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AN ARTIFICIAL INTELLIGENCE (AI) BASED OVERHEIGHT VEHICLE WARNING SYSTEM FOR BRIDGES

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Impact of overheight vehicles on bridges is a major problem that causes extensive damage and leads to frequent traffic and mobility issues. This research proposes conceptual development of a low-cost Artificial Intelligence-(AI)-based overheight vehicle warning system for bridges based on the use of cutting-edge camera technology and AI-based height detection. The proposed system consists of a long-range camera and an AI-based overheight detection module that can detect an overheight vehicle from safe stopping distance. Successful implementation of the proposed research will lead to the prevention of a significant number of impacts on bridges by overheight trucks, which will improve safety of bridges and traffic mobility, thereby saving millions of dollars in damage to bridges and preventing injuries and fatalities. However, further research is required to verify accuracy of detection and integration of hardware for implementation.</td></tr>
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An Artificial Intelligence (AI) Based Overheight Vehicle Warning System for Bridges

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Executive Summary

Impact of overheight vehicles on bridges is a major problem that causes extensive damage and leads to frequent traffic and mobility issues. This research proposes conceptual development of a low-cost Artificial Intelligence-(AI)-based overheight vehicle warning system for bridges based on the use of cutting-edge camera technology and AI-based height detection. The proposed system consists of a long-range camera and an AI-based overheight detection module that can detect an overheight vehicle from safe stopping distance. Successful implementation of the proposed research will lead to the prevention of a significant number of impacts on bridges by overheight trucks, which will improve safety of bridges and traffic mobility, thereby saving millions of dollars in damage to bridges and preventing injuries and fatalities. However, further research is required to verify accuracy of detection and integration of hardware for implementation.

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Section 1 Introduction

1.1 Background

Based on 2019 National Bridge Inventory (NBI) database available at the FHWA, there are a total of 617,084 bridges in the United States. Similarly, based on 2019 National Tunnel Inventory (NTI) database available at the FHWA, there are a total of 522 tunnels in the United States. It has been observed from previous research that collision, both caused by vessel and vehicles, is the second leading cause of bridge failures after hydraulic [Agrawal et al. (2018)], as illustrated in Figure 1 below. Most of the bridge and tunnel strikes, which is defined as an impact on bridges or tunnels by Overheight vehicles, have been observed to cause damages to bridge superstructure or tunnels and traffic congestions, and may sometimes cause significant enough damage to warrant the replacement of a bridge.

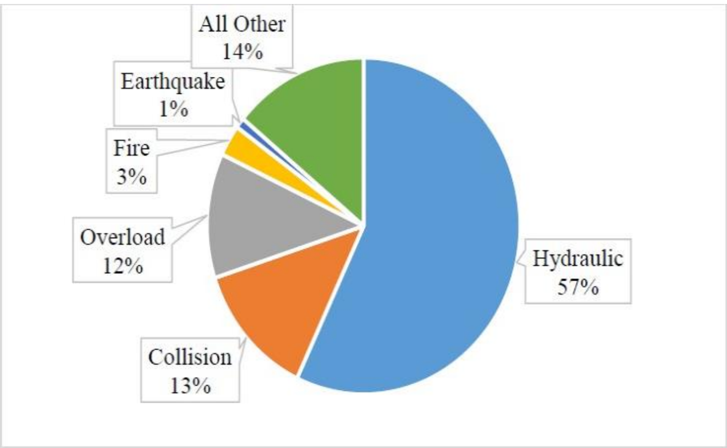

Figure 1. Causes of Failure of Bridges in USA

Although bridge/tunnel strikes have been a common occurrence, few studies have focused on systematic investigation on causes of occurrence and mitigation approaches. Bridges in New York State have been experiencing close to 200 documented strikes a year with many strikes going unnoticed or noticed during biennial bridge inspections. Primary causes of these overheight impacts include the use of consumer GPS by commercial truck drivers and other haulers, improperly stored equipment on trucks, violation of vehicle posting signs, illegal commercial vehicles on parkways, etc.

1.2 Literature Review

One of the earliest studies on collision of overheight vehicles with bridges was by Fu (2001) and Fu et al. (2003). They studied the problem of over-height vehicle collision using bridge collision data for bridges in Maryland. They found that 1,496 bridges were susceptible to over- height vehicle collision out of the total Maryland Bridge Inventory of 5,056 structures, and the frequency of overheight accidents reported in Maryland increased by 81% between 1995 and 2000. This study also showed a close correlation between bridge strike and vertical under- clearance. Prior to Fu (2001), Hilton (1973) investigated general accidents involving highway bridges in Virginia to characterize bridges that had been the scene of frequent accidents. “Inadequate vertical clearance” was listed as a key contributing factor. Shanafelt and Horn (1980, 84) reported on damage evaluation and repair methods for steel and prestressed concrete bridge members through a countrywide survey.

Following the studies described above, one of the most comprehensive studies on bridge and tunnel strikes, published as a report entitled “Bridge Vehicle Impact Assessment” was by the PI [Agrawal et al. (2011)], that investigated the key causes of bridge strikes in the New York state and nationwide through collection and analysis of the data and nationwide surveys of state DOTs.

Their survey of DOTs nationwide showed that over-height impact on bridge / tunnels is generally a serious problem across the country, as shown in Figure 2.

