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Effects of Preprocessing on Microscopic Images for the Giardia Lamblia Detection

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Abstract. This paper presents a comparison of deep learning architectures, MobileNetV2 and Inception v3, using different datasets to analyze the efficiency of Giardia lamblia parasite detection in bright field microscopy images. The datasets were preprocessed with techniques such as image cropping, and then used to train both architectures. The comparison was carried out using metrics such as accuracy, precision, and recall. The experimental results demonstrate that preprocessing techniques, particularly image cropping, significantly improved the models' performance. This comparative approach underscores the importance of preprocessing strategies in optimizing deep learning models for specific detection tasks.

Keywords: Giardia lamblia, deep learning, detection.

1 Introduction

In recent years, deep learning has significantly impacted computer vision tasks such as image classification, object detection, face recognition, and semantic segmentation, almost replacing traditional feature extraction methods [2]. Specifically on the detection of the waterborne parasite *Giardia lamblia*, there have been some advancements. However, some of these approaches are not up-to-date with recent deep learning architectures and more importantly, some still use traditional feature extraction methods because of the way the images were collected. These two factors can introduce significant variability in the deep learning models; thus the importance of exploring simple preprocessing approaches such as image cropping in order to improve the performance of deep learning models.

G. lamblia is a protozoan parasite that reproduces in the small intestine after being ingested, causing giardiasis in both animals and humans [7]. Symptoms of *giardiasis* include diarrhea, mild fever, fatigue, and myalgia. In rare cases, *G. lamblia* parasites can infect the lungs and trachea, resulting in coughing, dehydration, and extreme weight loss in humans [7]. The detection process of parasite involves sampling, isolation, staining, and microscopy. Under the

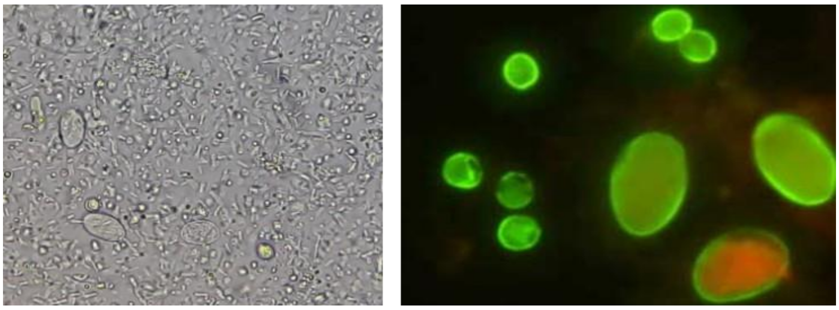


Fig. 1. *G. lamblia* parasites through clear microscopy; through immunofluorescence technique.

microscope, direct visual inspection is performed by an expert to detect the presence of the parasite, requiring a considerable amount of time.

In environmental samples, the gold standard is the immunofluorescence technique, as this parasite can be easily confused with other microorganisms [7,8]. Although the immunofluorescence technique offers advantages, it requires specialized equipment and trained personnel. On the other hand, detection of *G. lamblia* with brightfield microscopy has the advantages of being easy to perform and being cost-effective. However, it also has some disadvantages such as being time-consuming, low detection accuracy and difficulty for uncommon microorganisms detection [5]. For instance, in Fig. 1, *G. lamblia* parasites are shown in microscopic images under the two aforementioned techniques.

Although the references used in this section might appear dated, they provide foundational insights into the methods still relevant today. For example, Methods based on neural networks [11]; applying digital image processing techniques that use shape and color features [3]; or through the application of filters that seek to remove noise and preserve edges [1]. Nevertheless, in environmental water samples, low contrast and noise in microscopic images can significantly affect segmentation accuracy, as water samples may contain a low number of cysts and contamination components that hinder strain differentiation and multilocus molecular analysis of G. lamblia strains [7].

In the past two decades, the development of computational methods for the detection of microorganisms such as G. lamblia has relied on the use of deep learning-based architectures due to their high effectiveness [5]. Different approaches have been made, for instance, one study developed a field-portable, cost-effective imaging flow cytometer using lens-free holographic imaging accurately detected G. lamblia cysts in water samples at 100 mL/h, identifying cysts in real-time without labels [4].

Another approach involves microscopic images from fruit samples using a smartphone microscope, they used different deep learning architectures and compared them [6]. Although these proposals obtained favorable results using deep learning, both rely on specialized hardware with certain limitations such as cost, accessibility and quality issues.

