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DeepLeish

Deep Learning Based Image Pattern Recognition for Automated Detection of Leishmaniasis Parasites in Microscopic Images

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NEW TECHNOLOGIES RESEARCH CENTRE
UNIVERSITY OF WEST BOHEMIA
IN PILSEN

Presentation outline

01 Disease background

02 Diagnostic challenges

03 Research objectives and impact

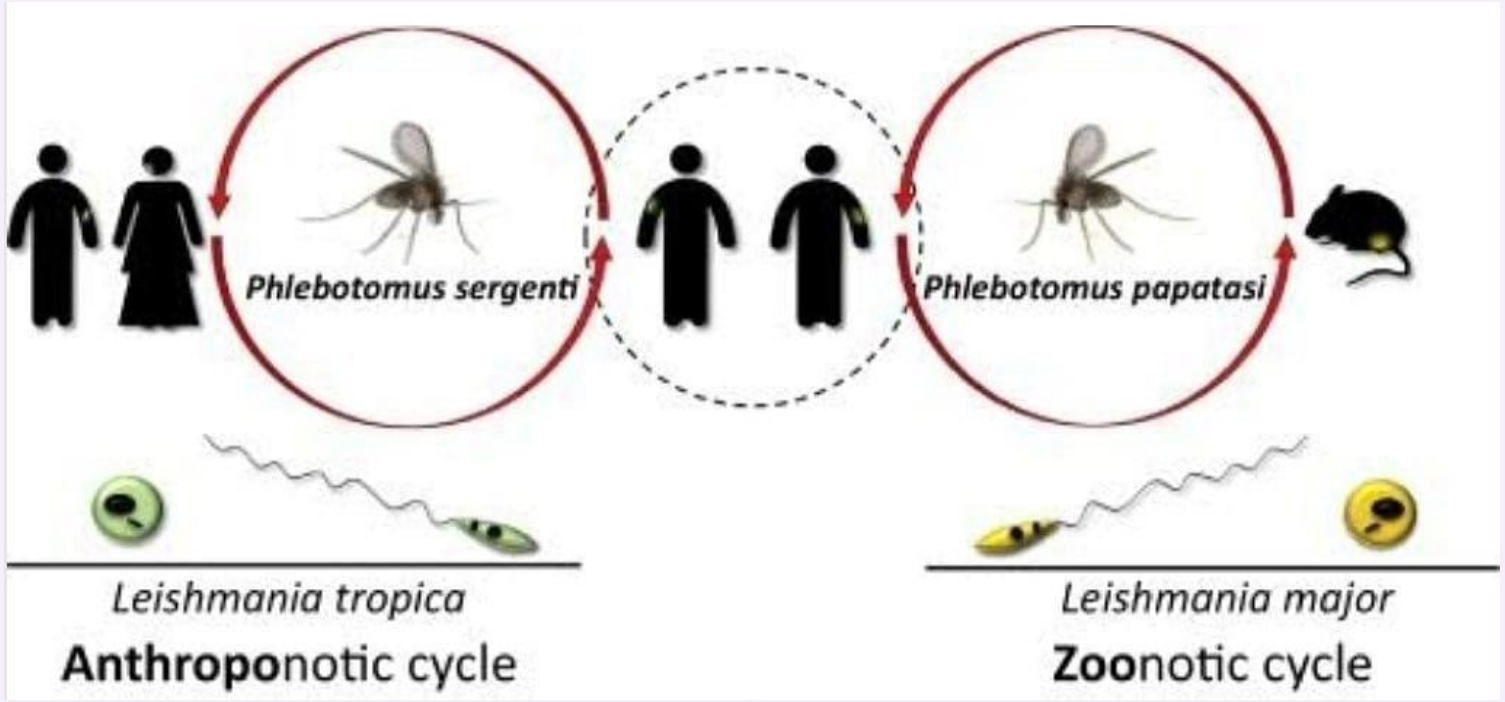
04 The DeepLeish approach

05 Results and discussion

06 Research advancements and Next Steps

Leishmaniasis

- A neglected tropical infectious disease.
- Spread by the bite of infected female phlebotomine sand flies.



Person-to-person and animal-to-person transmission cycles

Prevalence of Leishmaniasis

88

countries where the disease is found

350 M

people live in areas where it occurs

21 of 30

Leishmania species infect humans



The scale of the problem

15M

people infected worldwide

2M

new cases

70K

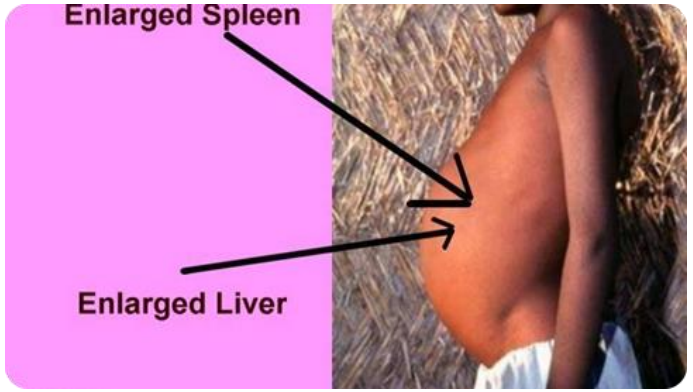
deaths reported

1.2M

people at risk of infection in Ethiopia

Visceral Leishmaniasis

95%+ **of cases are fatal if left untreated**

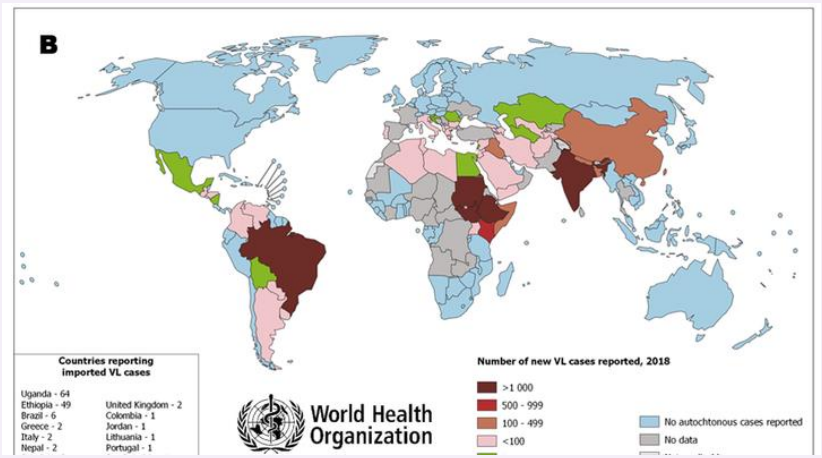


50–90K
new cases a year

25–45%
reported to WHO

- Attacks the spleen and liver.
- Irregular bouts of fever
- Weight loss
- Enlarged spleen and liver
- Anaemia



