Prediction of malaria plasmodium stage and type through object detection

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***Abstract* — The use of image processing, artificial intelligence in general, and objects detection in particular for the diagnosis of malaria is increasingly remarkable. In the present work, we suggested a comparison of two objects detection models which is not only capable of detecting the infected blood smears cells but also it enables to distinguish the plasmodium different species and the parasitic stage of malaria. To create our two models, transfer learning from the Faster-RCNN and YOLO models have been used with the MP-IDB database (Malaria Parasite Image Database for Image Processing and Analysis). Then, we have followed three main steps to develop our approach of objects detection for malaria: the creation of annotated databases, image preprocessing, and fine-tuning the two pre-trained models on our annotated database. The Faster R-CNN-based model produced better results than the Yolo-based one, with a mAP @.50IOU of 0.76 versus 0.3.**

Keywords— Malaria diagnosis, Object detection, Transfer learning, Machine learning, Deep learning, Plasmodium, Parasite stage

INTRODUCTION

In 2019, the World Health Organization (WHO) report showed a regressive assessment of the number of malaria cases [1]. Positive statistics that could be improved significantly if the diagnosis of malaria could be done with more precision. Microscopy examination of blood smears, which is the fastest and least expensive way of detecting the disease [2], has gaps that affect the quality of microscopic diagnosis [3]. In the area of the digital world where solutions are becoming more and more innovative and revolutionary, several approaches and methods for the diagnosis of malaria, based on image processing, artificial intelligence and the detection of objects have been introduced. Unfortunately, due to a lack of data, none of them worked on the distinction between the type of plasmodium and the parasitic stage. Therefore, this research paper mainly focuses on the creation of object detection models capable of distinguishing both the stage and the parasitic species.

II. CONCEPTUAL CLARIFICATION

A. Notions about the diagnosis of malaria

Malaria is caused by a parasite called *plasmodium*, which has mainly four different species (falciparum, malariae, ovale, and vivax) that can be found in mainly four different stages of evolution (trophozoite, schizont, gametocytes, and ring). Microscopy examination involves manually examining blood smears to detect and count cells infected by a plasmodium, with the specie and the stage. This operation is tedious and prone to medical errors. It is to automate and facilitate this work that researchers have striven over the last decade to use automatic learning methods and in particular object detection (a branch of artificial intelligence more precisely computer vision), for the diagnosis of the disease. The latter approaches produce the most encouraging results. As part of this work, object detection techniques have been implemented to create a solution for the detection of both the stage and the parasite species.

B. Object detection

Object detection is a computer vision technique aimed at detecting objects in images or videos. Object detection is the combination of localization and classification. Indeed, it makes it possible to locate the presence of an object in an image, assign it a class, and draw a frame (bounding box) around this object.

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C. AI-based detection methods

Artificial intelligence (AI) is a field of computing that focuses on creating intelligent machines that work and react like humans. It is now involved in almost all areas including speech recognition, learning, and planning. It includes many branches including Machine learning [4], Deep learning [4][5], and Transfer learning [4].

D. Object detection algorithms

Detecting objects in images is a complex challenge for standard convolutional neural networks due to the variable length of the output layer depending on the number of object occurrences. A naïve approach would be to take different regions of interest from the image and classify the presence of the object in that region. However, this method requires selecting a very large number of regions, which can lead to an explosion of calculations. To solve this problem, algorithms such as R-CNN, Fast R-CNN, Faster R-CNN, and Yolo have been developed to quickly find those occurrences of objects with different spatial locations in the image and different aspect ratios.

C. Object detection performance metrics

The main metric used to measure the performance of object detection models is mAP (mean Average Precision). It calculates the accuracy taking into account the accuracy of the classification and also the localization. Other metrics such as precision and recall as well as the Intersection on Union (IoU) threshold have been developed.

III. State of the art on works having applied the detection of objects on the diagnosis of malaria with object detection.

This document has found interesting the work of three scientists:

- The work of P.A. Pattanaik et al.[7], They proposed a three-step object detection procedure with the detection kernel and filtering process to detect Plasmodium falciparum parasites in thin blood smear images. Their experimental results demonstrate the efficiency of the proposed method of object detection, which had never before been tested in the field of malaria diagnosis compared to computer vision algorithms.
- The work done by J. Hung et al.[8], They applied for the first time the Faster R-CNN model to identify cells and recognize parasite stages on bright field microscope images of blood infected with malaria. They demonstrated that Faster R-CNN outperforms their baseline and puts the results in the context of human performance.
- Finally, the work of F.Yang et al.[9], Cascaded YOLO for the automated detection of Plasmodium vivax in thin blood smears. They developed a rapid and robust diagnostic system for the automated detection of P. vivax parasites using a YOLO cascade model. This system consists of a YOLO model and a classifier for extraction.

