Research on the extraction method of book number region based on Bayesian optimization and deep learning

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Abstract：The continuous development of artificial intelligence technology has promoted the construction of smart libraries and their intelligent services. In the process of intelligent access to books, the extraction of the requested book number region has become an important part of the process. The requested book number is generally affixed to the bottom of the spine of the book, which is small in size, and the height of the book is not always the same, so it's difficult to identify. By the way, due to the images' resolution, shooting angle and other practical problems, the difficulty of the extraction work will be increased. To improve the identification accuracy, in this paper, Bayesian Optimization (BO) and one kind of deep neural networks 'Faster R-CNN' are combined for the extraction work mentioned above. The data preparation, network training, optimization variable selection, establishment of BO objective function, optimization training, and network parameter evaluation have been introduced in detail. The performance of the designed algorithm has been tested with actual images of book spines taken in the academy library and compared with several other conventional recognition algorithms. The experimental results show that the requested book number region extraction method based on Bayesian optimization and deep neural network is effective and reliable, and its recognition rate can reach 91.82%, which has advantages in both recognition rate and extraction time compared with other algorithms.

Key Words：library, book access, Bayesian optimization, deep learning, Faster R-CNN, requested book number region

I. Introduction

The continuous development of artificial intelligence technology has promoted the construction and development of smart libraries. Intelligent access to books is an important function of smart libraries [1]. During this process, the identification of library collection information plays a decisive role in the correct storage and retrieval of books. In addition to RFID, QR code scanning and other technologies, direct identification of the requested book number on the spine using a camera has become an important technology [2]. This paper focuses on the method for extraction of the requested book number region in this process. As the book number is generally affixed to the bottom of the book spine, its own size is small and its position is not usually at the same height, so it is difficult to identify, meanwhile the practical problems such as images' resolution, different light intensity and angle will increase the difficulty of the extracting works, which [3]. To improve the accuracy of claim number identification, Bayesian Optimization (BO) has been combined with Faster regional convolutional neural network (Faster R-CNN) for the extraction works, then a series of performance tests for the designed extraction method have been conducted with the actual collected book spine images. Three other conventional recognition algorithms such as HSV color space, R-CNN, Faster R-CNN algorithms have been compared with the designed extraction method to verify its superiority.

II. Book intelligent access system and its key technology

Intelligent access systems for books are generally implemented in the form of "library robots", which are important tools for the integration of smart libraries [1]. Such robots can replace the manual work such as the automatic shelving and sorting of books, which can reduce the labor intensity of librarians and improve the work efficiency at the same time. Library robots are generally composed of moving devices, lifting devices, manipulators and vision systems, and need to have functions such as autonomous navigation, book information recognition, and book grasping and storage [4]. Figure 1 shows the German Humboldt University Science Library's book access robot, whose basic function is to automatically transfer the books and journals that need to be shelved and sorted between the main service desk and each functional area, the entire robot system cost 380,000 euros, equivalent to about seven librarians' annual salary.

Fig. 1 Library robot in the science library of Humboldt University, Germany

Currently, book information recognition relies on RFID, QR code scanning, and text recognition technologies [2]. he library robot use the text recognition technology to identify the requested book number pasted on the book spine when it takes them and get the collection information of the taken book. When it stores the book, it first performs text recognition on the requested book number and puts it back on the corresponding shelf according to the collection information. Several key techniques are involved in intelligent access to books, including image edge straight line detection, extraction of the requested book number region, character recognition and character segmentation [3]. In this paper, the research focuses on the key technique of the extraction of the requested book number region with book spine image dataset of different environments.

III. Principle of spine book number extraction algorithm based on Bayesian optimization and deep learning

After the book spine segmentation is completed, we have to determine the region of interest (ROI) for the segmented spine image, which is the region that best represents the content of the image and where the user focuses on the information [5]. For the purpose of intelligent access to books, the requested book number region is the specific area of interest in the study. Accurate extraction of the region area of the requested book number has an important impact on the efficiency of the book information extraction recognition. At present, there are many ROI extraction algorithms, and the commonly used algorithms are HSV color space algorithm, convolutional neural network extraction algorithm, morphological localization algorithm and so on.

