Super-Resolution with RCAN for Improved Malaria Cell Classification: A Performance Evaluation

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CONTENT

Super-Resolution with RCAN for Improved Malaria Cell Classification

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01 Background

Malaria Diagnosis:

•Fields: Medicine, Public Health, Machine Classification

Challenges:

•Variability in diagnostic accuracy

•Complexity of malaria cell images

Recognition Methods:

•**Non-deep learning:**

- Manual examination of blood smears
- Inefficient and variable

•**Deep learning:**

- Use CNN to extract complex features
- Improves classification accuracy

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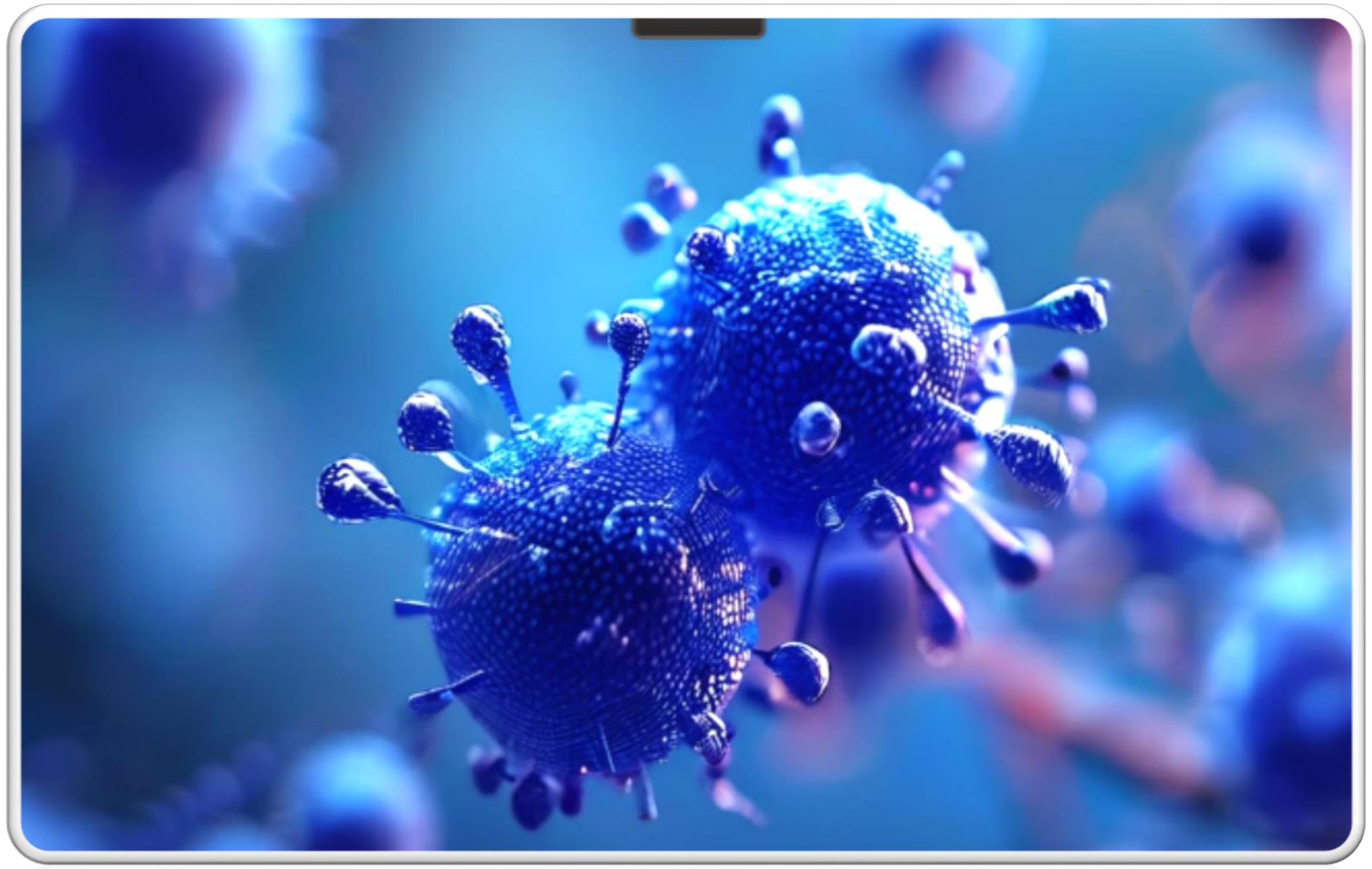
02 Aims



•**Enhance diagnostic accuracy of malaria cell classification:**
•Integrate RCAN for 2x super-resolution
•Improve image quality for precise feature extraction

•**Quantitative Assessment:**
•Use PSNR and SSIM to evaluate image resolution improvements
•Compare classification models on original and enhanced datasets

•**Comprehensive Evaluation:**
•Establish superior performance of super-resolved images
•Conduct thorough model comparison

•**Real-World Deployment:**
•Deploy the most effective model using ONNX Runtime
•Ensure compatibility and efficacy in diverse environments

Audience:
•Medical researchers
•Healthcare professionals
•AI and machine learning practitioners

03 Dataset

Source:

•Kaggle

Total Images:

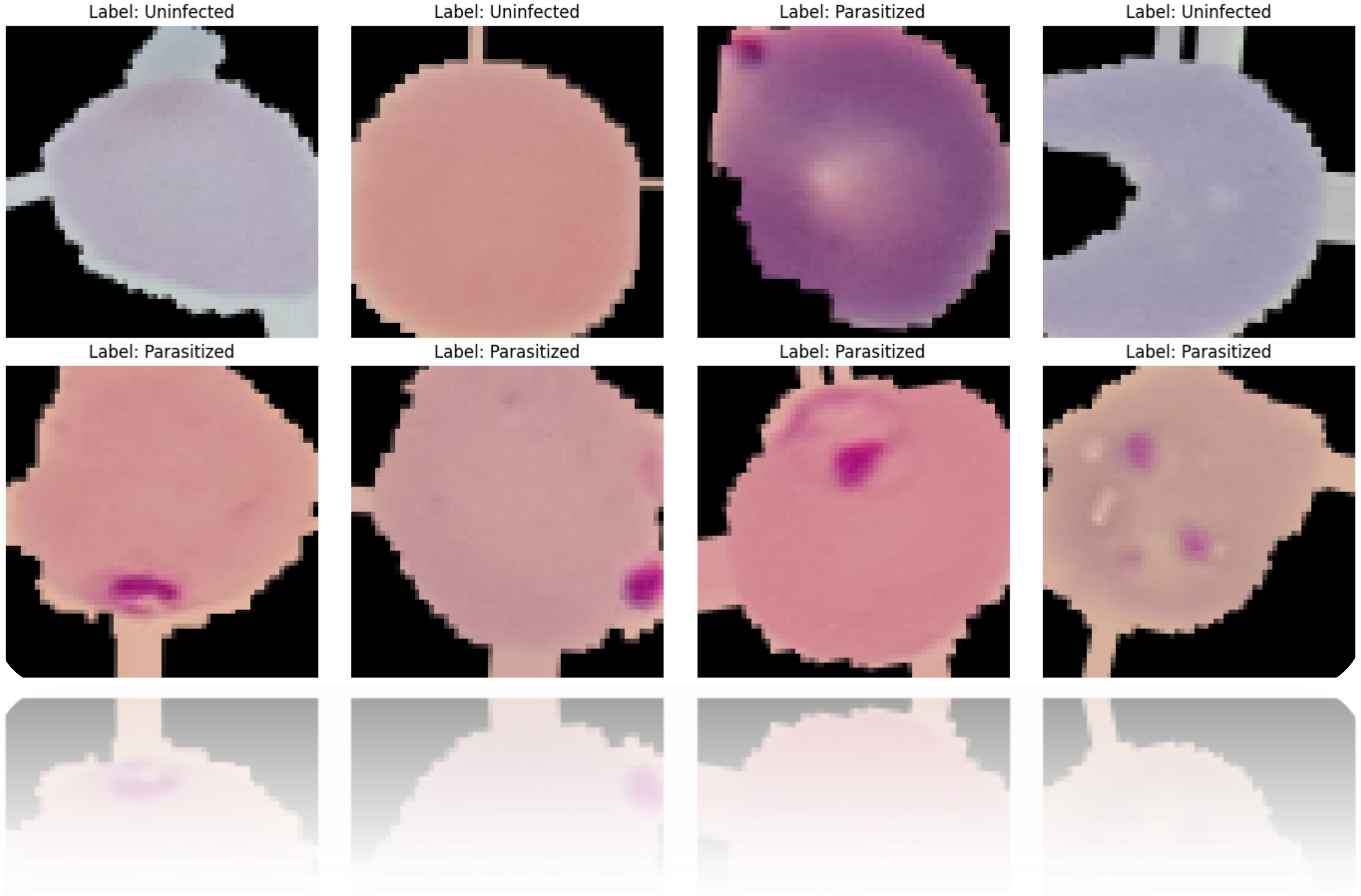
•27,558 images

•Divided into two categories: parasitized and uninfected

Categories:

•**Parasitized Images:** 13,799 images of infected cells

•**Uninfected Images:** 13,799 images of healthy cells

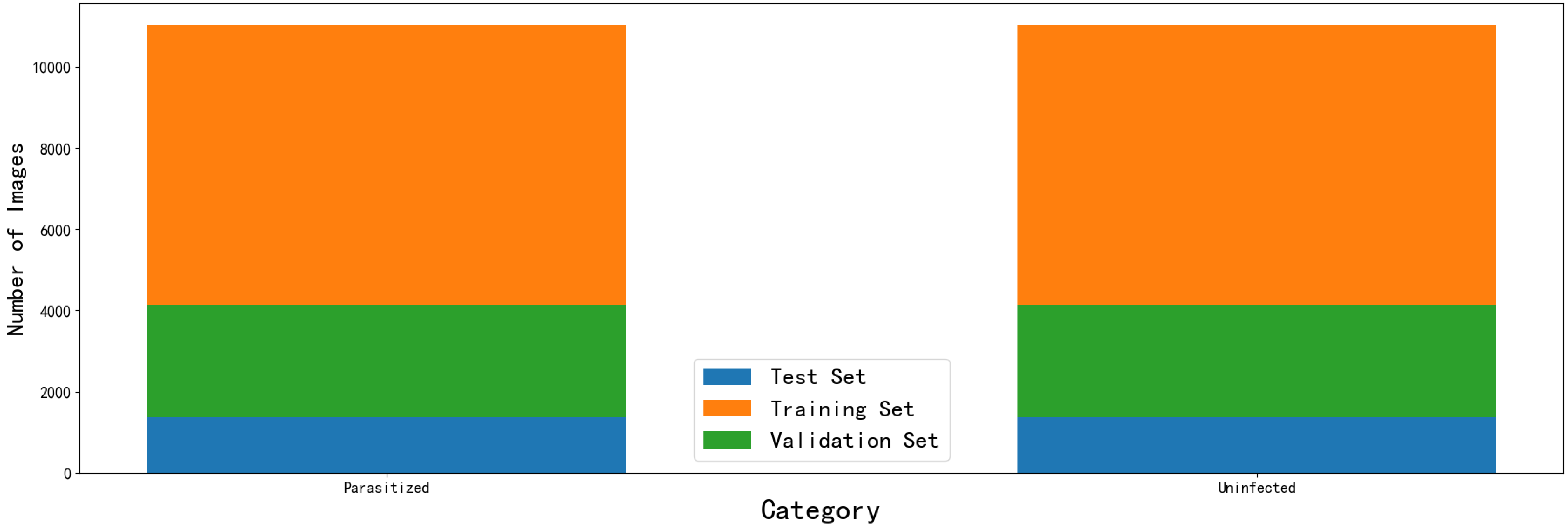


03 Dataset

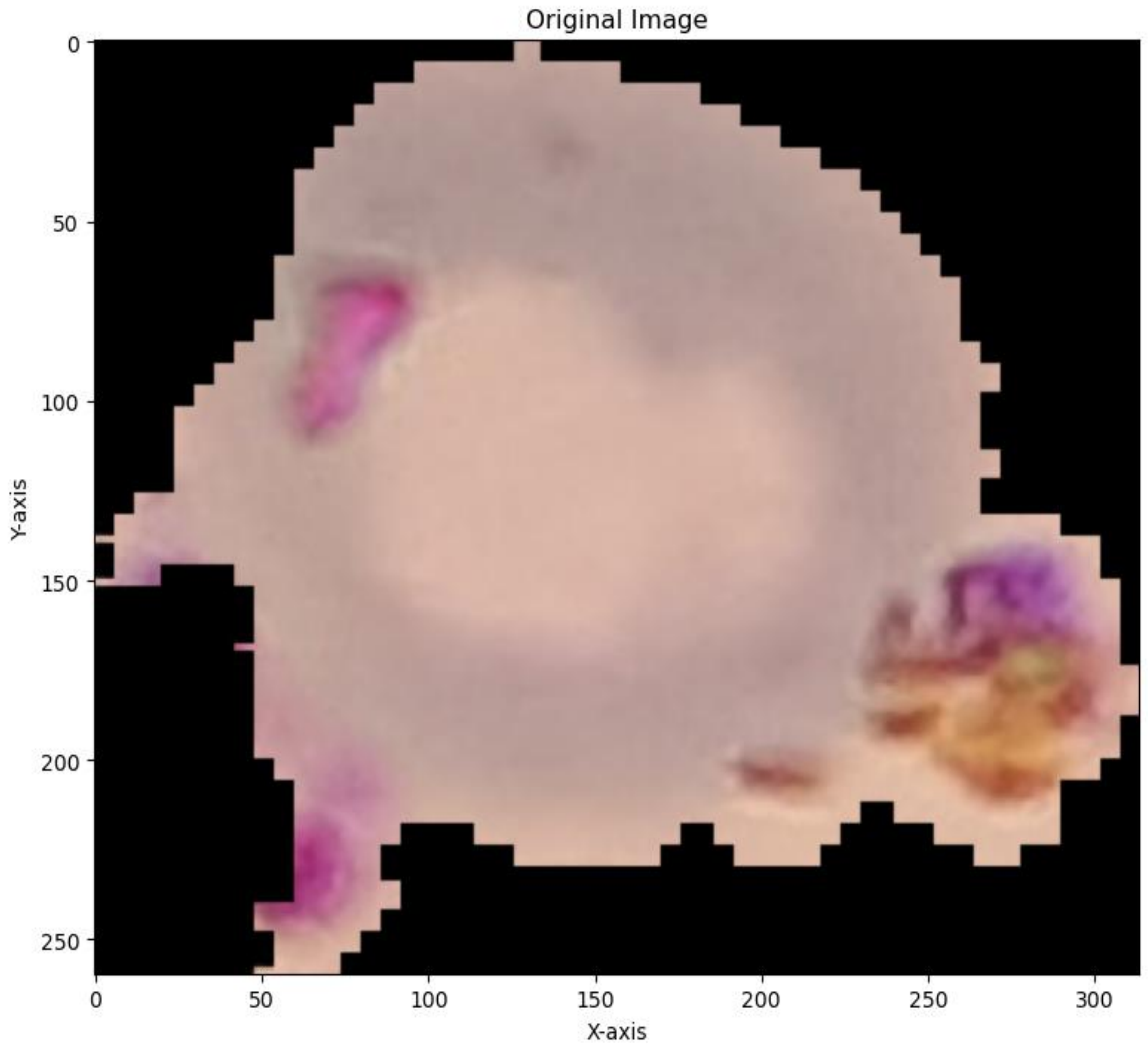
This dataset with 2 types of cells with total of 27,558 images.

Division of the data set:

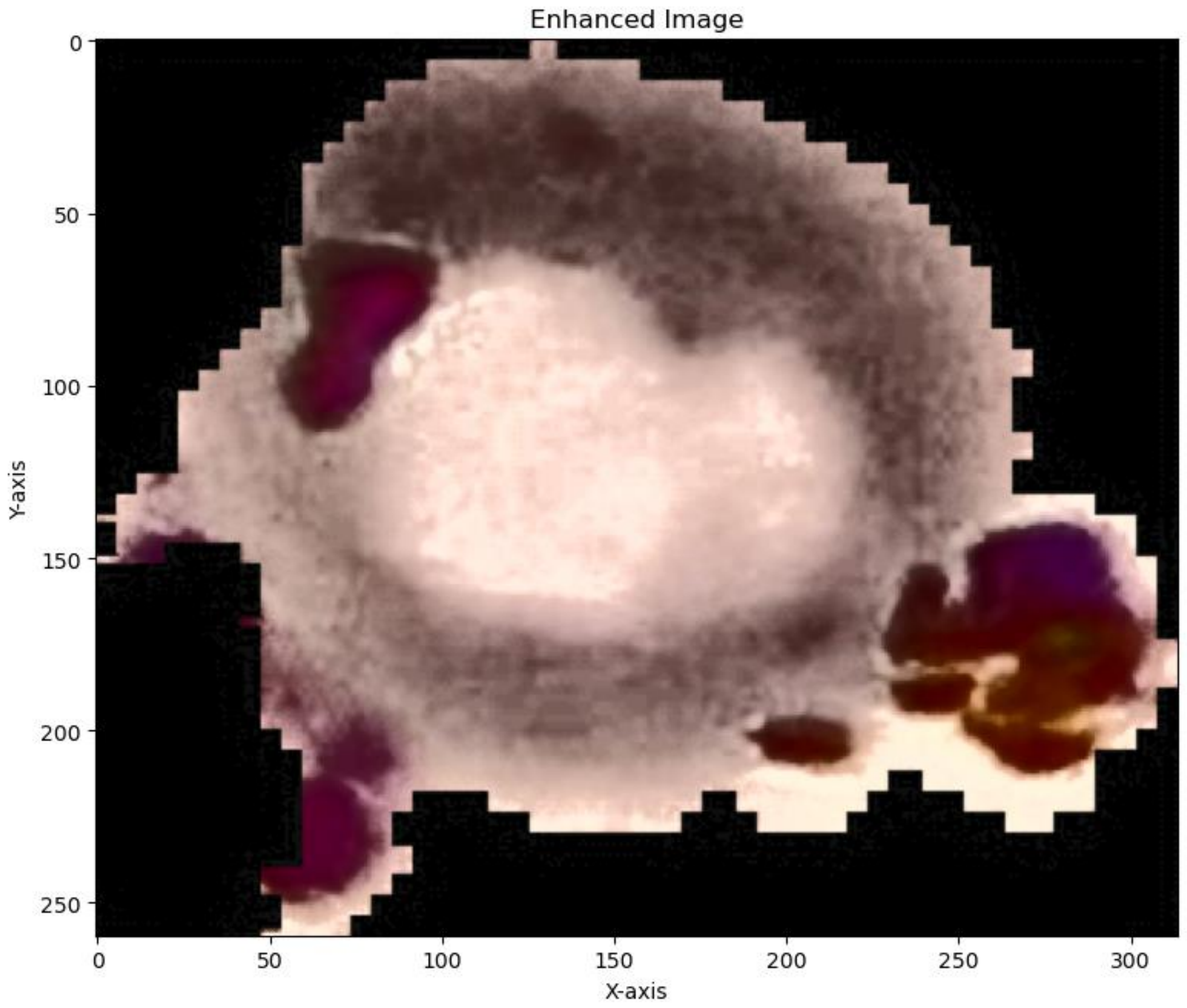
70% for training, 20% for validation, 10% for testing.