IV. Materials and methods

A. Database used

The dataset we have chosen is the main database of smear images allowing us to distinguish both the parasite stage and the type of plasmodium. It is called MP-IDB: The Malaria Parasite Image Database for Image Processing and Analysis [6].

B. Pre-trained models

Nowadays, there are several state-of-the-art object detection models. According to the study conducted by M. Priyanka and G. Ekansh[10] on a comparison of object detection techniques, the three main object detection approaches are R-CNN, Faster R-CNN, and YOLO. So the choice has been made on two of them namely Faster-RCNN illustrated by Figure 1, and Yolo.

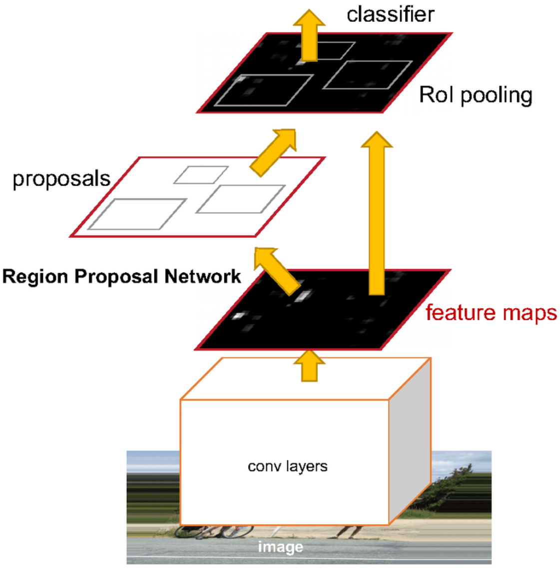

Figure 1: Faster R-CNN architecture [11]

C. Database annotation

The database structuring is not in the form of annotation required for training an object detection model using Faster RCNN or Yolo. In the dataset, each original image has its own ground truth, provided by expert pathologists, analyzed from left to right. Therefore, we created the bounding box annotation for each individual infected cell, for each database image. We used XML files for faster RCNN and Txt files for Yolo. We have also created and used sixteen classes to make the distinction between both species and stages (Table1).

	R	**S**	**T**	**G**
Falciparum	falciparumr	falciparums	falciparumt	falciparumg
Malariae	malariaer	malariaes	malariaet	malariaeg
Ovale	ovaler	ovales	ovalet	ovaleg
Vivax	vivaxr	vivaxs	vivaxt	vivaxg

Table 1: List of used-classes

D. Training configurations

In this section, it is important to note that some data augmentation techniques have been employed (rotation with various angles and distortion with various methods) to balance the size of the different classes and obtain a final database of 1903 images. Then, the data was split as follow: 70% for training, 20% for validation, and 10% for test data.

There are no standard subdivision percentages, but it appears that in the literature these percentages are very often used.

V. RESULTS AND DISCUSSION

A. Results with Faster R-CNN

For the Faster R-CNN model, the evolution curve of the average accuracy value mAP@.50IOU reached a performance of 76% (Figure 2), while the classification accuracy corresponding to the maximum value of mAP@ .50IOU is 0.47 (Figure 3). The localization accuracy corresponding to the maximum value of mAP@.50IOU is 0.54 (figure 4).