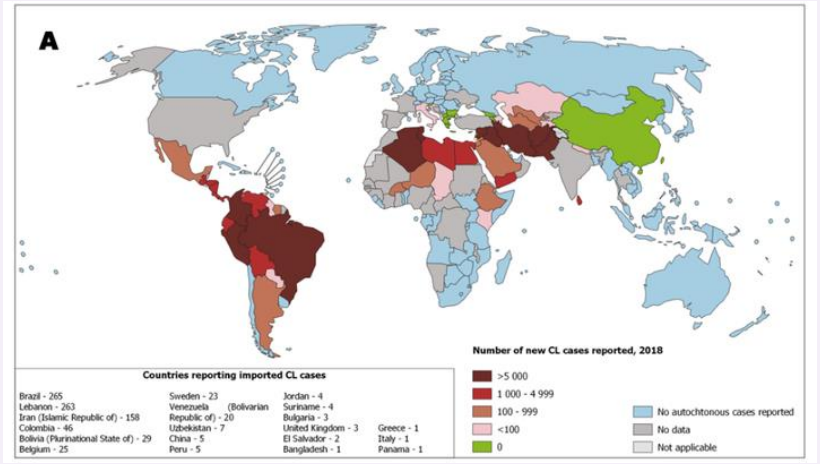


New visceral cases reported, 2018 (WHO)

Also known as kala-azar

Cutaneous Leishmaniasis





New cutaneous cases reported, 2018 (WHO)

The most common form of leishmaniasis

- Skin lesions and ulcers on exposed parts of the body
- Life-long scars that bring serious disability or stigma

600K-1M new cases every year

20k-50k new cases in Ethiopia

Most cases occur in:

Afghanistan | Algeria | Brazil | Colombia | Iran | Iraq | Syrian Arab Republic

Mucocutaneous Leishmaniasis





Partial or total destruction of the mucous membranes of the nose, mouth and throat.

It can develop as a complication of cutaneous leishmaniasis.

90%+

of cases occur in just four countries

Bolivia **Brazil** **Ethiopia** **Peru**

Complications of Leishmaniasis

Relapse

Disease returns after treatment

Secondary infections

Bacteria infect damaged tissue

Uncontrolled bleeding

Bleeding becomes difficult to stop

Splenic rupture

An enlarged spleen can burst

Metastatic lesions

Disease spreads to the nose and throat

Septicaemia

Bacteria and toxins enter the bloodstream

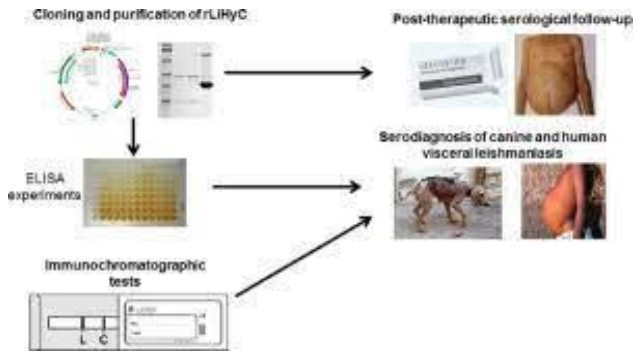
How is it diagnosed today?

GOLD STANDARD



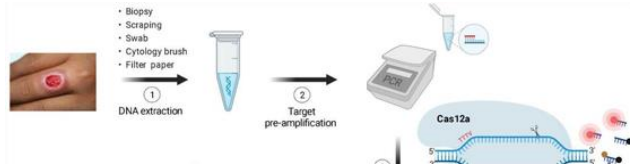
Microscope examination

A technician searches the stained sample for the parasite itself.



Serological tests

Antigen and antibody tests on the patient’s blood.



Molecular methods

DNA amplification detects the parasite’s genetic material.

Why diagnosis is difficult?

Relapsing disease

Patients need repeated diagnosis

Few treatment centers

Mainly ALERT, Black Lion and Gondar Hospitals

Family burden

Care places pressure on patients' families

Demanding microscopy

Slow, tedious and technically demanding

Tiny parasites

Can resemble other cells and debris

Limited research

Few studies, mostly on fluorescence images

Our goal

MAIN AIM

Design a deep learning decision-support tool that detects Leishmania parasites in Giemsa-stained microscope images.

1. Acquire Giemsa-stained microscope images
2. Fine-tune different deep learning models
3. Develop the parasite detection tool
4. Evaluate how well the tool performs

Potential research impact

Earlier diagnosis

Improve access in rural health centres and hospitals

Simpler workflow

Make diagnosis easier for health workers

Reduced workload

Shorten the time laboratory experts spend on diagnosis

More consistent results

Help reduce misdiagnosis

Epidemiological research

Support studies of disease distribution

Vaccine and drug research

Support vaccine and drug-efficacy studies

Computer vision: object detection

Object detection

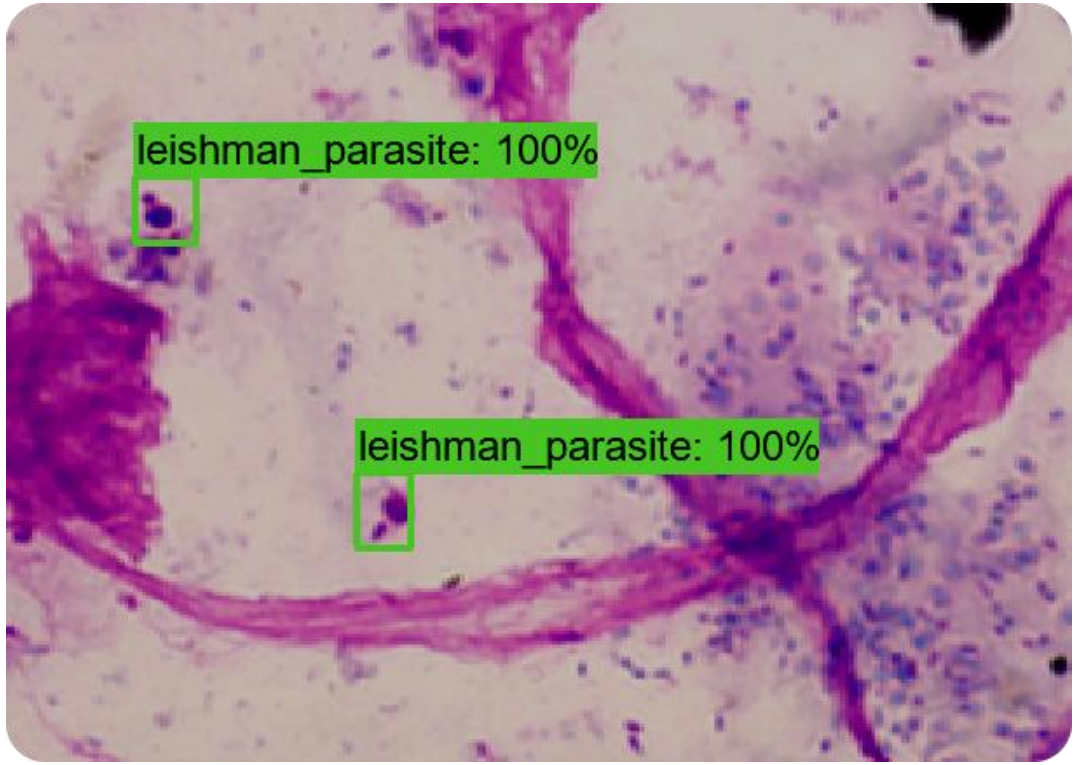
Finds each parasite and shows its location with a bounding box and confidence score.

