CATCHING SPEEDERS VIA MOBILE PHONES AND MACHINE LEARNING: AN OPPORTUNITY TO IMPROVE SPEED ENFORCEMENT

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ABSTRACT

Smartphone cameras and computer vision (CV) hold significant promise in assisting public agencies with enforcing traffic laws and enhancing road safety. This paper documents automated enforcement applications for speeding, illegal parking, red-light violations, and reckless driving around the world using stationary and non-stationary cameras. While fixed-camera surveillance enables effective enforcement in specific locations, violations continue to occur away from said locations. In this research, CV algorithms are developed with open-source methods to estimate vehicle speeds and identify license plates from mobile phone recordings, allowing for the identification of speed violators from any location. The algorithms successfully identified 47% of license plate characters in the UFPR-ALPR dataset and accurately estimated vehicle speeds in the VS13 public dataset. Improvements are possible by fine-tuning the plate-detection and super-resolution models, or by gathering larger datasets for applicable areas (like known speeds and plates). Notably, existing open-source vehicle identification models were not sufficiently accurate for current US vehicle fleets and require updated data to enhance performance. Overall, this paper serves as a foundational exploration, emphasizing the need for further research to transform the potential of smartphone-based CV technologies into practical tools for vital information on traffic violations, to improve roadway safety.

Keywords: Speed Estimation, Mobile Camera Video Recording Applications, Automated Enforcement, License Plate Recognition

BACKGROUND

Speeding is a major contributor to the amount, severity, and cost of crashes, with previous evidence showing that a 5% cut in average speed can result in a 30% reduction in fatal road crashes (WHO 2017). Speeding was a factor in 29% of all US traffic deaths in 2021, killing (on average) 33 people per day (National Safety Council 2022; Macias et al. 2023). Excessive speeding can be controlled, and thus lives saved, through the use of speed limit laws, active enforcement, road design strategies, speed limiters/governors, speed enforcement cameras, and intelligent speed adaptation (Hirst et al. 2005; Sadeghi et al. 2016). While active enforcement serves to discourage speeding, policing can also result in making the road more dangerous in the event of a police chase, though the majority of accidents occur without police involvement (Rivara and Mack, 2004; Today, 2015). Comparatively, the use of automated enforcement is a safe and cost-effective approach. According to Li et al. (2018), over the lifetime of an average NYC resident, the existing 140-speed cameras increase Quality-Adjusted Life Years (QALYs) by 0.00044 units (95% credible interval (CrI) 0.00027 to 0.00073) and reduce costs by US $70 (95% CrI US $21 to US $131) compared with no speed cameras. Automated speed enforcement (ASE) around the world currently relies on radar devices for detecting speeding vehicles and still camera shots for reading license plates to record traffic violations and issue warnings and fines to vehicle owners (GHSA, n.d.).

Crash counts were found to fall significantly after ASE implementation in the United States, Canada, Australia, Hong Kong, Finland, and many more nations (Wilson et al., 2010; Miller et al., 2016). Commonly, ASE is implemented through the use of single-camera systems or multi-camera systems. Single-camera systems are more common, but they face issues when drivers who are aware of the camera's location slow down before reaching the camera, only to speed up again after passing the camera, a so-called "kangaroo effect" (Elvik 1997). To avoid this issue, multi-camera systems, like some found in the UK and Australia, are designed with two or more cameras to operate over long, stop-free stretches of highway and then compute each vehicle's average speed between the cameras (Delaney et al. 2005; Owen et al. 2016; Bates et al. 2016). However, such systems run into issues where a vehicle's exact or momentary speed is unknown, so speeders go undetected if their average speed is below the camera's limit.

Though ASE has been proven to reduce injury and save lives, speed cameras are still largely unpopular. Many methods have been proposed to reframe how cameras are advertised to the public to make such surveillance and enforcement methods more acceptable, but some people remain skeptical of their use or are worried about privacy protections (Feldstein 2019; Ralph et al. 2022a & 2022b). US police ticketing frequency has fallen over time in many locations due to fewer officers, implementation of automated enforcement, and increases in highway speed limits (Tuttle, 2015; Logan, 2021). Another technology to restrict speed is speed limiters or governors, which are widely used to impose maximum speed limitations on heavy trucks in various countries. For example, Canada's speed governors limit trucks to 65 mph, while Australia's trucks are restricted to 65 mph or less - depending on the region (Canada 2013; Buchs 2022). The USA also plans to require speed governors for trucks, with a proposed limit of 70 or 75 mph (Gallagher, 2022).

