Parasitic Egg Detection and Classification

Ghebrebrhan Weldit, Murad Mebrahtu

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0.1 Introduction

[1] reported that intestinal parasitic infections are serious diseases that affect 24% of the world's population. It has several symptoms ranging from diarrhea to anemia, and malnutrition. Parasitic infections also lead to growth-related issues for children and more than 800 million children are in need of chemotherapy. As such, an automated detection approach is required to address the time-consuming and inefficient domain expert-based detection[2]. Therefore, several approaches are presented in the literature to find accurate and effective solutions for the problem. So, in this work, the literature review of the recently presented approaches to the automatic diagnosis of parasitic egg cells is performed. Afterward, YOLOv7 and fine-tuned ResNet-152 are also implemented to perform an efficient and accurate detection and classification of the parasitic egg cells. Our code can be found https://github.com/Murdism/Parasitic-Egg-Detection-and-Classification.

0.2 Litrature Review

Authors [3] ensembled five deep-learning models to detect parasitic eggs from fecal smear samples. The "Chula-ParasiteEgg-11" dataset, containing images of 11 kinds of Parasitic Helminth eggs is used for the experiment. The images are acquired using different devices; they have some variations and noise. Hence, ensemble learning is utilized to boost the performance (i.e., IoU of 91.5% and F1 score of 97.4%).

[4] proposed a parasitic eggs detection and classification from fecal examinations. The researchers used patch-based CNN and transfer learning to achieve an accurate classification. To generate a training set, patches of an image with parasitic eggs are labeled as parasitic while the patches with no parasitic eggs are labeled as a background. The overlapping patches of microscopic images are utilized to train the model.

To deal with low-quality, noisy images, [5] presented parasitic egg detection from stools by taking advantage of Generative adversarial networks(GAN) and Faster-region-based CNN (Faster-RCNN) for image enhancement and object detection respectively. Image enhancement is performed using GANs and the enhanced images(high-resolution images) are fed to the Faster-RCNN to detect parasitic eggs.

Similarly, in [6] an automatic diagnosis of schistosomiasis from impure fecal smears is presented. The researchers collected their own dataset set from patients and implemented a practical-level application based on Faster region-based convolutional neural network (Faster-RCNN). The result obtained from the research got an average precision of 76.5% for an IoU of 0.50.

Research [2] also performed a comparative analysis of the state-of-the-art deep learning-based object detection models, namely, Faster-CNN, Mask-RCNN, and Cascade Mask-RCNN. Moreover, variants of ResNet-50 and a Swin-Transformer as feature extractor backbones, and the output of these feature extractors are fed to the object detection models to detect the parasitic cells. The cascade Mask-RCNN with Swin-Transformer-Base feature extractor(backbone) achieved the best, promising results on the testing set with mean Intersection over Union (mIoU) and F1 score of 87.5% and 95.5% respectively.

In [7], a parasitic egg cells detection system is implemented using object detection techniques. To train the deep learning-based detection system, pseudo masks generated using class-agnostic instance segmentation and ensemble-learning-based bounding boxes are implemented. In other words, multiple deep-learning models are utilized to generate bounding boxes that indicate the existence of parasitic egg cells. Afterward, a weighted fusion of the bounding boxes and pseudo masks (i.e., pseudo-labels) is utilized for training the detection system.

For efficient computation efficiency, [8] presented a YOLOv5 (You Only Look Once) algorithm to detect

Class ID	Name	Train	Validation	Test	Total class images
0	Ascaris lumbricoides	716	80	199	995
1	Capillaria philippinensis	719	80	200	999
2	Enterobius vermicularis	716	80	199	995
3	Fasciolopsis buski	672	74	187	933
4	Hookworm egg	723	80	201	1004
5	Hymenolepis diminuta	719	80	200	999
6	Hymenolepis nana	721	80	200	1001
7	Opisthorchis viverrine	718	80	199	997
8	Paragonimus spp	719	80	200	999
9	Taenia spp. egg	726	81	202	1009
10	Trichuris trichiura	717	80	199	996
0-10	Total	**7,866**	**875**	**2,186**	**10,927**

Table 1: Dataset contents split into Training, Validation and Testing by class

parasitic eggs. Given the images dataset variations in resolutions, lighting, and setting conditions, the authors applied image augmentation and hyperparameter tuning concerning image resolution to get accurate and efficient detection and achieved a mean Intersection over Union(mIoU) result of 71.7%. Moreover, the GrabCut algorithm is applied to perform image segmentation and generate synthetic datasets for the classes with limited image samples.

