Artificial Intelligence for Automated Screening of Malaria Disease

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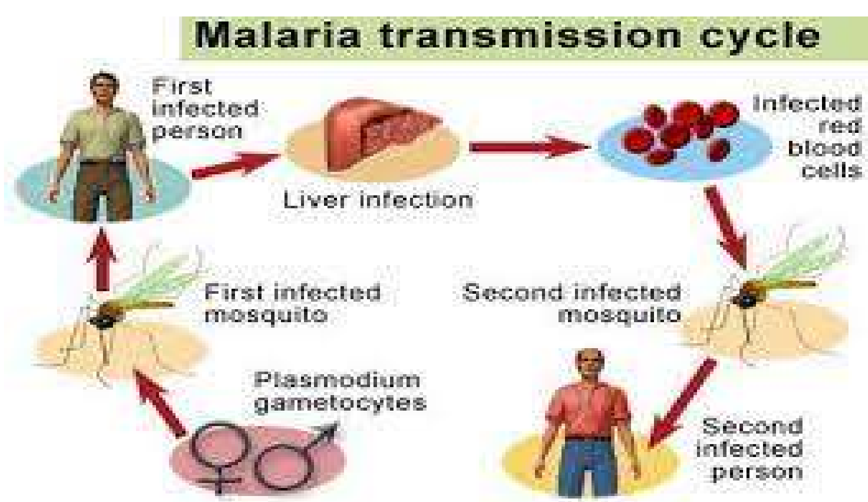
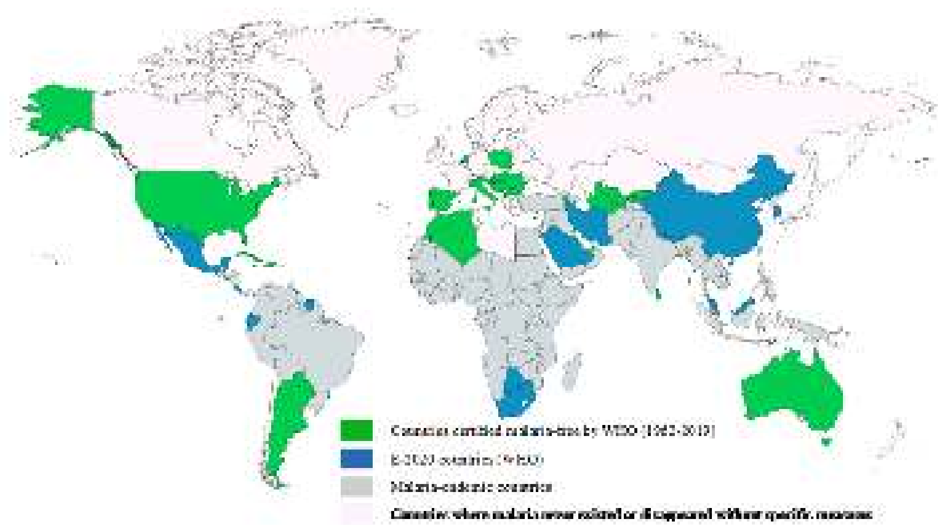
Malaria Disease

- Malaria: is one of the deadly diseases in the world, especially in the developing countries of Africa, Asia, and Latin America continents

- Caused by plasmodium parasite

- Malaria Global prevalence:
  - 2020: 241 million malaria cases and 627, 000 deaths [1]
  - WHO African Region accounted for about 95% of cases



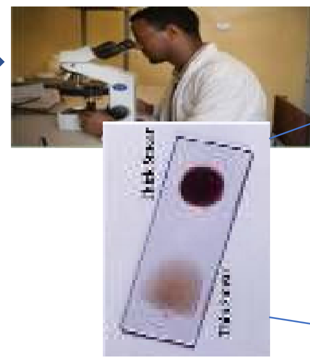


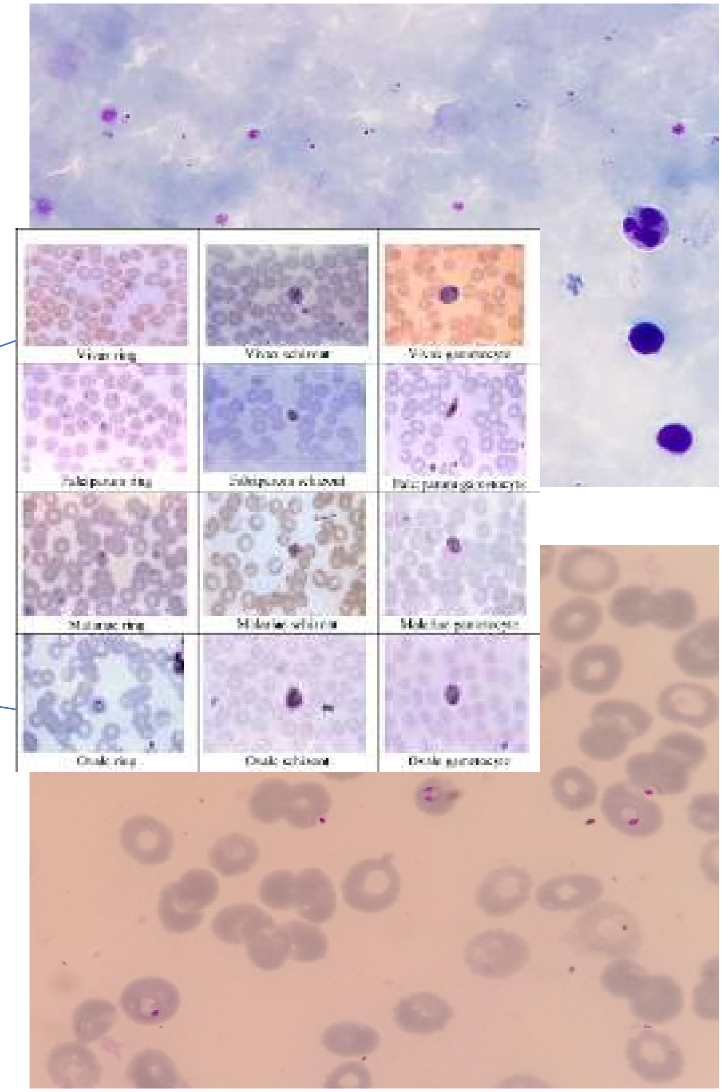
Source: WHO, 2019

[1] https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2021

Malaria Diagnosis

- Microscopy is the golden standard in the world





- Challenges
  - Manual screening is labor-intensive and experience-dependent
  - Shortage of trained experts at malaria endemic regions
  - Variation in diagnosis result due to subjectivity of observers

Automated Microscopic Image Analysis for Malaria Diagnosis

- ✓ Automate daily clinical tasks
- ✓ Increase sensitivity and reduce subjectivity due to interobserver disagreement
- ✓ Application of AI based malaria diagnosis in the absence of microscopists

Challenges for Automated Malaria Diagnosis

- ✓ Lack of standard set of publicly available data
- ✓ Lack of open source code or licensed software as a benchmark model for comparison and reproduce results
- ✓ SOTA deep learning models have low performance in detection of small objects such as malaria parasite

Challenges for Automated Malaria Diagnosis

- ✓ Lack of standard set of publicly available data
  - ✓ Most existing literatures use either private data or very few microscopic images to validate their proposed system
- ✓ Lack of open source code or licensed software as a benchmark model for comparison and reproduce results
- ✓ **SOTA deep learning models have low performance in detection of small objects such as malaria parasite**

Enhancing SOTA models Malaria Parasite Detection performance

1. Objective: To investigate and improve performance of existing SOTA DL OD models for malaria parasite (plasmodium falciparum using thick smear images)