Automated Enforcement Around the World

Automated vehicle identification for traffic law enforcement is useful in many settings, including the automatic collection of tolls and fees, identification of vehicles of interest (illegally parked vehicles, stolen vehicles, loud vehicles, and high emitters/dirty vehicles), and enforcement of other transportation-related laws (i.e., speed limits or red-light compliance). Automated parking enforcement using license plate recognition systems, in contrast to crash reduction, offers more efficient identification of parking violations than time-consuming manual checks of parked vehicles for valid parking permits. For instance, in Montgomery, a Texas county, a single police officer scanned 48,101 plates using such a system, resulting in 255 traffic citations, 26 suspended licenses, and other violations in 96 hours of use over 27 days (Wood, 2021). Automated cameras and CV techniques using license plate recognition systems are being used for parking enforcement in various locations worldwide, including Amsterdam, Melbourne, Texas, and California. These systems can be installed on enforcement officers' vehicles or at parking lot entrances and exits to scan and identify vehicles violating parking regulations. Once a vehicle is found in violation, the system can alert parking enforcement officers or automatically issue citations. These technologies can potentially increase compliance with parking regulations while reducing the need for manual patrols (Van Den Berg, 2014; Dinh and Kim, 2016; Wood, 2021; Kadah, 2022). Overall, automated parking enforcement using license plate recognition systems is a promising solution for efficient and effective parking enforcement, with potential benefits in reducing manual patrols and increasing compliance with parking regulations (Parking Network, 2021; Mulloy, 2023).

Furthermore, excessive noise and emissions are significant contributors to health problems such as sleep disturbance and cardiovascular and psychophysiological issues. Vehicles, particularly motorcycles, are a major source of these problems (Perna et al. 2021; Timperley 2022). To address this issue, some cities like Paris and New York have implemented automated noise enforcement using noise radars to detect excess noise and cameras to capture the license plate of the offending vehicle, allowing fines to be issued to the vehicle owner (Esteban 2019; The Official Website of the City of New York 2022). In addition, various tools can be used to identify high-emission vehicles, including remote sensing devices that detect pollutants in the exhaust using infrared and ultraviolet technology, on-board diagnostics that monitor engine performance and emissions control systems, and video analytics that analyze factors like vehicle speed (Huang et al. 2018; Oluwaseyi and Sunday 2020; Valido et al. 2022).

Many nations now subscribe to Vision Zero, which aims for zero road deaths (and near-zero debilitating injuries) (Tingvall et al. 1999; Marusin et al. 2018). Avoiding excessive speed and other illegal driving maneuvers (like left turns on red, wrong-way travel, and rapid lane changes in congested traffic) is one of the best ways to lower severe crash counts. It could save trillions of dollars a year around the globe (with US crashes alone costing nearly $1 trillion annually, or roughly $3,000 per capita per year (Liu and Subramanian 2009)). In Asia, at least eight countries predominantly rely heavily on automated enforcement to enforce speed limits, with another ten Asian nations using a mix of automatic and manual enforcement (UN.ESCAP, 2020). For example, in Hong Kong, speed cameras are used in conjunction with manual policing. While the cameras themselves are more effective in catching and reprimanding reckless driving, the threat of verbal reprimand adds an "embarrassment factor," which can be a deterrent to some reckless drivers. However, with both manual and automatic enforcement, an aforementioned "kangaroo effect" is seen when drivers know the location of cameras or police beforehand (Chen et al. 2020).

As of February 2023, 22 U.S. states, Washington D.C., and at least 35 Texas communities with preexisting contracts (The Texas Tribune 2019, KVUE 2022) (Figure 1a) use red-light cameras, and 18 states and Washington D.C. use speed cameras (Figure 1b).

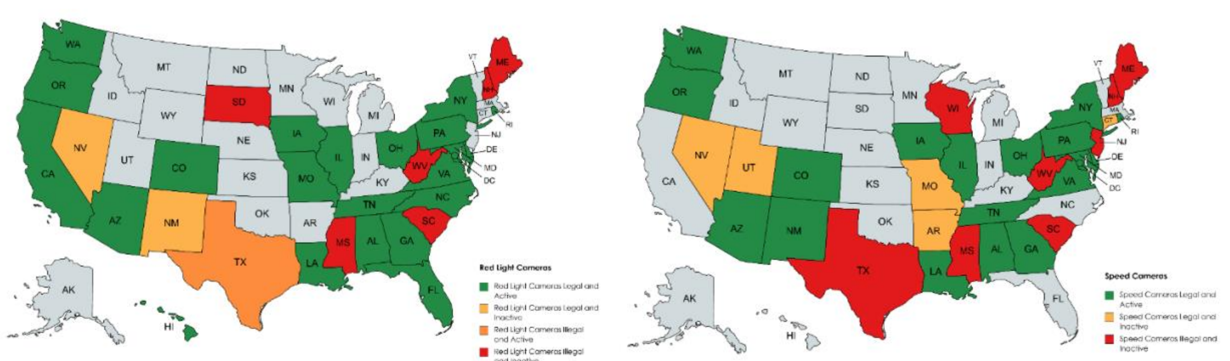

Figure 1a: Red Light Camera Use in US States **Figure 1b:** Speed Camera Use in US States

Figure 1. Automated Enforcement Laws across the US States (IIHS 2023)

In contrast, seven US states have outlawed red-light cameras, and seven have outlawed (agency-owned and operated) speed cameras (Figure 1b). Fortunately, privately owned cameras can record images and video in all public settings in the US, including public rights of way (typically roadways). Those images can be used to support traffic law enforcement and crime reduction.