Why not image classification?

Classification gives one label to an entire image. It does not show where a parasite is or count multiple parasites.

Why object detection fits this study

Microscope images may contain zero, one, or many parasites. Detection can locate each visible parasite, supporting review by a laboratory professional.



DeepLeish Approach



Giemsa-stained images from microscopes, cameras and online datasets

Rotation and blurring to enlarge and balance the dataset

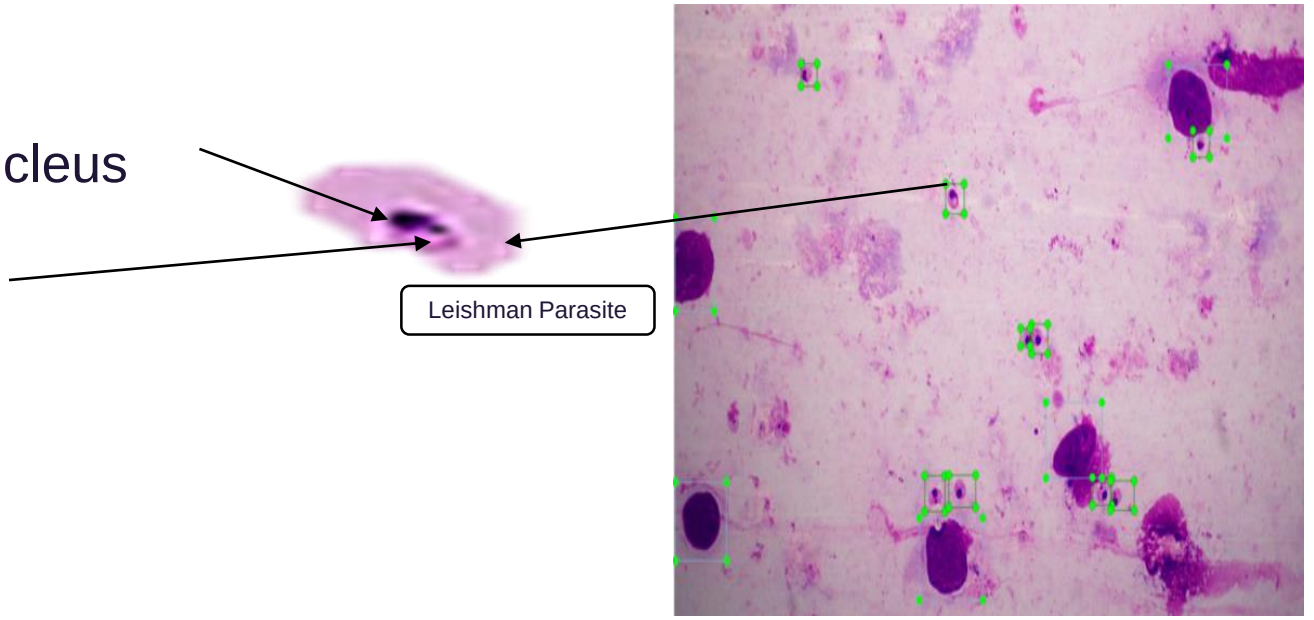
Train and Fine-tuning object detection Models

Measuring accuracy and building the final tool

Designed to work with existing microscopes fitted with a recommended camera.

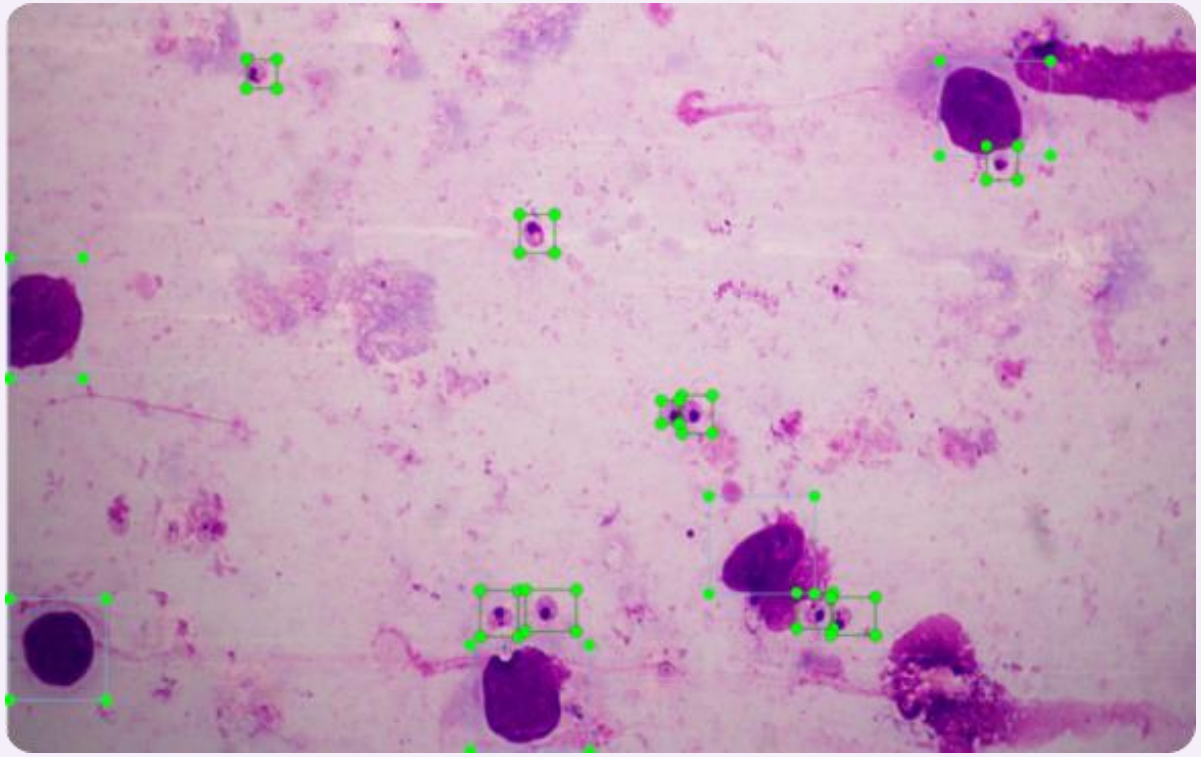
Image Acquisition

- Amastigotes are round to oval in shape with 2-10µm.
- The most prominent features are kenetoplast, larger nucleus, and cytoplasm.
- Deep red color: Larger nucleus
- Pink: Kenetoplast,
- Pale blue: Cytoplasm,



For scale: a red blood cell is about 7 µm across.

