ISSN: 2664-9640

Real-time counting of non-motorized vehicles on campus based on target detection

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Abstract

Education informatization plays a critical role in modern education technology and is essential for promoting education modernization and improving education quality. A smart campus represents an application of education informatization and is instrumental in enhancing teaching efficiency, education quality, students' learning experience, and the working environment of staff. However, despite its benefits, smart campuses still face numerous challenges that need to be addressed. Fortunately, new information technologies based on big data and artificial intelligence offer powerful tools to overcome these challenges. For instance, target detection technologies can significantly reduce the need for human and material resources and address tedious and inefficient tasks such as managing electric vehicles on campus, real-time monitoring of the canteen's occupancy, and studying classroom staffing flow. With over 1300 photos of non-motorized vehicles, we can use target detection and number statistics to provide data-driven support for managing non-motorized vehicles on campus and offer solutions to similar issues.

Keywords

Amart Campus, Target Detection, YOLO Algorithm, Non-motorized Vehicle Number Statistics.

1. Introduction

In recent years, the rapid development of new information technology has permeated all aspects of life. The advent of these technologies has not only brought convenience to our daily routines, but also transformed the way we work, communicate, and interact with each other[1], and also provided strong technical support for the construction of modern campuses[2, 3]. Higher education institutions' campuses serve multiple functions, including hosting lectures, providing living and dining arrangements for teachers and students, and facilitating sports and recreational activities. Therefore, these campuses are typically divided into different zones based on their functions, such as teaching areas, experimental areas, residential areas, recreational areas, sports facilities, green spaces, and leisure areas. For instance, the East Campus of Anhui University of Finance and Economics in Figure 1.1 is divided into the following zones:

Figure 1.1 Overall floor plan of Anhui University of Finance and Economics (https://aufevis.aufe.edu.cn/)

The East Campus of Anhui University of Finance and Economics has three gates: the West Gate, the East Gate, and the South Gate. While the West Gate is the main entrance, the South Gate is the most frequently used gate by students and faculty due to its proximity to the university town snack street, which provides convenient access to daily necessities. The living area of the campus is divided into two primary regions, north and south, centered around the South Court Canteen and the North Court Canteen respectively. The teaching area encompasses the Mingde Building, Duxing Building, and Guangxue Building near the South Gate of the campus, with the library located adjacent to the Mingde Building. The experimental area is situated in the southwest corner of the campus. Two rubber tracks, located in the northwest and southeast corners of the campus, provide a space for sports activities for the school's teachers and students. The green landscape of the campus surrounds the teaching and living areas, creating a pleasant and natural environment for everyone.

A university plays a significant role in teaching and educating individuals. With a large campus area and clearly defined functional zones, the population density within the campus is high. The East Campus of Anhui University of Finance and Economics, covering an area of more than 0.66 km^2, houses more than 20,000 students and teachers. In such a densely populated environment, it is imperative for higher education institutions to adopt intelligent campus big data management strategies. By collecting, analyzing, converting, and applying relevant data from within the school, the institution can drive and optimize its management processes[4-6].

Our research has revealed that our university has implemented a smart campus system that provides convenience to the daily lives of its teachers and students. However, with the rapid development of society and the recent impact of the epidemic, traditional modes of transportation for college students have undergone significant changes. As a result, the existing smart campus system lacks corresponding applications to address these changes[7]. For example:

1. The significant increase in electric vehicles on campus: In recent years, with the sudden outbreak of the 2020 epidemic, schools have frequently been closed, and campus transportation has become inconvenient[8]. Due to a lack of traffic knowledge, some students do not adhere to standard traffic rules and parking regulations, resulting in traffic congestion and unsafe situations. The proliferation of vehicles has also led to a severe shortage of charging stations, and the issue of "charging station hogging" has become prevalent[9, 10].

2. The school canteen experiences high footfall during meal times, with both students and staff crowding the area. However, our visits revealed that the flow of people in the school's canteens is uneven, with the North Court canteen being the most congested due to its proximity to

student dormitories. We suggest that providing real-time attendance data for each canteen would significantly address this resource imbalance on campus[11].

3. However, the study rooms in our university lack intelligent management, leading to inefficient use of resources and potential safety hazards. For example, during peak study hours, some students may occupy a study room for an extended period without actually studying, preventing other students from utilizing the room. In addition, some students may leave their belongings unattended in the study room, increasing the risk of theft or loss. Intelligent management systems, such as real-time monitoring of study room occupancy and automatic locking of unused rooms, could effectively address these issues and improve the efficiency and safety of study room usage on campus[12-15]. Existing studies show that the issue of insufficient intelligent management of study rooms could be addressed through the implementation of a smart scheduling system. This system could enable students to view the real-time availability of study rooms and reserve them in advance, thereby reducing the amount of time wasted in searching for a suitable study room. Additionally, the system could include automatic check-in and check-out features to monitor usage and ensure that rooms are being used efficiently. Furthermore, the system could use data analysis to identify patterns in usage and optimize room allocation, ensuring that study rooms are available when and where they are needed most[16], It seems that the lack of information on classroom occupancy and availability is causing inconvenience to the students. A real-time display system can be a great solution to this problem. It can provide information on the availability of classrooms in real-time, allowing students to quickly find an available classroom for self-study or group work. The system can also show the occupancy rate of each classroom, allowing students to choose a less crowded room to study in. Additionally, this system can optimize the usage of classrooms by directing students to under-utilized classrooms, which will also help to ease the overcrowding issue in popular areas of the campus.