"Malaria parasite detection in thick blood smear microscopic images using modified YOLOV3 and YOLOV4 models" [1]

2. Objective: To design a methodology for performing inference on high resolution microscopic images

"Tile Based Microscopic Image Processing for Malaria Parasite Detection" (undergoing)

[1] Abdurahman et al. (2021) Malaria parasite detection in thick blood smear microscopic images using modified Yolov3 and Yolov4 models

Malaria parasite detection in thick blood smear microscopic images using modified YOLOV3 and YOLOV4 models

Problems of Small Object Detection

- Existing SOTA deep learning based object detectors perform poorly on small object detection (Bochkovskiy A. et al, 2020)
- They can’t be applied directly for small object detection problems such as P. falciparum detection in thick smear images

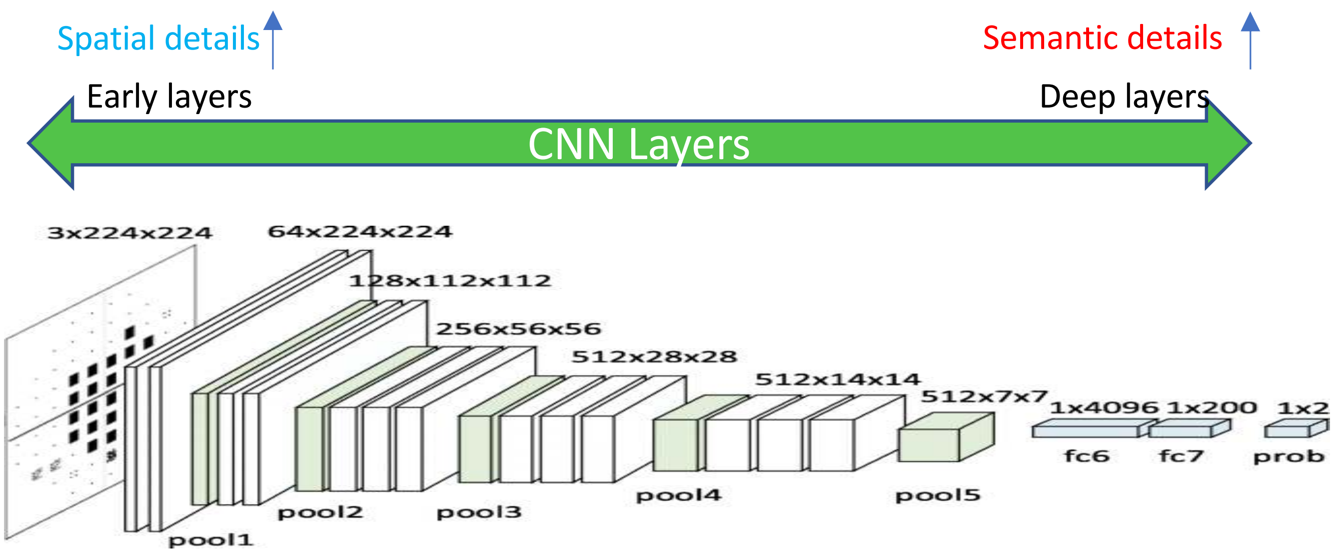
Method	Backbone	Size	FPS	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
YOLOv4: Optimal Speed and Accuracy of Object Detection									
YOLOv4	CSPDarknet-53	416	38 (M)	41.2%	62.8%	44.3%	20.4%	44.4%	56.0%
YOLOv4	CSPDarknet-53	512	31 (M)	**43.0%**	**64.9%**	**46.5%**	**24.3%**	**46.1%**	**55.2%**
YOLOv4	CSPDarknet-53	608	23 (M)	43.5%	65.7%	47.3%	26.7%	46.7%	53.3%
Learning Rich Features at High-Speed for Single-Shot Object Detection [84]									
LRF	VGG-16	300	76.9 (M)	32.0%	51.5%	33.8%	12.6%	34.9%	47.0%
LRF	ResNet-101	300	52.6 (M)	34.3%	54.1%	36.6%	13.2%	38.2%	50.7%
LRF	VGG-16	512	38.5 (M)	36.2%	56.6%	38.7%	19.0%	39.9%	48.8%
LRF	ResNet-101	512	31.3 (M)	37.3%	58.5%	39.7%	19.7%	42.8%	50.1%
Receptive Field Block Net for Accurate and Fast Object Detection [47]									
RFBNet	VGG-16	300	66.7 (M)	30.3%	49.3%	31.8%	11.8%	31.9%	45.9%
RFBNet	VGG-16	512	33.3 (M)	33.8%	54.2%	35.9%	16.2%	37.1%	47.4%
RFBNet-E	VGG-16	512	30.3 (M)	34.4%	55.7%	36.4%	17.6%	37.0%	47.6%
YOLOv3: An incremental improvement [63]									
YOLOv3	Darknet-53	320	45 (M)	28.2%	51.5%	29.7%	11.9%	30.6%	43.4%
YOLOv3	Darknet-53	416	35 (M)	31.0%	55.3%	32.3%	15.2%	33.2%	42.8%
YOLOv3	Darknet-53	608	20 (M)	33.0%	57.9%	34.4%	18.3%	35.4%	41.9%
YOLOv3-SPP	Darknet-53	608	20 (M)	36.2%	60.6%	38.2%	20.6%	37.4%	46.1%
SSD: Single shot multibox detector [50]									
SSD	VGG-16	300	43 (M)	25.1%	43.1%	25.8%	6.6%	25.9%	41.4%
SSD	VGG-16	512	22 (M)	28.8%	48.5%	30.3%	10.9%	31.8%	43.5%
Single-shot refinement neural network for object detection [95]									
RefineDet	VGG-16	320	38.7 (M)	29.4%	49.2%	31.3%	10.0%	32.0%	44.4%
RefineDet	VGG-16	512	22.3 (M)	33.0%	54.5%	35.5%	16.3%	36.3%	44.3%

Methods

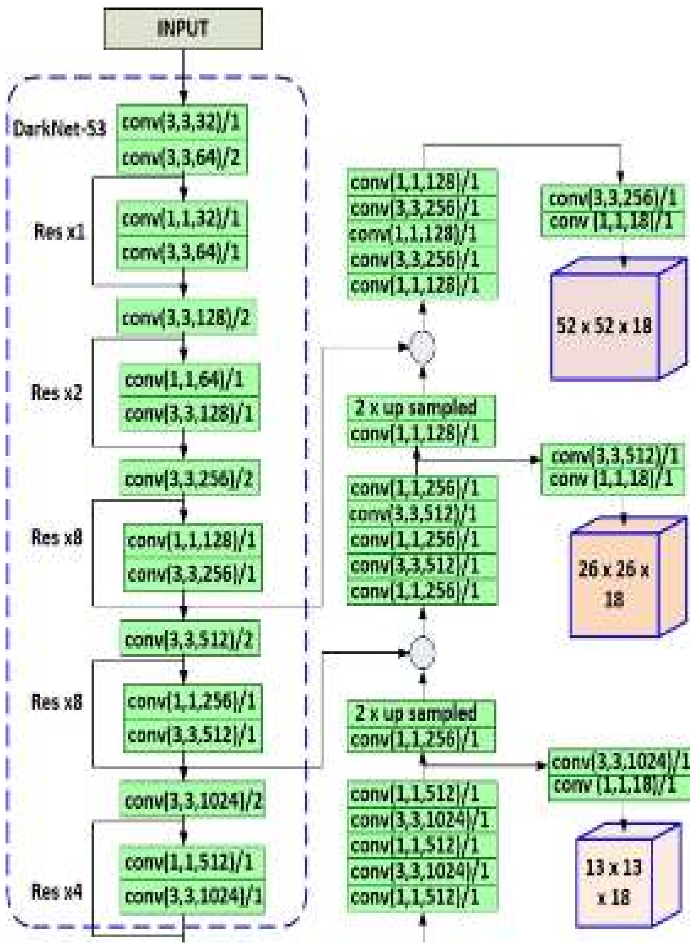
How can we improve SOTA models small object detection capability?