Building the image library



Every parasite is outlined with the LabelImg tool , which writes the label files for training.
Clinical Collaborator will label each Leishman Parasite in every image

Cameras and microscopes

12 MP Olympus BX-63 microscope, 10 MP Sony camera, 5 MP Olympus digital microscope

Local images

Original images collected in this study

Online datasets

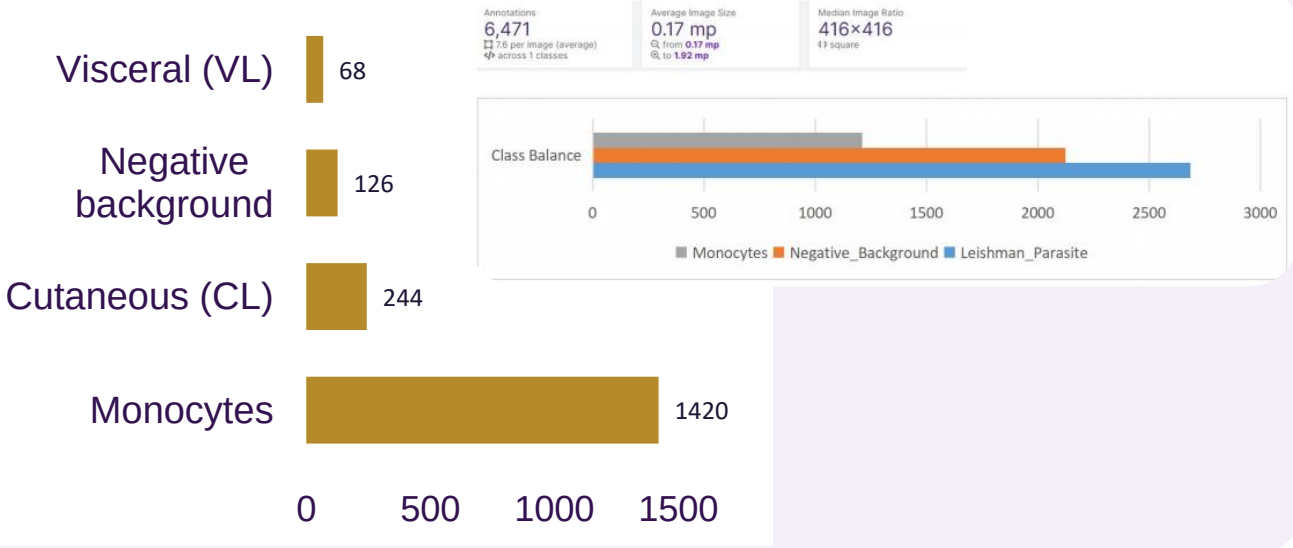
Isfahan University of Medical Sciences research center, Mendelay

Annotations

XML , YAML

What is in the library?

The 1,858 original images



2,779

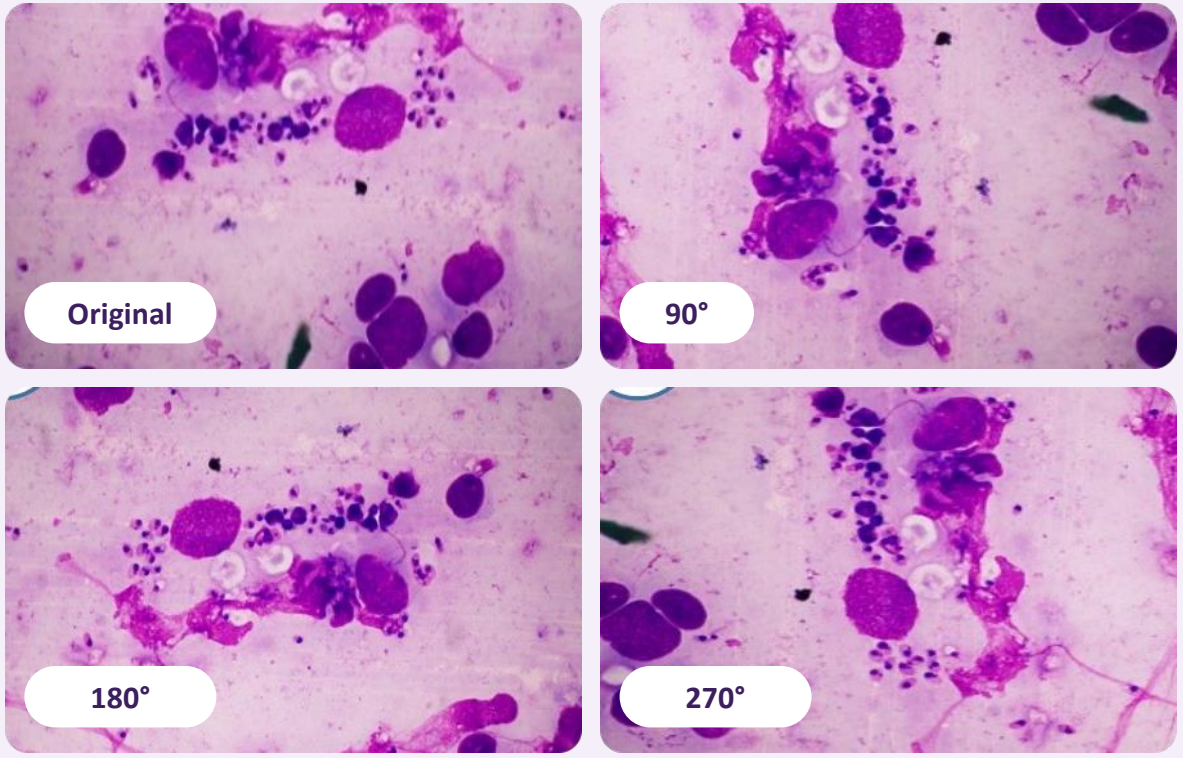
images in the final dataset (1,858 original + 921 augmented)

