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Deep learning model for Cutaneous leishmaniasis detection and classification using Yolov5

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Abstract:
Scars and skin ulcers are a feature of many skin diseases, including cutaneous leishmaniasis (CL). In endemic areas and developing countries, infection identification remains a challenge for the physician, the health system, and the patient. This study introduces an important new diagnostic method for rapid detection and accurate diagnosis by establishing a YOLOv5 training model to recognize cutaneous leishmaniasis (CL), under normal conditions based on the YOLOv5 network depends upon a deep learning approach. The development environment is related to Python language. The training data set contains a total of 160 photos taken from a mobile phone camera and converted to grayscale images to extract characteristic features and then applied image processing techniques such as flipping, rotating, and resizing to increase the dataset information. Image labeling was identified with a dermatologist to ensure the injury of cutaneous leishmanias (CL).In our approach, images were classified using polygonal bounding boxes to identify areas of interest so that dataset was divided into validation, training, and testing. flowed by feeding the dataset in the YOLOv5s. Our model was able to locate cutaneous leishmaniasis (CL) and achieved high accuracy in detecting and classifying infections, with an average accuracy of 70%. Which provides a speed technology for detection.

Keywords: cutaneous leishmaniasis, deep learning, YOLOv5, image processing

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نموذج التعلم العميق للكشف عن داء الليشمانيات الجلدي وتصنيفه باستخدام Yolov5

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الملخص
الندبات وتقرحات الجلدية هي سمة من سمات العديد من الأمراض الجلدية، بما في ذلك داء الليشمانيات الجلدي (CL) في المناطق الموبوءة والنائية، يظل تحديد العدوى يمثل تحديًا للطبيب والنظام الصحي والمريض. تقدم هذه الدراسة طريقة تشخيصية جديدة مهمة للكشف السريع والتشخيص الدقيق من خلال إنشاء نموذج تدريب YOLOv5 للتعرف على داء

الليشمانيات الجلدي (CL)، في ظل الظروف العادية بناءً على شبكة YOLOv5 التي تعتمد على نهج التعلم العميق. ترتبط بيئة التطوير بلغة بايثون. تحتوي مجموعة بيانات التدريب على إجمالي 160 صورة تم التقاطها من كاميرا هاتف محمول وتحويلها إلى صور ذات تدرج رمادي لاستخراج الميزات المميزة ثم تطبيق تقنيات معالجة الصور مثل التقليب والتدوير وتغيير الحجم لزيادة معلومات مجموعة البيانات. تم عنونة الصور مع طبيب الأمراض الجلدية للتأكد من إصابة داء الليشمانيات الجلدي (CL). في نهجنا، تم تصنيف الصور باستخدام مربعات إحاطة متعددة الأضلاع لتحديد مجالات الاهتمام بحيث تم تقسيم مجموعة البيانات إلى التحقق من الصحة والتدريب والاختبار. تدفقت عن طريق تغذية مجموعة البيانات في YOLOv5s. استطاع نموذجنا تحديد موقع داء الليشمانيات الجلدي (CL) وحقق دقة عالية في الكشف عن العدوى وتصنيفها، بمتوسط دقة بلغة 70٪. مما توفر تقنية سريعة للكشف.

الكلمات المفتاحية: داء الليشمانيات الجلدي، التعلم العميق، YOLOv5، معالجة الصور.

