Automatic Detection of Ascaris Lumbricoides in Microscopic Images using Convolutional Neural Networks (CNN)

Giovanni Gelber Martinez Pastor, Cesar Roberto Ancco Ruelas,
Eveling Castro-Gutierrez, Victor Luis Vásquez Huerta
Professional School of Systems Engineering, Universidad Nacional de San Agustín de Arequipa, Arequipa, Peru
Professional School of Medicine, Universidad Nacional de San Agustín de Arequipa, Arequipa, Peru

***Abstract*—Parasites are disease-causing agents both in Peru and worldwide. In many contexts, diagnosis is done manually by observing microscopic images, where it's necessary to identify parasite eggs. However, this process is notably slow, and sometimes image clarity may be insufficient, making rapid and accurate identification challenging. This can be due to various factors, such as image quality or the presence of noise. This paper focused on a Convolutional Neural Network (CNN) model. Through this approach, the training, testing, and validation stages of our CNN model to detect and identify Ascaris lumbricoides parasite eggs. The results show that the proposed CNN model, combined with image preprocessing, yielded highly favorable results in parasite egg identification. Additionally, very satisfactory values were achieved in model testing and validation, indicating its effectiveness and precision in diagnosing parasite presence. This research represents a significant advancement in the field of parasitological diagnosis, offering an efficient and accurate solution for parasite detection through microscopic image analysis. It is hoped that these results contribute to improving diagnosis and treatment methods for parasitic diseases.**

Keywords—Ascaris lumbricoides; Convolutional Neural Networks; OpenCV; microscopic images; moment-based detection

I. Introduction

Currently, not only in Peru but worldwide, parasites are agents causing multiple diseases in humans, mainly in tropical areas. There are many types of parasites in the world, as mentioned in research [1], [3], which provides a comparison of parasite appearance notifications. In Peru, according to this 2017 report [2], the most common parasites that threaten human health are Trichuris trichiura, Ascaris lumbricoides, Enterobius vermicularis, Necator americanus, causing multiple diseases in both children and adults,also in the article of Cabada [21], a study was conducted on the prevalence of parasites in the region of Paucartambo, Peru, where it was found that of the total number of children surveyed (334), 34.12% were infected with Ascaris lumbricoides among others, which concluded that it had a direct relationship with the anemia that has been occurring in the region, the article of Villamizar [22] also states that Ascaris lumbricoides is related to poor sanitation practices and is dangerous if not detected in time, since, as mentioned in his research, it causes intestinal severe obstructions that mainly affect children.

Various techniques exist in the global landscape. The manual [19] published by the WHO outlines these microscopic techniques. Health professionals use these techniques to detect parasites to diagnose patients and provide appropriate treatment. However, it can take considerable time to reach an accurate diagnosis with this method. This delay in diagnosis raises the question: Is it possible to develop an automated artificial intelligence tool to diagnose parasites using microscopic images of their eggs?

In this research, the following questions will be addressed: How can artificial intelligence be employed to detect parasite eggs? What automated tool could be developed using microscopic images? What impact would the use of artificial intelligence have on diagnostic time? What would this research contribute to the field of medicine?

In this study, a CNN model designed to predict the presence of parasites through microscopic images is presented., with a specific focus on detecting eggs of the Ascaris lumbricoides parasite using Computer Vision techniques because using this technique with artificial intelligence brings great benefits [23], [24]. The purpose is to provide an automated tool that reduces diagnosis time, supporting specialized doctors and less experienced practitioners. This study aims to improve the efficiency of parasitosis diagnosis and contribute to more effective and timely medical care.

This research focuses on developing an automated tool for the rapid and accurate diagnosis of parasites using microscopic images. By reducing diagnostic time, the efficiency of treatment is improved, and medical care is optimized, benefiting both health professionals and patients. Moreover, the implementation of artificial intelligence in this field is a significant step towards standardizing diagnostic quality, paving the way for innovative and advanced clinical processes.