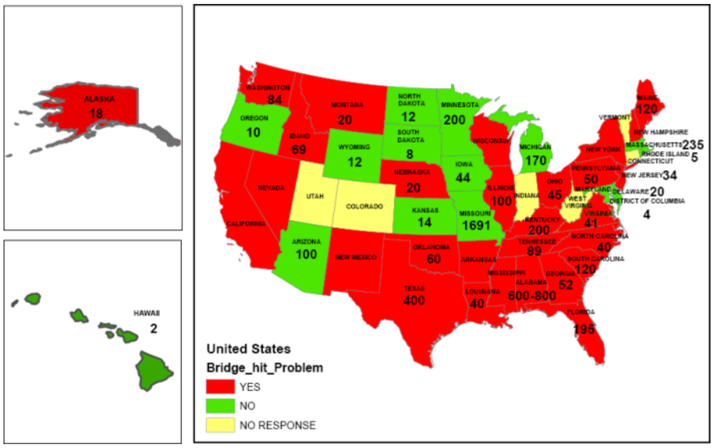

Figure 2. Bridge Strikes in the United States during 2005-2008 (Agrawal et al. 2011).

Several countermeasures have also been investigated for early warning against overheight impact. Horberry et al. (2002) experimentally evaluated a new design of markings for low bridges to prevent bridge strikes and noted that the type of bridge marking influenced the level of caution associated with decisions regarding bridge navigation. Mattingly (2003) investigated the use of overheight warning systems to mitigate bridge strikes through a nationwide survey of State DOTs USA. The prime focus of their survey was on early warning detection warning systems (EWDS), e.g., laser systems, infrared systems, etc. Out of forty-nine State DOTs surveyed, 29 State DOTs responded to the survey. Thirty-eight percent of the responding states (i.e., 11 states) indicated the use of EWDs. Eight out of eleven states using EWDs believed their systems reduced bridge strikes. States that used laser and infrared detection systems appeared to value the reduction in strikes regardless of the small operational difficulties that they experienced.

It has been noted from the survey carried out by Agrawal et al. (2011) a majority of responding states that installed automated vehicle height detection systems rated their systems very effective in reducing number of strikes, maintenance, and overall performance. All these systems run on a 120V power supply and have been supplemented by advanced signing systems to warn truck drivers about the low vertical under-clearance bridge ahead. Overall, it was noted that the Z-Pattern System manufactured by Trigg, with an installed cost in the range of $7,700 - $8,900 and a maintenance cost of $50 per year, was the most effective and economical system with almost no false positives and very few installation/operational issues. Another cost-effective system was the “Pulsed Infra-Red/Pulse LED & IR” system manufactured by Trigg. This system was used by Hawaii DOT with an installed cost range of $13,000 - $14,300.

One of the challenges associated with roadside technologies is the high installation costs in the range of $150,000 per location for some states like New York. In some installations, highway improvements may be required for a truck to safely merge back into traffic, without causing considerable traffic interruptions, in divided lane highways, making overall cost as much as $500,000. With this in consideration, the PI [Singhal et al. (2018)] led to the development of a new and enhanced LIDAR-based OHVDs (L-OHVDs), which can be installed on the face of a structure to be protected and can measure the height of an approaching vehicle before the safe stopping distance for the vehicle from the structure. Figure 3(a) illustrates the working principle of this device and Figure 3(b) shows prototype model of this device. Built using off-the-shelf components, it possesses desirable features like vehicle detection, actual height measurement, collision prediction with no reported false alarms and a height measurement accuracy of ±0.66 inches that is better than available OHVDs. This system has exceptional precision and is well suited to detect over height trucks and tractor trailers approaching a low vertical clearance bridge. At the same time, the device is very cost-effective and has the potential to drastically reduce occurrences of bridge / tunnel strikes. However, the LIDAR based OHVD system isn’t commercially available and its installation, if produced, will require approximately $10,000 per device.

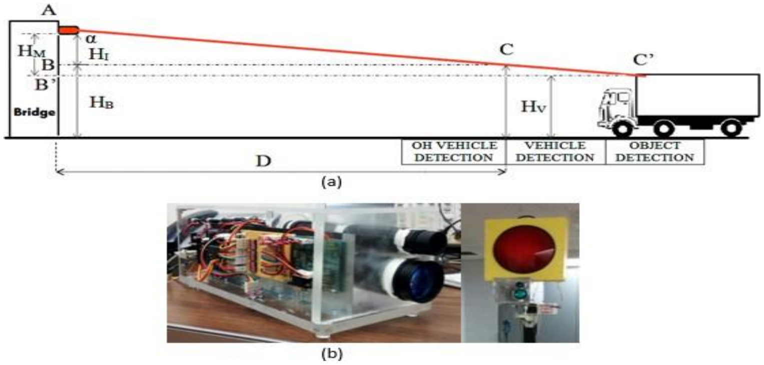

Figure 3. (a) Working Principle of the LADAR-based OHVDs (L-OHVD), (b) Prototype of L-OHVD.

