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Behavior and efficiency analysis of Asian neighborhood transportation based on object detection

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Abstract. The Asian city neighborhood transport is often congested and unbalanced. Hence, it is crucial for the policymakers to study the pattern and effectiveness of transportation in the Asian towns. This paper discussed transportation behaviors of cars, bicycles, and pedestrians on Asian block based on object detection using You Only Look Once (YOLO) algorithm. First, the major transportation objects such as buses and cars were identified through photos and videos of an ordinary Asian neighborhood. Then, the key efficiency indicators of the transport behavior were suggested and the time and road required different metrics were calculated. Lastly, diverse behavior patterns have been analyzed, and optimization suggestions based on the findings are being proposed. The result of the application was that various means of transportation in a certain neighborhood differed in terms of efficiency due to the behavior patterns, and object detection method was a suitable tool to find the suggestions about traffic management, safety, and city infrastructure.

Keywords: Transportation Behavior, Efficiency Analysis, Asian Neighborhood, Traffic Object, Yolo Object Detection

1. Introduction

The neighborhood transportation in Asian cities is often very crowded and unevenly distributed. Hence, evaluating the behavior and performance of transportation in Asian districts is essential. As self-driving cars and smart transportation networks are becoming a reality, object identification accuracy to effectively identify and respond to the entities around it is crucial for the systems to work.

A variety of objects that are visible along the road include cars, people walking, bicyclists, and traffic signals. It is important to scrutinize how people get around the community because it empowers local architects and lawmakers to make informed decisions when it comes to infrastructure development, traffic coordination, safety measures, sustainability initiatives, and equal access to transportation.

Deep learning-based object detection algorithms that can detect or track pedestrians and vehicles [1] are already powerful tools. The blending of computer vision and machine learning, driving the development of object detection for neighborhood transportation , has been made possible by the advancements of technology and the growing demand for safer and more effective transit systems [2]. The application of object detection in neighborhood transportation infrastructure has a critical role in guaranteeing safety and efficiency, hence this is an area of research and growth for the future.

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Although researchers utilize various algorithms to analyze transportation behavior, there are still existing problems:

(1) Identifying and tracking vehicles or objects of interest within the image and video data. This involves using computer vision techniques like object detection, classification, and tracking. While being able to detect and precisely follow objects in real time would be useful, accomplishing that feat is troublesome owing to variations in how the objects look, parts of them being hidden at times, and other things blocking them from view like trees or buildings.

(2) Various Asian modes of transportation are encountered through the day in different densities. The population of Asian cities can be as high as many. Moreover, flexible infrastructure, like dynamic traffic control systems, can help to address high load demands while also functioning effectively during time of fewer demands.

(3) Development of the infrastructure according to the patterns and the density of human behavior. Following the evaluation, safety and efficiency should be taken into account while giving the particular mode of transportation what it need as well as its unique behavior. This process starts with the flow analysis of traffic and pedestrians, and then designing separate lanes or paths for this occurrence. It is followed by traffic calming measures that is used to reduce the speed of fast-moving vehicles in areas where more vulnerable users of the road are present.

This research paper aims at three main objectives. Firstly, the paper aims at the implementation of an exhaustive analysis of behavioral patterns of human beings, cars, and bicycles in neighborhood transportation scenarios by the YOLO object detection model. This will facilitate addressing specific safety issues of each transportation mode and promote a more thorough understanding of their behaviors.

On the other hand, the study will be aimed at assessing the effectiveness of different means of transport, taking into account the factors such as speed, reliability and availability. The scholars are able to identify and list the advantages and disadvantages of each transportation mode, therefore, the researchers can provide the ways to boost each type’s performance.

This paper targets pinpointing realms for progress in nearby transit accoutrements and strategies and supplying worthwhile understandings into the scheme and scheduling of facilities and policies that prioritize security, productiveness, and maintainability.

The results of transportation behavior analysis in an Asian neighborhood will identify areas for improvement and suggest effective solutions. Therefore, the paper seeks to propose some detailed suggestions for the development of equitable and sustainable transportation systems that meet the possible needs of neighborhood communities.

