SpeedyGuard: Efficient abnormal behavior recognition for children via motion-triggered YOLOv4-tiny

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Abstract

To stop children being alone at home from reaching assistance requirement that delays medical attendance-this paper proposes a new system called SpeedyGuard using a motion-triggered YOLOv4-tiny method. In order to tackle the challenges posed by existing methods concerning their high resource demand and poor real-time detection, we trained the YOLOv4-tiny model such that it achieved efficiency in terms of both high precision and faster inference speeds. We also notice that most abnormal movements during motion can be distinguished by a motion-triggering mechanism that isolates moving objects from static ones for analysis and detection. Experimental results indicate the potential benefits of the motion-triggering mechanism on moving object detection, and SpeedyGuard is 6.1 % faster and improved in real-time detection.

CCS Concepts

• **Computing methodologies**; • **Artificial intelligence**; • **Computer vision**;

Keywords

background subtraction method,YOLOv4-tiny algorithm, abnormal behavior detection

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1 Introduction

As the number of children increases and urbanization accelerates, so does the amount of time children spend unsupervised at home. Children are considered a vulnerable demographic in society due to their underdeveloped physical functions, making them more susceptible to injuries from sudden accidents, particularly falls, which may occur without timely assistance. Making certain that a single child is physically safe has become an imperative concern to nurture wisdom and growth. Fall detection based on computer vision intends to process the video captured and identify instances of fall behaviour. The method has gained much attention due to its added advantages, including continuous power supply from fixed cameras for real-time monitoring, a lack of requirement for wearing extra equipment, negligible vulnerability to external interference, and a very high rate of accuracy in terms of fall detection. Thus, it presents itself as a prominent research area with respect to fall detection [1]. In practical application scenarios, high-precision convolutional neural network algorithms are widely favored as they can meet real-time requirements; notable examples include the YOLO series object detection algorithms. Building upon the advancements made by the YOLO series, literature [2] proposed a real-time fall detection algorithm based on an enhanced version of the YOLOv3 model. This involved utilizing residual modules to construct a rapid feature extraction network for images and incorporating the channel domain attention mechanism (SENet) to assign varying weights to each channel within the feature map and enhance model accuracy. Wang Pingye et al. [3] achieved detection by employing YOLO for human motion trajectory identification, localization, and recording purposes. Wang Xiaowen et al. [4], on the other hand, combined the Yolov5 algorithm with an attention mechanism and weighted box function to detect pedestrian falls effectively. Tsai et al. [5] introduced novelty into their proposed method through integrating pruning techniques. Additionally,Yin Xuan et al. [6] designed a system capable of detecting abnormal behaviors among elderly individuals based on YOLOv5. However, the aforementioned approaches still suffer from high computational resource requirements and insufficient real-time performance. On the other hand, we propose SpeedyGuard-an entirely new and robust approach that can attain real-time performance and ensures the correctness of the output. Essentially, the work is design on applying anomaly behavior detection with children, which has immense practical significance. The trained YOLOv4-tiny model

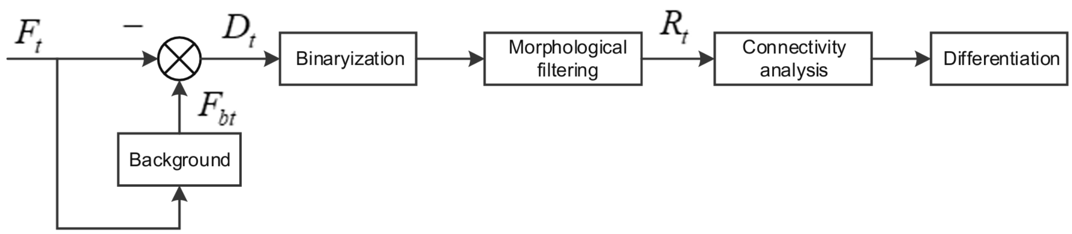

Figure 1: Background subtraction process.