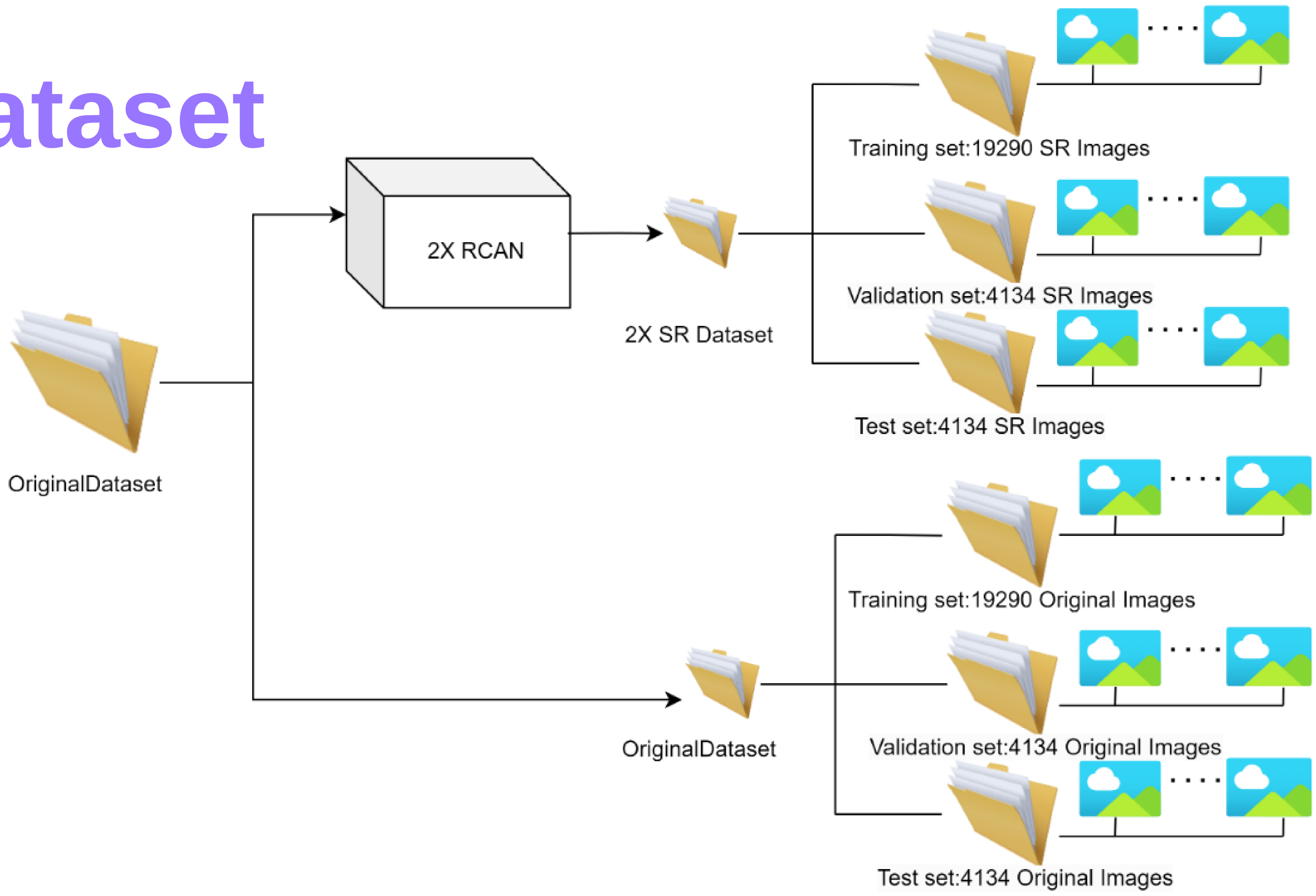
03 Dataset



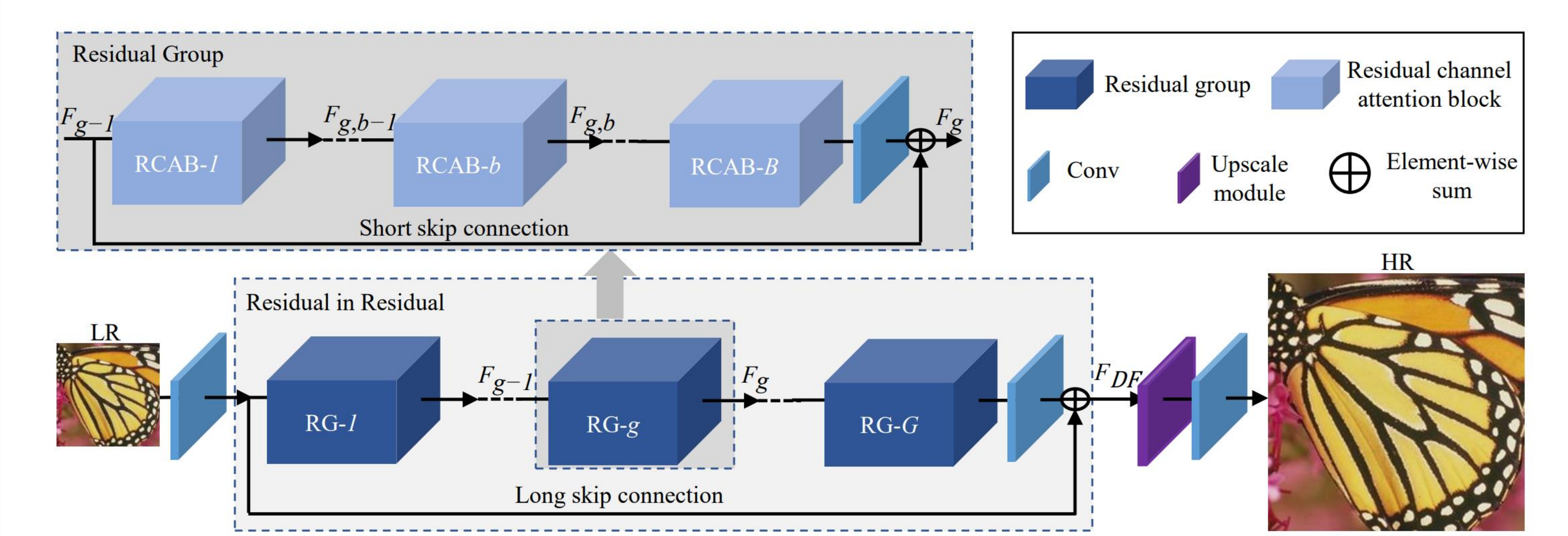
- Contrast Enhancement
- Downsampling and Upsampling(Make SR dataset)
- Horizontal Flipping
- Normalization



03 Dataset

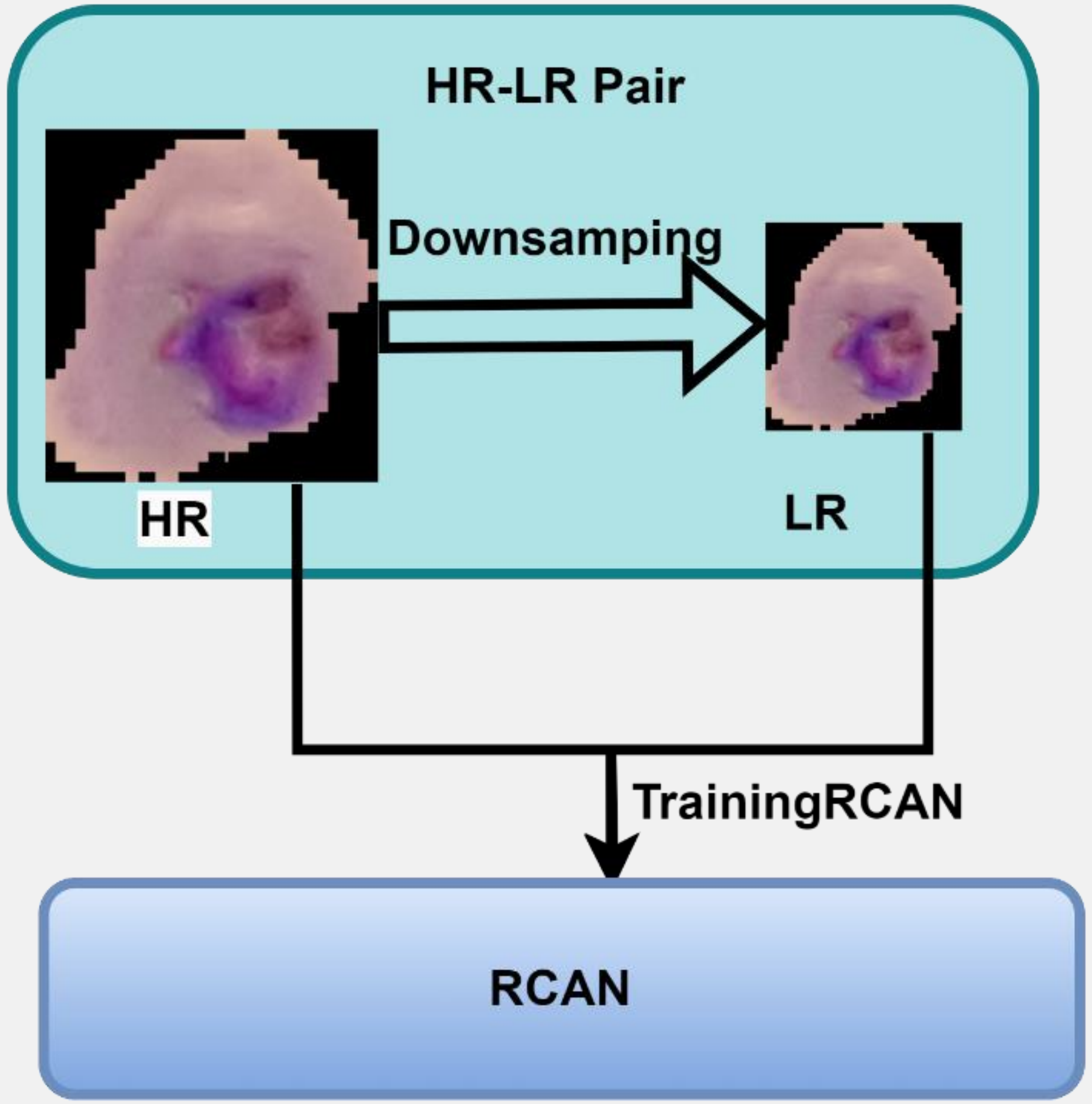

2X RCAN
Training set:19290 SR Images
Validation set:4134 SR Images
2X SR Dataset
Test set:4134 SR Images
OriginalDataset
Training set:19290 Original Images
Validation set:4134 Original Images
OriginalDataset
Test set:4134 Original Images

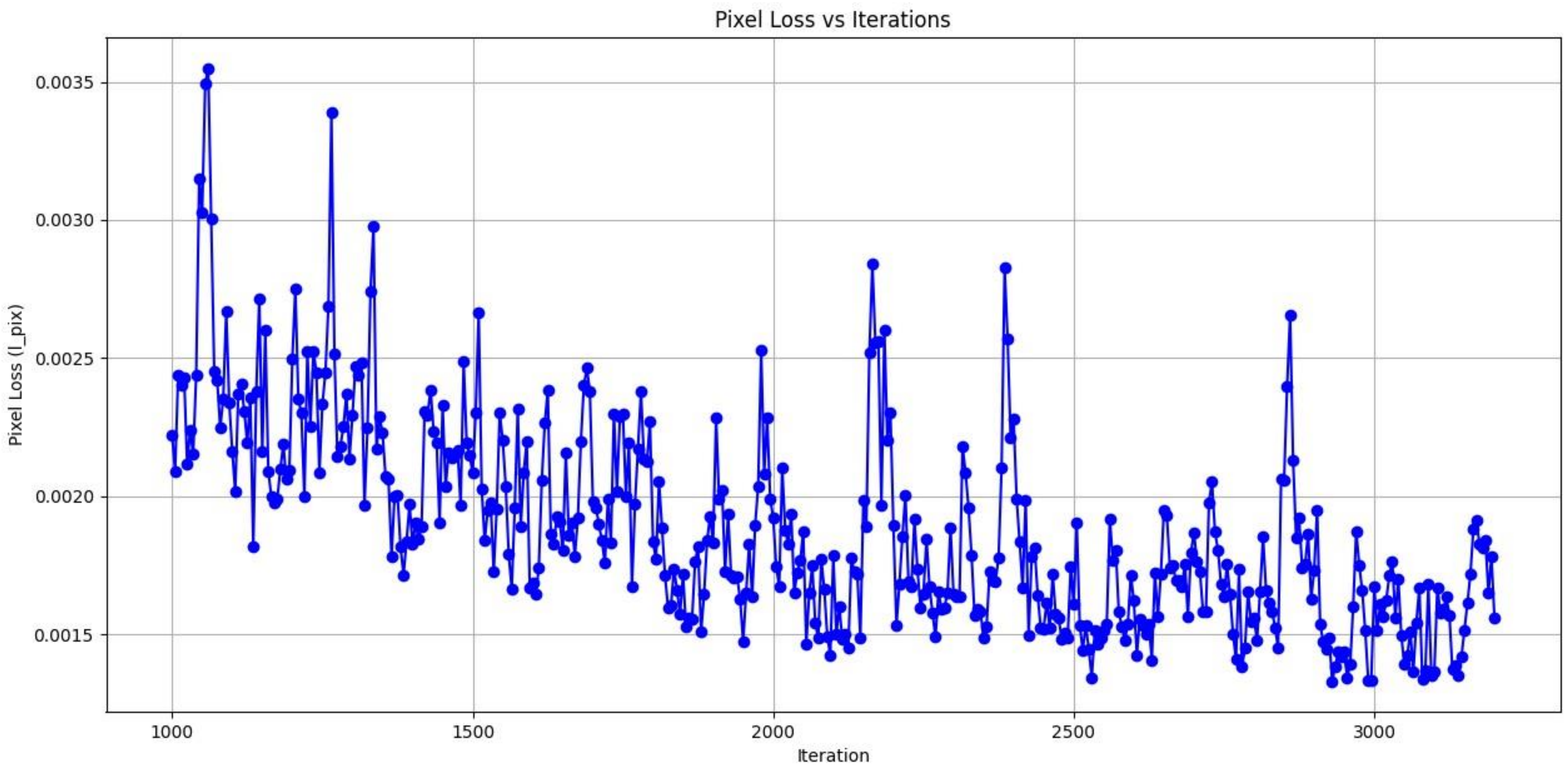
04 Model Architecture
RCAN Network



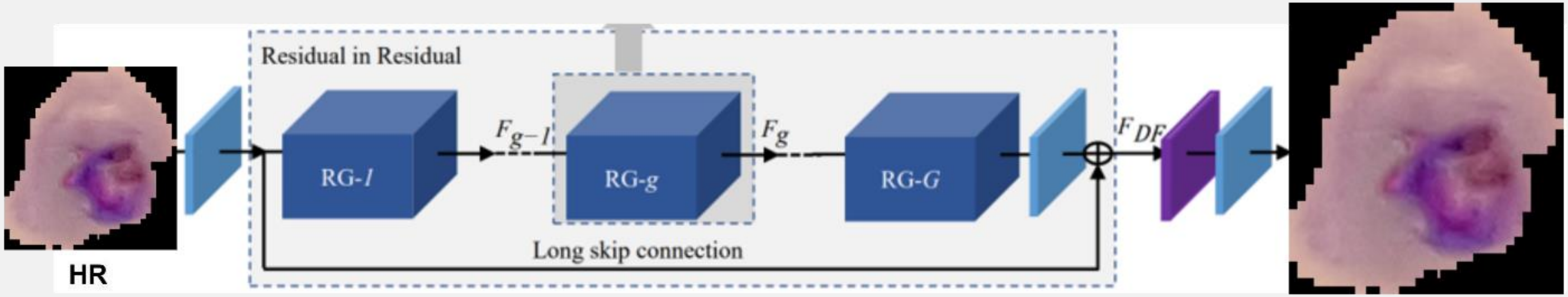
Architecture:
•Four main parts: shallow feature extraction, deep feature extraction (Residual in Residual), upsampling, and reconstruction
Shallow Feature Extraction:
•Single convolutional layer to extract initial shallow features
Deep Feature Extraction:
•Multiple Residual Groups (RGs) with Residual Channel Attention Blocks (RCABs) and short skip connections
Channel Attention Mechanism:
•Focuses on the most informative features to enhance high-resolution image reconstruction
Upsampling and Reconstruction:
•Uses deconvolution or sub-pixel convolution for upsampling, followed by final convolutional layer for reconstruction
Loss Function:
•Optimized using L1 loss, measuring pixel-wise difference between super-resolved and ground truth high-resolution images
Performance:
•Superior performance in enhancing image resolution, providing high PSNR and SSIM scores, particularly in medical imaging