It has been noted from discussions with engineers at many state departments of transportation that the cost of installation, including the cost of the device, is the most-significant impediment. in installation of overheight detection and warning systems at bridges vulnerable to overheight impact. This can be addressed by developing a low-cost Artificial intelligence (AI) based Overheight vehicle warning system by leveraging recent advances in the camera technology and AI based height detection approaches. The proposed system could be installed on the face of a bridge in the direction facing the traffic and could detect an incoming overheight truck from a safe stopping distance. Preliminary and extensive research presented in this report shows that the proposed low-cost system is feasible, although significantly more effort is required before implementation can be considered.

Long-range camera technology has advanced significantly during the last decade. As a result of this, cameras with the capability to clearly take pictures of trucks at distance more than 1000 ft, both during day and night times, are available. These cameras can take high resolution pictures of incoming traffic with trucks. From these images, trucks and their heights can be identified though object identification and segmentation.

There have been significant developments in object identification and segmentation from the image [Song et al (2005), Pasupa et al (2021)]. For the safety of the bridge, the vehicle(truck) dimension must be identified before the safe stopping distance. As mentioned above, current practice for the vehicle dimension detection is very expensive due to installation cost and expensive sensors. Sandidge et al (2012) proposed a cost-effective solution for the height detection of truck using stereo cameras. However, the method was only applicable to daylight with enough illumination and limited range. Recently, researchers estimated the height of object from the image using deep learning segmentation techniques and depth camera [Lee et al (2020), Ali et al, (2020)]. However, the distance of the object to be identified is very limited. Augmented reality (AR) is also being used with deep learning techniques in real time to improve the transparency and effectiveness in safety decisions [Sabeti et al (2021), Neshov et al, (2021)].

1.3 Objective

The main objective of this research is to develop a cost-effective early warning overheight vehicle detection system using the recent development in long-range cameras and artificial intelligence- based vehicle shape and height detection. This is achieved by identifying or customizing a long- range camera technology that can meet harsh field conditions, e.g., clear image up to safe stopping distance during day and night conditions, and during snow and rain and developing an AI based image detection tool that can identify the shape and height of the truck among the vehicles in the high-speed traffic flow.

Detection of overheight trucks in this research is a two-fold approach. It has been shown- by Agrawal et al. (2011) that a majority of overheight impacts in New York State have been on low- clearance bridges over parkways, although trucks are not allowed on parkways. Trucks in the traffic in real-time can be identified from pictures taken by a camera using image processing and artificial intelligence techniques. The detection model must be trained with a large vehicles database in different scenarios for an accurate identification and segmentation of a truck. The identified vehicle from the AI model can be used as input to further steps for the height estimation. Imminent impact by an overheight truck on a bridge will depend on the height of the truck with respect to the vertical under-clearance of the bridge.

In this research, we have developed an approach based on image processing and deep learning to identify the shape of a truck and its height at or before the safe stopping distance for the truck. In the status of the approach, the AI-based model can detect trucks reliably, while the estimation of the height requires significantly more work because of technological challenges encountered. Although many researchers have used artificial intelligence and augmented reality to identify objects [Song et al (2005), Pasupa et al (2021), Sandidge et al (2012), Lee et al (2020), Ali et al, (2020, Sabeti et al (2021), Neshov et al, (2021)], there are several limitations in these studies with respect to direct application to the detection of overheight vehicles. Our research on resolution of these issues is continuing and will be reported in future publications.

Section 2. Methodology

2.1 Problem Statement

The primary aim of this study is to enhance the safety of bridges, particularly those with low clearance heights, by preventing accidents involving overheight vehicles. The presence of such bridges poses a significant risk, as an overheight truck can not only cause substantial damage to the bridge's structure but also disrupt the smooth flow of traffic, resulting in substantial economic losses. Furthermore, these incidents jeopardize the lives of both the truck driver and individuals in the vicinity.

To address this challenge, we have identified two distinct scenarios. First, on roads with low clearance bridges where commercial vehicles (trucks) are not allowed to pass, our objective is to develop a system that can detect approaching trucks from a safe distance and activate warning signs. This approach ensures bridge safety. The second scenario is more complex and arises when trucks are permitted to pass through a bridge if their height is below the available clearance. In this case, our model must not only identify the presence of trucks, but also accurately determine their height from a safe stopping distance. This process involves several crucial steps:

a) **Truck Detection:** Initially, the proposed AI-based model needs to detect the presence of trucks in traffic images, typically at approximately 1000 feet.

b) **Instance Segmentation:** To precisely outline the boundaries of the identified truck, we employ instance segmentation techniques.

c) **Background Removal:** To eliminate background noise and shadows, the model extracts the truck image from the original scene.

d) **Vanishing Point Estimation**: We calculate vanishing points in mutually orthogonal directions to gain a better understanding of the truck's position.

e) **3D Bounding Box Generation:** A 3D bounding box is generated around the vehicle, enhancing our ability to estimate its height.

f) **Height Estimation:** Utilizing the 3D bounding box height in proportion to known objects in the image frame, we accurately estimate the truck's height.

Following the successful development of this height estimation algorithm, laboratory tests and preliminary field trials can be conducted to verify the approach in real-time. These tests will employ cameras with long-range capabilities and powerful processors to execute all the necessary algorithms.

Ultimately, this approach will create a robust system to protect bridges from overheight vehicles, minimizing the potential for accidents, damage, and economic losses.