The development of artificial intelligence and big data technology has opened up new opportunities for the intelligent construction of higher education campuses. With numerous teaching facilities scattered across the campus, the introduction of big data technology ensures stable transmission of the vast amount of generated data. Video surveillance is an essential tool for most universities, and real-time collection of on-campus information through this equipment, coupled with advanced deep learning algorithms, can fully integrate with the needs of an intelligent campus. This solution can solve the management difficulties of traditional colleges and universities and establish the foundation for the realization of a multi-functional intelligent campus[16]. Due to the limited time, we will focus on the real-time counting system of electric vehicles on campus and do our best to make Anhui University of Finance and Economics a harmonious, safe, and smart campus.

2. YOLOv5 model

YOLO (You Only Look Once) is a rapid target detection algorithm proposed by Joseph Redmon et al. in 2015. The YOLO model converts the target detection problem into a single regression problem, wherein the class and bounding box of all targets in the image can be directly obtained by one forward pass. Compared to other target detection algorithms, YOLO has a faster speed and higher accuracy.

YOLOv5 is a target detection model based on the PyTorch deep learning framework, developed by Ultralytics, a computer vision company based in the US. The model uses an Anchor-Free based detection algorithm that improves detection speed while ensuring accuracy. YOLOv5 has achieved outstanding performance on several datasets, such as the COCO and PascalVOC datasets, and its mAP (mean average precision) metric exceeds other existing target detection models[17, 18]. At the same time, the model is also very fast and can reach the level of real-time detection.

2.1. YOLO Development History

YOLOV5 is the latest version of the YOLO series target detection algorithm, and the following is its development history:

(1) YOLOv1: In 2016, Joseph Redmon proposed YOLOv1, which is the first real-time target detection algorithm that can detect multiple objects in a single image at the same time with high speed, but relatively low accuracy [19].

(2) YOLOv2: In 2017, Redmon et al. proposed YOLOv2, which uses a deeper neural network, incorporating techniques such as BN layers and anchor boxes, which greatly improves accuracy but slightly reduces speed [20-22].

(3) YOLOv3: In 2018, Redmon et al. released YOLOv3, which further improved the network structure and techniques based on YOLOv2, such as the use of FPN (Feature Pyramid Network) and other techniques to improve the accuracy while increasing the speed [23-26].

(4) YOLOv4: In 2020, Alexey Bochkovskiy et al. released YOLOv4[27], based on Redmon, with a deeper Darknet network architecture, using techniques such as Mish activation function and CSPNet structure, and adding strategies such as multi-scale training and data enhancement to achieve higher accuracy and speed[28-33].

(5) YOLOv5: In 2020, Ultralytics released YOLOv5, which is based on YOLOv4 and uses more efficient backbone network CSPNet, SPP, and PAN technologies, etc., to further improve accuracy and speed[34-36].

The YOLO family of target detection algorithms has become one of the classical algorithms in the field of target detection after years of continuous development and optimization, with advantages such as high efficiency and accuracy.

2.2. YOLOv5 network structure

YOLOv5 is a target detection algorithm and is the latest version of the YOLO (You Only Look Once) series, released by Ultralytics in 2020. Compared to previous versions, YOLOv5 has higher accuracy and faster speed.

The network structure of YOLOv5 consists of two main parts: Backbone and Detection head. The Backbone utilizes CSPNet (Cross-Stage Partial Network) as its backbone network, which reduces the number of parameters while enhancing feature extraction, ultimately resulting in improved accuracy. The Detection head is responsible for detecting objects and outputting information on their category and location[37].

YOLOv5's detection head incorporates a new technique called Spatial Pyramid Pooling (SPP), which pools feature maps of varying sizes to enhance the model's ability to detect objects of different scales. Additionally, YOLOv5 leverages Path Aggregation Network (PAN) technology to aggregate feature maps from different scales, further improving the model's ability to detect small targets.

The input to the YOLOv5 network is a 3-channel image of size 416x416 or 640x640. The main part of the network is composed of CSPDarknet53, a deep neural network architecture consisting of multiple convolutional layers and residual blocks. This architecture includes a large number of convolutional and pooling layers, which extract image features in the learning[38, 39].

Following CSPDarknet53, YOLOv5 employs a feature aggregation layer and multiple small detection heads, each responsible for detecting a specific set of targets. These detection heads are designed to identify targets of various sizes based on feature maps at different scales. To predict the probability of a target's presence, as well as its bounding box and class, YOLOv5 utilizes sigmoid functions[18, 40].

At the end of the YOLOv5 network is a fully connected layer that produces a probability distribution corresponding to the number of targets and categories. This output is then passed to a non-maximum suppression algorithm to eliminate overlapping detection frames, resulting in the final detection results. The network's architecture has demonstrated excellent performance and robustness across various datasets, including popular target detection datasets such as COCO, PASCALVOC, and COCO-Stuff.