1. Handling feature scale issues has crucial importance for small object detection

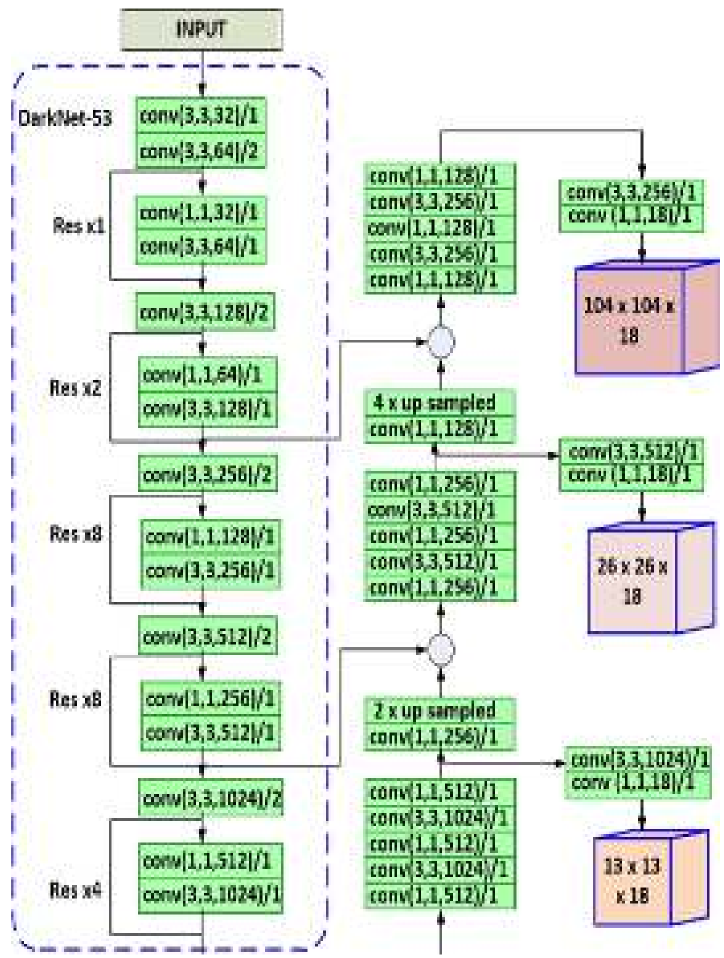
2. Adjustment of priors for better localization of small objects



Modified model architectures for better feature representation of p. falciparum detection

