Urine Calcium Oxalate Crystallization Recognition Method Based on Deep Learning

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***Abstract*-As a global disease, urolithiasis has a high incidence and recurrence rate, which can seriously threaten patients' life and physical and mental health. Calcium oxalate crystals are the major constituents of stones. The analysis of calcium oxalate crystals in urine has important clinical significance. The traditional identification methods include regional growth method, edge detection method, activity model method and mathematical morphology method. These methods have higher requirements for the identified urine sediment microscopy images, and the recognition accuracy rate is not high. In this paper, a novel identification method based on full convolution neural network is proposed, which consists of resnet50, FPN and a classification subnet. The recognition rate is significantly improved to 74% in our experiments.**

Keyword-Calcium oxalate crystal, Full convolution neural network, FPN.

I. Introduction

When French scholar ted first looked at urine under a microscope in 1630, he described "piles of long, diamond-shaped, brick-shaped deposits" in the urine, which are crystalluria [1]. In the 1830s, urine microscopy was introduced into clinical testing, and many crystals were known by then. Common urine crystals include calcium phosphate crystal (CAPH), calcium oxalate crystal (CAOX), Uric acid crystal (URIC), drug crystal, etc. Urinary crystallization is the basis for the formation of urinary calculi, which includes the nucleation, growth, aggregation, solid phase transformation of urolithiasis crystals, etc. [2]. Among them, urinary calculi is a common and frequently occurring disease worldwide, and its incidence is on the rise [3]. About 90% of the stones are calcium oxalate crystals [4], so the detection of calcium oxalate crystals has important clinical significance.

In clinic, urine crystallization was identified by urine sediment microscopy [5], due to the complexity of manual inspection and identification, and large error of human subjectivity. Therefore, an automatic identification system with high accuracy is particularly important. In recent years, many identification algorithms have been produced, such as regional growth method [6], edge detection method, activity model method, mathematical morphology method and adaptive urinary sediment image segmentation algorithm based on Canny [7-8] operator and watershed algorithm [9]. However, the recognition accuracy of these algorithms for urine crystallization is still not high, while the urine crystallization recognition algorithm based on deep learning has a high recognition accuracy, which has reached 74% at present.

II. Materials

The data used in this study were from urine samples of 80 patients provided by Nanshan hospital of Shenzhen city, and then manually made microscopic smear and took images. The equipment used to take pictures was a microscope with a CCD camera (Fig.1), Disposable urine sediment counter plate 81 lattice quantitative slides (Fig.2).

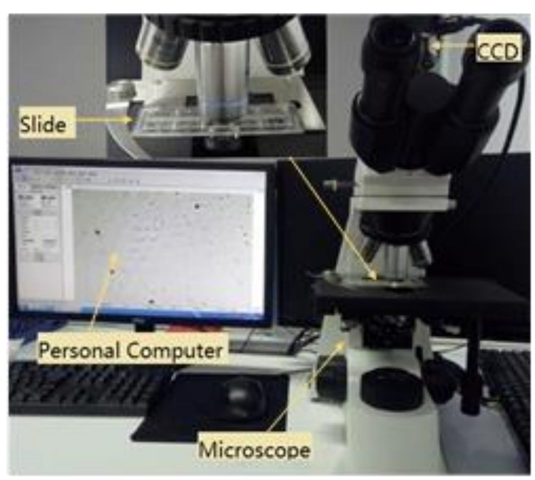

Fig. 1. Microscope Shooting System.

Adopt the unified shooting method: Take a urine sediment counter plate, use a pipette to add 40ul urine sample drops to the counter plate, and place the urine sample plate on the microscope carrier table and fix it; Use X40 times the objective lens to take several pictures of different areas of view, so that you can get 80 urine samples. A total of 749 images were calibrated to relevant clinical experts, including 135 pictures containing calcium oxalate crystals. The calibrated images were saved as VOC file, which was used as the data set of training test.

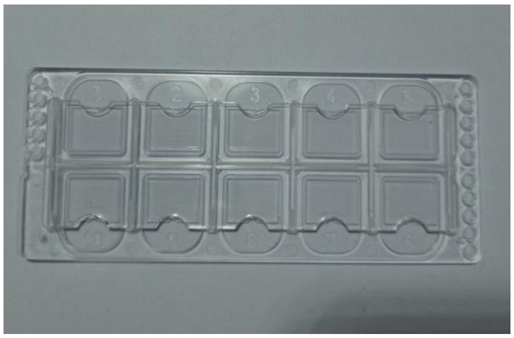

Fig. 2. Slide.

In order to ensure the diversity of the data set and the training model have stronger generalization ability, it is necessary to expand the data set. Therefore, I used rotation, translation, cropping, zooming, X and Y direction mirror image inversion to expand the image set.

