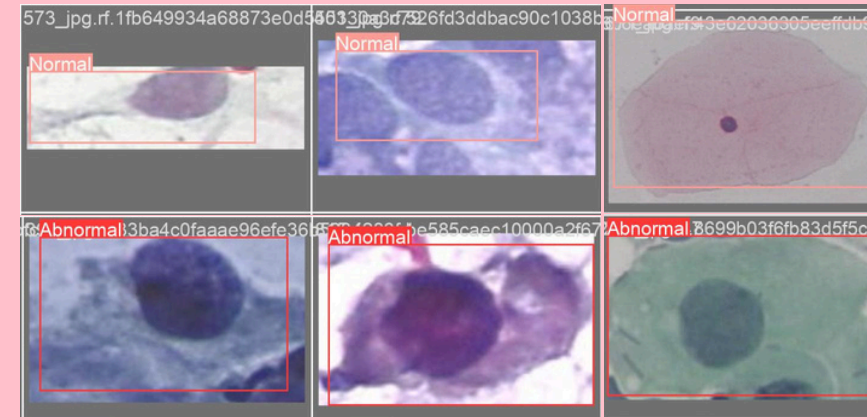


YOLOv10 FOR DETECTING NORMAL AND ABNORMAL CERVICAL CELLS

YOLOv10n

by: Raniah Mufidah Admayana

Code in Google Colab = <https://colab.research.google.com/drive/1rYcmZfWIKUdRPRUe1FWWhGSI0pjT7tufe?usp=sharing>.



INTRODUCTION

CERVICAL CANCER

Cervical cancer is the fourth most common cancer in women, with 660,000 new cases and 350,000 deaths reported worldwide in 2022 (World Health Organization, n.d.). Although cervical cancer is highly treatable when detected early, the Pap smear test—the most common and accessible screening method—requires analyzing microscopic images, making it a complex and time-consuming process. Even experienced cytopathologists must examine numerous micro-images for each patient, making the procedure prone to errors. Tiny cervical intraepithelial neoplasia and overlapping cell clusters, often obscured by blood or mucus, further increase the risk of missed abnormalities (Li et al., 2021; William et al., 2019).

YOLO

To improve accuracy and efficiency on analyzing the cervical cells, computer-aided detection systems, particularly those using deep learning, have been explored (Tan et al., 2023). Among them, You Only Look Once (YOLO) has shown great potential in medical image analysis, including cervical cancer detection. Recent advancements in YOLO, such as YOLOv8 and YOLOv10, offer improved object detection, making them valuable tools for automating and enhancing cervical cancer diagnosis. YOLOv8 has been successfully applied in diagnosing various cancers, including acute lymphoblastic leukemia, cervical, lung, colon, oral, and skin cancers (Palanivel et al., 2023). Meanwhile, YOLOv10 has shown effectiveness in detecting brain tumors and skin cancer (Ali et al., 2024; Byeon, 2024)

RESEARCH PURPOSE

This study aims to evaluate the performance of YOLOv10n in detecting cervical cancer cells using the Herlev dataset.

LITERATURE REVIEW

DEEP LEARNING

Deep learning has improved object detection by making it more accurate, faster, and more reliable, especially in complex situations. Unlike traditional methods that require manual feature design, deep learning learns patterns from data, resulting in better performance. This makes it especially useful for medical image analysis, where accurate and efficient detection is essential. (Yeerjiang et al., 2024)

YOLOv10

YOLO (You Only Look Once) is one of the most well-known deep learning-based object detection algorithms, recognized for its speed and efficiency. In the medical field, YOLO is widely used for image analysis, helping automate disease detection.

The model architecture of YOLOv10 consists of:

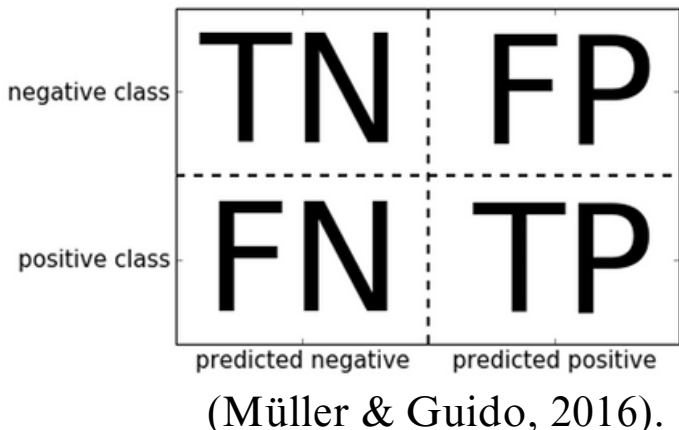
- **Backbone:** Uses an enhanced CSPNet for more efficient feature extraction.
- **Neck:** Employs Path Aggregation Network (PAN) to merge features from different scales.
- **One-to-Many Head:** Generates multiple predictions during training to enhance learning accuracy.
- **One-to-One Head:** Selects the best prediction during inference, eliminating the need for NMS, reducing latency, and improving efficiency.

YOLOv10 offers multiple model variants:

- **YOLOv10n (nano):** Nano version for extremely resource-constrained environments. This is the smallest and fastest model.
- **YOLOv10s (small), YOLOv10m (medium), YOLOv10b (balanced), YOLOv10l (large), YOLOv10x (extra-large):** Larger models provide higher accuracy but come with increased latency and computational demands.

YOLOv10n was selected for this study due to its low latency, making it the fastest among YOLOv10 models (Ultralytics, 2025).

PERFORMANCE MATRICS



$$Precision = \frac{TP}{TP + FP}$$

- **Precision:** The percentage of predicted positives that are actually correct.

$$Recall = \frac{TP}{TP + FN}$$

- **Recall (Sensitivity):** The percentage of actual positives correctly identified.

- **mAP50:** Mean average precision calculated at an intersection over union (IoU) threshold of 0.50. It's a measure of the model's accuracy considering only the "easy" detections.
- **mAP50-95:** The average of the mean average precision calculated at varying IoU thresholds, ranging from 0.50 to 0.95. It gives a comprehensive view of the model's performance across different levels of detection difficulty.
- **Speed :** The time required to predict from the testing dataset of 93 images.

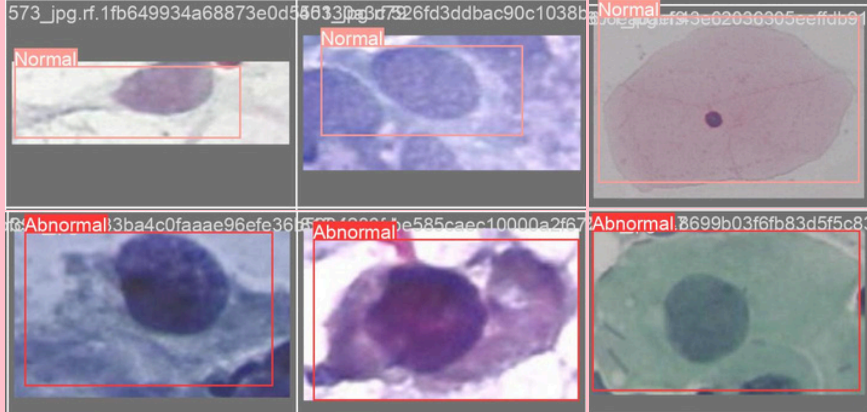
(Ultralytics, 2024)

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RESEARCH METHODOLOGY

DATA SOURCE → secondary data from Roboflow’s Herlev dataset https://universe.roboflow.com/datadetector/herlev_dataset, accessed on March 4, 2025.

RESEARCH VARIABLES

The dataset originally contained 917 images of cervical cell samples. To increase the dataset size, image flipping was applied as an augmentation technique, resulting in a total of 1,400 images. Augmentation was applied only to the training set, while the validation and test sets remained unchanged to ensure evaluation consistency.