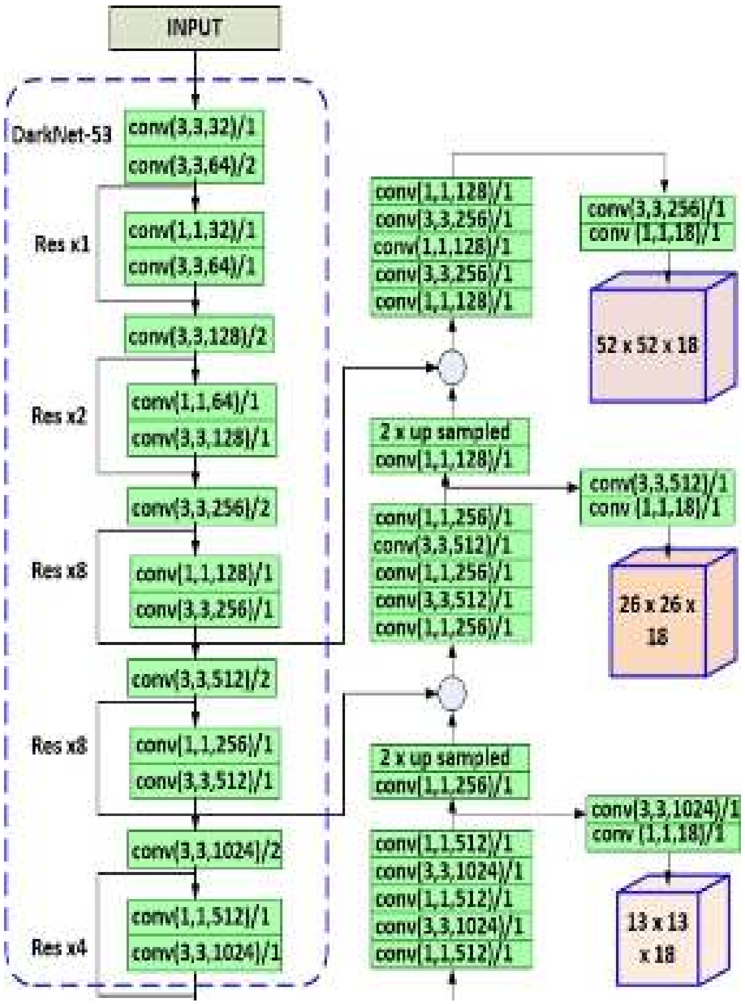


Original architecture

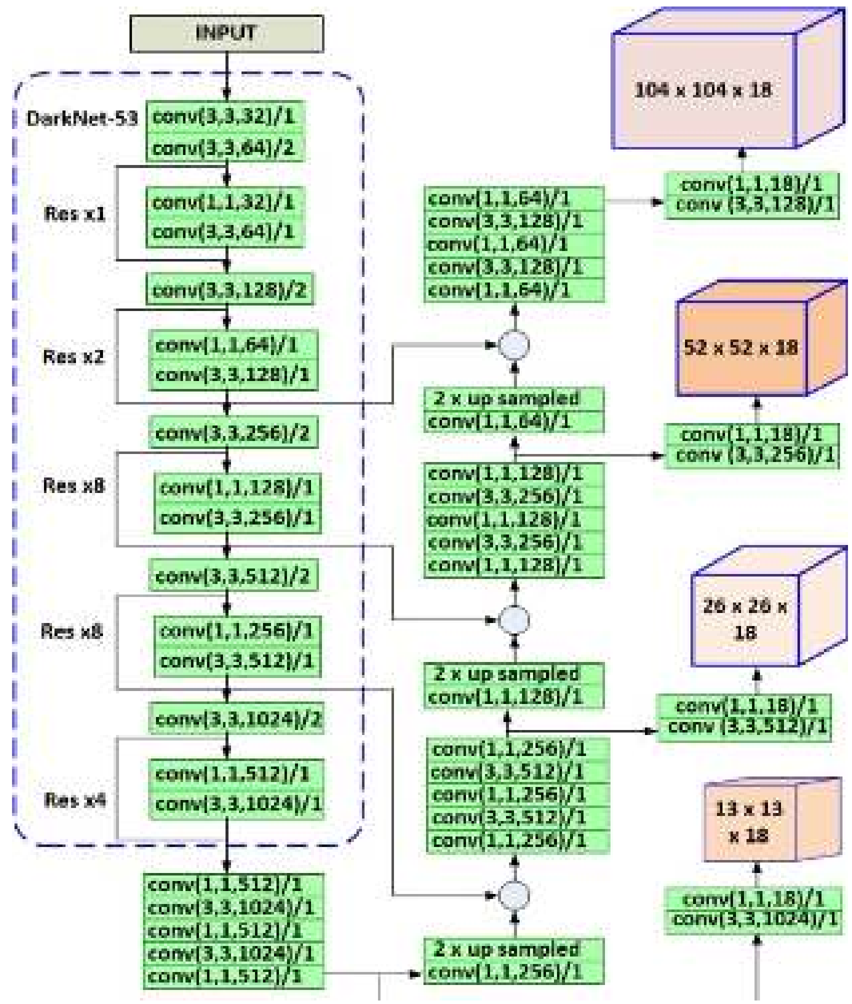


Modified architecture

Adding more detection layers



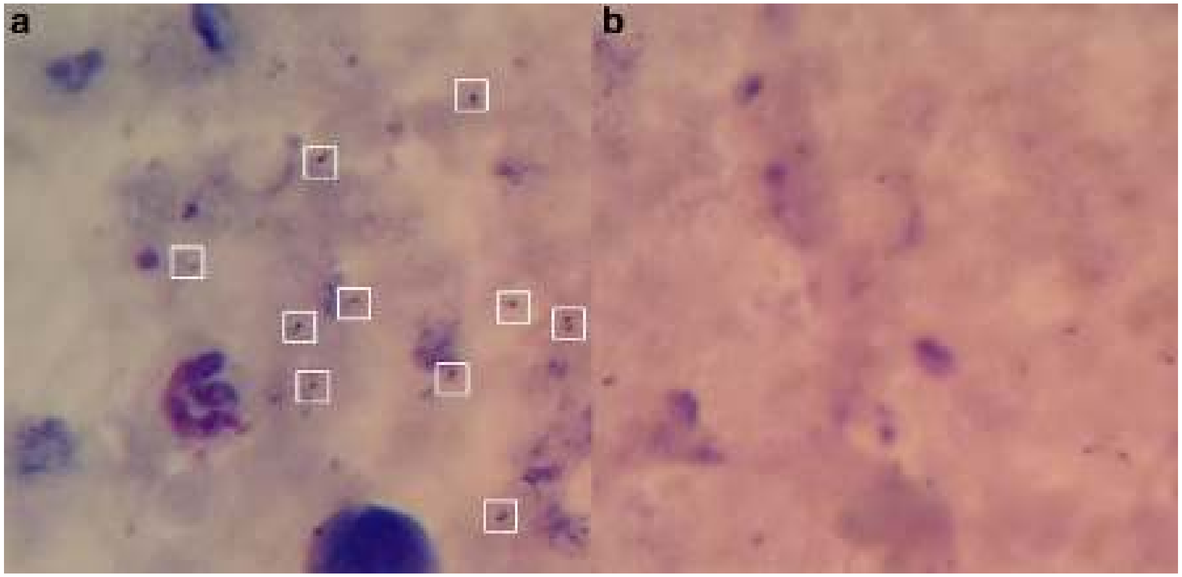
Original architecture



Modified architecture

Dataset and Experimental Results

- We have used a publicly available dataset [1] to evaluate our proposed models (resolution 750 x 750)



	Training	Validation	Testing	Total
Number of images	966	109	107	1182
Negative samples	191	23	20	234
Positive samples	775	86	87	948
Number of parasites	5695	924	1009	7628

. Transfer learning
. Pre-trained on MS COCO

[1] Quinn J. et.al. Automated blood smear analysis for mobile malaria diagnosis; 2014.

Performance Evaluation and Comparison using Test Data

Models	mAP@0.3 (%)	Precision (%)	Recall (%)	F1-Score (%)	Avg. IOU (%)	FPS
YOLOV4-MOD @608 × 608	**96.32**	**95**	**94**	**94**	**62.12**	**29.60**
YOLOV4-MOD @416 × 416	**96.20**	**93**	**93**	**93**	**61.84**	**30.56**
YOLOV3-MOD2 @608 × 608	96.14	92	93	92	61.77	15.30
YOLOV3-MOD2 @416 × 416	95.80	92	92	92	61.03	17.83
YOLOV3-MOD1 @608 × 608	95.46	92	92	92	61.03	21.40
YOLOV3-MOD1 @416 × 416	95.28	92	92	92	60.64	26.75
YOLOV4 @608 × 608 [50]	95.84	92	92	92	61.15	30.77
YOLOV4 @416 × 416 [50]	95.44	92	92	92	60.67	33.89
YOLOV3 @608 × 608 [49]	94.61	91	92	92	59.98	28.67
YOLOV3 @416 × 416 [49]	94.45	91	91	91	58.85	30.43
Faster R-CNN [47]	71.0	92.7	86.9	89.71	–	8
SSD @300 × 300 [48]	71.4	91	84	87	–	41

Bold values indicate best performing models

Conclusion

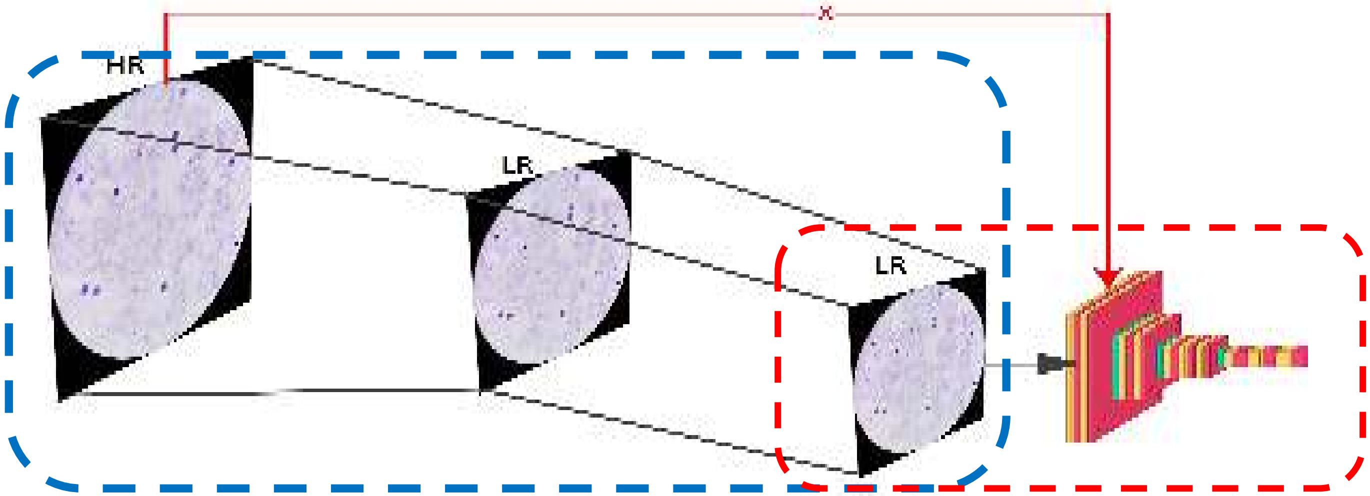
- We demonstrated that SOTA deep learning object detection models will be effective in malaria parasite detection

- Performance of modified YOLOV3 and YOLOV4 models are highly promising for detecting malaria parasites compared with the original versions

