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Research on Printer Barcode Localization Method Based on Deep Learning

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Abstract: *Efficient and accurate barcode recognition and localization play a crucial role in achieving automated and efficient management of medical printers. However, traditional barcode image localization algorithms are highly sensitive to environmental changes, and their accuracy often declines with variations in lighting conditions and shifts in the barcode's position. This paper proposes a deep learning-based recognition algorithm model, YOLO-BAR, which enhances the spatial semantic information extraction capability of the YOLOv8 backbone through the CBAM attention mechanism. Integrating YOLO-BAR into the CIS scanning process significantly improves the accuracy and efficiency of barcode recognition in medical printers.*

Keywords: *Image recognition; Medical printers; Deep learning; YOLO-BAR*

1. Introduction

The primary purpose of scanning barcodes with medical printers is to enable automation and efficient management. By scanning barcodes, medical printers can quickly identify patient information, such as name and ID number, reducing the risk of errors associated with manual data entry. Additionally, barcodes facilitate the retrieval and querying of patients' medical reports and imaging data, improving operational efficiency. They also support data analysis and electronic medical record (EMR) management, contributing to health management and disease prevention. To ensure the accuracy of barcode printing and prevent information errors, medical printers are equipped with monitoring systems. These systems use CIS scanning devices to verify printed barcodes. If the barcode can be correctly read and patient information retrieved, the print is deemed successful. Efficient barcode localization is essential for the smooth operation of printers. Traditional CIS devices rely on image processing algorithms, such as binarization and contour matching. However, these conventional algorithms are prone to misjudgments due to variations in lighting conditions or positional shifts, making it crucial to enhance their adaptability to maintain the printer’s efficiency[1-3].

Deep learning algorithms, which can autonomously learn object features, offer a level of adaptability to different environments[1, 4]. This makes them well-suited for barcode localization and detection under various conditions[1, 5, 6]. Many researchers have contributed to this field. Daniel Kold Hansen [7] applied the YOLO visual algorithm to barcode recognition and localization in retail settings, achieving significant results. Yiming Ren[8] integrated the Single-Shot Multibox Detector (SSD) into scanning devices to enhance barcode recognition accuracy in complex backgrounds, resulting in highly efficient detection. Hui Zhang[3] combined deep learning techniques with the HALCON vision library to develop a real-time barcode detection system. Akshata Kolekar[5] successfully used the SSD algorithm to accurately classify both one-dimensional and two-dimensional barcodes.

Deep learning technologies have played a key role in advancing barcode detection[4, 9-11]. However, the direct application of deep learning models may struggle with the specific requirements of medical barcode recognition. To address this, this paper integrates the CBAM attention mechanism into the YOLOv8 model to enhance its ability to extract spatial features of medical barcodes, thereby improving localization and recognition performance. The improved model, termed YOLO-BAR, was trained and tested on real-world medical barcode datasets. Compared to the original YOLOv8 algorithm, YOLO-BAR achieved 3% improvement in mAP, reaching 99.5% mAP, fully meeting the localization requirements of medical applications.