2. Literature review

2.1. Overview of object detection models

Object detection is the key issue in computer vision , and it has shown a great progress in recent years as deep learning models have been introduced. In the Faster R-CNN model, a two-stage approach is used for object detection. This method is more accurate than the most recent models, but slower as well [2]. Also, the YOLO (You Only Look Once) algorithm and YOLOv3 is very popular among these models due to its superior real-time performance and accuracy [3-4]. The Single Shot MultiBox Detector (SSD) is another common object detection model which includes one neural network for detecting objects [5]. It has been shown that the Feature Pyramid Network (FPN) improves the accuracy of YOLOv3 and other object detection models [6]. YOLOv4, the latest release of YOLO, was announced in 2020. It is a successor of YOLOv3 with some significant upgrades such as larger model size, better backbone structure, and better training methods [7]. In general, object detection is a fast-growing field with YOLO turning out to be one of the most popular and accurate object detection model due to its in-real-time performance and high accuracy. This writing is based on YOLO as the main component.

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2.2. Previous studies on object detection in neighborhood transportation

Object detection in neighborhood transportation, including pedestrians, cyclists, and vehicles in urban environments, is often being researched in the field of computer vision and transportation engineering. Object detection technologies, by the same token, deliver the results of neighborhood transportation application, which makes the process safer and more efficient. For example, a multi-modal object detection and tracking system was proposed that combines multiple sensors, such as LiDAR and cameras, to detect and track objects in urban environments [8].

Typical scenarios of road image detection raises in auto driving. An object detection framework can detect and classify different types of objects in real-time for autonomous driving in urban environments [9]. A deep learning-based object detection and tracking system is proposed specifically designed for urban autonomous driving [10]. The above systems often use a combination of convolutional neural networks and recurrent neural networks to detect and track objects in real-time. After determining useful patterns, different aspects of improvement suggestions are provided. Niranjan et al. focus on detecting vulnerable road users (VRUs), such as pedestrians and cyclists, in urban environments using deep learning-based object detection [11]. Object detection is also effective for night-time object detection and tracking [12].

The results of these investigations showcase the aptitude for methods to identify objects to facilitate the upgrading of motor transportation networks by issuing precise and instant knowledge concerning other automobiles, walkers, and obstructions in the route surroundings. By enabling safe and efficient navigation and decision-making, these systems can help reduce accidents, congestion, and emissions while improving mobility and accessibility.

2.3. Limitations of previous studies

Previous studies on the behavior and effectiveness of Asian neighborhood transportation have several limitations. Studies on particular Asian communities or urban areas commonly emphasize a specific locale, possibly inhibiting the generalizability of results to other parts or nations. Transportation dynamics and behavior can vary significantly across different locations, so generalizing the findings without considering regional differences could be problematic. Comparative studies across different neighborhoods or countries within Asia may be limited. Comparing multiple locations can provide valuable insights into the variations in behavior and efficiency across diverse contexts. Without such comparative analysis, it becomes challenging to identify common patterns or unique characteristics.

3. Methodology

3.1. The flow of this paper

In the current work, a holistic strategy for investigating and improving road situations was employed, utilizing real-time object identification. The flow of the paper has been organized into five main progressions (as depicted in Figure 1):

Data preparation: This step included examining the current state of road networks and identifying the challenges faced in traffic management, emphasizing the importance of efficient road usage.

Object identification and monitoring: From there, a real-time article noticing methodology is executed, like YOLO, to accurately place and pursue automobiles within the view. This allows for obtaining their positions and counting their numbers, providing essential data for further analysis.

(3) Metric calculation: Utilizing the data from object detection, the main metrics of vehicles on the road are calculated, for understanding traffic congestion and flow patterns.

(4) Transportation pattern analysis: The occupancy of the street is analyzed by an association mining algorithm. The patterns identified help identify bottlenecks and areas with high congestion, facilitating targeted interventions.

(5) Improvement and optimization suggestions: Finally, strategies to enhance traffic efficiency are proposed based on the insights gathered from the previous steps. These strategies may include traffic

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signal optimization, dynamic lane allocation, and smart routing systems, ultimately aiming to alleviate congestion and improve overall road usage.

