Research Article

Smart traffic monitoring with YOLOv9 object detection algorithm

Recep Bilal Sıkar [1*], Sinem Bozatlı Kartal [2]
[1*,2] Istanbul University-Cerrahpaşa, Faculty of Engineering, Department of Civil Engineering, Istanbul, TURKİYE
[2] Yalova University, Faculty of Engineering, Department of Transportation Engineering, Yalova, TURKİYE
*Correspondence: recep.sikar@iuc.edu.tr
DOI: 10.51513/jitsa.1527571

Abstract: Rapid advancements in artificial intelligence technology have enabled computer vision to be utilized across a wide range of engineering disciplines. This study examines the practical solutions offered by image processing technology in manual counting applications and the accuracy of advanced algorithms. The applicability and performance of the YOLOv9 algorithm in traffic counts have been evaluated. The research shows that the algorithm operates with high accuracy and minimizes human error. The study involves classification and counting operations for three different types of vehicles. According to the results, cars and trucks are detected with over 95% accuracy, while smaller objects like motorcycles have slightly lower accuracy. The successful application of YOLOv9 in vehicle counting and traffic management underscores the significance of object detection technology in intelligent transportation systems. This study illustrates how such technology can enhance traffic management efficiency, offering valuable insights for future implementations. The key role that advanced algorithms like YOLOv9 can play in the development of intelligent transportation systems is an important topic for future researchers and industry professionals.

Keywords: Artificial intelligence, YOLOv9, smart traffic monitoring, vehicle counting

YOLOv9 nesne tespit algoritması ile akıllı trafik izleme

Özet: Yapay zeka teknolojisindeki hızlı gelişmeler, bilgisayarla görmenin geniş bir mühendislik disiplini yelpazesinde kullanılmasını mümkün kılmıştır. Bu çalışma, görüntü işleme teknolojisinin manuel sayım uygulamalarında sunduğu pratik çözümleri ve ileri algoritmaların doğruluğunu incelemektedir. YOLOv9 algoritmasının trafik sayımlarındaki uygulanabilirliği ve performansı değerlendirilmiştir. Araştırma, algoritmanın yüksek doğrulukla çalıştığını ve insan hatasını en aza indirdiğini göstermektedir. Çalışma, üç farklı araç türü için sınıflandırma ve sayım işlemlerini içermektedir. Sonuçlara göre, arabalar ve kamyonlar %95'in üzerinde doğrulukla tespit edilirken, motosiklet gibi daha küçük nesneler biraz daha düşük doğruluk oranına sahiptir. YOLOv9'un araç sayımı ve trafik yönetiminde başarılı bir şekilde uygulanması, nesne algılama teknolojisinin akıllı ulaşım sistemlerindeki önemini vurgulamaktadır. Bu çalışma, bu tür teknolojilerin trafik yönetim verimliliğini nasıl artırabileceğini göstermekte ve gelecekteki uygulamalar için değerli içgörüler sunmaktadır. YOLOv9 gibi gelişmiş algoritmaların akıllı ulaşım sistemlerinin geliştirilmesinde oynayabileceği kilit rol, gelecekteki araştırmacılar ve sektör profesyonelleri için önemli bir konudur.

Anahtar Kelimeler: Yapay zeka, YOLOv9, akıllı trafik izleme, araç sayımı

ORCID: 0000-0002-5328-2844, 0000-0002-8285-6050
Received 03.08 2024; Received in revised form 04.10.2024; Accepted 26.10.2024

1. Introduction

Smart cities aim to achieve sustainable economic development based on new and smart technologies and to ensure a better quality of life. The purpose of building a smart city is a strategy developed to alleviate problems such as scarce resources, environmental pollution, and traffic congestion (De Paz et al, 2016). In this regard, intelligent transportation systems have become a rapidly developing field to meet the need to cope with the complex transportation systems of cities today. In this transformation, artificial intelligence technologies are pioneering groundbreaking innovations, especially in smart transportation systems. With its capabilities to analyse large data sets, recognize complex patterns, perform predictive analysis, and make fast decisions, artificial intelligence offers revolutionary solutions in several critical application areas, from traffic management to driver safety. For example, object detection algorithms, especially advanced artificial intelligence models such as YOLOv9, are used effectively in real-time vehicle counting, traffic density analysis and route optimization. Applications such as artificial intelligence-supported traffic signal control systems, smart parking management and autonomous vehicle technologies make the vision of making cities' transportation networks more efficient, sustainable, and safe come true. In this context, artificial intelligence technologies, as the cornerstone of smart transportation, play an important role in improving city life and providing solutions to the mobility needs of the future.