Introduction

In recent years, there has been great development in various fields of science. one example that illustrates the interrelationship between computer science and medical sciences. is artificial intelligence (AI) [1]. Computer vision and machine learning (ML) are an important application of artificial intelligence. Translating the ability of diagnostic algorithms to different fields of medicine [1-6]. Pattern recognition in the medical field using ML methods and classification in diagnosis improves the accuracy, speed, and efficiency of the inference procedure. The rapid development of vision has occurred with the use of computers and artificial intelligence, and technology has also rapidly improved in health complexes and other places, Interdisciplinary approaches are becoming increasingly popular in the health sector, especially in improving diagnosis using a variety of methods of processing and analyzing images and extracting valuable information from raw images taken from Mobile phone cameras [7]. to promote the concept of mobile health or mobile health with the increased use of smartphones and tablets among themselves and their contribution to image analysis applications, with the ability to take digital images and insert them into a smart system that creates a whole new field. for computer-aided decision support (CAD) systems in medical diagnostics and these systems aim to detect and classify various diseases, thus helping medical staff to improve diagnostic accuracy [8]. Cutaneous leishmaniasis is caused by leishmaniasis parasites It is transmitted through the bites of sandflies and causes skin lesions, especially in visible parts of the body. The patient may have skin ulcers that lead to scarring and can lead to severe deformities. Doctors diagnose the infection by analyzing samples of infected skin tissue [9]. Symptoms of infection are usually a bump at the site of the bite. As the infection spreads, more bumps may appear near the first bite, causing the bump to slowly swell, often becoming an open ulcer [10-12]. According to WHO, 700,000 to 1.2 million people suffer from cutaneous leishmaniasis (CL) every year around the world. During 2019 and 2020, Libya suffered from this disease, as the first manifestation of this disease was in the cities of Tawergha and the city of BaniWalid, and this disease reappeared in Al-Shati southern of Libya in the fall of 2021, according to the report of the Primary Health Care Office Al-Shati. This is to promote the concept of mobile health or mobile health with the increased use of smartphones and tablets among themselves and their contribution to image analysis applications, with the ability to take digital images and insert them into a smart system that creates a whole new field [13]. for computer-aided decision support (CAD) systems in medical diagnostics and these systems aim to detect and classify various diseases, thus helping medical staff to improve diagnostic accuracy [14]. In order to detect the infection, a large amount of data must be studied, which constitutes a burden on doctors. The common form of cutaneous leishmaniasis (CL) Most Patients with lesions often suffer from one or two foci of infection, usually at the site of the bite, ranging in size from 0.5-3.0 cm in dimensions. In the end, the focus peels off from the center and When the cortical layer is removed, a shallow ulcer with serrated, protruding edges appears The importance of this research lies in the use of various image processing techniques and pattern recognition to process images in various medical fields and are used at different stages of raw image conversion (i.e. image acquisition, image preprocessing, assembly, classification) such as color space to make it more useful to extract information that can be provided to medical staff, especially in remote areas that lack specialized doctors. make a medical decision at low wrong rates, allowing treatment to be given on time and increasing the chances of recovery.

However, Deep learning, a subtype of machine learning inspired by the human brain showed potential in the picture Classification by machine learning of complex patterns [15-18]. Recently, one-stage objection has attracted a lot of attention, such as YOLO and SSD [19]. The emergence of YOLO has greatly improved the speed of object detection. The application areas of YOLO are very wide. For example, in the medical field, related identification applications include cervical cancer [20], blood cells [21], and colorectal cancer [22]. Deep

Learning techniques have been widely adopted in various fields, including imaging medicine, safety, and image classification [23-25]. To meet this need, we propose a YOLO-based model for detecting and classifying (CL) ulcers in medical images. Our method leverages the benefits of deep learning, such as its ability to learn features automatically, use of increased data, and techniques to improve model performance. We also use a dataset aggregated from Multiple sources with hand-categorized images, providing a more comprehensive range and a variety of training examples. Our study aims to detect accurately and efficiently and classification of LC ulcers, which may lead to better patient outcomes and reduced healthcare costs Therefore, our work highlights the importance of image processing, computer vision. Machine learning and deep learning in the context of CL ulcer detection and classification using a more comprehensive dataset and more advanced model deep learning. We also aim to address some limitations of previous studies and provide a more accurate solution. Our main contributions were as follows:

- Develop a deep learning model based on YOLO for discovery and classification CL ulcers in photos of suspected CL cases, where CL ulcers can be accurately classified.
- Create a new dataset by manually labeling the images with bounding boxes and polygonal areas of interest using YOLO.
- A number of images of non-CL ulcers, including surgical wounds, have been added. These are burned into the dataset to make them more representative of real-world scenarios.
- Use data augmentation techniques, such as permutation and rotation, to increase the size of the data set and improve model performance.
- Compare the performance of the proposed model with that of advanced deep learning models as well as traditional methods of LC detection and classification, Refers to the advantage of the model in terms of accuracy and effectiveness.
- Demonstrate the potential of the proposed model to assist clinical components in appropriate diagnosis, potentially improving outcomes and reducing healthcare costs.
- Contribute to providing a new, accurate, and effective dataset solution to detect and classify potential injury to develop the latest technologies in the field of medical image analysis.