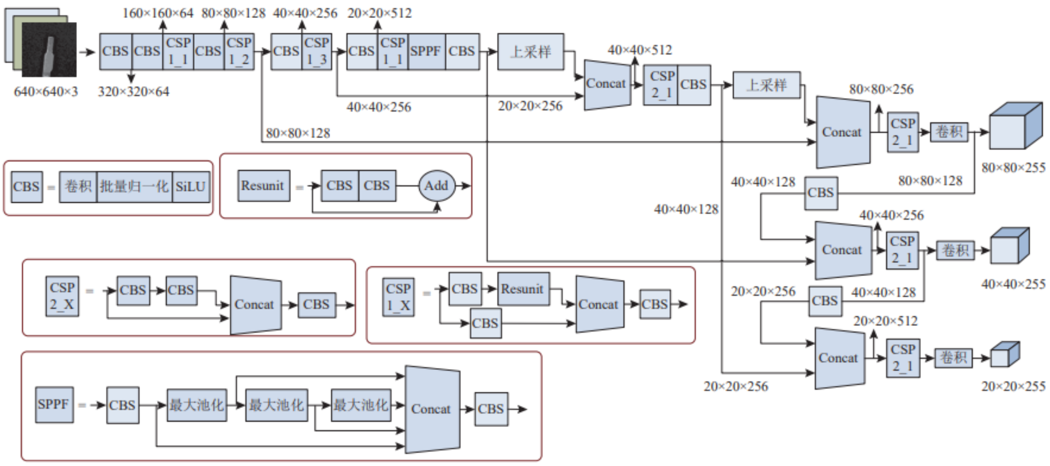


Figure 2.1. The network structure of YOLOv5[37]

In Figure 2.1, the YOLOv5 model inputs RGB images with three channels to the convolution layer through the input layer, where the CBS consists of a convolution layer, a convolution layer with a BN (BatchNorm2d) layer, and a SiLU (Sigmoid Linear Unit) function, and is input to the CSP_1 (Cross Stage Partial) layer through the convolution of two CBS layers, where the CSP_1 layer consists of a concert layer that splices the CBS and Resnet and then convolves them, and after several processing, stitching the result after slicing, and outputting the image result after convolution.

3. Experiment

We gathered images of non-motorized vehicles parked in high-traffic areas on campus and modified the YOLOv5 code to include a counting function. The resulting dataset exclusively features bicycles and electric vehicles, which are the primary modes of transportation on campus. These images were captured in various scenarios, including parking areas near the canteen, library, and dormitories. Factors such as lighting, background, and placement were taken into account during data collection.

3.1. Data set introduction

We gathered images of non-motorized vehicles parked in high-traffic areas on campus and modified the YOLOv5 code to include a counting function. The resulting dataset exclusively features bicycles and electric vehicles, which are the primary modes of transportation on campus. These images were captured in various scenarios, including parking areas near the canteen, library, and dormitories. Factors such as lighting, background, and placement were taken into account during data collection.

To train our convolutional neural network, we collected a total of 1302 photos. This included 610 photos of single bicycles, 692 photos of single electric vehicles, and 148 photos of multiple non-motorized vehicles, including a mix of bicycles and electric vehicles. Figures 3.1 and 3.2

ISSN: 2664-9640

showcase the non-motorized vehicle images captured in various areas of the campus, such as near the dormitory building and around the canteen, under well-lit conditions. We chose these areas because they are more representative due to their higher traffic volumes and faster vehicle turnover.

(a) Single Bicycle

(b) Multiple bicycles s

Figure 3.1. Partial dataset of bicycles

(a) Single electric vehicle

(b) Multiple electric vehicles

Figure 3.2. Partial dataset of electric vehicles

3.2. Non-motorized Vehicle Count

We added a counting function to YOLOv5 by modifying the code. The function is capable of recognizing and counting pedestrians, bicycles, and electric vehicles in both images and videos. Specifically, it includes functions for pedestrian counting, bicycle counting, and electric vehicle counting. Instead of using the term "target detection recognition rate", we replaced it with "Acc", which refers to the accuracy of the model's performance in recognizing and counting non-motorized vehicles.

ISSN: 2664-9640

3.2.1. Bicycle counting function

Figure 3.3. Single electric vehicle target detection count

In Figure 3.3, the recognition rates for single bicycle detection are 76% and 61%, respectively. The final accuracy results for bicycle recognition in the 610 images are generally distributed between 50% and 80%, as shown in Figure 3.3. In both cases, one bicycle is counted. The higher accuracy rate in the left figure may be attributed to the three-dimensional angle of the photograph and the more complete view of the filming location. In contrast, the right figure fails to capture some parts of the bicycle, which affects the recognition result.