After augmentation, the dataset was split into:

- 1,124 images for training (80% dataset)
- 183 images for validation (13% dataset)
- 93 images for testing (7% dataset)

ANALYSIS STEPS

1. Install YOLOv10 and Load Pre-trained Weights
2. Download the Dataset
3. Train and Validate Using YOLOv10n
4. Test the Model on Test Data

DISCUSSION

1. INSTALL YOLOv10 & LOAD PRE-TRAINED WEIGHTS

```
!pip install -q git+https://github.com/THU-MIG/yolov10.git
```

```
Installing build dependencies ... done
Getting requirements to build wheel ... done
Preparing metadata (pyproject.toml) ... done
363.4/363.4 MB 3.8 MB/s eta 0:00:00
13.8/13.8 MB 73.8 MB/s eta 0:00:00
24.6/24.6 MB 63.1 MB/s eta 0:00:00
883.7/883.7 kB 38.7 MB/s eta 0:00:00
664.8/664.8 MB 2.8 MB/s eta 0:00:00
211.5/211.5 MB 6.7 MB/s eta 0:00:00
56.3/56.3 MB 13.2 MB/s eta 0:00:00
127.9/127.9 MB 7.5 MB/s eta 0:00:00
207.5/207.5 MB 5.9 MB/s eta 0:00:00
21.1/21.1 MB 70.3 MB/s eta 0:00:00
Building wheel for ultralytics (pyproject.toml) ... done
```

```
!mkdir -p {HOME}/weights
!wget -P {HOME}/weights -q https://github.com/THU-MIG/yolov10/releases/download/v1.1/yolov10n.pt
!wget -P {HOME}/weights -q https://github.com/THU-MIG/yolov10/releases/download/v1.1/yolov10s.pt
!wget -P {HOME}/weights -q https://github.com/THU-MIG/yolov10/releases/download/v1.1/yolov10m.pt
!wget -P {HOME}/weights -q https://github.com/THU-MIG/yolov10/releases/download/v1.1/yolov10b.pt
!wget -P {HOME}/weights -q https://github.com/THU-MIG/yolov10/releases/download/v1.1/yolov10x.pt
!wget -P {HOME}/weights -q https://github.com/THU-MIG/yolov10/releases/download/v1.1/yolov10l.pt
!ls -lh {HOME}/weights

total 408M
-rw-r--r-- 1 root root 80M May 26 2024 yolov10b.pt
-rw-r--r-- 1 root root 100M May 26 2024 yolov10l.pt
-rw-r--r-- 1 root root 64M May 26 2024 yolov10m.pt
-rw-r--r-- 1 root root 11M May 26 2024 yolov10n.pt
-rw-r--r-- 1 root root 32M May 26 2024 yolov10s.pt
-rw-r--r-- 1 root root 123M May 26 2024 yolov10x.pt
```

2. DOWNLOAD THE DATASET

```
rf = Roboflow(api_key="xxxxxxxxxxxxx")
project = rf.workspace("datadetector").project("herlev_dataset")
version = project.version(3)
dataset = version.download("yolov8")

/content/datasets
loading Roboflow workspace...
loading Roboflow project...
Downloading Dataset Version Zip in Herlev_dataset-3 to yolov8:: 100%|
Extracting Dataset Version Zip to Herlev_dataset-3 in yolov8:: 100%|
```

