Blood Cell Detection in Microscopic Images

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Abstract: Machine learning has shown enormous development in recent years. Using the concepts of machine learning, one can find solutions to the use of year-old hardcoded algorithms and manual analysis that have a chance of developing false positives or vice-versa. With the advancements in medical imaging and computer technology, medical image processing has become increasingly important in diagnosis. X-ray radiography, CT, and MRI produce massive volumes of medical images. Studying the detection of red blood cells through medical imaging has taken us to explore deep neural networks in combination with the concepts of machine learning. The concept of the Efficient-Det-D0 Neural Network has been thoroughly revised in the paper to detect red blood cells. Microscopic imaging of the blood cells has resulted in a faster analysis of the cells than the conventional methods. This technique has proven to be a boon for microfluidic point-of-care medical devices.

Index Terms—**Deep Learning, Blood Cell, Object Detection, Efficient-Det, Medical Imaging, Computer Vision, OpenCV, Python**

I. Introduction (Heading 1)

With the advancement of medical imaging and computer technology, medical image processing has become increasingly crucial in diagnosis. X-ray radiography, CT, and MRI produce enormous quantities of medical images. They provide critical information for quick and accurate diagnosis depending on the findings techniques for advanced computer vision. White Blood Cells (WBC), also known as leukocytes, play an important role in the diagnosis of a variety of disorders. Although computer vision techniques have effectively led to the development of novel methods for cell analysis, resulting in more accurate and reliable disease diagnosis systems. The significant variation in cell structure, size, edge, and positioning complicates the data extraction technique. Furthermore, the contrast between cell boundaries and the image background may fluctuate due to changing lighting conditions during the capture process[1].

In recent times, medical image processing and Microfluidic technologies have developed rapidly in biological and medical applications, such as lab-on-chip and point-of-care (POC) diagnostic devices, which revolutionized personalized medicine and rapid disease diagnosis[2].

In this paper image processing techniques are used to detect and count red blood cells, white blood cells and platelets. If the image contains the normal red blood cells then it will make boundaries and detect their edges. Counting red blood cells in an image is very important but counting them manually is a very tedious and time-consuming process. There must be some counting conflicts also generated while manual counting. So in this paper cells are not only detected but also counted automatically[8]