3.2.2. Counting Function of electric vehicles

Figure 3.4. Single electric vehicle target detection count

The recognition rates for single electric vehicle detection were 54% and 63%, respectively, and the final accuracy results for electric vehicle recognition in the 692 images were generally distributed between 45% and 75%. By modifying the code of YOLOv5, the counting function was added, as shown in Figure 3.4, and both images were counted as 1 electric vehicle, respectively. The difference in filming angles may have affected the accuracy rate. The right figure was taken in a more three-dimensional way, allowing image processing to better resolve the two-dimensional information and resulting in more accurate recognition. Overall, the recognition rate for electric bicycles is lower compared to bicycle recognition in Figure 3.3, which may be due to the significant difference between the dataset used for testing and the model training set.

ISSN: 2664-9640

3.2.3. Multi-target detection accuracy analysis

Figure 3.5. Multi-target detection count

The accuracy of multi-target detection for electric vehicle recognition ranges from 55% to 80%, while the accuracy of bicycle recognition ranges from 35% to 70%. In the left figure of Figure 3.5, the image depicts bicycles and electric vehicles, and the result shows 2 bicycles and 2 motorcycles, which matches the actual count in the picture. However, in the right figure of Figure 3.5, the image also displays bicycles and electric vehicles, but the result shows 2 bicycles and 5 motorcycles. This is due to the relatively cluttered arrangement, which caused an electric vehicle to be incorrectly identified as a bicycle. Nevertheless, the electric vehicle count was relatively accurate.

From the results of image recognition, it is evident that the recognition rate for non-motorized vehicles with overlapping features is low. Overlapping may result in inaccurate image arrays during image pre-processing, which in turn affects the recognition accuracy.

Based on the target detection results provided above, it can be observed that the bicycle target recognition accuracy is approximately 70%, the electric vehicle target recognition accuracy is around 60%, and the mixed recognition accuracy is about 60% as well. These accuracies have some correlation with the photographing angle and lighting conditions, but the detection results ultimately meet the expected level of accuracy.

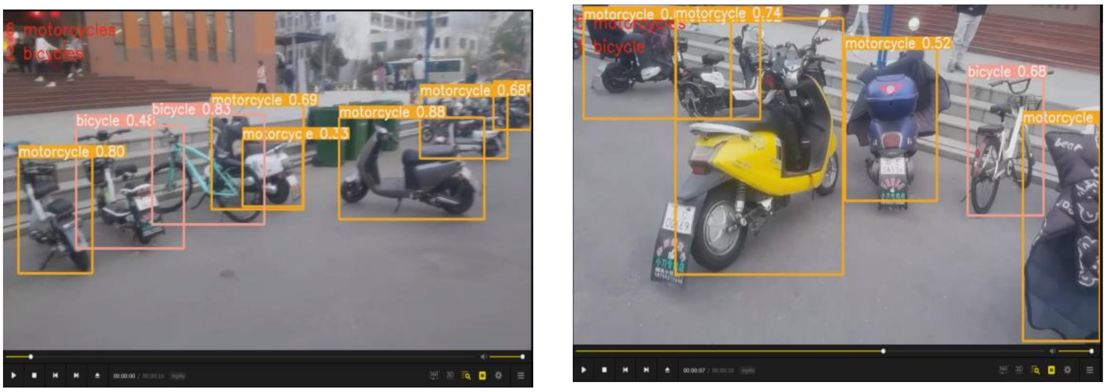
3.3. Real-time counting

We captured multiple sets of videos, each with a duration of approximately 10 seconds, underneath the canteen, library, and dormitory building of the campus. These locations are densely populated with electric vehicles and are crucial for analyzing the traffic flow of such vehicles within the school.

Moreover, to evaluate the impact of lighting conditions on the model, we captured a set of videos not only during the daytime with sufficient lighting but also during the nighttime when the lighting environment is poor. This comparison allowed us to assess the effects of lighting on the accuracy of the model's performance.

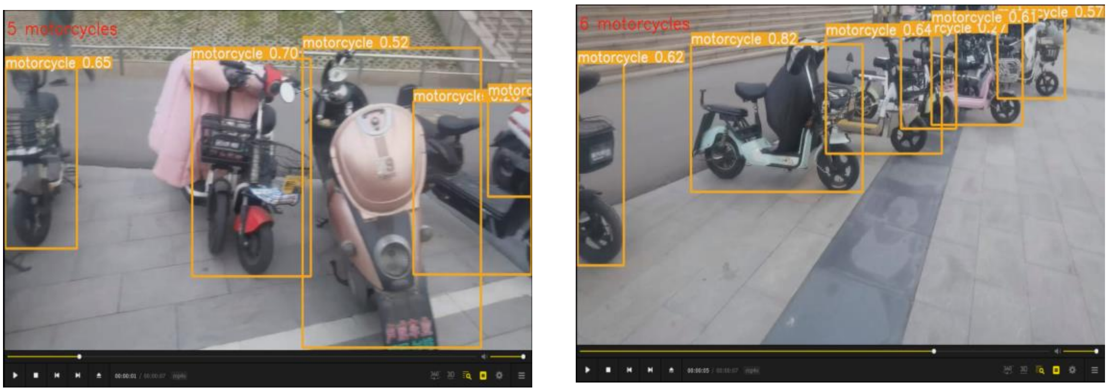
3.3.1. Plenty of light

We collected videos of bicycles and electric vehicles parked under the North Court Canteen, Library, South Court Canteen, and a dormitory building in North Court between 14:00 and 16:00 during the daytime for the purpose of target detection and real-time counting. By obtaining permission to access campus cameras, non-motorized vehicles can be counted in real-time to regulate parking and achieve a smarter campus environment.