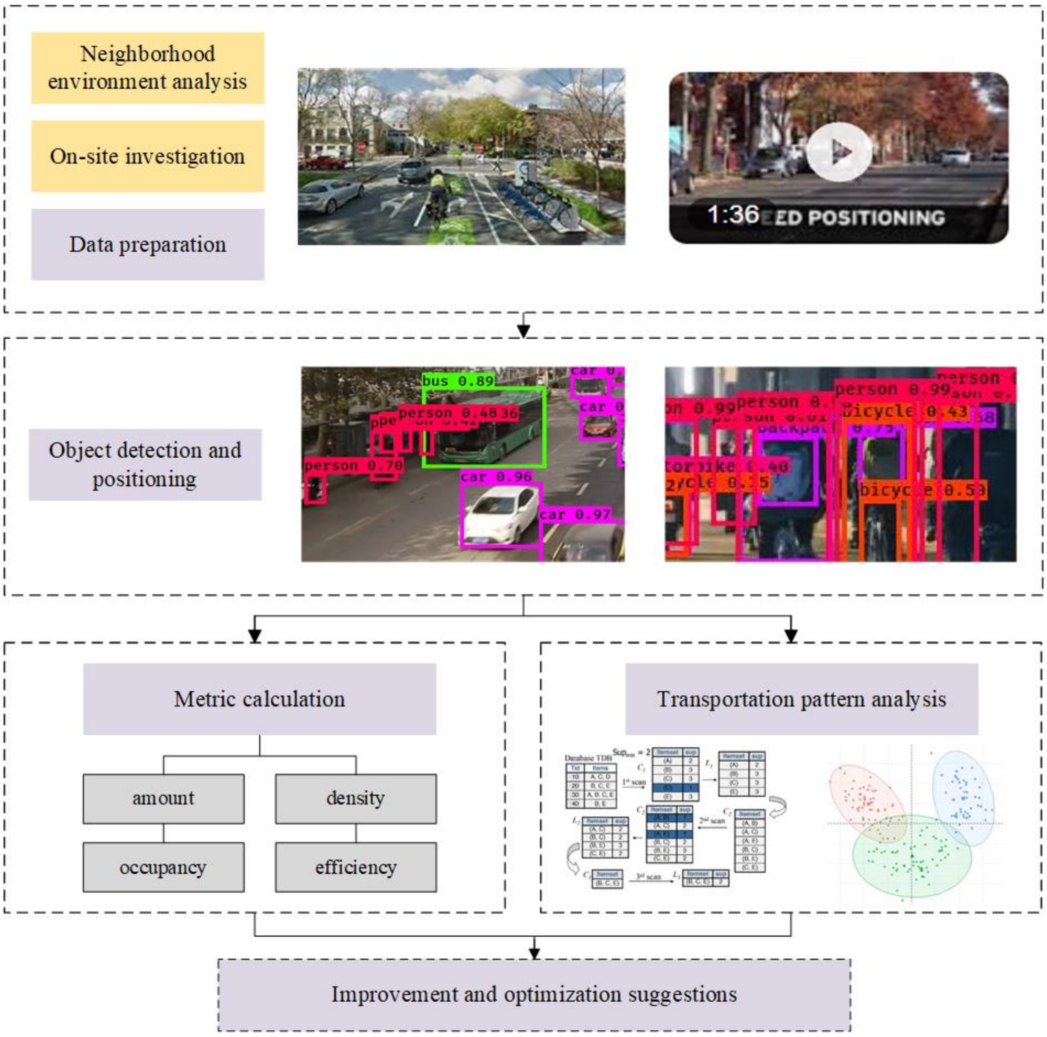

Figure 1. Process of this paper

3.2. Data collection and preprocessing

The data collection phase consisted of the purposeful gathering of visual information, namely pictures and video records, from specific spots that were carefully selected around the neighborhood. The main street and branch roads were identified as key observation points with the aim of capturing the entire traffic pattern. To have a clear picture of what factors influence transportation and how it varies temporally, data collection was done at different times of the day, morning, afternoon, and evening. After that, the data collected consisting of 200 images and 30 videos was submitted to the meticulous preprocessing stage (as shown Table 1).

