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DETECTION OF BLOOD CELLS WITH VARYING HYPER-PARAMETERS IN YOLO

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ABSTRACT

Blood cell count plays an important role at intervals in the sphere of clinical diagnosis Within recent times," the deep - learning- primarily, object-based detection technique YOLO" has been tested by a unique technique to counting the blood cells and platelets effectively. Albeit its potency, the YOLO detection technique incorporates a few limitations like meager positioning of the bounding boxes and in distinctive overlapping objects, so as to beat these limitations, we have a tendency to propose a novel deep-learning-based technique, termed Attention-YOLO. Attention - YOLO is accomplished by summing the channel attention mechanism and therefore the spatial attention mechanism to the feature extraction network. By exploiting the filtered and weighted feature vector to change the initial feature vector for residual fusion, Attention-YOLO will facilitate the network to spice up the detection accuracy. The experimental results recommend that the Attention-YOLO incorporates a higher detection performance in cell count while not introducing too several extra parameters compared to the YOLO network. In this paper, the hyper-parameters will be altered and checked for the best outcome available by plotting on a tensor board specialized platform.

Keywords: Machine Learning, YOLO, Blood cells detection, Deep learning Algorithms.

I. INTRODUCTION

Blood cell count is 1 of the most critical parts of the biopsy culture. The appropriate cell tally helps in diagnosing probable diseases and associated lesions, also early detection of the underlying pathology and in-turn help in proper treatment. The three common types of blood cells which are present in human body are the red plasma cells or red blood cells (RBCs), white blood cells (WBCs), and platelets. The role of RBCs is to stream the oxygen, while WBCs play an immune role, and platelets are involved in the progression of hemostasis. Generally, Normal RBC range is 4.5 to 6.5 million cells per micro of blood, Normal WBC range is 4500 to 11000 WBC per micro litre of blood and Normal platelet count is 1.5 Lakhs to 4.5 Lakhs Platelets per micro litre of blood, which is considerably a large amount. The quality manual detecting method is incredibly cumbersome and is liable to manual errors.

In the automatic reckoning method of blood cells, 2 totally different strategies, i.e., the image process strategies and deep-learning (DL)-based strategies are used for unit measurement. The first stage which involves the image process strategies unit wide uses the automated cell recognition technology-supported Hough rework, and watershed technique supported distance transformation, etc. But these image process strategies have some issues in cell detection, such as the accuracy of sleuthing cells cannot meet the necessities in areas with high cell overlap. By victimization convolutional neural network (CNN) as a classifier, Habibzadeh et al. proposed a corpuscle classification technique, which could mechanically classify WBCs into one in all 5 sorts from biology pictures. However, the speed of this system is slow. By employing a class-conscious erythrocyte patch extraction technique followed by a shape-invariant erythrocyte patch normalization technique, Xu et al. reduced the machine value throughout each of the coaching and learning procedures and classified RBC of ill patients. Moreover in 2019, with the help of YOLO (you only look once), Alam and Islam mechanically established and counted RBCs, WBCs, and platelets with the detection speed of a second. However, the YOLO technique has difficulties in characteristic overlapping objects and positioning the bounding box. Together, in cell experiments, blood cells might overlap each other, and seem as clusters within the image, which concludes that YOLO noticeon technique is not efficient to accurately detect every cell.

II. METHODOLOGY

2.1 YOLO system assembly and recognition

YOLO tends to use detection task as a regression analysis problem drawback and has been widely used in image method fields. Lately, many versions of YOLO (e.g., YOLOv1, YOLOv2, and YOLOv3) have to boot been planned. Compared to YOLOv1 and YOLOv2, YOLOv3 has the subsequent advantages:

1) The improved classification performance on sophisticated datasets.

2) The inflated amount of knowledge inside the feature map.

3) The deeper network layers

We've used YOLOv3 because it is advanced. Briefly, YOLOv3 uses Darknet-53 due to the feature extraction network and adopts the strategy rather like the feature pyramid network. it'll directly use the initial input photos and annotations for a training job. As a result, it saves computing resources. within the detection task, firstly, a picture is shipped as ANN input into the feature extraction network and extracted feature vectors square measure obtained that square measure then sent to a structure rather like the feature pyramid network, and so the grid cell is obtained at 3 scales. what is more, each grid cell predicts 3 bounding boxes, and each bounding box predicts a vector P, as follows:

(1) $P=(tx+ty+tw+th)+P0+(P1+P2+\cdots+Pn)$

with

(2) $P0=\Pr(\text{Object})\times \text{IOU}_{\text{predtruth}}$

where tx, ty, tw, th is that the coordinates associated with the bounding box. $Pr(Object)$ represents the likelihood that the thing is within the estimate box. IOU reflects the precision of the object's position. Finally, the non-maximum suppression is performed on the generated prediction to get the ultimate prediction result.