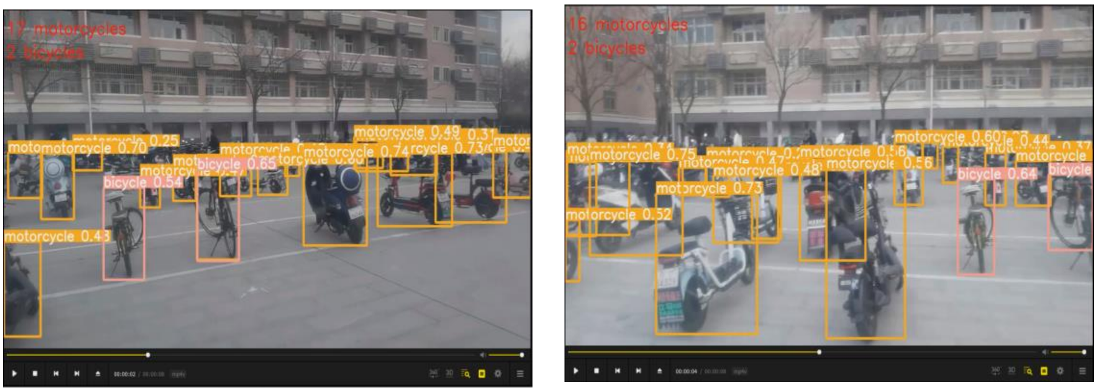
(a) Screenshot around 1s (b) Screenshot around 5s

Figure 3.6. Video of non-motorized vehicles under the North Court canteen



(a) Screenshot around 1s (b) Screenshot around 5s

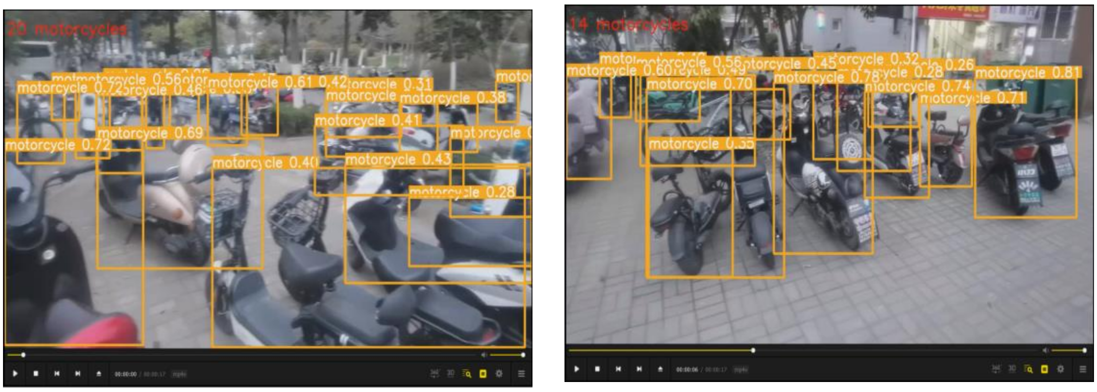
Figure 3.7. Video of non-motorized vehicles under the library



(a) Screenshot around 1s (b) Screenshot around 5s

Figure 3.8. Video of non-motorized vehicles under the South Court Canteen n

ISSN: 2664-9640



(a) Screenshot around 1s (b) Screenshot around 5s

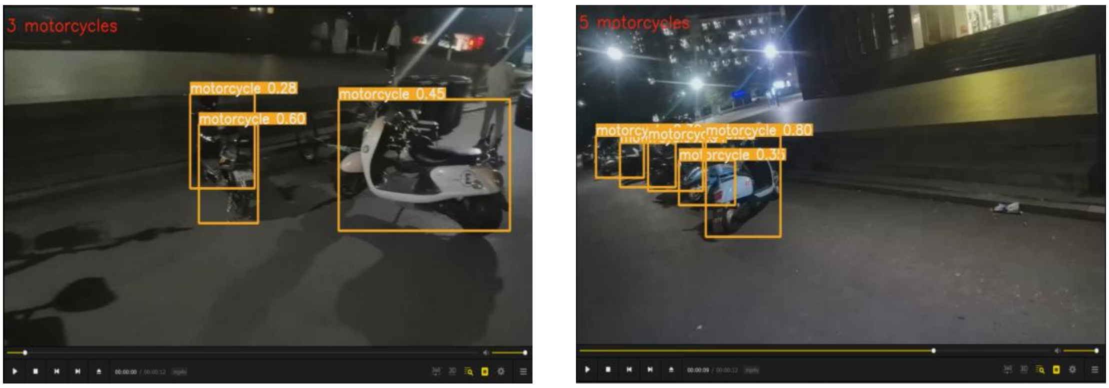
Figure 3.9. Video of non-motorized vehicles under the dormitory building

Under well-lit conditions, we recorded videos of non-motorized vehicles under the library, canteen, and dormitory building to perform target recognition and counting, as depicted in Figures 3.6-3.9. We observed that the recognition accuracy was mostly concentrated between 50% and 75%. Non-motorized vehicles that were closer to the camera were successfully recognized and counted, while those farther away were mostly unrecognized. This outcome is greatly influenced by the photographing angle, and using a camera with a higher filming angle is expected to improve recognition accuracy.