For Example, video evidence from devices such as red-light cameras, traffic and toll booth cameras, and patrol car cameras can be submitted as evidence in court (Global Justice Information Sharing Initiative, 2016). However, law enforcement cannot currently issue a ticket to people based on someone recording a speeding violation on their mobile camera or any other personal camera, as traffic violations typically require a credible witness like a law enforcement officer. This requirement does not exist for other violations, though. Video evidence of someone engaging in criminal activities, such as causing destruction to private property or breaking into a car, can be submitted to law enforcement, potentially leading to an arrest, regardless of the presence of a police officer (Montiero, 2021; Lucido & Manzella, P.C, 2023). When presenting video evidence in a courtroom, several factors determine its admissibility. These factors include the relevance of the video to the case, two-party consent laws for audio, the video's authenticity and lack of editing, and the completeness of the recording to prevent the introduction of potentially misleading evidence. In addition to these considerations, perception factors, such as lighting conditions, camera angles, and obstructions, can affect the video's accuracy and reliability. Judges often consider these perception factors when evaluating the admissibility and probative value of video evidence (Axon, 2022; Stechschulte, 2020).

Additionally, it is essential to note that privacy concerns can arise in cases involving video evidence. In the case of ASE, the publication of license plate information may raise questions about privacy rights, but since license plates are openly displayed on vehicles, it is difficult to establish any expectation of privacy concerning their disclosure. This is especially true when the vehicle owner is doing something that draws particular attention to their vehicle, such as driving recklessly. First Amendment Coalition, 2013 states that the publication of information about another will amount to an invasion of privacy only if the person has a reasonable expectation of privacy in that information if the information is published in such a way as to create a false and offensive impression about that person, or if it is presented in such a way as to imply that the person with whom the license plate is associated is endorsing a product.

In California, one can report reckless driving to the local state police agency's non-emergency number, and the enforcement agency may choose to issue a warning letter to the driver (Scott, 2023). However, the driver would only receive a citation if an officer witnessed the incident. In Colorado, there are dedicated phone lines for reporting reckless driving, where you can call *277 to make a report, while in Tennessee, you can call *847 to report a reckless driver (Jarger et al., 2023; Steelhorse Law, n.d.). Additionally, there are websites where you can report various traffic violations, such as smoking vehicles, vehicle idling (in New York and Dallas), and aggressive driving (in Nashville) (City of New York, n.d.; North Central Texas Council of Governments, n.d.; hub Nashville, n.d.).

The following section describes the existing computer vision (CV) techniques for vehicle detection, identification, and speed inference and explains why the present work is necessary.

VEHICLE IDENTIFICATION AND SPEED INFERENCE

Object detection is a well-studied CV topic (Padilla et al. 2020; Ren and Wang 2022) and includes vehicle detection. Detection algorithms can be classified as one-stage (You Only Look Once (YOLO) and Single Shot Detector (SSD)) or two-stage detectors (Region with Convolutional Neural Network (R-CNN) and faster R-CNN). Two-stage detectors use two neural networks: one to find regions of interest (in each image or frame) and another to classify those regions, so they take more time to deliver higher accuracy (Kim et al. 2020). YOLO is a popular method for object detection due to its efficient performance (Mao et al. 2020; Akhtar et al. 2022). It has also been used to detect various traffic violations, such as riding a bike without a helmet, not wearing a seat belt, and red light signal jump (Ravish et al. 2021). The latest version of the YOLO algorithm, version 7 at the time of writing, appears to outperform two-stage detectors in terms of both time and accuracy (Wang et al., 2022). This paper uses both YOLOv7 and Faster R-CNN frameworks.

Vehicle or object-tracking algorithms use deep learning (a series of neural networks) to predict object positions across video frames using spatial and temporal features. Tracking tools generate bounding boxes to improve object detection and identification. DeepSORT (Wojke et al. 2017) is a popular tracking algorithm that extends the Simple Online and Realtime Tracking (SORT) (Bewley et al. 2016) technique by using two association matrices (for object velocity and appearance) to create downstream-frame boxes via Kalman filters. This paper uses DeepSort and its further improvement, called StrongSort (Du et al., 2023), for faster and more accurate vehicle tracking.

License Plate Detection and Recognition

Automatic License Plate Recognition (ALPR) algorithms are the most common way to identify unique vehicles. It is a three-step process: first, the license plate is localized, then character segmentation is done, and recognition techniques are applied to extract the text. License plate localization is done in two ways: traditional, handcrafted, feature-based (Du et al. 2013) and deep learning-based methods (Laroca et al. 2019) with object detection techniques like YOLO (Zhu et al. 2022; Akhtar et al. 2022). Current techniques use separate YOLO models to extract vehicles and license plates. Text recognition on these license plates is accomplished through segmentation (a two-step process involving segmentation and a recognition model) or segmentation-free methods (a one-step process). There are several optical character recognition (OCR) techniques available (EasyOCR, 2021; Kuang et al., 2021; Pytesseract. 2022), which can pre-process images (de-skewing, smoothing edges, and converting images to black and white) to boost the chances of recognition (Karandish, 2019). ALPR improvements are hindered mainly by poor image quality and low-resolution cameras. Much research has gone into improving image quality (Dong et al.