A pilot model was sought to achieve at least 90% accuracy. The following stages were carried out: a) Collection of the dataset, considering images where the parasite can be visualized cleanly or with minimal noise, and others where the Ascaris lumbricoides egg is heavily obscured. b) Preprocessing of the dataset, aiming to extract the most essential features of the image using OpenCV moments. c) Training of the Deep Learning model with the preprocessed data.

The work demonstrated that OpenCV moments can assist CNNs in object detection by identifying objects of interest in images. These objects can then be extracted to simplify the network's detection task.

The article is structured into six sections. Section I covers the introduction, while Section II examines related Works. Section III details the methodology used, followed by the presentation of results and discussions in Section IV. Section V consolidates the findings obtained, while Section VI details conclusions and future work.

II. Related Works

In his thesis work in 2019, Eduar Vásquez developed an algorithm for detecting Trichuris trichiura eggs using microscopic images of coprological samples. For this purpose, 1000 images were selected as samples, dividing the set into 30% for verifying the algorithm's performance and 70% for training it. The algorithm was implemented in Python, using libraries such as OpenCV, Numpy, and Matplotlib, among others.

The original images were 1280 x 960 pixels, and fragments of size 65 x 65 pixels were extracted for analysis. For image processing, a color vector was generated using the HSV model with three hue intervals, four saturation intervals, and four brightness intervals, using a Manhattan distance metric. Additionally, another vector was implemented for classification, achieving a sensitivity of 99.35% and an accuracy of 96.1%.

In a study conducted in 2022 [5] by C. Lee et al., the limitations faced by specialists in manually counting parasite eggs were addressed. The Helminth Egg Analysis Platform (HEAP) was developed in response to this issue. This platform focuses on automating egg counting by processing images using Python code. Eggs are identified using moment-based techniques and TensorFlow for prediction, leveraging GPU performance. This system is integrated into an Apache web environment and uses PHP scripts for queue system management.

The main objective of HEAP is to facilitate the identification of microscopic helminth eggs, aid technicians in diagnosing parasitic infections, streamline the process, and reduce the possibility of errors associated with manual counting.

1) Convolutional Neural Networks (CNNs): In the work published in 2021 [6] by T. Suwannaphong et al., a technique based on Convolutional Neural Networks (CNNs) is proposed to improve the automatic classification of parasites in low-quality microscopic images using transfer learning. All images used were captured and extracted from a low-cost USB microscope. Additionally, a sliding window technique was implemented to detect the location of parasite eggs in the images. Two neural networks, AlexNet and ResNet50, were evaluated, considering the architecture size and classification capacity. Both networks were trained with a mini-batch of 100 and 20 iterations, achieving highly satisfactory results in terms of accuracy. This approach demonstrates its effectiveness even in the case of examination with low-cost microscopes.

In the study published in 2022 [7], a Deep Neural Network (CNN) is presented. It is designed to improve the accuracy in diagnosing malaria, a deadly disease transmitted by female mosquitoes of the genus Anopheles found in various regions of the world. The study focuses on analyzing microscopic images of red blood cell smears.

For this purpose, three pre-trained CNN models were used: VGG19, ResNet50, and MobileNetV2. However, these neural networks performed poorly when using small datasets. Therefore, a transfer learning technique was implemented, which allowed overcoming this limitation and improved the system's performance. The three pre-trained models were evaluated using a malaria dataset provided by the National Institutes of Health (NIH), achieving an accuracy close to 100%.

In 2023, the work [8] by M. Faruq Goni et al. introduced an unconventional method for forecasting malaria based on an Extreme Learning Machine (ELM) algorithm. This approach arises due to the problems related to delays and inaccuracies in malaria forecasts when using antigen tests and microscopy. Convolutional Neural Networks (CNN), ELM, and Double Hidden Layer (DELM) were used as classifiers to implement this method. The CNN acted as a feature extractor and classifier for comparative analysis, while ELM and DELM were used for training. The datasets consisted of malaria images, divided into two versions: one with original images and another with modified samples where ambiguous samples were removed. The comparison between both methods revealed that CNN-DELM showed superior performance in terms of accuracy compared to CNN-ELM. The optimal results obtained were 97.79% and 99.66% for the original and modified versions, respectively.