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2. Methods

2.1 The overview of YOLOv8

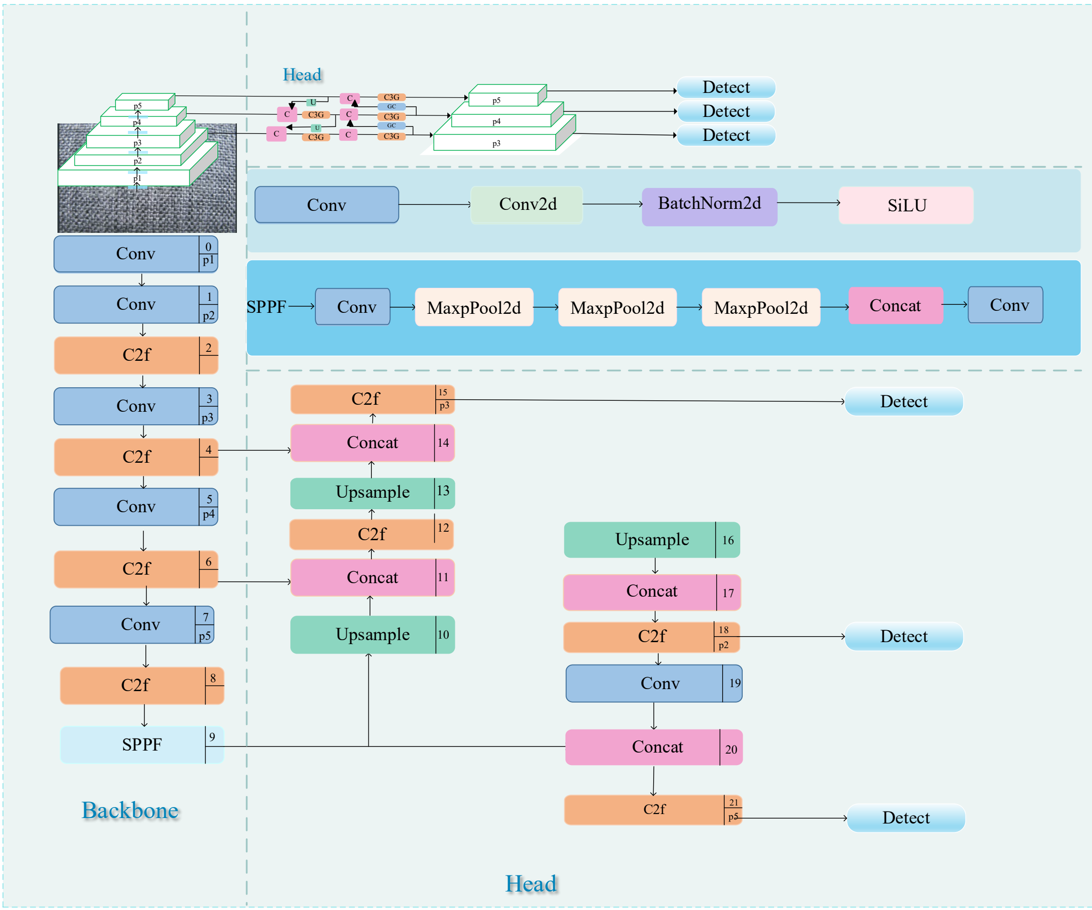

Figure 1: The structure of YOLOv8

As shown in *Figure 1*,YOLOv8 [12] uses the C2f module instead of the C3 module, with specific improvements as follows: the kernel size of the first convolutional layer is changed from 6×6 to 3×3. All C3 modules are replaced with C2f modules, as illustrated below, introducing more skip connections and additional split operations. The number of blocks changes from the C3 module configuration of 3-6-9-3 to the C2f module's configuration of 3-6-6-3.BN refers to Batch Normalization, which optimizes training by alleviating issues of gradient vanishing and explosion; "batch" denotes the number of images set for training the model. The YOLO series models incorporate BN layers added after each convolutional layer, preventing overfitting and reducing the inference speed of the model. The BN computation process is as follows:

$$x_{\text{out}} = \frac{\gamma\left(x_{\text{conv}} - \mu\right)}{\sqrt{\sigma^2} + 1\times10^{-6}} + \beta = \frac{\gamma\left(\sum_{i=0}^{n}\left(x_i\omega_i\right) - \mu\right)}{\sqrt{\sigma^2} + 1\times10^{-6}} + \beta = \sum_{i=0}^{n}\left(\frac{x_i\gamma\omega_i}{\sqrt{\sigma^2} + 1\times10^{-6}}\right) - \frac{\gamma\mu}{\sqrt{\sigma^2} + 1\times10^{-6}} + \beta$$

where γ is scaling parameter; μ is mean; δ is variance; β is bias; ω is weighting parameter; X_{conv} is the convolutional computation values of the channel feature map. After merging the convolutional layer and the BN layer, the weight parameters become:

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$$\omega_i' = \frac{r\omega_i}{\sqrt{\sigma^2} + 1\times 10^{-6}}$$

The bias term becomes:

$$\beta' = \beta - \frac{\gamma\omega_i}{\sqrt{\sigma^2} + 1\times 10^{-6}}$$

Finally, the calculation formula for the merged BN is:

$$x_{\text{out}} = \sum_{i=0}^{n}\left(x_i\omega_i'\right) + \beta'$$

YOLOv8 may introduce an anchor-free mechanism to reduce the complexity of anchor box design. By dynamically adjusting convolutional kernels, the model improves its adaptability to objects of different scales. This reduces the number of parameters and computational resource consumption, thereby enhancing the inference speed of the neural network model. As the latest version of the YOLO series, YOLOv8 achieves new breakthroughs in the field of object detection through various optimizations and improvements. Its efficiency, ease of use, and robustness make it an essential tool in computer vision applications. In the future, with continuous technological advancements, YOLOv8 is expected to play a more significant role across a wider range of fields.

2.2 Convolutional Block Attention Module (CBAM)

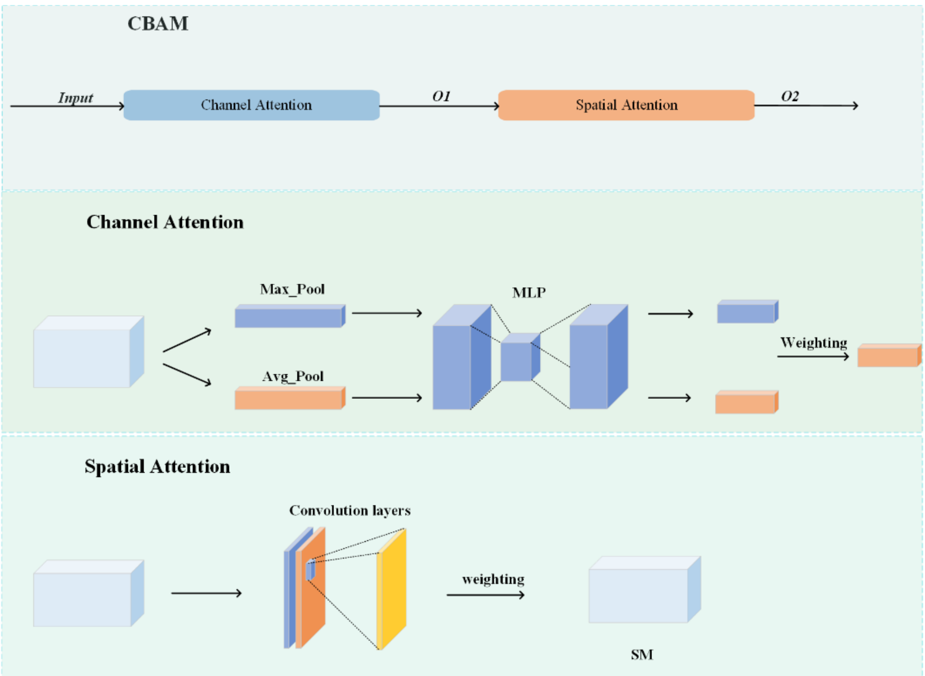

Figure 2: The structure of Convolutional Block Attention Module (CBAM)

As shown in *Figure 2*,CBAM (Convolutional Block Attention Module)[13] is a lightweight and effective attention mechanism that enhances the model's ability to capture and utilize key information by introducing channel attention and spatial attention. The CBAM (Convolutional Block Attention Module) consists of two independent but sequentially connected sub-modules: the Channel Attention Module and the Spatial Attention Module. These modules enhance features along the channel and spatial dimensions, respectively. Channel Attention Module focuses on identifying which channels are more important for the final outcome and assigns higher weights to those channels. Spatial Attention Module emphasizes the spatial positions within the feature map that contain more critical information and assigns higher weights to those positions. By processing features step-by-step through these two modules, CBAM refines feature representations and enhances the model’s predictive capability.

