Department of Electronic and Telecommunication
University of Moratuwa

EN3160- Image Processing and Machine Vision

ICIP 2022 Challenge on Parasitic Egg Detection and Classification in Microscopic Images
Project Report

Team Hawks

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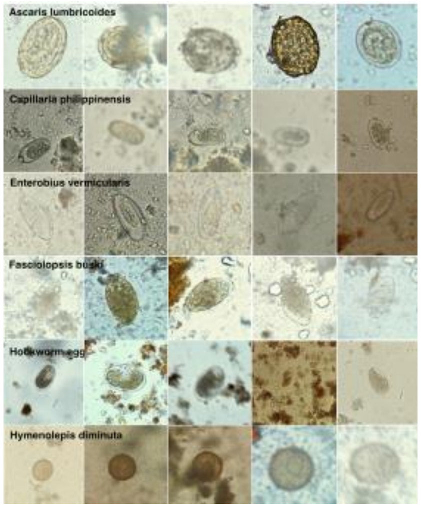
1. **Introduction**

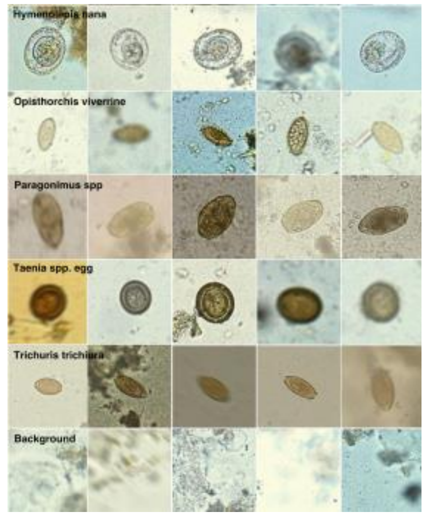
Intestinal parasitic infections are a significant global health concern, especially in tropical regions. In 2020, the World Health Organization (WHO) reported that about 1.5 billion people, a quarter of the world's population, were affected by soil-transmitted helminth infections (STH). These infections lead to health issues, particularly in children, causing symptoms like malnutrition and anemia. Infected individuals can unknowingly transmit parasite eggs, requiring improved diagnostics. The current laboratory-based examination is time-consuming and impractical for on-site use.

This project automates the detection and classification of parasitic eggs in microscopy images, introducing a comprehensive dataset of 11 egg types. It emphasizes robustness and accuracy, promoting collaboration among experts in image processing, medical imaging, and computer vision.

Table 1: Parasitic Egg Types and Characteristics

Parasitic Egg Type	Size (µm)	Width (pixels)
Ascaris lumbricoides	60×85	131-439
Capillaria philippinensis	20-22×36-45	56-234
Enterobius vermicularis	20-30×50-60	76-272
Fasciolopsis buski	80-85×130-140	170-806
Hookworm egg	36-40×64-76	114-410
Hymenolepis diminuta	60-80	132-461
Hymenolepis nana	30-47	95-300
Opisthorchis viverrine	11-12×22-32	41-186
Paragonimus spp	77-80	116-477
Taenia spp. egg	30-35	85-244
Trichuris trichiura	22-23×50-54	76-395