III. Methodology

This section describes the methodology used for creating the model, illustrated in Fig. 1. These stages include Extracting images from the 'Chula-ParasiteEgg' dataset [9].

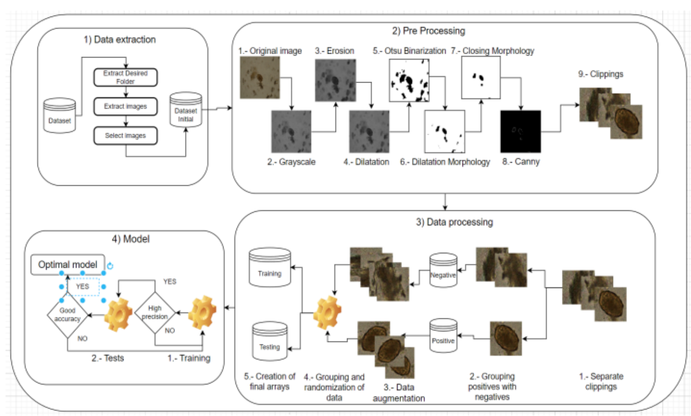

Fig. 1. The stages of the methodology used for creating the CNN model are as follows: the first section is Data Extraction, followed by Data Preprocessing, Data Processing, and Architecture.

A. Data Extraction

The first step was to create a dataset to train the CNN model, which is why two datasets were combined: A) Images of Ascaris lumbricoides eggs from the "Chula-ParasiteEgg" dataset, which contains medical images of various types of parasite eggs, PARASITIC EGG from IEEE DataPort, and b) microphotographs dataset obtained from the Laboratory of the Faculty of Medicine of UNSA, processed by specialists. This dataset, named DATASET GASTROPARS_UNSA, contains images of parasite eggs obtained through stool examination. Images were extracted and selected from both datasets based on the following criteria:

- It belongs to an Ascaris lumbricoides egg.
- The image is rectangular and complete.
- It has a name corresponding to the parasite.
- The image does not show objects or designs that alter it.

Once the images were selected, they were saved in a folder to group them and process them in an organized manner.

B. Data Preprocessing

In this stage, the previously generated dataset is worked on to extract the essential features of the image using OpenCV moments through the proposed procedure in Fig. 2. These processes are 1) Image normalization, 2) Color normalization, 3) Erosion, 4) Dilation, 5) Otsu Binarization, 6) Dilation Morphology, 7) Closing Morphology, 8) Application of the Canny Filter, and 9) Cropping of detected objects.

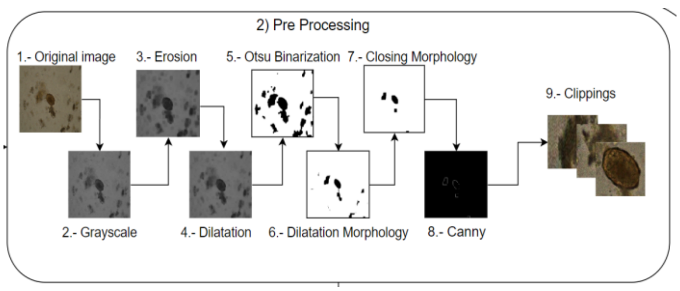

Fig. 2. Stages of preprocessing carried out on the frames.

1) Image normalization: According to Sudeep [10], the first step in processing the images is to scale them to 500x500 pixels, which is a process for obtaining normalized variance.

2) Color normalization: As mentioned in the work of H. M. Bui [17], normalizing images to grayscale reduces them to a single channel, as observed in Fig. 3, making CNNs more efficient compared to using three channels (RGB).