III. Methods

The network structure diagram of the algorithm (Retinanet model structure), as shown in Fig 3. The basic network structure of the feature graph of the entire input image is obtained by convolution network calculation –resnet. At present, the best recognition result is resnet (original) -50, and the network used imagenet pre-training model to initialize parameters.

FPN(feature pyramid net)The main purpose is to generate more characteristic graphs of different sizes, so that the image size of the input network layer is not strictly required to be fixed, and it is also conducive to improve the accuracy of identifying small targets. FPN with different convolutional layer at the end of the output characteristics of figure as input, and then through the bottom - pathway, top - down pathway and lateral connection structure of the three, use among upsampling (sampling) technology to combine convolutional network characteristics of high-level with the underlying network generated different resolution figure to form the new characteristic graph inputting with both the underlying semantics at the same time and the high-level semantic into the back of the classification and regression network to classify recognition and positioning.

Classification subnet is a subnetwork responsible for classification recognition. This is a small full convolution network (FCN) linked to the previous structure input of different levels (dimensions) of the characteristics of the pyramid feature map. Specifically, the FCN feature graph input above passes through four convolution kernel convolutions of 3x3, activates the layer through ReLU, and finally gives different prediction probabilities of each prediction category through sigmoid activation layer.

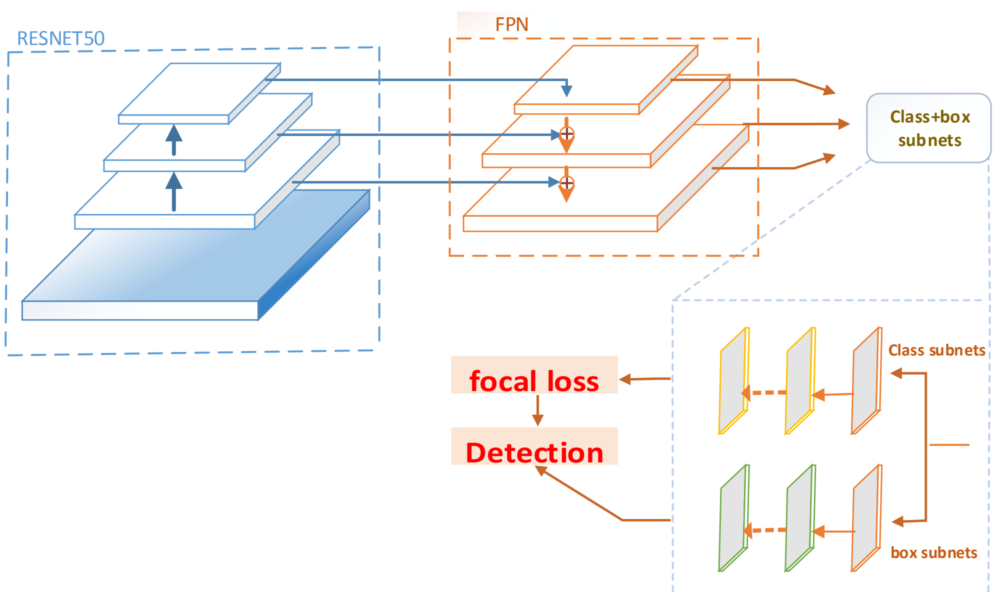

Fig. 3. Network Structure Diagram.

Box regression subnet is responsible for the regression of the coordinates of different targets. The previous structure is the same as the classification subnet. The only difference is that the last layer is linear output based on the location of each specific target space (4A) (four coordinates of the target in the image coordinate system).

The loss function, as in (1), can achieve down-weight loss in the training process, and up weight because of the small number of samples, there are more misclassification samples. ∂_t=0.25 , γ =2 are used in the algorithm framework, as in:

$$FL(Pt)=-\partial(1-Pt)^{\gamma}\log(Pt) \qquad (1)$$

The whole network is through inputting an image, through the RESNET network in the last few layers of convolution network to get different scales of the feature map, then each possible target area by anchors form different resolutions, different scale of the target area characteristic figure respectively parallel input classification subnet configures and boxes regression subnet configures Classification and position, and detection result is obtained.

TABLE I. ACCURACY TABLE OF CALCIUM OXALATE CRYSTAL RECOGNITION

Type of sediment	*Total no.*	*Number of correctly identified*	*Number of false recognitions*	*Number of missed recognitions*	*Accuracy (AR)*
Calcium oxalate crystal	344	258	32	16	0.74