Tile Based Microscopic Image Processing for Malaria Parasite Detection

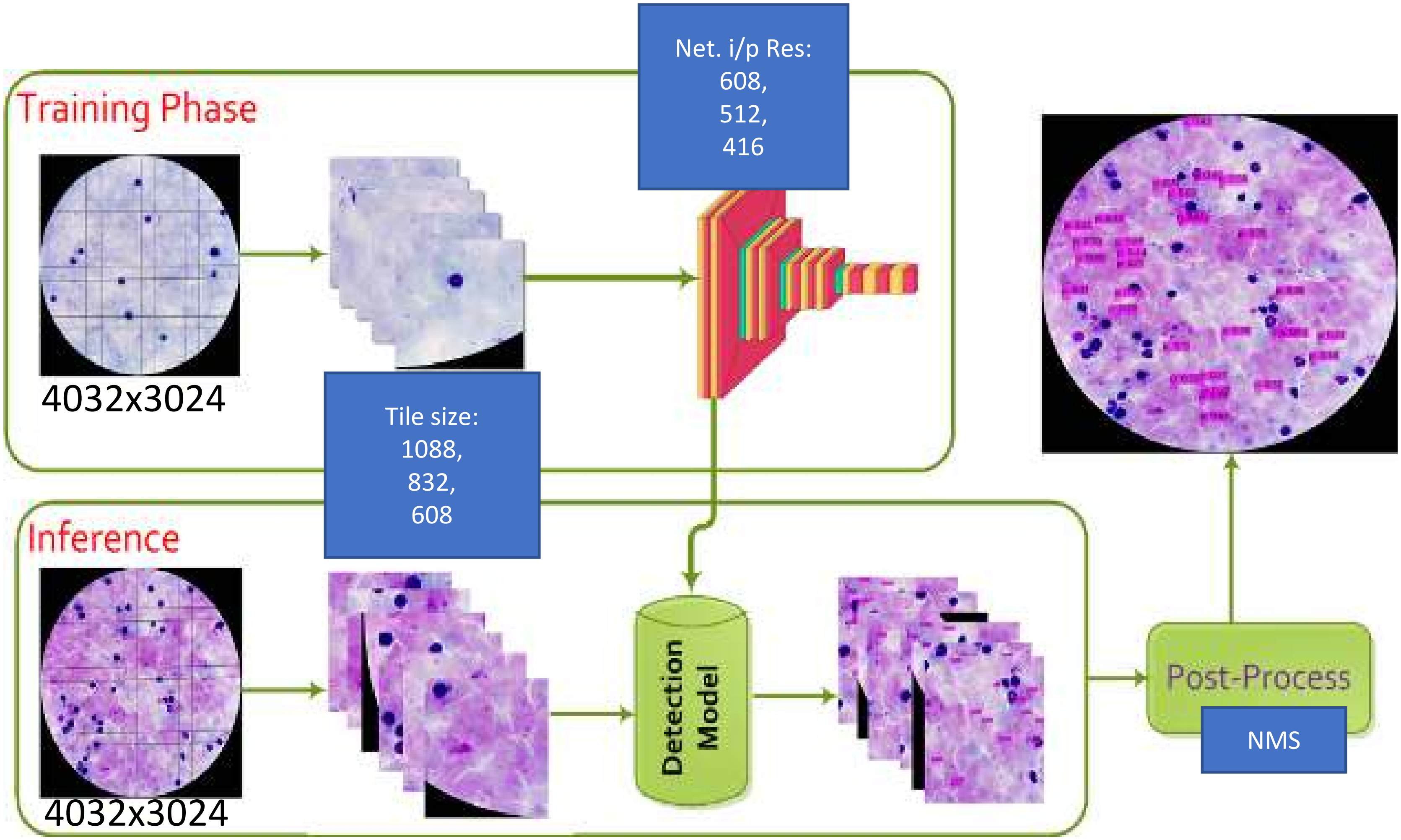
Challenges in SOTA DL Models in Terms of Input Image Resolution

- Existing SOTA models are trained on low resolution (e.g, 265x256) images to keep the computational demands low
- Feature map downscaling makes small object detection difficult for low resolution input images (try to solve in our previous work)



- Resizing high resolution images to low resolution images leads to massive information loss and performance degradation of DL models

Proposed Method



Experimental Analysis and Results

- **SOTA Detection Model Selection:**
- We evaluate 3 different YOLOV4 based detection models in order to identify the one that provides the best trade-off between accuracy and inference speed
  - ✓ Modified large YOLOv4 network based on our previous work (~75 BFLOPS)- YOLOv4-MOD
  - ✓ Yolov4 Tiny with 2 detection heads (~7 BFLOPS) – YOLOV4-tiny
  - ✓ Yolov4 Tiny with 3 detection heads (~8 BFLOPS) - YOLOV4-tiny-3l

- **Dataset Used:**
  - Thick smear microscopy images [1] collected from Chittagong Medical College Hospital, Bangladesh
  - The resolution of the images is 4032 x 3024 pixels

	Training	**Validation**	**Testing**	**Total**
Number of patients	96	24	30	150
Number of images	1140	266	374	1780
Number of parasites	49,520	11,174	22,783	83,477

[1] Feng et.al, Deep Learning for Smartphone-Based Malaria parasite detection in thick blood smear

Performance evaluation using test set

DL MODEL	Input Resolution	Tile size		Precision (%)	Recall (%)	sec/img
		train	inference			
YOLOV4-tiny@512	4032 x 3024	608 x 608	608 x 608	87.1	95.3	1.5
YOLOV4-tiny-3l@608	4032 x 3024	608 x 608	608 x 608	87.4	95.1	1.9
YOLOV4-MOD@416	4032 x 3024	1088 x 1088	832 x 832	85.5	95.1	4
with out tiling						
YoloV4-tiny@608 with original image	4032 x 3024	-	-	76	57	0.15
YoloV4-tiny-3l@512 with original image	4032 x 3024	-	-	79.4	78	0.2
YoloV4-MOD@512 with original image	4032 x 3024	-	-	79.78	80	0.25

- YOLOV4-tiny and YOLOV4-tiny-3l performs 2.6× and 2× faster compared to YOLOV4-MOD with better sensitivity and precision respectively
- Lightweight Models achieve best trade-off between detection accuracy and inference speed for P. falciparum detection
- Comparison with benchmark models: lightweight models perform 10× slower but their detection sensitivity increase by ~17% for yolov4-tiny-3l and ~38% for yolov4-tiny model

Comparison with Related Work

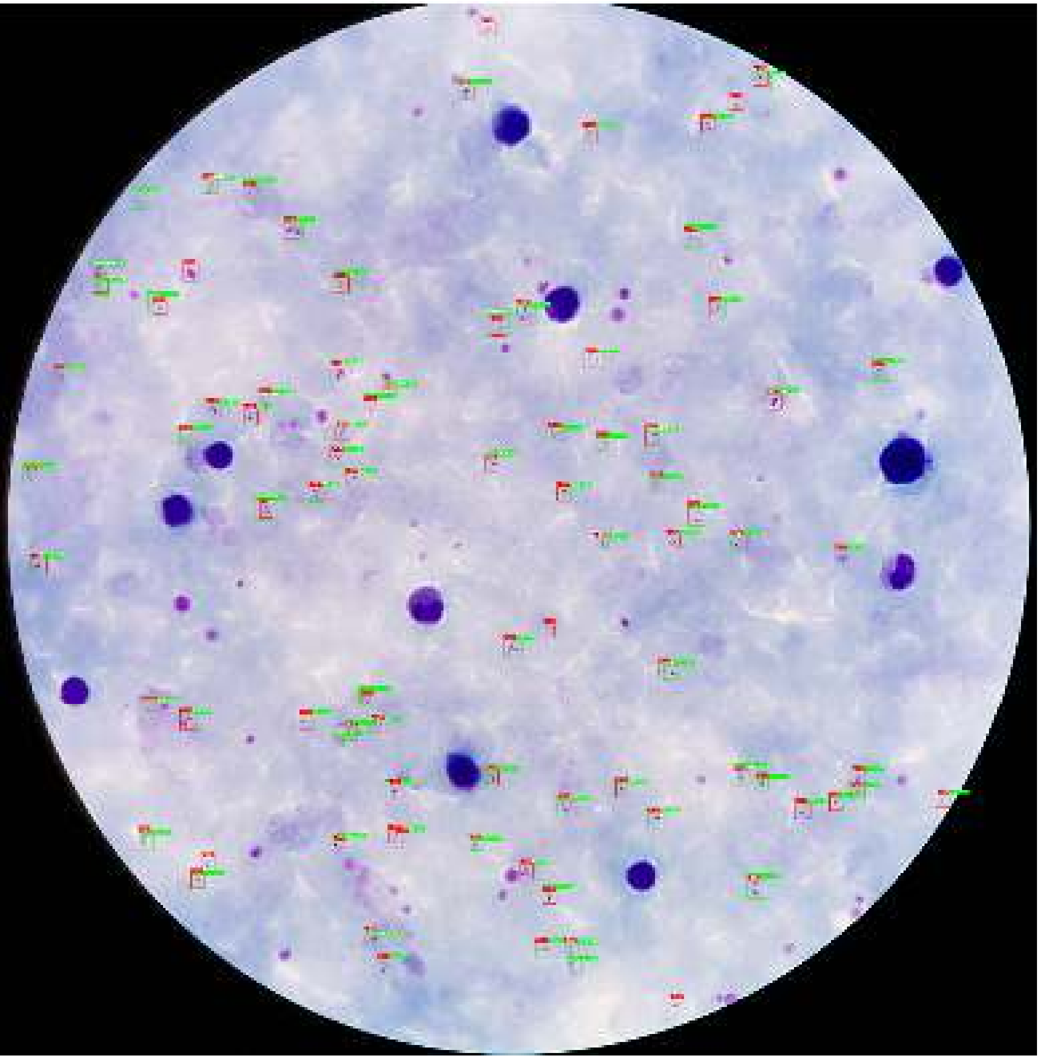
- Performance at patch level using test set data

Method	Techniques used	Precision	Sensitivity
Feng et.al[1]	Pre-segmentation followed by CNN classifier	78.98%	82.73%
Our Proposed Method	End-to-end CNN based object detector (one-stage detectors)	87.1% ~7% improve	95.3% ~12% improve

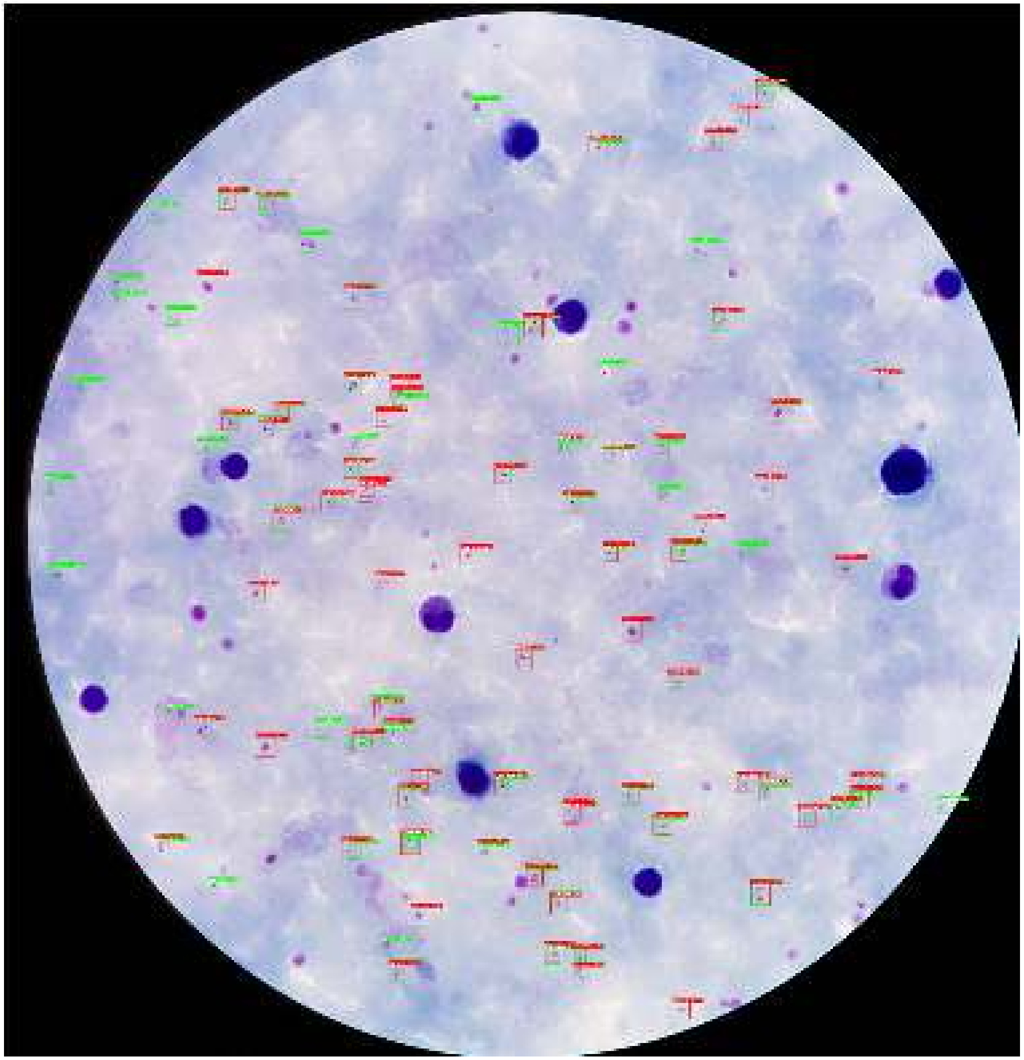
[1] Feng et.al, Deep Learning for Smartphone-Based Malaria parasite detection in thick blood smear