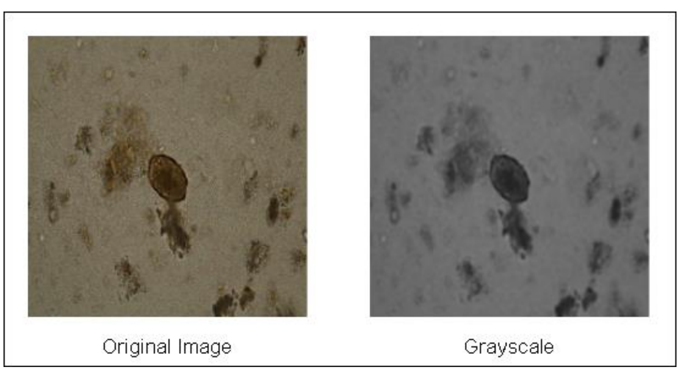

Fig. 3. Grayscale scaling in images.

3) Erosion: According to Viera's article [11], erosion removes spurious image features, as observed in Fig. 4.

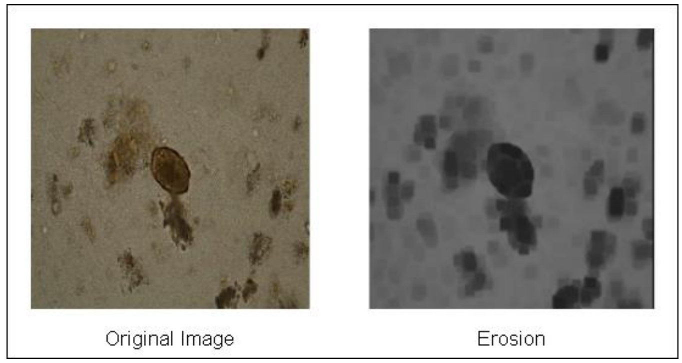

Fig. 4. Erosion in images.

4) Dilatation: Through this step, the edges of objects were structured to define the contours after erosion, as seen in Fig. 5, where imperfections are removed and some essential aspects of the image, such as the parasite, are highlighted.

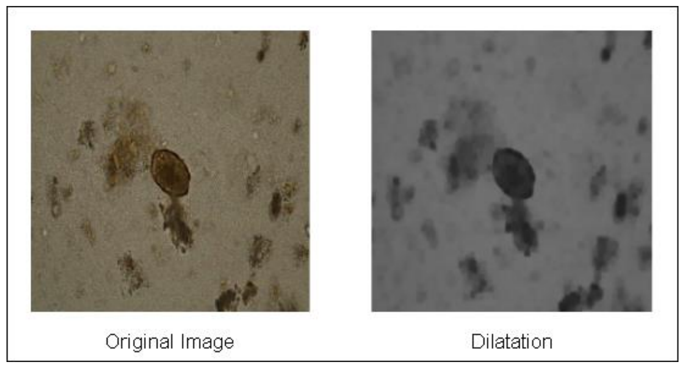

Fig. 5. Dilatation in images.

5) Otsu binarization: The latter was extracted once spurious features were eliminated or significantly reduced, and the larger ones were highlighted. Binarization was used, as mentioned in the article [12]. This binarization assumes linear discriminant criteria with which the image is processed, assuming it is a single object and a background that is sought to be ignored.

The method described in Yousefi's work [12] explains how the process depicted in Fig. 6 operates.

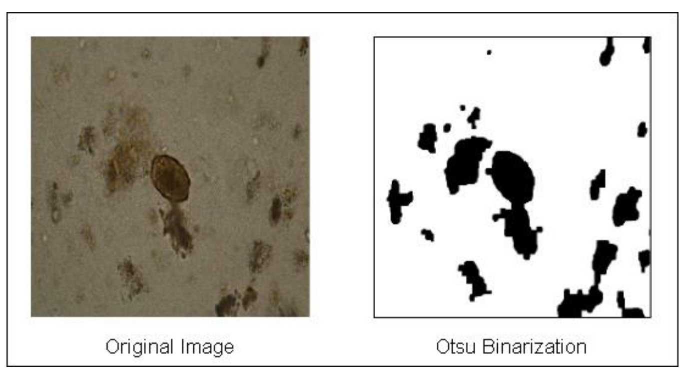

Fig. 6. Otsu Binarization in images using OpenCV.