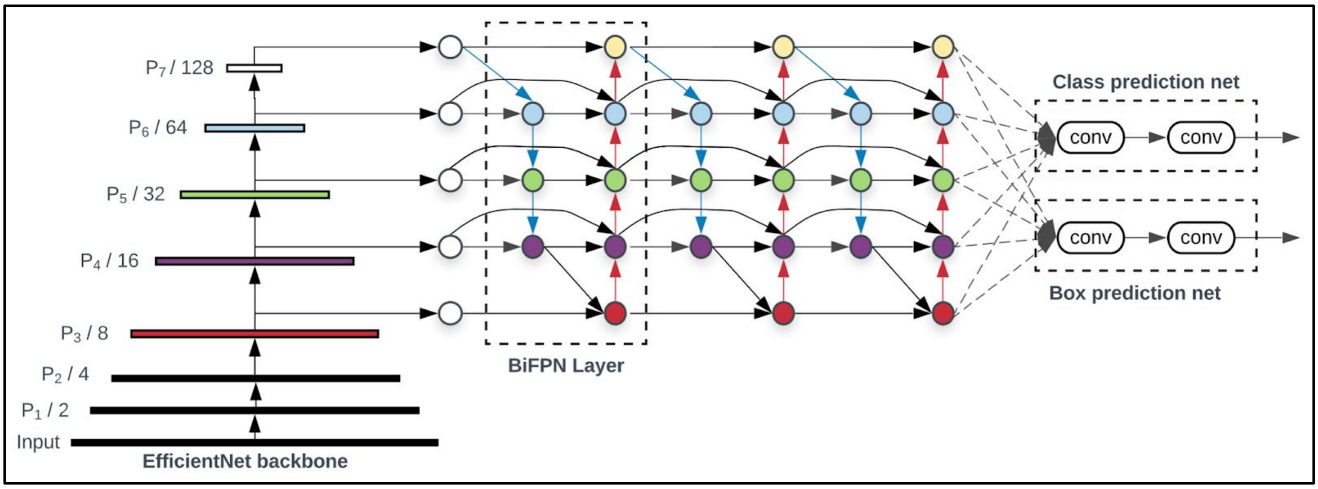
II. Related Work

1. The technique for automatic detection of blood cell pictures based on the DE algorithm is discussed in An enhanced computer vision method for detecting white blood cells. Five edge points are used as candidate ellipses in the smear edge map in the method provided in the paper. An objective function allows to accurately measure the resemblance of a candidate ellipse with an actual WBC on the image. Guided by the values of such objective function, the set of encoded candidate ellipses are evolved using the DE algorithm so that they can fit into the actual WBC on the image. The approach generates a sub-pixel detector that can effectively identify leukocytes in real images[1]. The study's key contribution is the development of a new WBC detector algorithm that recognizes WBC under a variety of difficult situations while treating the entire process as an elliptical detection problem. Even though elliptical detectors based on optimization have several intriguing qualities, they have yet to be applied to any medical image processing to our knowledge.
2. Counting via Deep Learning for Microfluidic Point-of-Care Medical Devices, study the ways of live cell identification techniques based on recently established artificial intelligence approaches in the second paper, which is about the integration of automated microscopic image analysis into microfluidic POC devices for blood cell counts[2].

III. Proposed Method

EfficientDets are a family of object detection models, which achieve state-of-the-art 55.1mAP on COCO test-dev, yet being 4x - 9x smaller and using 13x - 42x fewer FLOPs than previous detectors. Our models also run 2x - 4x faster on GPU, and 5x - 11x faster on CPU than other detectors.

EfficientDet is developed based on the advanced backbone, a new BiFPN, and a new scaling technique:



Backbone network: Same width/depth scaling coefficients of EfficientNet-B0 to B6 are used so that ImageNet pre-trained checkpoints can be used.

BiFPN network: The authors exponentially grow BiFPN width (#channels) as done in EfficientNets, but linearly increase the depth (#layers) since depth needs to be rounded to small integers.

$$W_{bifpn} = 64 \cdot \left(1.35^{\phi}\right), \qquad D_{bifpn} = 2 + \phi \qquad (1)$$

Box/class prediction network: The width is kept the same as the BiFPN but the depth (#layers) is linearly increased.

$$D_{box} = D_{class} = 3 + \lfloor \phi/3 \rfloor \qquad (2)$$

Input image resolution: Since feature levels 3–7 are used in BiFPN, the input resolution must be divisible by $2^7 = 128$, so we linearly increase resolutions using the equation.

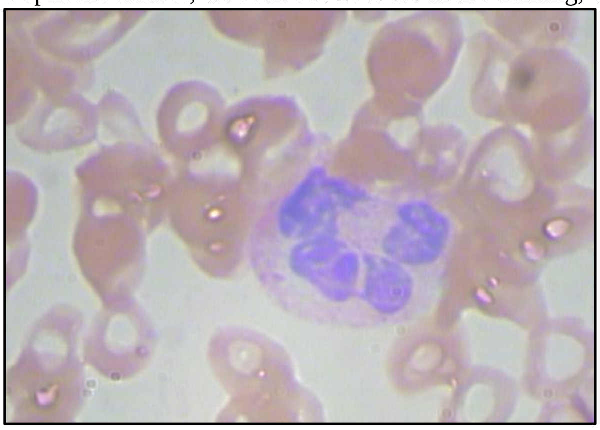
$$R_{input} = 512 + \phi \cdot 128 \qquad (3)$$

Our model family starts from EfficientDet-D0, which has comparable accuracy to YOLOv3. Then we scale up this baseline model using our compound scaling method to obtain a list of detection models EfficientDet-D1 to D6, with different trade-offs between accuracy and model complexity.

IV. EXPERIMENTS

Experimental Setup

Originally our dataset consisted of a total of 364 images. There are 364 images across three classes: WBC (white blood cells), RBC (red blood cells), and Platelets. There are 4888 labels across 3 classes. The image was jpeg type. The Dimensions of the images are 640x480. We resize the images to 416x416. We performed different augmentation techniques to increase the size of our dataset. We flipped the images horizontally and vertically. We rotated the images 90 degrees clockwise, counter-clockwise and upside down. Cropped the images by a minimum of 0% and a maximum of 15%. Hue and Saturation were tweaked between -25% and +25% whereas the brightness and exposure were tweaked between -15% and +15 and -20% and +20%. After augmenting the dataset, we got a total of 874 images. To split the dataset, we took 88%:8%4% in the training, validation and testing set.



Experiment Results

After the experiment, the result yields a pretty good mAP@.50IOU of around 90.14%. The classification loss was 8.29%, localisation loss was 2.84%, regularization loss was 3.35% and total loss was 14.4%. The results have been shown in the following figures.