Furthermore, high-angle recognition can add a more three-dimensional perspective to image acquisition. Using a camera for image recognition can also solve the issue of overlapping bicycles, which can negatively affect recognition accuracy to some extent.

3.3.2. Insufficient light

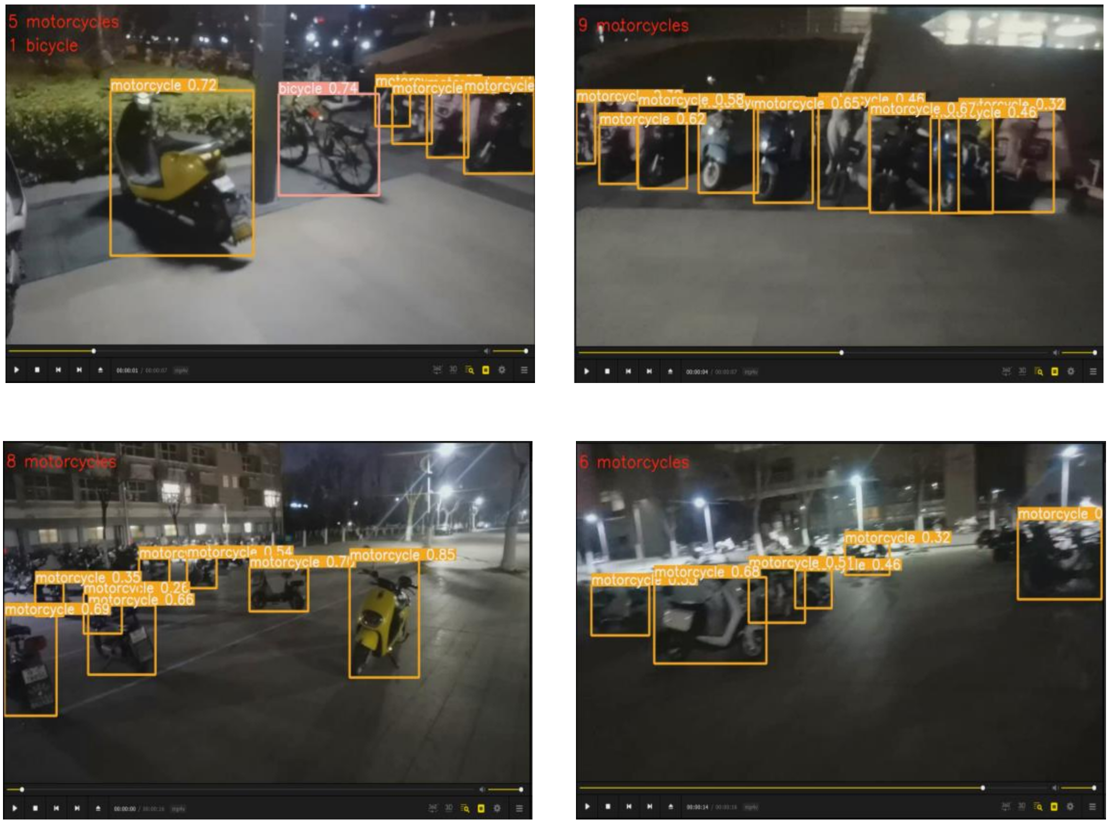
To compare results, we also recorded four sets of 10-second videos at the same locations mentioned earlier between 20:00 and 22:00 on the same day at night. We used the YOLOv5 model for detection and obtained results within 1 and 7 seconds, as illustrated in Figures 3.10-3.13.



(a) Screenshot around 1s (b) Screenshot around 7s

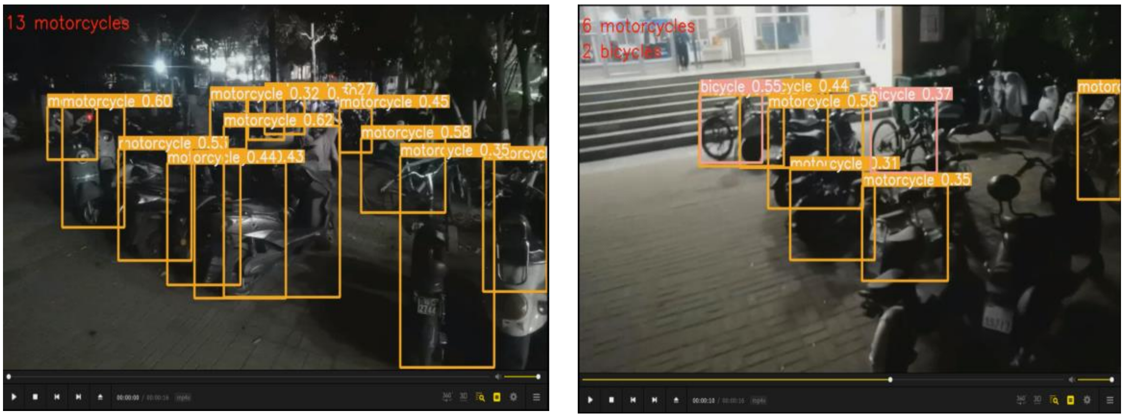
Figure 3.10. Video of non-motorized vehicles under the North Court canteen