A. Introduction of traditional region extraction algorithm methods

(1) HSV color space extraction algorithm

Considering the high correlation between the color components R, G and B, the subjective color model HSV color space is usually used for color comparison and color segmentation of images, where the three parameters in the color model, H and S components, reflect the essential characteristics of colors and V represents the luminance [6]. The core of the HSV color space extraction algorithm is to distinguish the ROI and interference information on the spine by the H and S component value domains of the requested book number label margin. But due to the wide value domains of H and S component, the false detection often occurs during the test [7].

(2) Convolutional neural networks algorithm (CNN)

The convolutional neural network area has a feature extractor consisting of a convolutional layer and a pooling layer that hasn't been used in ordinary neural networks. The convolutional layer of CNN contains several feature planes (FeatureMap) that share weights through convolutional kernel pairs [8]. The convolutional neural network is trained by a large number of samples of the area of the requested book number and the spine of the books without those numbers, and the convolutional neural network algorithm selects the features in the image. After training, a series of operations of convolution layer, activation function, pooling layer and fully connected layer are performed to finally obtain the output of the image of the requested number region.

(3) Regional convolutional neural network (R-CNN)

R-CNN is the first algorithm that uses deep learning convolutional neural networks for target detection and recognition. The target is detected at different observation distances using an exhaustive method of adding target features. The input image is divided into several small rectangular images by selective search, after which the merging rules are defined and strictly followed until the original image is output. At this point all the small images in the merging process are the Regional proposal [9]. The R-CNN determination of categories is performed using a linear SVM two-class classifier. For each class a linear regressor is used for refinement to improve the accuracy of the entry and exit positions [10]. The R-CNN model is trained with SVM for each class of objects and determines the target region based on the score value of each feature. This model significantly improves the recognition accuracy of target detection, increasing MAP from 35.1% to 53.7% on the PASCAL VOC2012 dataset [9-10].

(4) Faster regional convolutional neural network (Faster R-CNN)

As an improved algorithm of R-CNN, for the problem of time-consuming region nomination, the Faster R-CNN network integrates the feature extraction and candidate region generation parts into one network model by sharing convolutional layers for feature extraction of each image, and the feature matrix is directly used in the Region Proposal Network (RPN) to generate candidate regions in batch, which solves the problem of too long time for candidate frame generation in batch [11-12].

In summary, it can be seen that the Faster R-CNN algorithm based on deep learning has substantially improved the recognition speed and accuracy of images, but there is still room for improvement in the recognition accuracy. Therefore, this paper aims to further improve the recognition accuracy of Faster R-CNN with Bayesian optimization.

B. Bayesian optimization (BO)

Bayesian optimization is a model-based sequential optimization method, i.e., the next evaluation is performed only after this evaluation, with the outstanding advantage of being able to obtain a model-based approximate optimal solution at little evaluation cost. Bayesian optimization effectively solves the classical machine-intelligence (MI) problem in sequential decision theory, which is to find the next evaluation position based on the information obtained for an unknown objective function "f" to reach the optimal solution as fast as possible [13].

Bayesian optimization is called "Bayesian" because the optimization process makes use of the well-known "Bayes' theorem".

$$p(f|D_{1:t})=\frac{p(D_{1:t}|f)p(f)}{p(D_{1:t})} \tag{1}$$

Where f denotes the unknown objective function (or the parameter in the parametric model). $D_{1:t}=\{(\boldsymbol{x}_1,y_1),(\boldsymbol{x}_2,y_2),\ldots,(\boldsymbol{x}_t,y_t)\}$ denotes the observed set. $\boldsymbol{x}_t$ denotes the decision vector. $y_t=f(\boldsymbol{x}_t)+\varepsilon_t$ denotes the observed value, and ε_t denotes the observation error. $p(D_{1:t}|f)$ denotes the likelihood distribution of y distribution. $p(f)$ denotes the prior probability distribution of f, i.e., the assumptions about the state of the unknown objective function. $p(D_{1:t})$ denotes the marginal likelihood distribution of the marginalized f. and $p(f|D_{1:t})$ denotes the posterior probability distribution of f[14].

The Bayesian optimization framework consists of two main core components, which are the probabilistic surrogate model and the acquisition function[15].The Bayesian optimization is an iterative process consisting of the following 3 main steps[16].

①Selecting the next most "promising" assessment point $\boldsymbol{x}_t$ based on maximizing the acquisition function.