04 Training of RCAN Network



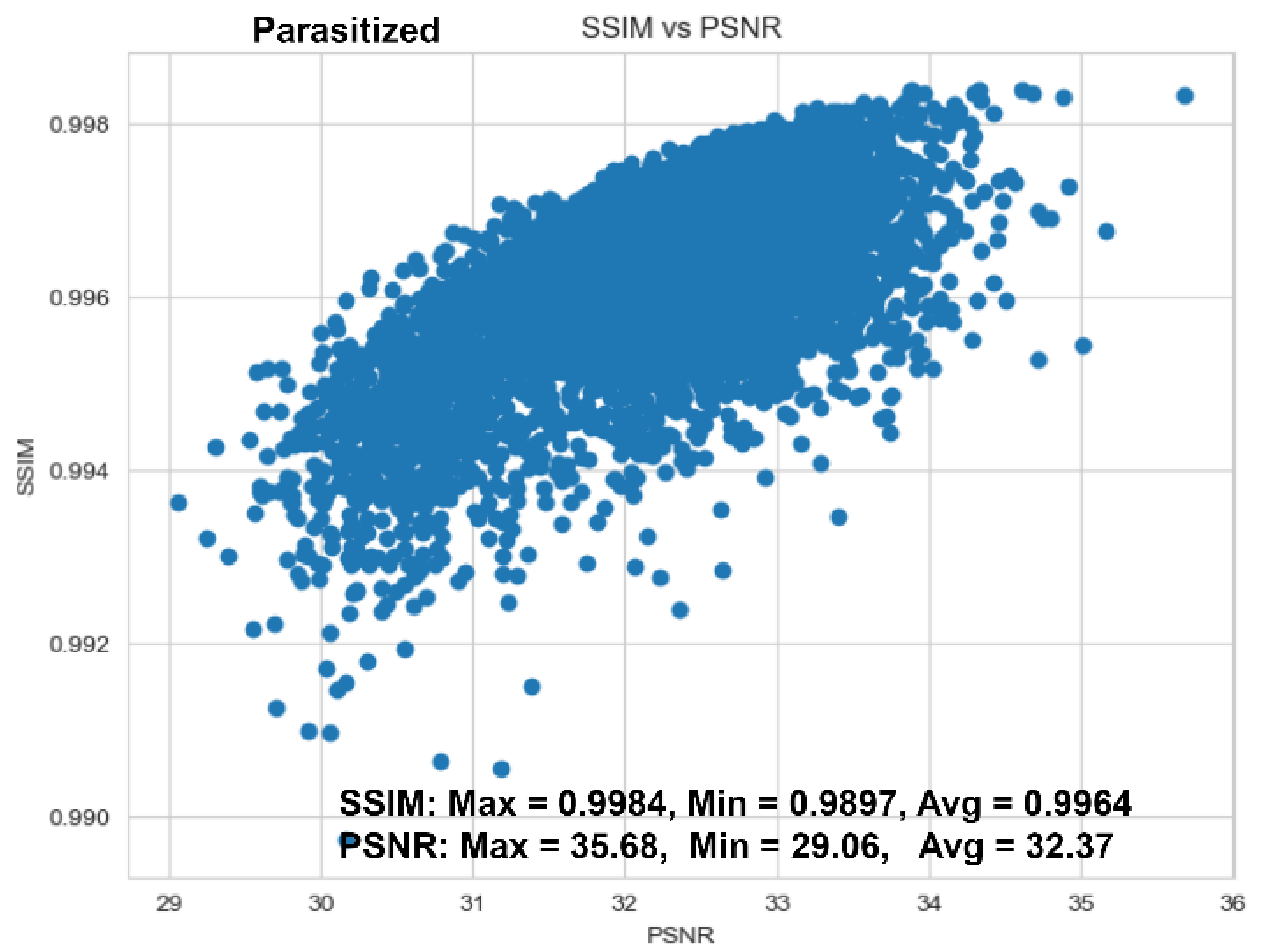


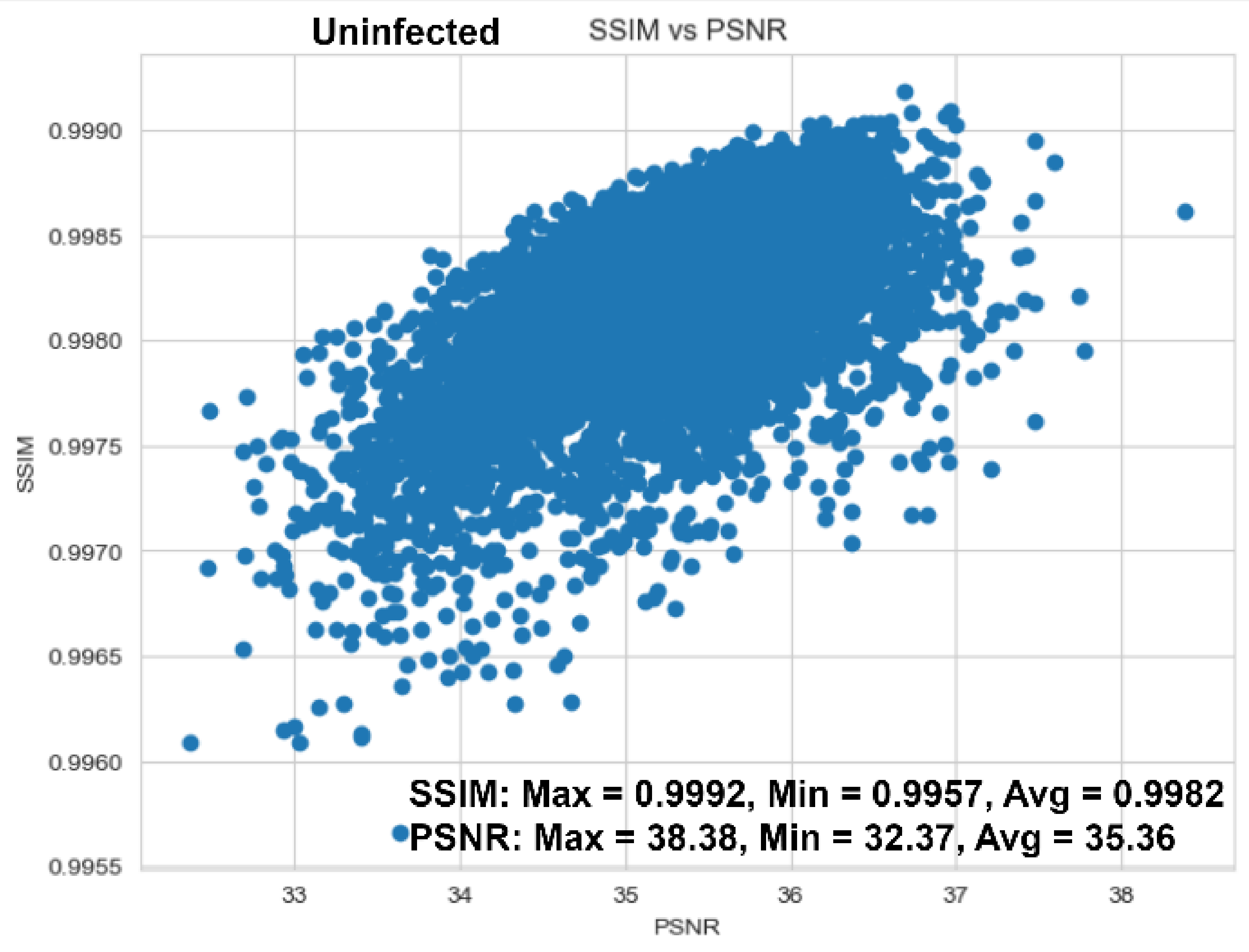
04 Training of RCAN Network



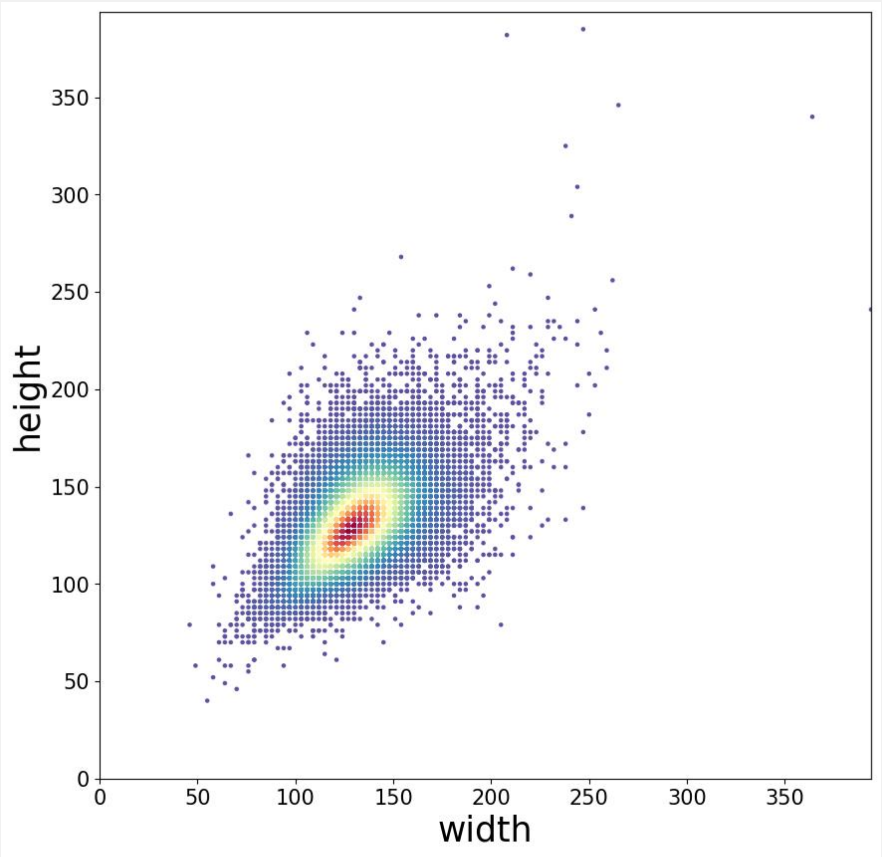
Trained RCAN(3K iterations)

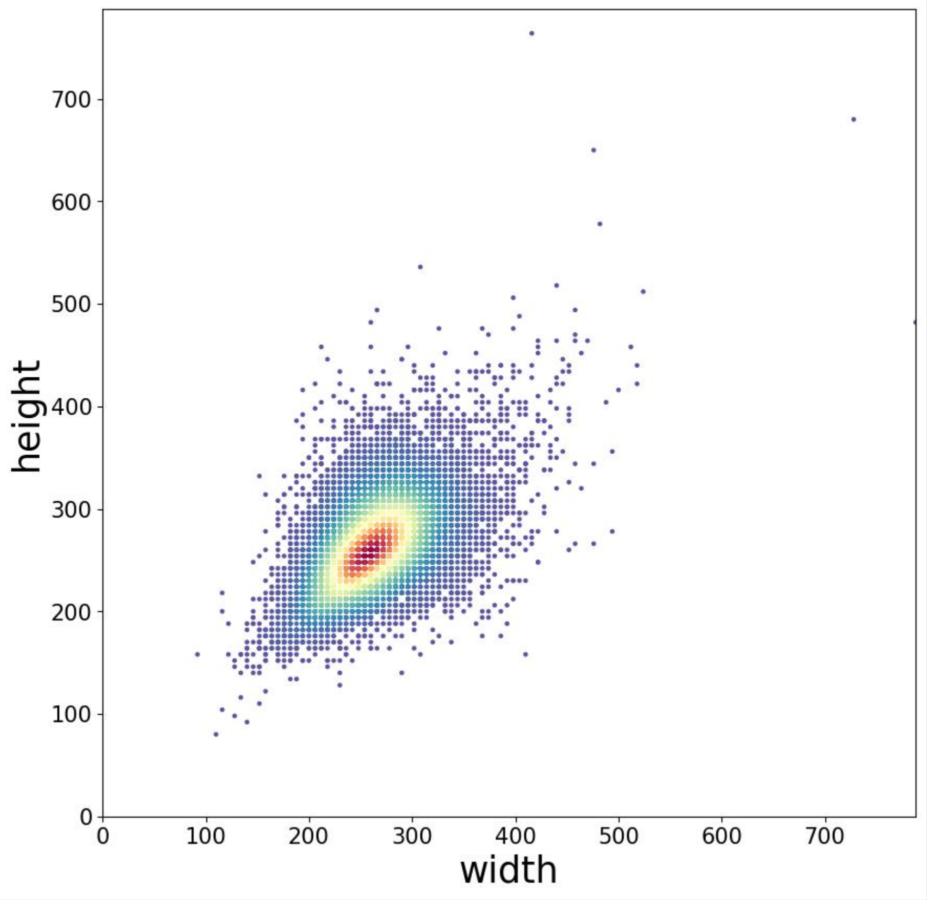
2X SR

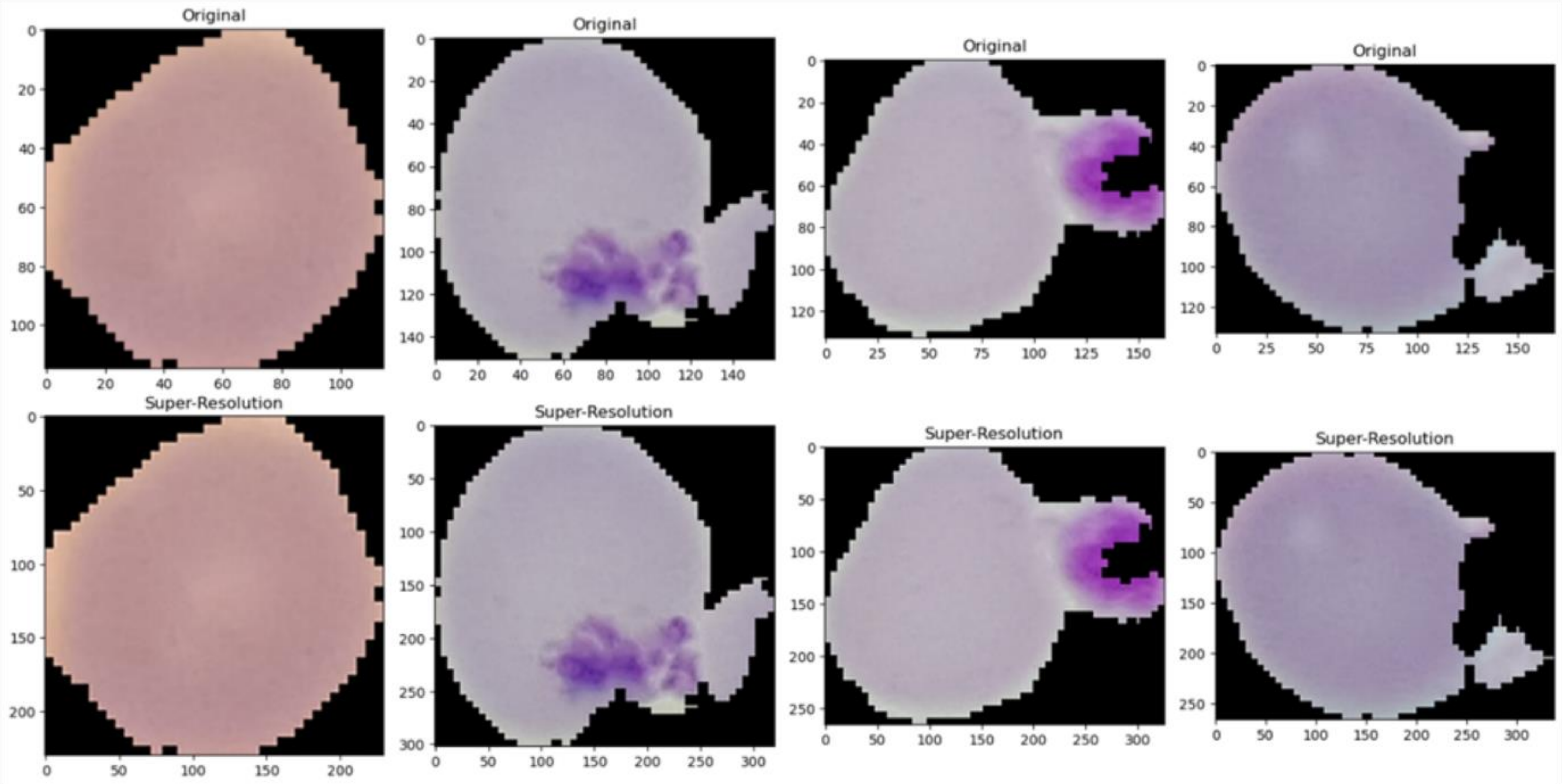




04 Training of RCAN Network







SSIM:0.9883, PSNR 37.71

SSIM:0.9929, PSNR 34.73

SSIM:0.9929, PSNR 34.72

SSIM:0.9933, PSNR 37.97

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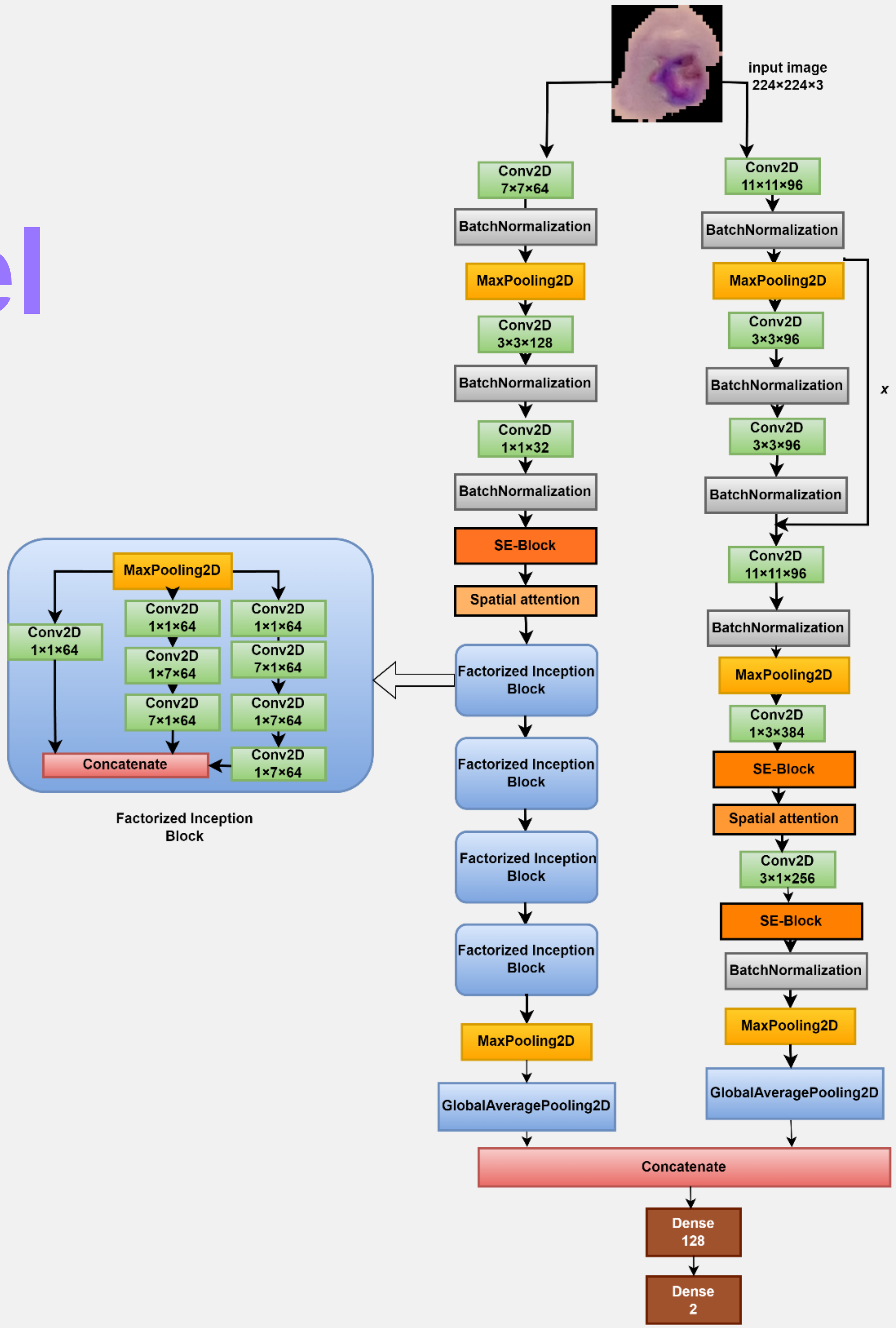
04 Ensemble Model Architecture