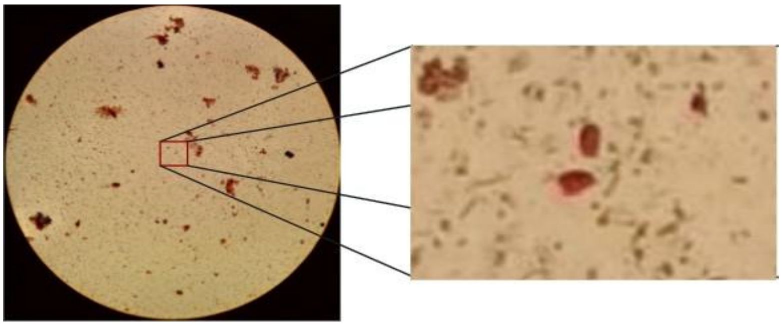


Fig. 2. *G. lamblia* in idoine seen through 10x.

Considering the above, in this work a comparison between two deep neural network methods was done, the models were trained using bright field microscopic images taken from a cheap and accessible way of sampling. The images were preprocessed in three different ways resulting in three datasets. The preproccesing consisted in different image cropping sizes. The models were trained on these datasets in order to analyze the effects of each cropping size on the detection of the G. lamblia parasite in microscopic images.

2 Datasets

The images were collected using a Xiaomi Redmi Pro smartphone camera and a ZEISS Primo Star commercial microscope. To ensure the stability of the smartphone and reduce image blurring caused by movement, a phone holder was employed to attach the phone to the microscope. This setup minimized vibrations and maintained consistent focus during image capture.

For the preparation of the samples, a 15-micrometer micropipets was used. This allowed precise handling and placement of the samples onto microscope slides, ensuring clear and detailed imaging under the microscope. The careful preparation and mounting of the samples were crucial to obtaining high-quality images for the dataset.

The photos captured included both positive and negative G. lamblia samples stained with iodine, with the microscope set to 10x magnification (e.g. see Fig.2).

No additional filters or zoom were applied to the smartphone camera during the process.

Subsequently, different processes were performed on the images to facilitate their analysis and use. First, the images were processed to meet specific criteria necessary for subsequent tests. Each image had a substantial black spot that occupied more than half of the frame (e.g. see Fig.3), which rendered those portions unusable for analysis. To enhance the quality and usability of the images, these black spots were meticulously removed. This preprocessing step ensured that the remaining parts of the images were suitable for accurate and reliable testing.

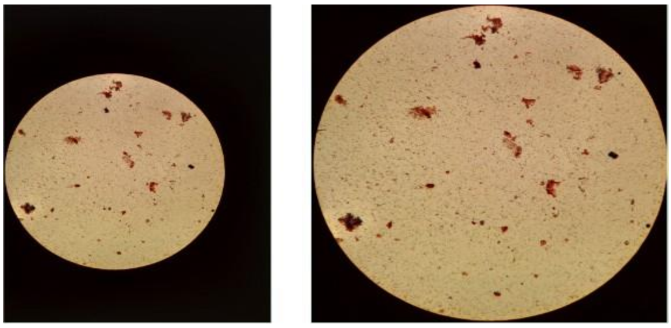


Fig. 3. Image before taking out the black spot (3120×4160), and after taking out the black spot (2580×2580).

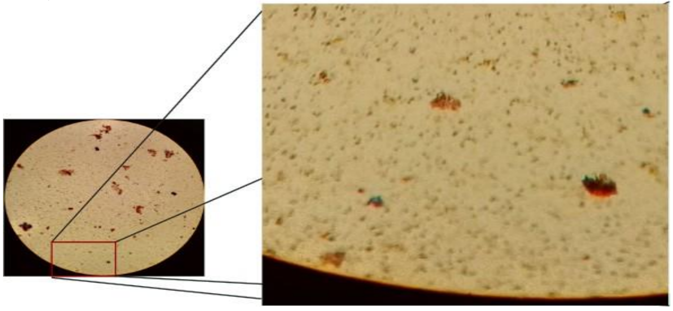


Fig. 4. Blurry parts from the images.

Another issue that arose was the blurriness around the outer parts of the field of view (e.g. see Fig.4). To address this problem, the images were cropped by approximately 18% from the edges. This cropping significantly improved the clarity of the images, ensuring that the central portion, which remained in focus, was used for analysis. By eliminating the blurry edges, the overall quality and reliability of the images were enhanced, making them more suitable for detailed examination.