6) Dilation morphology: After completing the previous step, the essential features of the image were determined, which may still include a large part of unwanted objects. Therefore, two more morphologies were applied to reduce these objects, with the first being dilation morphology. As mentioned in the work of Roy [20], dilation and erosion are shape-sensitive operations that help to discriminate the objects in the image. A [20 x 20] kernel was established, and objects were separated, such as a parasite with a stain attached to it and not part of the parasite, as seen in Fig. 7.

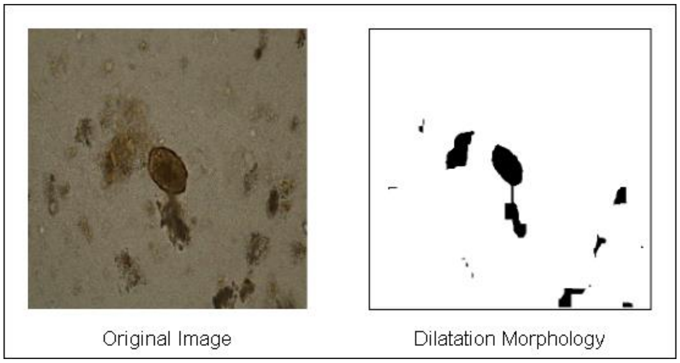

Fig. 7. Dilation morphology in images using OpenCV.

7) Closing morphology: It consists of applying the dilation morphology again, including the resulting image from the erosion process, obtaining the most significant objects detected previously, and eliminating the smaller ones.

Monday [16] allows applying filters to the image, improving its processing, as shown in Fig. 8.

Fig. 8. Closing morphology with OpenCV.

8) Application of the canny filter: To conclude, the "Canny Filter" was applied, which helps us obtain the contours of the images, serving as a preliminary step to applying OpenCV moments.

As mentioned in Mohd Anul's work [14], applying the Canny filter is useful because it allows separating objects from the background of the image and prevents unwanted detection, as shown in Fig. 9.

9) Object cropping: After completing the process, the images were cropped based on the identified contours, which were separated for further analysis and classification. This classification was divided into two groups: a) crops containing parasite eggs and b) crops that did not contain parasite eggs. These crops were stored in separate folders for future reference.

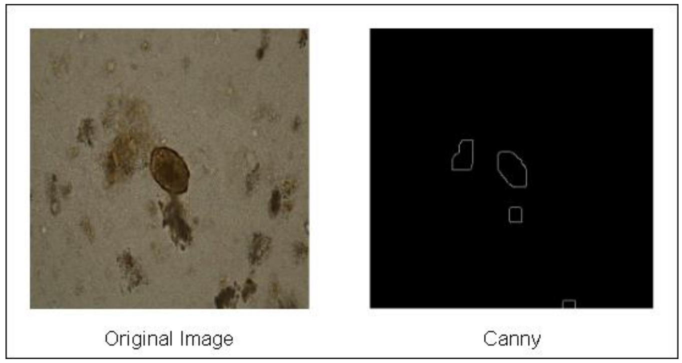

Fig. 9. Canny filter on the preprocessed image.

C. Data Processing

The frames were normalized, dividing them by 255 to obtain values between 0 and 1.

Arrays of the images were created, to which a data augmentation technique was applied, as explained in the work of [13] and [18]. The rotation geometry technique is one of the most popular for this task (see Fig. 10).

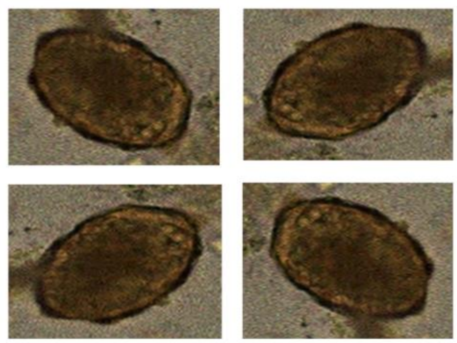

Fig. 10. Example of the rotations that were applied.