Figure 2: Application effect of background subtraction method.

set could accomplish better efficiency and faster recognition speeds for target behavior. Further, the motion-generated mechanism through the background subtraction technique greatly boosts real-time detection performance and accuracy. This eventually gives notification about any strange behavior of solitary children without delay.

2 Algorithm selection

2.1 Background subtraction method

The background subtraction method detects moving objects from an image sequence by identifying the difference between the current frame and the background frame. Its conceptual flowchart is given in Figure 1

Let $D_t(x, y)$ be in the grayscale representation of an image the absolute difference between foreground grayscale $F_t(x, y)$ and background grayscale $F_{bt}(x, y)$ for pixel (x,y) at time t, $D_t(x, y)$ can be calculated based on (1). The pixel is the binarized according to formula (2). Let T be the threshold under which the image will be converted into binary values. And from the comparison of T with $D_t(x, y)$, we obtain the binarized image R_t, which denoted by $R_t(x, y)$ the pixel value in R_t.

$$D_t\ (x, y) = \left|\ F_t\ (x, y) - F_{bt}\ (x, y)\ \right| \tag{1}$$

$$R_t\ (x, y) = \begin{cases} 255, D_t\ (x, y) > T \\ 0, D_t\ (x, y) \leq T \end{cases} \tag{2}$$

An $R_t(x, y)$ value of 255 in formula (2) means pixel (x,y) belongs to the foreground and therefore it is a moving target. On the other hand, an $R_t(x, y)$ of 0 indicates that pixel (x,y) belongs to the background. Then we use morphological filtering and region connectivity analysis to find the area of the moving target in order to locate its minimum rectangle. Figure 2 shows the results of applying KNN algorithm to the background subtraction mentioned in this paper.

Moving people are correctly identified and detected in the image, and stationary people are not recognized, therefore the expected result is achieved. The background subtraction technique effectively focuses on changes in the target due to the capture of image data at different time points which reduces the effects of lighting and shadow. Such a method is very appropriate for monitoring dynamic scenes, improving the accuracy and robustness of target detection.

2.2 YOLOv4-tiny algorithm

YOLO [7] network is a one-stage object detection algorithm, which directly considers the detection task as a quick detection regression way. It can provide better detection speed than two-stage object detection networks and allow end-to-end prediction. The YOLOv4 [8] is an evolution of the YOLO series algorithms, and it has advantages like fast inference speed, lightweight network structure, and high detection accuracy for objects, which make it widely used.

Yolov4-tiny [9] is a smaller model intended to run on small mobile devices, specializing in Object detection [10]. The architecture of its network is shown in Figure 3 [11].

(1)Input: The YOLOv4-tiny network input layer is simplified to improve the model's real-time performance and adapt to environmental changes, and this also reduces the number of model parameters. Replacing the CSPBlock module in YOLOv4-tiny by ResBlock-D module, we manage to simplify the computational complexity. In addition, an auxiliary residual network block is designed able to extract richer feature information, reduce detection errors, and improve model inference speed and object detection accuracy.

(2) Backbone feature extraction network: Mainly consists of the CSPDarknet53-tiny network, which divides the feature map

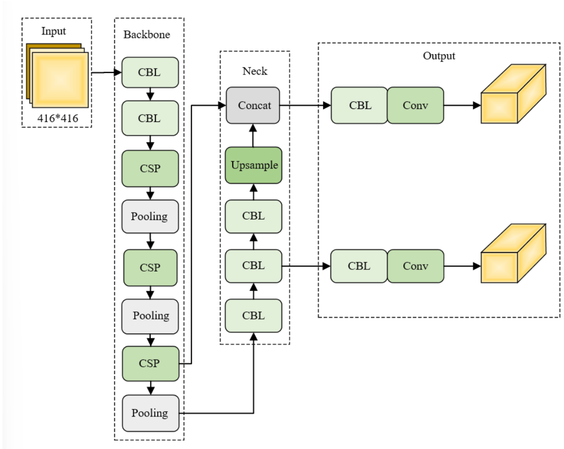

Figure 3: YOLOv4-tiny Network structure.

into two parts through the CSPBlock module and fuses them back together through cross-stage residual edges. This method increases the correlation difference of gradient information and extends the learning ability of the convolution network. Boasting a decrease in computational bottleneck, CSPBlock improves the accuracy of the model while increasing computational load by only 10%-20% as compared to the existing ResBlock module, and it does this at the same or less computational cost.

