Three-Step Deep Learning System for Cancer Cell Detection

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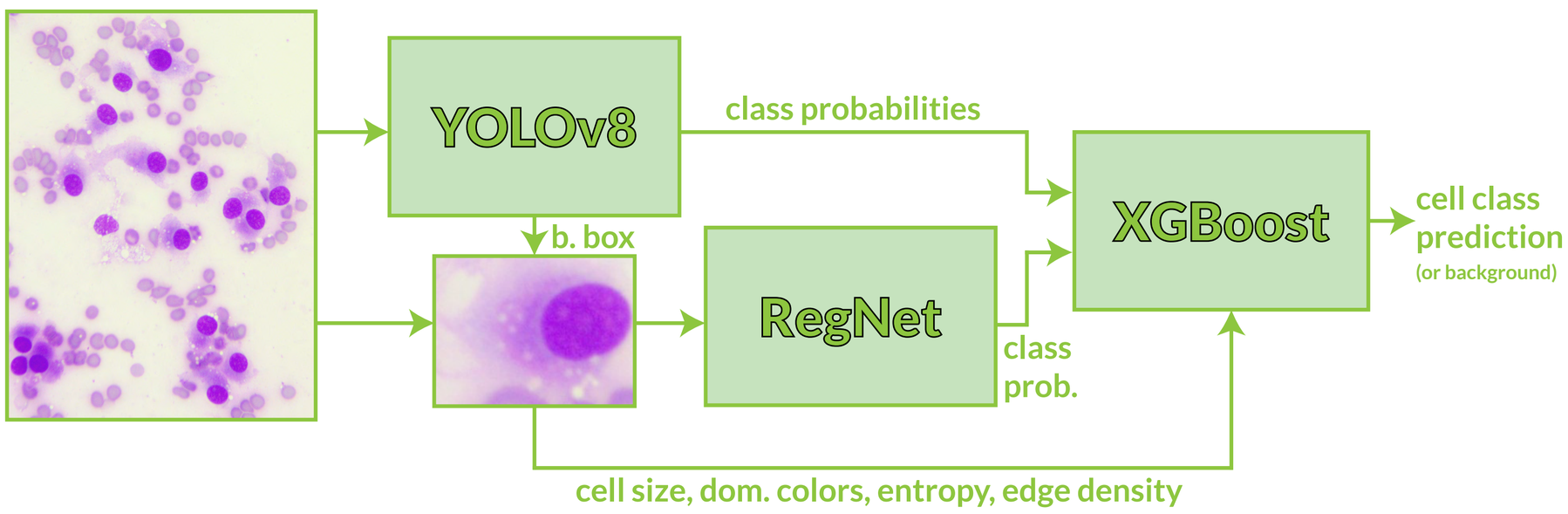
Introduction

AI can be used to detect and classify cancer cells in microscope images. However, this presents a few obstacles:

- Even specialists can find cytological image analysis challenging
- Classifying single cells is subjective
- Data quality, diversity and quantity is crucial

Three-Step System

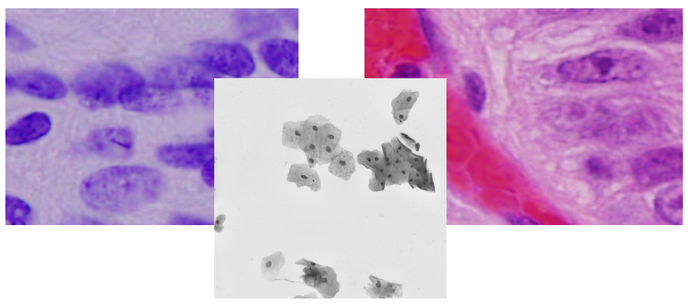


We propose a novel three-step system, consisting of three separate AI models:

1. Object detection model (**YOLOv8**) working on the whole image
2. Cell classification model (**RegNet**) for out of context cell inference
3. Gradient Boosted Trees (**XGBoost**) for the combined final classification

Further cell classification models can be added to improve the system's accuracy.

Nucleus Detection



Nucleus detection on the DSB2018 dataset. With only one class, the 2nd and 3rd steps were used to discard erroneous detections.

- 700 images containing 6,000 nuclei
- Single class (nuclei)
- Limited image quality and resolution
- Unknown (but high) number of patients
- Varied techniques and sample sources

The accuracy increased when compared to single-step models, or the cell instance segmentation model ASF-YOLO.

Model	ASF-YOLO	3-S System
Accuracy	0.801	0.858
F1 macro	0.871	0.871

Cervical Cancer

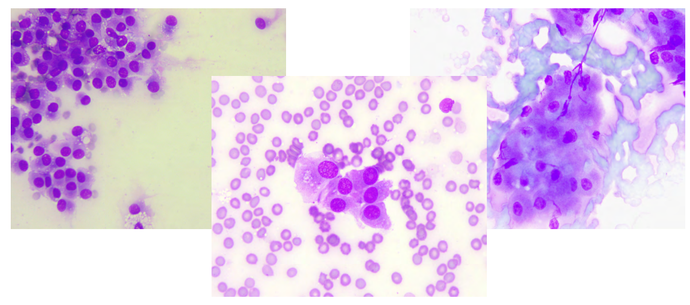
Detection of epithelial cell abnormalities from pap smear slices for cervical cancer screening on the APACC 2024 dataset.

- 21,000 images, over 100,000 annotations
- Four classes: healthy, unhealthy, both, rubbish
- High image quality, varied annotation quality
- 107 patients (none healthy), single hospital
- Single image acquisition method

While out of context classification was good:
RegNet accuracy: 83% F1 weighted: 84%
Cell detection metrics were poor due to many unlabeled image regions. Whole groups of cells were annotated in the dataset (as opposed to single cells) making the detection task difficult.

Model	YOLOv8	3-S System
Accuracy	0.220	0.232
F1 macro	0.189	0.208

Small Animal Skin Cancer



Detection of cancer cells in small animals for skin cancer diagnostics. Dataset collected during the CyfroVet project.

- 3,500 images, over 100,000 annotations
- 13 classes: 9 cancer, 4 white cell classes
- High image quality
- Limited number of patients
- Single image acquisition method

Using two additional neural networks (a small convolutional network and ViT-B) the performance increased slightly.

Model	YOLOv8	3-S System
Accuracy	0.668	0.670
F1 macro	0.642	0.654

Conclusions

The presented three-step system for cell detection and classification may give better results when compared to the state-of-the-art methods on the three datasets presented. Nevertheless, nowadays, deep learning models are very sophisticated, and the improvements may be limited. Any problems with the datasets are still apparent, having a negative impact on the system's performance. In particular:

- For optimal detection the cells need to be labelled individually, and not as clusters. It's best to label all relevant objects.
- The non-diagnostic cells, which cannot be conclusively classified, still improve the system's performance when included in the training.
- Varied imaging and staining techniques should be taken into account when gathering data.
- Healthy patients should also be included in the data.

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