There are three methods generally used for traffic control. The first of these is manual control with the traffic police. This method requires a lot of manpower. The other is traditional traffic lights with static timers. Traffic signal timers operate on fixed periods and do not consider real-time traffic density. The last method is electronic sensors. It is the method in which traffic-related data is obtained with the help of detectors and sensors placed on the roads and traffic signals are arranged according to this data. The most important disadvantages of this method are the limited sensor ranges and the need for expensive technologies to collect high-quality information. With the increase in the number of vehicles in recent years, these methods have been insufficient to provide solutions to problems such as traffic congestion, waiting times in traffic, unwanted fuel consumption and therefore air pollution, rule violations, and accidents caused by driver stress. This situation increases the need for intelligent transportation systems (Gökcan et al, 2023).

Object detection, a key aspect of computer vision, involves identifying and classifying objects while determining their location within an image by creating bounding boxes. Traditional methods include background subtraction, optical flow, and interframe differences. In contrast, deep learning-based algorithms enhance vehicle detection by training on datasets and extracting relevant features, leading to more accurate and efficient object recognition (Gökcan et al, 2023).

Convolutional neural networks (CNNs) have made a breakthrough in computer vision tasks and have achieved great success in traffic signs classification. YOLO (You only look once) has become a central real-time object detection system for robotics, driverless cars and video surveillance applications. Literature studies conducted in this context Terven et al. provide a comprehensive analysis of the evolution of YOLO by examining the innovations and contributions in each iteration from the original YOLO to YOLOv8 (2023). In another study, Kıvrak & Gürbüz (2023) conducted a case study on various YOLO models to determine the best performing version. Their research focused on vehicle classification, emphasizing the importance of accurate and efficient classification methods for transportation applications. The study also provides insights into the development of new algorithms and methods for improving vehicle classification. Zhang et al. (2017) introduced a Chinese traffic sign detection algorithm utilizing a deep convolutional network. They developed an end-to-end network, inspired by YOLOv2, to achieve real-time detection of Chinese traffic signs. As research in this field has advanced, newer versions of YOLO have been developed, building upon these initial methods to improve detection accuracy and efficiency. Yang optimized the YOLOv3 network to improve road traffic sign recognition. By improving the original FPN structure and using techniques such as color enhancement, the modified YOLOv3 achieves better accuracy, speed and efficiency in recognizing traffic signs compared to the traditional YOLOv3 algorithm (Yang, Z. 2022). Onar et al. (2023) investigated the effectiveness of various image enhancement algorithms in improving low-light images. In their work, they evaluate the effects on object detection using the YOLOv3 computer vision algorithm. Huang et al. (2023) proposed the YOLOv8 method, a version of YOLO developed as a solution to the low accuracy problem in detecting traffic signs.

YOLOv9 is an object detection model that pushes the boundaries of both speed and accuracy. Developed by Chien-Yao Wang, I-Hau Yeh and Hong-Yuan Mark Liao, this algorithm offers innovative techniques to increase efficiency and precision. Wang et al (2024) designed generalized ELAN (GELAN) based on ELAN. This design enables users to select computation blocks tailored to different inference devices. The integration of PGI and GELAN led to the creation of the YOLOv9 object detection system, which was tested on the MS COCO dataset. The results showed that YOLOv9 outperformed previous models across all benchmarks. The source code for YOLOv9 was later made publicly available, allowing users to train their own models.

With developing technology, artificial intelligence-based solutions in the fields of traffic management and city planning play an important role in managing traffic efficiently and increasing the safety of drivers. In this context, the YOLOv9 algorithm, which has an important place in the field of object detection, exhibits superior performance, especially in tasks such as vehicle counting and traffic density detection. In this article, we will focus on their success in real-time vehicle type detection and vehicle counting using the YOLOv9 algorithm. While the fast and effective object detection capabilities provided by YOLOv9 open new horizons in traffic analysis and management, we will provide an in-depth look at the potential of this technology.

2. Material and Method

2.1. Deep Learning and YOLOv9

Deep learning is a sub-branch of machine learning that uses mathematical model-based algorithms called artificial neural networks. This method is designed to extract meaningful features from large and complex data sets and learn complex tasks automatically. Deep learning is usually achieved through multilayer artificial neural networks, which process information in a way like the neural networks of the human brain.

Deep learning algorithms, designed to mimic the human brain's learning process by extracting features from large datasets, have surpassed human performance in some complex computational tasks. Their success across various domains has led to increased adoption in remote sensing applications (Saralıoğlu and Güngör, 2022).