- Training: 2,222 images
- Validation: 279 images
- Testing: 278 images

Making more from less: data augmentation

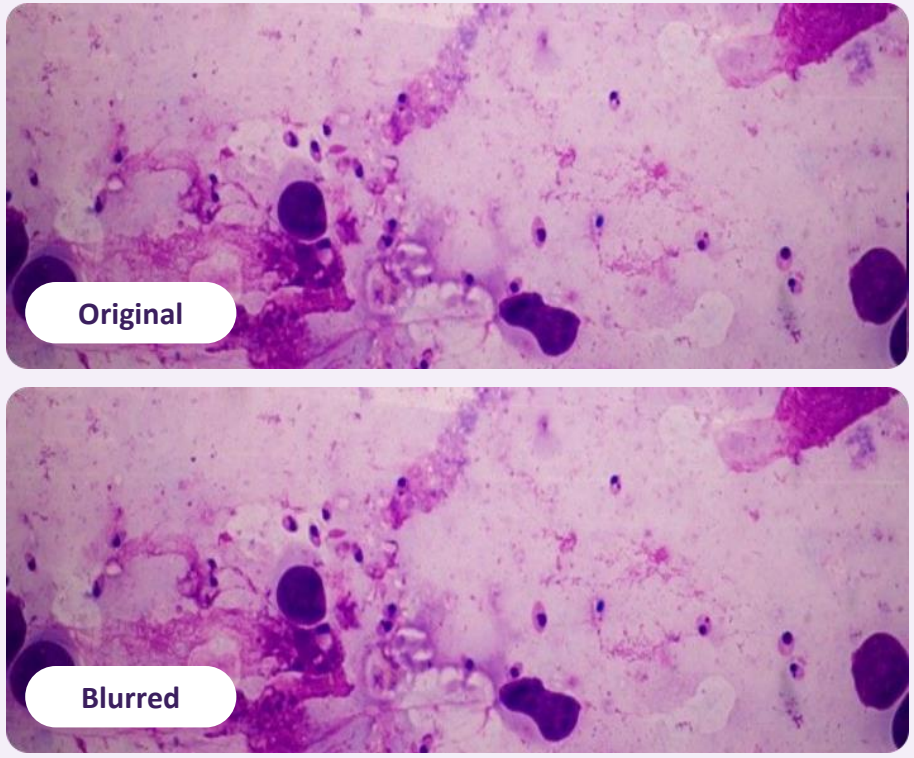
Rotation

Turn each image by 90°, 180° and 270°



Gaussian blur

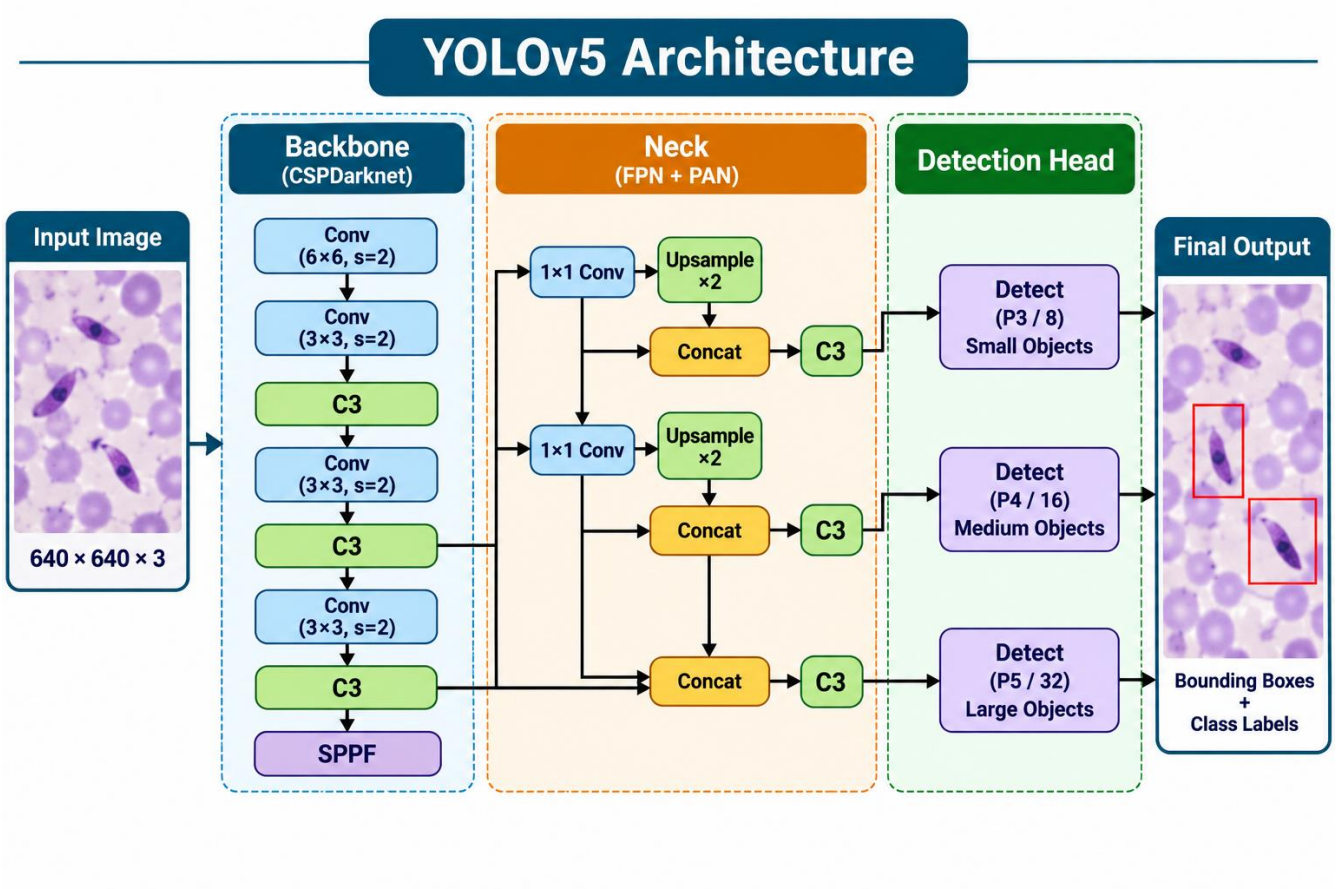
A gentle 3×3 blur makes a new variation



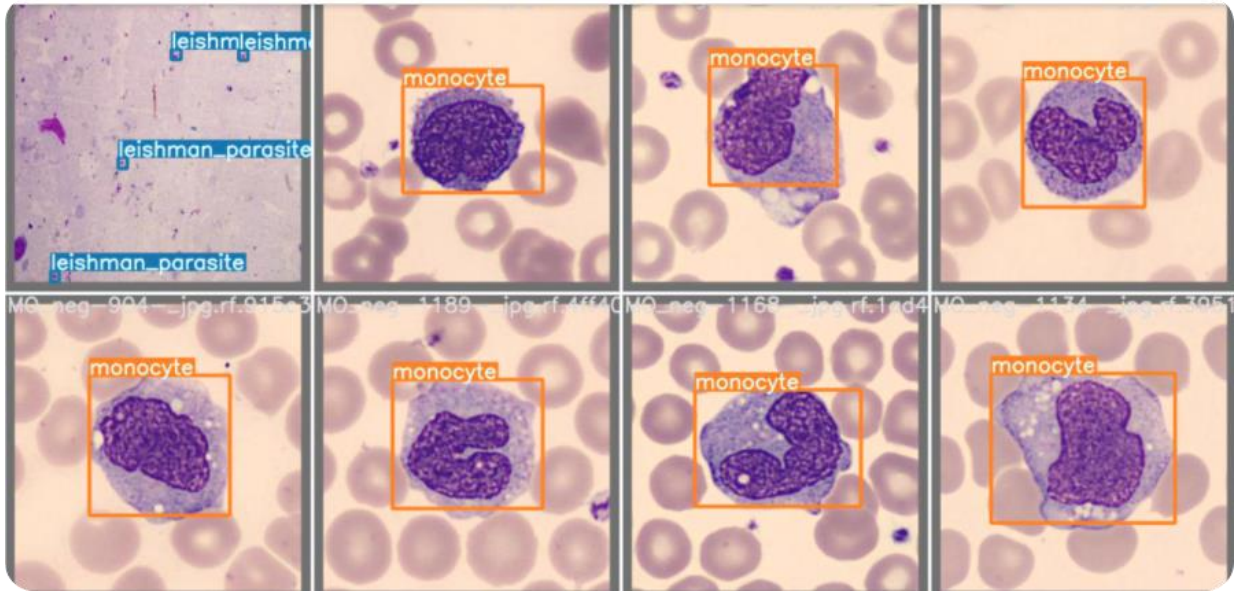
Model Training

YOLO V5 Architecture

- **Backbone (CSPDarknet)**
  - Extracts visual features using Conv and C3 modules.
  - Captures multi-scale features using SPPF.
- **Neck (FPN + PAN)**
  - Combines features from different backbone levels.
  - Enhances multi-scale feature fusion through upsampling and concatenation.
- **Detection Head**
  - Detects objects at three scales (P3, P4, P5).
  - Predicts bounding boxes, confidence scores, and class labels.