② Evaluate the objective function value $y_t=f(\boldsymbol{x}_t)+\varepsilon_t$ according to the selected evaluation point $\boldsymbol{x}_t$.

③The newly obtained input-observation pairs $\{\boldsymbol{x}_t, y_t\}$ are added to the historical observation set $D_{1:t-1}$ and the probabilistic proxy model is updated in preparation for the next iteration.

C. Algorithm for extraction of the requested book number region based on Bayesian optimization and deep learning

In order to improve the recognition accuracy more recently, the following section will specifically study how to apply Bayesian optimization to the training of Faster R-CNN, find its optimal network hyper-parameters and training options, and then apply the corresponding optimal network to the extraction of the requested book number region. The entire training and optimization process is divided into the following six steps.

① Preparing a dataset of training data to test the image classification model.

② Training the Faster R-CNN network.

③ Specifying the variables to be optimized using Bayesian optimization.

④ Defining an objective function that takes as input the values of the optimization variables, specifying the network architecture and training options, training and validating the network, and saving the trained network to the PC hard disk.

⑤ Performing Bayesian optimization by minimizing the classification error on the validation set.

⑥ Evaluate the trained mode's performance with a test set.

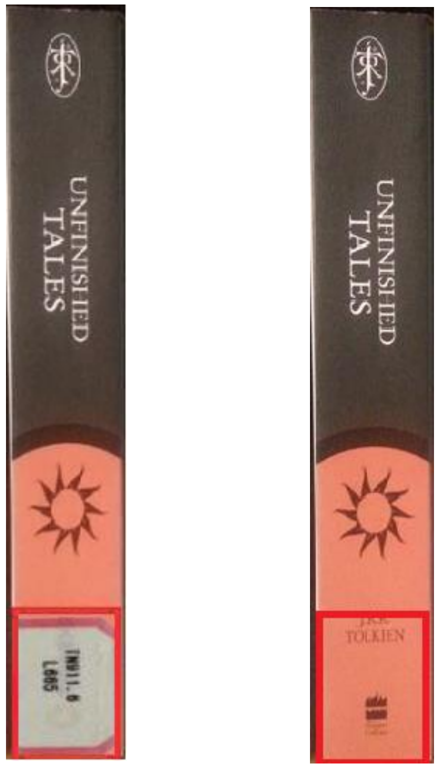
The specific network parameter training and optimization experiments will be described in Section 4.

IV. Training of Faster R-CNN and Bayesian optimization of its parameters

A. Preparing training data

① Taking images during different time periods such as morning, noon and evening respectively to make the light intensity conditions more comprehensive and to train the recognition of images with different light intensities, collecting images of books on the shelves in the reading rooms on different floors of the academy library using cell phone cameras randomly within the floors and processing them to obtain the corresponding spine images, obtaining a total of 5000 spine images, of which are positive samples with the requested book number label and negative samples without a label.

② The 2500 book spine images are annotated with Photoshop, and the book spine areas are marked with green solid lines, as shown in Figure 2. The training samples of Faster R-CNN are these 2500 annotated book spine images (with positive and negative samples).



(a) the positive sample (b) the negative sample

Fig. 2 Labeling the requested book number region of a book with Photoshop

Matlab procedure has been compiled to load the training sample dataset to be used as training images and labels and test images and labels, while 500 test images are randomly selected as the validation set.

B. Faster R-CNN network training

The main steps of Faster R-CNN network training are as follows: first, the training sample set is input into the VGG network to obtain the corresponding feature maps. Then the feature maps are input into the RPN network and processed to obtain the deep feature maps to continue to pass down. The region proposals marked on the feature map by RPN are processed using non-maximal value suppression and the region proposals conforming to the algorithm are output. Then the acquired feature map and the region proposals are passed to the ROI pooling layer together to obtain the corresponding features.

The Faster R-CNN model training process is shown in Figure 3. Among them, the job of tuning the network and optimizing the parameters is left to the Bayesian optimization algorithm.