Also, in Omar's work [15], this process is useful for improving the balance of the dataset and generating more useful cases for training.

When the image augmentation was completed, 4852 data were obtained.

D. Model

For the final step, the training and validation of the model were conceived. The training arrangement was divided into 80% for the training phase and 20% for the validation phase.

Then, the created model was tested for accuracy and loss using images that it had never seen during its training, and based on that, the most optimal model was chosen.

E. CNN Model Architecture

The CNN model has four convolution layers (32, 64, 128, and 256 filters, respectively) applying a 3x3 kernel and a ReLU activation function per convolution layer, four MaxPooling layers between the convolution layers applying a 2x2 kernel, a flattening layer to be able to connect to the neural network, for such a network, one (1) input layer, two (2) hidden layers and one (1) output layer, with a ReLU and "sigmoid" activation function as shown in Fig. 11.

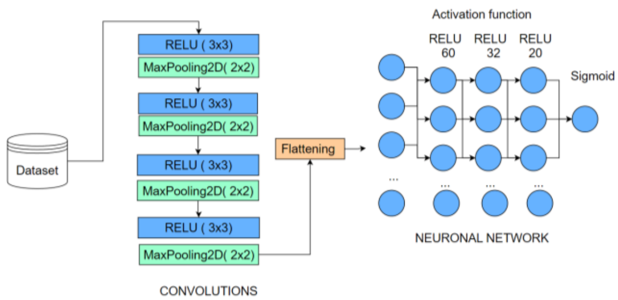

Fig. 11. Example of the rotations applied.

IV. Experimentation

In this stage, we tried to run and adjust the parameters and values of both the processing and the architecture of the model; four stages of experimentation influenced the construction of the model, and the accuracy and its success in new cases were used to determine the model to be chosen.

A. First Experimentation

There were 1,213 initial frames, which conformed to the original positive and negative cases. The initial configuration was four convolution layers (32,64,64,128, respectively, with a 2x2 kernel) and four hidden layers (32,64,128,1, respectively), results shown in Table I.

TABLE I. Result of the Iterations in the First Experimentation

Iterations per Batch	% Training	% Validation	% Testing
10	80.07 %	86 %	70 %
20	90 %	95%	65.89 %

B. Second Experimentation

For this test, 2426 frames were contemplated for training and testing the model. At this stage, the images were mirrored to increase the data the model will have. Table II and Fig. 12 show the percentages obtained as the same architecture configuration.

TABLE II. Results of the Iterations in the First Experimentation

Iterations per Batch	% Training	% Validation	% Testing
10	85.25 %	92.13 %	80.12 %
15	95.90 %	93.04 %	89.45 %

C. Third Experimentation

The image mirroring was performed in the four directions to increase the data delivered, reaching 4852 (3880 for training and 972 for testing). At the same time, adjustments were made to the architecture to obtain better results; being the changes in the convolution layer, we used 32,32,64,64,64 with a 3x3 kernel and four hidden layers in the neural network with 32,32,64,1 respectively, obtaining the results shown in Table III and Fig. 13.

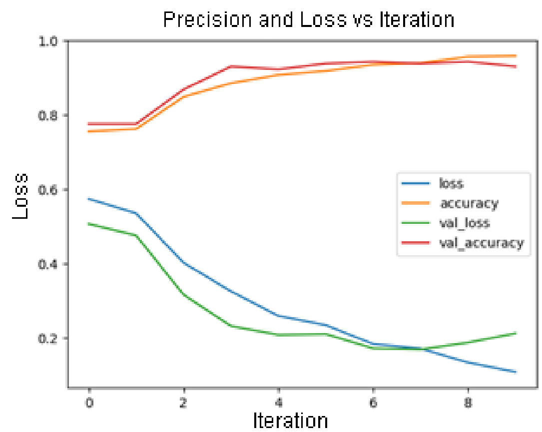

Fig. 12. Graph of the results of the second experimentation, the upper part being accuracy vs. val_accuracy and the lower part loss vs val_accuracy.