Next, we created two additional datasets with different image sizes where each image was divided into quadrants as shown in Fig. 4, i.e. from the original we created the second one and the third one. The first dataset did not have any cropping and consisted of 940 images with a size of 1650×1650 pixels. The second dataset had a four quadrant crop and consisted of 3,760 images with a size of 825×825 pixels. And the third dataset had a sixteen quadrant crop and consisted of 15,040 images with a size of 412×412 pixels. Two classes were considered: one with the presence of G. lamblia and one without. No data augmentation techniques were applied.

It is important to note that there was a considerable class imbalance in the datasets, with a significantly higher number of images in the class with the presence of G. lamblia compared to the class without its presence. It is expected that this imbalance could influence the performance of the models, leading them

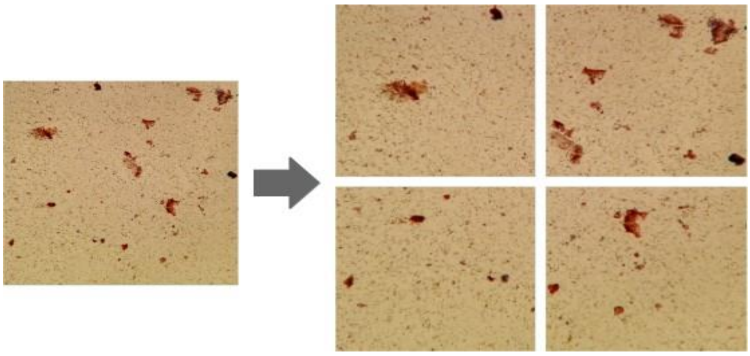


Fig. 5. Images divided into quadrants.

to favor the class with Giardia, and thus impacting the accuracy and reliability of the results.

3 Experiments and Results

The main objective of this work is to understand the effects of image cropping in a deep learning model's performance for identifying microorganisms, i.e., G. lamblia parasite. To achieve this, three datasets were used: one without cropping, a second with images cropped into four quadrants, and a third with images cropped into sixteen quadrants. Each dataset was split into the same images with 80% for training and 20% for testing the architectures, although these images are fed with different sizes in the evaluated architectures. A comparison was performed to analyze the resulting effects.

3.1 Deep Learning Architectures and Settings

Two deep learning architectures were selected: MobileNetV2 [9] and InceptionV3 [10]. MobileNetV2 is highly efficient and simple, it uses depth wise separable convolutions and inverted residual blocks to reduce parameters and operations. It has an excellent balance between precision and efficiency, making it ideal for resource-constrained devices like mobile phones [9].

On the other hand, InceptionV3 is able to extract complex features, depth, and it has proven performance in benchmarks. Its architecture allows for capturing detailed image information while reducing the risk of overfitting, making it ideal for demanding image classification tasks [10].

The experiments were conducted using an Nvidia 1050ti 4GB GPU and 24 GB of RAM. For a fair comparison both models were trained for 20 epochs with a learning rate of 0.001 and compiled using the Adam optimizer. The MobileNetV2 model used a GlobalAveragePooling2D layer, followed by Dense layers with regularization, while InceptionV3 was set up similarly with dropout to prevent

Table 1. Performance metrics for different experiments.

Datasets	Architecture	Accuracy	Precision	Recall
without crop	MobileNetV2	89.9	100	88.3
without crop	InceptionV3	86.2	100	84.7
Four quadrant	MobileNetV2	93.6	100	92.3
Four quadrant	InceptionV3	90.4	100	88.8
Sixteen quadrant	MobileNetV2	94.7	100	93.5
Sixteen quadrant	InceptionV3	93.6	80.4	98.5

overfitting. Key metrics such as precision, recall and accuracy were used to evaluate the model's performance.

3.2 Evaluating Deep Learning Architectures

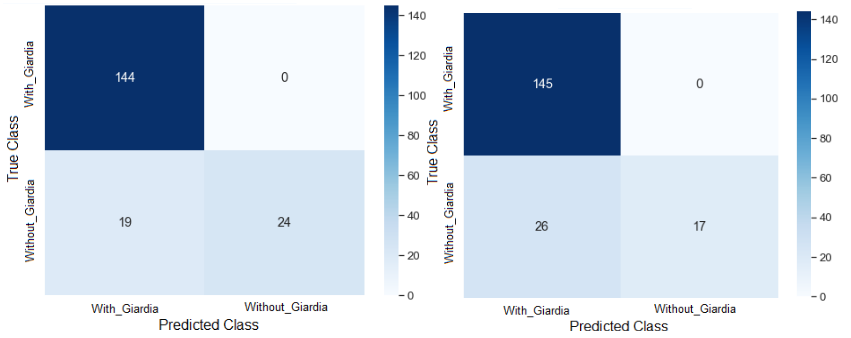
Both models showed better results with the sixteen quadrant crop dataset and among the two architectures, MobileNetV2 had the best results achieving an accuracy of 89.9% on the without crop dataset, 96.6% on the four quadrant dataset and 94.7% on the sixteen quadrant dataset (Table 1).