During the preprocessing, the location, timestamp and file type would be noted and incorporated into structured directories or databases to facilitate further processing. Furthermore, the data was subjected to preprocessing methods including the image and video stabilization, noise reduction, and resolution normalization which helped to improve the quality of data for further analysis. These preprocessing steps were intended to help raise the data quality and reliability. It was done to make sure that it fit in terms of obtaining meaningful insights and patterns concerning transportation in the Asian community.

Table 1. Collected data in different locations

No.	Location	Morning	Afternoon	Evening	Night
1	main street crossing	20P/2V	10P/1V	20P/2V	10P/1V
2	main-branch	20P/2V	10P/1V	20P/2V	10P/1V
3	branch-branch	20P/1V	10P/1V	20P/1V	10P/1V
4	main street	20P/2V	10P/1V	20P/2V	10P/1V
5	branch street No.1	20P/2V	10P/1V	20P/2V	10P/1V
6	branch street No.2	20P/2V	10P/1V	20P/2V	10P/1V

Note: "P" denotes picture captures, and "V" denotes video records.

3.3. *YOLO object detection model*

The capability of YOLO to identify multiple objects within an image at the same time, with great exactness, in only a single processing cycle through the neural web serves as its chief benefit. The YOLO algorithm employs a convolutional neural network (CNN) to detect objects. The YOLO model structure, consisting of three main components as shown in Figure 2, has a framework with said three constituent elements: the backbone network, the detection layers, and the final output layer. The backbone network, typically a pre-trained CNN like Darknet, VGG, or ResNet, extracts features from the input image. These features are then passed through the detection layers, which predict bounding box coordinates, objectness scores, and class probabilities. Lastly, the output layer combines these predictions and applies non-maximum suppression to remove duplicate detections.

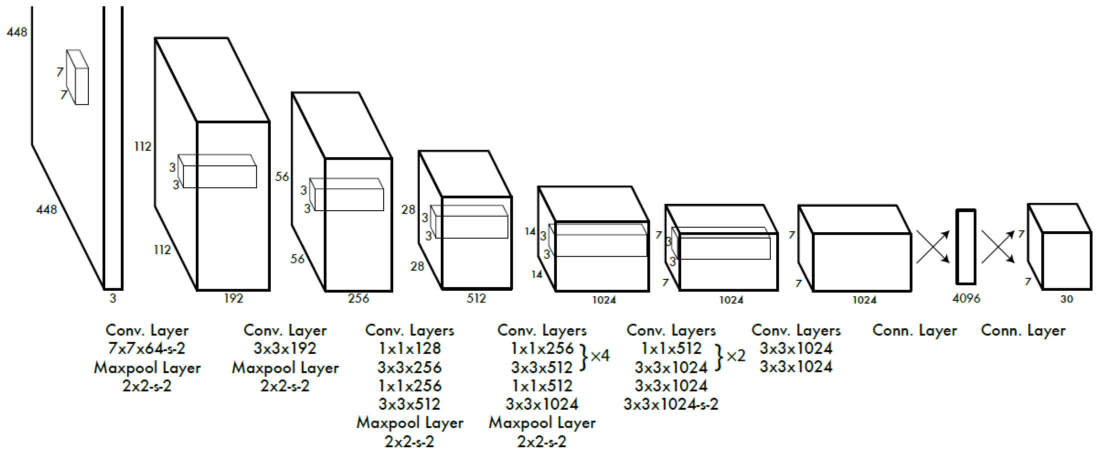

Figure 2. Typical structure of YOLO

3.4. *Transportation metrics*

3.4.1. Accuracy of YOLO model. To evaluate the accuracy of the YOLO model for object detection, the mean Average Precision (mAP) metric is used. mAP is the average of the Average Precision (AP) values calculated for all object classes in the dataset. AP is the area under the precision-recall curve, which plots precision (true positive rate) against recall (sensitivity) at different confidence thresholds. Higher mAP values indicate better model performance.

3.4.2. Metrics used in the analysis. For the analysis of transportation in a neighborhood, the following four metrics can be calculated using the YOLO model and other data sources:

Amount: Utilize the YOLO model to detect and count various means of transportation (cars, bicycles, etc.) in real time or from recorded footage. This tallies the aggregate count of motor vehicles traveling during a given time frame.

To calculate the density of vehicles traversing along the roadway, divide the amount demarcated from the YOLO model by the spatial volume of the roadway. The space volume can be estimated using the road's length, width, and the average height of the vehicles. This metric helps in understanding traffic congestion and flow patterns.