2016, Hamdi et al. 2021), and general adversarial networks (GANs) have proven successful in super-resolution reconstruction. GANs also have the potential to be leveraged to perform image-denoising pre-processing (Hamdi et al. 2021). Some publications present the entire pipeline used for ALPR on fixed camera videos (Silva and Jung, 2020; Zhang et al., 2021), including drone-recorded videos (Kaimkhani et al., 2022). However, no work appears to have been published on the inference of ALPR from mobile phone video recordings.

Recognizing Vehicle Make and Model

Many agencies and businesses rely on humans to identify vehicle make and model as well as obscured or hard-to-read license plate information from videos. Make and model help agents identify vehicles whose plates are covered or damaged (Lee et al. 2019; Hu et al. 2022).

Identifying the make and model is challenging due to the similarity between different vehicles, as shown in Figure 2 (Hsieh et al. 2014b). To address this, algorithms reflect vehicle dimensions, shapes, and vehicle logos (Yang et al. 2013) - with special detail typically visible on a vehicle's front view and sometimes also its rearview (Saravi and Edirisinghe 2013; Hsieh et al. 2014b; Baran et al. 2015). To estimate vehicle models, these methods use support vector machines (SVMs) (Hearst et al. 1998) or measure the closest distances between feature vectors. Researchers are also using compact CNNs to identify make and model more efficiently (Dehghan et al. 2017; Lee et al. 2019).

Figure 2. Similar Vehicle Models: Toyota Highlander 2023 and GMC Terrain 2022 (Edmunds. (n.d.).)

Speed Estimation

Various CV techniques are proposed to estimate vehicle speed (Llorca et al. 2021). These techniques generally have three high-level components, as shown in Figure 3. They start by taking video recordings and external environmental parameters like scale factor. Then, detection and tracking algorithms are used to calculate the distance traveled by the vehicles in the 2D domain. Finally, the automobile's speed is calculated with an estimated distance in the real world (calculated with a scale factor) and the time difference between the frames.

There are a few prominent methods implemented in the existing literature. Real-world distance estimation is difficult as it is usually computed with assumptions, such as all roads being flat. Methods for distance calculation include – homography-based (Kim et al. 2018), augmented intrusion line-based, pattern- or region- (Dahl and Javadi, 2019) based, or based on prior knowledge about the actual dimensions of some of the objects, such as the size of the vehicles (Moazzam et al. 2019). These restrictions are reduced when using stereovision (Jiang et al. 2019).

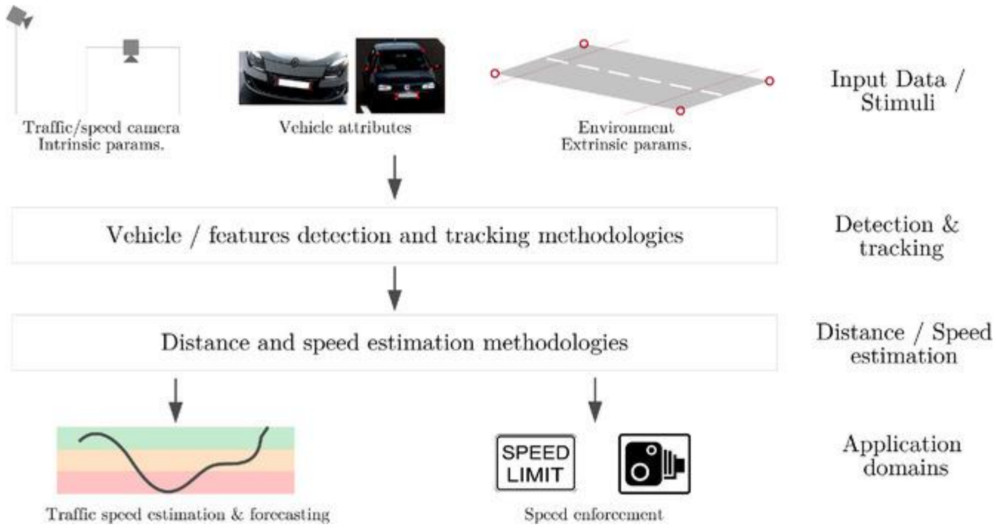

Figure 3. High-level components of vision-based speed estimation (Source: Llorca et al. 2021)

In almost all the methods, calibration is an essential part of estimating the speed of the vehicles. Calibration helps to calculate the intrinsic camera parameters (sensor size and resolution, focal length) and extrinsic camera parameters (location with respect to the road surface). A common method for camera calibration is done using vanishing points (Orghidan et al., 2012). Vanishing points (VPs) can be estimated by various algorithms, which can be separated into two groups. The first group, known as geometry-based methods, leverages the fact that the VPs occur at the intersections of straight lines. Geometry-based methods estimate the VPs by associating lines to VPs (Feng et al., 2010; Wu et al., 2021), line clustering (Barinova et al., 2010; Bazin et al., 2012), or searching within a Gaussian sphere (Collins and Weiss, 1990; Straforini et al., 1993). The second group of methods focuses on learning to infer VPs from large-scale datasets containing VP annotations. Borji (2016) used a convolutional network to infer VPs. Zhai et al. (2016) extracted global image context with a deep convolutional network to constrain the location of possible VPs. Chang et al. (2018) trained models on one million Google street-view images.