(3) Neck network: The YOLOv4-tiny employs feature pyramid network to extract feature maps of multiple sizes, which can improve the speed of object detection. In this way, we can substitute the spatial pyramid pooling and path aggregation network in YOLOv4. At the same time, YOLOv4-tiny will also use two scale feature maps (13×13 and 26×26) for prediction on detection results, effectively improving the ability of the target detection at multiple scales.

(4)Output: The output structure of YOLOv4-tiny changes with the input image size, splits the image into S×S grids, and uses B bounding boxes in each grid to predict object categories. It adds a confidence threshold to the prediction so that reduces the redundancy of bounding boxes, keeping only high-confidence bounding boxes. In the end, the output shows the location, category and confidence of the predicted object. This method enables YOLOv4-tiny to retain real-time performance while achieving the exacting detection accuracy requirements of real-world applications.

2.3 Motion-triggered YOLOv4-tiny algorithm

In this paper, we thus combined the background subtraction method and the YOLOv4-tiny algorithm to improve the accuracy and speed of object detection inference to monitor abnormal behavior of unattended children in real time. This integration provides faster and accurate identification of abnormal behaviors in the unattended children. The algorithm presented in this paper firstly adopts the background subtraction to extract moving objects from the detection video, and then performs identification on the extracted moving objects with YOLOv4-tiny, which promotes speedup and accuracy of recognition of unattended-child abnormal behaviors. The algorithm diagram is shown in Figure 4.

3 Experimental verification

3.1 Experimental environment

For testing, a machine with an NVIDIA GeForce RTX 3060 GPU has been used. Software Environment: Windows 11, CUDA 11.7, PyTorch. The experiment is conducted on YOLOv4-tiny pre-trained model with 200 epochs and a batch size of 32.

3.2 Production of data sets

The data sets utilized in this paper primarily originate from multiple data sets published on the Roboflow website, including Fall Down [12] [13], Stand [14], Sit [15], [16] and other related data sets. These comprehensive data sets encompass diverse scenes and various human poses, thereby enhancing the accuracy and robustness of the system. Building upon these two foundational data sets, a total of 11,894 images were manually annotated by incorporating publicly available network photos for training purposes. The training set to test set ratio is maintained at 9:1.

3.3 Evaluation index

The accuracy of the trained model is evaluated using frequently employed metrics in binary classification, such as the Precision-Recall curve, F1 Score, and mean Average Precision (mAP). The metrics of the models recognition and classification mostly are TP (True-Positive), TN (True-Negative), FP (False-Positive), and FN (False-Negative). Precision (P) is defined as the number of correctly predicted positive samples (TP) among all the predicted positive samples (TP + FP), computed by formula (3).

$$P = \frac{TP}{TP + FP} \tag{3}$$

Recall (R) is the number of correctly predicted positive samples divided by the total number of positive samples in actual, which we compute using formula (4).

$$R = \frac{TP}{TP + FN} \tag{4}$$

To measure both precision and recall, the F1 Score is defined in formula (5).

$$F1 = \frac{2PR}{P + R} \tag{5}$$

The Average Precision (AP) is calculated as the integral of the precision-recall curve, which can be derived from formula (6).

$$AP = \sum_{i=0}^{n-1} \left[R\left(i\right) - R\left(i+1\right) \right] * P\left(i\right) \tag{6}$$

The multi-class average precision mean mAP is then derived using formula (7):

$$mAP = \frac{1}{n} \sum_{i=1}^{n} AP_i \tag{7}$$

where n is the number of categories.