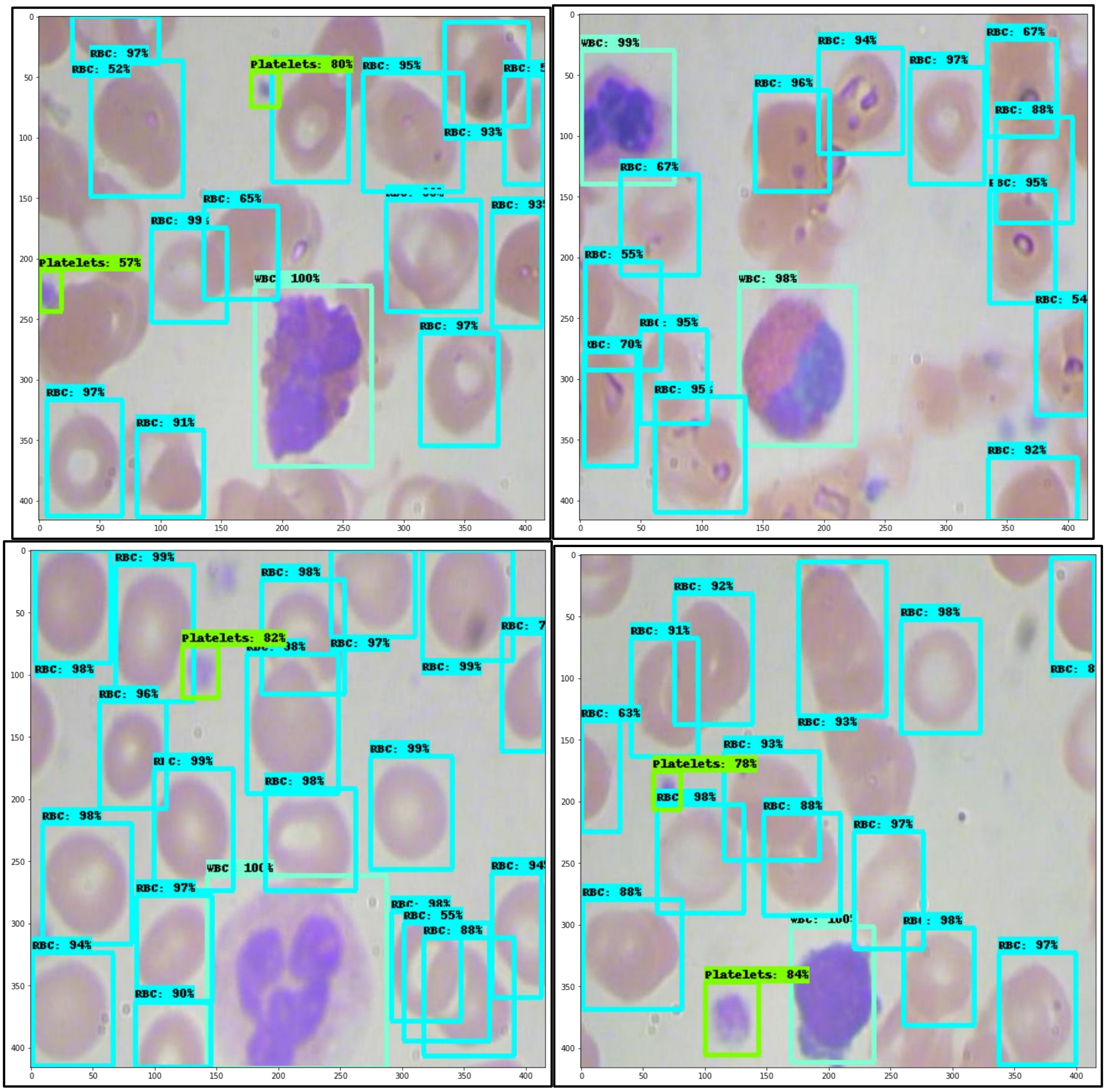


Fig: Results on our exported model

Conclusion

In this paper, we have investigated blood cell detection using deep learning methods and validated the accuracy of the model. Our work can be a new pathway for analyzing the blood cell using laboratory microscopes.

The performance of our Efficient-Det model yields a pretty good result of Mixed Average Precision(mAP) @.50IOU of 90.14% and Classification Loss is around 0.2%. Experimental results demonstrate the high performance of the proposed method in terms of detection accuracy, robustness and stability

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