Based on the estimated VPs, the camera's parameters can be inferred. When assuming the camera is free of skew and the principal point is at the center of the frame, deriving the intrinsic camera parameters becomes straightforward with the position of VPs. By considering the camera positions, the extrinsic parameters could also be calculated. These estimated camera parameters enable the creation of a transformation between the camera's coordinate system and the world coordinate system.

In this work, we aim to develop an integrated framework that combines the aforementioned techniques to identify speeding vehicles with mobile devices, which differs from previous works developed with fixed cameras.

METHODOLOGY

This section describes the computer methods used in this study to infer speed and identify vehicles for community support of policing dangerous driving and related behaviors. A deep learning framework is proposed for the aforementioned unified objective, incorporating object detection, object tracking, character recognition, vanishing point techniques, and perspective transformation to infer information from videos recorded via a mobile device. The research assumes that the mobile phone is held steady while recording the video, as inclination angles and phone movements were not considered, and most of the existing research focused on fixed cameras. Although this assumption may not always be realistic, this paper aims to demonstrate the feasibility of using a CV to infer a vehicle's speed and license plate from a mobile recorded video. Moreover, it enables mobile phone users to identify speeding vehicles at places where no fixed cameras are installed, such as roads in neighborhoods. The architecture of the vehicle speed inference and recognition system is depicted as shown in Figure 4. It is described as follows -

After performing object detection and tracking using the object detection framework (e.g., MaskRCNN and YOLOv7) and tracking algorithms such as DeepSort and StrongSort, each cropped image of the tracked vehicle is sent to the license plate detection model (Anpr-Org (2023)), which is the YOLOv7 model finetuned on the license plate dataset taken from college-dbbrk/anpr-x1a2o project in Roboflow (Dwyer 2022). Once the bounding box of the license plate is detected, the cropped vehicle image is passed to a super resolution model (Wang, X. et al. 2018) to enhance the image; this image is then passed to the EasyOCR model for text recognition. In addition, the cropped image of the vehicle is also sent to the vehicle make and model recognition model (Pells, n.d.), which is trained on Stanford cars and the Vehicle Make and Model Recognition dataset (VMMRdb) which contains cars in US metro areas. The generated outputs for each frame, including the bounding boxes, name and classification confidence of both vehicles, license plate, OCR output, car make, and vehicle ID, are stored in a text file for further analysis.

This paper employs the speed estimation pipeline proposed by Dubská et al. (2014) to accurately determine the 3D bounding boxes of vehicles and subsequently estimate their speeds. The algorithm initially obtains the contours of each vehicle using the MaskRCNN framework. A pretrained ResNet-50 network is used as the feature extractor for the framework to extract the masks of vehicles from video frames. While assuming the mobile phone is stationary during video recording, the camera’s perspective remains unknown. Consequently, estimating the vanishing points (VPs) from the video is necessary. This paper adopts two different modes to obtain the VPs. The first relies on the users to provide the estimated locations of VPs. The users are instructed to infer the approximate locations of VPs by themselves. Generally, the first VP can be located by finding the intersection of the left and right sides of the road in the video, and the second VP can be approximately located by extending the edges of the vehicles. The second mode employs an automatic estimation of VPs. It utilizes the VP detection algorithm proposed by Lu et al. (2017). They used two lines to get the first vanishing point V_1, then uniformly takes a sample of the second vanishing point V_2 on the circle of V_1 on the equivalent sphere. Although this is not a deep learningbased method, it has a fast inference speed that potentially allows for real-time mobile applications. In our experiment, we estimate the VP only once using the first frame.

The estimated VPs enable the estimation of 3D bounding boxes of vehicles. Specifically, the algorithm finds tangent lines of the vehicle blobs (a group of pixels in a frame of a video that represents a vehicle) that coincide with the vanishing points (Dubská et al., 2014). Starting from each VP, the algorithm finds two lines tangent to the vehicle blob; the 3D bounding boxes of vehicles are decided by all these lines and the intersections between these lines following Dubská et al. (2014). Meanwhile, these VPs also enable the construction of the perspective transformation. From each of the estimated VPs (V_1 and V_2), two lines are extended to intersect with the points inside the frame. Four intersection points of these extended lines can construct a rectangle in world coordinates (these lines were selected to avoid including one of the VPs in the rectangle). Assuming the vehicles are moving towards one of the VPs, the perspective transformation f could be constructed to rectify this rectangle so only the vehicles' vertical (or horizontal) movement is preserved.