The rest of this article is organized as follows: In Section 2, we provide a summary Refer to the original YOLOv5 model, and suggest the improved YOLOv5 model. In Section 3, we list the experimental materials and methods, including details of the dataset, image labeling process, and data augmentation techniques used

Principle of Object detection

Object detection algorithms can be classified into different groups depending on the use of tagging methods and anchor frames. YOLO and SSD are algorithms that adopt a single-stage approach, while the two-stages generally considered are R-CNN, Fast R-CNN, and Faster R-CNN. Anchor Boxes Help Select Objects A set of predefined boxes that enable objects to be detected using the information scale and aspect ratio [26]. Anchor based algorithms include YOLOv2 to YOLOv5 and Faster R-CNN and SSD.

1. YOLO algorithms

You Only Look Once (YOLO) is an algorithm designed for single-stage object detection. The first model, YOLOV1, was proposed in 2016 by Joseph Redmon [29]. It is formulated as a regression problem, with which the bounding boxes and class probabilities of whole images can be directly predicted in a single evaluation [50]. Comparing the two-stage object detection methods, the YOLO series has greatly improved the detection speed. YOLO is the deep learning framework adopted for YOLOv1 to YOLOv4, while the YOLOv5 framework is PyTorch. YOLOv1, inherited from GooLeNet, however, the processing speed is fast, and the recognition accuracy is lower than that of the two-stage algorithm. In particular, recognizing the results of small things need a certain degree of improvement. In the second generation of YOLOv2, there have been some advances in accuracy and processing speed as well, using the darknet-19 framework [30]. However, the recognition of small objects is still not satisfactory. In YOLOv3, where the neck module was added to combine features, increase the output dimensions to three, and better recognize small objects. Similarly in YOLOv4, technical studies and experimental results provide better accuracy in object detection [31-35]. YOLO is known for its speed and accuracy and has been used in many applications such as: healthcare, security monitoring, and self-driving cars. Since 2015 the Ultralytics team has been working on improving this model and many versions have been released since then. YOLOv5 is newly developed, and has a much smaller model size than previous YOLO generations of algorithms [36].

2. YOLOv5 Network Module

YOLOv5 [37] is divided into four versions of the YOLOv5 network model with five different sizes:

- n for a very small (nano) size model.
- s model is small in size.
- m for medium-sized models.
- l for a large size model
- x for an extra-large model

YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x.

YOLOv5s network has computational speed, but the average accuracy is the lowest, while YOLOv5x network has the opposite characteristics. YOLOv5 is about one-tenth the size of the YOLOv4 network. It can locate sites quickly, has recognition speeds, and is nearly as accurate as YOLOv4. The YOLOv5 network has three components: the spine, the neck, and the head. After image interference, the backbone compiles and shapes image features with different levels of image resolution. Then, Neck collects the image features and sends them to the prediction layer, and Head selects the image features to generate bounding boxes and predicted classes. The YOLOv5 network also uses GIOU as the network loss function, shown in Equation (1).

$$.\mathrm{GIOU} = \mathrm{IOU} - \frac{|C-(A\cup B)|}{|C|} \qquad (1)$$

where $A, B \subseteq S \subseteq R^n$ Rn represent two arbitrary boxes, C represents the smallest convex box, $C \subseteq S \subseteq R^n$, enclosing both A and B and $IOU = |A \cap B|/|A \cup B|$.
When the input network predicts image features, the optimal target frame is filtered by combining the loss function GIOU and the non-maximum suppression algorithm.

YOLOv5 Network constructed as shown in figure [1]