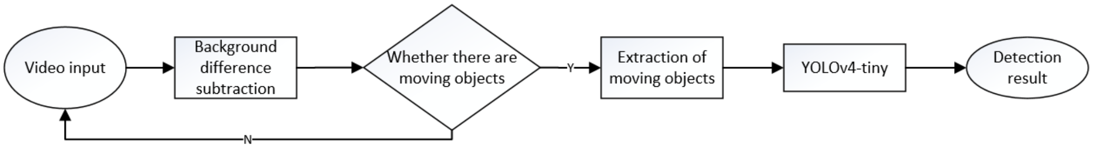

Figure 4: Motion-triggered YOLOv4-tiny algorithm Schematic drawing.

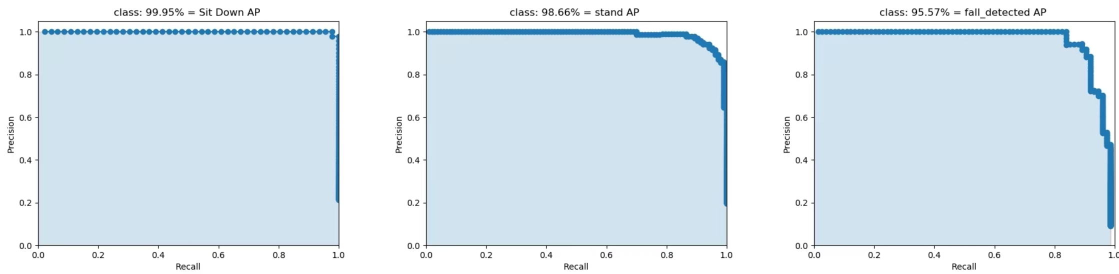

Figure 5: Precision-Recall curve.

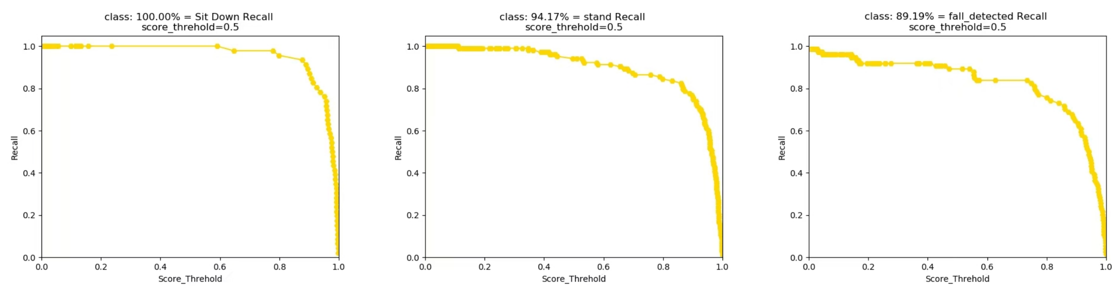

Figure 6: Recall-IoU curve.

3.4 Model training results

After undergoing 200 rounds of training, the Average Precision (AP) for the ”Sit down” category achieved an impressive accuracy rate of 99.95%, while the AP for the ”Stand” category reached 98.66%. Additionally, the AP for fall detection stood at a commendable level of 95.57%. When considering an IoU threshold of 0.5, the AP for fall detection remained consistent at 95.57%. The overall average precision mAP attains a remarkable value of 0.9806, underscoring the model's high accuracy performance. Figure 5 illustrates the Precision-Recall curve depicting AP as the area under this curve.

The Recall-IoU curves for ”Sit down”, ”Stand”, and ”Fall_detected” is illustrate in Figure 6. The recall for the three aforementioned categories at the IoU is 0.5 could reach 100%, 94.17%, 89.19%, which illustrates the high sensitivity of the model.