Having obtained the coordinates of the 3D bounding boxes of the vehicles, the vehicle speed was then estimated from the movement of the bounding boxes. Denote the two points at both ends of the 3D bounding box as $A = [a_x, a_y]^T$ and $B = [b_x, b_y]^T$, respectively. These two points move to $A' = [a'_x, a'_y]^T$ and $B' = [b'_x, b'_y]^T$ at the next frame. The relative movement of vehicles between frames is then derived by $\lambda = \frac{\| f(A) - f(A') \|}{\| f(A) - f(B) \|}$. To determine the distance vehicles have moved during a single frame, the actual distance is calculated by multiplying by the median size of real-world vehicles. The median size is used to show the proof of concept of this approach, which will be replaced with a length specific to each vehicle in the future. This paper specifies the real-world cars' length to be 4.5m (Michael., 2020; Meyer, S., 2023). The speed is then the distance multiplied by frame per second (FPS).

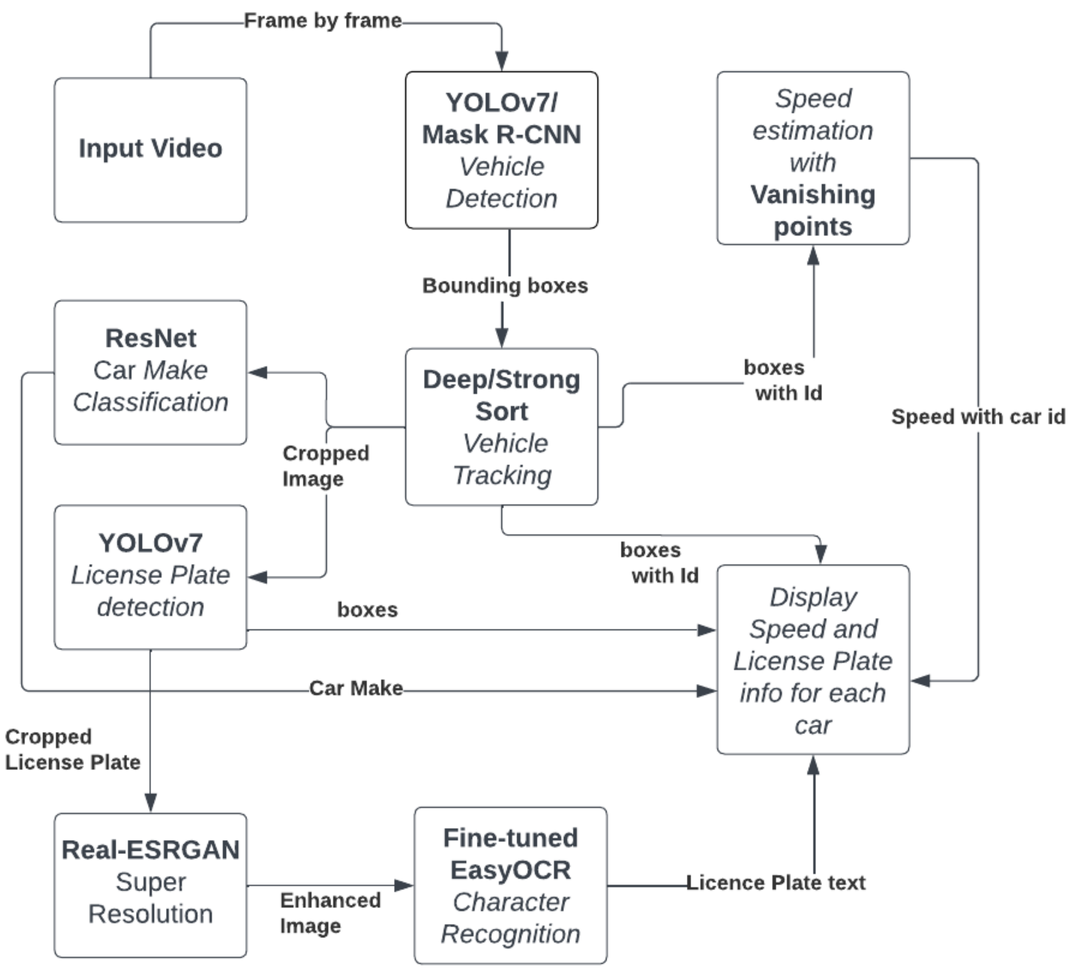

Figure 4. Software workflow of the Vehicle Speed Estimation and Identification System

RESULTS

The paper presents an integrated model for both speed inference and vehicle identification. However, due to time constraints, experiments were conducted using different object detection models (Mask R-CNN and YOLOv7) and tracking models (DeepSort and StrongSort). As these models yielded similar levels of accuracy, the paper reports the results of license plate detection and vehicle make identification obtained using YOLOv7 and StrongSort as the baseline. Additionally, Mask-RCNN and DeepSort were used for speed inference. The results for license plate and vehicle make recognition are presented here. Only the vehicle make is considered in these experiments because the model identification test on sample data has too much variation. Since no work has been done before on inferring vehicle features like speed, license plate, and make and model from mobile-recorded videos, this paper discusses the performance of existing algorithms and how they have been improved.

