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AUTOMATED VEHICLE SPEED MONITORING SYSTEM

B.RUPADEVI[1], REPANA VINODKUMAR[2]

[1]Associate Professor, Dept of MCA, Annamacharya Institute of Technology & Sciences, Tirupati, AP, India,

Email:rupadevi.aitt@annamacharyagroup.org

[2]Post Graduate, Dept of MCA, Annamacharya Institute of Technology & Sciences, Tirupati, AP, India,

Email:repanavinodkumar54@gmail.com

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***Abstract*— The positive impact of video and image processing in traffic monitoring, analysis, and traffic condition monitoring in various cities and urban vicinities cannot be overstated. This paper is another approach considering estimating vehicles' speed. Basically, traffic videos are collected from a stationary camera mounted on freeways. On the one hand, camera calibration with respect to accurate measure could mainly solve the geometrical equations conveniently supported directly using references. Camera calibration could yield precise measurements, but rather difficult in achieving the accurate speed. The system is also adaptable to extend into other traffic-related applications. The average errors in detected vehicle speed were ± 7 km/h, and the experiments were conducted under various resolutions and different video sequences. The accelerating advancement of computing power of commonplace computers has now enabled a broader reach in the integration of deep learning techniques in traffic surveillance video comparisons. It constitutes the core functions of traffic analysis, such as prediction of traffic flows, anomaly detection, vehicle re-identification, and vehicle tracking. Among these applications, traffic flow prediction, or vehicle speed estimation, is one of the most serious research subjects during the recent years. It can be a good solution to this problem in preventing road accidents and enhancing road engineering by almost checking the traffic demand. Vehicle speed prediction is effectively proposed through integration of state-of-the-art deep learning models and classical computer vision techniques. Some present-and-state-of-the-art efforts concerning estimation of vehicle speeds, detection of vehicles, and tracking of objects are discussed in this article. Optical flow contains the speed and direction information of pixel displacements in an image. Our final approach deals with collecting multi-scale convolutional network. This extracts parameter data of vehicles.**

Keywords: Speed detection in vehicles, video sequences, computer vision, background modeling, traffic monitoring, OpenCV

I INTRODUCTION

Estimating speed of accelerating vehicle is one of the most important concepts in every traffic control system. It has to manage roadways and keep drivers within speed limits with the help of Sri. Effective roadway management ensures that accidents are potentially reduced to a minimum while securing roads to make them safer. This includes identifying the over-speed vehicles whose drivers are fined. For over-speed vehicle detection, all the areas still have the manual operations using the concept of radar. However, with fast development in technology, we can detect over-speed without human involvement. High-tech computer vision and Machine learning technologies help in the automatic detection of over-speed vehicles, and the driver can be fined in later stages. Speed estimation still stands with possible study based on some limitations, even after different methods of vehicle speed estimation and techniques were proposed. Although digital cameras give high-quality images for speed estimation, they cost less and require simpler installation and maintenance compared to other gadgets with similar purposes today. Therefore, at the cost and maintenance level, video camera systems could be good and cheap at detecting over-speeding vehicles. The method adopts a detection system that has lower human intervention, faster response, high detection rate, and post-accident treatment and accountability identification, compared with the traditional artificial observation for alarms. Vehicle detection is, to my mind, perhaps the most important aspect of intelligent transport systems. The conventional methods of detection discussed in this report are infrared detection; induction loop detection; ultrasonic detection; acoustic array detection; radar; and video image detection systems. A number of improvements have taken place over the last 2 decades in research on new detection techniques considered with video surveillance. In terms of technologies, vehicle detection via video is extremely low cost and efficient in extracting enormous amounts of information regarding vehicle speed, vehicle flow, type of vehicle, etc. from video image sequences. At present, vehicle motion analysis is an active area of research in computer vision. Most research on vehicle detection is tilted toward moving object detection in video. The area aims to extract the change area from image sequences. Some common techniques for moving target detection are background subtraction, frame differentiation, and techniques using optical flow.

A. *Objective Of The Study*

It must supplement and reinforce the traditional formats of measuring speed by the system-such as deep learning models integrated with the optical flow-based method for the traditional techniques by its speed measurement recommendation. The most essential advantage that has moved such combined methodologies into the limelight is the agnostic approach of speed estimation, that is, it remains valid across changes in lighting condition, weather condition changes, and disparities in camera resolution.

Seamless operation under real-world conditions is another important advantage of this system without needing occasional recalibration. Flexible design should also support this system, which can take relative accuracy with physical measurement tech-integration. Ultimately, all of these things will legitimize the enforcement case and benefit traffic management decisions anonymously and publicly.