2.2 Attention-YOLO network structure and detection principle

It is to be noted that in YOLOv3 detection processes, each region in entire feature map is treated equally. That is, each area is taken into consideration with identical contribution to the final word detection. However, in experiments, blood cells may overlap each other, or appear as clusters inside the image.

Based on the on top of considerations, to boost the detection accuracy, the attention mechanism module is introduced into the network. channel attention mechanism can filter and weight choices in channel dimension, that's helpful for up the detection performance. The spatial attention mechanism can model choices on the spatial relationship, which could supplement the purpose relationship data that the channel attention mechanism cannot get. Considering that: 1) Convolutional Block Attention Module (CBAM) combines every house and channel attention mechanisms, that allows to quickly notice necessary feature from numerous choices, suppresses the moot or unimportant choices, and improve the efficiency and accuracy of necessary choices processing; 2) CBAM are handily embedded in network structures, and thus the end-to-end work are distributed whereas not high-power the initial network structure, throughout this work, CBAM is chosen and introduced into YOLOv3 network.

In detail, as shown in Fig. 1, the input feature maps area unit subjected to world most pooling and world average pooling operations, thus they're sent to the multilayer perceptron (MLP) for channel data filtering. After that, the MLP output choices supported the constant element-wise for generating the channel attention feature map. consecutively, the foremost pooling and average pooling area unit performed on the channel dimension on high of that, the output of the two operations is combined and a feature descriptor is obtained. Finally, the convolution attention module is introduced into the outstanding module.

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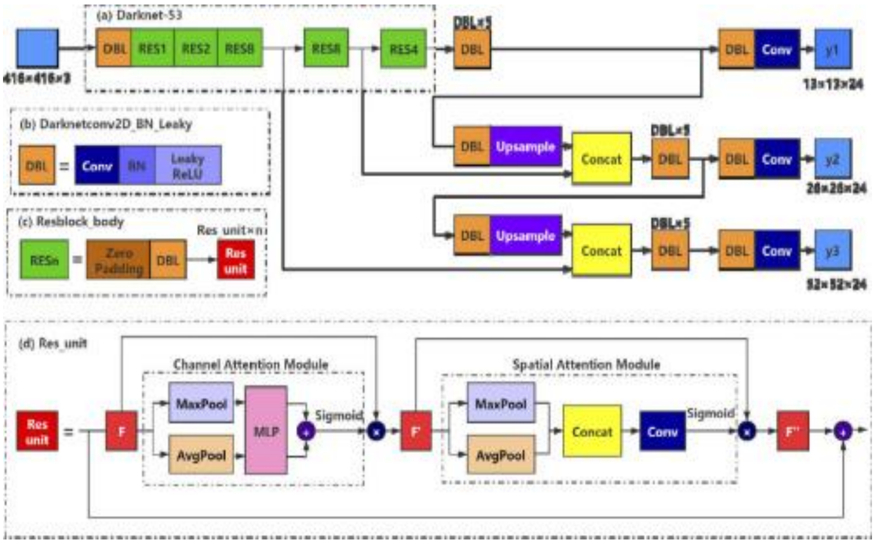


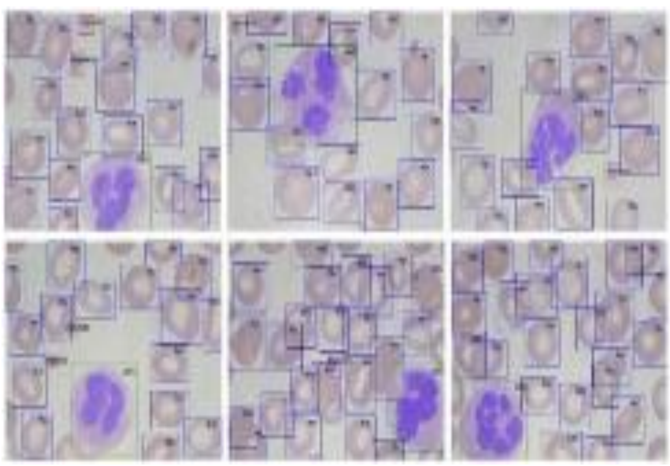
Figure 1: - Attention-YOLO system assembly

It should be noted that the initial application of the YOLO configuration is trained for 80 different labels of categories. once mistreatment YOLO for blood count, the quantity of categories is modified from eighty to three (RBCs, WBCs, and platelets). Corresponding, the quantity of filters within the final convolutional layer is modified to twenty-four. relating, the quantity is calculated by $NF=NA\times(NC+5)$ **NF=NA×(NC+5)** with NA being the quantity of anchor boxes and Old North State being the quantity of categories.

