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Research on Leukocyte Recognition Method Based on Convolutional Neural Network

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Abstract | **Original Research Article**

There are various types of leukocytes in blood cells, and various types of leukocytes play an important role in fighting fungal, bacterial, viral and other infections in the human body, so studying and classifying leukocyte types is an important task for medical researchers. Based on the low efficiency and accuracy of traditional methods for detecting leukocytes, an efficient processing of leukocyte images using convolutional neural networks is proposed, which can perform tasks such as classification and localization of leukocytes. The proposed method and previous detection networks were also compared in experiments, and the experimental results proved that the proposed Yolov5 convolutional neural network has the highest detection speed and accuracy, with mAP reaching 86.47%.

Keywords: convolutional neural network, leukocytes, efficient recognition and classification, Yolov5.

1. INTRODUCTION

Human blood contains four main components: red blood cells (RBC), white blood cells (WBC), plasma and platelets, of which white blood cells are the protective guardians of the human body and are a very important type of cell in blood cells [1]. There are many types of leukocytes, including neutrophils, eosinophils, lymphocytes, basophils, and monocytes, and each type of leukocyte may be abnormal when the body is suffering from certain diseases [2], so efficient and accurate identification of leukocytes to understand the health of the patient is a common test in medicine. Early leukocyte detection and identification mainly used traditional image processing methods [3], which required tedious operational processes, such as manual stain preparation and then manual microscopic examination. The problems of many types of leukocyte images, diverse morphologies, large numbers and overlapping adhesions make the early detection methods inefficient and inaccurate [4]. The convolutional neural network method is used to build a computational network model, which can efficiently identify and process images and solve the difficulties of manual image recognition [5]. In recent years, convolutional neural networks have also been widely used in medical research, Xu *et al*., [6] used convolutional neural networks to identify and classify cells, and Liu *et al*., [7] based on convolutional neural networks to detect red blood cells. In order to address the shortcomings of traditional methods for detecting leukocytes, this paper proposes a convolutional neural network-based method to identify 15 types of leukocytes efficiently and accurately.

2. Convolutional neural network theoretical foundation

2.1 Convolutional neural network basic principle

Convolutional neural network is one of the typical network models in deep learning, where artificial neurons can respond to surrounding units and can perform large scale image processing, and it is often used for image recognition and speech recognition. Compared with the traditional neural networks with fully connected neurons, the neurons in convolutional neural networks are locally connected [8], which can improve the network training speed. Convolutional neural networks consist of five structures: input layer, convolutional layer, activation layer, pooling layer, and output layer, as shown in Figure 1, and the corresponding operation and role of different classes of layers are different. The input layer, i.e., the model performs pre-processing operations on the input initial image, such as normalization, de-meaning and PCA/SVD dimensionality reduction methods. The main role of the convolution layer is to extract feature values from a fixed range of images, and each output feature value may be a convolutional combination of multiple

input feature values. The output value a_j^l of the jth cell of the convolution layer l is calculated as (1):

$$a_j^l = f(b_j^l + \sum_{i \in M_j^l} a_j^{l-1} * k_{ij}^l) \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where M_j^l is the set of input feature values and k is the learnable convolutional kernel. The activation layer is a nonlinear mapping of the output of the convolutional layer, which allows better redundancy of the data. The pooling layer generally comes after the convolutional layer, and the two are crossed. Each convolutional layer has a corresponding pooling layer, which is used to improve the learning efficiency of the network by using the pooling function to output all the feature values that are close to each other. In the output layer, the model integrates and normalizes all the high quality features learned in the previous process, and the final output is obtained by the softmax function, and the whole convolutional network model is trained.

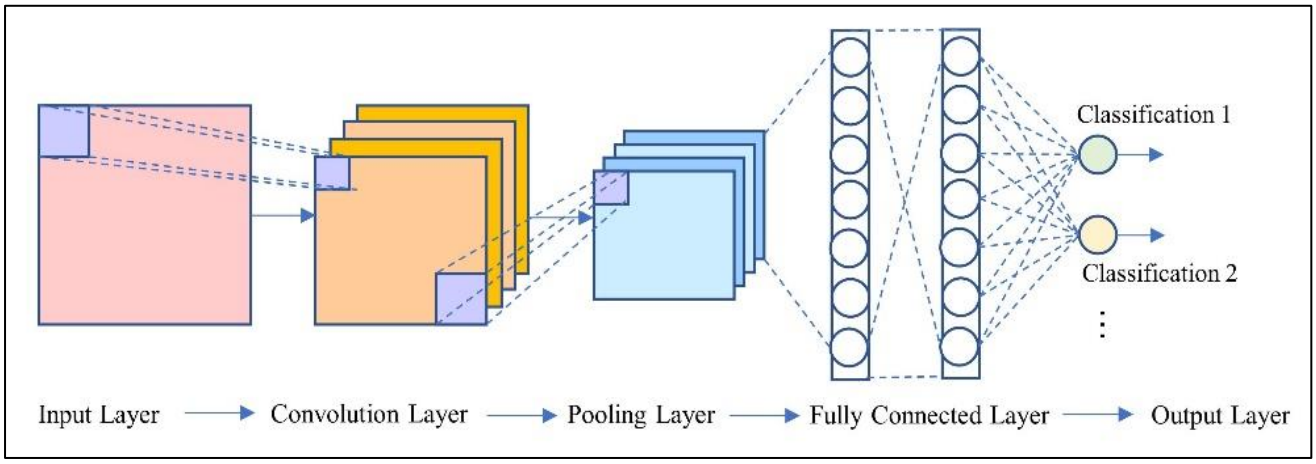

Figure 1: Convolutional neural network structure diagram

2.2 Convolutional neural network algorithm

2.2.1 Random initialization of probability distributions

Before the convolutional neural network model is trained, the parameters need to be initialized, and a large number of experiments have proved that the normal distribution and the uniform distribution are the two more effective probability distributions in the initialization method of neural network parameters. The probability density function corresponding to the normal distribution is shown in Equation 2.

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} wxp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \ldots\ldots\ldots\ldots (2)$$

Where σ is the scale parameter and μ is the loc ation parameter. The uniform distribution f-unction para meters a and b defined by, denote the minimum and ma ximum values on the nu-mber axis, and its probability d ensity function as in Equation (3) and (4).

$$f(x) = \frac{1}{b-a}, a < x < b \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$f(x) = 0, else \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

2.2.2 Regularization strategy

In the training of convolutional networks, we often encounter the problem of model overfitting, i.e., the training error is small but the testing error is large, which will lead to poor final detection and poor generalization of the model. Regularization is an important method to solve this problem. Regularization can impose certain restrictions on the model to reduce the effective capacity of the model to alleviate the overfitting problem. There are several regularization strategies, including soft constraints on parameters, such as adding additional constraints to the objective function, and hard constraints on parameters, such as adding restrictions on the parameters.

3. MATERIALS AND METHODS

3.1 Data sets and codes

The dataset used in this paper was sourced from an open source cancer imaging archive (TCIA) and contained a total of 15 blood cell types. Basophils (BAS), Erythroblast (EBO), Eosinophil (EOS), Smudge cell (KSC), Atypical Lymphocytes (LYA), Typical Lymphocytes (LYT), Metamyelocyte (MMZ), Monoblast (MOB), Monocyte (MON), Myelocyte (MYB), Myeloblast (MYO), Neutrophil (band) (NGB), Neutrophil (segmented) (NGS), Promyelocyte (bilobed) (PMB), Promyelocyte (PMO), respectively. A total of 15,111 data sets were used in this paper, and the number of training and test sets were divided by 9:1. The specific data distribution is shown in Table 1. The source code of the convolutional neural networks used in the experiments and several typical networks used in the comparison experiments are open source.

Table 1: Training set and test set

Class	Training	Testing	Total
BAS	933	104	1037
EBO	935	104	1039
EOS	948	105	1053
KSC	899	99	998
LYA	840	93	933
LYT	991	110	1101

Class	Training	Testing	Total
MMZ	888	99	987
MOB	895	99	994
MON	971	108	1079
MYB	794	88	882
MYO	928	103	1031
NGB	894	99	993
NGS	936	104	1040
PMB	859	95	954
PMO	891	99	990
Total	13602	1509	15111

3.2 Design of Convolutional Neural Network

The Yolov5 network [9] in the convolutional neural network can be divided into the input side, Backbone structure, Neck structure and Prediction structure. Comparing with the Yolov1 [10], Yolov2 [11], Yolov3 [12], and Yolov4 [13] networks in the Yolo series of networks, the improved Yolov5 network is the fastest and has the highest AP accuracy. Considering the speed and accuracy aspects, the convolutional neural network Yolov5 is used in this paper to design as our leukocyte recognition model.

3.2.1 Inputs to Convolutional Neural Networks

Due to the imbalance in the number of samples in the dataset, the Yolov5 network will use the Mosaic [13] data augmentation method to give data augmentation to the dataset after preprocessing at the input side of the network. The length of the initial anchor frame will be set for different datasets in Yolov5, and then during the training process, the network outputs the prediction frame based on the initial anchor frame, and then compares the prediction frame with the real frame, calculates the error between the prediction frame and the real frame, and then reverses the update to correct the position of the prediction frame, so that the network can predict the correct position of the target more accurately.

3.2.2 Backbone structure of convolutional neural network

Compared with the previous Yolo series, Yolov5 has added the Focus structure and designed the CSP structure, the most critical part of the Focus structure is the slicing operation, as in Figure 2, when a 416*416*3 size image is input into the Focus structure, after the slicing operation, it will first become a 208*208*12 feature map, and then after After one convolution operation with 32 filters, it will become a 208*208*32 feature map. CSPDarknet53 is a Backbone structure based on the Darknet53 network [12], which contains five CSP modules, based on the experience of CSPNet. structures are applied to the Backbone structure and Neck structure respectively, which can enhance the learning ability of the convolutional neural network and reduce the computational cost and memory cost while ensuring the accuracy rate.