Image processing is a field that involves the ability of computers to extract information and make predictions from images and videos. This technology focuses on the ability of computers to distinguish images with desired characteristics and recognize these images through neural networks. Neural networks significantly improve the image processing capabilities of computers by analyzing complex visual data and being used effectively in tasks such as recognizing patterns, classifying objects, and making predictions.

Stable and efficient system for object detection. Following RCNN, Fast RCNN, and Faster RCNN, YOLO was developed as a new way to solve object detection most simply and efficiently (Sirphy and Revathi, 2023).

YOLO is known as the most common algorithm using CNN for real-time object tracking. The first version was released in 2015, and newer and more advanced models followed in the following years (Wang et al, 2024). In this study, the version called YOLOv9, released on February 21, 2024 was used. YOLO differs from other methods by working faster and providing more accurate results. It also provides flexibility in terms of optimizing between accuracy and speed at any time. Figure 1. demonstrates the architecture of YOLOv9.

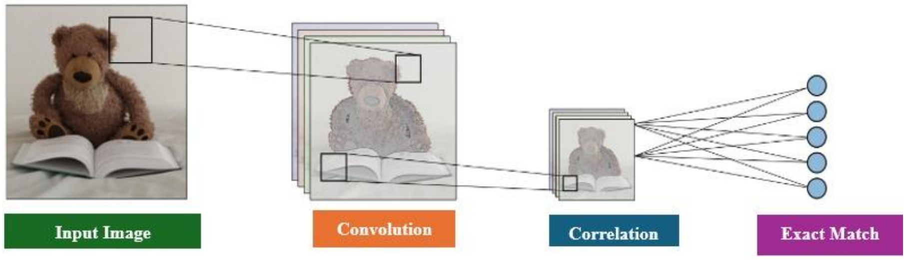

Figure 1. YOLOv9 Model Architecture (Amidi and Amidi, 2019).

YOLO is a real-time object detection algorithm based on a Convolutional Neural Network (CNN). It detects objects with a single pass through the image, treating object detection as a regression task. YOLO divides the image into grids and predicts class probabilities and bounding boxes simultaneously. This approach allows for efficient and accurate object detection in one run. (Sirphy and Revathi, 2023).

The YOLO family, introduced in 2015, is a well-known object detection framework. It stands out for its single-stage approach, which has made it a leading and efficient detection algorithm, quickly becoming a mainstream choice in the field.

The original YOLO, also known as YOLOv1, approaches detection as a regression task. It uses a single convolutional network to simultaneously predict multiple bounding boxes and the corresponding class probabilities for each (Du, 2018). The systematics of CNN is shown in Figure 2.

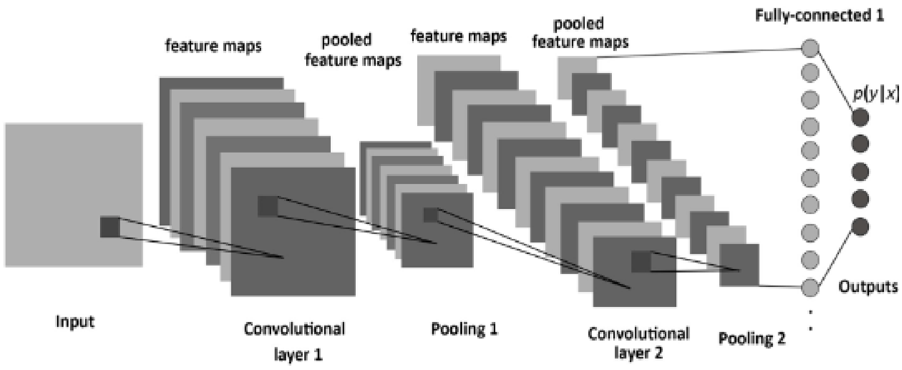

Figure 2. CNN systematics (Albelwi and Mahmood, 2017).

YOLOv9 represents a significant step forward in real-time object detection, offering significant improvements in efficiency, accuracy, and adaptability. Addressing critical challenges with innovative solutions PGI and GELAN, YOLOv9 sets a new example for future research and applications.

YOLOv9 emerges as a powerful model that offers innovative features that will play an important role in further improving object detection and even image segmentation and classification in the future.

In this study, the YOLOv9c model, which was trained on the MS COCO dataset, was utilized. The COCO (Common Objects in Context) dataset is widely used for object detection, segmentation, and captioning tasks, serving as a comprehensive resource for computer vision applications. It was developed to support research across a broad range of object categories and is commonly utilized for benchmarking the performance of computer vision models. As a key dataset, it is indispensable for researchers and developers working on tasks such as object detection, segmentation, and pose estimation.

MS COCO is a widely used benchmark dataset for object detection, segmentation, and captioning tasks. It contains over 200,000 labeled images, with more than 80 object categories, and provides rich contextual information about the objects in various real-world scenarios (Lin et al., 2014).