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2.3 The overview of YOLO-BAR

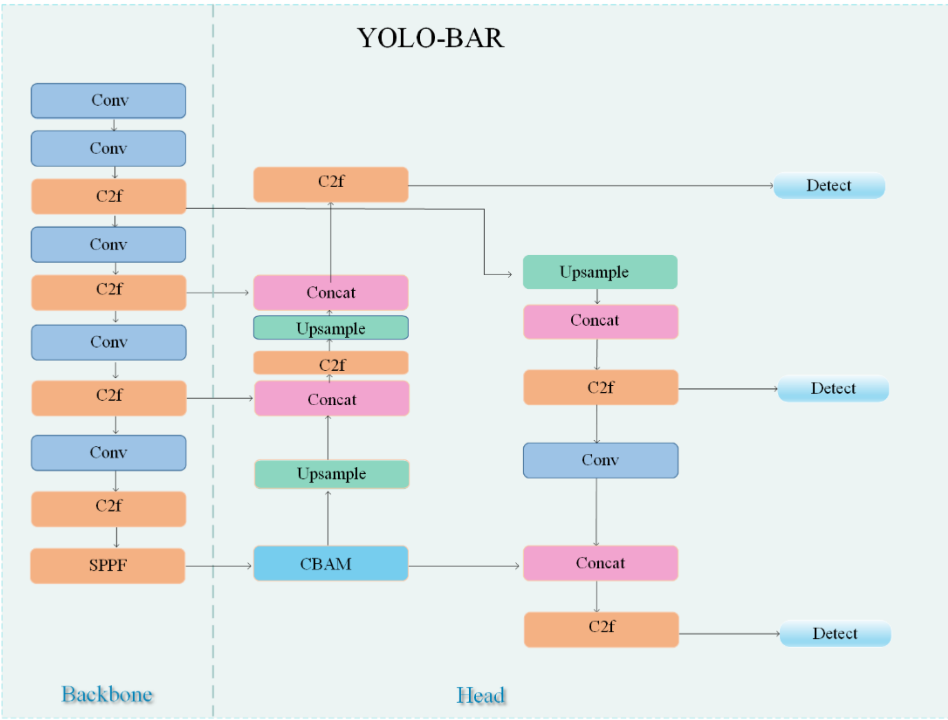

Figure 3: The structure of YOLO-BAR

To enhance the model's ability to extract spatial information from medical barcodes, this paper integrates the CBAM method into the backbone of YOLOv8. Channel and spatial dimension feature weighting is applied to the feature maps with 32x down sampling, improving the model's feature extraction capability with minimal parameter overhead. As shown in the figure 3, YOLO-BAR achieves more precise barcode localization by fine-tuning the structure of YOLOv8.

3. Experimental results

3.1 Experimental Deployment Details

The methods in this study were implemented using an NVIDIA GeForce RTX 2080 SUPER GPU. Network parameters were initialized following a normal distribution. Stochastic Gradient Descent (SGD) served as the optimizer, with a momentum of 0.9 and a weight decay set to 0.0001. Training employed a batch size of 4 and began with an initial learning rate of 0.01, which was reduced by a factor of 0.1 at the 24th and 30th epochs, across a total of 50 epochs.

During both training and testing, input images were resized to 640X640 pixels. Image augmentation techniques included horizontal and vertical flips, each applied with a probability of 0.5.

3.2 Datasets and Evaluation Metrics

The dataset used in this study consists of medical barcodes collected through real-world sampling. To enhance data diversity, scene transformations and adjustments in lighting conditions were applied, resulting in a dataset of 1,400 images. The images can be shown in Figure 4. We randomly sampled 30% of the data as the test set, while the remaining images were used for model training.

