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Improved fall detection algorithm based on yolov8s

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Abstract: For the problem of physical injuries caused by untimely fall relief, this paper proposes an improved fall detection algorithm based on YOLOv8s.First, through many experiments, in the YOLOv8 algorithm model, select the YOLOv8s framework. Second, in the backbone part insert SE (Squeeze-and-Excitation) attention mechanism, strengthen the network feature extraction ability and adaptive ability, makes the network in the process of feature extraction network can pay more attention to the target, improve the network in the fall scene, improve the model accuracy. Lastly, Spatial and channel reconstruction convolution (SCConv) and C2f module are introduced into the network, reconstructed into C2f_SCConv module to integrate multi-scale features and reduce spatial and channel redundancy in the convolutional neural network, so as to improve the efficiency and accuracy and improve the representation ability of the model. After the improved YOLOv8s algorithm, the mAP increased from the initial 57.6% to 65.1%, which provided a good reference value for the subsequent study of the fall detection algorithm.

Keywords: YOLOv8s; SE-Attention; C2f_SCConv; Fall detection.

1. Introduction

In the field of computer vision, with the emergence of new models and the continuous improvement of computing power, the fall detection technology based on deep learning has become a hot topic of research and application. The technology uses advanced deep learning models to automatically identify and classify fall movements, realize the rapid and accurate detection of fall events, and timely alarm. This can not only help to respond quickly to falling situations, but also help to help people to take timely response measures.

With its high detection speed and accuracy, the YOLO series model has become a widely used and highly respected detection framework in the industry. This series of innovation and development not only meets the needs of industrial testing, but also leads the application trend of target detection technology in various industrial fields with its characteristics of high efficiency. Since its launch in 2015, YOLO series has experienced many iterations, from the beginning of YOLOv1, to combine the latest target detection technology speed and precision of the best balance of YOLOv4, to the network improvement after YOLOv5, YOLOv6, YOLOv7 and the latest YOLOv8, they with unique advantages and potential to become efficient detector in the scientific research and industrial applications.

LUO Bdesigned the human fall detection method in smart home monitoring based on Yolo network, and compared the YOLOv5n, YOLOv5s and YOLOv6s versions, and concluded that the performance of YOLOv5s is optimal.Zhuoya J et al. proposed a fall detection technology based on the YOLOv5s algorithm to solve the problem of hit injury. The method is designed based on the embedded ARM development board of Orange Pi Zero 2.Pranavan et al.introduced a model that combines YOLOv7 and YOLO-Pose, capable of recognizing various scenarios including falls, bending, crawling, sitting and walking.Khan H et al.proposed optimizing YOLOv8 for faller detection using a large-scale benchmark dataset.In order to reduce the problem of secondary loss caused by people unable to call for help or unable to save themselves, this paper will improve the YOLOv8 algorithm model to make the improved algorithm detection effect better.

2. Methodology

2.1. YOLOv8

On January 10,2023, Ultralytics released YOLOv8, a target detection algorithm with high speed and accuracy. YOLOv8 Is another SOTA model in the YOLO series, which is updated relative to YOLOv5. Like YOLOv5, models of different sizes of N, S, M, L, and X scales are also provided to meet the requirements of different scenarios. Based on the practice of the fall detection, this paper selects the model YOLOv8s target detection model with small parameter number and calculation quantity and fast detection speed. Building on the success of the previous version, YOLOv8 introduced new features and improvements, including a new backbone network (Backbone), a decoupling detection head (head), and a new loss function (Loss).

2.2. SE-Attention Module

To enhance the model's attention to critical information, introducing SE-Attention[10]into the network to adaptively adjust the importance of channel features to optimize the performance of the model. The core idea of SE (Squeeze-and-Excitation) attention mechanism includes two main steps: Squeeze and Excitation. Squeeze Step: The input feature graph is compressed into a vector through a global average pooling operation. The purpose of this step is to generate a channel attention matrix through global information. Excitation Step: You compress each element in this vector to between 0 and 1 using a sigmoid function to get a weight vector. Then, this weight vector is multiplied with the original input feature map to obtain the weighted feature map.

2.3. C2f_SCConv Module

In order to solve the significant redundancy of C2f module in the space and channel dimensions of model parameters and feature maps, this paper introduces SCConv[11]and C2f module to optimize the convolution operation in an innovative way, improving the feature extraction ability and detection accuracy of the model while reducing the computational resource consumption. The core idea of SCConv (Spatial and Channel Reconstruction Convolution, namely spatial and channel reconstruction convolution) lies in its unique spatial and channel reconstruction mechanism. Specifically, it contains two key components: the spatial reconstruction unit (SRU) and the channel reconstruction unit (CRU). SRU is responsible for reorganizing feature maps in spatial dimensions to improve the expressive ability of features by reducing redundant spatial information or introducing a more efficient spatial representation. CRU focuses on the optimization of channel dimension, enhancing the model of the model to capture critical information while reducing the interference of non-critical information.

