Mitosis Detection With Tiny-YOLO

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Background

National Cancer Institute reported that breast cancer was the most common type of cancer diagnosed in 2019 with 271,270 new cases. One in eight U.S. women will develop invasive breast cancer at some point in their lives. The current process to obtain an accurate breast cancer prognosis is tedious and time consuming, requiring a trained pathologist to manually examine histopathological images in order to identify the features that characterize its severity. We propose a novel convolutional neural network, namely "You Only Look Once (YOLO)" to characterize one of criteria in Nottingham Grading System: mitotic count. YOLO has gained recognition for its fast and efficient object detection tasks. Tiny-YOLO is a smaller CNN model suited to quickly assess if YOLO can learn a task. If Tiny-YOLO can perform to learn a task, it is very likely that a larger CNN models such as YOLOv3 can perform even better.

Objective

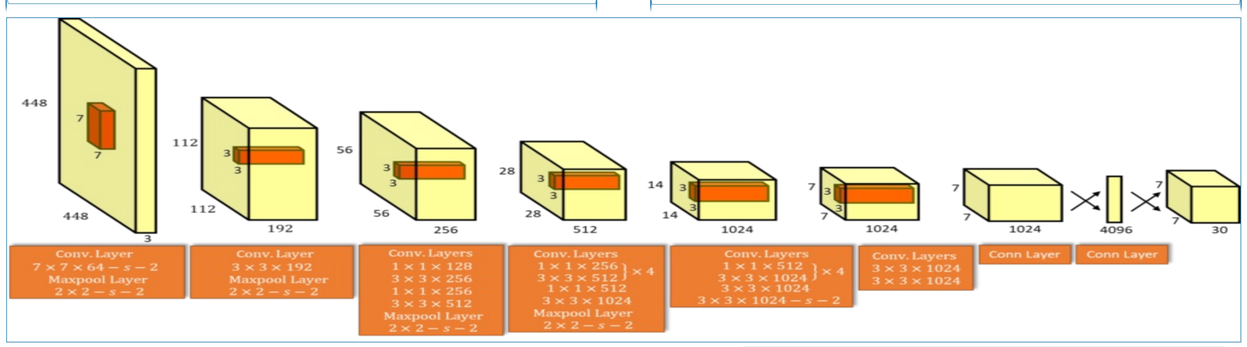
In this study we tested if Tiny-YOLOv3 can learn to detect mitoses from digitally scanned histology images from breast cancer. We also tested if it can generalize over different scanners with various image qualities.

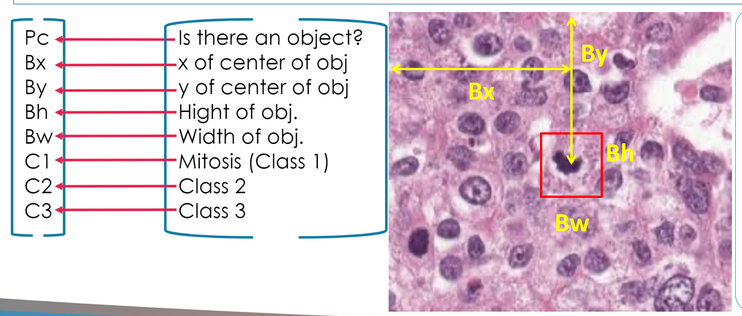
Materials & Methods

Tiny-YOLO architecture was downloaded from https://github.com/pjreddie/darknet/wiki/YOLO:-Real-Time-Object-Detection. We utilizes breast cancer images downloaded from a publicly available repository: https://mitos-atypia-14.grand-challenge.org/. The training set was composed of 928 histological images at 40x magnification from an Aperio scanner. For each image, we made a CSV file with following information: 1) whether or not mitoses exist in the image, 2) the coordinates of where the mitotic figures are located, and 3) height and width of mitotic figures. Test set is composed of 20 unique H&E slides scanned at our institution on Aperio and 3D Histech (total of 40 images). They are HE-stained slides prepared from canine oral melanoma tissues. The "gold standard" of mitosis is when three out of five pathologists mark an object as mitosis. Tiny-YOLO was configured to have batch size of 64 and run for approximately 135 epochs. Performance was evaluated based on recall/sensitivity, precision, and F-measure:

$$F_1 = 2 * \frac{precision * recall}{precision + recall}$$

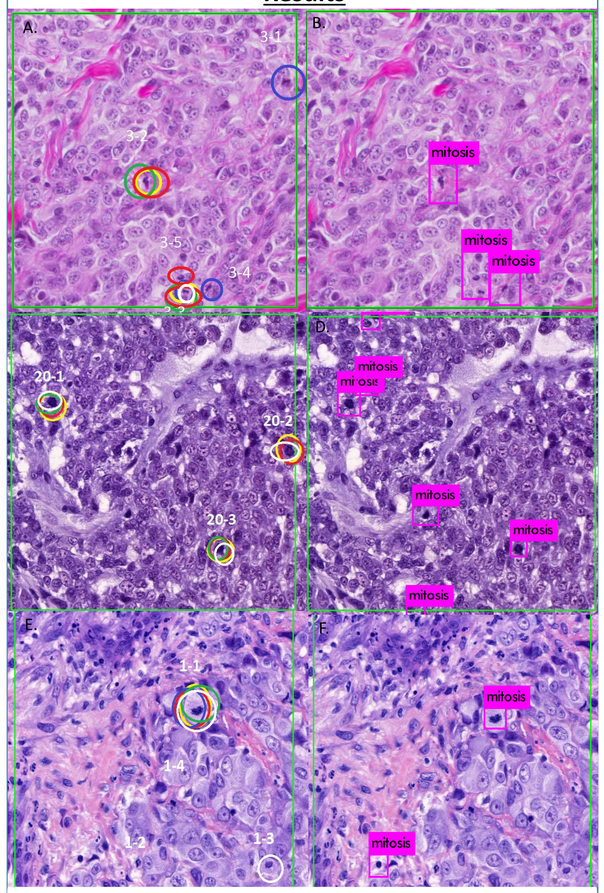
We also took random images from online to see if Tiny-YOLO is able to generalize and detect mitosis on different image quality and aspect ratio.





YOLO architecture (above) with 24 convolutional layers followed by 2 fully connected layers. Training set images are fed into the CNN along with vectors (left) with information regarding where the object to detect is located. The values are given in terms of ratio of the entire image rather than absolute pixel size/length.

Results



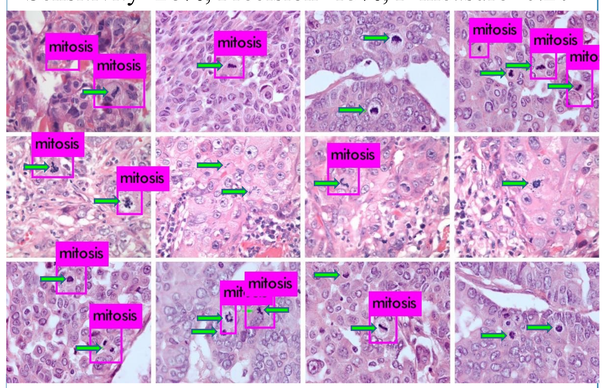
Tiny-YOLO output (pink box) and annotation by 5 pathologists (each with different color circle.)

Fig A&B: Tested on the Aperio images:

Sensitivity=20%, Precision=19%, F-measure=0.20

Fig C, D, E, & F: Tested on 3DHistech images:

Sensitivity=28%, Precision=15%, F-measure=0.20



Random image online. Green arrows are annotation by a pathologist. YOLO was able to generalize.

Conclusion

Although our evaluation score appears low, it clearly shows that tiny-YOLO is learning to distinguish mitosis from non-mitosis. From this result, we anticipate that full YOLOv3 architecture can also learn to detect mitosis and with higher performance. Tiny-YOLO was also able to transfer what it learned from Aperio images to 3D Histech scanned images. Further more it was able to detect mitosis from randomly selected images from online with different image quality and aspect ratio. These findings show the potential that YOLO is very good at generalizing what it has learned. Moving forward, we plan to expand data set through image augmentation and add images from various scanners to acquire further generalizability.

Discussion & Future

The strength of YOLO is that it reasons globally about the image when making predictions. Unlike sliding window and region proposal-based techniques, YOLO sees the entire image during training and test time so it encodes contextual information about classes as well as their appearance. In addition, the input variables in training are given in terms of ratio so that it can generalize to other images with different aspect ratios. Finally, YOLO runs its convolutional neural network once to analyze the entire image unlike the sliding window approach. This makes is much faster and possibly able to use it in real time analysis.

Reference

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