Lastly, study[9] utilized transfer learning, YOLOv5, and a variant of Cascade RCNNs are utilized to perform intestinal parasitic eggs detection. To deal with the challenging nature of the dataset, standard and biological augmentation techniques are applied to allow the models to learn rich features. Finally, Weighted Boxes Fusion (WBF) is applied to ensemble or integrate models' detection. In other words, they use suitable feature extractors (backbones) and ensemble learning to obtain state-of-the-art performance.

0.3 Methodology

In parasitic detection and identification literature, the most common dataset is provided by IEEE as part of the 2022 ICIP challenge [10]. This dataset contains around 11,000 images from 11 classes of parasitic egg cells. The dataset contains about 1000 images per class. After processing and splitting the data into 3 sets i.e training, validation, and testing; the dataset contains around 72% of each class as training data, 8% as validation, and 20% as testing data. Table 1 shows the number of samples used in each set for each class.

The images in the dataset vary greatly in resolution. Some images are of very low quality and the labeled parasitic egg cells are not clear. Due to their low image resolution and small, it is hard to correctly detect and classify some of the parasitic egg cells. As shown in figure 1, it is clear that Opisthorchis viverrine cells and Capillaria philippinensis tend to be smaller and hard to detect compared to other types such as hookworm eggs.

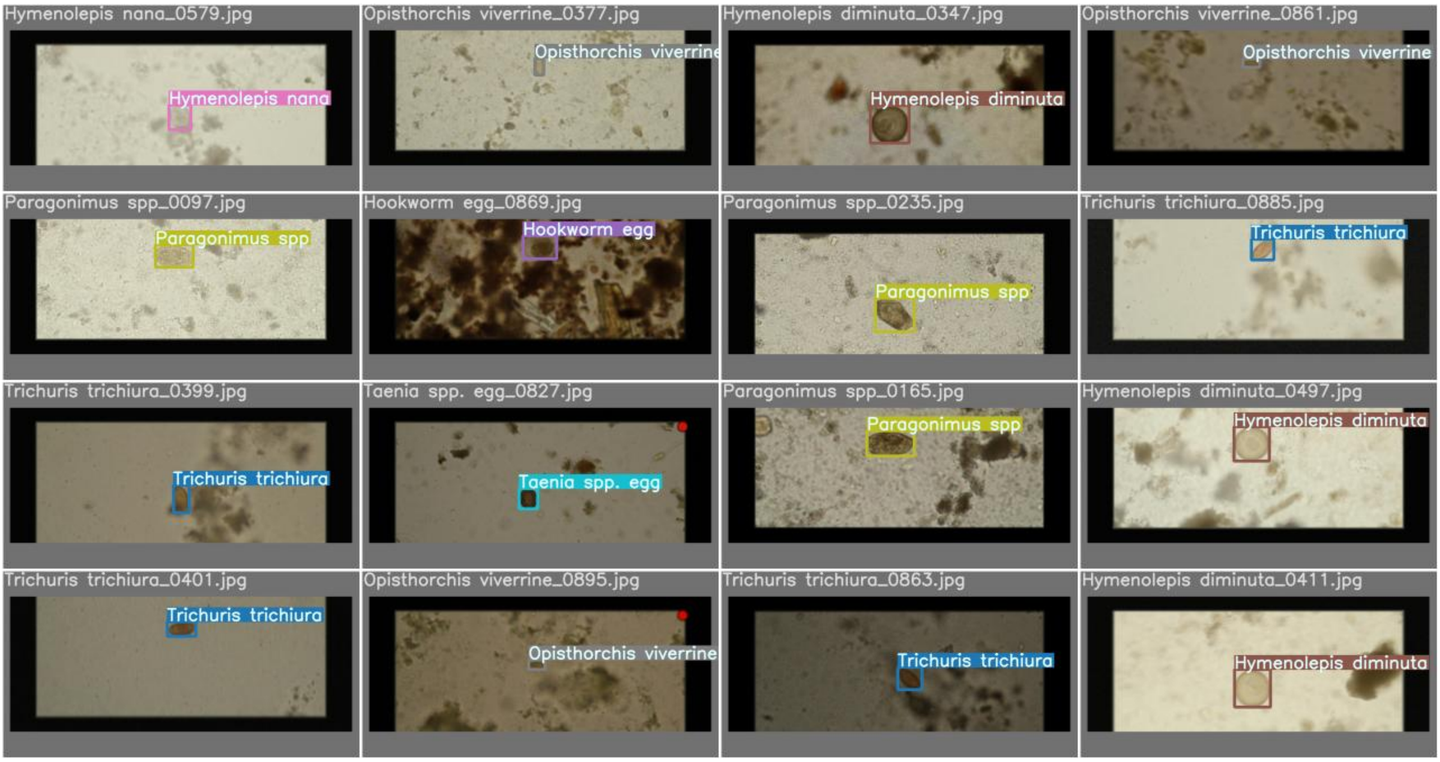

Figure 1: Sample images from Datset

0.3.1 Detection and Classification Method

Since the goal of this project is to detect and identify parasitic egg cells we can think of the task as two-stage detection as it is called in computer vision literature. These two tasks can not be done in one end-to-end system since they are two different tasks with different goals. The first task is to detect the cell and create a bounding box label around it. The second task is to identify or classify the cell as one of the 11 classes of parasitic cells. To perform those two tasks we employ two methods, namely YOLOV7 and ResNet152.

YOLOV7

YOLOV7 is an object detection algorithm that is produced as a successor of the other object detection methods of the same family. YOLO (You Only Look Once00) algorithms have been one of the most popular object detection methods used in literature. YOLOV7 is the most recent version of the YOLO algorithms created by Chien-Yao Wang and etl in 2022 [11]. This model is ranked first in object detection in papers with code. Papers with Code is an open-source site that compares different algorithms in the same literature and ranks them based on their performance. The YoloV7 has shown very promising results surpassing such as Cascade-Mask R-CNN, YOLOX, YOLOV5, and many others in speed and accuracy [11].