III. BLOOD CELLS DATASET

The dataset used for this project could be a free blood corpuscle dataset (Blood Cell Count Dataset, BCCD), that is offered on https://github.com/Shenggan/BCCD_Dataset. BCCD contains 874 cell pictures and four, 870 annotations (RBCs, WBCs, and platelets). The image resolution is 600×416 pixels. The selection of those datasets is target-hunting by the very fact that they're open supply and absolutely accessible to the analysis civic and also the overall public.

It ought to be recognized that in a very BCCD dataset, some pictures contain RBCs, however the provided annotation file doesn't contain the corresponding RBCs. The mismatches might have an effect on the accuracy of the analysis. to deal with the matter, during this work, supported the antecedental provided annotations, we have a tendency to manually annotate the dataset once more, that is achieved by LabelImg image annotation software package (https://github.com/tzutalin/labelImg). Here, the annotation operation follows 2 principles: 1) For the native cells at the sting of the image, if the realm is a smaller amount than half-hour of the complete cell, it'll not be labelled; For the extremely adherent cells if the cell overlap exceeds eightieth, only 1 cell is marked. Figure a pair of shows some labelled pictures manually.



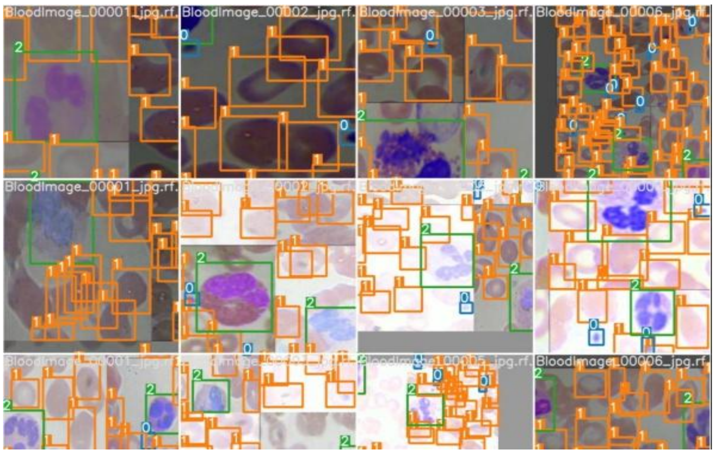


Figure 2: - The directly above is example annotated data

IV. RESULTS AND DISCUSSION

The project has been done using Google Collaboratory tool which is founded by Googles team for Data Science and Machine learning activities on the server, without actually using the local machine. So, this enables everyone to use High GPU Tesla K100/Nvidia, 12 GB RAM. So, for the project the Epoch ranges from 10, 50, 100 and 500.

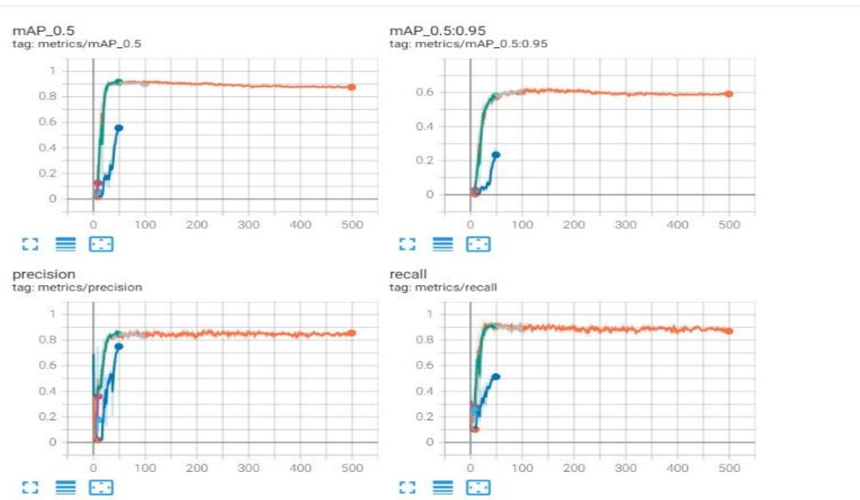


Figure 3: - Different Parameter for Epoch 10, 50, 100 and 500

The above figure shows the comparison between mAP (mean average precision), precision and recall. Where it is observed that after 100 epoch the curve is constant in nature.