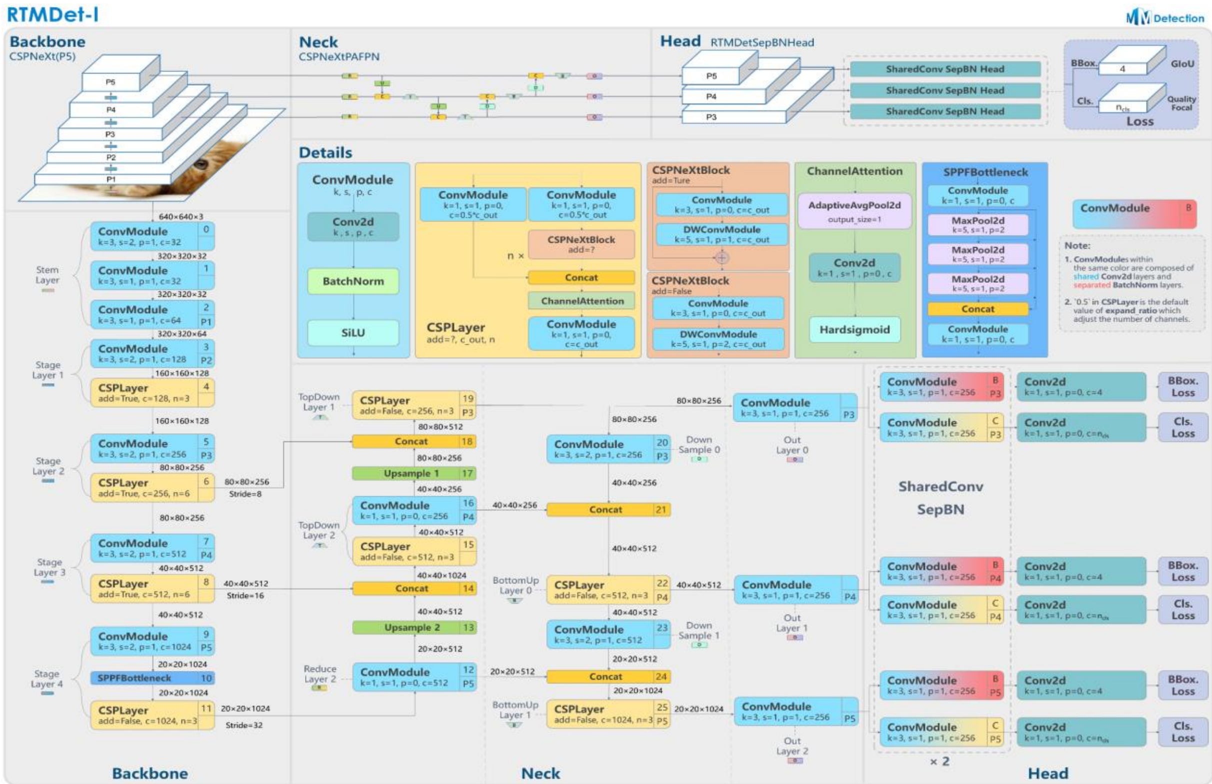
2. Related Work

Current datasets and techniques for microscopic parasitic egg detection have limitations. For example, the Parasitology Laboratory of Kansas State University offers five types of parasitic eggs with just 33 images, and the Japan Advanced Institute of Science and Technology provides eight types with 213 images. Recent advances in deep learning, especially convolutional neural networks (CNNs), have shown promise. State-of-the-art methods leverage CNN technology, transfer learning, and object detection techniques to achieve impressive results in parasitic egg detection and classification. Some approaches involve semantic segmentation using architectures like UNet and FCN. Modern object detection methods, like Faster-RCNN, also demonstrate potential.

This project extends these methodologies to address challenges posed by a substantial dataset of parasitic egg images, with a focus on robustness and accuracy.

3. Method Section

Our method is also based on the state of the art in object detection. For our implementation, we mainly use the mmdetection and sahi libraries. In the given data set, the visual quality of images has been degraded by adding gaussian and poison noise, applying motion blur, adjusting image saturation, and adjusting image contrast using gamma correction to replicate a real-world scenario. Therefore, we did not apply those image augmentation methods again. In the data preprocessing part, after dividing the data set into 5 folds, we sliced images to enhance the diversity of the dataset and improve model training. For configuration, rtmdet tiny is used. RTMDet is an efficient and high-performance one-stage object detection model introduced in MMDetection. Model has pretrained using COCO dataset.

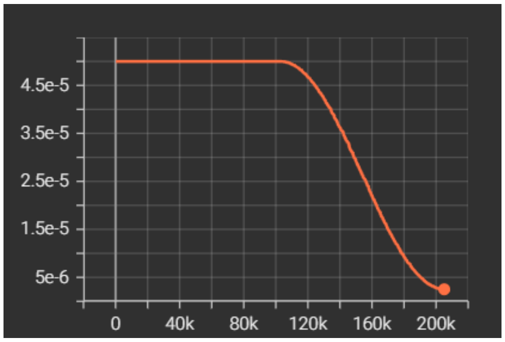


- Optimization

The AdamW optimizer, a variant of Adam that includes weight decay as a regularization technique was used and the learning rate (lr) is set to a specific base value which is 0.00008, and a weight decay of 0.05 is applied to control the magnitude of the model's weights.