ResNet-152 Model

ResNet-152 is a convolutional neural network (CNN) architecture based on the ResNet-50 model and its architecture has 152 layers deep [12]. Due to residual connections and few parameters compared to the ResNet-50 model, ResNet-152 is efficient to train and perform inference while it provides the ability to learn or extract more complex features and achieve superior results. Hence, in this task, a fine-tuned version of the ResNet-152 model is implemented to classify the parasitic eggs. The fine-tuned ResNet model is created using a pre-trained ResNet-152 model with its weights frozen. Also, the last fully connected layer of the ResNet-152 model was replaced by a fully connected (FC) layer with 11 neurons to perform the classification task at hand.

0.4 Experiments and Results

In our project, we leveraged the power of transfer learning to train YOLOV7 and ResNet-512 models. Transfer learning is a machine learning technique in which a model trained on one task is reused as the starting point for a model on a second task. It is a powerful technique that allows you to quickly and effectively leverage the knowledge gained from a pre-trained model to solve a different, but related problem. This allows the use of much less data than would be required to train a model from scratch, which can save time and resources. Making use of transfer learning, both models were trained to perform different tasks. The YOLOV7 model was trained to detect and classify while the ResNet model was only used for classification. Since YOLOV7 is a two-stage object detection method it can detect and identify parasitic cells. This means the results of the model are bounding boxes of the detected cells and the types of cells. On the other hand, the ResNet models can only classify images as containing a certain type of parasitic cell.

As mentioned earlier the two proposed models are trained separately. Both models were trained on

7, 866 samples, validated on 875 samples, and tested 2, 186 samples. This means the dataset contains around 72% training data, 8% validation data, and 10% testing data. The YOLov7 model was trained for 100 epochs with a batch size of 12 on a single GeForce RTX 2080 Ti. ResNet model was trained on the similar format but for 50 epochs. The reduction on the number of epochs is due to the over-fitting problem observed when training.

Evaluation Metrics

To evaluate the models we use mAP, accuracy, precision, recall, and f1scores. The mAP or the mean average precision is a model evaluation metric used to measure the accuracy of object detectors such as YOLO and Mask R-CNN. It is mainly used in the literature on object detection especially when the COCO dataset is used. the mAP is the Average Precision(AP) for each class over the number of classes. It is calculated for a selected IOU (intersection over union) threshold.