TABLE III. Results of the Iterations in the Third Experimentation

Iterations per Batch	% Training	% Validation	% Testing
10	87.45 %	85.36 %	89.28 %
15	94.72 %	92.14 %	93.72 %

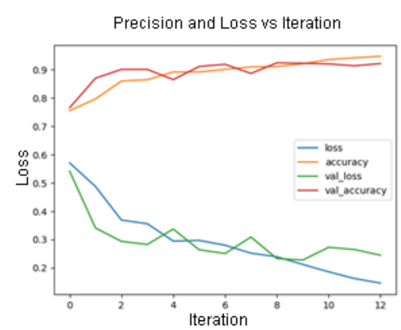

Fig. 13. Graph of the results of the third experimentation, the upper part being accuracy vs. val_accuracy and the lower part loss vs. val_accuracy.

D. Fourth Experimentation

In this last stage, 4852 frames from the previous stage are still preserved. However, mainly changes were made to the architecture, which was altered based on trial and error, based on the accuracy of the model when testing with the corresponding dataset as well as a new one to check that the accuracy of the model does not decrease to a great extent, being these changes, in the convolution layer 32,32,64,128 were used respectively with a 3x3 kernel, keeping the initial maxpooling, in the neural network layers it is still kept in 4 but with 60,32,20,1 nodes respectively, obtaining the results shown in Table IV and Fig. 14.

TABLE IV. Result of the Iterations in the Fourth Experimentation

Iterations per Batch	% Training	% Validation	% Testing
10	85.62 %	87.59 %	86.93 %
20	97.68 %	91.75 %	90.03 %

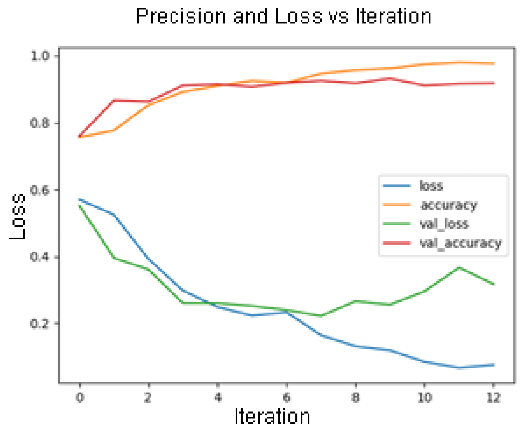

Fig. 14. Graph of the fourth experimentation results, with the upper part showing accuracy vs. val_accuracy and the lower part showing loss vs. val_accuracy.

For the choice of the last model (experiment 4), a new test dataset was created with 320 frames, whose images had not been observed by the model, in order to evaluate the result of these last three experiments and thus verify which model could generalize better, the results being those presented in Table V:

TABLE V. RESULT OF THE TESTS ON THE MODELS WITH THE NEW DATASET

No. of experimental stage	% Validation
2	70.85 %
3	74.68 %
4	89.69 %

V. RESULTS AND DISCUSSION

This work utilized a dataset of 400 microscopic images of the Ascaris lumbricoides parasite. All these images underwent preprocessing to obtain a clean image of the parasite and include negative cases. With all this preprocessing, 1,213 images were obtained, and after data augmentation, 4,852 images were achieved. Each image was processed to be inputted and trained into the CNN model. Differences were observed in the model configuration compositions, and with these new configurations, obtaining the most optimal CNN model possible was possible.

Four stages of experimentation were conducted with different iterations of the model to obtain training, validation, and test percentages.