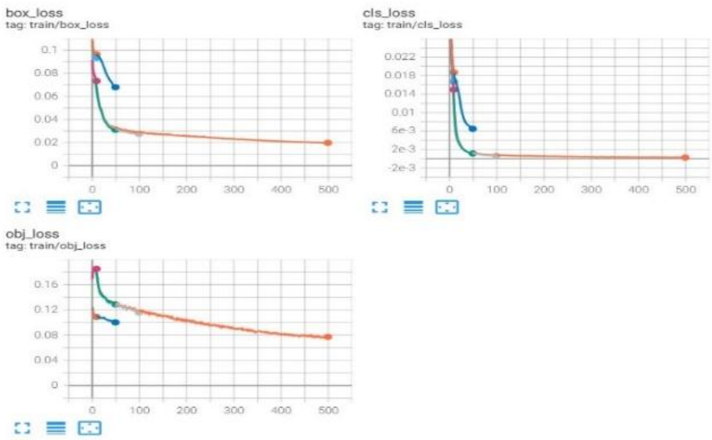


Figure 4: - Loss comparison for different epochs

In the above figure, it is being observed that there is change of loss curve which diverges at the epoch 100 and remains same for the 500th epoch.

V. CONCLUSION

It concludes that, 100 epochs are enough to train this particular dataset to give out the maximum precision, recall and accurate result. Accurate cell reckoning is important in medical image analysis. In clinical applications, generally, varied varieties of cells area unit manually counted, leading to an effortful work. The DL-based detection methodology, like YOLO, can automatically establish and count RBCs, WBCs, and platelets. However, this YOLO methodology has difficulties in distinctive overlapping objects and positioning the bounding box. The aim of this paper is to spice up cell detection accuracy, that's achieved by adding channel attention and spatial attention mechanisms to the feature extraction network.

VI. REFERENCES

[1] M. Alomari, S. N. H. S. Abdullah, R. Z. Azma, and K. Omar, "Automatic detection and quantification of WBCs and RBCs using iterative structured circle detection method," Comput. Math. Method. Med. 2014, 1–17 (2014). [CrossRef]

[2] S. Acharjee, S. Chakrabartty, M. I. Alam, N. Dey, V. Santhi, and A. S. Ashour, "A semiautomated approach using GUI for the detection of red blood cells," 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT) (2016), pp. 525–529.

[3] Z. Ejaz, C. A. Ahmad, and H. Justin, "Automatic red blood cell detection and counting system using Hough transform," Am. J. Pharm. Sci. 5(8), 267–271 (2018). [CrossRef]

[4] V. Acharya and P. Kumar, "Identification and red blood cell automated counting from blood smear images using computer-aided system," Med. Biol. Eng. Comput. 56(3), 483–489 (2018). [CrossRef]

[5] S. M. Mazalan, N. H. Mahmood, and M. A. A. Razak, "Automated red blood cells counting in peripheral blood smear image using circular Hough transform," 2013 International Conference on Artificial Intelligence, Modelling and Simulation (AIMS) (2013), pp. 320–424.

[6] J. Hari, A. S. Prasad, and S. K. Rao, "Separation and counting of blood cells using geometrical features and distance transformed watershed," 2014 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPR) (2014), pp. 77–82.

[7] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sanchez, "A survey on the deep learning in medical image analysis," Med. Image. Anal. 42, 60–88 (2017). [CrossRef]

[8] S. Q. Liu, S. D. Liu, W. D. Cai, H. Y. Che, S. Pujol, R. Kikinis, D. G. Feng, and M. J. Fulham, "Multimodal neuroimaging feature learning for multiclass diagnosis of Alzheimer's disease," IEEE. Trans. Biomed. Eng. 62(4), 1132–1140 (2015). [CrossRef]

[9] "Improved detection performance in blood cell count by an attention-guided deep learning method" Zhengfen Jiang, Xin Liu, Zhuangzhi Yan, Wenting Gu, and Jiehui Jiang.

[10] Comparison of YOLOv3, YOLOv4 and YOLOv5 Performance for Detection of Blood Cells Ramya.A[1], Venkateswara Gupta Pola[2], Dr. Amrutham Bhavya Vaishnavi[3], Sai Suraj Karra[4] (2021).