The mAP will be used to evaluate the ability of the YOLOV7 model to detect and identify while accuracy, precision, recall, and f1scores will evaluate the ability of its classification. Similarly, the ResNet model is evaluated on all the above-mentioned metrics except mAP.

Results

Retrained YOLOV7 model has shown very promising results, which are comparable to the state of the art. As shown in figure 2 and 3. A detailed analysis of the model's performance on the test dataset can be seen in 2. A sample of labeled data after prediction is shown in 5. Overall The model shows very good results with overall mAP@0.5 reaching 98.5% on the test dataset.

In addition, as shown in figure 4, the classification performance of the fine-tuned ResNet-152 model seems to be poor compared to YOLOv7.

Comparison with state-of-the-art

In this section, we compare our two models with other models trained on the same dataset. The YOLOV7 model outperforms the rest on mAP@0.5 and it comes close on other metrics. The ResNet model however does not perform as well as others. Our YOLOv7-based model's results show that faster models such as YOLO could give a reasonable performance or even outperform other complex models. In the future by adding a more robust classifier with YOlOv7, the classification scores could be improved. The results of the comparison are shown in 3.

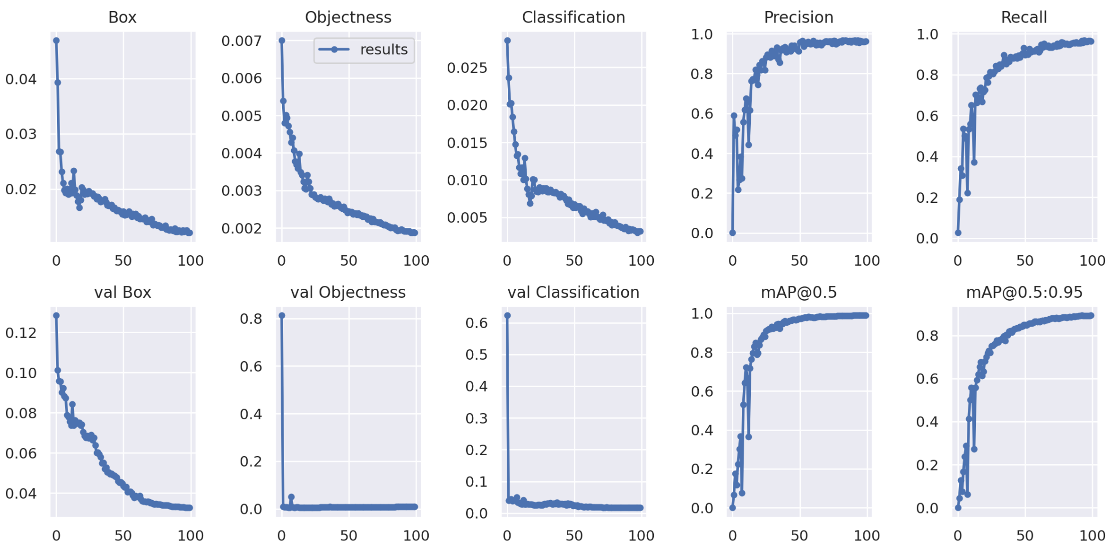

Figure 2: Performance of finetuned YOLOV7 Model on training sets

Class	**Images**	**Labels**	**Precision**	**Recall**	**mAP@.5**	**mAP@.5:.95**
all	2186	2186	0.965	0.952	0.985	0.891
Ascaris lumbricoides	2186	199	0.951	0.879	0.964	0.91
Capillaria philippinensis	2186	200	0.956	0.97	0.98	0.845
Enterobius vermicularis	2186	199	0.964	0.951	0.986	0.862
Fasciolopsis buski	2186	187	1	0.823	0.981	0.853
Hookworm egg	2186	201	0.962	0.955	0.982	0.803
Hymenolepis diminuta	2186	200	0.994	0.995	0.996	0.979
Hymenolepis nana	2186	200	0.973	0.975	0.99	0.879
Opisthorchis viverrine	2186	199	0.972	0.96	0.99	0.866
Paragonimus spp	2186	200	0.896	0.99	0.986	0.953
Taenia spp. egg	2186	202	0.971	0.986	0.983	0.927
Trichuris trichiura	2186	199	0.972	0.99	0.993	0.926