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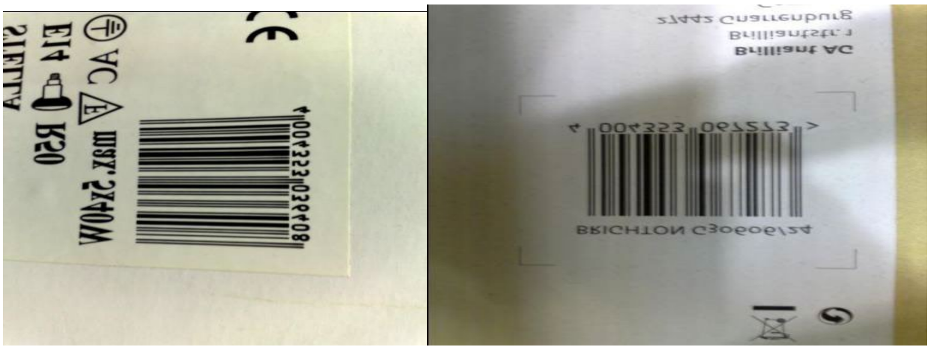

Figure 4: The images of barcode datasets

To comprehensively assess the performance, this study employs mean average precision (mAP), computed as the average AP value at a threshold of 0.5, served as the overall metric. In addition, Recall, Precision and F1-scores are also applied to evaluate the performance of models.

3.3 Ablation analysis

Table 1: Ablation analysis

Models	Recall	Precision	F1-scores	mAP
YOLOv8	95.1	97.4	96.2	96.5
YOLO-BAR	99.5(+4.5)	100.0(+2.6)	99.7(+3.5)	99.5(+3.0)

As shown in Table 1, compared to the baseline model YOLOv8, the integration of CBAM enhances the model's feature extraction capability, resulting in a 4.5% increase in Recall, a 2.6% improvement in Precision, and a 3% boost in mAP. This demonstrates the effectiveness of YOLO-BAR in the localization and detection of medical barcodes.

3.4 Performance analysis of YOLO-BAR

To provide a more comprehensive analysis of YOLO-BAR's detection performance, this study compares YOLO-BAR with other YOLO models. As shown in Table 2, in terms of the Recall metric, YOLO-BAR achieves an impressive 99.5%, significantly outperforming other YOLO models. In terms of the Precision metric, YOLOv9 reaches 99.5%, while YOLO-BAR achieves 100%, also significantly surpassing YOLOv8 and YOLOv5. In terms of the mAP metric, YOLOv9 and YOLO-BAR show similar performance, with YOLO-BAR slightly higher by 0.4%, reaching 99.5%. This demonstrates superior performance compared to YOLOv8 and YOLOv5. Through experimental analysis, it can be concluded that YOLO-BAR effectively meets the localization requirements for medical barcodes.

Table 2: Ablation analysis

Models	Recall	Precision	F1-scores	mAP
YOLOv8	95.1	97.4	96.2	96.5
YOLOv9	96.1	99.5	97.8	99.1
YOLOv5	96.4	96.1	96.3	98.9
YOLO-BAR	**99.5**	**100.0**	**99.7**	**99.5**

4. Conclusion

To address the issues of misdetection in the localization of medical barcodes caused by variations in lighting intensity and positional angle shifts inherent in traditional methods, this study employs a deep learning approach for barcode detection. To further enhance the model's ability to perceive semantic features in the feature space, the CBAM attention mechanism is integrated into the YOLOv8 backbone, strengthening the model's feature extraction capabilities and providing spatial semantic weighting for the 32x downsampled features. The enhanced model is referred to as YOLO-BAR. Through experiments and comparisons with other YOLO algorithms, YOLO-BAR demonstrates superior performance and fully meets the localization requirements for medical barcodes.

Acknowledgements

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