3. Experiment Design and Result Analysis

3.1. Dataset

The data set used in the experiment in this paper is a self-made fall data set, from which 480 clear images were selected as the training set, and 160 clear images were selected as the validation set. The labelimg annotation tool was used to mark the images as "fall" and "person".

3.2. Experimental Setup

For renting a remote server on Autodl, the GPU of the server is RTX 4090 (24GB), PyTorch: 2.0, CUDA version: 11.8 running environment. After 200 rounds of operation, mAP data is generated, and the performance of the model is improved by data comparison.

3.3. Performance Metrices

The index used to evaluate the improvement of the algorithm is the mean mAP expression, as shown in (1):

$$mAP = \sum_{i=1}^{N-1} \frac{AP_i}{N} \tag{1}$$

where N represents the total number of categories, and mAP refers generally to the mean of the average accuracy (AP) of all categories within all images.

3.4. YOLOv8 Comparative analysis of each model YOLOv8

The pair of time, P, R, and mAP results of each network model are shown in the Table 1:

Table 1. YOLOv8 Comparison table of the results of each network model

Network model	Time/h	P	R	mAP
YOLOv8n	0.098	0.624	0.517	0.536
YOLOv8s	0.129	0.552	0.554	0.576
YOLOv8m	0.219	0.635	0.612	0.601
YOLOv8l	0.328	0.626	0.523	0.585
YOLOv8x	0.497	0.584	0.517	0.521

As shown in Table 1, the training time of the three YOLOv8, YOLOv8m, YOLOv8l and YOLOv8x, is 0.219h,0.328h,0.497h, respectively YOLOv8n and YOLOv8s. Among the various network models of YOLOv8, the YOLOv8n network model has the shortest training time, followed by YOLOv8s. The mAP of YOLOv8s was 0.576, was 4% higher than the mAP of YOLOv8s, but the detection rate was only 0.031h slower. Comprehensive comparative analysis, the detection speed of YOLOv8s has obvious advantages in different models of YOLOv8. Therefore, YOLOv8s will be chosen as the basic framework for identifying the fall detection algorithm in this paper.

3.5. Results Analysis

YOLOv8s is the basic framework for identifying the fall behavior detection algorithm in this paper. On this basis, SE-Attention attention module is inserted into Backbone, and C2f_SCConv is introduced in neck, so that the efficiency of the improved algorithm model detection is improved. Table 2 shows the performance comparison of the original YOLOv8s algorithm model and the improved YOLOv8s algorithm model. Figure 1 shows the structure diagram of the improved YOLOv8s algorithm after the addition of SE-Attention module and C2f_SCConv.

Table 2. Comparison table of the model performance before and after the improvement

Model	P	R	mAP
The original YOLOv8s model	0.552	0.554	0.576
The improved YOLOv8s model	0.632	0.626	0.651

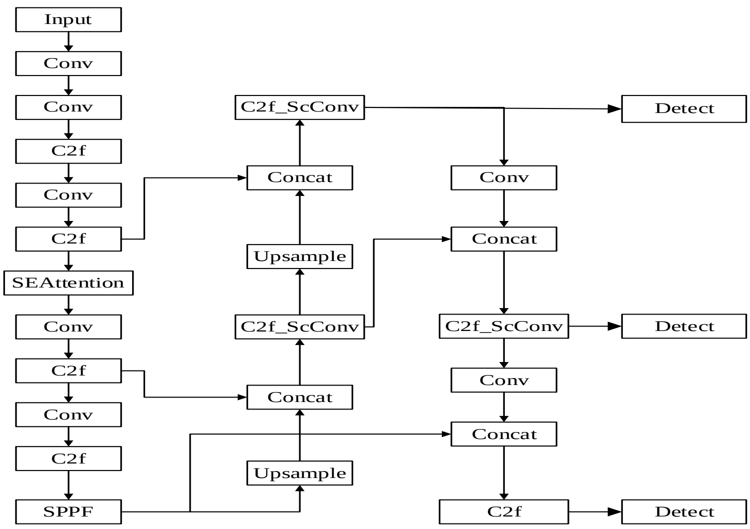

Figure 1. The improved YOLOv8s model

4. Conclusion

Based to the inaccuracy of the traditional detection algorithm,an improved fall detection algorithm based on yolov8s is proposed. Through many experiments, YOLOv8s was selected as the benchmark model in the algorithm model of YOLOv8. In order to make the model more accurately locate and identify the targets of interest, SE attention mechanism was inserted in backbone to improve the accuracy of the model. The introduction of C2f_SCConv module in neck network reduces redundant computation and memory access, more effectively extracts spatial features, and improves the expression ability of the model. After the improved YOLOv8s algorithm, mAP increased from the initial 57.6% to to 65.1%, which provided a good reference value for the subsequent study of fall detection algorithm.

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