TRAIN DATASET

Abnormal Cells:
815 images
Normal Cells:
309 images

VALIDATION DATASET

Abnormal Cells:
127 images
Normal Cells:
56 images

TEST DATASET

Abnormal Cells:
59 images
Normal Cells:
34 images

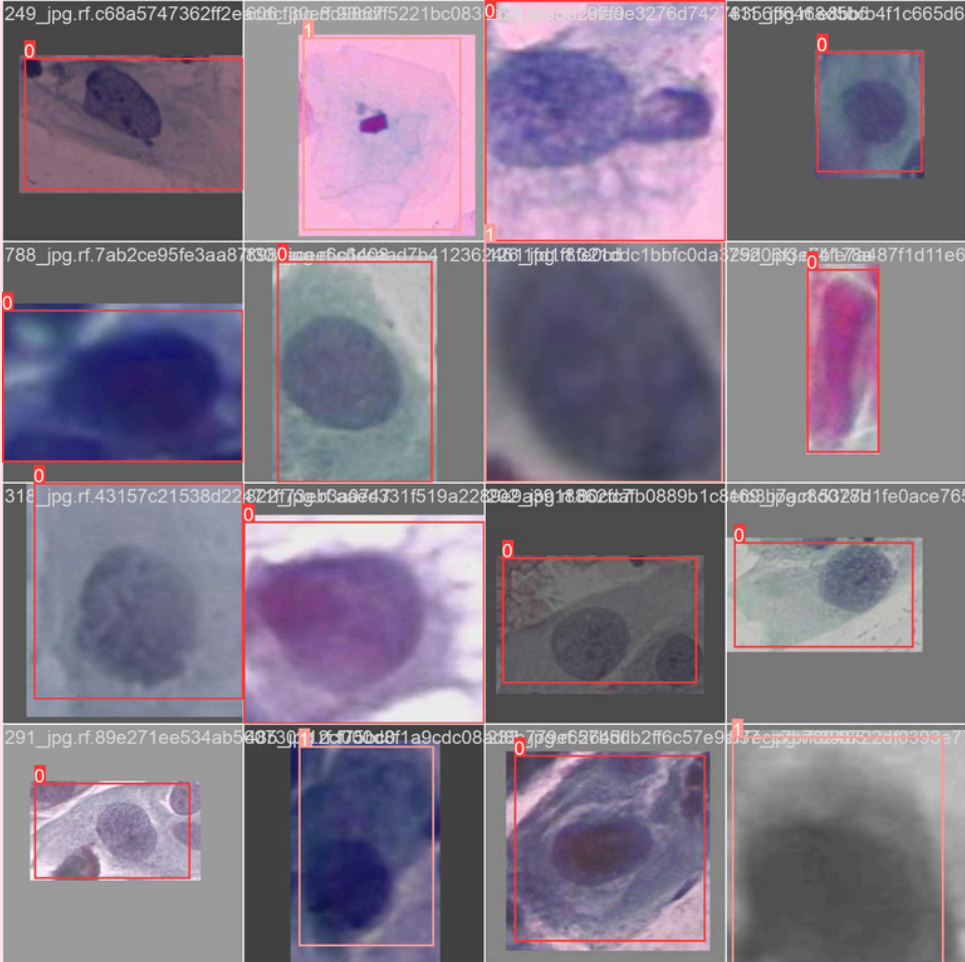
3. TRAIN & VALIDATE DATA USING YOLOv10n

The YOLOv10n model is trained for 50 epochs using the training dataset.