Sample Visualization Results for Best Performing Model

With Tile

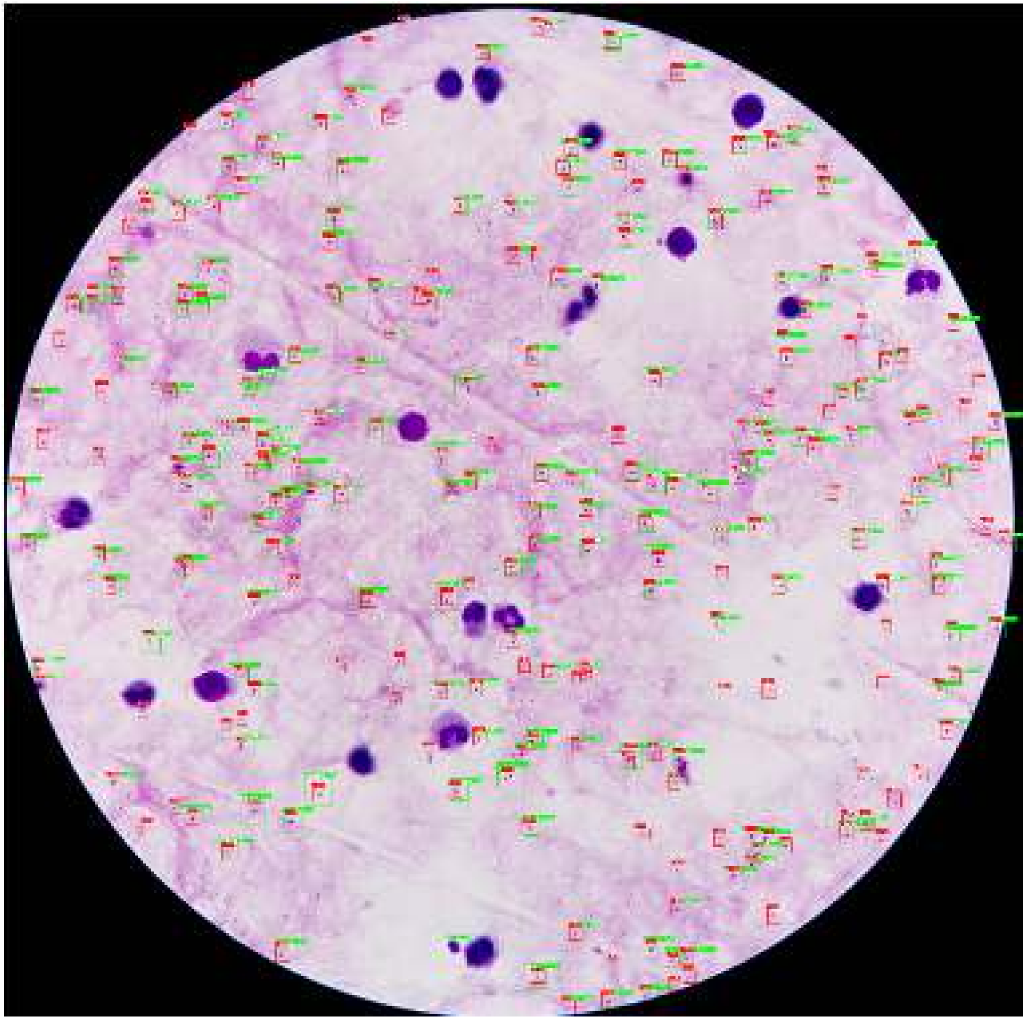


With out Tile

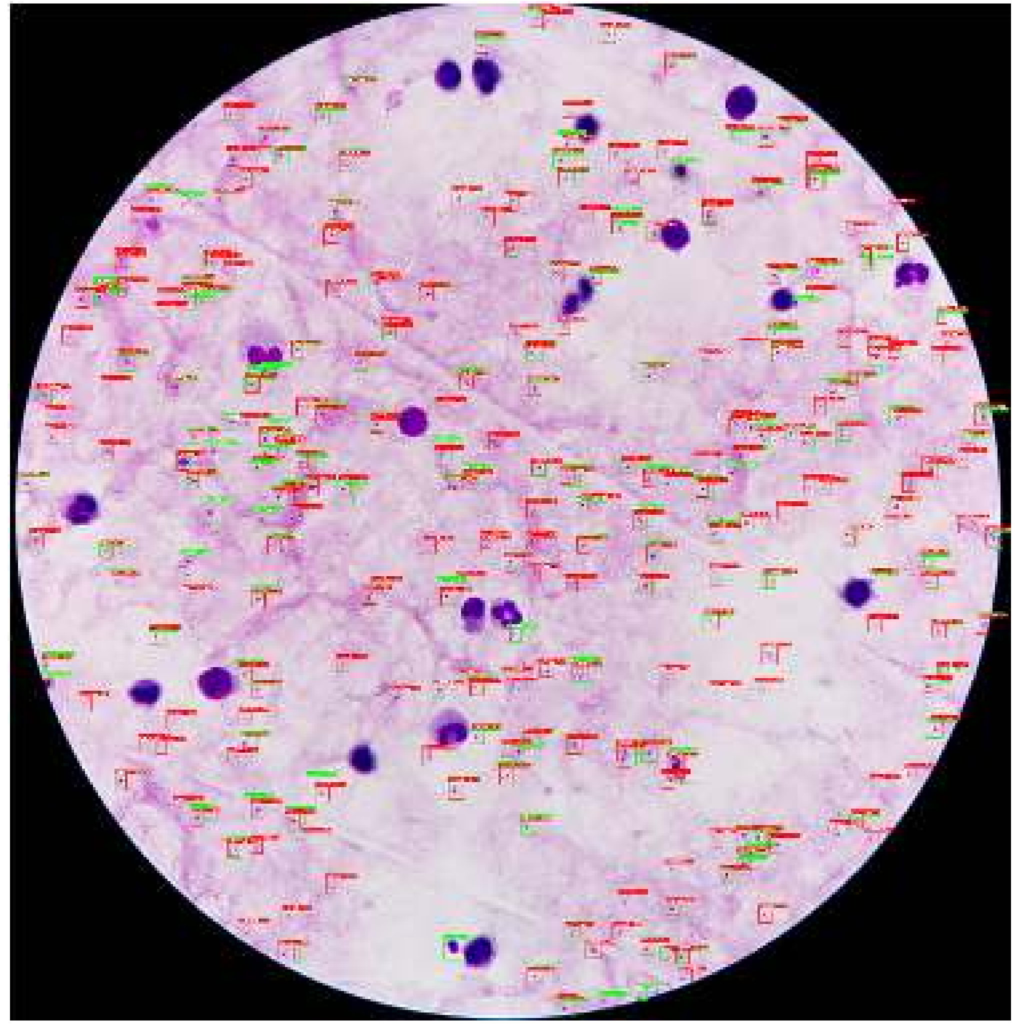


Sample Visualization Results for Best Performing Model

With Tile



With out Tile



Conclusion

- By avoiding resizing of the input HR image, there is a big improvement on detection performance but simultaneously the average processing time was increased by 10×

- Lower precision due to large number of false positive cases which is due to distractors in the image

- Future steps:
  - Include other parasite species and their life stage as well
  - Performance improvement by adding false positive filter classifier

Thank you for your attention and time!

Detection performance of large YOLOv4 models

DL MODEL	Input Resolution	Tile size		Precision (%)	Recall (%)	sec/img
		train	inference			
YOLOV4-MOD@416	4032 x 3024	1088 x 1088	1088 x 1088	83.1	94.3	3
YOLOV4-MOD@416	4032 x 3024	1088 x 1088	832 x 832	85.5	95.1	4
YOLOV4-MOD@416	4032 x 3024	1088 x 1088	608 x 608	82.8	91.3	8
YOLOV4-MOD@512	4032 x 3024	1088 x 1088	1088 x 1088	81.8	90.5	4
YOLOV4-MOD@512	4032 x 3024	1088 x 1088	832 x 832	82.5	92.6	5
YOLOV4-MOD@512	4032 x 3024	1088 x 1088	608 x 608	78.2	91.7	9
YOLOV4-MOD@416	4032 x 3024	832 x 832	1088 x 1088	80.6	90.8	3
YOLOV4-MOD@416	4032 x 3024	832 x 832	832 x 832	85.0	93.5	4
YOLOV4-MOD@416	4032 x 3024	832 x 832	608 x 608	75.0	86.1	7
YOLOV4-MOD@512	4032 x 3024	832 x 832	1088 x 1088	66.1	82.3	4
YOLOV4-MOD@512	4032 x 3024	832 x 832	832 x 832	82.5	93.2	5
YOLOV4-MOD@512	4032 x 3024	832 x 832	608 x 608	79.6	92.7	10
YOLOV4-MOD@416	4032 x 3024	608 x 608	1088 x 1088	43.5	63.3	3
YOLOV4-MOD@416	4032 x 3024	608 x 608	832 x 832	66.7	82.5	3.5
YOLOV4-MOD@416	4032 x 3024	608 x 608	608 x 608	76.8	90.6	6
YOLOV4-MOD@512	4032 x 3024	608 x 608	1088 x 1088	55.3	85.7	3
YOLOV4-MOD@512	4032 x 3024	608 x 608	832 x 832	69.0	85.6	5
YOLOV4-MOD@512	4032 x 3024	608 x 608	608 x 608	77.9	90.1	8.5
with out tiling						
YoloV4-MOD@512 with original image	4032 x 3024	-	-	79.78	80	0.25
YoloV4-MOD@416 with original image	4032 x 3024	-	-	72.8	76	0.2