2.2 Identification of the Long-range Camera Technology

The safe stopping distance for a fully loaded commercial truck driving at 65 mph is approximately 600 ft. Hence, a long-range camera should be able to take pictures of the moving traffic at 600 ft for detection of trucks and their heights. The camera should also be able to operate in outdoor conditions, e.g., night exposure, snow, rain, etc. To ensure effective detection of trucks and their heights, it is crucial to consider the safe stopping distance for a fully loaded commercial truck traveling at 65 mph, which is approximately 600 feet. Therefore, a long-range camera capable of capturing moving traffic at this distance is necessary. Furthermore, this camera should be able to operate reliably in various outdoor conditions, including low-light situations, snow, rain, and more.

In recent years, there has been remarkable progress in camera technology. Based on current advancements, we propose the use of the HXVIEW PTZ Security Camera1 for our application. This camera boasts several impressive specifications:

- It features a 5-megapixel (2560x1920) image resolution and a capture speed of 15 frames per second, ensuring high-quality image capture.
- With a 30 times optical zoom capability, the camera is well-suited to capture clear truck images at the safe distance of 600 feet. The effectiveness of this 30x optical zoom is visually demonstrated in Figure 4.
- In low-light conditions, the camera's night vision capability extends up to 1000 feet, as illustrated in Figure 5, enabling it to capture clear images even in the dark.
- The camera offers the convenience of wireless Wi-Fi connectivity, allowing for seamless data transmission to computers and other communication systems as needed.

[1] HXVIEW PTZ Security Camera Link

(a) (b)

Figure 4. Collaborative approach

Figure 5. Spatial distribution and scale of the selected camera systems in the U.S.

By utilizing the HXVIEW PTZ Security Camera, we can confidently address the challenges posed by varying outdoor conditions and achieve accurate and reliable truck detection and height measurement within the specified safe stopping distance.

2.3 Identification of Trucks in No-truck Regions

There have been significant advancements in artificial intelligence technology, particularly in the field of object detection. Among various object detection algorithms, YOLO (You Only Look Once), initially released in 2015, stands out as the most accurate and efficient. Unlike traditional object recognition algorithms, which involve multiple steps to identify objects, YOLO employs a single- step process to analyze the entire image. This characteristic enhances its speed and efficiency. YOLO predicts bounding boxes and class probabilities for multiple objects within a grid-based framework. Furthermore, YOLO utilizes anchor boxes to enhance detection accuracy and accommodate objects of varying sizes and aspect ratios. The YOLO algorithm can be summarized in the following steps:

1. **Image Preprocessing**: Input images are resized to a standardized square size while maintaining their original aspect ratios and pixel values are scaled to a common range.

2. **Neural Network Framework**: A convolutional neural network (CNN), specifically inspired by the GoogleNet model, is chosen as the backbone architecture.

3. **Grid-based Partitioning**: The resized image is divided into a grid of cells, each responsible for identifying objects within its designated region.

4. **Anchor Boxes**: Predetermined bounding boxes of varying size and aspect ratio (anchor boxes) are introduced to assist in predicting object shapes and locations.

5. **Forward Propagation**: The preprocessed image is passed through the neural network, generating feature maps with different resolutions.

6. **Object Predictions**: For each grid cell-anchor box combination, predictions are made, including object presence likelihood, bounding box coordinates (x, y, width, height), and class probabilities.

7. **Non-Maximum Suppression**: Non-maximum suppression is applied to enhance accuracy by removing redundant or heavily overlapping bounding box predictions with low confidence scores.

8. **Post-processing**: Bounding box coordinates are adjusted from local grid cell coordinates to global image coordinates. Bounding boxes with low probability scores can be filtered out.

9. **Final Object Detection**: Filtered bounding box predictions are merged to yield the ultimate object detections within the image, providing class labels, bounding box coordinates, and confidence scores.

10. **Visual Representation**: Bounding boxes are overlaid onto the original image to visually display the detected objects.

11. **Overall Output**: The YOLO algorithm delivers a comprehensive output, including a list of detected objects, their associated class labels, and corresponding bounding boxes.

Since its introduction, YOLO has evolved through several versions, with each successive version outperforming its predecessor in terms of speed, accuracy, and functionality. As of the current year (2023), Ultralytics2 has introduced YOLOv8 (YOLO version 8), representing a significant leap forward in both speed and accuracy compared to all previous versions of object detection. Notably, YOLOv8 has the capability to perform instance segmentation in addition to object detection. Ultralytics has made available various YOLOv8 models, as detailed in Table 1, all of which come pre-trained on the COCO3 detection dataset. These models vary in size, leading to differences in accuracy (mAP: mean average precision) and speed, allowing users to choose the one that best suits their specific requirements.

	Size (pixels)	mAP^{val}	Speed CPU ONXX (ms)	Speed A100 TensorRT (ms)	Params (M)	FLOPs (B)
YOLOv8n	640	37.3	80.4	0.99	3.2	8.7
YOLOv8s	640	44.9	128.4	1.2	11.2	28.6
YOLOv8m	640	50.2	234.7	1.83	25.9	78.9
YOLOv8l	640	52.9	375.2	2.39	43.7	165.2
YOLOv8x	640	53.9	479.1	3.53	68.2	257.8

Table 1. YOLOv8 Detection Model Features.