YOLOv5 finds the L. parasite best



Sample test images detected by the custom YOLOv5 model.

Including monocyte cells: mAP 65% precision 70% recall 69%

73%

mAP

Overall detection quality for IoU: 0.5

68%

Precision

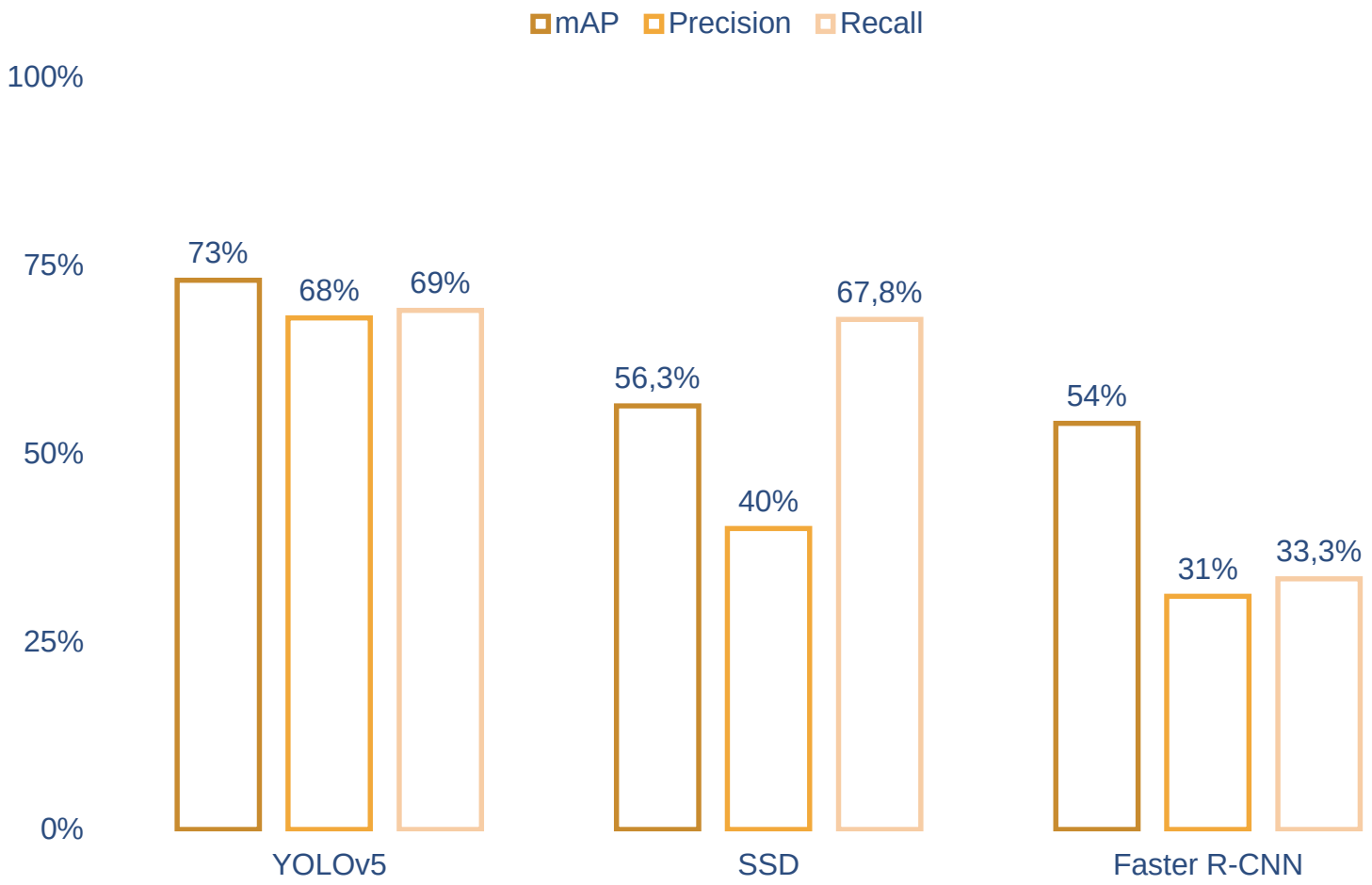
When it flags a parasite, how often it is right