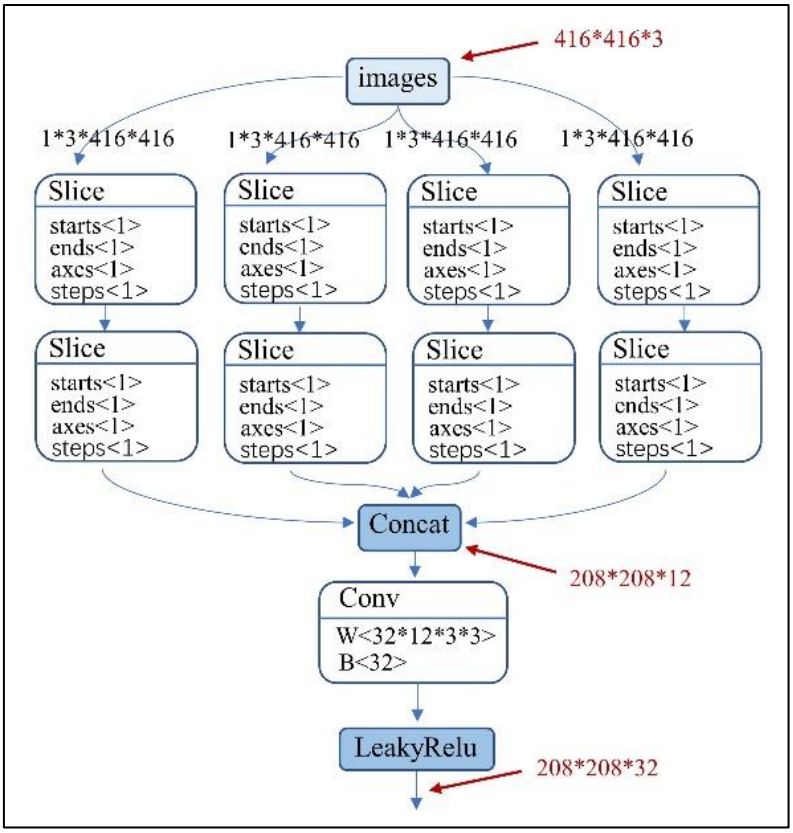

Figure 2: The Focus slicing process

3.2.3 Prediction of convolutional networks

The loss function of convolutional neural network for target detection task generally consists of two parts, Classification Loss and Bounding Box Regression Loss. The loss of Bounding Box Regression mainly consists of IOU Loss, GIOU Loss, DIOU Loss and CIOU Loss. DIOU Loss considers the centroid distance and overlap area, which can make the network converge faster, but does not consider the length and width. In contrast, the CIOU Loss used by Yolov5 considers three important geometric factors, namely overlap area, centroid distance, and aspect ratio, and solves all the problems arising from the previous loss functions, as in equation (5) and (6). Where v is a parameter that measures the consistency of the aspect ratio.

$$CIOU_{Loss} = 1 - CIOU = 1 - (IOU - \frac{Distance_{2}^{2}}{Distance_{C}^{2}} - \frac{v^2}{(1-IOU)+v}) \quad (5)$$

$$v = \frac{4}{\pi^2}(arctan\frac{w^{gt}}{h^{gt}} - arctan\frac{w^{p}}{h^{p}})^2 \quad (6)$$

4. EXPERIMENTAL ANALYSIS

4.1 Evaluation index

The evaluation criterion of the mainstream target detection network in convolutional neural networks is the AP value, the average accuracy, and AP@.5 and AP@[.5,.95] are used in this paper as the evaluation criteria for this experiment. AP@.5 it refers to the average AP value when IoU is set to 0.5. AP @ [. 5,. 95] refers to the average value of the AP value every 0.05 when the IoU threshold is 0.5 to 0.95. The AP value is the mean value of the Precision value on the PR curve, and the calculation formula is as shown in (7). P is Precision, and the calculation formula is as shown in (8), which is the probability that the positive case is the correct positive case. R is Recall, and the calculation formula is (9), which is the probability that the network detection is the correct positive case. TP indicates that the model correctly judges positive samples as positive cases, FP indicates that the model wrongly judges negative samples as positive cases, and FN indicates that the model wrongly judges positive samples as negative cases.

$$AP = \int_0^1 PdR \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

4.2 Comparative experiments

In order to verify that the convolutional neural network model proposed in this paper can identify 15 categories of leukocytes accurately in real time to solve the difficulties of detecting leukocyte categories on practical problems, Yolov5 and Yolov1, Yolov2, Yolov3, Yolov4 were compared and evaluated with mAP indexes, and the results of the comparison experiments are shown in Table 2.

Table 2: Comparison experiments

Modul	AP@0.5/%	AP@[.5,.95]/%	FPS
Yolov1	83.21	53.52	30.3
Yolov2	84.16	54.87	36.1
Yolov3	85.24	55.31	42.5
Yolov4	85.56	56.72	46.1
Yolov5	86.47	57.61	56.7

4.3 Analysis of experimental results

Table 2 lists the experimental comparison of the convolutional neural network Yolov5 and the previous Yolo series networks to improve the data. As can be seen from Table 2, Yolov5 AP@.5 for 86.47% with AP@[.5,.95] is 57.61%; Yolov1 AP@.5 is 83.21% and AP@[.5,.95] is 53.52; Yolov2 AP@.5 for 84.16% and AP@[.5,.95] is 54.87%; Yolov3 AP@ .5 for 85.24% and AP@[.5,.95] for 56.72%; Yolov4 AP@.5 for 85.56% and AP@[.5,.95] for 56.72%. The experimental results show that the Yolov5 network has the highest accuracy in recognizing white blood cells, compared with Yolov1, Yolov2, Yolov3, Yolov4 AP@.5 It increased by 3.2, 2.31, 1.23, and 0.91 percentage points respectively on AP @ [. 5,. 95], and 4.09, 2.74, 2.3, and 0.89 percentage points respectively on AP @ [. 5,. 95]. Figure 3 shows the effect of partial leukocyte identification.