Key Components

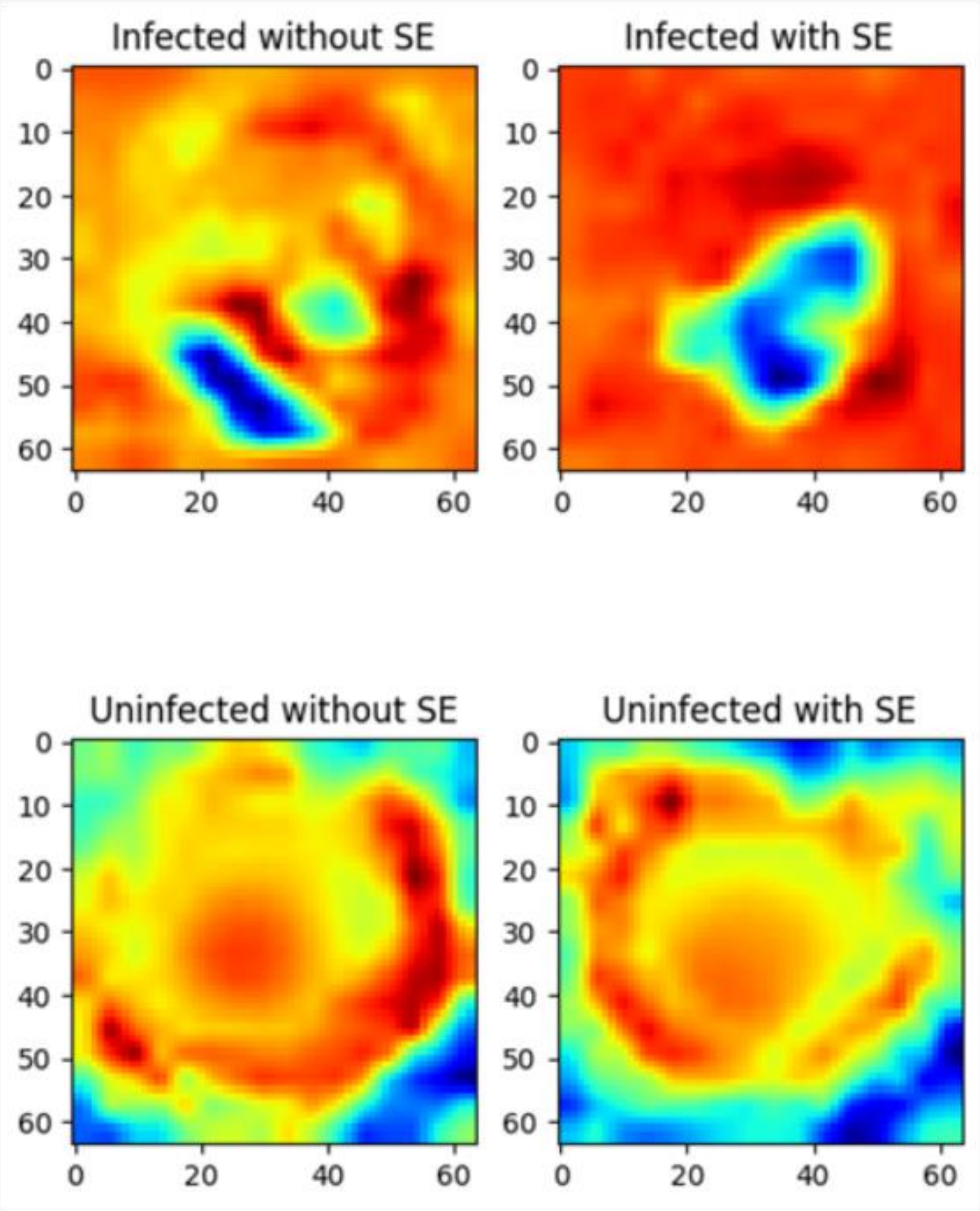
- Factorized Inception Block
- Residual Block (Skip Connection)
- SE-Block (Squeeze-and-Excitation Block)
- Spatial Attention
- Dual CNN Architecture



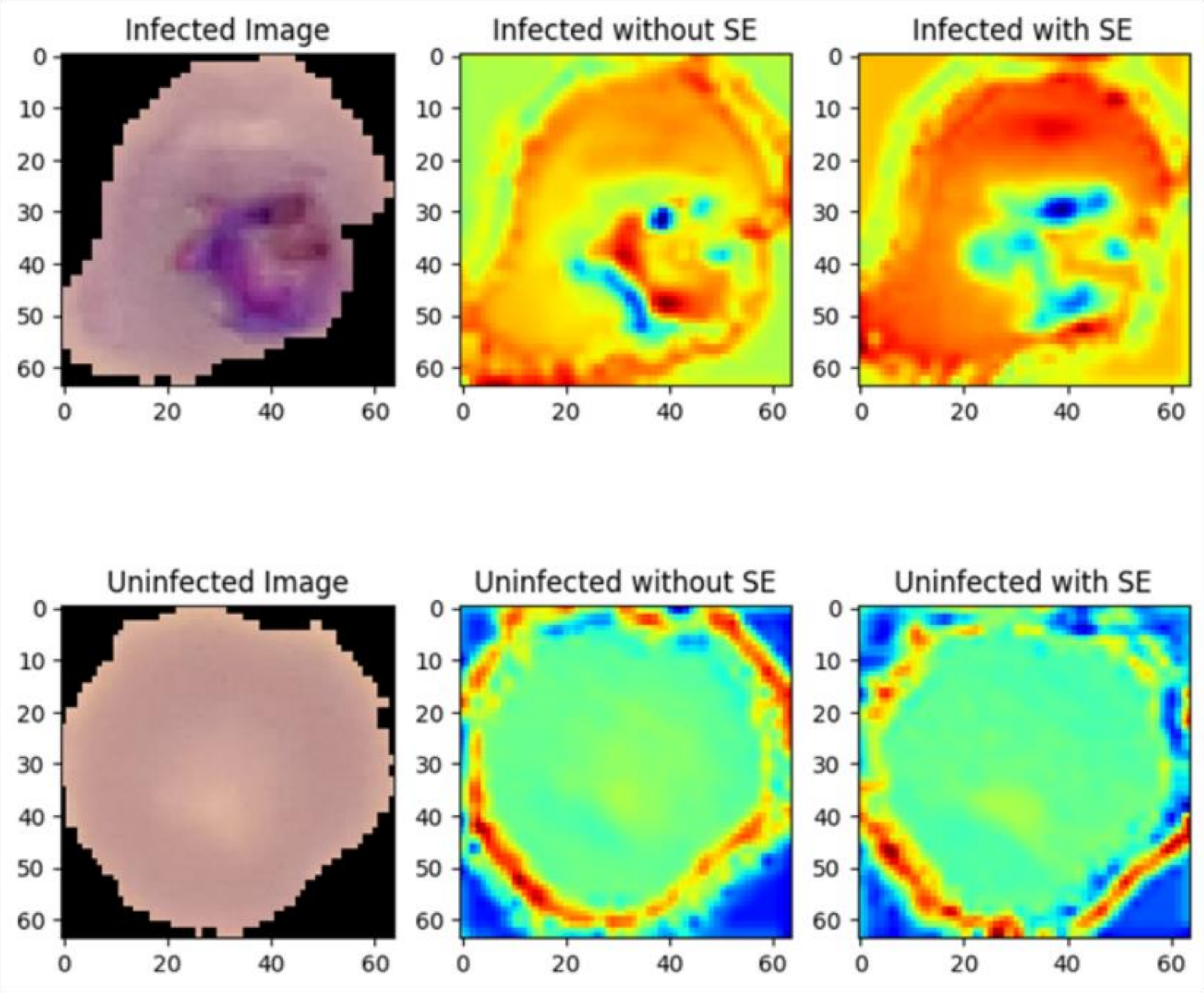
Factorized Inception Block

04 Model Architecture Heat Map

Grad-CAM Chart In Model 1



Grad-CAM Chart In Model 2



05 Hyperparameter Tuning

Parameters	Values
Batch size	32
Number of workers	4
Epoch	10
Step size	5
Gamma	0.5
Optimizer	Adam
Input size	SR:3 * 224 * 224 OR:3 * 112 * 112

After many rounds of experiments, it is finally determined that the model performs best with the above hyperparameters set.

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06 Results

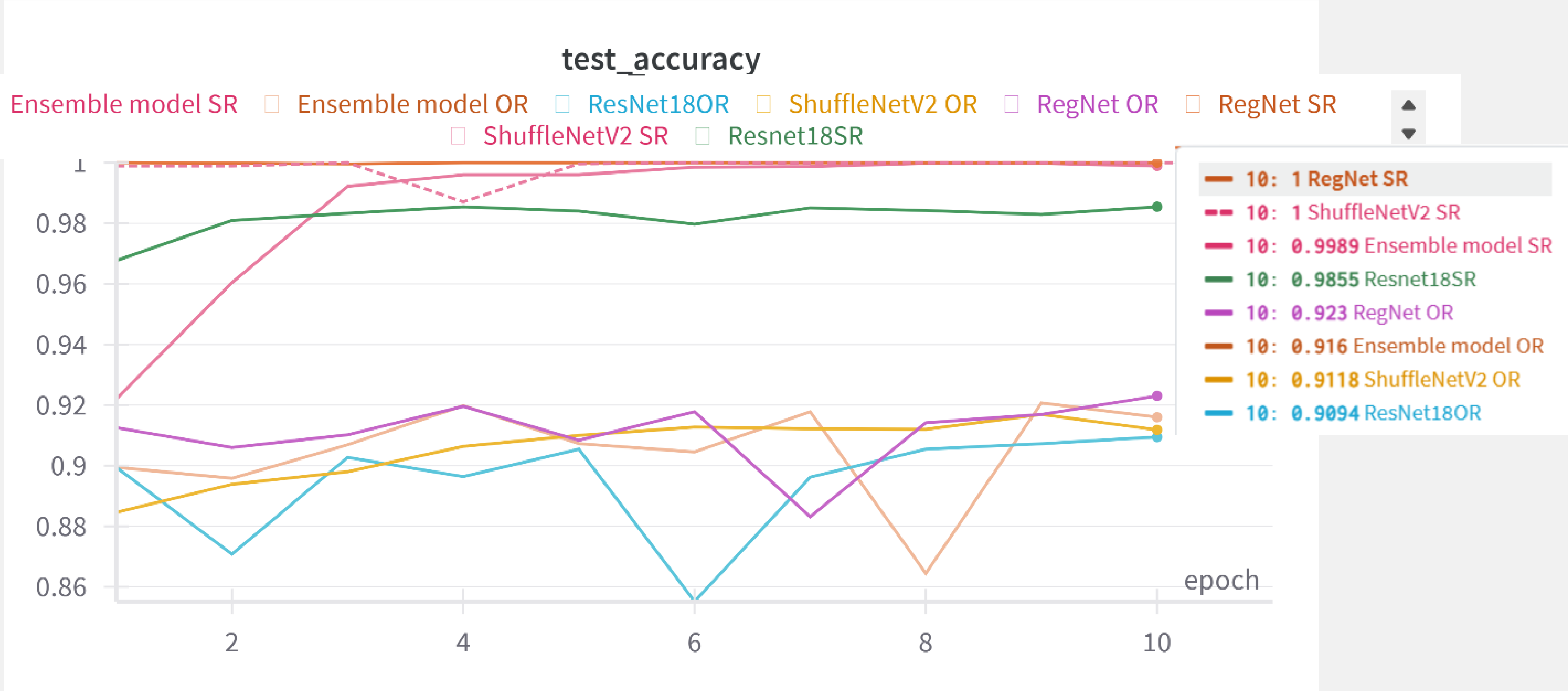
Model	Test loss		Test accuracy		Test precision		Test recall		Test F1-score	
Dataset	**SR**	OR	**SR**	OR	**SR**	OR	**SR**	OR	**SR**	OR
ResNet18[18]	**0.043079194**	0.2527289	**0.9855119013**	0.9094373865	**0.9855159981**	0.9095280867	**0.985511901**	0.909437386	**0.9855118722**	0.9094323719
ShuffleNetV2 [38]	**7.682e-7**	0.24736631	**1.0**	0.9168784029	**1.0**	0.9170049874	**1.0**	0.916878402	**1.0**	0.9168720944
RegNet[39]	**0.0002685788**	0.21360655	**1.0**	0.9230490018	**1.0**	0.9230492247	**1.0**	0.923049001	**1.0**	0.9230489916
Ensemble model	**0.0004389874**	0.2188132	**0.9989185776**	0.9206896551	**0.9989186434**	0.9208454062	**0.998918577**	0.920689655	**0.9989185776**	0.9206823164

06 Results

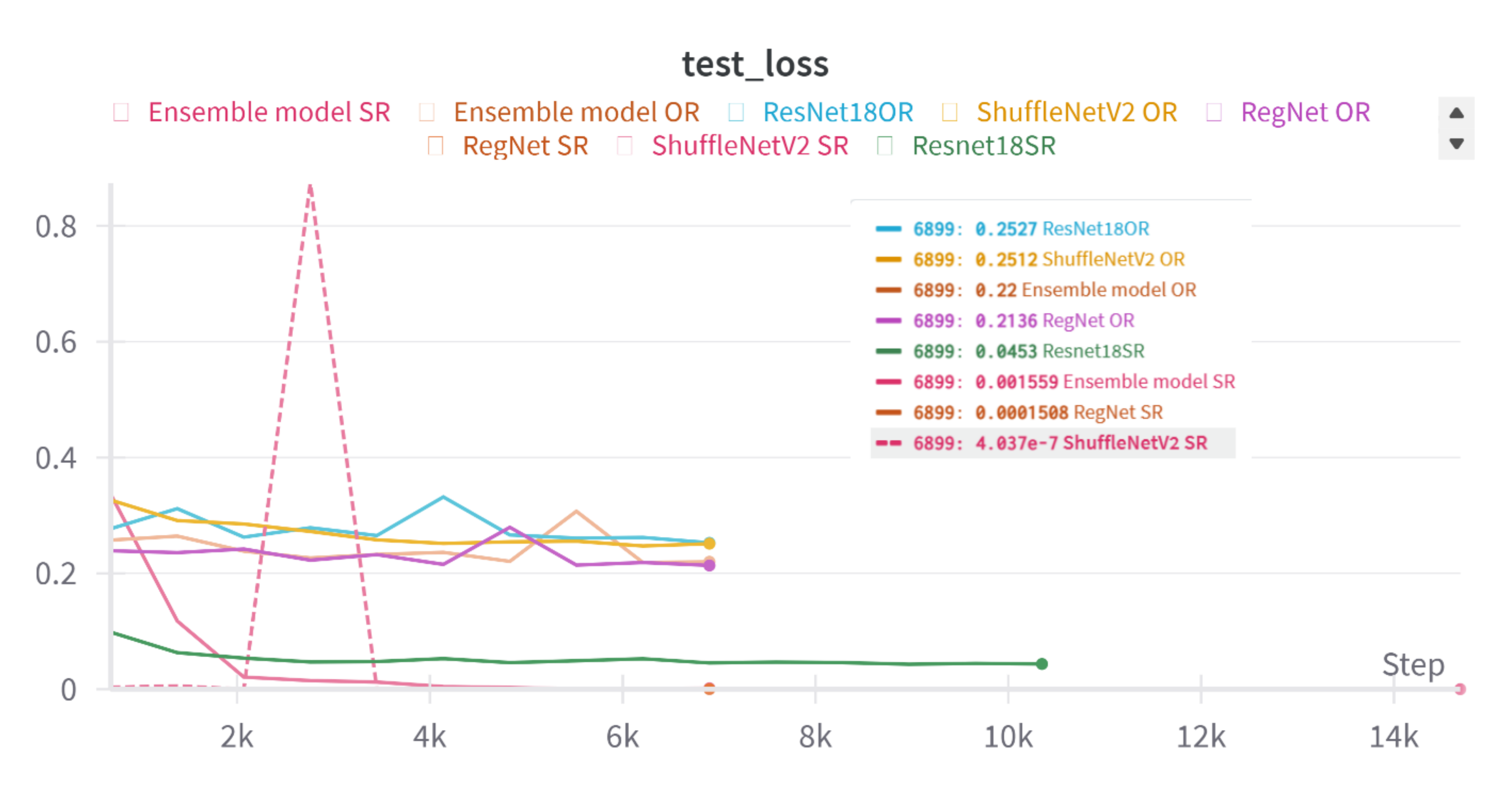
Indirect comparison With Existing Literature