Occupancy of the Street: To determine street occupancy, add up the space occupied by all the detected means of transportation (cars, bicycles, etc.) and divide this by the total available road space. The indicator of how effectively the road area is being taken advantage of as well as potential bottlenecks or places with heavy congestion is provided by this ratio.

Efficiency: In order to analyze the efficiency of the transportation system as well as to measure the number and occupancy rates over time. Look for patterns and trends, like when the traffic is the heaviest and the congestion hotspots, to find out where improvements are needed. Efficiency can be improved by doing traffic management such as signal optimization or dynamic lane allocation according to the data analysis from these metrics.1·

3.5. Analysis of behavior patterns in neighborhood transportation

3.5.1. Objects of analysis. Human behavior patterns in neighborhood transportation range from cars, bikes, and human interactions within the entire ecosystem of transportation. The behavioral patterns of these creatures are the key for the understanding of the dynamics, efficiency, and security of the neighborhood transport system.

Studying the behavior of automobiles in this particular area of transportation is crucial for optimizing the traffic management, improving safety, planning the infrastructure, and dealing with the environmental issues. These patterns can be analyzed to find out how the traffic flows, where the congestion occurs, and the overall safety of the road. Additionally, bikes have a big impact on neighborhood transportation system as well. The way bikes and motorcycles move around the neighborhood for transportation is an issue to be looked at for the improvement of cycling infrastructure as well as traffic safety. It supports planning of the bike-friendly infrastructure and the detection of possible risks and intervention points. Finally, human behavior which is exhibited by pedestrians and commuters plays a vital role in neighborhood transportation. Analyzing human behavioral patterns, including density and speed, gives information to accessibility, pedestrian safety, and effectiveness of the design of transport infrastructure.

3.5.2. Pattern mining after object detection. By applying object detection algorithms, relevant transportation-related objects are extracted, such as cars, bikes, and pedestrians, from the visual data collected in an Asian transportation context. In this paper, the utilization of the Apriori algorithm is proposed to identify frequent patterns in Asian transportation based on the raw results obtained from image and video object detection.

The Apriori algorithm is a widely employed method for association rule mining. The Apriori algorithm enables the identification of frequently co-occurring transportation patterns, such as certain vehicles appearing together or specific traffic flow patterns observed at particular times of the day. The discovered frequent patterns provide valuable insights into the dynamics and behavior of Asian transportation, assisting in traffic management, infrastructure planning, and transportation policy development.

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4. Results

4.1. Metrics of the detected objects in neighborhood transportation

The behavior analysis of neighborhood transportation yielded insightful results, providing a comprehensive overview of various key metrics. Initially, the study involved the quantification of essential variables: the number of cars, street density, occupancy levels, and transportation efficiency. To accomplish this, a series of formulas were devised to calculate these metrics based on the detected car count by Yolo.

The basic metric is N, the count of objects observed on the street segment (cars, bicycles, humans, etc. were counted separately). There are three more metrics:

(1) Density (DEN) represents the transportation density of the street segment.

$$\mathrm{DEN} = \frac{\mathrm{N}}{\mathrm{L}} \tag{1}$$

where L is the length of the segment under analysis, measured in meters. The road segment analyzed in this paper is 35m for main street occasions, and 18m for branch streets.

(2) Occupancy Level (OL) represents the percentage of occupied space by objects on the street segment. Therefore,

$$\mathrm{OL} = \frac{\mathrm{N}}{\mathrm{LW}} = \frac{\mathrm{DEN}}{\mathrm{W}} \tag{2}$$