Table 1. presents a comprehensive comparison of state-of-the-art real-time object detectors, illustrating YOLOv9's superior efficiency and accuracy.

Table 1. MS COCO Dataset.

Model	Size (pixels)	mAPval 50-95	mAPval 50	Parameters (M)	FLOPs (B)
YOLOv9t	640	38,3	53,1	2	7,7
YOLOv9s	640	46,8	63,4	7,2	26,7
YOLOv9m	640	51,4	68,1	20,1	76,8
YOLOv9c	640	53	70,2	25,5	102,8
YOLOv9e	640	55,6	72,8	58,1	192,5

The YOLOv9 model architecture outperforms popular YOLO models like YOLOv8, YOLOv7, and YOLOv5 in terms of mAP (mean Average Precision) when evaluated on the MS COCO dataset (Wang et al, 2024). The fact that YOLOv9 is much superior to scratch training methods in terms of computational complexity is revealed in the model performance obtained from the study, seen in Figure 3.

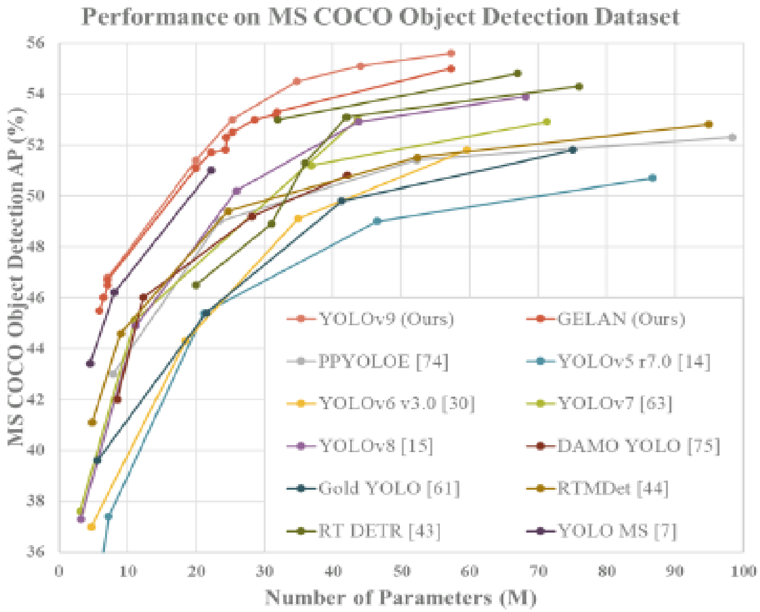

Figure 3. YOLOv9 model performance (Wang et al, 2024).

2.2. A Case Study using YOLOv9

This study was carried out on Deniz Street in the Mudanya District of Bursa Province and is based on data obtained from camera recordings. The time examined covers between 18:00 and 19:00. The image of Deniz Street on the map is shared in Figure 4, and the traffic image is shared in Figure 5.

Deniz Street is located geographically close to Mudanya Pier, so the street examined within the scope of the research is a line where vehicle traffic is relatively intense.

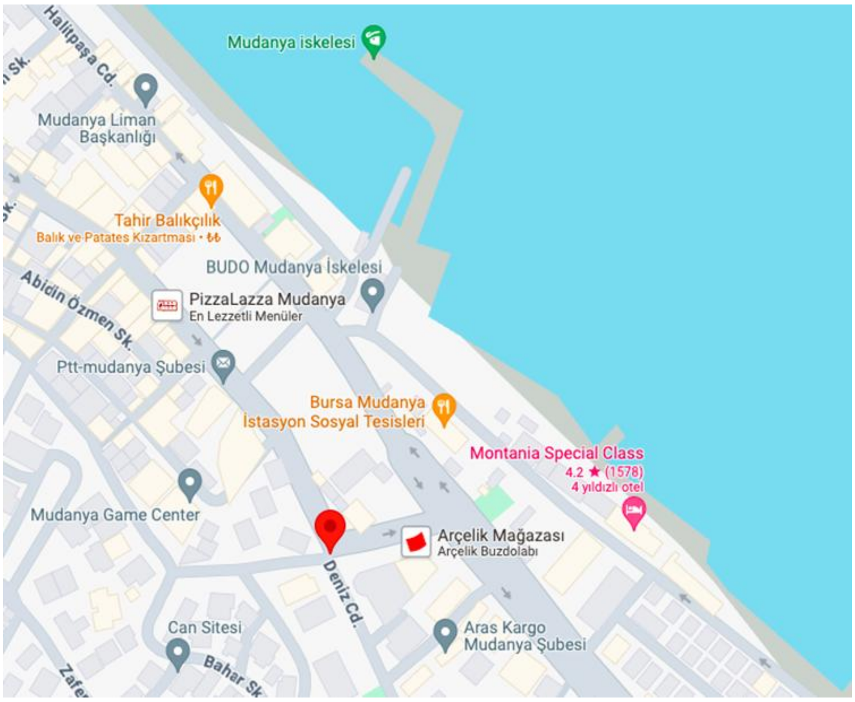

Figure 4. Location of Deniz Street.