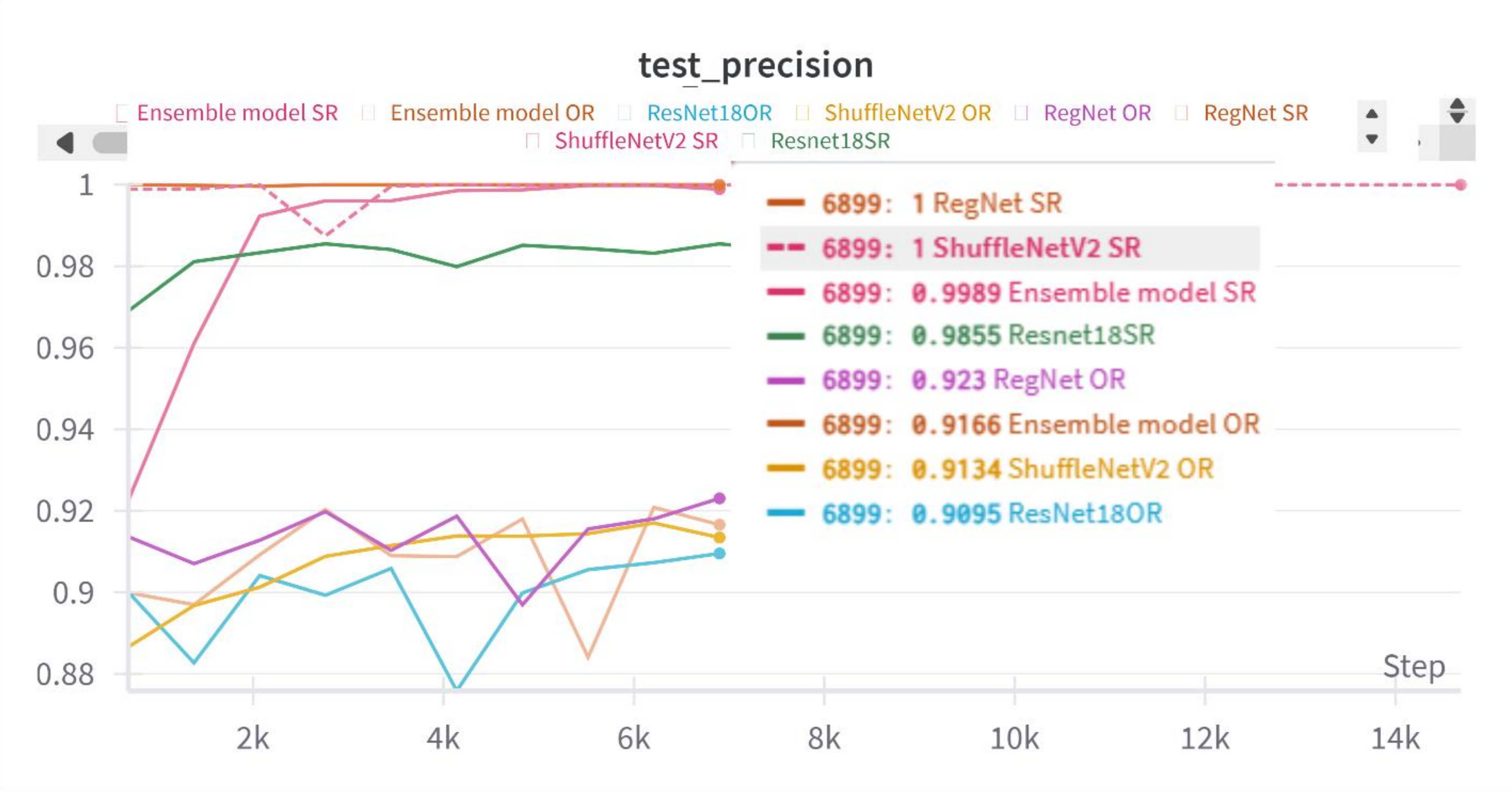
Model	Test Loss	Test Accuracy	Test Precision	Test Recall	Test F1-score
AlexNet[4]	402.7	48.11%	0.4875	0.4817	0.4875
MobileNet[33]	0.6267	64.44%	0.6441	0.6441	0.6441
ResNet-50[18]	0.5363	93.31%	1.00	0.9331	0.9331
VGG 19[27]	0.2174	94.79%	0.9479	0.9479	0.9479
GoogLeNet [7]	0.0938	96.27%	0.9729	0,9852	0.9582
RCCNet[34]	0.4974	96.09%	0.9729	0.9729	0.9609

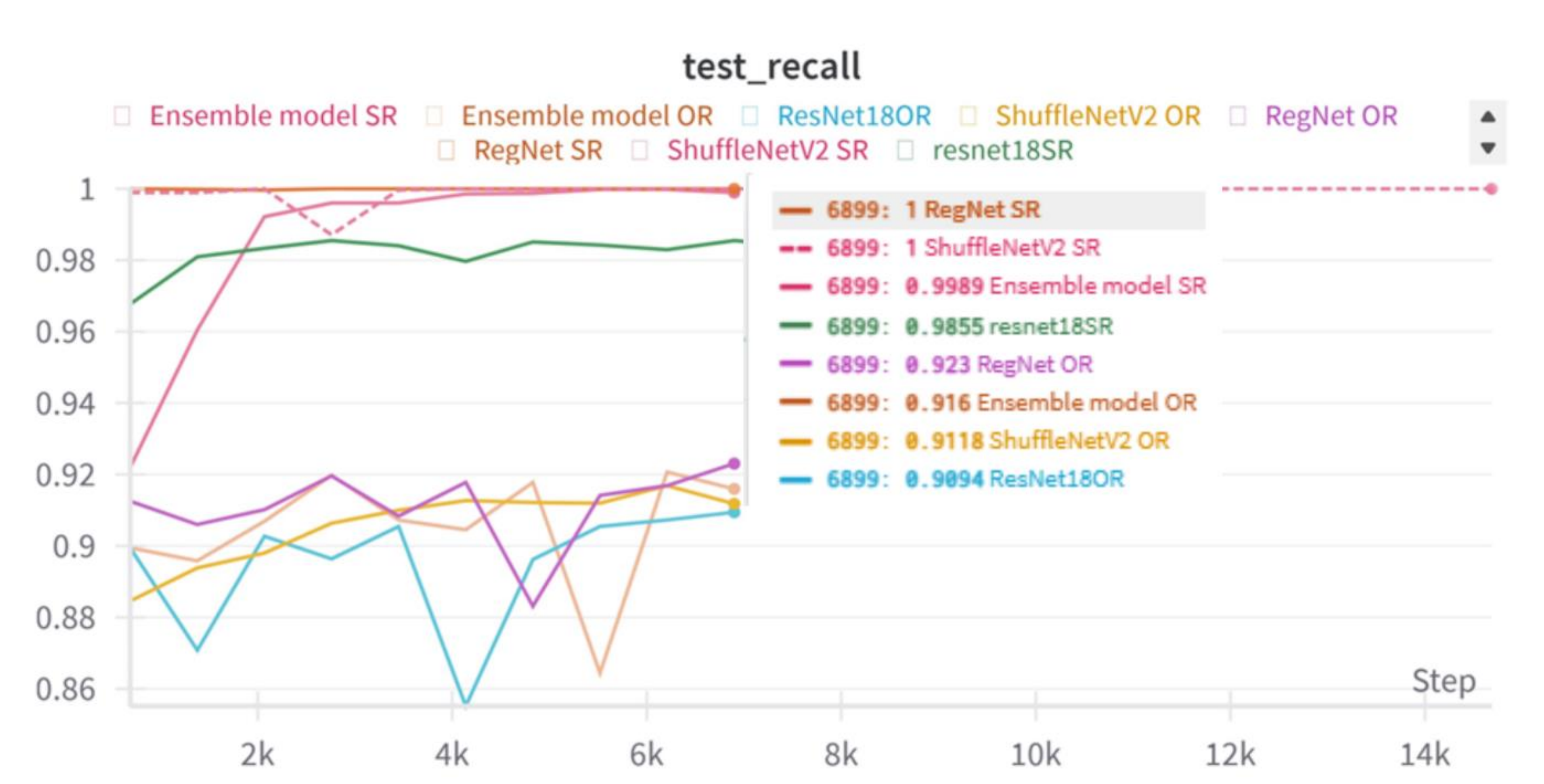
06 Results

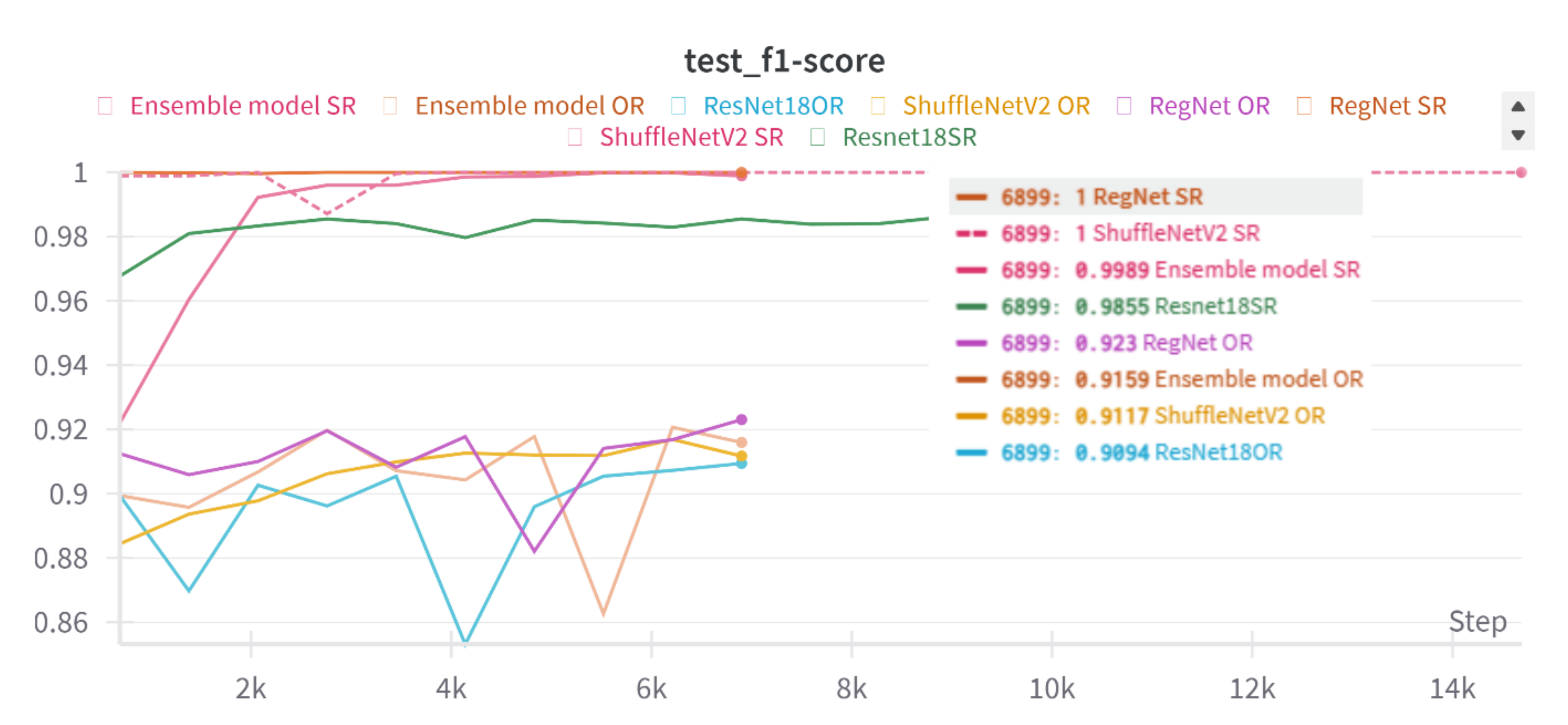

test_accuracy
Ensemble model SR
Ensemble model OR
ResNet18OR
ShuffleNetV2 OR
RegNet OR
RegNet SR
ShuffleNetV2 SR
Resnet18SR
1
0.98
0.96
0.94
0.92
0.9
0.88
0.86
2
4
6
8
10
epoch
10: 1 RegNet SR
10: 1 ShuffleNetV2 SR
10: 0.9989 Ensemble model SR
10: 0.9855 Resnet18SR
10: 0.923 RegNet OR
10: 0.916 Ensemble model OR
10: 0.9118 ShuffleNetV2 OR
10: 0.9094 ResNet18OR

06 Results

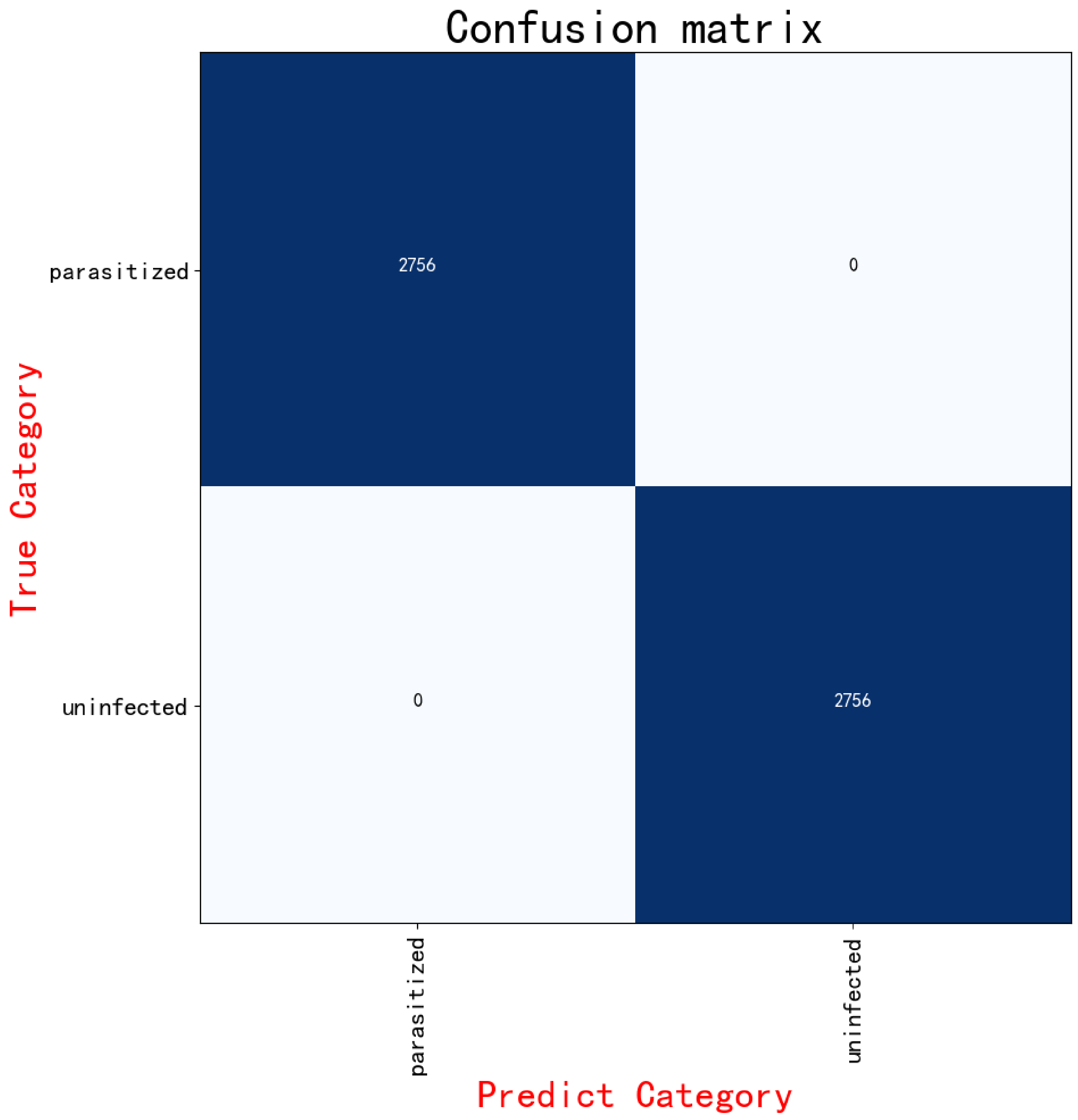

test_loss
Ensemble model SR
Ensemble model OR
ResNet18OR
ShuffleNetV2 OR
RegNet OR
RegNet SR
ShuffleNetV2 SR
Resnet18SR
6899: 0.2527 ResNet18OR
6899: 0.2512 ShuffleNetV2 OR
6899: 0.22 Ensemble model OR
6899: 0.2136 RegNet OR
6899: 0.0453 Resnet18SR
6899: 0.001559 Ensemble model SR
6899: 0.0001508 RegNet SR
6899: 4.037e-7 ShuffleNetV2 SR
Step