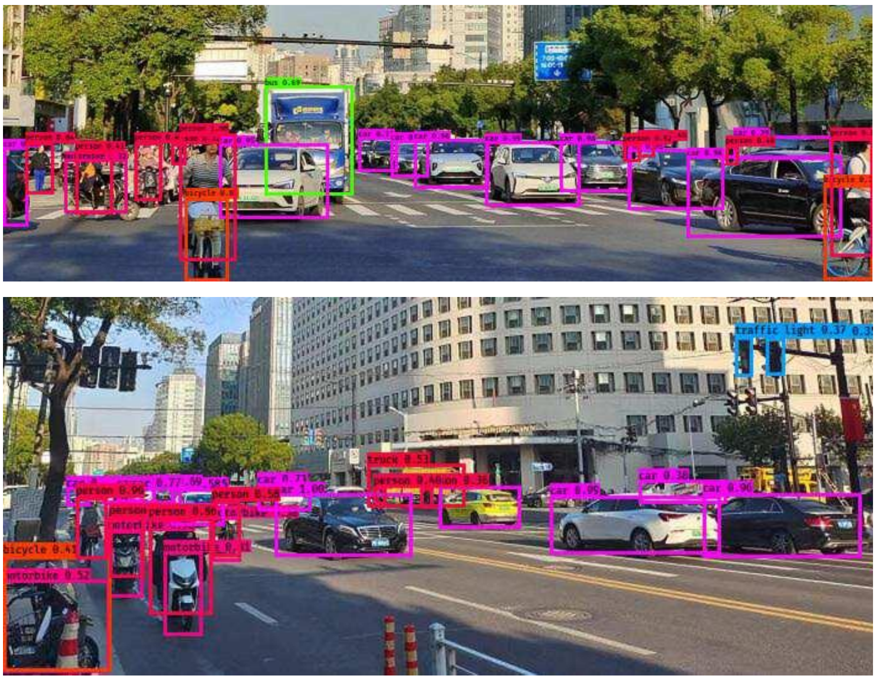
where W is the width of all permitted lines for a certain object. For example, there are 6 lanes for cars in a main street, W=21.5m. But only two narrow lanes for bicycles, here W=3.2m.

(3) The effectiveness index is about the limited velocity of a certain object:

$$\mathrm{EFF} = \mathrm{OL}\left(\frac{\mathrm{V}}{\mathrm{V_{lim}}}\right)^2 \tag{3}$$

where V is the detected velocity, and vlim is the limited velocity of this kind of object.

Figure 3 illustrates some visual examples in different scenarios.



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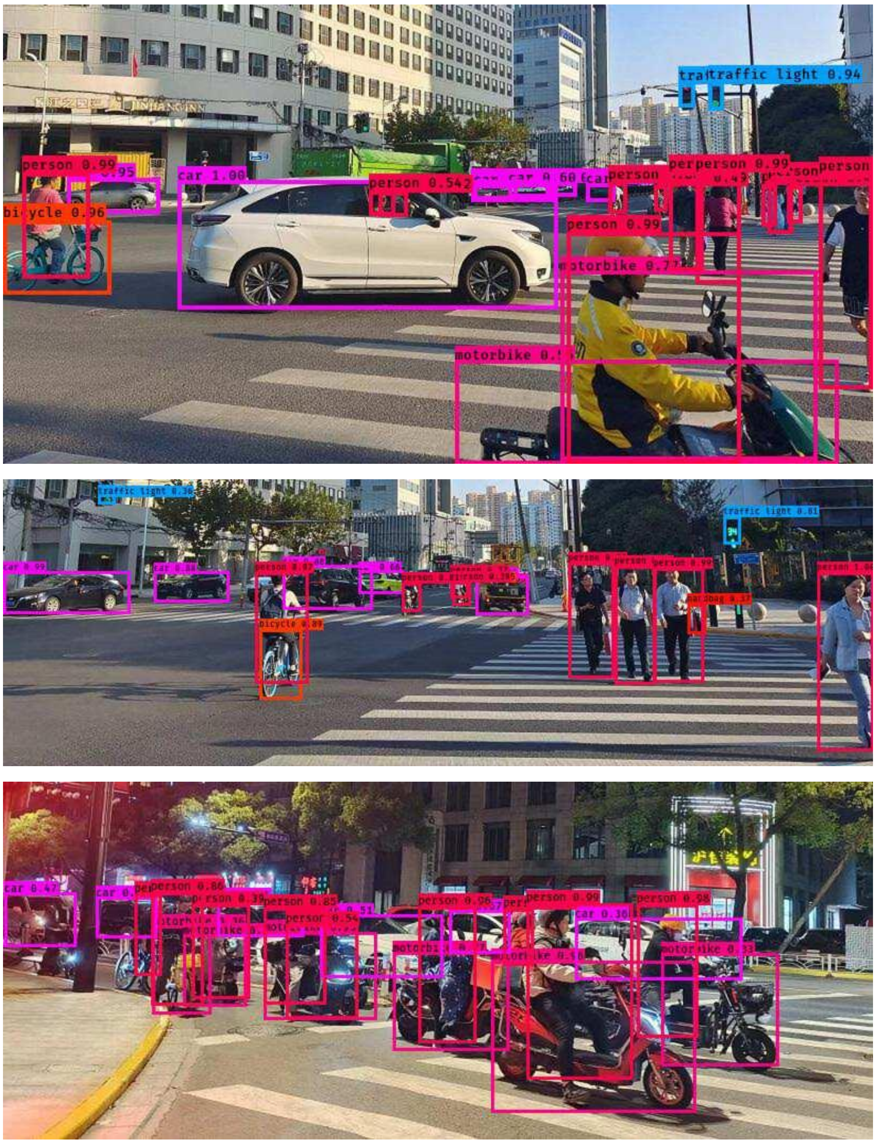