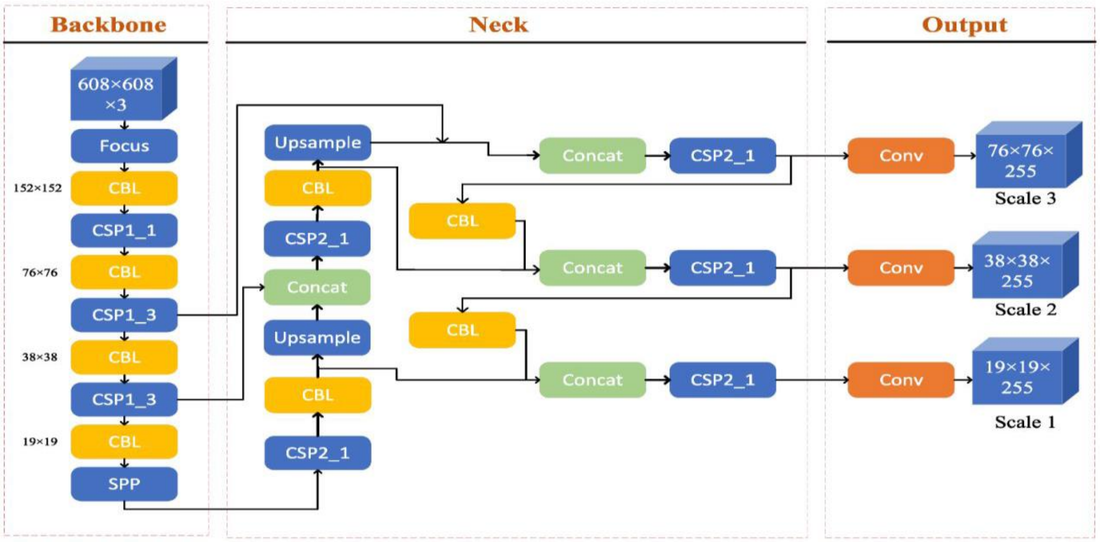

Figure 1. Architecture diagram for YOLOv5, adapted from [33]

Material and methods

We selected YOLOv5s for CL detection and classification due to its high accuracy in object detection, real-time performance, and flexibility in training on custom datasets. Additionally, YOLOv5 has been successfully applied in several other medical imaging tasks, including lung nodule detection and diabetic retinopathy detection, which suggests that it could be effective for CL detection and classification as well.

1. Experimental Materials

Leishmaniasis (CL) images were collected from the database of the Primary Health Care Office in Brak -Al Shati. Were captured using A mobile phone camera from different angles, with an image resolution of 459 x 720 pixels. There were 160 images of CL in the database from different parts of the body, including 70 images on the arms and hands, 50 images on the face, and 40 images on the feet and legs.Which we used in training and testing in order to develop a deep-learning model to identify CL infection with high accuracy.

2. Data processing.

Before entering images into the YOLOv5s model, we converted the image to a grayscale so that it can be easily manipulated so that the ulcer site appears light white, different from the rest of the places in the image, in addition to that we increased the different gray levels in the image. And we increased the size of the data set using advanced techniques including image resizing, rotating, and flipping in order to create accurate selection and augmentation of this data set, which makes the deep learning model powerful and able to recognize changes in input data, image features. as well as new images. Figure 2. The class distribution of the dataset after inclusion of these additional images and data augmentation techniques is shown.

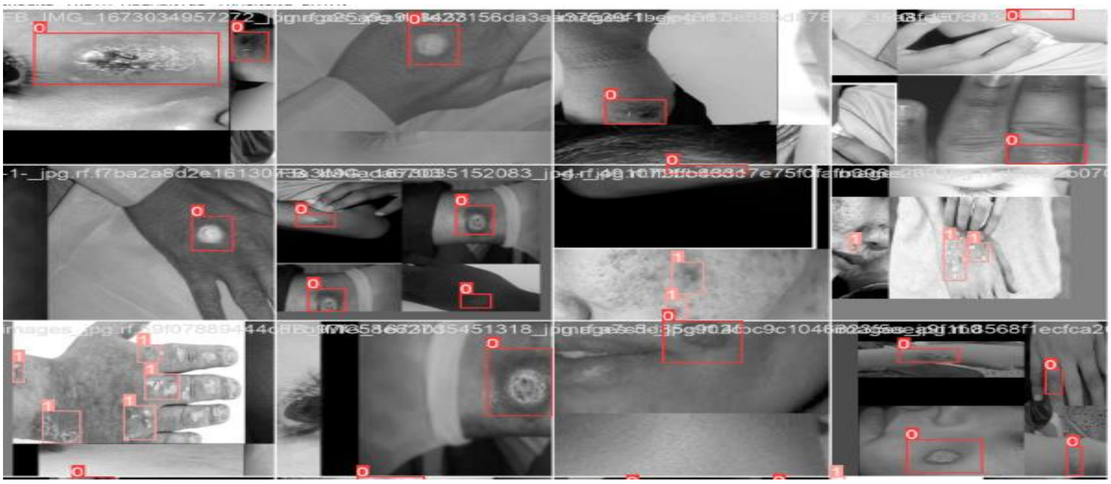

Figure 2. Image processing result.