YOLOv8m has been used in this project. Our simulation shows that this model is effective in overheight truck detection.

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[2] www.ultraly*cs.com

[3] COCO Dataset

2.4 Vehicle Segmentation and Extraction

Traffic images often contain extraneous elements in the background, such as mountains, electric poles, rocks, bushes, and more. These elements introduce background noise that can impede the accurate identification of trucks during image processing. Additionally, shadows cast by vehicles pose a significant challenge, as they can lead to erroneous estimations of vehicle edges. To address these issues effectively and enable precise height estimation, it is essential to isolate the truck vehicles from the traffic image.

Instance segmentation is effective in achieving this objective. Unlike basic object detection, instance segmentation goes a step further by identifying individual objects within an image and separating them from the surrounding context. For our purposes, YOLOv8 segment models from Ultralytics offer highly accurate instance segmentation capabilities, having been pre-trained on the COCO dataset. Notably, the COCO dataset includes a specific class for truck vehicles. The output of an instance segmentation model is a set of masks or contours that outline each object in the image, along with class labels and confidence scores for each object. Instance segmentation is useful when you need to know not only where objects are in an image, but also what their exact shape is. The YOLOv8 segment pretrained models come in various sizes, each offering a corresponding trade-off between speed and accuracy, as detailed in Table 2. This variety allows users to select the model that best aligns with their specific requirements.

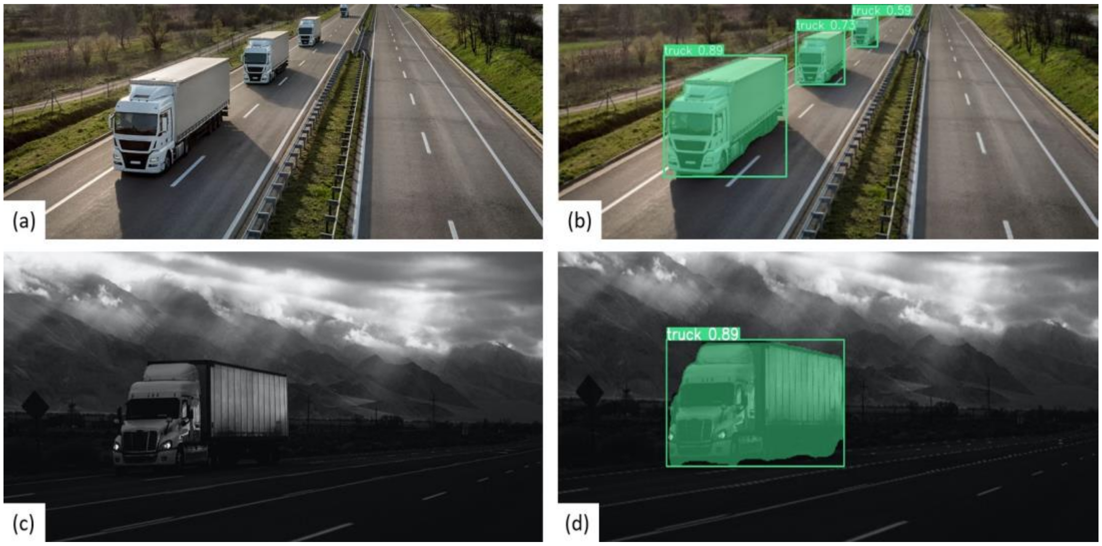

Figure 6. (a) Trucks on Highway, (b) Trucks segmentation for (a), (c) Truck on Highway at night, (d) Truck segmentation for (c).

	Size (pixels)	mAP^{box}	mAP^{mask}	Speed CPU ONXX (ms)	Speed A100 TensorRT (ms)	Params (M)	FLOPs (B)
YOLOv8n-seg	640	36.7	30.5	96.1	1.21	3.4	12.6
YOLOv8s-seg	640	44.6	36.8	155.7	1.47	11.8	42.6
YOLOv8m-seg	640	49.9	40.8	317.0	2.18	27.3	110.2
YOLOv8l-seg	640	52.3	42.6	572.4	2.79	46.0	220.5
YOLOv8x-seg	640	53.4	43.4	712.1	4.02	71.8	344.1

Table 2. YOLOv8 segmentation model features

YOLOv8m-seg model has been applied to evaluate the performance of the truck images in a traffic scenario. The model has shown impressive performance by accurately outlining the truck boundaries. We tested it in various scenarios, including both daytime and nighttime scenarios, as depicted in Figure 6. After a successful segmentation of the truck image, an algorithm to extract the truck from the image has been developed. This algorithm utilizes the mask information obtained during the instance segmentation process. It essentially captures the part of the image covered by this mask, while the rest of the image is filled in black, as illustrated in Figure 7.