Figure 5. Deniz Street.

In the study, the pre-trained YOLOv9c model using the YOLO (You Only Look Once) algorithm from the Ultralytics library was used. This model is a deep learning model that can detect and classify objects in visual data. The prediction was made on the video file. During this process, the input image size of the model was determined as 320 pixels and the confidence threshold of the determinations was determined as 0.5. The predictions made were processed and recorded, including the types and locations of objects on the image. Figure 6 shows that the class is determined for each object and a different identification number is assigned to each object.

Figure 6. Object detection using YOLOv9.

2.2.1. Vehicle counting

This study was carried out on a computer with an i7 processor and a GTX 3050 Ti graphics card. This is very advantageous for YOLOv9's performance. Deep learning-based object detection models such as YOLOv9 accelerate computational operations by leveraging the parallel processing capabilities of GPUs (Graphics Processing Unit). In this case, a computer powered by a powerful graphics card such as a GTX 3050 Ti will enable the YOLOv9 model to run faster and more effectively.

GPU enables parallel calculations in the detection and tracking phases of YOLOv9, providing much faster results. Especially when working with large datasets or high-resolution images, GPU-based computing can be much faster and more efficient compared to the processor.

Therefore, the fact that this study was carried out on a computer with an i7 processor and a GTX 3050 Ti graphics card allows maximum efficiency from the performance of YOLOv9. This combination of hardware can perform complex image processing tasks such as object detection and counting faster and more precisely.

Additionally, the following steps were followed for vehicle counting with YOLOv9:

1. Preparation of Inputs: In the first step, the OpenCV (cv2) library is used to read a video file. This video contains the footage from which to track the vehicles and determine the line. The YOLOv9 model is loaded to be used for detecting and tracking vehicles.

2. Tracking and Detection: Vehicles are detected and tracked using the YOLO model on each frame. This process is applied to determine the types of vehicles (car, truck, motorcycle) and ensure that each vehicle is tracked.

3. Defining the Line: A line is defined to determine the passage of vehicles. This line is used as a visual reference point and a counter is incremented when the line is detected to be crossed.

4. Tracking and Counting: In each frame, the program keeps tracking the detected vehicles and checks whether they cross the designated line. When a vehicle crosses the line, a counter is incremented depending on the vehicle type involved.

5. Visualization of Results: In each frame, detected vehicles and line-crossing states are visually displayed. These are achieved through drawn rectangles and texts.

Figure 7 shows the vehicle counting output for the northbound traffic flow.

Figure 7. Vehicle counting using YOLOv9.

3. Results and Discussion

3.1. Model Performance

As a result of the study, vehicle counts obtained with YOLOv9 were compared with vehicle counts made via video recording by two different observers. Metrics evaluated include the number of cars, trucks, and motorcycles over 15 minutes. The results are seen in Table 2 and Table 3.

Table 2. Vehicle counting results 1.

	YOLOv9			**Observer 1**		
Duration	Car	Truck	Motor cycle	Car	Truck	Motorc ycle
15 min	271	3	13	275	3	18
15 min	267	0	11	278	0	20
15 min	291	2	13	305	2	15
15 min	265	3	8	267	2	9

Table 3. Vehicle counting results 2.

	YOLOv9			Observer 2		
Duration	Car	Truck	Motorcycle	Car	Truck	Motorcycle
15 min	271	3	13	279	3	18
15 min	267	0	11	278	0	19
15 min	291	2	13	307	2	16
15 min	265	3	8	267	2	8

In the context of car detection, YOLOv9 achieves results comparable to human observers, although it shows slight variations in different samples. The algorithm demonstrates its effectiveness by correctly detecting most cars. However, in some cases, differences occurred between the observers and the algorithm.