Using the previous Precision and Recall values, the different F1 Scores can be obtained for the three classes for an extensive analysis. The F1 Scores (at IoU level 0.5) of all three actions ”Sit down,” ”Stand,” and ”Fall-detected,” are 0.99, 0.94, and 0.91 which shows a balanced performance across all categories. F1 Score-IoU curves of these three categories is shown in Figure 7.

To make the experiment more persuasive and to prove that our trained model was accurate, publicly available photos depicting children's daily activities including falling, standing, and sitting were chosen. The detection results are shown in Figure 8. The experiment therefore demonstrates that a fully trained model is able to successfully identify a variety of human behaviors with high accuracy.

3.5 Experimental results of fusion algorithm

The fusion algorithm was tested using Multiple cameras fall dataset [17]. Figure 9 illustrates the recognition outcomes of the fusion algorithm for fall behavior, while Table 1 presents the algorithm's processing time per frame before and after improvement.

The results obviously indicate that the elapsed time of the fused algorithm per frame was reduced by 6.1%. This not only improves the detection speed of abnormal behaviors in unattended children, but also greatly alleviates the false detection problem caused by YOLOv4 to non-moving objects. Table 1 summarizes the frame-level processing time comparisons pre and post improvements.

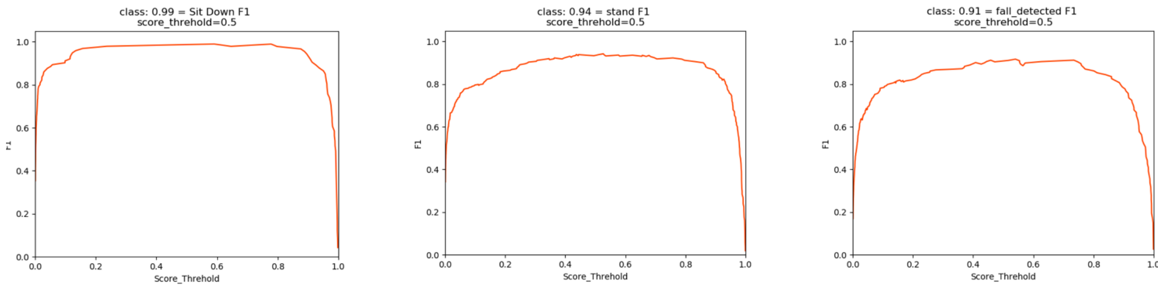

Figure 7: F1 score-IoU curve.

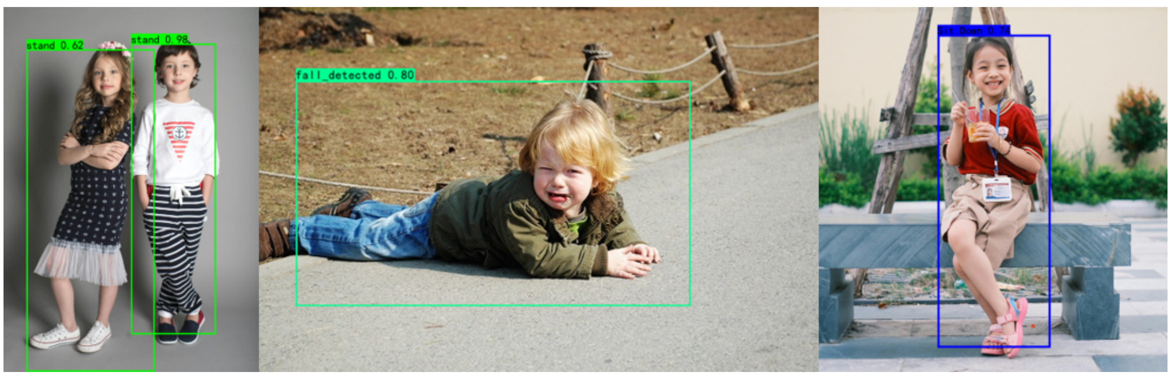

Figure 8: Test results.