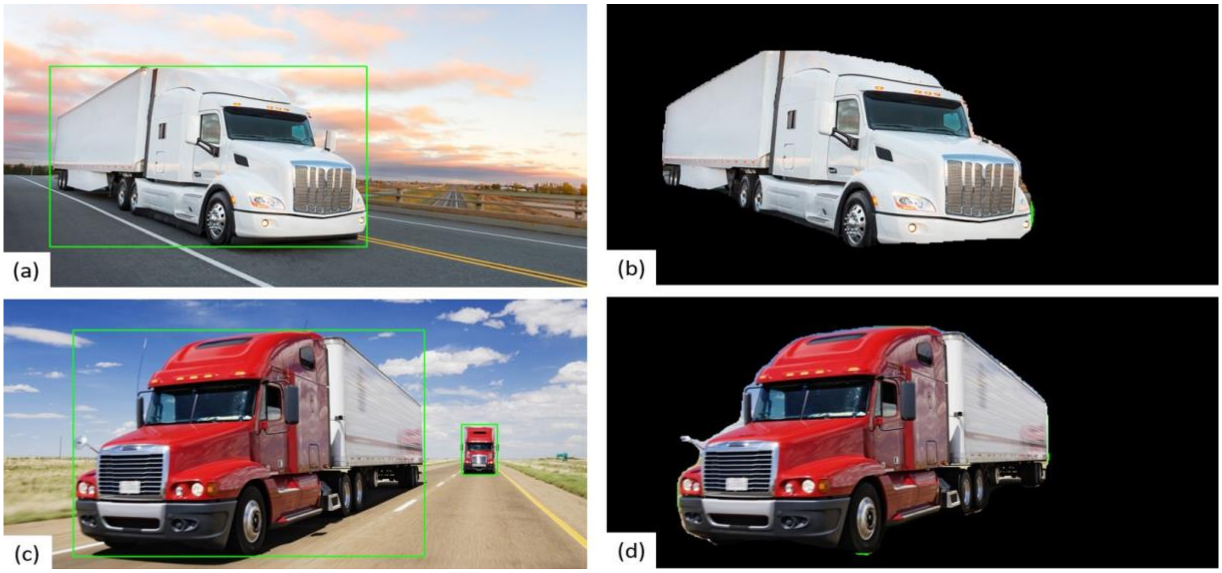

Figure 7. (a) Truck on Highway, (b) Extracted Truck Image from [a], (c) Trucks on Highway, (d) Extracted Truck Image from [c].

The traffic image can have multiple trucks in single frame. To address this situation, we've explored two different methods. The first approach involves selecting the most prominent truck, typically the one closest to the camera, and ignoring the others. However, this approach can be challenging when there are multiple lanes, and trucks are closely spaced in different lanes, as shown in Figure 8. To address this issue in the second approach, we extract all the trucks separately from each frame, as depicted in Figure 9. This way, we make sure that every truck in the image is considered. We've also evaluated the extraction of trucks from traffic images in nighttime scenarios, as shown in Figure 10.

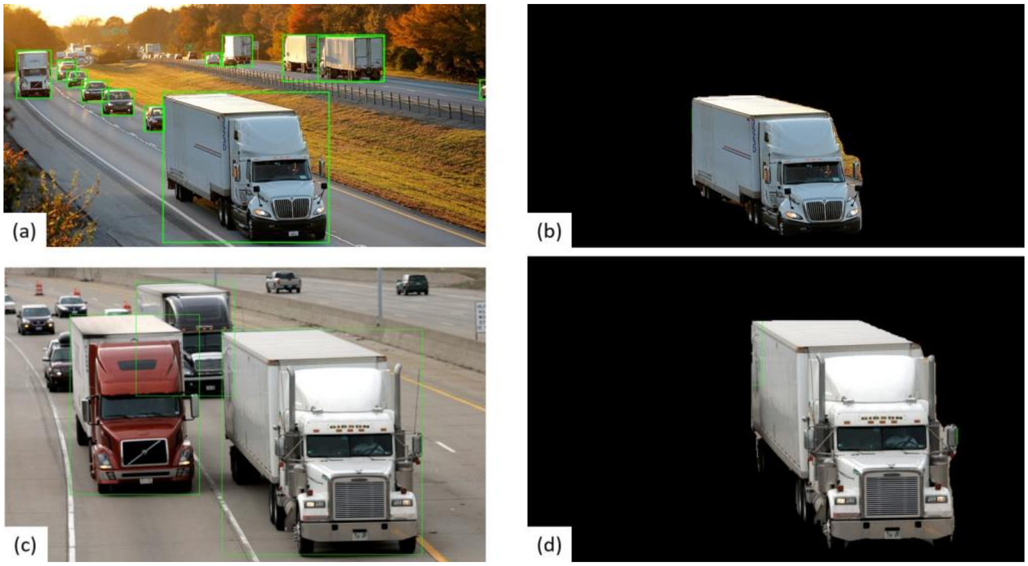

Figure 8. (a) Multiple Trucks on Highway, (b) Extracted Truck Image from [a], (c) Multiple Trucks overlapping on Highway, (d) Extracted Dominant Truck Image from [c].