Equation 1 expresses the ratio of the number of motorcycles detected by YOLOv9 to the number of motorcycles detected by human observers. This ratio shows how accurate the algorithm produces results compared to human observers. This ratio being close to 1 indicates that YOLOv9 produces similar results to human observers. However, if the ratio moves away from 1, it can be understood that the algorithm is experiencing some difficulties or there are areas for improvement.

$$\text{Motorcycle detection ratio} = \frac{\text{YOLOv9 Motorcycle Count}}{\text{Human Observer Motorcycle Count}} \quad (1)$$

$$\text{First 15 minutes for observer 1 and 2 motorcycle detection ratio} = \frac{13}{18} = 0.72 \quad (2)$$

$$\text{Second 15 minutes for observer 1 motorcycle detection ratio} = \frac{11}{20} = 0.55 \quad (3)$$

$$\text{Second 15 minutes for observer 2 motorcycle detection ratio} = \frac{11}{19} = 0.58 \quad (4)$$

$$\text{Third 15 minutes for observer 1 motorcycle detection ratio} = \frac{13}{15} = 0.87 \quad (5)$$

$$\text{Third 15 minutes for observer 2 motorcycle detection ratio} = \frac{13}{16} = 0.81 \quad (6)$$

Regarding motorcycle detection, YOLOv9 shows that it can identify motorcycles and the results closely match human observation. However, as seen in equations 2,3,4,5, and 6 some differences are observed from time to time due to difficulties in accurately detecting smaller objects such as motorcycles in crowded environments.

To improve the performance of the algorithm for motorcycle detection, a deeper and more comprehensive feature extraction process is required. For small objects such as motorcycles, better extraction of salient features is critical for more accurate identification. Additionally, image quality improvement is necessary to improve the performance of the algorithm. Low light conditions or blurry images can make it difficult for the algorithm to detect objects accurately. Therefore, the use of higher resolution and clearer images can contribute to the algorithm producing more reliable results.

Regarding truck identification, YOLOv9 also performs reasonably well and maintains consistency in its detections across experiments. There are very small differences between YOLOv9's counts and those of human observers. These differences are at a margin level and do not affect the overall performance of the algorithm.

3.2. Performance Metrics

As seen in Figure 8., the precision value for each second over 60 seconds was consistently achieved as 1. The model generally operates with high accuracy. Precision measures how many of the model's positive predictions are true positive. Therefore, obtaining a precision value of 1 at every second indicates that the model consistently and accurately detects objects. The fact that the precision value remains stable and high demonstrates that the model performs effectively, regardless of object density or scene conditions.

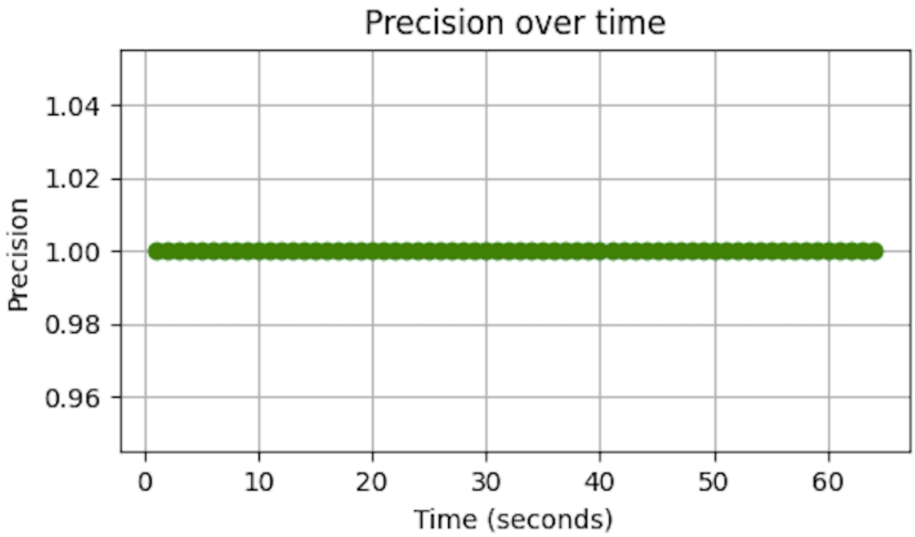

Figure 8. Precision over time

The recall value, calculated for each second over 60 seconds, starts at 0.46 and rises to 0.56, where it stabilizes. This indicates an improvement in the model's detection performance and shows that it can detect a large portion of the positive classes. The model can be further optimized to achieve higher recall values, especially in more complex scenes.