3. experimental process

We performed the labeling process of the dataset was conducted in collaboration with a dermatologist to ensure accuracy and consistency in the identification of CL. Images have been labeled with polygonal bounding boxes to identify areas of interest in a deep learning model.We created a special class for CL, which we called leishmaniasis , and we created another class for a group of skin ulcers that were not CL that was present in the study area, which we called other. The image set was divided into 70% training, 20% validation, and 8% testing. It is presented in a YOLOv5 Enhanced network of different structures for training. The training process contains 100 images each. The random gradient descent algorithm was used to optimize the network model during the cycle training process, and the optimal weight of the network was obtained after training.

4. Experimental equipment

A laptop computer was used as the processing platform, and it was the operating system WINDOWS 10, PyTorch Framework, and YOLOv5 We ran our tests on Colab GPU with YOLOv5 version 7.0-114-g3c0a6e6, Python version 3.11.3, Torch version 2.00 + cu118 and it was 10.1. As for the hardware, the processor was Intel Core i7-3612QM, the main frequency was 2.10 GHz, the memory was 3G and the graphics card was GeForce GTX 1060 6G.

5. Results

We trained the model with the following hyper parameters: learning rate (lr0) of 0.01, momentum of 0.937, decrement of 0.0005, and batch size of 18. We used a random regression optimizer (SGD) for 300 epochs with patience set to 100, and keeping the best model weights. According to the YOLOv5s model we trained, we achieved good results in terms of overall map and individual class performance. The model achieved an overall mAP50 of 0.769 and a mAP 50–95 of 0.398 in the validation cohort. This means that the model was able to detect and classify CL with high accuracy.

Figure 3 shows the loss values for box loss, object loss, and separation loss at each period during the training process. Box loss represents the difference between the truth and predicted bounding box coordinates, object loss represents the confidence score for each detected object in an image, and class loss represents the probability that each detected object belongs to a particular class. The primary goal of training the object detection model is to reduce the total loss, which is a combination of box loss, element loss, and class loss. The loss values should show. a decreasing trend as training progresses, showing an improvement in the efficiency of the model on detecting different stages of CL in images.

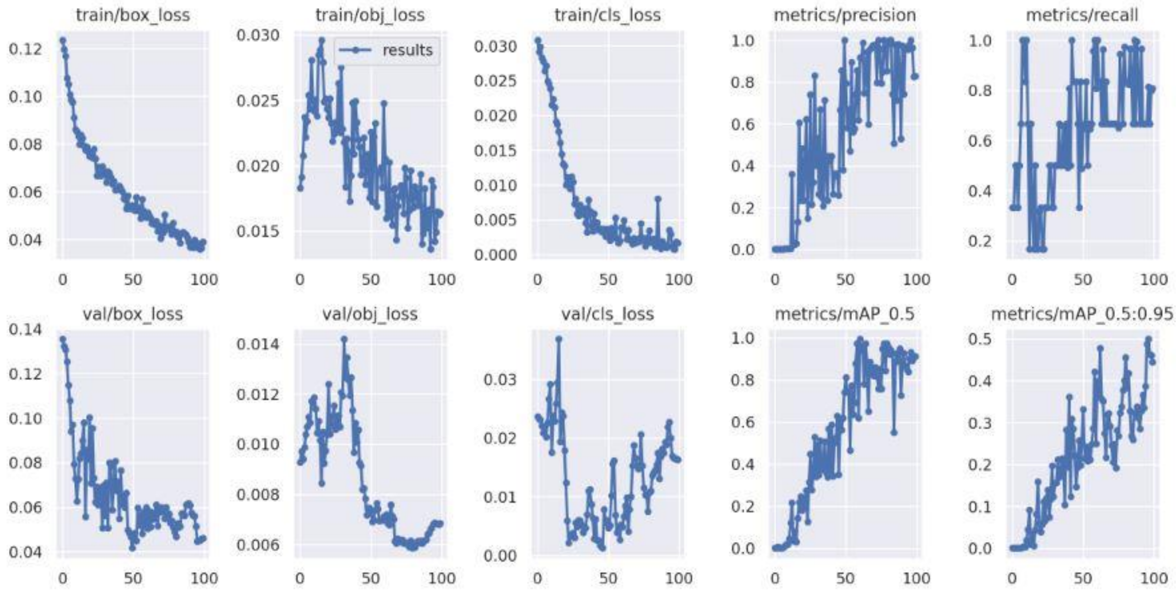

figure 3. The training results

In phase 1, a relatively low accuracy level was shown, with average accuracy (50mAP) of 0.00168.

In phase 4, our model achieved intermediate accuracy (50mAP) at 0.2, indicating an average accuracy level in identification and localization. In phase 96, the model showed average accuracy (50mAP) at 0.828, as shown in Table 1.