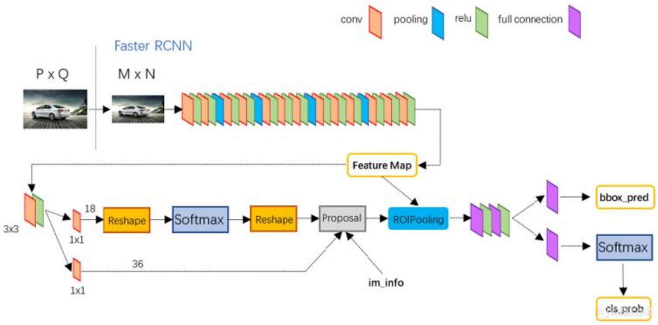


Fig. 3 Faster R-CNN model training flow chart

C. Selecting the variables to be optimized

The variables of Faster R-CNN are selected for Bayesian optimization, of which the search range and variable type are specified. The variables to be optimized are as follows.

(1) Network section depth

This parameter controls the depth of the network, which has three sections, each with SectionDepth of the same convolutional layer, and the total number of convolutional layers is 3*SectionDepth. The objective function of Bayesian optimization uses the convolution filters proportional to 1/sqrt(SectionDepth) in each layer.

(2) Initialized learning rate

The optimal learning rate depends on the training data as well as the network being trained.

(3) Stochastic gradient descent momentum

Momentum adds inertia during the update by including a contribution to the current parameter update proportional to the update in the previous iteration.

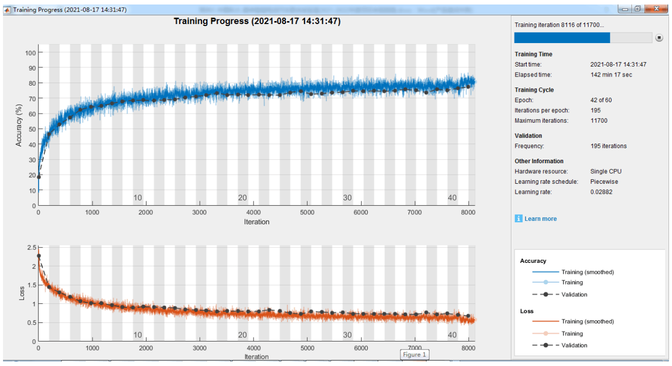
(4) L2 regularization strength

Regularization is used to prevent overfitting, the space of regularized strengths is searched to find good values.

D. Performing Bayesian optimization

Using the training and validation data as input, an objective function is created for the Bayesian optimization. After the objective function is created, Bayesian optimization will minimize the classification error of the validation set. To fully exploit the capabilities of Bayesian optimization, the network optimization procedure here is designed to run with a total optimization time of 50400 seconds (14hours*60min*60sec) for the objective function evaluation according to the procedure settings.

Then Matlab procedure has been compiled to realize Bayesian optimization for the network. The optimization curves are displayed in a command line window as shown in Figure 4 (a), and its optimization process and results are shown in Figure 4 (b) and (c).



(a) Matlab interface of Bayesian optimization training for Faster R-CNN

```
>> maketry
```

Iter	Eval result	Objective	Objective runtime	BestSoFar (observed)	BestSoFar (estim.)	SectionDepth	InitialLearn-Rate	Momentum	L2Regulariza-tion
1	Best	0.2426	7480.3	0.2426	0.2426	3	0.013975	0.97799	7.4198e-10
2	Best	0.2296	7400.1	0.2296	0.23024	3	0.79373	0.95112	1.0671e-09
3	Accept	0.4482	4069.6	0.2296	0.23135	1	0.11135	0.87303	0.0076609
4	Accept	0.2928	7411.7	0.2296	0.22968	3	0.014941	0.87366	1.3299e-05
5	Best	0.2078	6296.7	0.2078	0.20781	2	0.9584	0.89487	1.0364e-10
6	Accept	0.2176	6344.5	0.2078	0.20783	2	0.31388	0.80035	1.6346e-09
7	Accept	0.3204	4194.1	0.2078	0.20778	1	0.89764	0.97569	1.0808e-10
8	Accept	0.3624	6412.1	0.2078	0.2078	2	0.010018	0.86313	1.0663e-10
9	Accept	0.2258	7687.9	0.2078	0.20779	3	0.13024	0.83386	1.0739e-10