69%

Recall

Of all real parasites, how many it finds

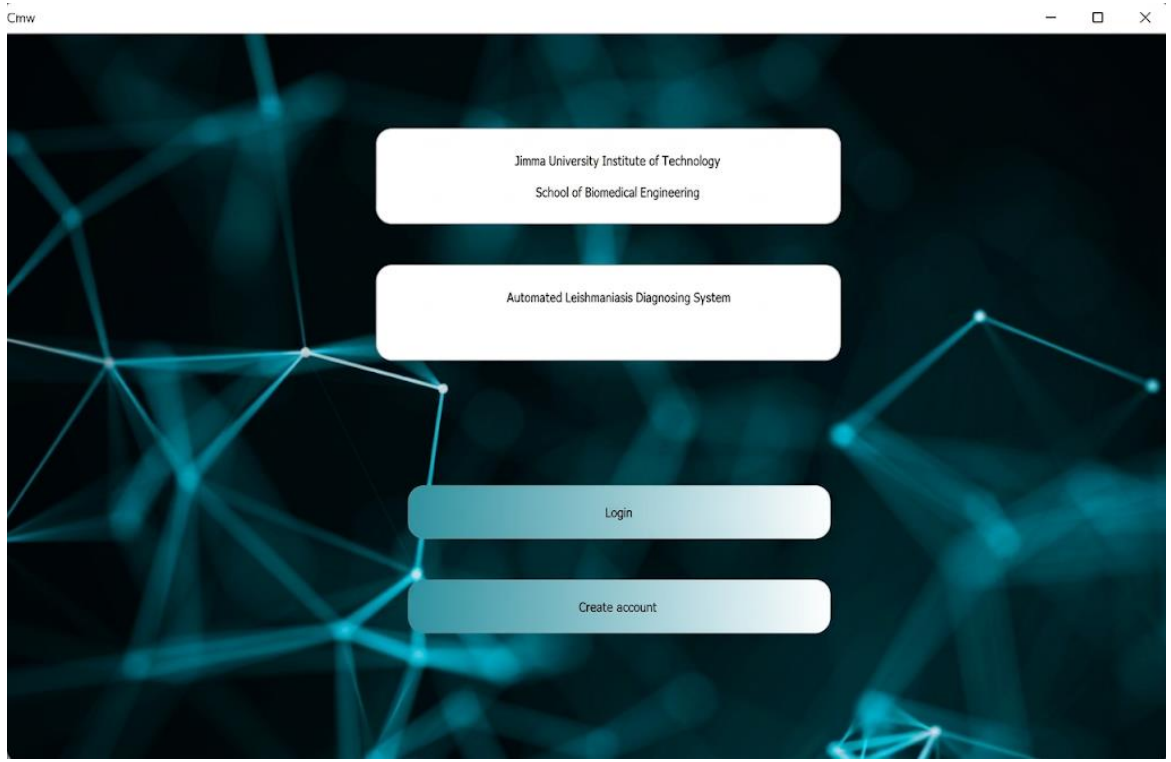
YOLOv5 comes out ahead on every measure



Why YOLOv5?

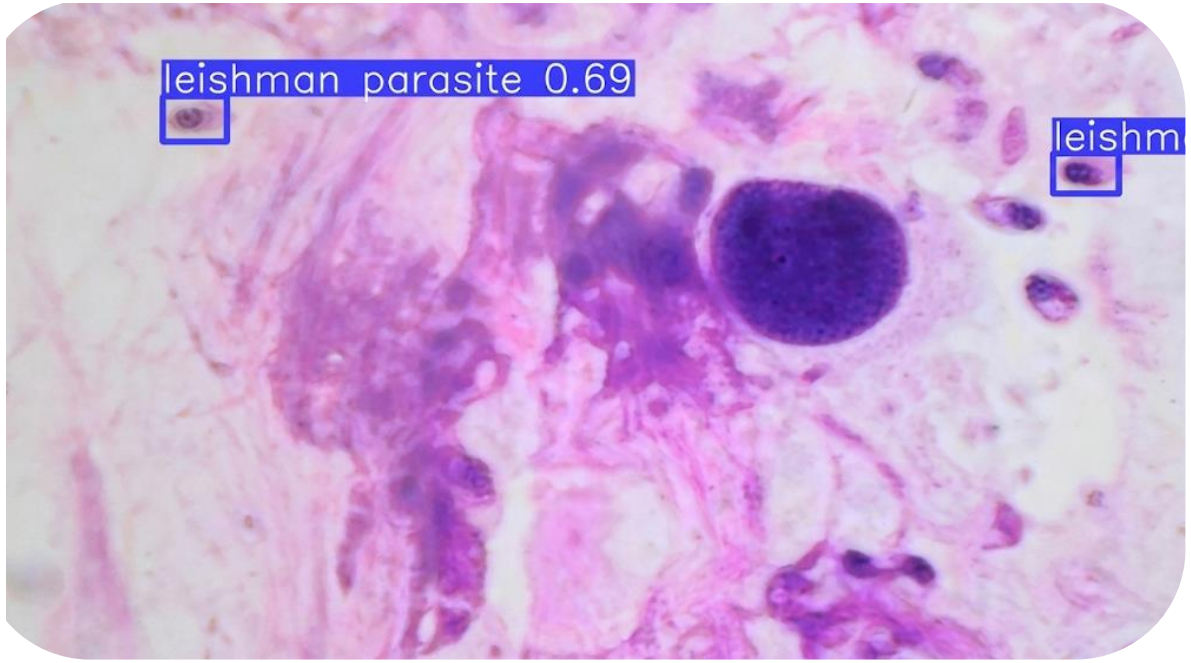
- Best Performed model among all three
- About 10× faster per image than SSD: 0.19 s vs 1.95 s

From model to working tool



Start screen

The prototype application opens here.



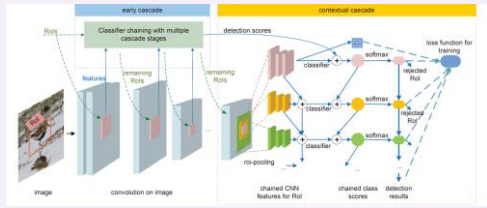
Detection result

Parasites are boxed and given a confidence score.

Discussion

The gold standard is a heavy load

- Microscopy puts a huge burden on laboratory technologists.



Built for real-world variation

- Images came from different microscopes, cameras and sources.



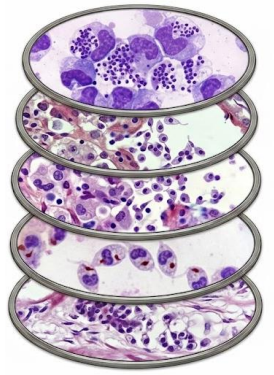
YOLOv5 recognised the parasite best

- Large-size difference affects the detection precision
- Dataset limitation can be improved by collecting more datasets
- Further studies are required for optimized better results

Collaborative research

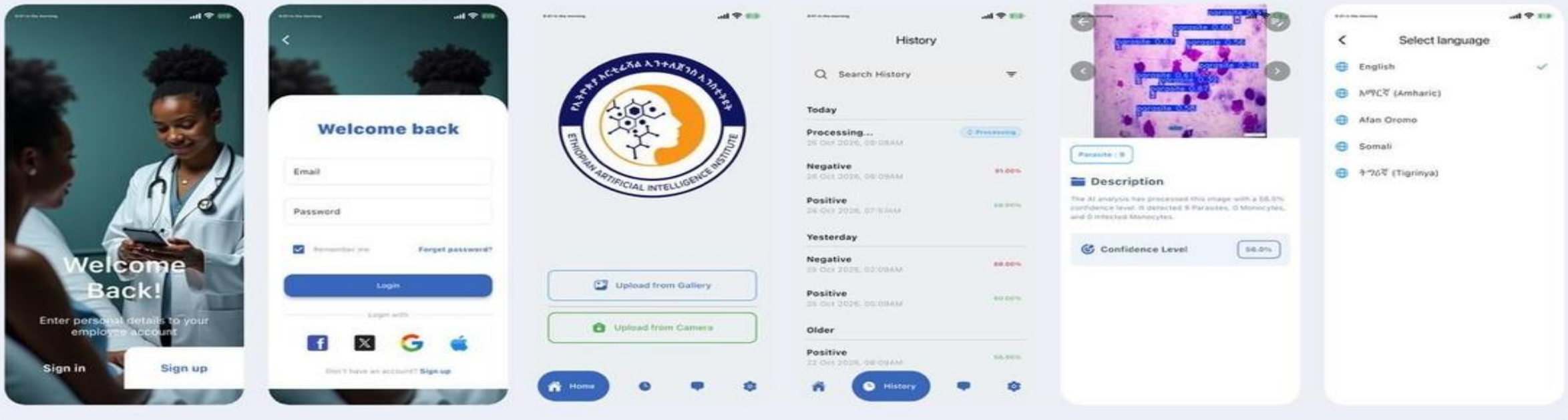
- **Dataset Scaling:** Expanded image collection across diverse real-world environments, dramatically boosting model generalizability.
- **Enhanced Performance:** Achieved superior detection precision and higher mAP scores following the architectural upscale.
- **Advanced R&D Focus:** Conducting deeper technical research on edge acceleration, quantization, and real-time latency optimization.
- **Collaborative Expansion:** Establishing strategic inter-institutional partnerships to ensure successful field implementation and deployment.