Detection performance of light YOLOv4 models

DL MODEL	Input Resolution	Tile size		Precision	Recall	sec/img
		train	inference			
YOLOV4-tiny-3l@416	4032 x 3024	1088 x 1088	1088 x 1088	55.4	59.8	1
YOLOV4-tiny-3l@416	4032 x 3024	1088 x 1088	832 x 832	65.9	71.2	1
YOLOV4-tiny-3l@416	4032 x 3024	1088 x 1088	608 x 608	76.9	84.6	1.4
YOLOV4-tiny-3l@512	4032 x 3024	1088 x 1088	1088 x 1088	67.2	72.8	1.3
YOLOV4-tiny-3l@512	4032 x 3024	1088 x 1088	832 x 832	78.0	84.3	1.4
YOLOV4-tiny-3l@512	4032 x 3024	1088 x 1088	608 x 608	83.4	92.3	2
YOLOV4-tiny-3l@608	4032 x 3024	1088 x 1088	1088 x 1088	78.4	84.3	1.2
YOLOV4-tiny-3l@608	4032 x 3024	1088 x 1088	832 x 832	86.1	93.0	1.6
YOLOV4-tiny-3l@608	4032 x 3024	1088 x 1088	608 x 608	81.6	89.3	2
YOLOV4-tiny-3l@416	4032 x 3024	832 x 832	1088 x 1088	50	53.7	1
YOLOV4-tiny-3l@416	4032 x 3024	832 x 832	832 x 832	64.3	70	1
YOLOV4-tiny-3l@416	4032 x 3024	832 x 832	608 x 608	80.5	87.7	1.5
YOLOV4-tiny-3l@512	4032 x 3024	832 x 832	1088 x 1088	64.9	71.4	1.1
YOLOV4-tiny-3l@512	4032 x 3024	832 x 832	832 x 832	78.1	84.5	1.4
YOLOV4-tiny-3l@512	4032 x 3024	832 x 832	608 x 608	85.7	94.2	1.9
YOLOV4-tiny-3l@608	4032 x 3024	832 x 832	1088 x 1088	74.5	81.0	1.3
YOLOV4-tiny-3l@608	4032 x 3024	832 x 832	832 x 832	85.4	92.6	1.6
YOLOV4-tiny-3l@608	4032 x 3024	832 x 832	608 x 608	84	91	2
YOLOV4-tiny-3l@416	4032 x 3024	608 x 608	1088 x 1088	41.8	57.1	0.8
YOLOV4-tiny-3l@416	4032 x 3024	608 x 608	832 x 832	64.4	71.4	1
YOLOV4-tiny-3l@416	4032 x 3024	608 x 608	608 x 608	81.7	89.7	1.4
YOLOV4-tiny-3l@512	4032 x 3024	608 x 608	1088 x 1088	51.8	57.2	1
YOLOV4-tiny-3l@512	4032 x 3024	608 x 608	832 x 832	74.6	81.1	1.3
YOLOV4-tiny-3l@512	4032 x 3024	608 x 608	608 x 608	87.1	95.0	1.9
YOLOV4-tiny-3l@608	4032 x 3024	608 x 608	1088 x 1088	69.2	85.7	1
YOLOV4-tiny-3l@608	4032 x 3024	608 x 608	832 x 832	83.8	91.9	1.4
YOLOV4-tiny-3l@608	4032 x 3024	608 x 608	608 x 608	87.4	95.1	1.9
with out tiling						
YoloV4-tiny-3l@416 with original image	4032 x 3024	-	-	71.46	71	0.2
YoloV4-tiny-3l@512 with original image	4032 x 3024	-	-	79.4	78	0.2
YoloV4-tiny-3l@608 with original image	4032 x 3024	-	-	78.73	76	0.2

Detection performance of light YOLOv4 models

DL MODEL	Input Resolution	Tile size		Precision	Recall	sec/img
		train	inference			
YOLOV4-tiny@416	4032 x 3024	1088 x 1088	1088 x 1088	56	60	1
YOLOV4-tiny@416	4032 x 3024	1088 x 1088	832 x 832	67	73	1
YOLOV4-tiny@416	4032 x 3024	1088 x 1088	608 x 608	78	86	1.4
YOLOV4-tiny@416	4032 x 3024	1088 x 1088	416 x 416	65	75.8	1.4
YOLOV4-tiny@512	4032 x 3024	1088 x 1088	1088 x 1088	70	75.9	1
YOLOV4-tiny@512	4032 x 3024	1088 x 1088	832 x 832	80.4	86.1	1.2
YOLOV4-tiny@512	4032 x 3024	1088 x 1088	608 x 608	82.6	91.4	1.6
YOLOV4-tiny@608	4032 x 3024	1088 x 1088	1088 x 1088	77.9	83.4	1
YOLOV4-tiny@608	4032 x 3024	1088 x 1088	832 x 832	85.9	92.7	1.3
YOLOV4-tiny@608	4032 x 3024	1088 x 1088	608 x 608	81.9	89.3	1.7
YOLOV4-tiny@416	4032 x 3024	832 x 832	1088 x 1088	53.3	57.6	1
YOLOV4-tiny@416	4032 x 3024	832 x 832	832 x 832	66	71.9	1.1
YOLOV4-tiny@416	4032 x 3024	832 x 832	608 x 608	81.4	88.1	1.6
YOLOV4-tiny@512	4032 x 3024	832 x 832	1088 x 1088	66.7	72.8	1
YOLOV4-tiny@512	4032 x 3024	832 x 832	832 x 832	79.1	85.0	1.1
YOLOV4-tiny@512	4032 x 3024	832 x 832	608 x 608	86.0	94.1	1.6
YOLOV4-tiny@512	4032 x 3024	832 x 832	416 x 416	78.8	89.2	2.7
YOLOV4-tiny@608	4032 x 3024	832 x 832	1088 x 1088	76.7	82.6	1
YOLOV4-tiny@608	4032 x 3024	832 x 832	832 x 832	86	92.9	1.3
YOLOV4-tiny@608	4032 x 3024	832 x 832	608 x 608	84.4	91.5	1.6
YOLOV4-tiny@416	4032 x 3024	608 x 608	1088 x 1088	48	57.1	1
YOLOV4-tiny@416	4032 x 3024	608 x 608	832 x 832	60.9	67.1	1
YOLOV4-tiny@416	4032 x 3024	608 x 608	608 x 608	83.2	90.1	1.3
YOLOV4-tiny@416	4032 x 3024	608 x 608	416 x 416	84.0	91.1	2
YOLOV4-tiny@512	4032 x 3024	608 x 608	1088 x 1088	54.3	60.8	1
YOLOV4-tiny@512	4032 x 3024	608 x 608	832 x 832	76.4	79.8	1
YOLOV4-tiny@512	4032 x 3024	608 x 608	608 x 608	87.1	95.3	1.5
YOLOV4-tiny@512	4032 x 3024	608 x 608	416 x 416	84.0	94.9	2.6
YOLOV4-tiny@608	4032 x 3024	608 x 608	1088 x 1088	69.4	85.7	1
YOLOV4-tiny@608	4032 x 3024	608 x 608	832 x 832	84.3	92.1	1.3
YOLOV4-tiny@608	4032 x 3024	608 x 608	608 x 608	87.0	95.3	1.9
with out tiling						
YoloV4-tiny@416 with original image	4032 x 3024	-	-	54	21	0.15
YoloV4-tiny@512 with original image	4032 x 3024	-	-	69	48	0.15
YoloV4-tiny@608 with original image	4032 x 3024	-	-	76	57	0.15