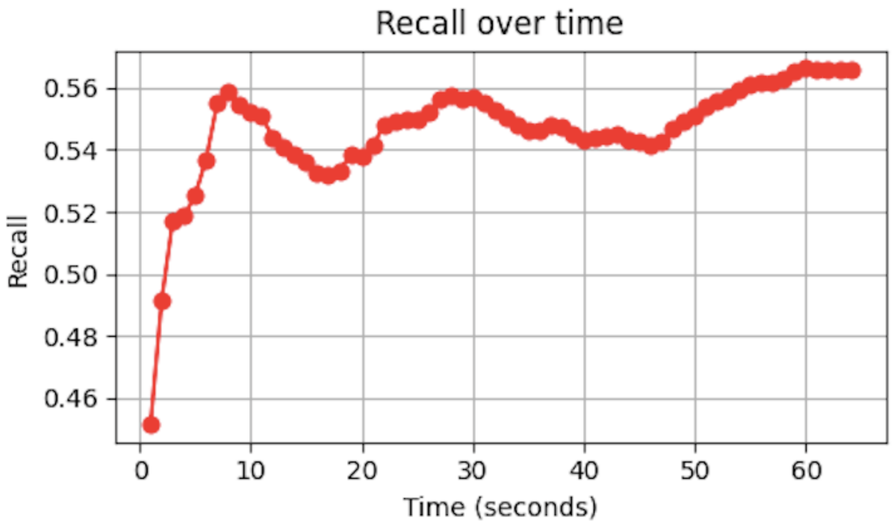

Figure 9. Recall over time

The Intersection over Union (IoU) values obtained over the 60 seconds, ranging between 0.70 and 0.85, indicate that the objects detected by the model are very close to the ground truth. IoU measures how much the predicted bounding boxes overlap with the actual object. This value represents the ratio between the intersection area and the union area of the detected object and the real object.

The IoU values fluctuating between 0.70 and 0.85 demonstrate that the model accurately detects the position and boundaries of objects in most cases. Particularly, IoU values close to 0.85 suggest that the predicted boxes almost perfectly overlap with the real objects. This shows that the model operates with high precision and performs strongly in object localization, with detected objects being very close to the actual objects.

On the other hand, when IoU drops to around 0.70, it indicates that the model sometimes predicts the boundaries of objects less accurately. Still, an IoU value of 0.70 is considered acceptable in most applications, as it means the model generally provides correct boundaries for the objects. These results suggest that the YOLOv9 algorithm used in the study offers consistent and reliable performance in object detection, especially in real-time applications, and that the errors in object boundary prediction are minimal.

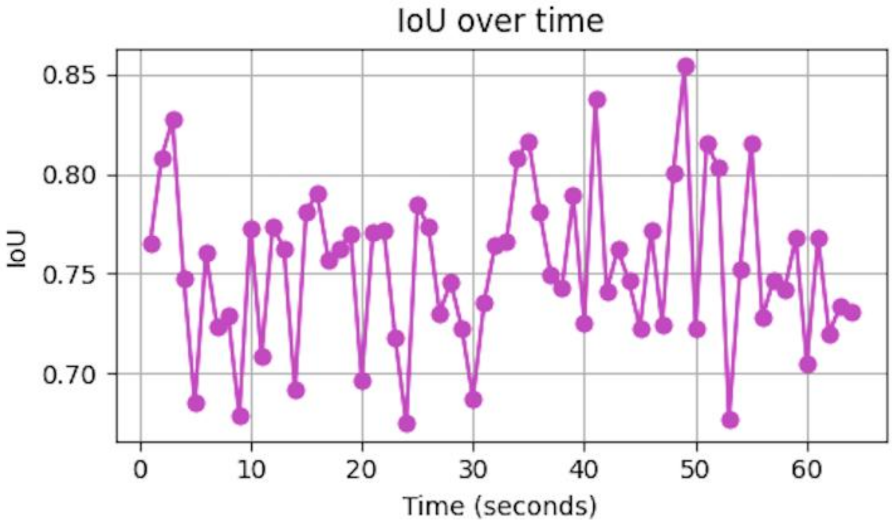

Figure 10. Intersection over Union (IoU) over time

4. Conclusion and Recommendation

Accurate computer-based operations, such as vehicle identification, are crucial due to their wide range of applications in areas like traffic monitoring, autonomous vehicles, and intelligent transportation systems. Various deep mesh-based deformations have been proposed for classifying and identifying vehicles, including convolutional neural networks (CNNs), YOLO runs, template matching, and feature-based techniques. YOLO provides useful information on various options to increase productivity, safety and reliability for real-time monitoring and decision-making possibilities. YOLOv9's object detection and design software is prepared with original software. YOLO's real-time image processing capability makes it ideal for vehicle features and appearances.

In this study, YOLOv9 performed above 95% on car and truck detection tasks, except for small objects such as motorcycles. This demonstrates the usability of the algorithm as a reliable automatic system in real-world applications. Although there are minor differences compared to human observation, the algorithm's ability to consistently detect and classify vehicles highlights its usability in a variety of environments. Additionally, continued advances in deep learning techniques and model improvements are expected to further improve YOLOv9's performance and applicability in various environments, as well as its performance in detecting small objects such as motorcycles.