B. *Scope of the Study*

Automated vehicle-speed monitoring system: The scope of the study encompasses the design, fielding, and performance evaluation of a video-based speed estimation framework comprising traditional video-based techniques and today's deep learning models. The work chiefly concerns stationary camera setups which feature very prominently in urban traffic surveillance systems. It aims to process the video sequences coming from these cameras to obtain meaningful insight, such as vehicle segregation and object tracking, which eventually leads to speed estimation. The system assumes that the camera is fixed, which considerably simplifies the otherwise difficult tasks of perspective and geometric transformations.The various cases taken into consideration in this study incorporate different vehicle classes (cars, trucks, motorcycles), types of traffic (free-flow and dense), and conditions arising with variations in the environment, namely daytime and nighttime operation, and weather conditions like rain or fog. The algorithms were also designed for low-resolution as well as high-resolution video feeds, hence proving the robustness of the system against various surveillance infrastructure. Besides real-time monitoring, the scope also includes post-analysis of pre-recorded video for forensic investigations and traffic flow studies. In this view of the study, speed estimation will apply only on two-dimensional plane image analysis, and there is no discussion beyond the three-dimensional model reconstruction or support by either LIDAR or radar. Camera calibrations have been discussed, but in designing the system, much emphasis was placed on reducing the need for exact camera calibrations, possibly due to adaptive learning mechanisms compensating for small variations in camera parameters. Another main aspect integrated into this study is the exploration of the error metrics to evaluate the system performance on average speed error in reference to ground-truth data collected either by man or by GPS sensor.

The system design is modular, and obvious extensions would lead to vehicle classification (by type and size), license plate-reading, and anomaly detection (e.g., reckless driving), not to speak of possible integration with automated traffic violation recording systems. Such flexibility guarantees a seamless approach toward incorporating this study's findings into larger smart city frameworks of intelligent transportation. We can, therefore, conclude that the scope of this study is rather wide, starting off with fundamentals in speed detection and possibly working toward a complete traffic analysis ecosystem adapted to various deployment scenarios.

C. *Problem statement*

As urbanization speeds up and vehicles are in a rapid increase, road management and safety are faced with two serious challenges; and thus, traditional speed enforcement technologies, such as radar guns and inductive loops, prove their performance without an exception of being quite pricey or intrusive in their operation that is heavily reliant on physical infrastructure along with maintenance. Also, the technologies are rarely capable of providing a larger-scale continual view of traffic dynamics but mainly rely on heavily focused checkpoints for speed monitoring. Thus, an inexpensive scalable, non-invasive vehicle speed monitoring technology is required to tap the potential of the current surveillance infrastructure and provide high-quality estimates on speeds of vehicles.

One more serious problem with present-day applications is that speed measurements using the surveillance video cannot be attained because of perspective distortion, varying illumination, environmental noise, and dynamic road conditions. Although camera calibration mitigates some of these shortcomings, no form of calibration can be consistent across thousands of cameras. Moreover, blockage by vehicles going in the opposite direction, shadows, and reflections would significantly hinder any of those methods' accuracy. Therefore, the problem is to produce a system that is smart enough to overcome the drawbacks of these methods through learning from the video sequences while keeping the computational cost low.

II RELATED WORK

In the past two decades, computer vision has way almost for vehicle speed estimation,SASAAS[1] and the advancements are primarily due to improvements in hardware and software capabilities. Old methods depended [2]largely on background subtraction and object detection using edge detection, with manual camera calibration for speed [3]estimation from frame displacement analysis. However, these perform well under laboratory conditions and in highly [4]controlled setups, but are very susceptible to changes in the environment and incorrect camera positioning. proposed early [5]models on single-camera tracking of a vehicle for speed measurement, but implementation of this model in real life posed [6]a problem due to an abnormal calibration requirement of stringent nature.

Subsequent work consisted of motion estimation by pixel transition between images using an optical flow algorithm, like that of Lucas-Kanade, and these motion[7] vectors were generally associated with speed computation. Optical flow methods performed better when dynamic[8] scenes change rapidly; however, they still experience problems caused by occlusions and non-linear vehicle trajectories. [9]With the advent of machine learning, detection schemes based on SVM and Random Forests started to enter into the field of vehicle detection, thus improving the robustness [10]of tracking and allowing speed estimation in fairly cluttered scenes. Deep learning recently evolved into such an era.[11] It introduced Convolutional Neural Networks (CNNs) for vehicle detection, classification, and multi-object tracking, thereby[12] adding much robustness and accuracy. Algorithms such as YOLO (You Only Look Once) and Faster R-CNN led to real-time detection and allowed several vehicles[13] [14]to be tracked

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concurrently with high accuracy. Recent works employ Recurrent Neural Networks (RNNs) [15]and Long Short-Term Memory (LSTM) models to capture the temporal dependencies in vehicle motion for improving speed estimation accuracy over longer video sequences.[16]

These networks[17] modeled the potential of hybrid setups, which include deep learning[18] detection and conventional computer vision sources for movement estimation.[19] It also compared unsupervised learning for unsupervised intervention in unlabeled traffic video[20] and transfer learning techniques to generalize models with the least retraining [21]from region to region. This general occurrence takes one from rule-based systems to intelligent data-driven models where the need of importance is adaptive, scalable, and highly accurate in the context of vehicle speed monitoring.