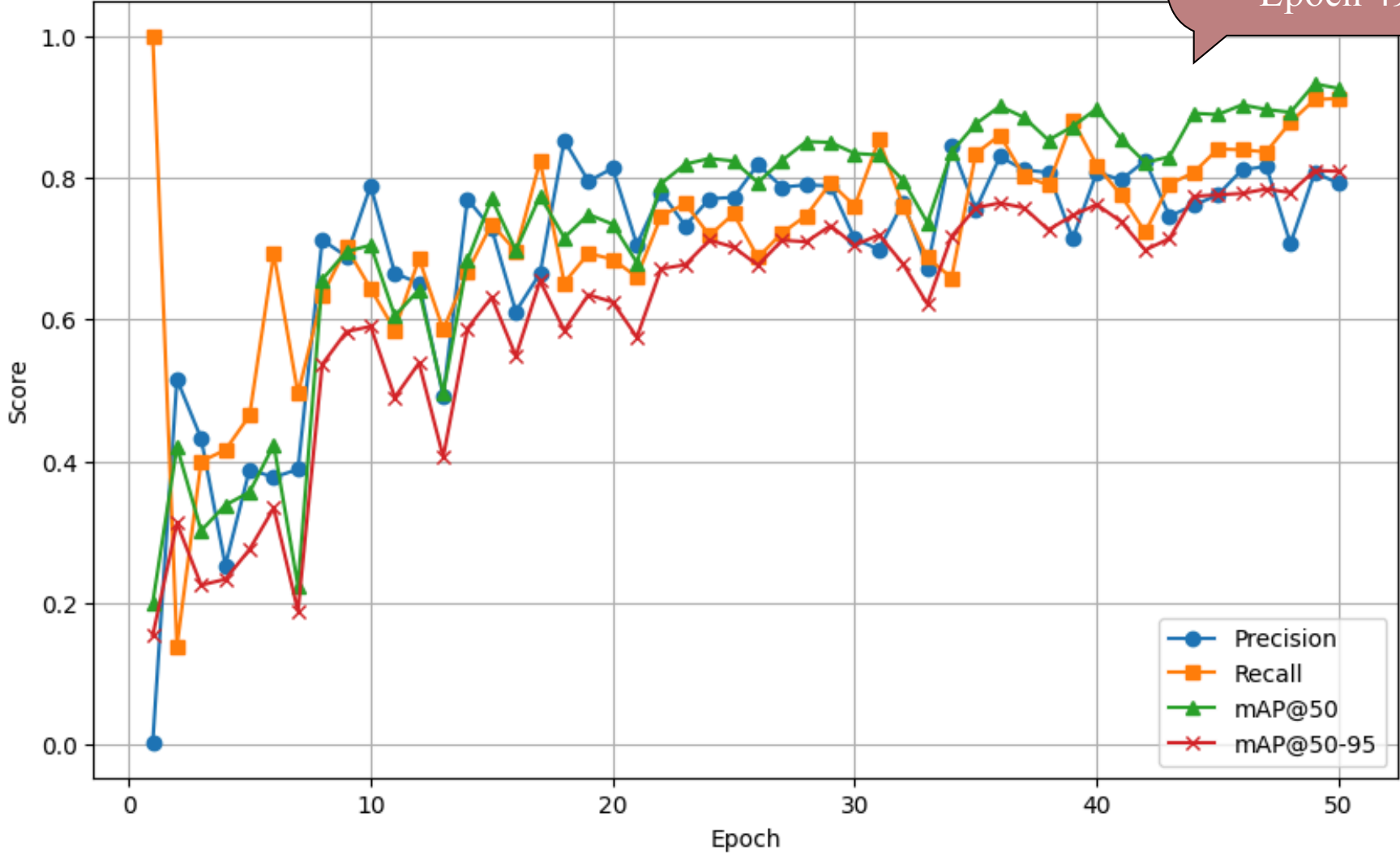
An epoch represents one full cycle of training a neural network on the entire train dataset. During each epoch, the model processes every data point once, adjusting its internal parameters (weights and biases) based on previous errors. This process helps minimize the loss function and gradually improves the model’s accuracy (Ultralytics, n.d.).