YOLO outperforms other object detection algorithms by offering faster and more accurate real-time detection. The integration of convolutional neural networks and advanced machine learning techniques has greatly improved the precision and efficiency of vehicle detection and classification, enabling the real-time processing of large datasets. This technology enhances driving safety, optimizes traffic flow, and enables autonomous driving. It is increasingly important to develop models for tracking, identifying, and categorizing vehicles to detect traffic violations and manage congestion. Vehicle counting helps authorities assess traffic conditions, preventing accidents and bottlenecks. This study contributes valuable insights to the literature on these methods.

Researchers' Contribution Rate Statement

He has contributed to the code. She has spent effort on literature search. They have spent effort on determining the conceptual and design processes of the study, management, and other processes.

Acknowledgment and/or disclaimers, if any

There are no acknowledgment and/or disclaimers.

Conflict of Interest Statement, if any

There is no conflict of interests.

References

Albelwi S, Mahmood A. (2017). A Framework for Designing the Architectures of Deep Convolutional Neural Networks. *Entropy*. doi: 10.3390/e19060242

Amidi A. ve Amidi S. (2019, Nisan 30). CS230-Derin Öğrenme, Evrişimli Sinir Ağları El Kitabı. Stanford Üniversitesi (A. Kızrak ve Y. Kömeçoğlu Çev.). https://stanford.edu/~shervine/l/tr/teaching/cs-230/cheatsheet-convolutional-neural-networks

De Paz, J. F., Bajo, J., Rodríguez, S., Villarrubia, G., & Corchado, J. M. (2016). Intelligent system for lighting control in smart cities. *Information Sciences*, *372*, 241-255.

Du, J. (2018). Understanding of object detection based on CNN family and YOLO. *Journal of Physics: Conference Series* (Vol. 1004, p. 012029). IOP Publishin"g.

Gökcan, A. O., Çöteli, R., and Avcı D. (2023). DETECTION AND CLASSIFICATION OF VEHICLES BY USING TRAFFIC VIDEO BASED ON YOLOV8. *UMTEB – XIV International Scientific Research Congress*, 14–15 September, ss. 530-538.

Huang, Z., Li, L., Krizek, G. C., & Sun, L. (2023). Research on traffic sign detection based on improved YOLOv8. *Journal of Computer and Communications*, *11*(7), 226-232.

Kıvrak, O., & Gürbüz, M. Z. (2022). Performance comparison of yolov3, yolov4 and yolov5 algorithms: A case study for poultry recognition. *Avrupa Bilim ve Teknoloji Dergisi*, (38), 392-397.

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., & Zitnick, C. L. (2014). Microsoft COCO: Common Objects in Context. *European Conference on Computer Vision (ECCV)*. https://doi.org/10.1007/978-3-319-10602-1_48

Onar, O., Akkuş, B., and Çavuşoğlu, G. (2023). Düşük Işıklı Görüntüler için Görüntü İyileştirme Algoritmalarının Değerlendirilmesi ve YOLO V3 Kullanılarak Nesne Algılama Üzerindeki Etkisi. *3. ULUSLARARASI AKILLI ULAŞIM SİSTEMLERİ KONFERANSI* ITSC'23, 15–17 November.

Saralıoğlu, E., & Güngör, O. (2022). Yüksek çözünürlüklü uydu görüntülerinden daha hızlı bölge tabanlı derin öğrenme modeli ile bina tespiti. *Gümüşhane Üniversitesi Fen Bilimleri Dergisi*, *12*(2), 550-563.

Sirphy, S., & Revathi, S. T. (2023). Adaptive Traffic Control System Using YOLO. *2023 International Conference on Computer Communication and Informatics (ICCCI)* (pp. 1-5). 23-25 January.

Terven, J., Córdova-Esparza, D. M., & Romero-González, J. A. (2023). A comprehensive review of yolo architectures in computer vision: From yolov1 to yolov8 and yolo-nas. *Machine Learning and Knowledge Extraction*, *5*(4), 1680-1716.

Wang, C.-Y., Yeh, I.-H., & Liao, H.-Y. M. (2024). YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information. Retrieved from http://arxiv.org/abs/2402.13616

Yang, Z. (2022). Intelligent recognition of traffic signs based on improved YOLO v3 algorithm. *Mobile Information Systems*, *2022*(1), 7877032.

Zhang, J., Huang, M., Jin, X., & Li, X. (2017). A real-time Chinese traffic sign detection algorithm based on modified YOLOv2. *Algorithms*, *10*(4), 127.