Figure 3. Some object detection results (day and night)

Additionally, statistical measures of three means of transportation were computed for the raw data, with the results succinctly presented in Table 3~5.

Table 3. Average metrics for cars

	N	DEN	OL	EFF
main street crossing	35.6	1.02	0.047	0.0089
main-branch	20.0	0.57	0.027	0.0030
branch-branch	12.4	0.69	0.125	0.0176
main street	17.4	0.50	0.023	0.0113
branch street No.1	6.2	0.34	0.063	0.0245
branch street No.2	7.8	0.43	0.079	0.0359

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Table 4. Average metrics for bicycles

	N	DEN	OL	EFF
main street crossing	41.2	1.18	0.055	0.0137
main-branch	24.3	0.69	0.032	0.0098
branch-branch	8.0	0.44	0.081	0.0164
main street	19.2	0.55	0.026	0.0144
branch street No.1	6.0	0.33	0.061	0.0152
branch street No.2	9.2	0.51	0.093	0.0335

Table 5. Average metrics for human

	N	DEN	OL	EFF
main street crossing	45.2	1.29	0.060	0.0601
main-branch	36.9	1.05	0.049	0.0490
branch-branch	31.2	1.73	0.315	0.1135
main street	22.0	0.63	0.029	0.0105
branch street No.1	15.1	0.84	0.153	0.0976
branch street No.2	10.9	0.61	0.110	0.0705

4.2. Analysis of behavior patterns

The Apriori algorithm is used to find important patterns of neighborhood transportation. There are trivial but also interesting transportation patterns at main road crossings or main-branch road intersections.

(1) Rush hour in the morning: During the morning rush hour on main roads, street density is high as cars converge, leading to increased congestion. Occupancy levels rise due to the substantial number of vehicles. However, transportation efficiency can be compromised due to congestion, resulting in slower traffic flow and potential delays. On the one hand, main road crossings usually have the higher street density, as cars come from different directions. Vehicles are observed to be more closely spaced at the intersection while pedestrian presence may also be lower due to safety concerns. As a result of the traffic jam that could be caused by the dense flow of the vehicles, transportation efficiency may be affected.

(2) Residential flow in the morning: Also, during rush hour, residential areas with branch roads notice a moderate flow of traffic as residents travel locally. The occupancy levels could be increased because on-street parking and driveways are used up. While the density is moderate, the efficiency of transport is still relatively fair and therefore, the flow of movement is smooth.

(3) Increase of occupancy in the afternoon: Branch roads are likely to have more street density as people return home and spend time in the local community. Income increases when cars are parked, and when driveways are used. The transportation efficiency would be slightly affected by the intensified activity, but the mixed modes of transportation make it a dynamic balance. In the afternoon, at main-branch intersections, street density might rise due to increased residential vehicle activity. Occupancy levels reflect the influx of cars entering branch roads. Pedestrian and bicycle movement adds vibrancy, and while transportation efficiency might be slightly affected by the higher vehicle volume, the diverse mode utilization maintains a dynamic balance.