Table 2: Performance of YOLOV7 on testing set

Method	mAP	mIoU	Acc	Recall	Precision	mF1score
[1]	0.925	**0.942**	-	-	-	0.995
[7]	0.956	0.934	-	-	-	**0.988**
YOLOv5[8]	-	0.717	-	-	-	0.864
Ensemble [3]	-	0.915	-	-	-	0.974
ResNet-152 (ours)	-	-	0.900	0.900	0.900	0.900
YOLOv7 (ours)	**0.985**	-	-	0.965	0.952	0.958

Table 3: Comparison of the presented approach with state of the art

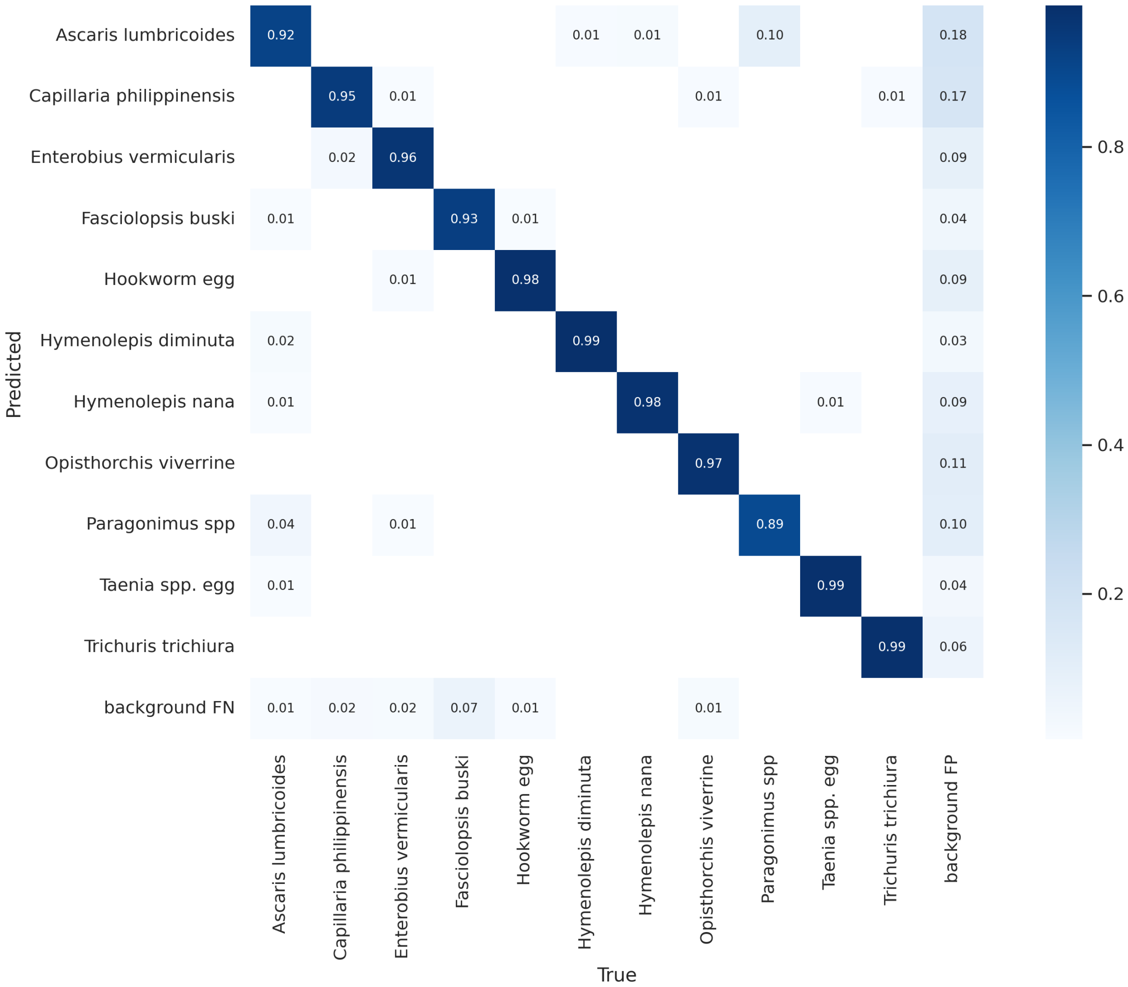

Figure 3: Confusion Matrix on Test Dataset

```
...  mean acc score = 0.9002744739249772
     mean recall score = 0.9002744739249772
     precision score = 0.9002744739249772
     mean f1 score = 0.9002744739249772
                   precision    recall  f1-score   support

                0       0.87      0.81      0.84       199
                1       0.89      0.88      0.89       200
                2       0.95      0.89      0.92       199
                3       0.96      0.83      0.89       187
                4       0.99      0.99      0.99       201
                5       0.98      0.76      0.85       200
                6       0.94      0.92      0.93       200
                7       0.80      0.96      0.88       199
                8       0.79      0.96      0.87       200
                9       0.87      0.98      0.92       202