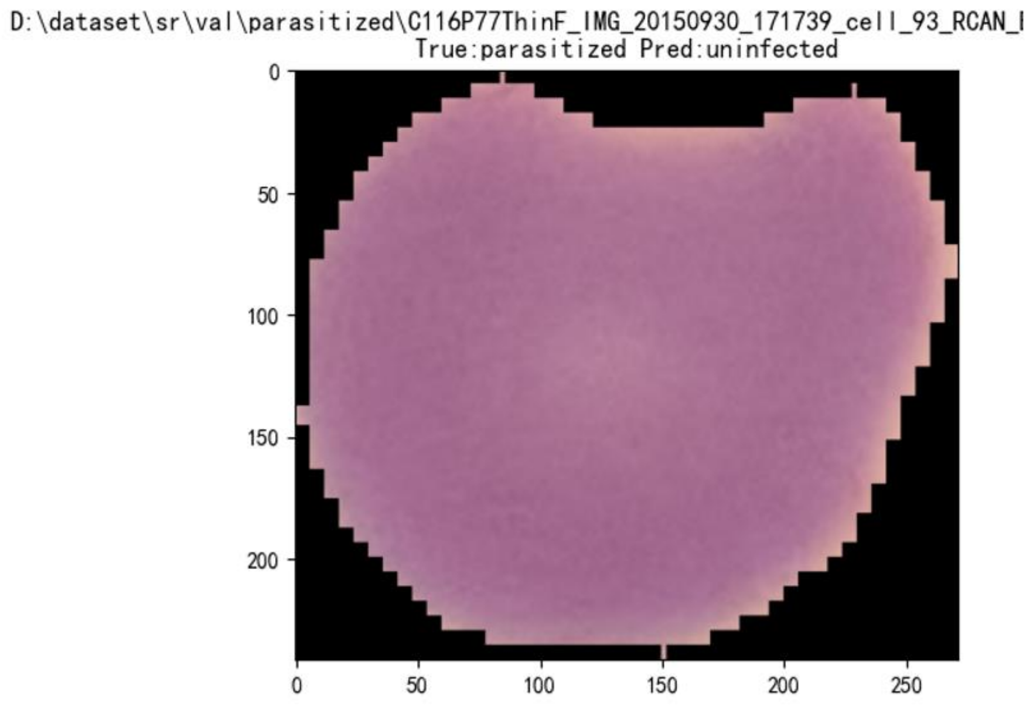

test_precision
Ensemble model SR
Ensemble model OR
ResNet18OR
ShuffleNetV2 OR
RegNet OR
RegNet SR
ShuffleNetV2 SR
Resnet18SR
6899: 1 RegNet SR
6899: 1 ShuffleNetV2 SR
6899: 0.9989 Ensemble model SR
6899: 0.9855 Resnet18SR
6899: 0.923 RegNet OR
6899: 0.9166 Ensemble model OR
6899: 0.9134 ShuffleNetV2 OR
6899: 0.9095 ResNet18OR
Step

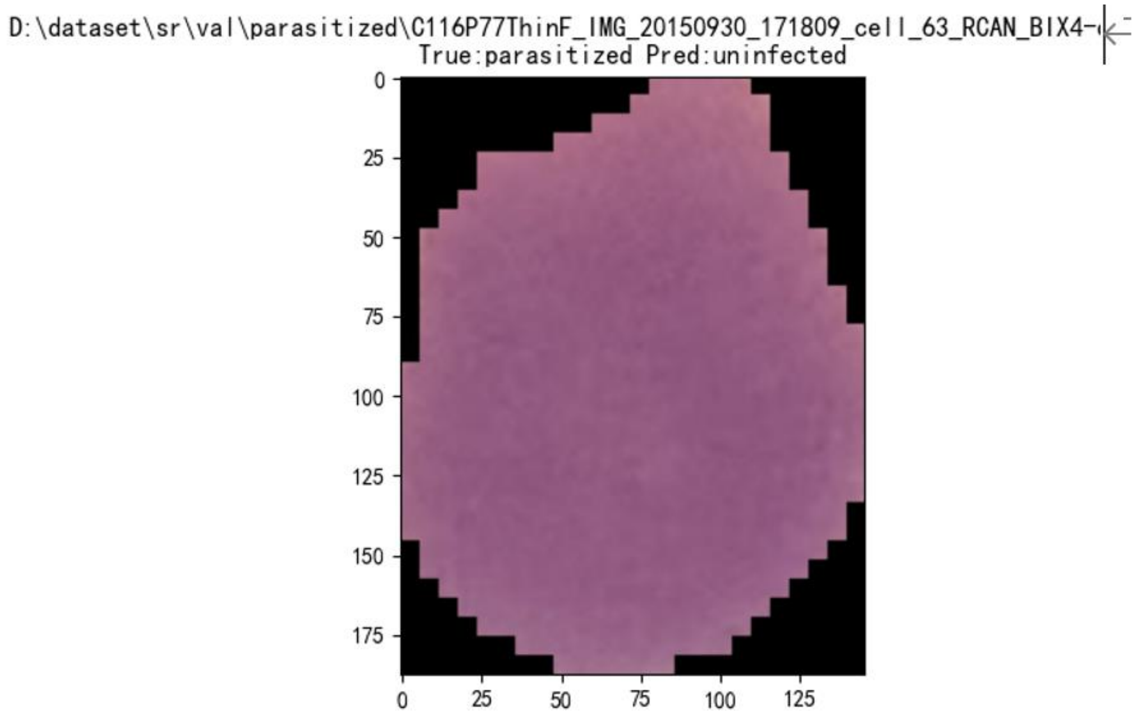

test_recall
Ensemble model SR
Ensemble model OR
ResNet18OR
ShuffleNetV2 OR
RegNet OR
RegNet SR
ShuffleNetV2 SR
resnet18SR
6899: 1 RegNet SR
6899: 1 ShuffleNetV2 SR
6899: 0.9989 Ensemble model SR
6899: 0.9855 resnet18SR
6899: 0.923 RegNet OR
6899: 0.916 Ensemble model OR
6899: 0.9118 ShuffleNetV2 OR
6899: 0.9094 ResNet18OR
Step

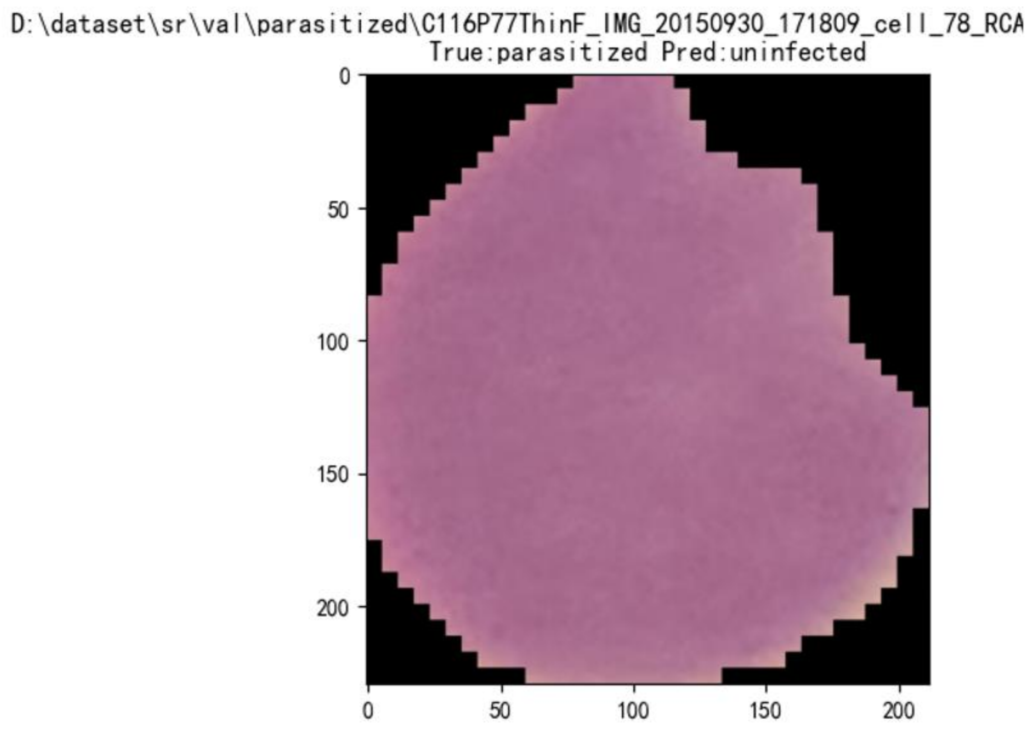

test_f1-score
Ensemble model SR
Ensemble model OR
ResNet18OR
ShuffleNetV2 OR
RegNet OR
RegNet SR
ShuffleNetV2 SR
Resnet18SR
6899: 1 RegNet SR
6899: 1 ShuffleNetV2 SR
6899: 0.9989 Ensemble model SR
6899: 0.9855 Resnet18SR
6899: 0.923 RegNet OR
6899: 0.9159 Ensemble model OR
6899: 0.9117 ShuffleNetV2 OR
6899: 0.9094 ResNet18OR
Step