(4) Small raise in the evening: Branch roads could have a moderate street density as residents engage in recreational activities during the evening. Occupancy levels might be slightly higher due to social gatherings. Transportation efficiency could be influenced by the mix of modes, particularly if pedestrians require extended crossing times.

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At the same time, main road crossings exhibit fluctuations in street density based on leisure activities. Occupancy levels could vary, but pedestrian presence becomes more prominent as social gatherings and events take place. Bicycles could contribute to a balanced transportation mix. Transportation efficiency may fluctuate, particularly if pedestrians require extended crossing times.

(5) Calm at nighttime: Both main and branch roads experience low street density at night, ensuring a quiet transportation environment. Occupancy levels decrease significantly, leading to efficient movement. Transportation efficiency is heightened due to the absence of congestion and reduced vehicle presence.

At night, main road crossings display reduced street density, creating a calm traffic environment. Occupancy levels are lowered, providing safer opportunities for pedestrian crossings. Bicycles are less common due to visibility concerns, and transportation efficiency is heightened as traffic eases, ensuring smoother transitions.

4.3. Improvement and optimization suggestions

Based on patterns, some optimizing suggestions for the neighborhood are provided to improve transportation efficiency, safety, and quality of residential life. Here are some suggestions for optimizing the patterns, considering street density, occupancy levels, and transportation efficiency. Additional suggestions were proposed for optimizing patterns at main road crossings or main-branch road crossings.

(1) Optimizations for rush hour in the morning: For main roads, smart traffic management systems should be installed to adjust traffic signal timings dynamically based on real-time traffic conditions. This can help reduce street density, enhance transportation efficiency, and minimize delays.

(2) Improvements for residential flow in the morning: This pattern only happens on branch roads. The city planning bureau should create designated bicycle lanes and pedestrian walkways to encourage non-motorized transportation. Install traffic calming measures like speed bumps to enhance safety. This reduces street density, promotes active transportation, and enhances safety for pedestrians and cyclists.

Specific crossings as pedestrian priority zones should be built with enhanced markings, textured surfaces, and elevated visibility to encourage drivers to yield to pedestrians.

(3) Optimizations for the increase of occupancy in the afternoon: Public service of additional off-street parking facilities should be built to reduce on-street parking demand and enhance road capacity. This helps reduce occupancy levels, improves transportation efficiency, and minimizes parking-related congestion. Also, fine-tune traffic signal timing to allow for longer pedestrian crossing times, ensuring that pedestrians have ample time to cross without feeling rushed. The community should gather input from pedestrians, cyclists, and drivers to ensure that solutions address specific needs and concerns.

(4) Suggestions for small raise in the evening: At certain points of branch roads, the government should design pedestrian-friendly zones in certain areas during the evening hours, closing them off to vehicular traffic. Enhance street lighting and provide bicycle parking facilities. Doing this helps reduce street density, promotes pedestrian and cyclist safety, and creates inviting community spaces. Night vision is relatively low, and additional traffic calming measures near crossings are essential, such as textured road surfaces, speed tables, or chicanes, to encourage lower speeds and safer crossings.

By implementing these optimization suggestions, neighborhood transportation can become more efficient, safer, and more conducive to different modes of movement. It’s important to involve local stakeholders, transportation planners, and urban designers to tailor these solutions to the specific needs and characteristics of the neighborhood.

5. Conclusion

In conclusion, this paper has examined the transportation behavior of cars, bicycles, and pedestrians in an Asian neighborhood using YOLO object detection. Key methods of transportation objects and behaviors in traffic were emphasized. First, the major transportation objects such as buses and cars were identified through photos and videos of an ordinary Asian neighborhood. Then, the key efficiency indicators of the transport behavior were suggested and the time and road required different metrics were calculated. Lastly, diverse behavior patterns have been analyzed, and optimization suggestions based on the findings are being proposed. The result of the application was that various means of transportation in a certain neighborhood differed in terms of efficiency due to the behavior patterns, and object detection method was a suitable tool to find the suggestions about traffic management, safety, and city infrastructure. Limitations of this paper may exist regarding seasonal variations and local factors. And YOLO object detection has limitations in handling crowded and complex traffic scenarios. Future research should consider long-term data collection, incorporating weather and cultural factors, and consider more into the dynamic features of the Asian neighborhood.

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