(b) Data of 9 rounds optimization to reach the optimal network

```
Observed optimal parameters:
    SectionDepth    InitialLearnRate    Momentum    L2Regularization
    ------------    ----------------    --------    ----------------

         2               0.9584         0.89487        1.0364e-10

Observed objective function value: 0.2078
Estimated objective function value: 0.20779
Calculation time of the observation function : 6296.661

Optimal parameters estimated from the model:
    SectionDepth    InitialLearnRate    Momentum    L2Regularization
    ------------    ----------------    --------    ----------------

         2               0.9584         0.89487        1.0364e-10

Estimated objective function value: 0.20779
Optimal parameters estimated from the model: 6212.7935
```

(c) Optimal network parameters

Fig. 4 Optimization results of Bayesian algorithm for the Faster R-CNN network parameters

It can be seen from Figure 4 (b) that within 50400 seconds the program has completed a total of 9 rounds of Bayesian optimization. After comparison, the best results are shown in Figure 4 (c). The optimal parameters are as following: Network section depth = 2, Initialized learning rate = 0.9584, Stochastic gradient descent momentum = 0.895, and L2 regularization strength = 1.036e^{-10}, which are all good. The observed and estimated function values are very close to each other, which means the optimized model has good recognition performance. The time required to optimize the model is more than 6200 seconds, but this is completed in single CPU mode with a lower computer hardware configuration. The time required to optimize the model can be significantly reduced by strengthening the hardware configuration in the future.

E. Error evaluation of the optimized network

The optimal network parameters found by Bayesian optimization and their validation accuracy are loaded, and the Wald method is used to calculate the standard error (testError) and the approximate 95% confidence interval (testError95CI) of the generalization error rate. That is, the extraction of each requested book number region in the test set is considered as an independent event with a certain probability of success, then the number of misclassified images should follow a binomial distribution. The bayesopt in the Matlab program uses the validation set to determine the best network. Therefore, the test error may be higher than the validation error.

Then Matlab procedure has been compiled for the network evaluation and the performance evaluation results of Faster R-CNN after Bayesian optimization are shown in Figure 5.

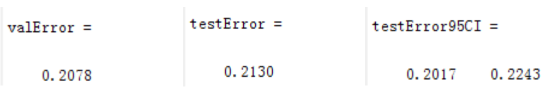


Fig. 5 Error evaluation results of the optimized Faster R-CNN

It can be seen that the test error is 0.2130, the validation error is 0.2078 and they are both with the the approximate 95% confidence interval. The test error is almost the same as the validation error, which means the Bayesian optimized Faster R-CNN model has achieved good performance.

In addition, the hardware environment in this paper to perform the network training and optimization experiments is 16GB RAM, 1TB SSD, Intel i7-9700K CPU (3.6GHz-4.9GHz), Nvidia GTX1060 (6G). The operating system is Windows 10 Professional, and the software environment for code development and running is Matlab R2020b.

V. Performance test and comparison with other algorithms

To test the performance of the proposed algorithm, experiments on the extraction of the requested book number region based on HSV color space, R-CNN, Faster R-CNN and Bayesian optimized Faster R-CNN algorithms have been carried out. First, the network is trained by selecting three number sizes of positive and negative samples without overlapping, and the number of the training sets are 900 (700 positive & 200 negative), 1560 (1200 positive & 360 negative) and 2400 (1800 positive & 600 negative). Then, 400 positive samples and 100 negative samples without repetition are selected to form a test set and input into the model trained with the four different algorithms mentioned above to extracting the book request number region. The experimental results are shown in Figure 6 and Figure 7.

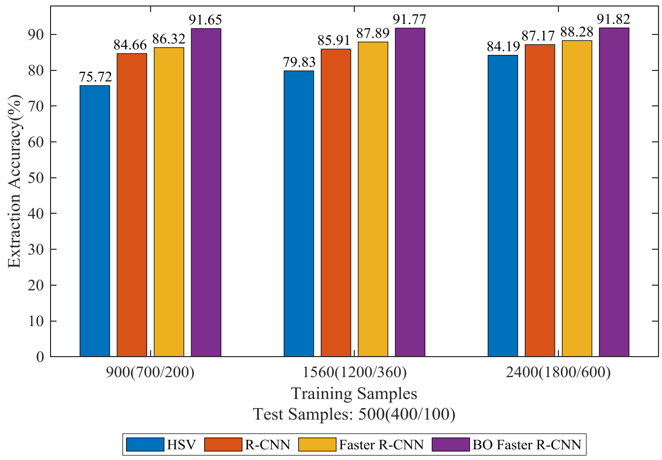


Fig. 6 Accuracy of extracting the requested book number region with four kinds of networks