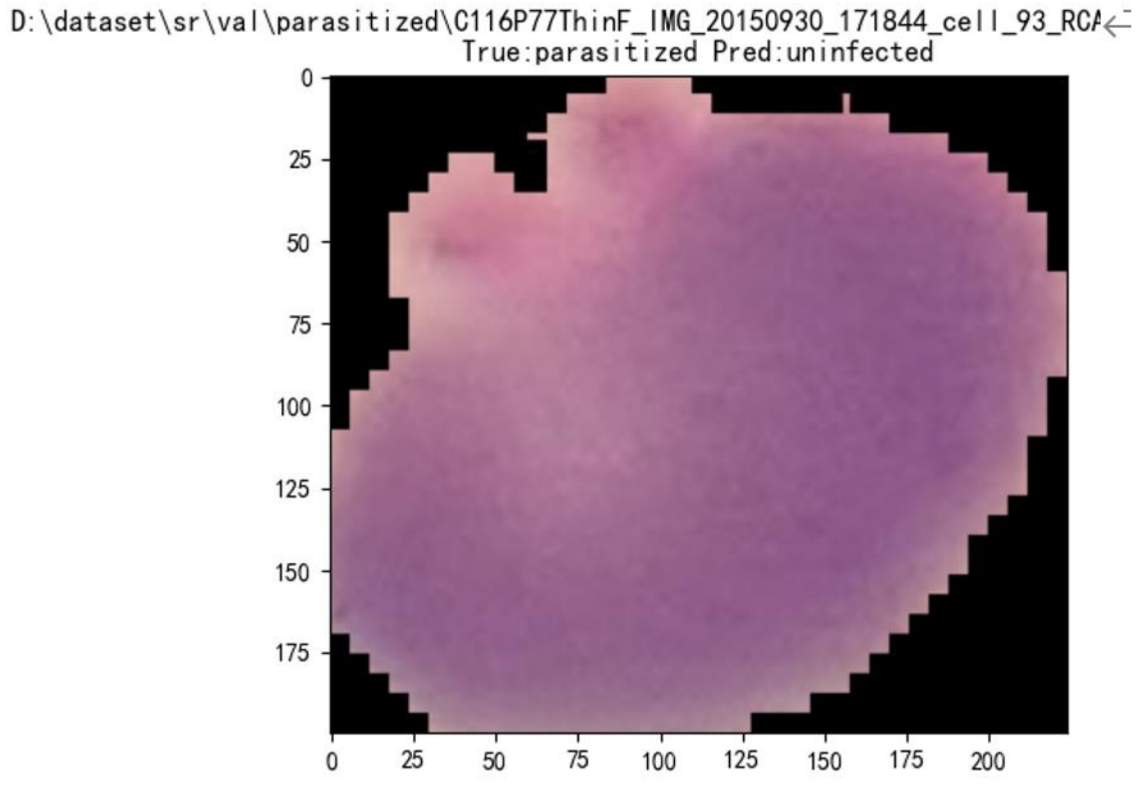
06 Results





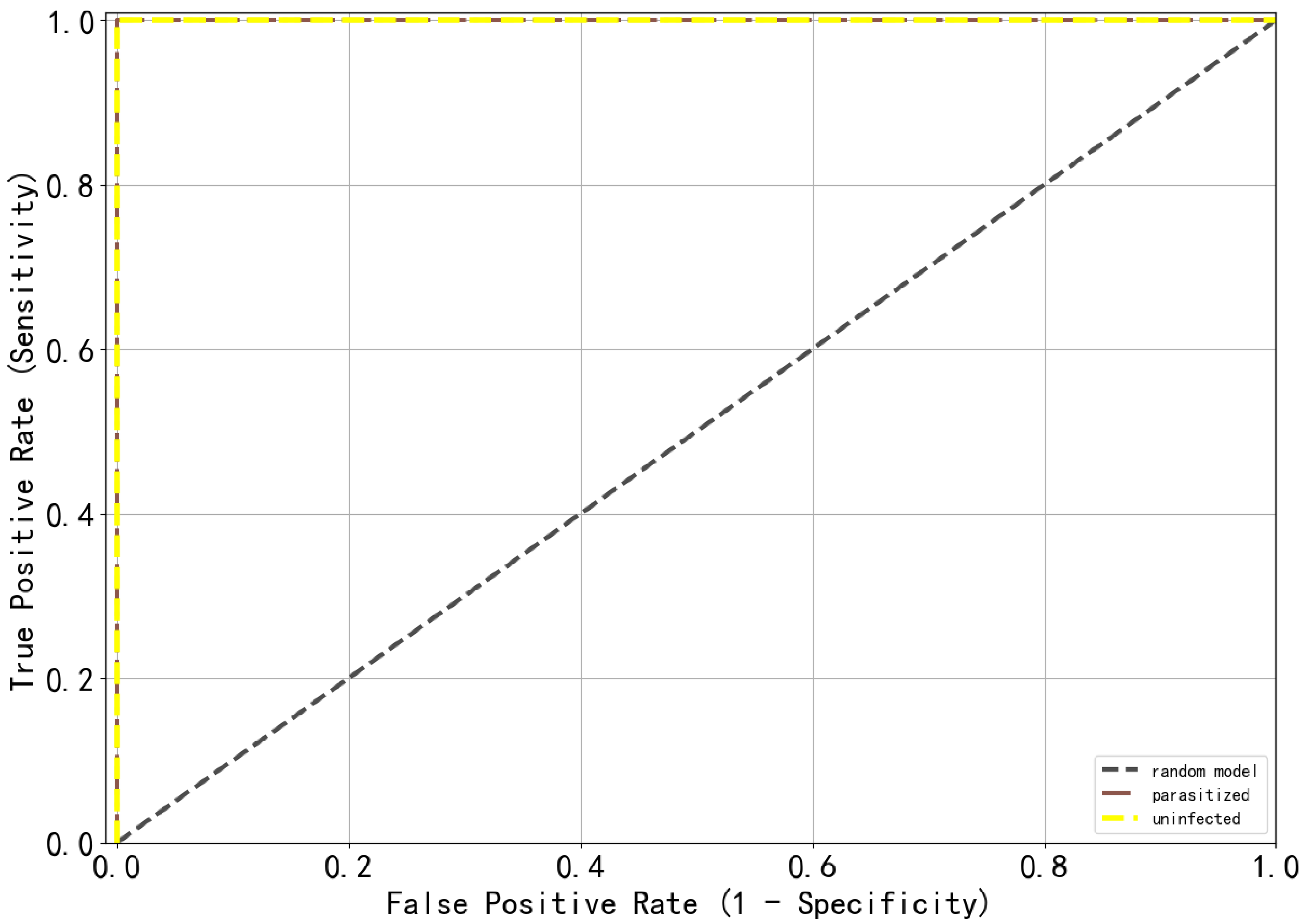


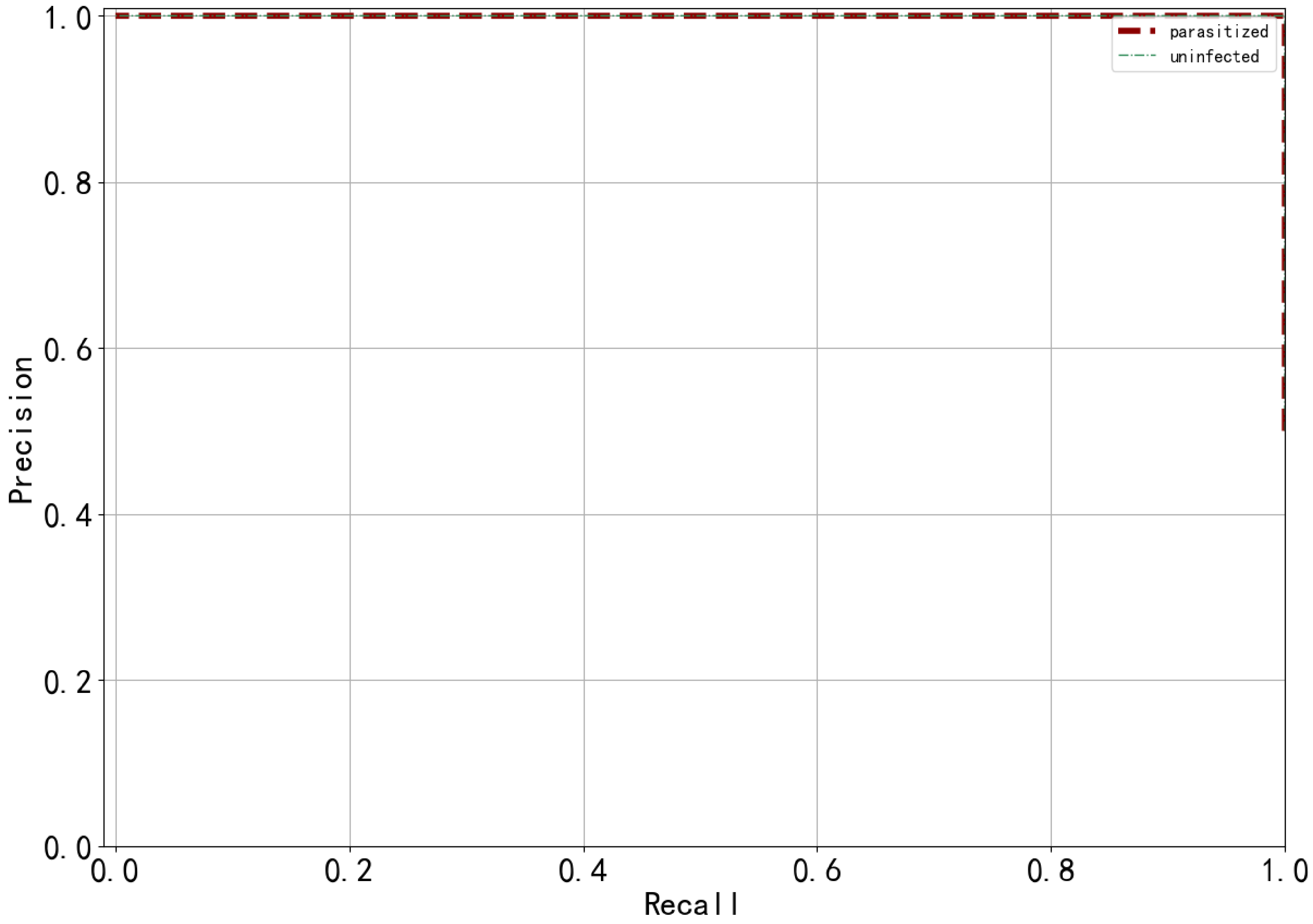




A relatively Slightly poorer model screen out misclassified cells

06 Results

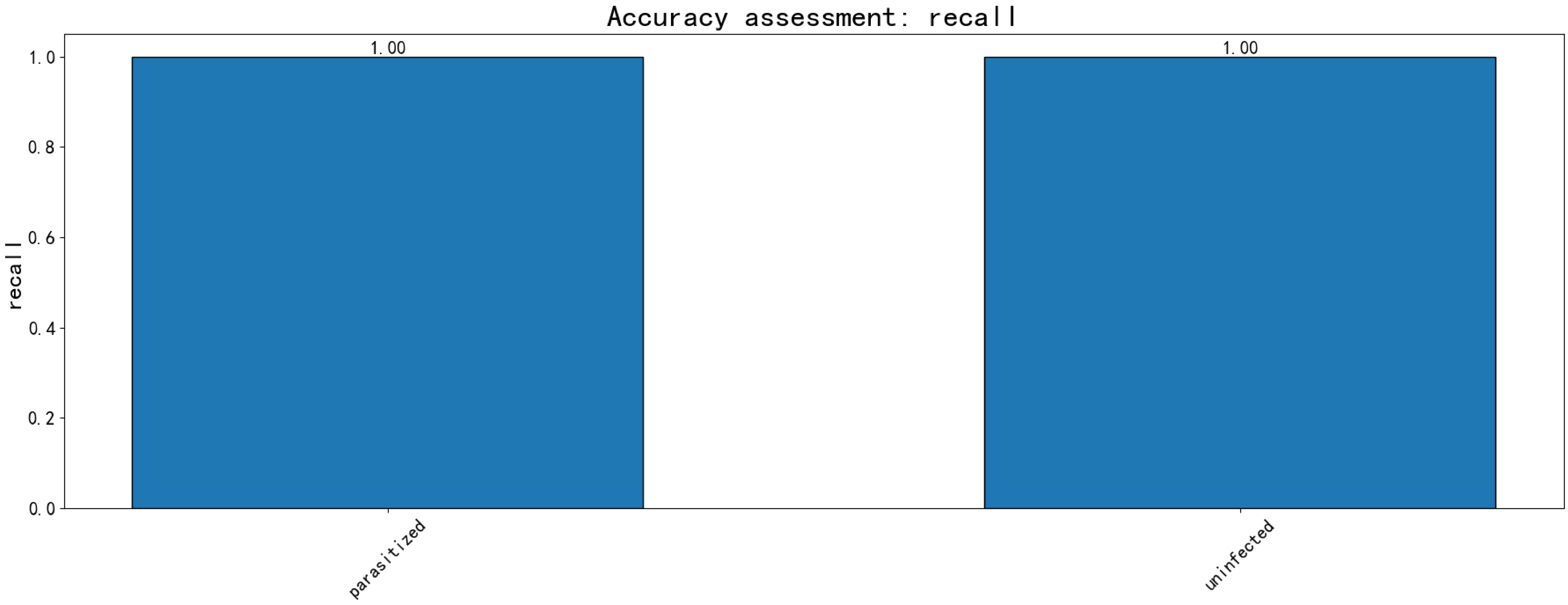




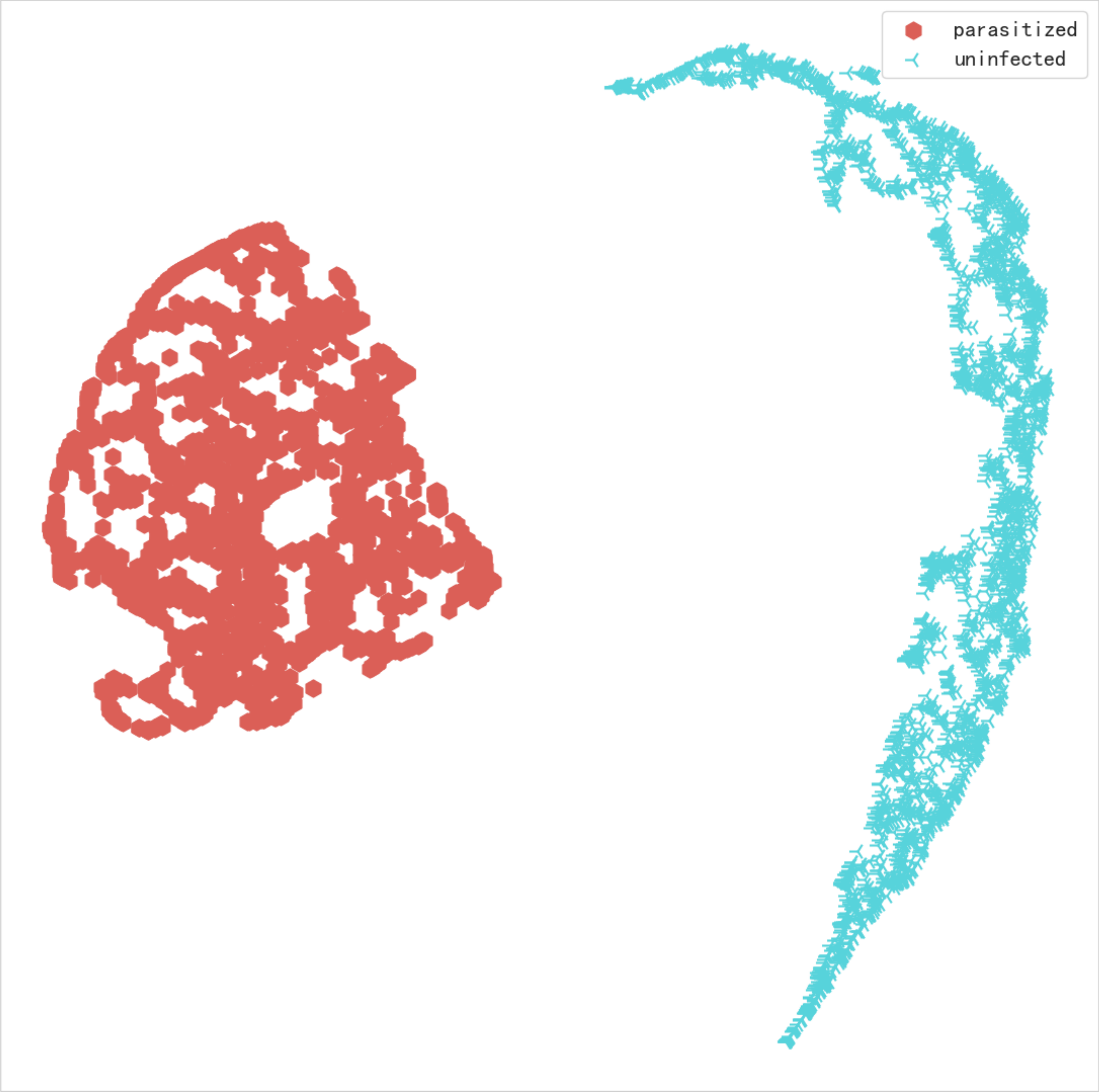
The Receiver Operating Characteristic (ROC) curve is a quantitative measure utilized to assess the effectiveness of a classifier across various decision thresholds. The AUC, or area under the curve, measures the model's ability to accurately differentiate between several groups.

The precision-recall (PR) curve depicts the performance of the model. The area under the curve (AUC) indicates a high level of recall and precision. Achieving high scores in both precision and recall indicates that the model generates correct outcomes (high precision) and catches a substantial proportion of positive outcomes (high recall).

06 Results


Accuracy assessment: recall
1.00
1.00
1.0
0.8
0.6
0.4
0.2
0.0
recall
parasitized
uninfected

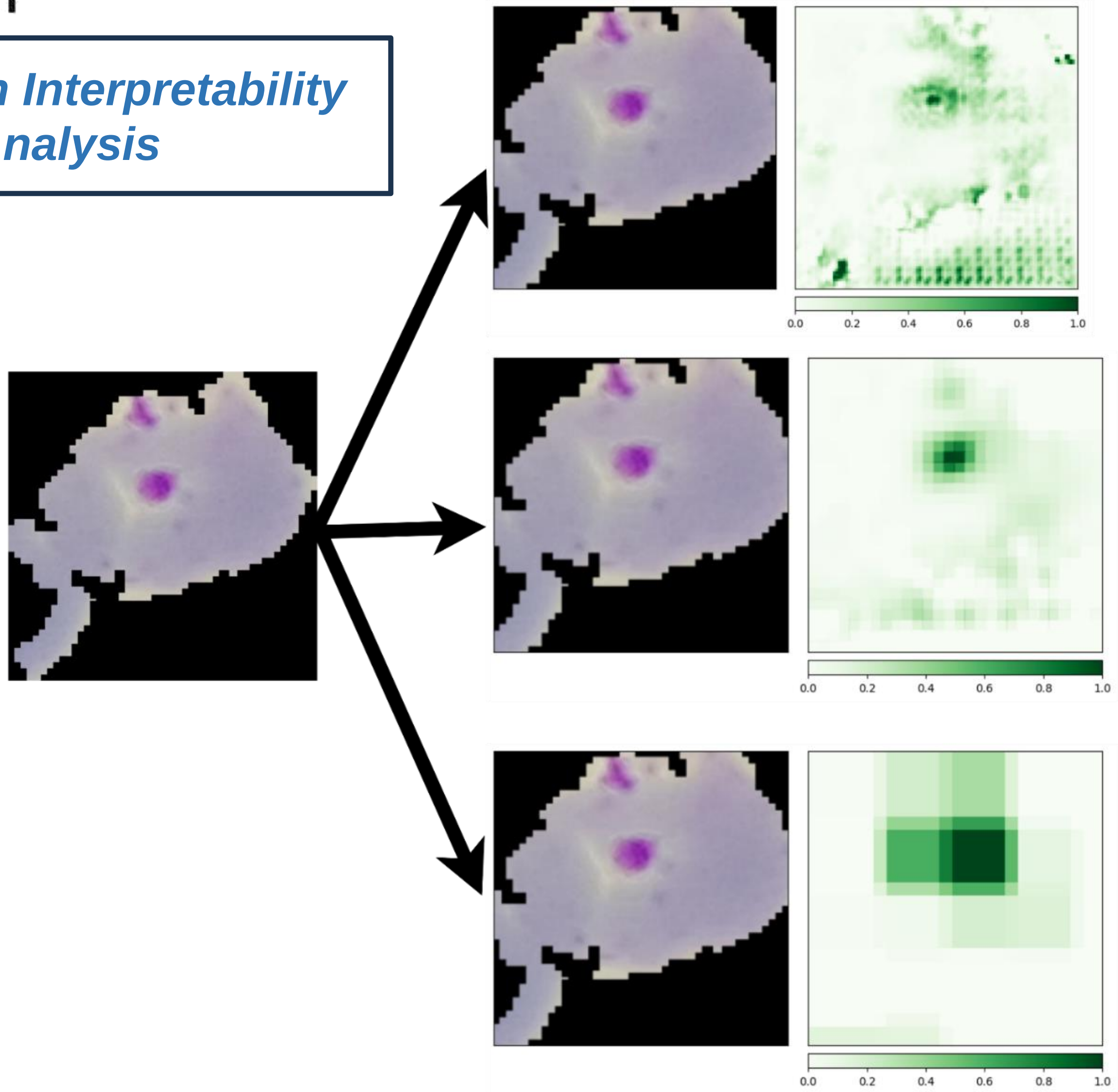
06 Results



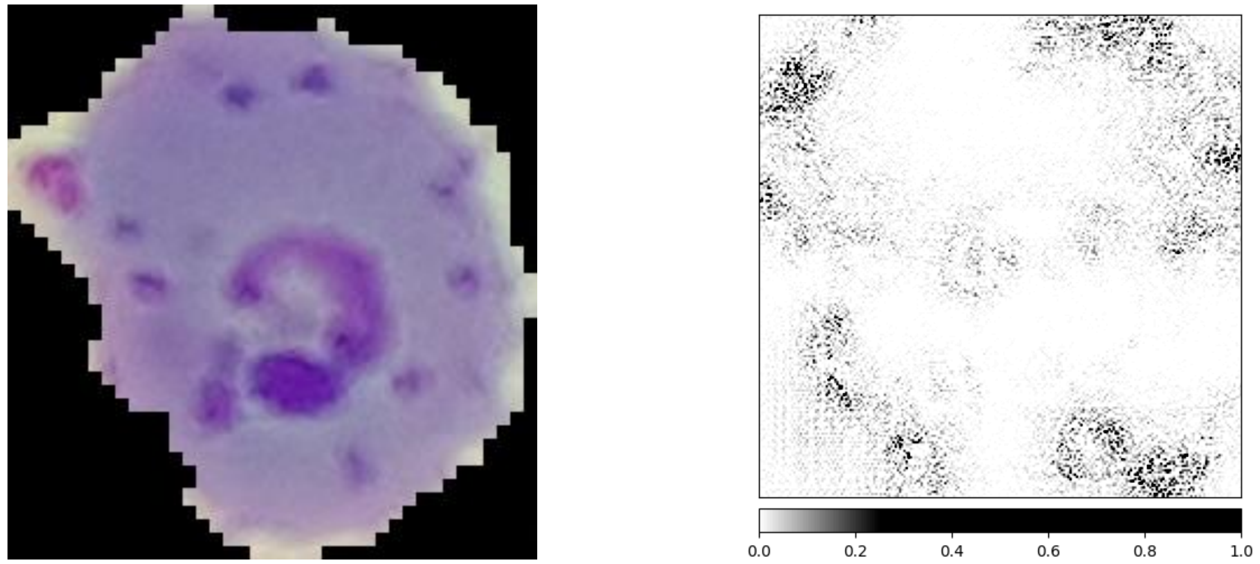
When the input of a new image, after the neural network encoding, will become a high-dimensional semantic features, the semantic features for the downscaling of the visualization will be able to intuitively feel which semantic features are similar, which semantics are confusing, interconnected or far apart