In this research, YOLOv10n will go through the train dataset (1,124 images) 50 times (50 epochs). After each epoch, the model is evaluated using the validation dataset (183 images). The best-performing epoch is saved as ‘best.pt,’ which is then used again for evaluation with the validation & test dataset.

Images from training
on the train dataset using YOLOv10n
0 is abnormal cells & 1 is normal cells



Performance metrics of validation data for YOLOv10n (Epochs 1-50)

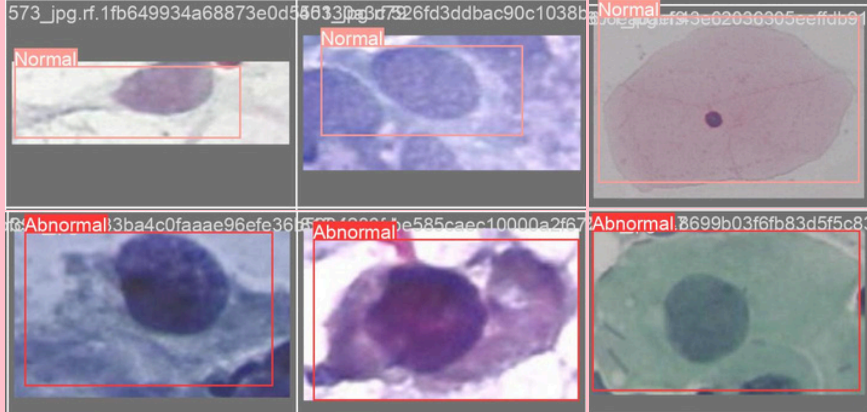


YOLOv10 FOR DETECTING NORMAL AND ABNORMAL CERVICAL CELLS

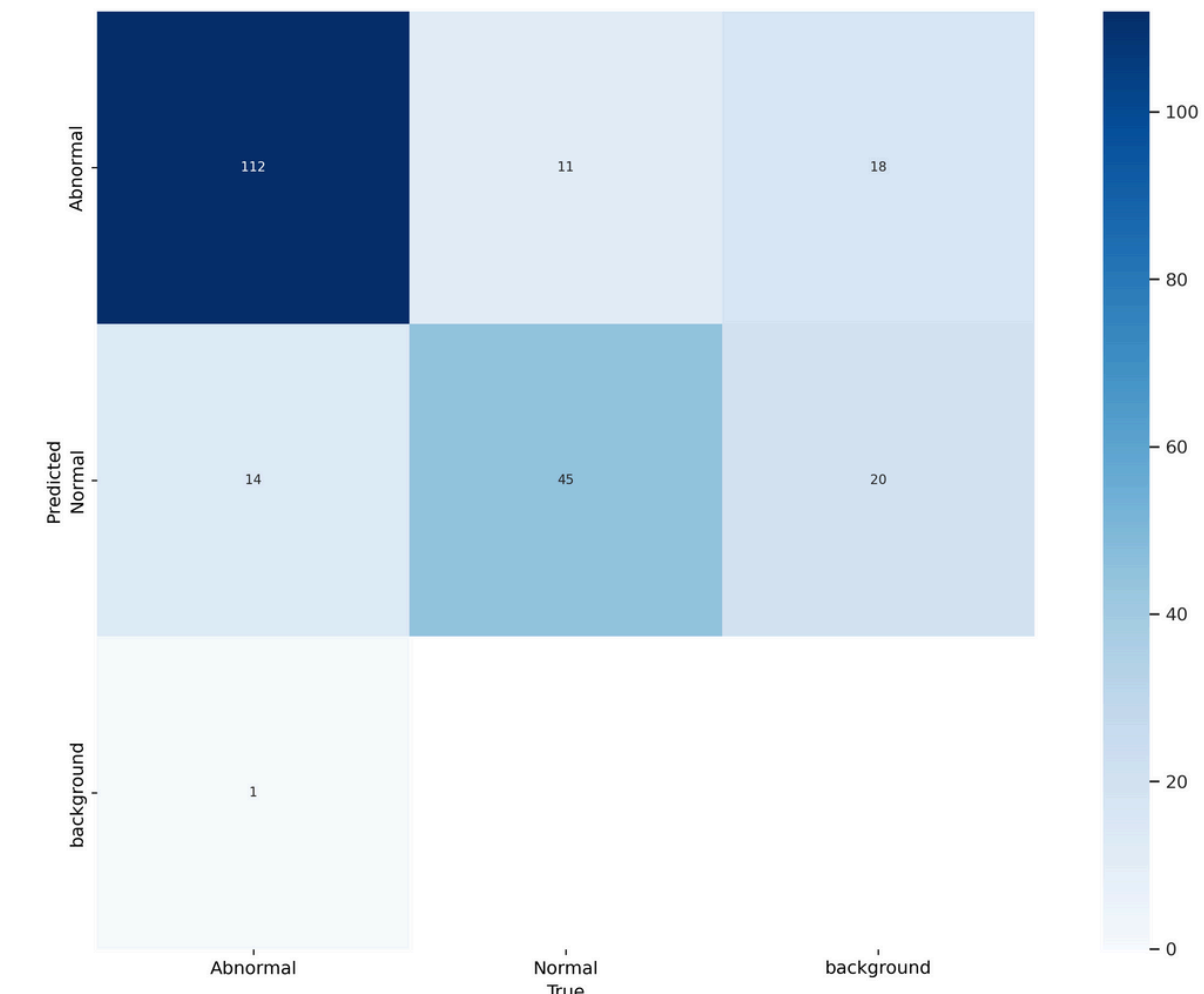
YOLOv10n

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Code in Google Colab = <https://colab.research.google.com/drive/1rYcmZWikUdRPRUe1FWWhGSJ0pjT7tufe?usp=sharing>



4. TEST THE MODEL ON TEST DATA



| True Label | Predicted Abnormal (Images) | Predicted Normal (Images) | Predicted Background (Images) | Total (Images) |
|----------------------|-----------------------------|---------------------------|-------------------------------|----------------|
| Abnormal (59 Images) | 51 | 7 | 1 | 59 |
| Normal (34 Images) | 2 | 32 | 0 | 34 |

In YOLO, "background" likely means the model failed to classify an image as Abnormal or Normal, so it ignored the prediction instead of assigning a wrong label.