Table 1: Time required for each frame image recognition before and after algorithm improvement

	Pretreatment time(ms)	Reasoning time (ms)	NMS time(ms)	Total time spent (ms)
Before improvement	3.5	42.3	6.1	51.9
After improvement	2.2	40.7	5.8	48.7

Figure 9: The results of the fusion algorithm.

4 Conclusion

This paper successfully uses the background subtraction method with the moving object detection system and it also proved it by using public dynamic fall dataset. Moreover, a complex detection model using the YOLOv4-tiny model was trained for abnormal behaviors of unattended children. The model produces an impressive mean Average Precision (mAP) metric of 0.98 and an F1 Score of 0.94 at IoU = 0.5, which highlights the accuracy and reliability of the model. To accelerate object detection, this paper presents a novel fusion method of background accumulation difference Moreoveres approach to YOLOv4-tiny. Through strict experimental validation, this approach is shown to lead to a 6.1% reduction in recognition time per frame, which greatly improves real-time detection capabilities. In combination, these advances will allow unattended children to be observed more accurately and more efficiently, resulting in an improved ability to enhance safety and response times during emergencies.

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References

[1] L. J. Zhu, Z. Y. Chen, and C. L. Tian, 'Review of fall detection method based on wearable devices', *Comput. Eng. Appl.*, vol. 55, no. 18, pp. 8–14, 2019.

[2] Gao Zhengzhong, Sun Jian, Zhang Tianhang, and Zhao Liang, 'Indoor fall behavior detection algorithm based on improved YOLOv3', *Exp. Technol. Manag.*, vol. 39, no. 11, pp. 132-137+149, 2022, doi: 10.16791/j.cnki.sjg.2022.11.023.

[3] Wang pingye, 'YOLO-based Video Fall Detection Algorithm', *Comput. Program. Ski. Maint.*, no. 11, pp. 137–139, 2019, doi: 10.16184/j.cnki.comprg.2019.11.049.

[4] Wang Xiaowen, Liang Bo, and Liu Fangfang, 'YOLOv5 Pedestrian Fall Detection Algorithm Based on Attention Mechanism and Weighted Box Function', *J. Shanxi Univ. Sci. Ed.*, vol. 46, no. 02, pp. 334–341, 2023, doi: 10.13451/j.sxu.ns.2022067.

[5] T.-H. Tsai and C.-W. Hsu, 'Implementation of Fall Detection System Based on 3D Skeleton for Deep Learning Technique', *IEEE Access*, vol. 7, pp. 153049–153059, 2019, doi: 10.1109/ACCESS.2019.2947518.

[6] X. Yin *et al.*, 'A Behavior Recognition Method for Elderly People Based on Background Cumulative Subtraction and YOLOv5 Algorithm', in *Proceedings of the 3rd International Conference on Computer, Artificial Intelligence and Control Engineering*, in CAICE '24. New York, NY, USA: Association for Computing Machinery, 2024, pp. 724–729. doi: 10.1145/3672758.3672879.

[7] J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, 'You Only Look Once: Unified, Real-Time Object Detection.', *CoRR*, vol. abs/1506.02640, 2015, [Online]. Available: https://kns.cnki.net/kcms2/article/abstract?v$=$tH39KOVtnoHR3v8q-SzKBEyi6oTM3kV-ke1q69xqPqu9Dkz-uxTyGslEfEmQAX620VoNgipnVrJ6N7TpiS2sSG2dp_THhfeGzjxAn_xC3Cd2zdKjiLRXbQnhxjpNfUsPozaktL0ZnLSe_479berLAhaGsNNWdKbcT3tUwGAFIxvYLqpKXSR2foyUXCo2U9oY6mv6vOCjZBK\protect\penalty-\@MxL89eSo0NyILYtGZ1NZ3-&uniplatform$=$NZKPT&language$=$CHS

[8] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, 'YOLOv4: Optimal Speed and Accuracy of Object Detection', *ArXiv E-Prints*, p. arXiv:2004.10934, Apr. 2020, doi: 10.48550/arXiv.2004.10934.