Table 1. Performance evaluation of the CL detection model.

CLASS ALL	P	R	mAP@50	mAP@50-95
Phase 1/99	0.00167	0.5	0.00864	0.00112
Phase 4/99	0.00333	1	0.02	0.0102
Phase 26/99	0.132	0.25	0.129	0.0432
Phase 70/99	0.308	0.783	0.401	0.119
Phase 96/99	1	0.691	0.828	0.272

Overall, our YOLOv5s model indicates a high level of accuracy for CL detection and classification of the image dataset we used for training and validation, We also created additional evaluation metrics to analyze the performance of our YOLOv5 model further. The accuracy confidence curve, retrieval confidence curve, exact retrieval (PR) curves, and confusion matrices can be found in Fig. 4, Fig. 5, Fig. 6, and Fig. 7, respectively. These evaluation scales provide a more detailed understanding of the model's ability to detect and classify CL in images. Confusion matrices show information on the number of true positives, true negatives, false positives, and false negatives for each class.

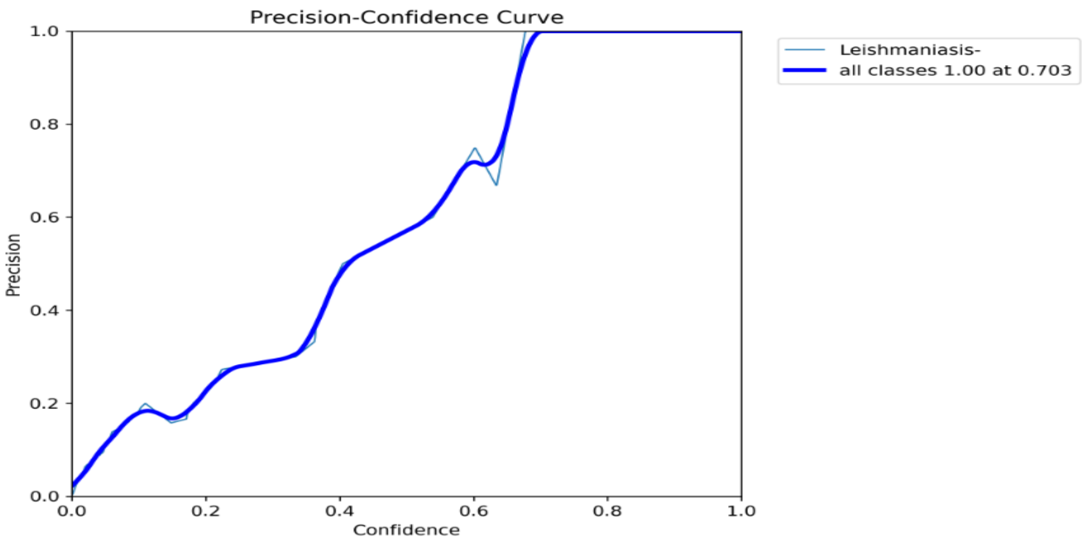

Figure 4. Precision confidence curve

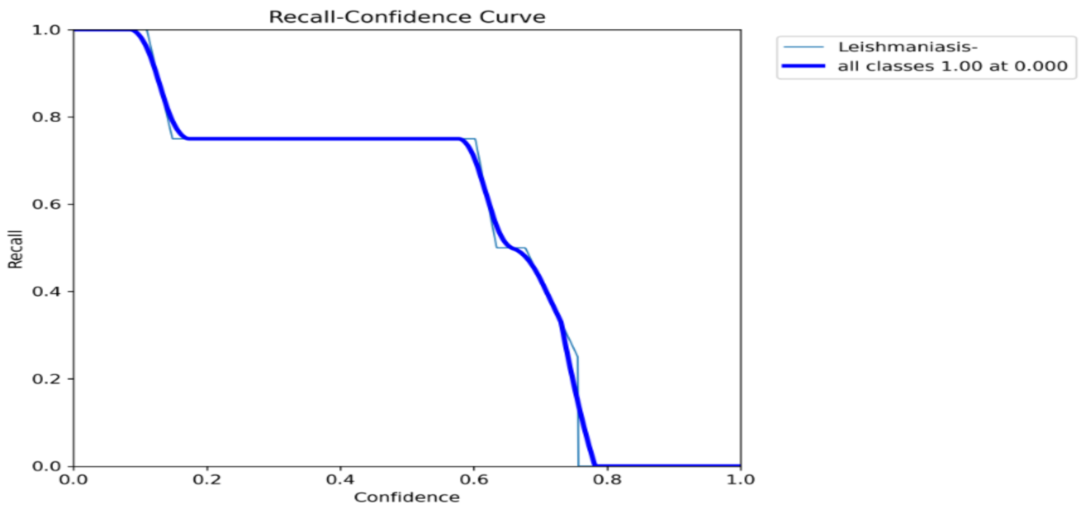

Figure 5. Recall confidence curve

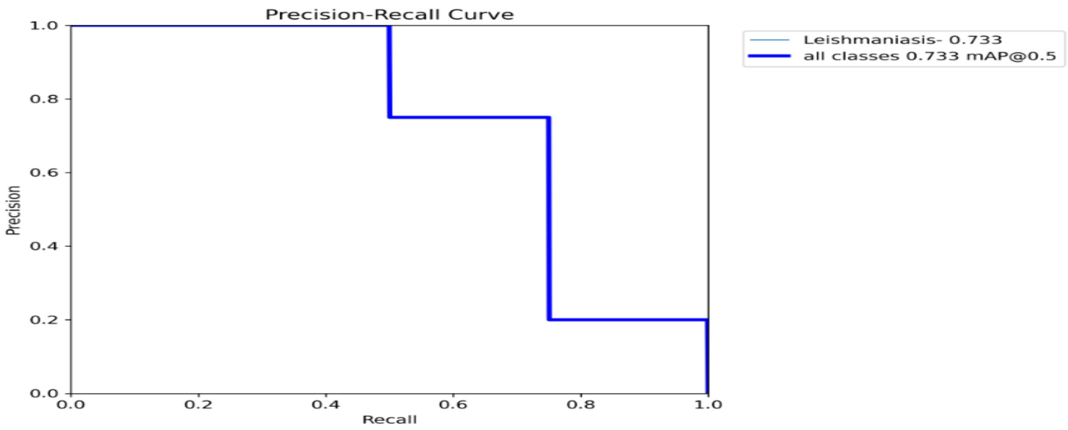

Figure 6. precision–recall (PR) curves

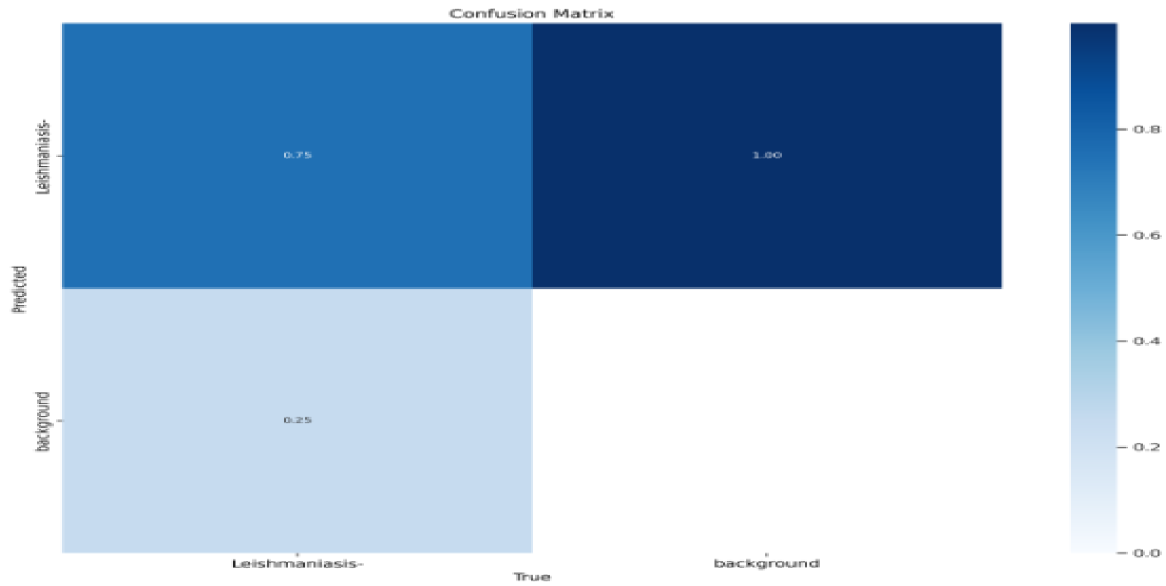

Figure 7. Confusion matrices

Desiccation