06 Results

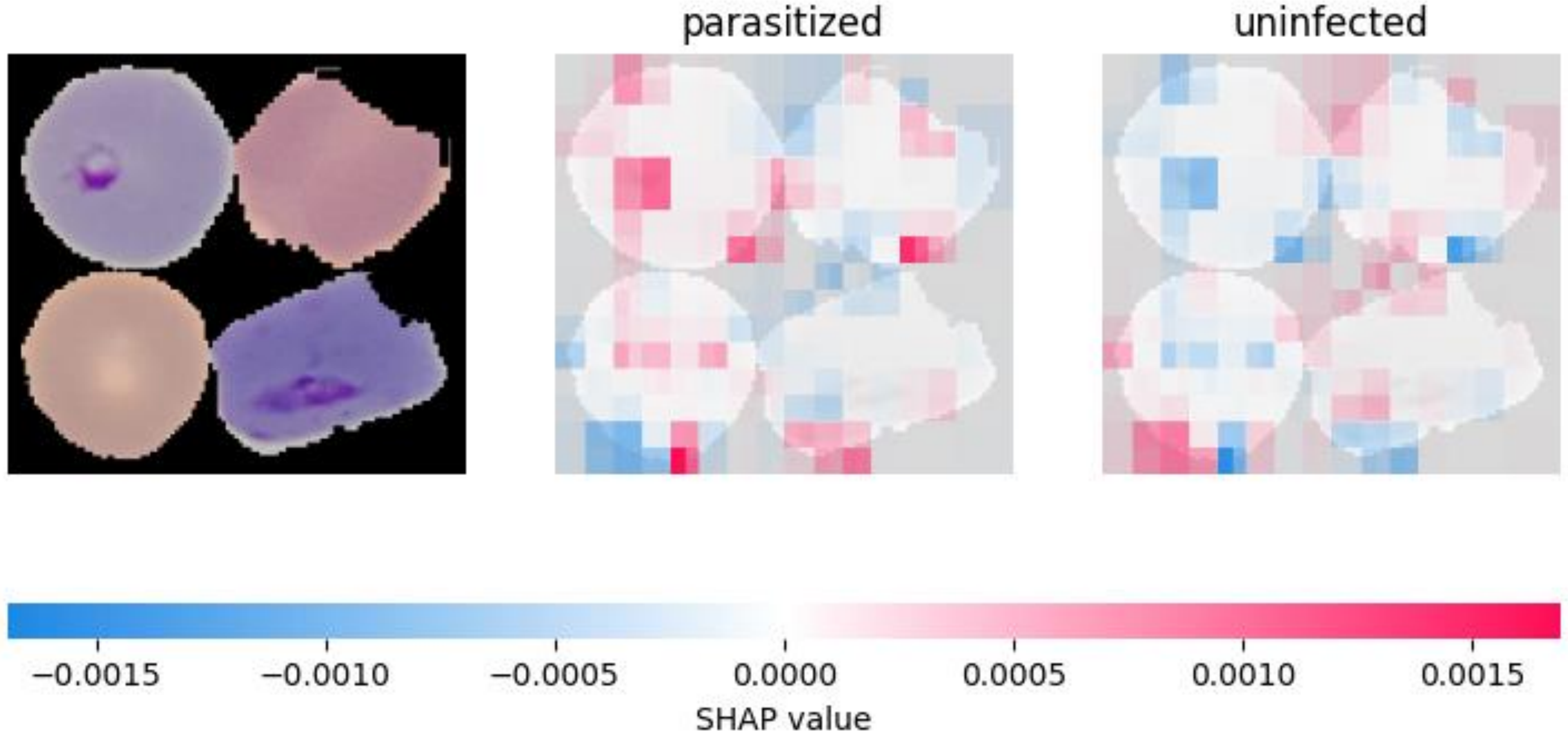
Occlusion Interpretability Analysis



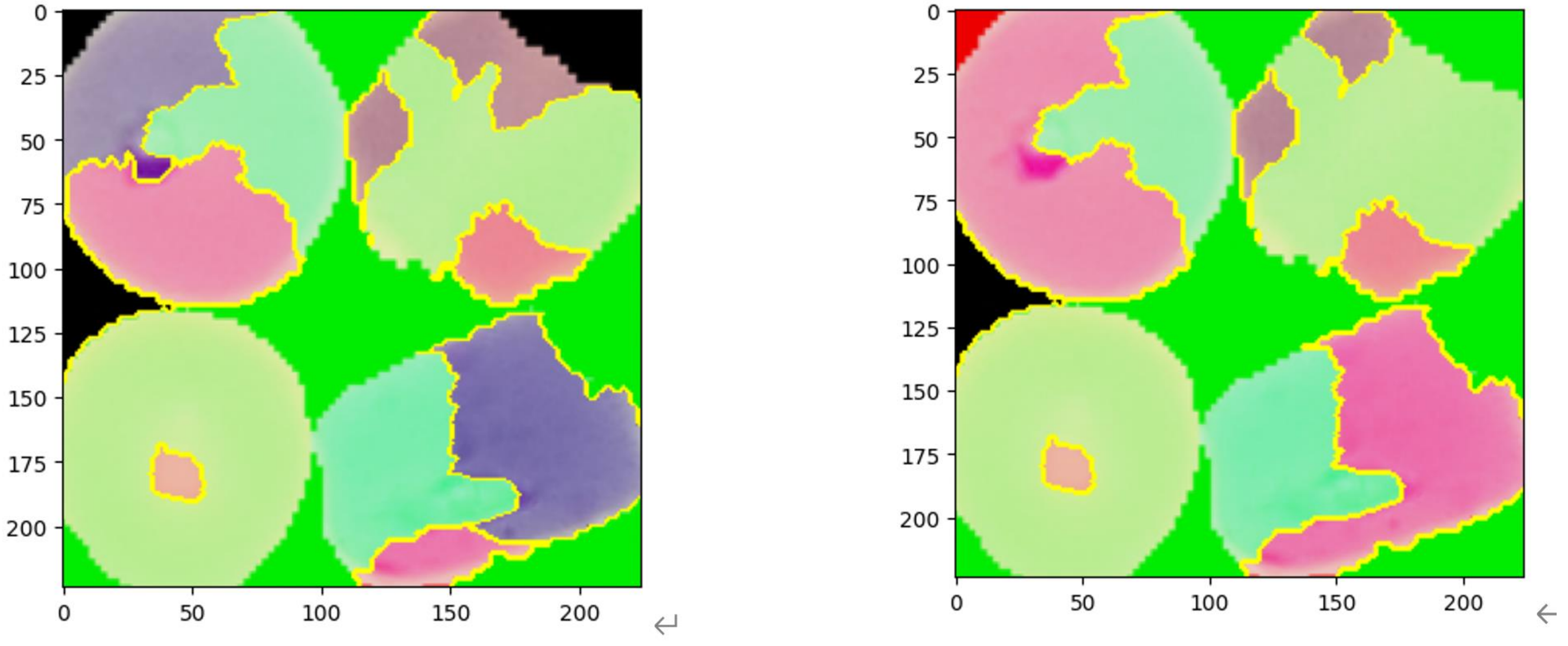
Integrated Gradients Interpretable Analyses



The shap interpretability analysis algorithm

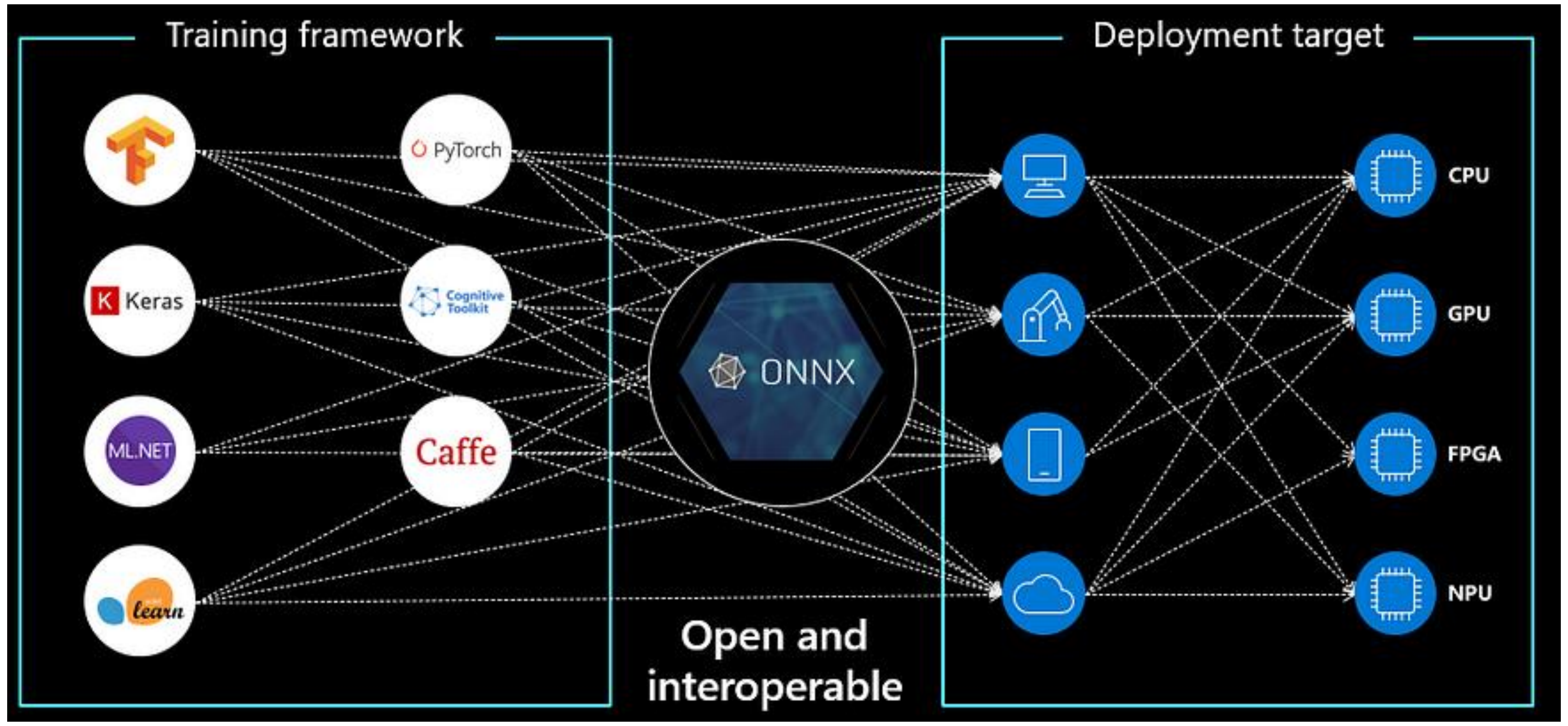


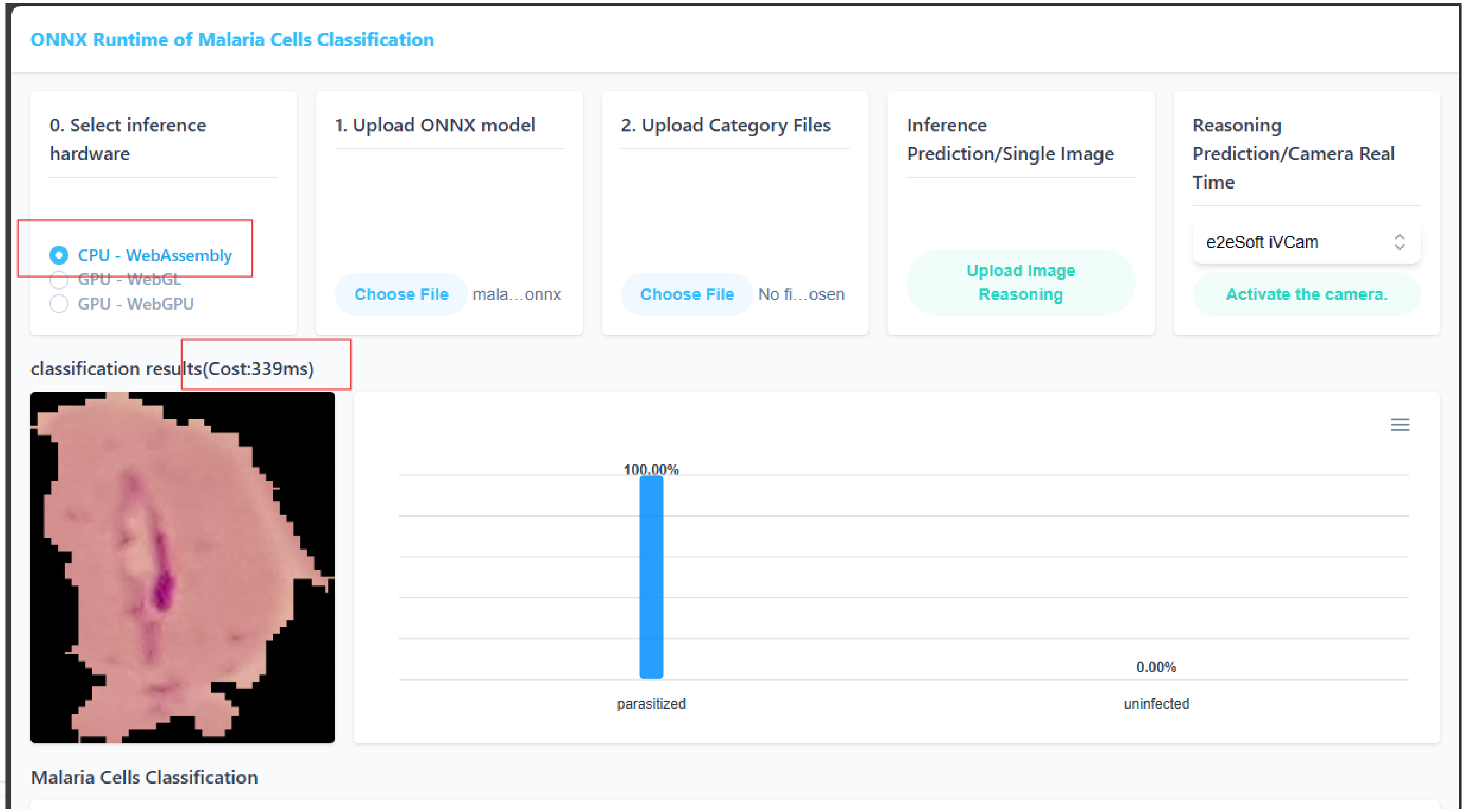
LIME Interpretability Analysis

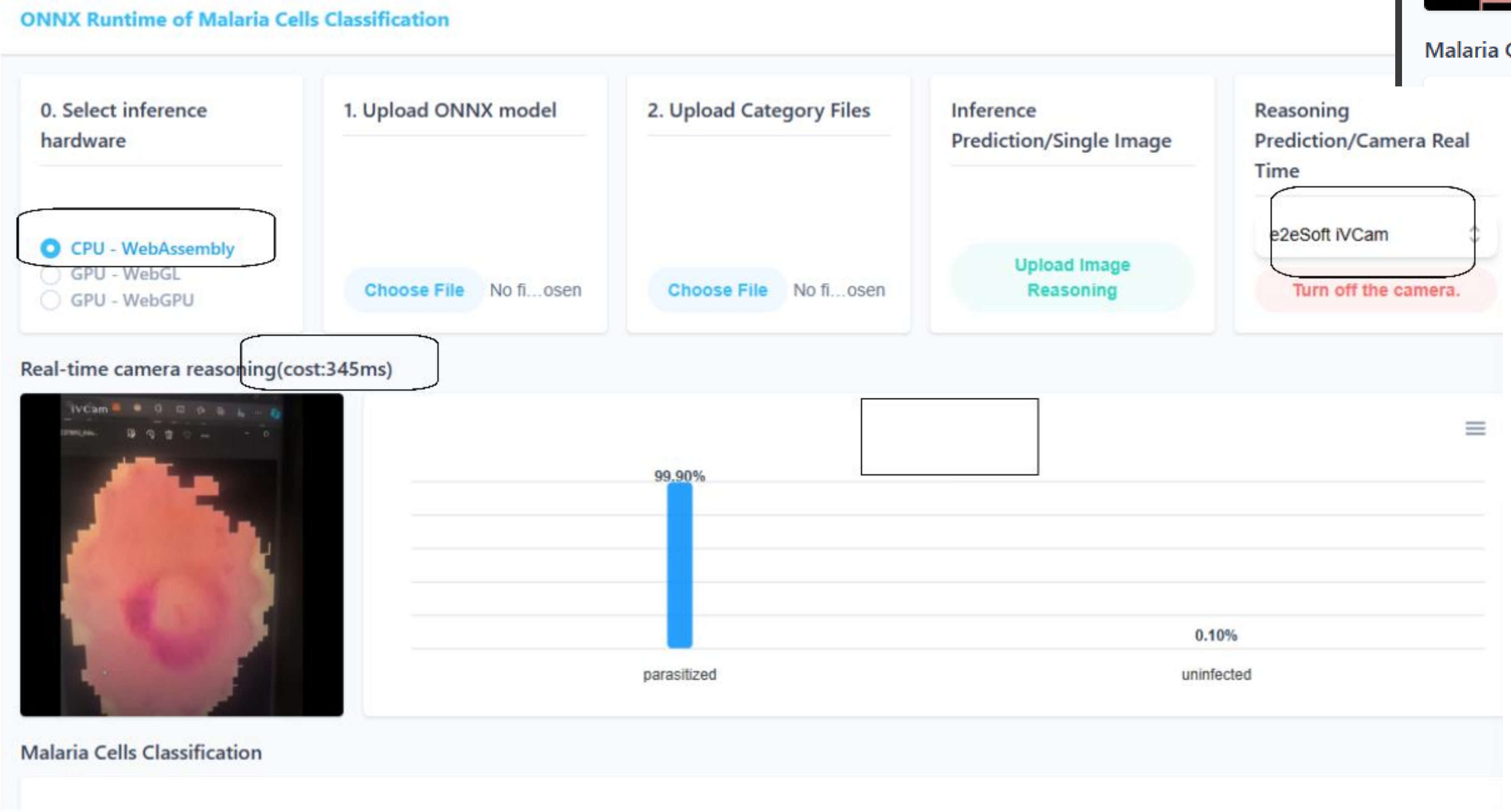


Parasitized **Uninfected**

06 Results







- **Performance Optimization:**
  - Utilizes hardware accelerators and optimized libraries for faster inference times and improved efficiency
- **Scalability:**
  - Supports deployment across various environments, from edge devices to cloud services, ensuring consistent performance
- **Cross-Platform Compatibility:**
  - Compatible with multiple operating systems (Windows, Linux, macOS), enabling deployment in diverse environments
- **Interoperability:**
  - Standardizes model representation, making it easier to manage and maintain models, and reduces deployment complexity

07 Reflections & Conclusion

RCAN Super-Resolution Implementation:

•Used RCAN to enhance classification of parasitized and uninfected malaria cells

•Achieved PSNR of 35.36 and SSIM of 9.982

Classification Model Performance:

•Integrated 3 CNN models and developed an ensemble model with attention mechanism

•Best model achieved 100.00% test accuracy, loss of 7.682e-7, and 100.00% in precision, recall, and F1-score

Effectiveness of Super-Resolution:

•RCAN with super-resolution outperformed original classification method

•Demonstrated significant benefits in medical image classification

Attention Mechanism and SE Block:

•SE blocks and attention mechanisms improved focus on relevant cell properties

•CAM observations showed better focus on cells with attention mechanisms

Semantic Focus and Interpretability:

•Improved categorization by focusing on semantics, interpretability, and saliency

•Enhanced understanding and trust in model predictions

08 Limitations

Comparison of Super-Resolution Models:

•No evaluation of different SR models for classification performance
•Investigating other SR techniques could provide additional insights

Performance :

•Strong performance specific to dataset and experimental design

Computational Cost:

•High computational resources needed for RCAN
•Challenging for resource-limited environments

Data Quality and Variability:

•Performance depends on quality and variability of training data
•Inconsistent or biased data affects generalizability

Generalization to Other Medical Conditions:

•Model only tailored for malaria cell classification
•Significant modifications needed for other medical tasks

08 Future work

Evaluation of SR Approaches:

•**Comparative Analysis:** Evaluate and compare single image super-resolution (SR) approaches
•**Additional Models:** Investigate advanced SR techniques like SwinIR and Real-ESRGAN
•**Assessment:** Evaluate the enhancing effects of SR models on malaria cell images

Focus on Lightweight CNN Models:

•**Optimization Techniques:** Use pruning, quantization, and knowledge distillation to reduce model size and computational overhead
•**Automated Compression:** Explore parameter-free optimization approaches for automated model compression

Collection of Additional Clinical Data:

•**Collaboration with Medical Institutes:** Obtain more clinical malaria cell imaging data
•**Dataset Augmentation:** Use data augmentation to create a larger, more diverse training dataset

Development of AI-Assisted Diagnosis System:

•**System Features:** Develop a hospital AI-assisted system for malaria cell diagnosis, including:

- Automated image processing and inference pipeline

Thank You!