ISSN: 2664-9640



(a) Screenshot around 1s (b) Screenshot around 7s

Figure 3.12. Video of non-motorized vehicles under the South Court Canteen



(a) Screenshot around 1s (b) Screenshot around 7s

Figure 3.13. Video of non-motorized vehicles under the dormitory building

Under low-light conditions, we recorded videos for non-motorized vehicle target recognition and counting at the library, canteen, and dormitory building, as shown in Figure 3.6. By analyzing different periods of the same video, we found that recognition accuracy was mostly concentrated in the range of 30% to 70%. The lighting conditions have a certain influence on the accuracy rate, and in conditions of insufficient light at night, only non-motorized vehicles in close proximity can be recognized and counted. Additionally, the filming angle also affects the recognition rate, which can be improved with a camera that has a higher photography angle.

When compared with the well-lit conditions, Figure 3.13 (b) had a lower recognition accuracy, with about five electric vehicles not detected. When compared to Figure 3.9 (b), which was taken at the same location and viewpoint, it can be concluded that lighting conditions have a significant impact on recognition rates. However, in Figures 3.10-3.13, where there was some light, recognition rates were higher.

Overall, more than half of the non-motorized vehicles can be successfully recognized under both well-lit and low-light conditions, which meets expectations. It was also observed that messy non-motorized vehicle parking is a significant issue on our school campus that needs to be addressed.

4. Conclusion

It is commendable that we have collected images and videos of bicycles and non-motorized vehicles around the campus to construct image recognition models using convolutional neural networks. By using the YOLOv5 algorithm for real-time counting, it is possible to identify peak vehicle gathering places and analyze the traffic flow of non-motorized vehicles in the school. However, it is important to note that there were some unsuccessful detections, which could be attributed to the photographing angle. Therefore, further improvements may be required to optimize the recognition accuracy.

Our efforts to assist the school in developing bicycle and electric vehicle management policies through artificial intelligence visualization technology are also noteworthy. By providing real-time data on vehicle counts and parking locations, the school can take steps to regulate parking and improve the overall traffic flow. Overall, our work can be considered a step towards creating a smart campus that promotes sustainable transportation practices.

Overall, the application of artificial intelligence technology in the development of a smart campus has great potential and can significantly improve the efficiency and convenience of campus life.

Acknowledgements

This work is supported by the Quality Engineering Project of Anhui University of Finance and Economics (acszjyyb2021031) and the Anhui University of Finance and Economics Provincial-level College Students' Innovation and Entrepreneurship Training Program (S202110378146).

References

[1] Yiming Chen. Study on optimization of campus electric vehicle operation simulation [J]. Electronic Technology and Software Engineering, 2017, (In Chinese): 215-6.
[2] Yuzhao Chen. Personalized design and research of micro electric vehicle modeling parts based on c2b model [D]; China Academy of Art, 2020. (In Chinese)
[3] Si Y M, Wu B. Construction and management method of university information platform based on big data technology [J]. Mobile Information Systems, 2022, 2022:
[4] Yuting Chen. Research on Student Affairs Based on Smart Campus Big Data [D]; Capital University of Economics and Business, 2020. (In Chinese)
[5] Xia Y J. Big data based research on the management system framework of ideological and political education in colleges and universities [J]. Journal of Intelligent & Fuzzy Systems, 2021, 40(2): 3777-86.
[6] Xu B, Liu Y. The role of big data in network public opinion within the colleges and universities [J]. Soft Computing, 2022, 26(20): 10853-62.
[7] Wang Q P, Yan C M, Zhang X. Yolov5-light: Efficient convolutional neural networks for flame detection [J]. Journal of Electronic Imaging, 2022, 31(6):
[8] Xiaojian Tian. The "shuttle" congestion needs to be cracked [J]. Disaster Prevention Expo, 2020, (In Chinese): 52-5.