The developed YOLOv5 model was tested in collaboration with the Dermatology Monitoring Team at the Dermatology Department at Barak Al-Shati Healthcare Centre. A group of new images has been added to confirm the extent of the model's ability to identify CL, and this test was done before the laboratory detection process, and samples were taken from the site of infection. The developed YOLOV5 model was tested on 40 images of suspected cases of infection, as our model was able to locate the infection well, and was able to identify 27 images out of 30 images of laboratory-confirmed cases as being infected with CL. The model was able to detect images of cases classified as non-CL ulcers from 13 images of cases classified as non-CL ulcers. It was also observed that the model for recognizing early-stage CL was 75% better than the advanced stages of CL, as shown in Figure 8.

Figure 8. The difference appears in the recognition stages.

The model was tested on some skin diseases that are somewhat similar to CL and the results of the detection and classification showed an average accuracy (50 mAP) of 0.767 indicating a high level of accuracy in determining CL. Figure 9 shows the result of applying the improved YOLOV5 networks to a number of images.

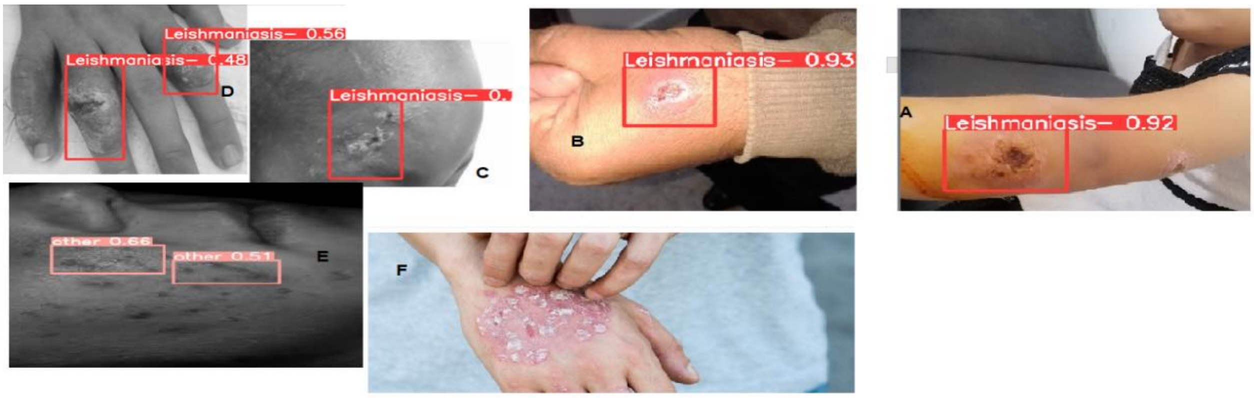

Figure 9. Image detection result

The accuracy and efficiency of the output are determined by the generally accepted rules in diagnostic systems sensitivity, accuracy (AC), and medical classification [18], which accurately define the diagnosis They were calculated using the laws: specificity (SP) and specificity, sensitivity (SE).

Sensitivity $=\frac{TB}{TB+FN} \times 100 = 99\%$

Specificity $= \frac{TN}{TN+FB} \times 100 = 98\%$

Accuracy $=\frac{TN}{TN+FB} \times 100 = 98\%$

where:

(TP) Number of correctly classified images containing cutaneous leishmaniasis = 155/160=0.969

(FP)Number of misclassified normal images = 100/2= 0.02

(TN) Number of images correctly classified B = 97/100=0.97

(FN)Number of images with ulcers classified as non- cutaneous leishmaniasis =2/160=0.013

Conclusion

Determining the incidence of cutaneous leishmaniasis clinically in normal circumstances by non-specialized medical staff, using artificial intelligence techniques is considered a great matter. Which contributes to avoiding errors resulting from a bad diagnosis. This study, presented an important new diagnostic method for rapid detection and Accurate diagnosis by using the cutaneous leishmaniasis recognition model based on the YOLOv5 network, by using a model that follows a deep learning approach. The integration development environment is designed using the Python. Image samples were collected to develop a diverse data set to enhance the robustness of the model. Our model achieved high performance in locating cutaneous leishmaniasis, and also achieved high accuracy in detection and classification of the infection, with an average swallowing accuracy of 70%, which provides a reference technique for the detection of leishmaniasis. Despite the good results achieved by the model, the classification accuracy still needs to be improved in the future.

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