The results presented in this study were obtained using the UFPR-ALPR dataset's test images, constituting 40% of the entire dataset. The UFPR-ALPR dataset consists of 4,500 fully annotated images (including over 30,000 license plate characters) from 150 vehicles captured in real-world scenarios in Brazil where both the camera and the vehicle were moving. The images were captured using three different cameras, namely, GoPro Hero4 Silver, Huawei P9 Lite, and iPhone 7 Plus (Laroca et al., 2019). When using pre-trained weights, the license plate detection model detected 78.5% of license plates with a predicted and true box intersection greater than 70%. The OCR results presented in Table 1 were obtained as part of the first author's Adv Computer Vision course project. It was observed that applying super-resolution with pre-trained OCR gave better results than using just OCR. The super-resolution technique has improved the results, as demonstrated in Figure 5. In the figure, the 'Input image' output from EasyOCR is 'EE', while the prediction for the Real-ESRGAN output image is 'IU B6t5o62', with both predictions having a confidence score of less than 0.5. Nevertheless, as seen in the second image in Figure 4, processed by EasyOCR, some characters are identified correctly.

Table 1. OCR model results

Model	**# Correct OCR**	**Accuracy**
OCR	252/1800	14.2%
Super Resolution + OCR	407/1800	22.6%
Super Resolution + Fine-tuned OCR	847/1800	47.0%

However, even after applying super-resolution, the EasyOCR pre-trained model could only correctly identify 22.6% of the license plates. The main reason for the low character recognition accuracy in license plate recognition is the lack of clarity in the extracted license plate image, coupled with the use of an OCR model that is not specifically trained to recognize license plate information but instead designed to recognize regular text. So, the OCR model was fine-tuned on a small subset of UFPR license plates and synthetic data, improving accuracy. The model was then able to identify 47.0% of the license plates.

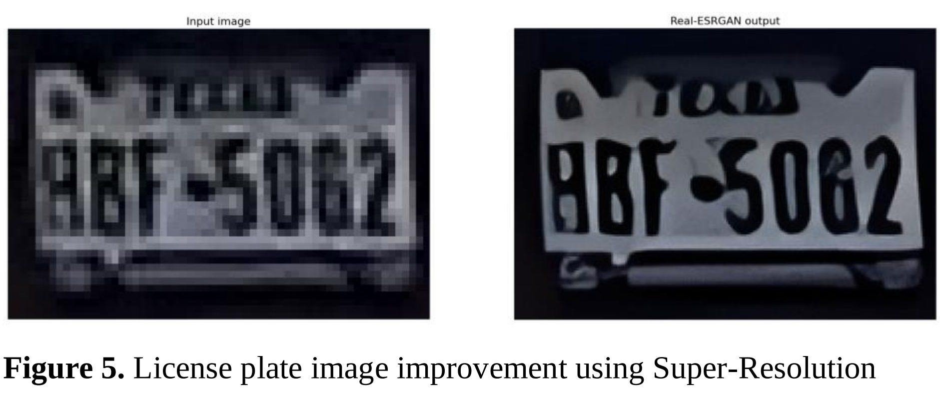

Figure 5. License plate image improvement using Super-Resolution

Table 2. Cell Phone Resolution Examples (Source: GSMArena.com)

Phone Type	Camera Resolution	Video Resolution
iPhone 14 Pro	48 megapixels (MP)	1080 pixels width at 30 frames per second Full HD (high-density)
Samsung M33	50 MP	2160p@30fps Ultra HD
Oneplus Nord2	50 MP	1080p@30fps Full HD

The license plate and vehicle make/model algorithms were tested on 2-3 videos collected using each smartphone type from Table 2. Analyzing algorithm outputs for speeds under 40 mph, the ALPR algorithm excelled when vehicles in the nearest lane were observed, with performance decreasing as distance increased. In Figure 6, the ALPR predicts the license plate of the closest lane vehicle at 30-40 mph, with a detection confidence of 0.96. The text 'TEXAS' is predicted with a confidence score of 0.61, while the number is predicted as 'RL* 23**' with a confidence score of 0.28. The vehicle is identified as a Mini Cooper 2009.

The ALPR model did not provide estimates for speeds between 40 and 60 mph due to low-quality plate images (Figure 7). Although the model detected a vehicle's license plate, no text prediction was possible. The predicted make and model, the GMC Terrain SUV, differed from the actual Toyota Sienna. The vehicle make and model algorithm accurately identified makes but struggled with model types. Make estimates were occasionally inconsistent, as shown in Figures 6 and 7.