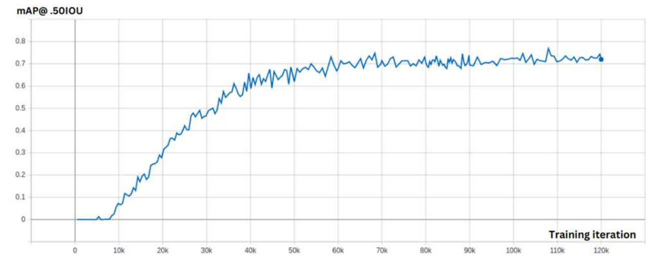

Figure 2: Evolution curve of mAP @.50IOU with faster RCNN

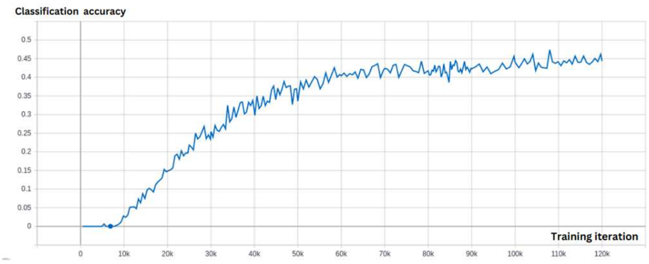

Figure 3: Accuracy curve with faster R-CNN

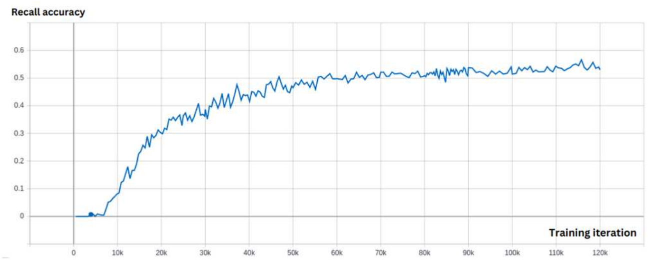

Figure 4: Recall curve with faster R-CNN

Figure 4.1 shows an example of an inference made with the resulting final model.

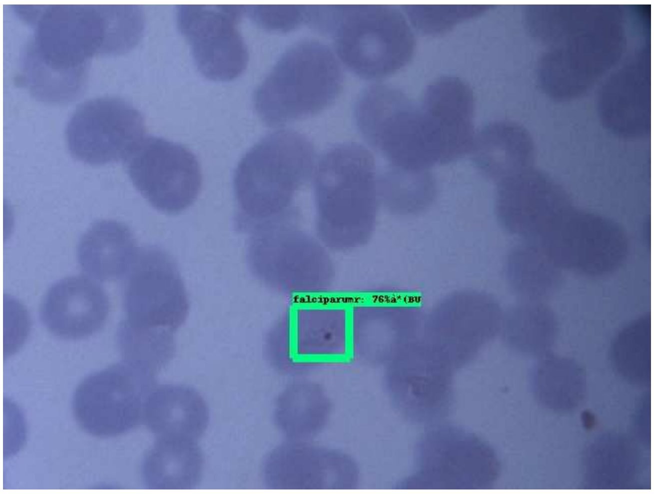

Figure 4.1: Example of a blood cell infected by a plasmodium falciparum at ring stage detected with the fine-tuned Faster RCNN model.

B. Results with Yolo

For the YOLO model, the evolution curve of the average accuracy value mAP@.50IOU has reached a performance of 30%, (figure 5) while the accuracy of the classification corresponding to the maximum value of mAP@.50IOU is 0.74. (Figure 6). The localization accuracy corresponding to the maximum value of mAP@.50IOU is 0.048 (figure 7).

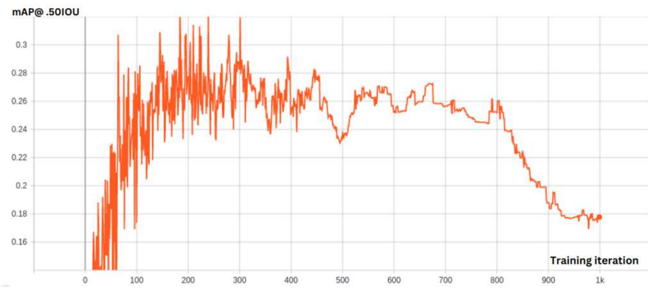

Figure 5: Evolution curve of the mAP @.50IOU with Yolo.

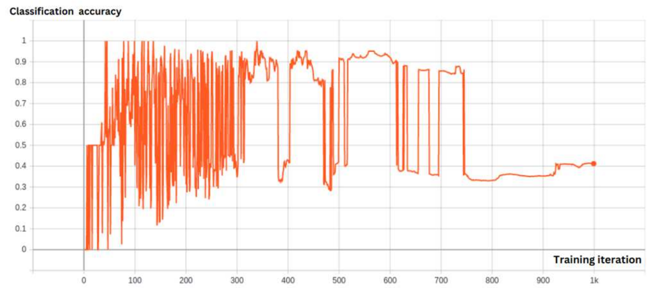

Figure 6: Accuracy curve with Yolo.