               10       0.93      0.91      0.92       199

         accuracy                           0.90      2186
        macro avg       0.91      0.90      0.90      2186
     weighted avg       0.91      0.90      0.90      2186
```

Figure 4: Performance of finetuned ResNet-152 Model on testing sets

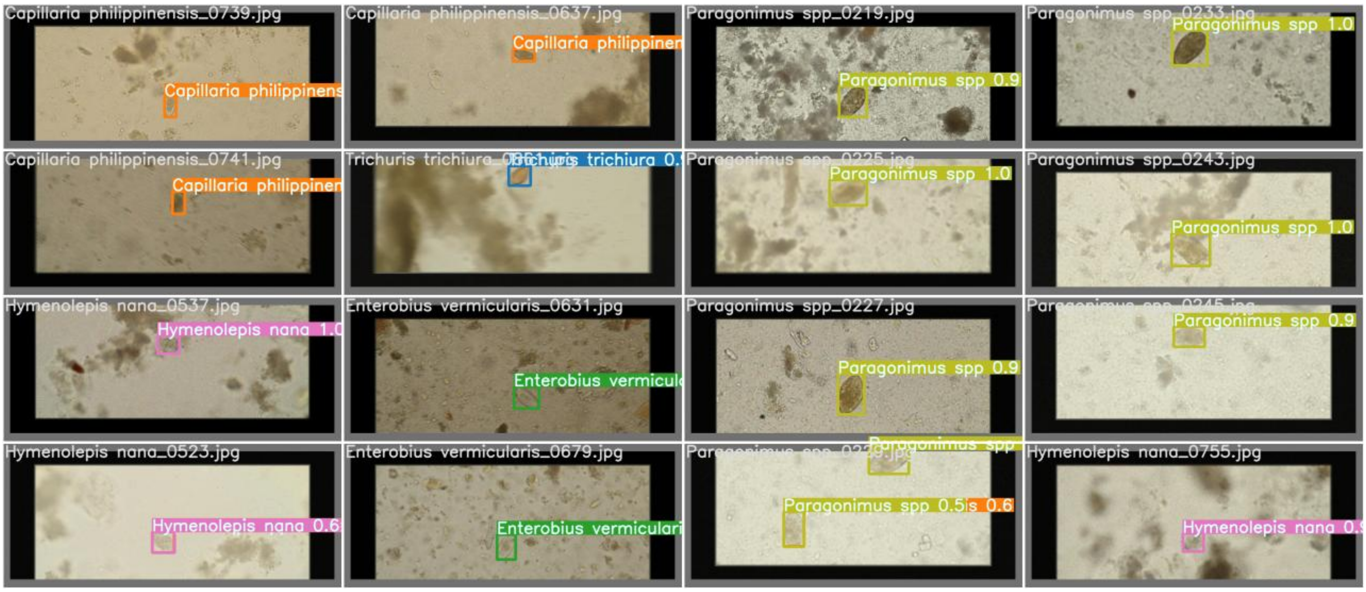

Figure 5: Sample output of prediction on test dataset

0.5 Conclusion

In this work, a short literature review related to parasitic egg detection and classification is provided. Afterward, an efficient and accurate approach using transfer learning combined with recent deep learning architectures (YOLOv7 and ResNet-152 models) is implemented. The experiment has provided promising results. In the future, exploring different data augmentation techniques to improve the detection and classification performance of YOLO7 might be crucial. Furthermore, integrating YOLOv7 and the ResNet model's outputs to build an even more accurate classifier seems interesting. We already started the integration part, however, due to the time constraint we decided to wrap it up here. Our code can be found https://github.com/Murdism/Parasitic-Egg-Detection-and-Classification.

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