[9] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, 'Scaled-YOLOv4: Scaling Cross Stage Partial Network', in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021, pp. 13024–13033. doi: 10.1109/CVPR46437.2021.01283.

[10] Z. Jiang, L. Zhao, S. Li, and Y. Jia, 'Real-time object detection method based on improved YOLOv4-tiny', 2020. [Online]. Available: https://arxiv.org/abs/2011.04244

[11] J. Wang and H. Gao, 'Research on the Pedestrian Detection Algorithm for Improving YOLOv4-tiny', *Automobile Applied Technology*, vol. 49, no. 16. pp. 40–43, 2024.

[12] R. U. Projects, 'Fall Detection Dataset', *Roboflow Universe*. Roboflow, Mar. 2023. [Online]. Available: https://universe.roboflow.com/roboflow-universe-projects/fall-detection-ca3o8

[13] university of strathclyde, 'fall_detection Dataset', *Roboflow Universe*. Roboflow, Aug. 2023. [Online]. Available: https://universe.roboflow.com/university-of-strathclyde-m436x/fall_detection-shgkx

[14] project-ejbpl, 'stand Dataset', *Roboflow Universe*. Roboflow, Oct. 2023. [Online]. Available: https://universe.roboflow.com/project-ejbpl/stand-uyb2h

[15] project-ejbpl, 'sit Dataset', *Roboflow Universe*. Roboflow, Oct. 2023. [Online]. Available: https://universe.roboflow.com/project-ejbpl/sit-aamly

[16] rr, 'sitting Dataset', *Roboflow Universe*. Roboflow, Sep. 2023. [Online]. Available: https://universe.roboflow.com/rr-qhwfw/sitting-x9rcm

[17] E. Auvinet, C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau, 'Multiple cameras fall dataset'. Jul. 2010. [Online]. Available: https://www.iro.umontreal.ca/$\sim$labimage/Dataset/