Figure 6. Processed output: Vehicle at 30-40 mph on I35 frontage road in Austin

Figure 7. Processed output: Vehicle at 50-60 mph on IH-35 in Austin, Texas

Speed estimation on public datasets

This paper's speed estimation algorithm was first tested on a public dataset called VS13 (Djukanović et al. 2022). It contains video recordings of 13 different car models (i.e., the Citroen C4 Picasso, Kia Sportage, Mazda 3 Skyactive, Mercedes AMG 550, Mercedes GLA 200D, Nissan Qashqai, Opel Insignia, Peugeot 208, Peugeot 3008, Peugeot 307, Renault Captur, Renault Scenic, and VW Passat B7) at different speeds. Each video is captured in full HD, 10 seconds long, and 24 frames per second. The ground-truth speeds of vehicles are provided in this dataset, which ranges from 30 to 105 kilometers per hour. Since these videos were captured from similar perspectives, the Mazda was arbitrarily selected to assess the performance of the speed estimation algorithm. The 13 vehicles' speeds were estimated between the 100^{th} to 160^{th} video frames for user-estimated VP and 100^{th} to 130^{th} frames for algorithm-estimated VP. The median speed estimates are used for error calculations, as shown in Table 3.

Table 3. CV- and user-estimated speeds versus ground-truth speeds, with associated errors.

(1) CV-estimated Speed (km/h)	**(2) User-estimated Speed** (user-input VPs) (km/h)	**Actual (Ground-truth) Speed** (km/h)	**Errors in Estimated Speeds** (Estimated minus Actual) (km/h)	**% Relative Error** (Automatically Estimated VPs/User-input VPs)
29.30	28.04	30	-0.70 & -1.96	-2.3 & -6.5
39.28	42.30	40	-0.72 & 2.30	-1.8 & 5.8
50.11	56.16	50	0.11 & 6.16	0.22 & 12.3
73.87	81.47	60	13.87 & 21.47	23.1 & 35.8
22.07	77.97	70	-47.93 & 7.97	-68.5 & 11.4
81.47	85.32	81	-0.47 & 4.32	-0.58 & 5.3
86.33	100.30	90	-3.67 & -10.30	-4.1 & -11.4

Table 3 showcases the estimated speed of vehicles using both automatically estimated VPs and user-input VPs. It can be observed that automatically estimated VPs give better predictions on speed except for one case. The absolute errors are smaller than 5 kilometers per hour on five out of seven cases that have been tested. The user-input VPs can also provide an accurate estimation of speeds, despite the fact that the errors are slightly larger compared to using the automatically estimated VPs on several cases. However, the VPs specified by users would still be valuable as they can serve as the backup solutions for speed inference once the VP estimation algorithm cannot provide reliable results.

CONCLUSIONS

This study demonstrates the potential and challenges of smartphone-based computer vision technologies in the context of traffic management and safety. The performance of speed estimation is generally satisfactory, with errors typically staying within 5% and 5 km/h in five out of seven test cases. The exploration into improving license plate text recognition unveiled the benefits of using a super-resolution OCR model, although initial accuracy remained suboptimal. Fine-tuning the OCR model resulted in a significant performance improvement, and the potential for further enhancement by fine-tuning the super-resolution model specifically for license plate recognition was also identified. The need for extensive finetuning on current make and model data and real-time testing on annotated images was highlighted to improve the make and model identification system. The lowest error rates were observed when filming lower-speed vehicles in landscape view with a three-camera phone. Overall, it's clear that existing open-source models alone are insufficient to tackle the complexities of the problem at hand. However, a customized system, designed explicitly for this use case and incorporating various open-source techniques, has notably improved accuracy. This research not only highlights the potential of smartphone-based computer vision technologies for addressing speeding-related accidents and traffic violation verification, but also emphasizes the need for further exploration and development in this field. As we look to the future, it is evident that these technologies can play a pivotal role in enhancing road safety and traffic management, and additional research will be key to realizing these goals.

Limitations and Future Work

Directions for future research include extending the analysis to more complex scenarios such as nighttime videos (in lighted and unlighted settings) when speed and plate inference will probably prove more difficult and with moving cameras (as is common with hand-held devices and/or when inside nearby vehicles). In addition, integrating models capable of identifying a vehicle's make, model, year, and/or color will prove useful in cases where license plates are obstructed or missing, increasing the likelihood of successful enforcement. Mobile camera properties, like aperture size and shutter speed, can be experimented with to improve video recordings without motion blur. Furthermore, for better speed estimation, using the specific length of each vehicle (by make/model) instead of an average or median vehicle length will be useful (especially for very long or unusually short vehicles). Another extension is developing a mobile smartphone application for regular or automated submission of flagged video segments with precise position/location details (during actual recording rather than user-estimated values). Of course, recording videos while driving poses a safety risk to everyone, so app designs should help ensure drivers do not use the app while driving.

Thanks to inexpensive cameras and well-trained CV algorithms, the public at large can soon begin submitting evidence of dangerous driving (and other) behaviors to enforcement agencies. Warnings or tickets would be issued after formal review by deputized officers only when there is clear and compelling evidence. Data storage security is also key, similar to existing expectations of law enforcement agencies. Those who receive tickets have the right to challenge the process, mainly if the images appear fuzzy or unclear, ensuring the protection of due process. Due process is a fundamental concept in American law that refers to the idea that individuals are entitled to fair treatment and legal protections when facing government actions that may adversely affect their life, liberty, or property. The concept is enshrined in the Fifth and Fourteenth Amendments of the United States Constitution (Chemerinsky 2019).

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