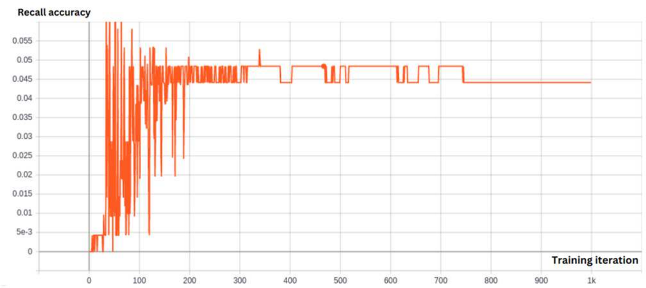

Figure 7: Recall curve with Yolo

Figure 7.1 shows an example of inference made with the resulting final model.

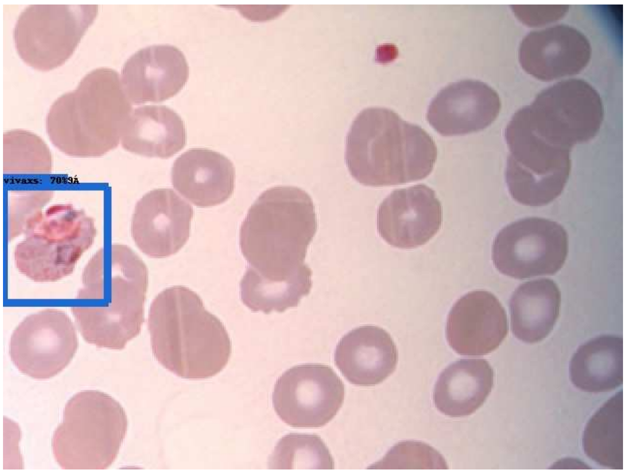

Figure 7.1: Example of a blood cell infected by a plasmodium vivax at schizont stage detected with the fine-tuned Yolo model.

C. Discussion of results

We can note that the most efficient model from the point of view of mAP, IoU = 50 is faster-RCNN with a value of 76% against 30% for Yolo. From the classification point of view, Yolo has a score of 74.2% against 47% for Faster R-CNN. However, Yolo is really inefficient from the localization point of view, with only 4.8% against 54% for Faster R-CNN. Overall, it can be inferred that Faster R-CNN model gave the best results.

Moreover, as shown in Table 2, our results are not really high as compared to other works. This can be justified by the small size of our dataset (223 images), the number of classes to predict on this dataset (16 classes), and the non-uniformity of the numbers between the classes. Although, the results are interesting and could lead to better performances if we have a well-balanced and larger dataset.

Authors	**Method**	**Dataset**	**Results**
P.A. Pattanaik et al., 2017	Three-stage object detection procedure of computer vision with Kernel-based detection and Kalman filtering process	- Dataset 1: plasmodium falciparum at ring stage (count not specified) - Dataset 2: plasmodium falciparum at trophozoites stage - Dataset 3: plasmodium falciparum at the schizont stage	sensitivity: **81.58%** specificity: **97.11%** sensitivity: **91.82%** specificity: **95.23%** sensitivity: **91.70%** specificity: **94.90%**
J. Hung et al., 2018	Applying Faster R-CNN (Fine tuning on malaria dataset)	1300 images of thin blood smear fields of plasmodium vivax (stage not specified)	accuracy (classification): **98%**
F. Yang et al., 2020	Cascading YOLOv2 model and a classifier.	2567 images of thin blood smear of plasmodium vivax	mAP: **79.22%**
Our work	Applying and comparing Faster R-CNN and YOLO for Object Detection on Malaria Images.	223 images of thin blood smear fields of plasmodium falciparum, malariae, ovale and vivax and at stage trophozoite, schizont, gametocyte, and ring.	Faster-RCNN: mAP **76%** YOLO: mAP **30%**

Table 2: Results in comparison with other state-of-the-art methods

VI. Conclusion

The system proposed in this research document satisfies the objectives that were defined at the beginning of the work. To recall, this paper aimed to create and compare two object detection models, one based on Faster RCNN and the other based on Yolo, which will be capable of predicting the stage (ring, trophozoite, schizont, gametocytes) and type (falciparum, malariae, ovale, vivax) of malaria plasmodium. The obtained-results are satisfactory compared to the initial objectives, with a higher localization accuracy for the Faster R-CNN model than for the Yolo model. However, potential improvements were identified, namely the use of other pre-trained models, larger databases, and exploring methods for handling imbalanced datasets. To cap it all, this work shows that object detection models can be used for malaria classification and suggests avenues for future improvements of the method.

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