In Fig. 6, the confusion matrices show that MobileNetV2 had better results than InceptionV3 in terms of balancing true positives and minimizing false negatives on all datasets. MobileNetV2 handled the class imbalance better, achieving higher true negative rates. However, InceptionV3, while slightly less consistent, had a significant reduction in false negatives with the four and sixteen quadrant datasets, this suggests that image cropping into quadrants helped the model to focus on relevant features. Furthermore, given the class imbalance, the models still managed to perform well on the minority class, suggesting a robustness that warrants further exploration. The incidence of false positives was acceptable, considering the nature of the problem, which suggests it's preferable to classify a sample as contaminated rather than incorrectly stating otherwise, prioritizing caution.

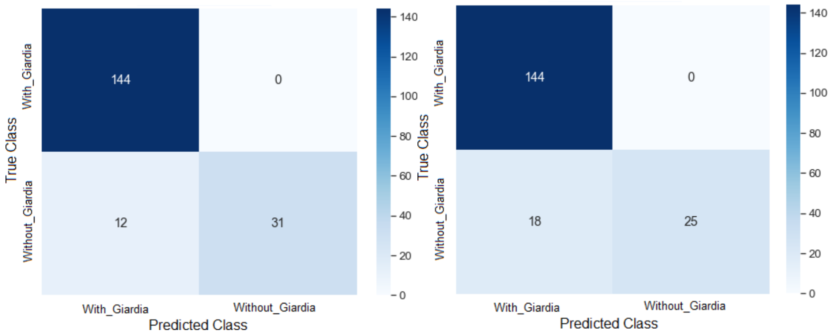
4 Conclusions

The findings of this study indicate that image cropping has better results on the two architectures for the detection of G. lamblia. In fact, the sixteen quadrant crop achieved the best results. This suggests that selectively cutting relevant portions of an image enhances the model's ability to capture essential features, leading to improved performance in identifying G. lamblia cysts.

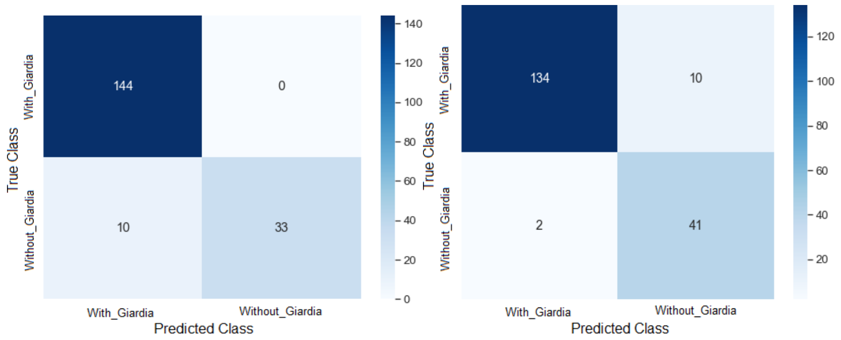
MobileNetV2 was the top-performing architecture, consistently achieving superior results in the three proposed datasets. This results show the effectiveness of MobileNetV2 in handling image variations and extracting relevant information



(a) MobileNetV2 without crop (b) InceptionV3 without crop



(c) MobileNetV2 - 4 quadrant crop (d) InceptionV3 - 4 quadrant



(e) MobileNetV2 - 16 quadrant crop (f) InceptionV3 - 16 quadrant crop

Fig. 6. MobileNetV2 and InceptionV3 confusion matrices.

for the G. lamblia detection task. On the other hand, InceptionV3 also had good results but it did not surpass MobileNetV2.

The observed trend suggests that smaller crop sizes result in better outcomes for G. lamblia detection. This aligns with the intuition that finer granularity in selecting relevant image regions allows the model to focus on more discriminative features, leading to enhanced detection accuracy. However, the presented results between cropping sizes were not remarkable, so it can also be said that making smaller images means a bigger effort in manual classification which is time consuming specially for G. lamblia detection, which may not be worth it even if the results were better slightly better.

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