6,000



Microscopic images in the larger dataset were collected

Collaborative research



Mobile app Interface starting screen

Performance results

81.6%

Precision

71.3%

Recall

For comparison, our first YOLOv5 model reached 68% precision and 69% recall.

Where we go from here

Pilot Testing

Taking it to the clinic

With a recommended camera mounted on an existing microscope, DeepLeish can be used where microscopes already are.

- **Measure the parasite load**
- **Test more models, including cascaded networks**
- **Collect more images with cellphones**
- **Extend to other infectious diseases**
- **Add image-processing methods**

Summary

1 Diagnosis needs help

Leishmaniasis has three clinical forms. Microscopy is still the gold standard, but it is slow and burdens lab staff.

2 DeepLeish

Our deep learning system detects the parasite automatically in Giemsa-stained microscope images.

3 YOLOv5 works best

73% mAP, 68% precision, 69% recall. It can run on existing microscopes fitted with a camera.

4 More to do

Tiny parasites are harder to spot than large monocyte cells. More data and optimisation are needed.

THANK YOU

Stakeholders involved









Thank you

Questions and discussion

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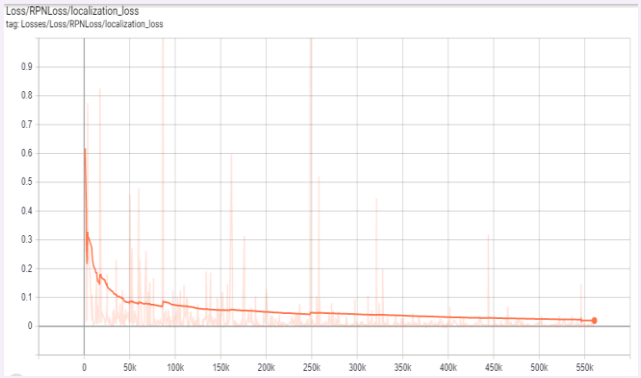


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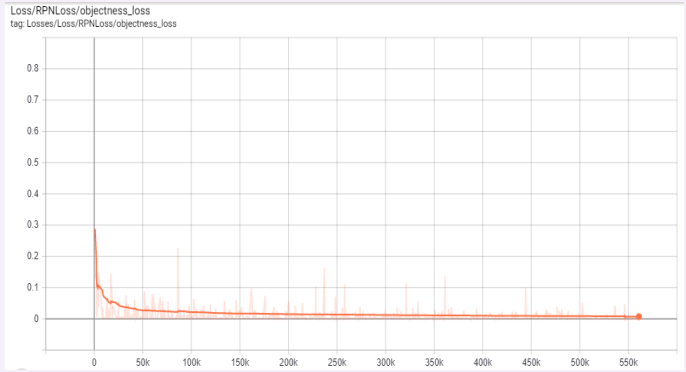
Back up

The two runners-up

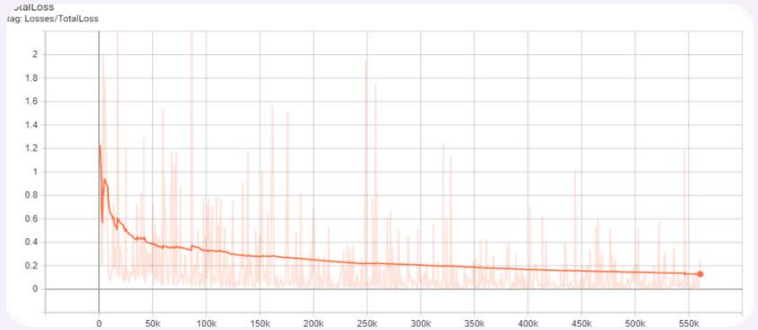
Faster R-CNN



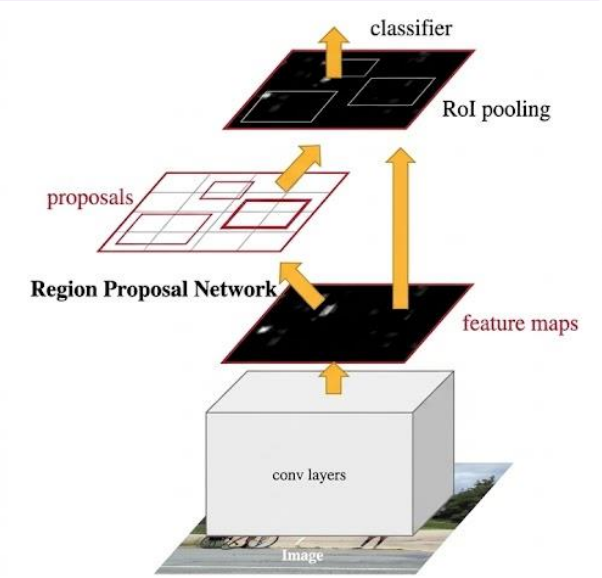
RPN Localization Loss

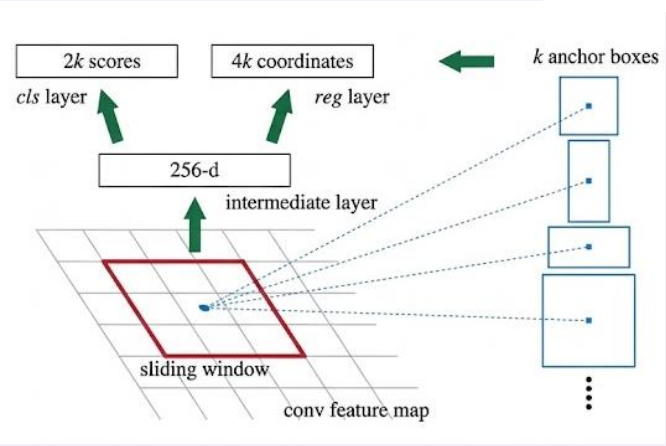


Objectness Loss



Cloning Loss





The two runners-up

Single Shot Detector (SSD)

- **Backbone:**
  - ResNet-50 extracts features (C3, C4, C5 at strides 8, 16, 32)
- **Neck:**
  - FPN fuses them top-down into 256-channel maps (P3-P7) for multi-scale detection
- **Head:**
  - Shared 3×3 conv branches predict class scores and box offsets for anchors at each level
- **Output:**
  - Single forward pass, then NMS to remove duplicate boxes
- **Loss:**
  - Classification (cross-entropy or focal) + Smooth L1 box regression