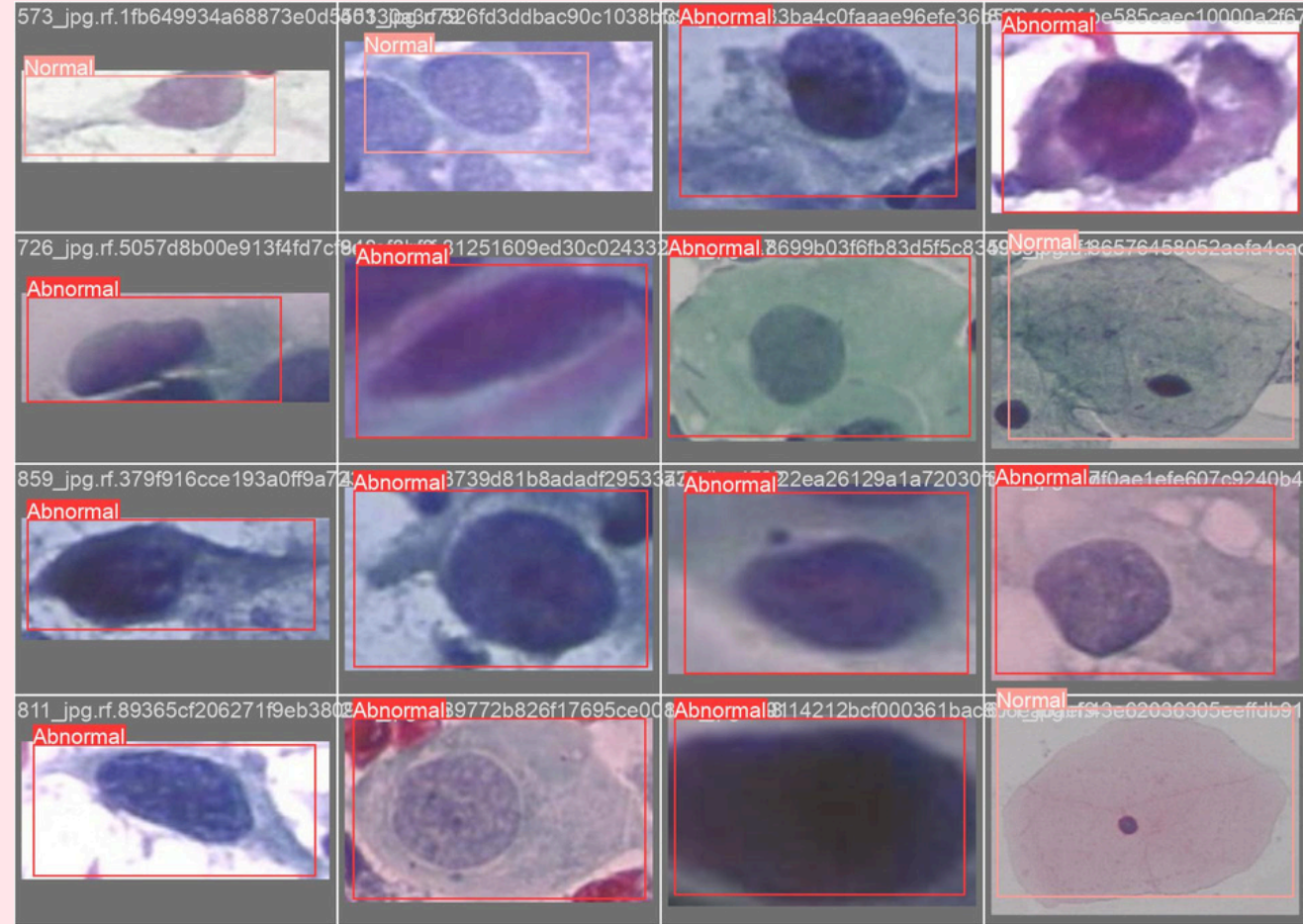
Model Complexity YOLOv10n: 285 layers, 2695196 parameters, 0 gradients, 8.2 GFLOPs

| Class | Precision (P) | Recall (R) | mAP50 | mAP50-95 |
|----------|---------------|------------|-------|----------|
| All | 0.901 | 0.863 | 0.958 | 0.820 |
| Abnormal | 0.951 | 0.881 | 0.977 | 0.868 |
| Normal | 0.852 | 0.844 | 0.939 | 0.772 |