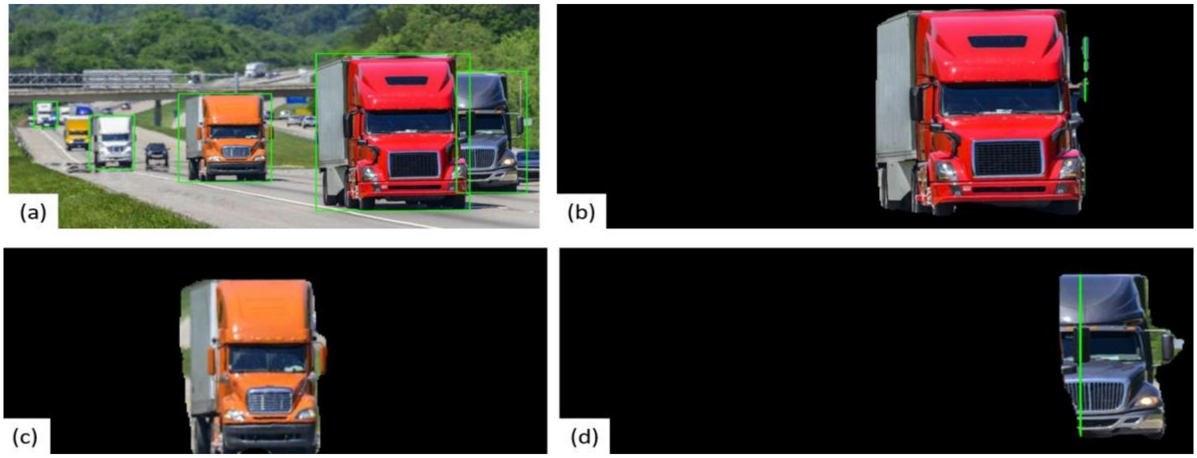

Figure 9. (a) Multiple Trucks on Highway, (b), (c) & (d): Extracted truck image separately.

The model we use for extraction, which employs instance segmentation, performs exceptionally well in accurately identifying the trucks while disregarding background noise. We'll discuss the impact of background noise in the next section.

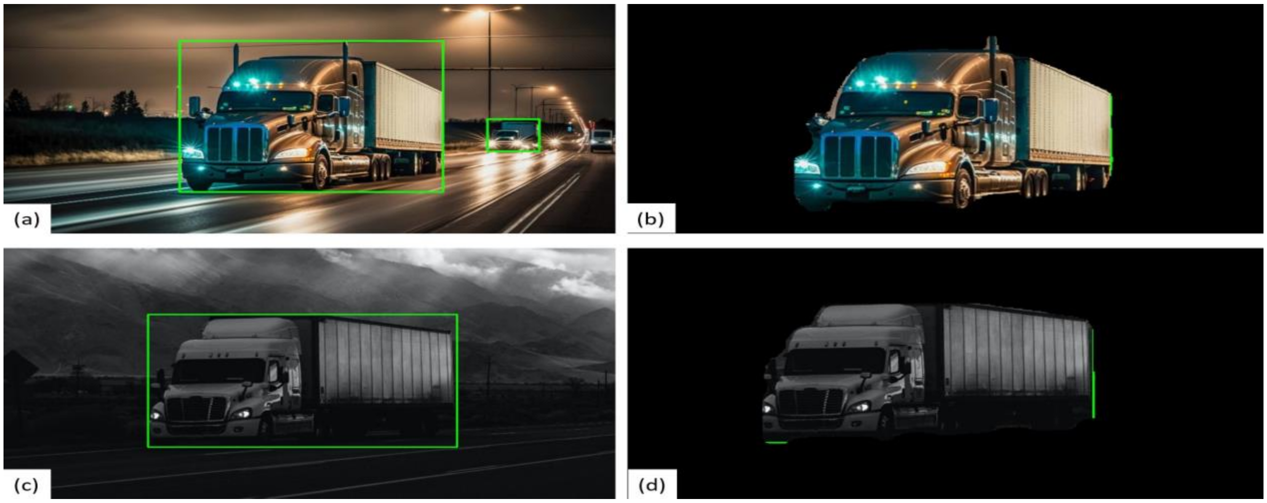

Figure 10. (a) Truck image in Night, (b) Extracted truck image for [a], (c) Truck image in Night, (d) Extracted truck image for [c].

2.5 Vanishing Point Estimation

Estimating vanishing points is a critical step in determining the height of trucks from traffic images. The size of a truck in the image can vary depending on its distance from the camera. To accurately scale the truck's dimensions and match them with their actual size, we need to estimate vanishing points. First, we extract the truck from the traffic image using instance segmentation, employing the state-of-the-art YOLOv8 segment models. Once we have the isolated truck image, we use a technique called Canny edge detection to identify its edges. Line segments need to be obtained to find the vanishing points in each orthogonal direction. To identify these line segments, we employ a method known as the Hough Transform in computer vision. This can be understood as plotting each line as a point on a graph with two axes: one for the slope (steepness) of the line and another for its position. The Hough Transform examines every point along a line in the image and "votes" for where it believes the line might be located on this graph. After counting all the votes, the positions with the most votes represent the lines in the picture. This technique is valuable because it can detect lines even if they aren't perfectly straight. It's particularly useful for tasks such as edge detection or identifying shapes in images. Additionally, the Hough Transform is robust when it comes to handling noisy backgrounds during line detection.

When the entire image is considered, there can be issues in obtaining the lines segments since there would be so many random uncontrollable entities in the background, which can result in wrong estimation for vanishing points. As illustrated in Figure 11, undesired line segments highlighted within the yellow circle can be seen. These segments are a result of the background noise and can persist even after adjusting the threshold values to suit the specific scene. This underscores the importance of carefully filtering out these unwanted line segments to ensure the accuracy of vanishing point estimation, especially in situations where there is a significant amount of background noise and complexity.