[9] Jiawei Zeng, Bin Zhang, Dongyue Zhou, et al. Thoughts on the management of electric vehicle chaos: Hunan Province as an example [J]. Industry and Technology Forum, 2022, 21 (In Chinese): 209-10.
[10] Dan Li. Countermeasures and thoughts on the management of campus traffic environment in colleges and universities--a university in Hunan Province as an example [J]. Journal of Guangxi College of Education, 2021, (In Chinese): 38-41.
[11] Zhuocheng Luo, Jingheng Song, Jianmin Yang. Exploring the optimization of university life in the context of "Internet+" [J]. Technology and Innovation, 2022, (In Chinese): 32-3+6.
[12] LJ Cao, HX Zhong, YJ Zhou. Design and implementation of an optimal recommendation system for campus study rooms in the Internet of Things environment [J]. Electronic Production, 2021, (In Chinese): 27-9.
[13] Y Li, SJ Wang, JL Wu, et al. IoT-based statistics and guidance system for available seats in campus study rooms [J]. Computer Programming Skills and Maintenance, 2015, (In Chinese): 67+74.
[14] Ziqi Zhu, Yueyao Liu, Xiaomei Zhang. Research on the construction of shared study room software in universities under the perspective of sharing economy theory [J]. Internet Weekly, 2022, (In Chinese): 61-3.
[15] Chenwei Wang. Design and implementation of intelligent control system for classrooms in colleges and universities [D]; Anhui University, 2021. (In Chinese)
[16] X. C. Chen, J. N. Lin, T. Gao, et al. Analysis of the current situation of study room utilization--an example of vacant study rooms in Henan Normal University [J]. Western Leather, 2017, 39(In Chinese): 249.
[17] Liu W M, Xiao Y, Zheng A Y, et al. Research on fault diagnosis of steel surface based on improved yolov5 [J]. Processes, 2022, 10(11):
[18] Wang H, Jin Y, Ke H C, et al. Ddh-yolov5: Improved yolov5 based on double iou-aware decoupled head for object detection [J]. Journal of Real-Time Image Processing, 2022, 19(6): 1023-33.
[19] Ahmad T, Ma Y L, Yahya M, et al. Object detection through modified yolo neural network [J]. Scientific Programming, 2020, 2020:
[20] Chang Y L, Anagaw A, Chang L N, et al. Ship detection based on yolov2 for sar imagery [J]. Remote Sensing, 2019, 11(7):
[21] Sang J, Wu Z Y, Guo P, et al. An improved yolov2 for vehicle detection [J]. Sensors, 2018, 18(12):
[22] Wu Z Y, Sang J, Zhang Q, et al. Multi-scale vehicle detection for foreground-background class imbalance with improved yolov2 [J]. Sensors, 2019, 19(15):
[23] Huang J H, Zhang H Y, Wang L, et al. Improved yolov3 model for miniature camera detection [J]. Optics and Laser Technology, 2021, 142:
[24] Mao Q C, Sun H M, Liu Y B, et al. Mini-yolov3: Real-time object detector for embedded applications [J]. Ieee Access, 2019, 7: 133529-38.
[25] Sun Y C, Peng Q, Zhang D Y. Light-yolov3: License plate detection in multi-vehicle scenario [J]. Ieice Transactions on Information and Systems, 2021, E104D(5): 723-8.
[26] Zhang Y, Shen Y L, Zhang J. An improved tiny-yolov3 pedestrian detection algorithm [J]. Optik, 2019, 183: 17-23.
[27] Liu C A, Wang X C, Wu Q L, et al. Lightweight target detection algorithm based on yolov4 [J]. Journal of Real-Time Image Processing, 2022, 19(6): 1123-37.
[28] Cai Y F, Luan T Y, Gao H B, et al. Yolov4-5d: An effective and efficient object detector for autonomous driving [J]. Ieee Transactions on Instrumentation and Measurement, 2021, 70:
[29] Fu H X, Song G Q, Wang Y C. Improved yolov4 marine target detection combined with cbam [J]. Symmetry-Basel, 2021, 13(4):
[30] Singha S, Aydin B. Automated drone detection using yolov4 [J]. Drones, 2021, 5(3):
[31] Tan L, Lv X Y, Lian X F, et al. Yolov4_drone: Uav image target detection based on an improved yolov4 algorithm [J]. Computers & Electrical Engineering, 2021, 93:
[32] Wu L, Ma J, Zhao Y H, et al. Apple detection in complex scene using the improved yolov4 model [J]. Agronomy-Basel, 2021, 11(3):
[33] Yu Z W, Shen Y G, Shen C K. A real-time detection approach for bridge cracks based on yolov4-fpm [J]. Automation in Construction, 2021, 122:
[34]Chen Z Y, Wu R H, Lin Y Y, et al. Plant disease recognition model based on improved yolov5 [J]. Agronomy-Basel, 2022, 12(2):

ISSN: 2664-9640

[35] Jubayer F, Soeb J A, Mojumder A, et al. Detection of mold on the food surface using yolov5 [J]. Current Research in Food Science, 2021, 4: 724-8.
[36] Song Q S, Li S B, Bai Q, et al. Object detection method for grasping robot based on improved yolov5 [J]. Micromachines, 2021, 12(11):
[37] Y. Zeng, F. Chin Gao. Improved yolov5-based surface defect detection algorithm for electronic components [J]. Journal of Zhejiang University (In Chinese): 1-11.
[38] Li H Q, Yu H, Gao H T, et al. Robust detection of farmed fish by fusing yolov5 with dcm and atm [J]. Aquacultural Engineering, 2022, 99:
[39] Ning Y, Zhao L N, Zhang C, et al. Std-yolov5: A ship-type detection model based on improved yolov5 [J]. Ships and Offshore Structures:
[40] Qiao Y L, Guo Y Y, He D J. Cattle body detection based on yolov5-asff for precision livestock farming [J]. Computers and Electronics in Agriculture, 2023, 204: