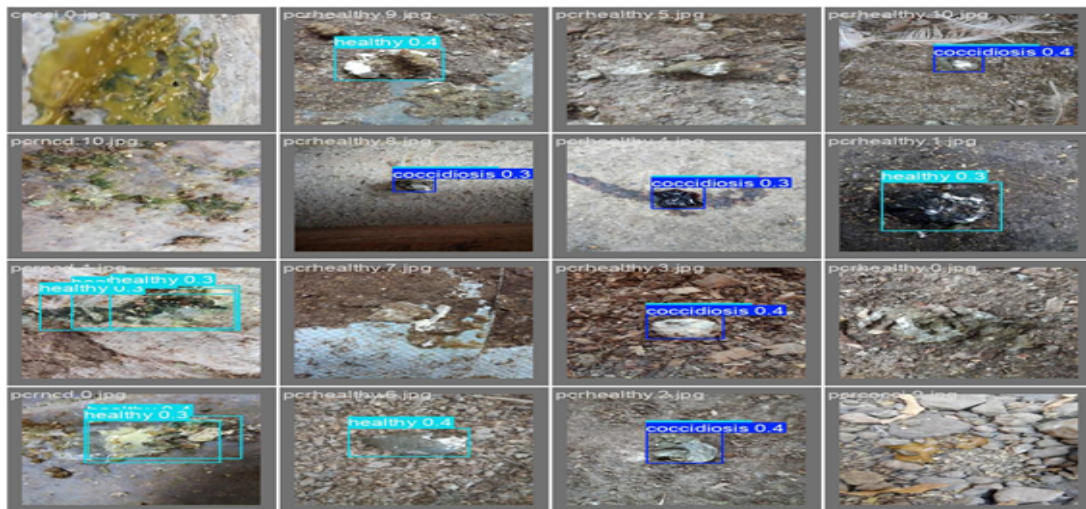


Figure 5: Coccidiosis classification using YOLO V8s custom

The end result of Bounding boxes and confidence ratings for both healthy and infected samples are highlighted in Figure 5, which shows how to classify fecal images using YOLOv8s custom model. This model successfully distinguishes between healthy droppings and those impacted by coccidiosis, with confidence scores varying from 0.3 to 0.53, showcasing its accuracy in detecting the

disease. It demands that the mode be set to "predict," which indicates that the model should make predictions for fresh data using the weights that have been trained. Since accuracy is set to 0.25 in this case, the confidence score will not be shown below 25% of matching with taught weights.

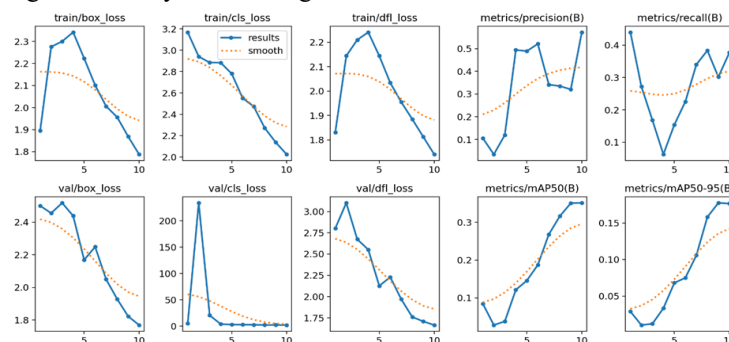


Figure 6: Accuracy Metrics of YOLO V8s

The training and validation performance metrics for the YOLOv8s custom model are shown in detail in Figure 6 above. The section that follows describes the metrics and their significance:

train/box_loss: The training box loss is approximately 1.9 at the beginning, 2.3 at the peak during epochs 3–4, and 1.8 at the end. Before the model settled, the initial spike could indicate some instability or an excessively high learning rate.

train/cls_loss: At epochs 2-3, the training classification loss peaks at 3.2 after commencing at 3.0 and then gradually declines to slightly above 2.0. There is an initial increase followed by improvement, much like box loss.

train/dfl_loss: At epoch 3, the training distribution focal loss peaks at 2.2 after beginning at 1.8 and then falls to roughly 1.6. This demonstrates an early increase as well.

metrics/precision(B): There are notable variations in training precision. It begins at 0.15, increases to over 0.5, falls, and then rises once again, culminating at 0.4. Although there is a lot of variety, the "smooth" line displays a general growing trend.

metrics/recall(B): There is a lot of variation in training recall as well. It begins at 0.45, falls sharply to less than 0.1, then rises once more to finish at 0.4. There is a broad dip followed by a rise in the "smooth" line.

val/box_loss: At epochs 2-3, the validation box loss peaks at 2.5 after beginning at 2.4 and then gradually declines to less than 1.8. The initial instability observed in training losses is reflected in this.

val/cls_loss: There is a noticeable decline in the validation classification loss. It begins at more than 200, falls sharply to about 5 in the first few epochs, and then stabilizes for the rest of the epochs at an extremely low number (near 0).

This sharp decline may indicate rapid learning or even a large initial loss value that was readily lowered.

val/df1 loss: Between 2.4 and 3.1 at epochs 2-3, the validation distribution focal loss peaks and subsequently falls to less than 1.7. This similarly exhibits a rise at first, followed by a decline.

metrics/mAP50(B): A general increase appears in the validation mean Average Precision at IoU 0.50. It begins at 0.1, takes a little drop, and then rises steadily to more than 0.3. Improvement is evident in the "smooth" line.

metrics/mAP50-95(B): The validation mean Average Precision throughout IoU 0.50-0.95 likewise exhibits a general upward trend, beginning at less than 0.0, dipping, and then climbing steadily to more than 0.15. Consistent improvement is seen in the "smooth" line.

Identifying the optimal YOLO variation for object classification is essential, especially given the unique challenges and requirements of the veterinary care industry. Factors such as variations in texture, color, size, and backdrop within a single image make classification challenging. A powerful YOLO variant ensures accurate grouping despite these variations.

Invalid classifications might lead to erroneous evaluations or treatments. A competent YOLO model reduces false positives by identifying only meaningful situations.

If an important problem (false negatives) is ignored in this field of study, animal health may suffer significantly.

Numerous veterinary clinics operate in places with little resources, such rural areas. Models like YOLOv8n (nano) are small and capable of functioning well on edge devices with reasonable precision.

For sophisticated clinics with better computing capabilities, YOLOv8s—which provide greater precision at the cost of higher resource consumption—might be useful.

A YOLO variant that works well on custom datasets helps ensure scalability across various veterinary applications.

By selecting the appropriate YOLO version, veterinarians can leverage deep learning innovation to enhance diagnosis, enhance treatment outcomes, and protect animal welfare.

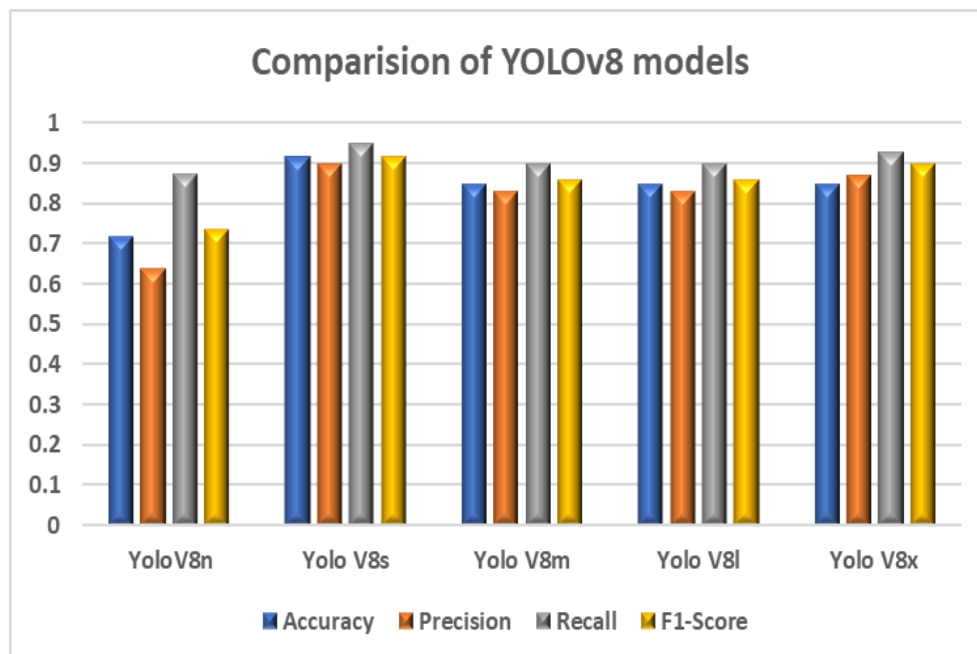


Figure 7: Precision Matrices comparison between various Yolo V8 models

The validation criterias of the Yolo model variants are shown in Figure7. When Yolov8 model versions are trained on identical data sets and assessed on a shared validation or test set, the aforementioned score is achieved. Based on accuracy and precision figures, the YoloV8s custom variant is regarded as the greatest of all the variants. It has an astounding 92% overall accuracy and 90% precision. It guides us that accurate forecasts with few false positives. Nonetheless, the model's ability to detect actual positive cases is demonstrated by the stated 95% recall. Remarkably, the F1 score, which establishes the equilibrium between precision and recall, is 92%.

The major criteria is to determine which model is the best. Since the main goal of this experiment is to classify the fecal matter of the chicken, a model that performs well overall with good accuracy and minimal false positive value detection is necessary. Thus, high categorization accuracy is essential. An incorrect categorization or a significant number of false positives causes the system to fail during implementation.

B. Outcomes Of Yolov9

Another real-time object detection methods designed to manage the loss function is called YOLOv9. Because of its

capacity to handle the loss function and incorporation of reversible functions, this model has become well-known. Additionally, it offers good computational speed and accuracy. All of the YOLOv9 models are used for the

categorization and detection of fecal images because each experiment will only perform better for one specific subvariant.



Figure 8: Classification using YOLO V9m custom

The figure 8 demonstrates the identification of coccidiosis for the given image using Yolov9m which worked better for the carried out work. This identification is done by the customized model obtained after training. In this figure it

detects two coccidiosis images with 0.8 and 0.5 accuracy. This accuracy indicates that the object detected compared with training knowledge gained.



Figure 9: Coccidiosis classification using YOLO V9m custom

The classification of fecal images and the percentage of similarity with the training dataset are shown in figure 9. Here, it classifies the fecal images of chickens into three categories: healthy, coccidiosis and other. One advantage of employing this approach is that it will effectively

categorize the object detected even if the image was taken against a dark background. The confidence score will not be displayed below 25% of matches with taught weights because accuracy is set to 0.25 in this instance.

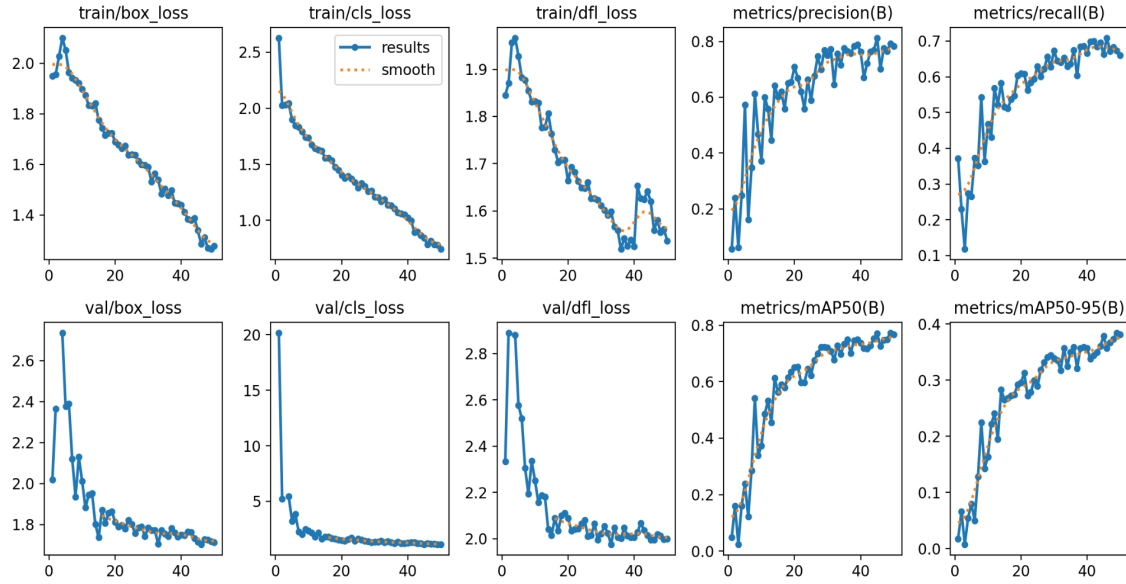


Figure 10: Accuracy Metrics of YOLO V9m

The training and validation performance metrics for the YOLOv9m custom model are shown in detail in Figure 10 above. This section describes the metrics and their significance:

train/box_loss: Reports the loss of the training box. The model continues to enhance its ability to estimate bounding boxes throughout training, as evidenced by the loss, which begins at about 2.1 and steadily drops to just above 1.4.

train/cls_loss: Specifies the classification loss during training. It starts at about 2.6 and gradually drops to just over 1.2, much like box loss, indicating better classification performance over training.

train/dfl loss: Displays the focal loss of the training distribution. Additionally, this loss diminishes over epochs, beginning at about 1.9 and finishing just above 1.4, suggesting that the model is becoming more proficient at learning the distribution of predicted box positions.

metrics/precision(B): Indicates the accuracy of training. During training, this metric typically rises from less than 0.2 to about 0.8, with some oscillations, showing that the model is getting better at making positive predictions.

metrics/recall(B): Represents the recall of training. Indicating that the model is more adept at detecting all pertinent instances during training, this metric similarly exhibits an increasing trend, beginning below 0.2 and rising to above 0.65.

val/box_loss: Gives the loss of the validation box. This loss exhibits good generalization of bounding box prediction to unknown data, first decreasing dramatically from above 2.6 to below 1.8, then stabilizing and showing a tiny additional decline.

val/cls_loss: In the first few epochs, this loss falls precipitously from around 20 to less than 2.0, and then it gradually declines and stabilizes at 1.5, suggesting good categorization generalization.

val/dfl loss: Depicts the validation focal loss distribution. Like other validation losses, it shows good generalization of distribution prediction after dropping precipitously from about 2.8 to below 2.0, then continuing to decline and stabilizing at 1.5.

metrics/mAP50(B): Demonstrates the average precision of validation at an intersection over union (IoU) criterion of 0.50. Strong object detection performance on the validation set is shown by this metric, which gradually rises from less than 0.2 to over 0.75.

metrics/mAP50-95(B): Reflects the average precision of validation across IoU thresholds, ranging from 0.50 to 0.95. The model is performing well over a range of strictness for object detection on unseen data, as evidenced by this metric's obvious upward trend, which rose from close to 0.0 to over 0.35.

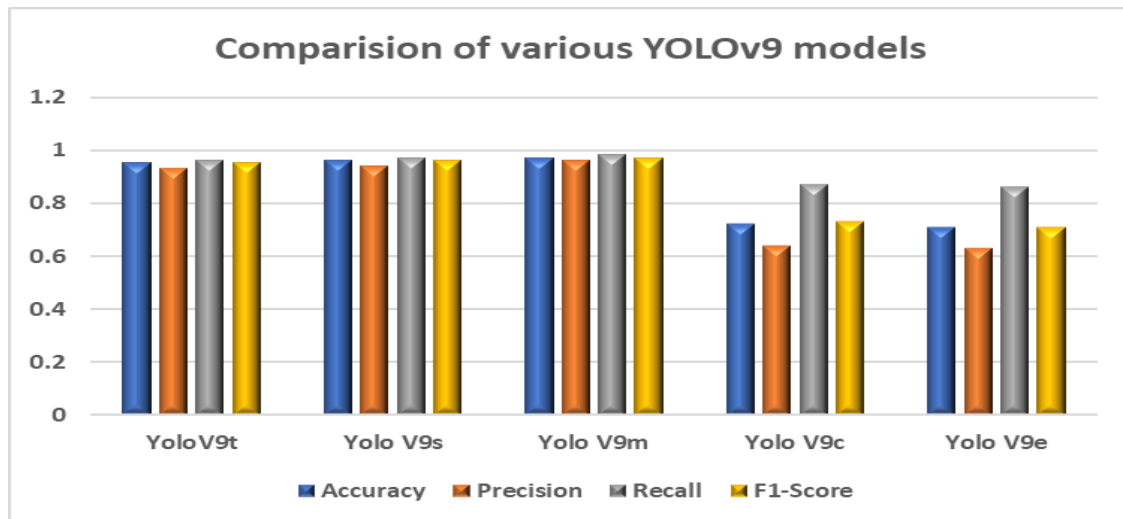


Figure 11: Precision Matrices comparison between various Yolo V9 models

The various factors for evaluation of the several Yolo model variations are shown in Figure 11. When YoloV9 model versions are trained on identical data sets and assessed on a shared validation or test set, the aforementioned score is achieved. Based on its remarkable overall accuracy of 97% and precision of 96%, the YoloV9m custom variant is regarded as the greatest by comparison with all other subvariants. This determines that it can result accurate forecasts with few false positives. The model's capacity is to detect true positive cases is demonstrated by the claimed 98% recall. Remarkably, the F1 score, which establishes the equilibrium between precision and recall, is 97%.

Determining which model is optimal is necessary. Categorizing the chicken's feces is the primary objective of this research, hence a model that performs well overall with good accuracy and barely false positive

value detection is needed. High categorization accuracy is therefore crucial. During implementation, the system fails due to either a large number of false positives or an inaccurate categorization.

COMPARISON

In order to prove the efficacy of the introduced algorithm that shows a better accuracy rate than the existing methods (Baseline CNN, RESNET50, VGG16, K- InceptionV3, MobileNetV2 and Xception), on arrange this in a graph with table contents and a bar chart to illustrate the enhancements.

A detailed accuracy comparison of baseline CNN, RESNET50, VGG16, InceptionV3, MobileNetV2, Xception, YOLOv8s and YOLOv9m coccidiosis detection models is presented in Figure 12. The given accuracy percentage of each model corresponds to the rate of infection provisioned by the model.