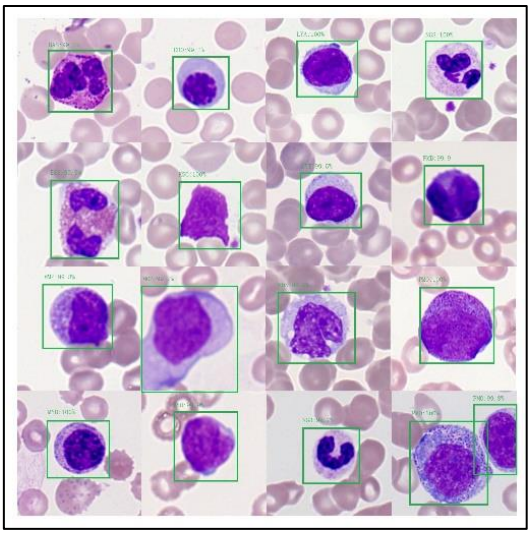

Figure 3: 15 types of leukocyte recognition effect map

5. CONCLUSION

In this paper, a convolutional neural network-based leukocyte recognition algorithm Yolov5 is proposed and compared with the algorithm of Yolo series for experiments. It is experimentally verified that Yolov5 achieves the best results in terms of accuracy and speed, with an average accuracy of 86.47%. The relevant experimental results show that the convolutional network can accurately and quickly identify 15 leukocyte classes and has excellent recognition ability for cell classification.

REFERENCES

1. Mohammed, E. A., Mohamed, M. M., Far, B. H., & Naugler, C. (2014). Peripheral bloodsmear image analysis: A comprehensive review. *Journal of pathology informatics*, *5*(1), 9. Https://doi.org/10.4103/2153-3539.129442.
2. Chan, L. L., Laverty, D. J., Smith, T., Nejad, P., Hei, H., Gandhi, R., Kuksin, D., & Qiu, J. (2013). Accurate measurement of peripheral blood mononuclear cell concentration using image cytometry to eliminate RBC-induced counting error. *Journal of immunological methd-s*, *388*(1-2), 25–32. https://doi.org/10.1016/j.jim.2012.11.010.
3. Lehmann, T. M., Güld, M. O., Thies, C., Fischer, B., Spitzer, K., Keysers, D., Ney, H., Kohnen, M., Schubert, H., & Wein, B. B. (2004). Content-based image retrieval in medical applications. *Methods of information in medicine*, *43*(4), 354–361.
4. Krizhevsky, A., Sutskever, I., & Hinton, G. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25(2).
5. Alam, M. M., & Islam, M. T. (2019). Machine learning approach of automatic identification and countin of blood cells. *Healthcare technology letters*, *6*(4), 103–108. https://doi.org/10.1049/htl.2018.5098. LIU Shu-jie. (2017). Red blood cell detection and counting based on convolutional neural network [D]. Guangzhou: South China University of Technology, 40–57.
6. Xiaotao, X., Yadong, S., & Jun, Z. (2020). Automated counting of blood cells based on YOLO framework. Computer Engineering and Applications.
7. Parab, M. A., & Mehendale, N. D. (2020). Red Blood Cell Classification Using Image Processing and CNN. *SN Computer Science*, *2*.
8. Karpathy, A., Toderici, G., Shetty, S., Leung, T., & Li, F. F. (2014). Large-Scale Video Classification with Convolutional Neural Networks. Computer Vision & Pattern Recognition. IEEE.
9. Zhu, X., Lyu, S., & Wang, X. (2021). TPH-YOLOv5: Improved YOLOv5 Based onTransformer Prediction Head for Object Detection on Drone-captured Scenarios. IEEE.
10. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: unified, real-time object detection. IEEE.
11. Redmon, J., & Farhadi, A. (2017). Yolo9000: better, faster, stronger. IEEE, 6517-6525.
12. Redmon, J., & Farhadi, A. (2018). Yolov3: an incremental improvement. arXiv e-prints.
13. Bochkovskiy, A., Wang, C., & Liao, H. M. (2020). YOLOv4: Optimal Speed and Accuracyof Object Detection. *ArXiv*, *abs/2004.10934*.