- Learning rate schedule

For the first ten epochs, a linear learning rate schedule is used, and for the other ten epochs, a cosine annealing learning rate schedule is used.

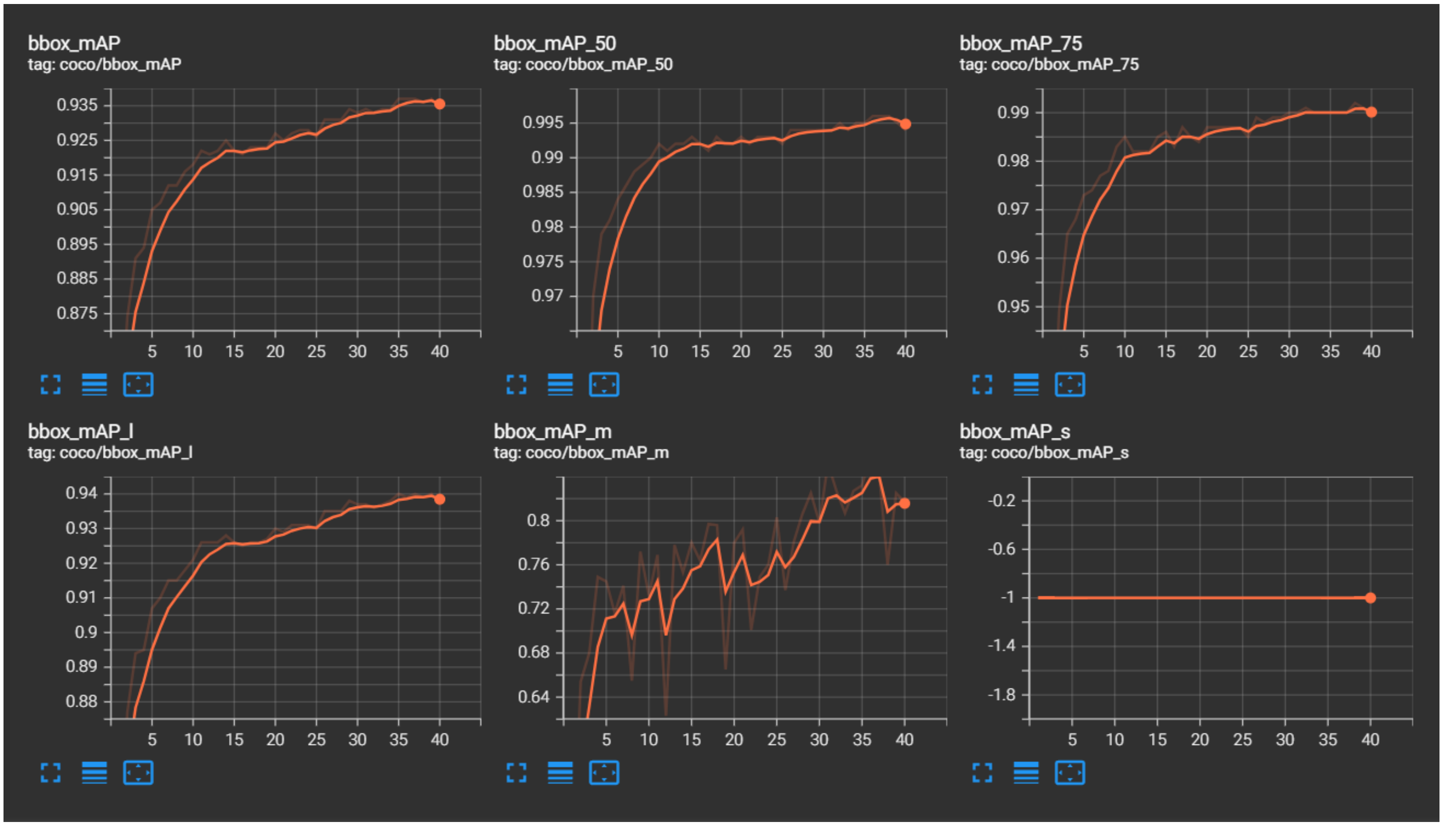


- Data Augmentation

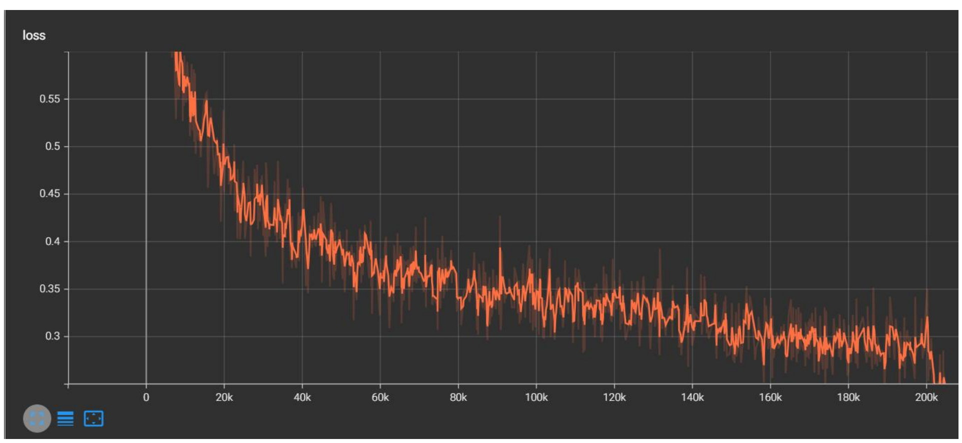
Random Resize: Images are randomly resized within a range of (640, 640) pixels while maintaining their aspect ratio.
Random Crop: Randomly cropping the images to a fixed size of (640, 640) pixels.
Random Horizontal Flip: Images are randomly mirrored horizontally with a probability of 0.5.
Padding: Padding the images to (640, 640) pixels ensures uniform input sizes for the model.

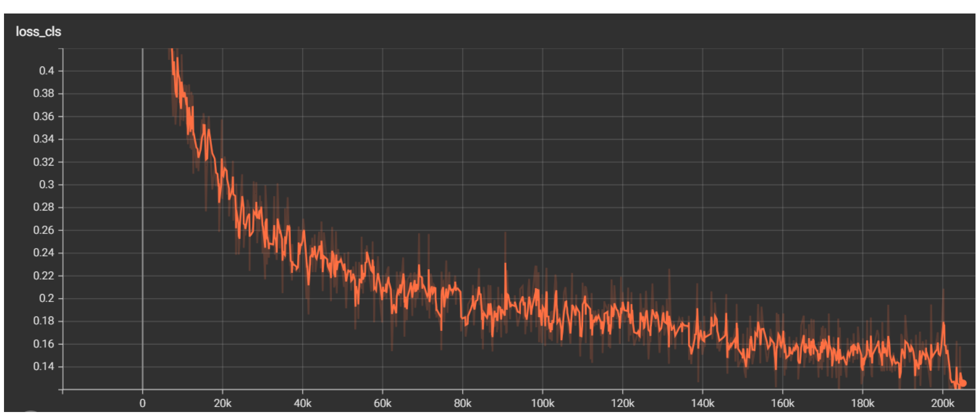
4. Results

- <u>Mean average precision</u>



- <u>Loss</u>





The mean average precision has increased to 0.935, and the loss for the classes has been lowered to 0.165. More loss reduction is required as compared to a good state-of-the-art model. But given the complexity of the work, the precision is at an acceptable level.

5. Future improvements and possible extensions.

In order to further reduce loss and improve mean average accuracy, our project is focused on exploring advanced fine-tuning strategies within the MM Detection framework. While our previous work was constrained by limited hardware resources, we are actively seeking the appropriate hardware setup to leverage the increased accuracy potential of a two-stage object detection framework. This transition promises higher accuracy levels but necessitates dedicated hardware resources for optimal performance and fine-tuning success.

6. Resources used

Google Collaboratory
Kaggle

7. References

https://ieeexplore.ieee.org/document/9897267

https://github.com/open-mmlab/mmdetection/tree/main/demo

GitHub link for codes

https://github.com/pesalaG/Parasitic-Egg-Detection-and-Classification