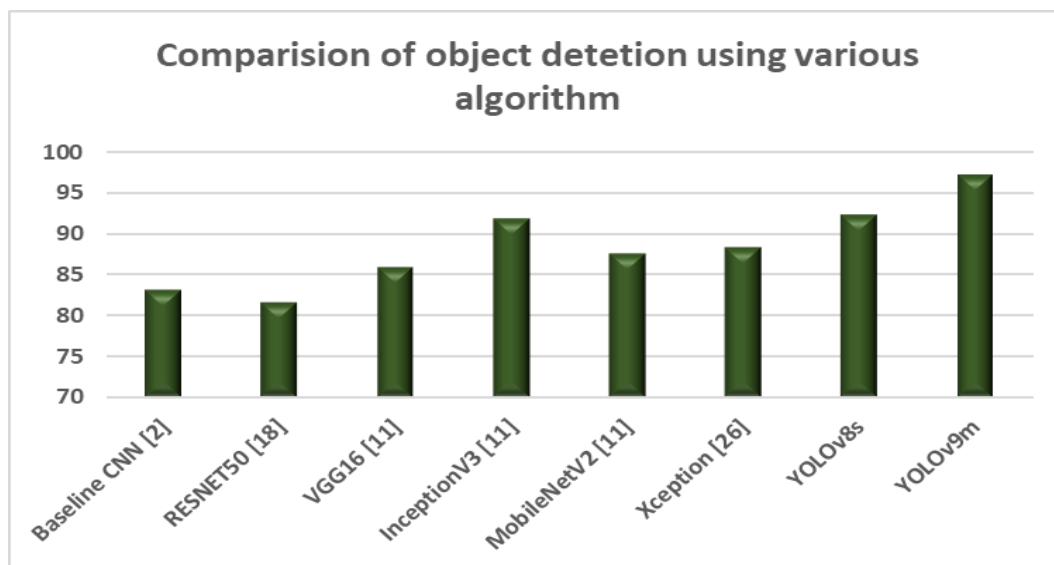


Figure 12: Accuracy comparison of existing methods with experimental results

Among the existing methods as shown in figure 11, InceptionV3 achieves the greatest accuracy of 91.76%

while Xception comes second at 88.27%. The proposed algorithms that are YOLOv8s and YOLOv9m are

intended to improve on this based on the aim to exceed an accuracy of 92.3% and 97.1% respectively. Not only does this provide better detection that can be achieved using the existing best method; Xception, there is an implication of better quality in real applications of coccidiosis diagnosis.

Based on the experiment conducted on the fecal images of chicken with varied conditions it proved that the YOLOv9m model produces the best result. The main reason for this is that the architecture of this algorithm is designed in such a way that it will handle most of the challenges of deep neural networks such as loss and efficient custom model creation. This algorithm creates an efficient custom model by handling data loss during forward and backward propagation during the time of custom model creation. It introduced the feature of PGI which helps to store the critical information and generate more reliable gradients to the depth of the network. It incorporates the GELAN which helps to balance the parameters such as accuracy, computational complexity and inference speed. It is observed that the development of the YOLO version always considers the drawback of underlying versions.

CONCLUSION AND FUTURE ENHANCEMENTS

The results of the trial demonstrate that YOLOv9 reduces loss and produces an effective result with good precision. And this approach minimizes false positive and false negative values while performing better for object recognition and classification.

The capacity of the to identify the objects with a very high IoU and to operate well across a varied range of IoU thresholds—both of which are critical for real-world applications—is demonstrated by the consistent improvement in mAP50 and mAP50-95. Its architecture's use of PGI and GELAN is the primary driver of improved performance.

GELAN's effective parameter usage and adaptable aggregation, along with PGI's capacity to preserve rich gradient information across the network, greatly enhanced YOLOv9m's performance, enabling it to attain high accuracy without sacrificing speed or efficiency. YOLOv9m is a very good option for challenging object detection circumstances since it stands out from the other versions, such as YOLOv9c and YOLOv9e, displayed in the bar chart.

Since that the chicken's feces are the object of this experiment, it is possible that the feces will accumulate and become partially or somewhat covered in materials such as husks or dried leaves. Therefore, this model can be modified to handle images that are partially or slightly obscured, as well as to detect and analyze small objects. In order to provide faster interference on other systems, it can also be optimized to use other formats. It is also possible to improve this method to recognize 3D images. By working toward these improvements, YOLOv9m's capabilities can be further developed, securing its place as a top model for a range of practical object identification applications.

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