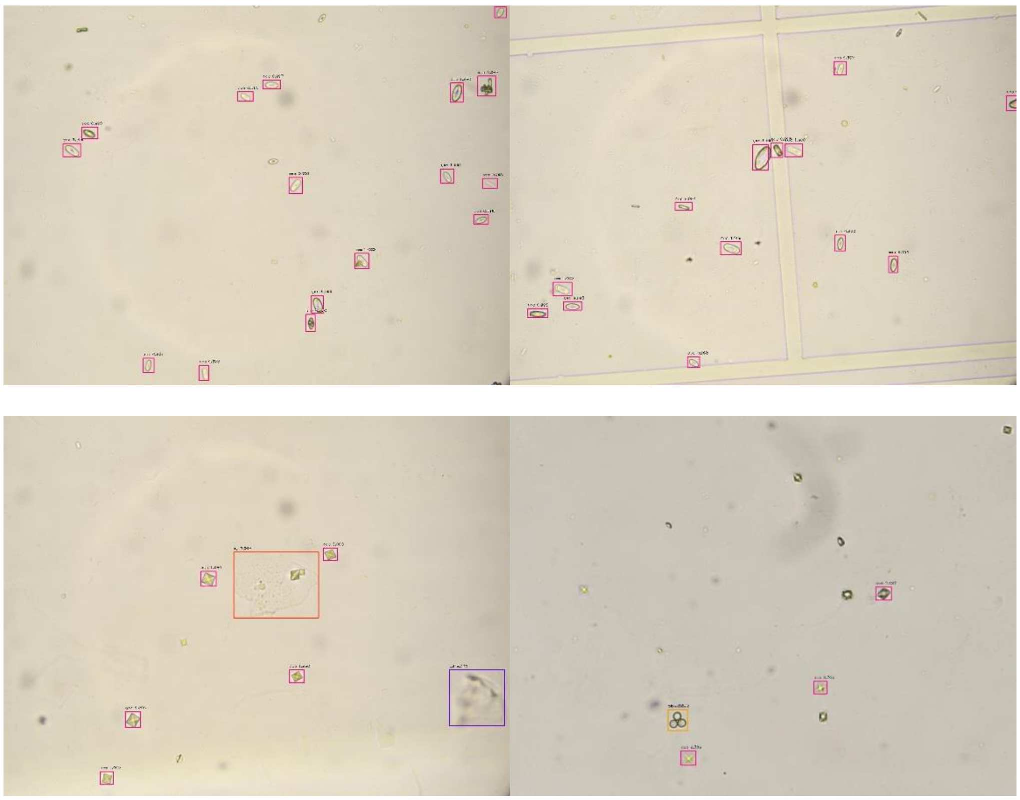

Fig. 4. Crystal Recognition of Calcium Oxalate.

IV. RESULTS

We evaluate the algorithm by the coincidence rate between the result of automatic recognition and the expert's artificial discrimination. The following table is the results I have obtained. It can be known that the recognition accuracy rate is much higher than the traditional recognition algorithm. The effect processed by the full convolution neural network model is shown in Fig 4:

V. DISCUSSION

In this study, we proposed a new recognition method based on the full convolution neural network, which is a new recognition method for microscopic examination of calcium oxalate crystals in urine sediments. This method can automatically identify the image of the microscopic examination of calcium oxalate crystal calculation, and the coincidence rate of artificial recognition with clinical experts is as high as 74%. However, the following three situations will reduce the recognition accuracy.

First, for some urine samples, crystal overlaps will occur, as shown in Fig 5. For this phenomenon, the algorithm recognition error probability is very high, and there will be some count errors.

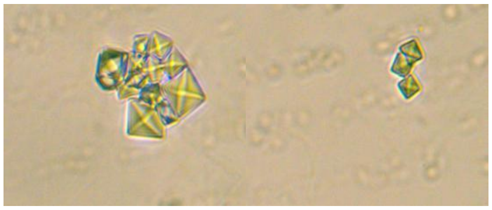

Fig. 5. Crystal overlapping.

Secondly, for the automated instruments, it only focuses once in each visual field and take a picture, but the sample solution in the visual field has a certain thickness, as shown in Fig. 6, which will lead to multiple focal points in the visual field. For the more obscure layer of tangible components, the algorithm is difficult to identify.

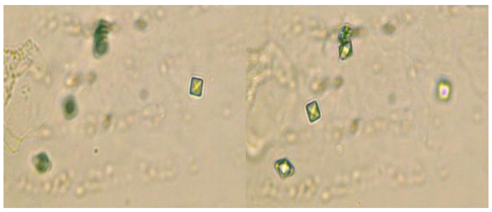

Fig. 6. Crystal stratification diagram.

Although this algorithm has many limitations, but it can quickly identify calcium oxalate crystals, which is 100 times faster than the artificial recognition speed, and has a high recognition accuracy rate, which can completely replace the artificial recognition under certain conditions.

VI. ACKNOWLEDGMENT

This research was supported by National Natural Science Foundation of China-Shenzhen Joint Fund (Grant No. U1713220). Shenzhen Science and Technology Project (GrantNo.JCYJ20170302152605463,JCYJ20170306123423907, JCYJ20160307114925241).

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