Figure 11. (a) Truck Image on Highway, (b) line segments filtered from [a], (c) Truck Image at Night on Highway, (d) line segments filtered from [c].

Even with effective background noise control, another challenge arises when dealing with daylight images, which is the presence of shadows. Shadows can create boundaries that confuse the algorithm, making it appear as though there is an object there, resulting in the generation of line segments around as seen in Figure 12(b). To address this issue, the algorithm is modified to generate line segments based on the orientation of the truck once it has been successfully extracted from the image, as shown in Figure 12(d). This approach ensures that the line segments used for vanishing point estimation align with the truck's orientation, allowing for more precise and accurate estimation of vanishing points, despite the presence of shadows.

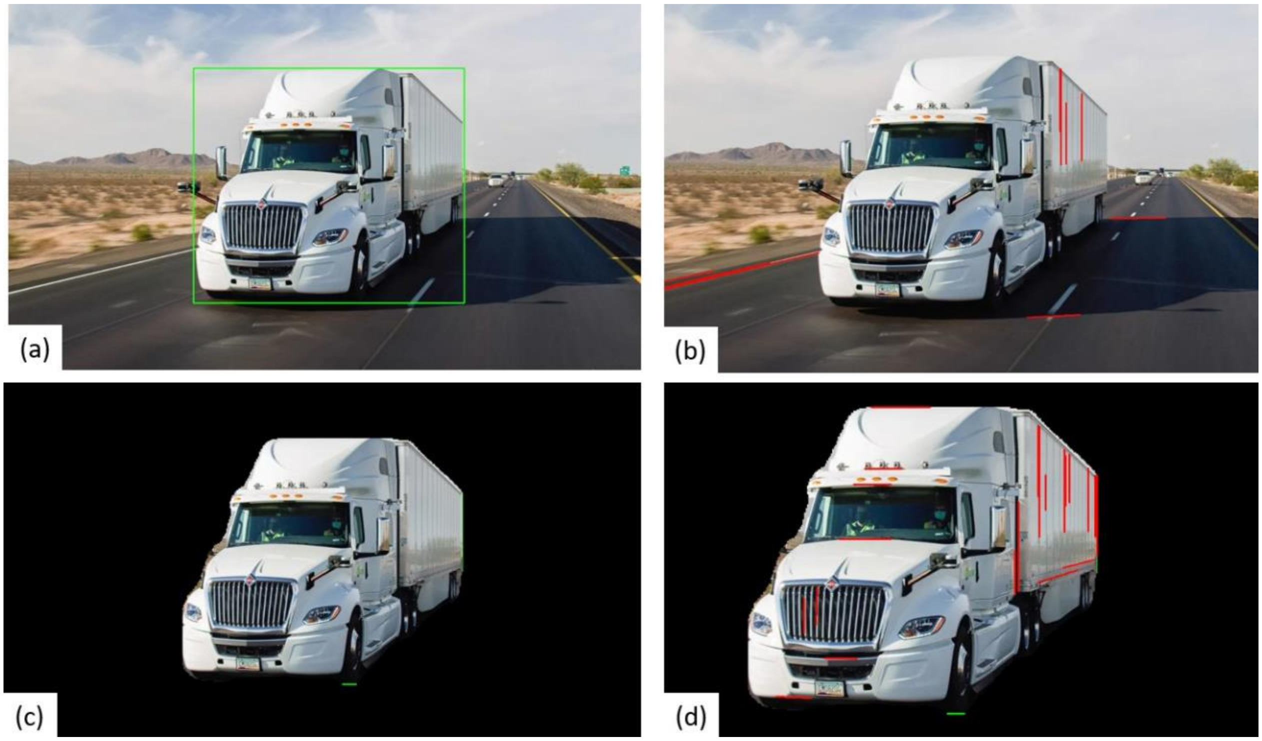

Figure 12. (a) Truck Detected with Shadow, (b) Line Segments Generated around Shadow, (c) Truck Extracted, (d) Modified Line Segments Generated around the Vehicle only.

2.6 Technological Challenged and Future Approach

Obtaining precise vanishing points presents a challenge in various scenarios, especially when dealing with different truck shapes. It's difficult to establish a universal thresholding filter to consistently obtain the desired line segments in three mutually orthogonal directions. Additionally, line detections can deviate slightly from the actual edges due to factors like poor image resolution or patterns on the truck. Incorrect inclinations can lead to erroneous vanishing point estimations, which are typically calculated by intersecting these line segments and averaging the results for all combinations of lines. To address this, ongoing efforts are focused on developing a robust method for vanishing point estimation that can be applied across various scenarios and for different truck types. Several algorithms found in research papers hold significant potential for delivering more dependable vanishing point estimates. However, further time and experimentation are required to apply, modify, and adopt these algorithms effectively.

Once the vanishing point is accurately obtained, a 3D bounding box can be established around the vehicle which can further be used to estimate the height of the truck. We are actively exploring various techniques to overcome this issue. Once resolved, our model for truck detection will successfully provide a good estimate of the height of the truck. This height detection algorithm will need to be further verified through height detection using images of traffic with trucks of known heights.

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