In this research, we are developing a CNN model to detect the Ascaris lumbricoides parasite using preprocessed microscopic images. Compared with the literature, we observed no studies explicitly addressing Ascaris lumbricoides. A study [4] focused on Trichuris trichiura eggs, and an algorithm was developed to extract a vector using HSV colors. Work [5] centered on creating a helminth egg analysis platform (HEAAP) to identify helminth eggs and support technicians in parasite infection examinations. In study [6], a CNN model was developed using a sliding window technique to identify parasite egg positions. Study in [7] focused on the Malaria parasite, employing a CNN model with three pre-trained models. The study in [8] also evaluated the Malaria parasite but implemented an Extreme Learning Machine (ELM) algorithm and used a CNN as a feature extractor and classifier.

Our research addresses the Ascaris lumbricoides parasite and explicitly compares it to existing literature. While some studies have used CNN and other approaches, our model incorporates additional techniques, like object detection using OpenCV moments. Furthermore, our study focused on identifying and detecting parasite eggs from microscopic images.

This proposed method used all available hardware resources, including the GPU and CPU, to reduce the model's training time during experimentation. A noticeable difference in training times was observed between the GPU and CPU, with an average improvement of 1.6159% achieved using the GPU. This disparity is outlined in Table VI.

TABLE VI. TIME EMPLOYED FOR TRAINING AND EXPERIMENTATION OF CNN MODEL

GPU	CPU
17 seconds (0:17 minutes)	1052 seconds (17:32 minutes)

Two models were developed during the testing phase, achieving training and validation accuracies exceeding 90%. Table VII details each model.

TABLE VII. COMPARISON OF RESULTS FOR SELECTED MODELS IN THE TESTING PHASE

Indicator	Model 1	Model 2
Image Size	500x500	300x300
Training		
loss	0,1087	0,15
accuracy	0,959	0,948
val_loss	0,2125	0,252
val_accuracy	0,9304	0,899
Validation		
loss	0,2191	0,214
accuracy	0,95679	0,93

This entire process was carried out using two sets of images for training and validation to create a model with the highest prediction percentage. The first group comprised 3,396 images used for training; the model utilized these images for its training phase. The second group consisted of 1,456 images not used for training but entirely new images dedicated solely to testing the model and evaluating its prediction percentage.

After analyzing the results obtained, the study's strengths and limitations were identified. In terms of strengths, the model's versatility in detecting various types of parasite eggs and its reliability in classifying images containing these eggs stood out. Additionally, creating a dedicated dataset for testing facilitated comprehensive evaluation and significantly improved the model's reliability. On the other hand, limitations included a) disk space constraints on the equipment used, b) limited availability of only two small datasets for model training and c) restrictions on the capabilities of the computer equipment employed.

Expanding the preprocessing stages enhances the parasite recognition capability in less clear medical images and diversifies the range of parasites detected by CNN. Given the potential of the presented model to identify the Ascaris lumbricoides parasite with the current preprocessing, there are high expectations of detecting a greater variety of parasites. This implementation would be crucial in supporting specialists, as intestinal parasites need to receive more attention. Specialists' availability of diagnostic assistance software is paramount in this context.

VI. CONCLUSIONS AND FUTURE WORK

This paper presents a convolutional neural network (CNN) model designed to analyze microscopic images. This work implemented a moment-based object detection approach, allowing us to identify the parasite within the image and separate it from other components (such as noise). This process was carried out using OpenCV and Python, which allowed to isolate the Ascaris lumbricoides parasite in a separate image. This image was used in the model's training and testing phases.

In the proposed model, four experiments were conducted, each with different numbers of iterations, resulting in significant variations in performance percentages. The most notable results were obtained in the third experiment, using 15 iterations per batch. In this case, accuracy percentages in the Training, Validation, and Testing phases reached 94.72%, 92.14%, and 93.72%, respectively, leading to an acceptable model. However, a final experiment incorporated a new set of images with a difference of 20 iterations, resulting in percentages of 97.68%, 91.75%, and 90.03%, respectively. These results highlight the model's great potential, especially regarding image preprocessing handling and object detection using Moment-based techniques.

Future work involves replicating the methodology with different parasite egg datasets to evaluate its efficiency, refine the approach, and develop a system to assist students and doctors in identifying parasite eggs.

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