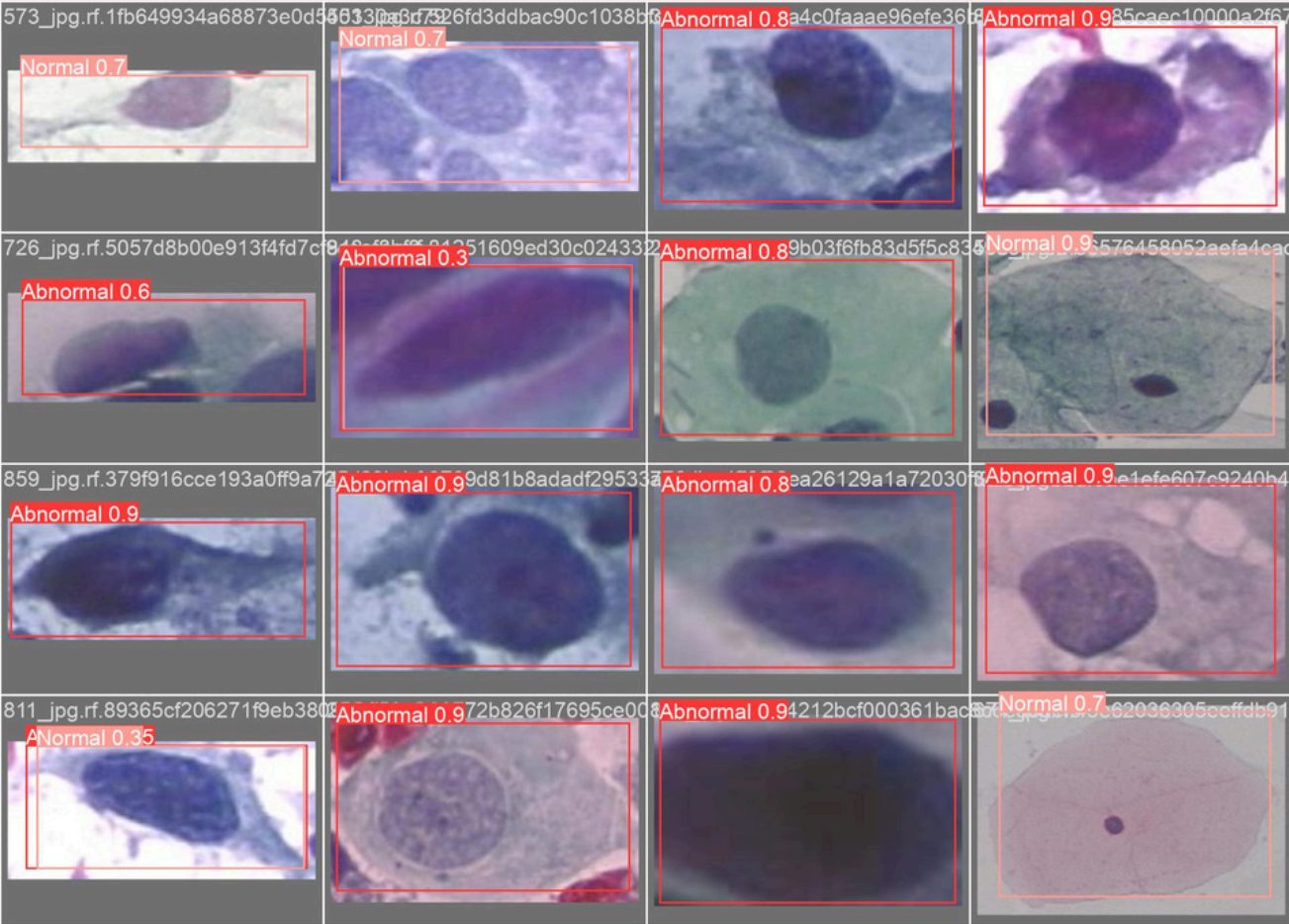
Speed: 7.2 ms preprocess, 13.9 ms inference, 0.0 ms loss, 1.0 ms postprocess per image

Speed: (7.2 + 13.9 + 1.0) ms = 22.1 ms per image

TRUE LABEL
on some test data



PREDICTED LABEL
on some test data



CONCLUSION

- Detecting Abnormal cells → Precision = 0.951 & Recall = 0.863
- Detecting Normal cells → Precision = 0.852 & Recall = 0.844
- Overall mAP50 = 0.958 → indicating that it can recognize objects effectively
- Speed → 22.1 ms per image

CODE IN COLAB



Google Colab <https://colab.research.google.com/drive/1rYcmZWikUdRPRUe1FWWhGSJ0pjT7tufe?usp=sharing>

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