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成绩报告单编号：242242003008436

> 您在报名期间已选择需要纸质成绩报告单，2月26日6时至2月28日17时可再次登录报名网站（cet-bm.neea.edu.cn）进行修改。

全国大学英语四级考试(CET4)成绩详情

姓　　名：杨**

证件号码：34*************616

学　　校：武汉理工大学

笔试成绩

准考证号：420030241113510

总　　分：**614**

听　　力：**208**

阅　　读：**225**

写作和翻译：**181**

口试成绩

准考证号：--

成　　绩：--

成绩报告单编号：241142003004701

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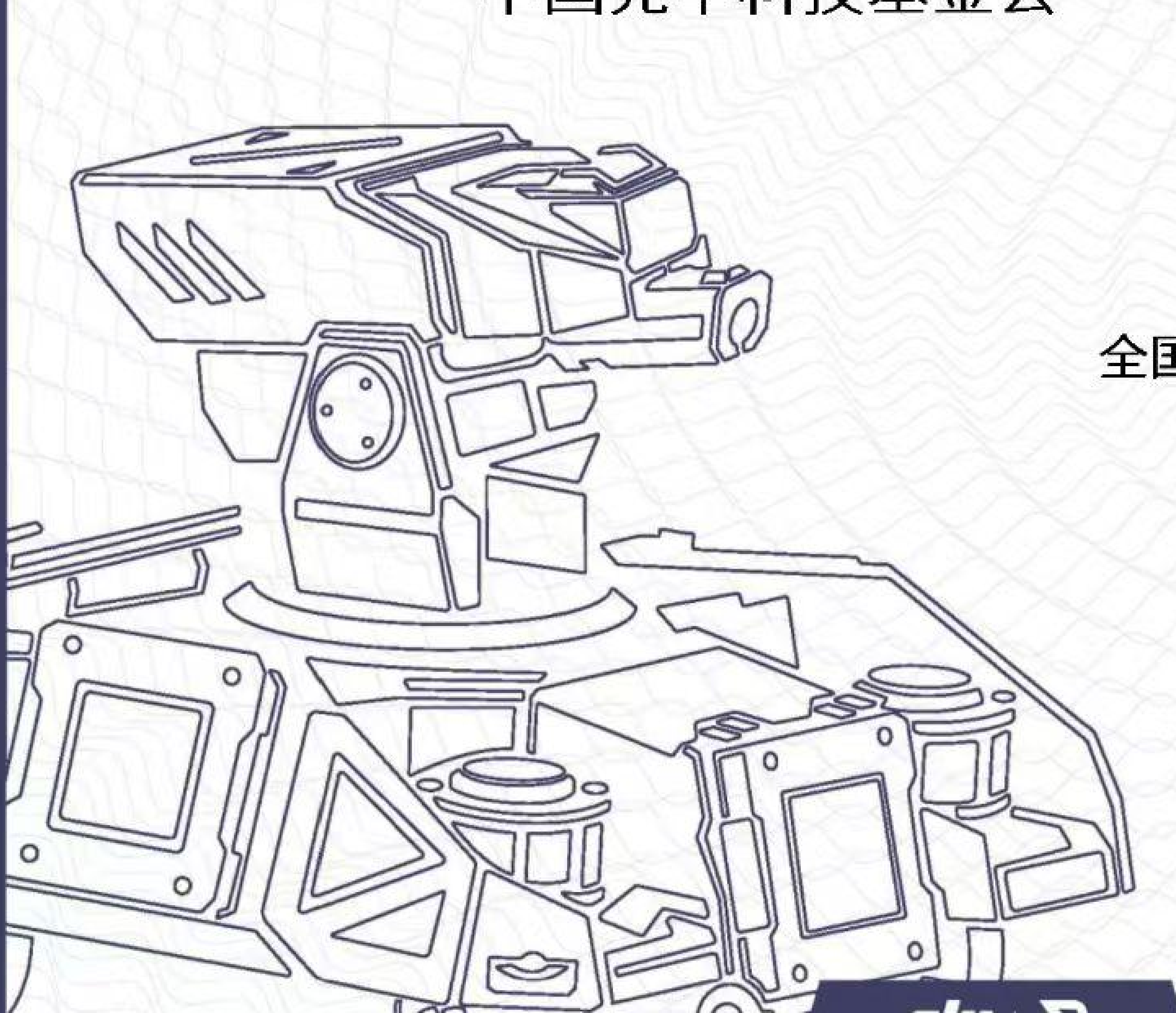
指导单位：中国高等教育学会
中国工程院战略咨询中心
中国光华科技基金会

全国大学生机器人大赛组织委员会

2026 年 4 月



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全国大学生机器人大赛组织委员会
2026 年 4 月

证书编号：RUML2026088G391135180

NO：24014904

武漢理工大學
WUHAN UNIVERSITY OF TECHNOLOGY

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二〇二四年十一月

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WUHAN UNIVERSITY OF TECHNOLOGY

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荣 誉 证 书

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武汉理工大学

二〇二五年十一月

2024年全国大学生电子设计竞赛(湖北赛区TI杯)
暨模拟电子系统设计专题赛选拔赛

获奖证书

National Undergraduate
Electronic Design Contest

全国大学生电子设计竞赛
National Undergraduate Electronic Design Contest

学校名称：武汉理工大学

参赛学生：杨博元、任浩然、韩朋

指导教师：田猛、陈跃鹏

荣获二〇二四年全国大学生电子设计竞赛（湖北赛区TI杯）暨模拟电子系统设计专题赛选拔赛（本科组）贰等奖。

特颁此证

电证字（2024）721号

全国大学生电子设计竞赛
湖北赛区组委会

二〇二四年八月