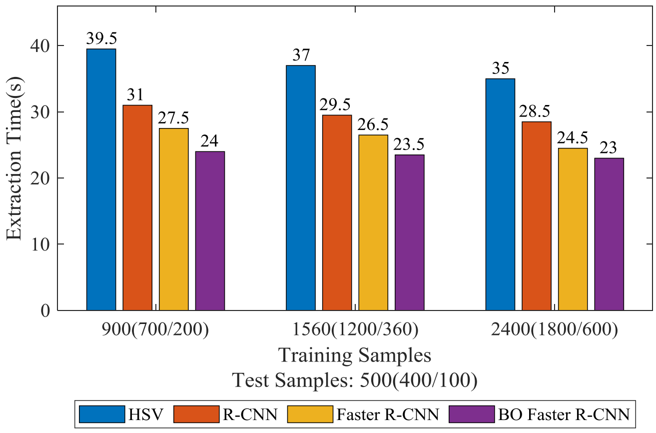


Fig. 7 Extraction time of the requested book number region with four kinds of networks

First, the accuracy of extracting the requested book number region with the four kinds of networks are shown in Figure 6. All three sets of experiments were tested using 500 samples, and the recognition accuracy were 75.72% (HSV), 84.66% (R-CNN), 86.32% (Faster R-CNN), and 91.65 (BO Faster R-CNN) when training four different recognition models with 900 samples. When trained with

1560 samples, the recognition accuracy were 79.83%(HSV), 85.91% (R-CNN), 87.89% (Faster R-CNN), 91.77 (BO Faster R-CNN), respectively. When trained with 2400 samples, the recognition accuracy were 84.19% (HSV), 87.17% (R-CNN), 88.28% (Faster R-CNN), 91.82 (BO Faster R-CNN), respectively. From the three sets of experimental results, it can be seen that the other three algorithms are more dependent on the number of samples, and the accuracy rate increases significantly with the increase of samples, while the advantage of Bayesian optimization requiring fewer samples is fully demonstrated. It's less dependent on the number of samples and the recognition accuracy of the models trained with different sample numbers is almost as high.

Second, the extraction time of the requested book number region with the four kinds of networks are shown in Figure 7. All three sets of experiments were tested using 500 samples, and the recognition time were 39.5s (HSV), 31s (R-CNN), 27.5s (Faster R-CNN), and 24s (BO Faster R-CNN) when training four different recognition models with 900 samples. When trained with 1560 samples, the recognition time were 37s (HSV), 29.5s (R-CNN), 26.5s (Faster R-CNN), and 23s (BO Faster R-CNN), respectively. When trained with 2400 samples, the recognition time were 35s (HSV), 28.5s (R-CNN), 24.5s (Faster R-CNN), and 23s (BO Faster R-CNN), respectively. From the results of the three sets of experiments, it can be seen that the other three algorithms have a higher dependence on the number of samples, and the recognition time decreases significantly with the increase of samples, while Bayesian optimization has a lower dependence on the number of samples, and the models trained with different sample numbers take almost the same time.

In summary, using the proposed optimized recognition method, the recognition accuracy in the area of the book number is already on the same level with the most advanced methods[17-18], and at the same time, there are obvious advantages in recognition time consumption compared with the traditional methods.

VI. Conclusion

In the paper, the Bayesian optimization algorithm is combined with Faster R-CNN for the extraction of the requested book number region. The performance of the designed optimization algorithm has been tested with actual spine images taken at the academy library and compared with three other conventional extraction algorithms.

The experimental results show that the designed extraction method based on Bayesian optimization and deep neural network is effective and reliable, and its recognition rate can reach 91.82%. Bayesian-optimized Faster R-CNN algorithm outperforms all the other three extraction algorithms in terms of accuracy and the extraction time consumption when using the same test dataset.

Moreover, since the Bayesian algorithm has optimized the Faster R-CNN to the best, changing the number of training samples of the network is no longer able to improve its performance. It means the designed optimization algorithm can get the best performance recognition model with the least training samples to obtain the highest extraction accuracy of the book request number area and the least recognition time consumption, which can provide technical support for intelligent access to books better.

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Declaration of interest statement

No conflict of interest exits in the submission of this manuscript, and it's approved by all authors for publication.

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