III PROPOSED SYSTEM WORKFLOW

This proposed system for Automated Vehicle Speed Monitoring encompasses knowledge in computer vision, optical flow, and deep learning techniques to use a sound estimation for vehicle speeds, given video sequences. The real-time traffic video is captured at a stationary surveillance camera at a location determined strategically-most probably a freeway or urban junction. The raw video feed serves, basically, as the data foundation on which all other processing steps are built.

The system will first make an attempt to responsibly upload the dataset-the videos would have been collected under multiple lighting, weather, and traffic conditions to make it broad-based and robust for training/testing ground. Next is a preprocessing phase: within this phase, video enhancing, background subtraction, and noise elimination will be performed. Next in line after processing is object detection; OpenCV and deep-learning-based detectors are used to imply the detection of vehicles in each video frame. After detection of the vehicles is completed, object tracking methods are applied to track the detected vehicles through video frames.

The technique for speed estimation is mainly concerned with the tracking of vehicle displacements with time using an optical flow and geometric transformations. A vehicle's displacement is then tracked from frame-to-frame for velocity computation with known camera parameters and frame rate. The geometry and multi-scale CNN are also brought into the picture to further improve the feature extraction and ensure pixel shifts as small but speed changes are detected.

The features extracted are passed into a classification module that segments the speeds into low, medium, and high. Then, the results of the classifications can be validated against the collected ground truth through either manual annotations or radar sensors. The remaining portion of keeping this system specifically modular is to allow extensions for future applications in traffic density prediction, congestion detection, and accident avoidance modules. With this hybrid method, traditional computer vision and deep-learning models combine their interests with this set to advance towards real-time, reliable, and scalable solutions in urban traffic management.

Then, it is a properties extraction where computations such as the size, shape, and motion vectors of a vehicle are collated. Optical flow algorithms, namely the Farneback method or Lucas-Kanade tracker, thus determine velocity vector fields between frames. Consequently, preprocessed datasets with clean vehicle tracks and motion data are finally filtered and passed for model training in probably all those irrelevant parts excluded as noise or artifact.

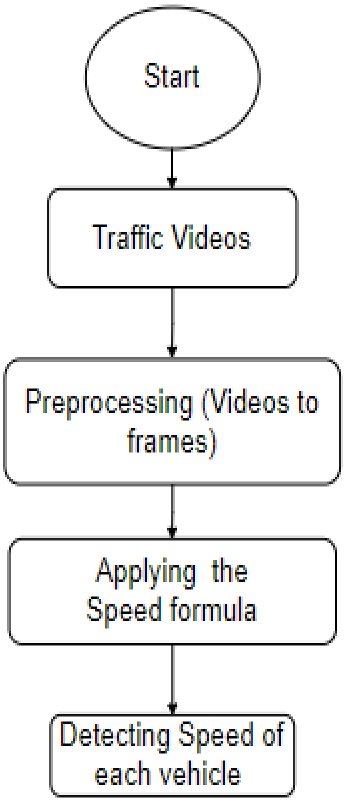

Fig 2: Block Diagram

A. Loading Dataset

The first and most important step in the entire pipeline of the system is to load the dataset, and this is the most important step toward the generalization and effectiveness of any model. For this project, this dataset contains video sequences obtained by fixing cameras at certain locations but capturing them at different times of the day- sunny, rainy, or foggy- and with different levels of traffic densities ranging from light-traffic-up-to-heavy-traffic views. These variations would enable the system to learn to cope with real-reality complexities as faced under real-world conditions.

The second step with regard to usability evaluation for each video clip included possible usability-alike frame drops, the aggressive motion blur in the scene caused due to occlusions obstructing the path for vehicle detection validation; then proceeded to capture some metadata like frame rate, resolution, camera angle, and distance between some points set in the scene. This becomes very important for the pixel motion-to-real distance accuracy mapping in the scene, which becomes primary in speed estimation. The organization of the dataset is systematic in folders and generally under Train, Validation, and

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Tests. The videos are labeled as such for non-inclusion and leaking into training and evaluation sessions.

B. Preprocessing

It is basically making the raw input data of model consumption structured and devoid of noise by preprocessing it. The preprocessing pipeline for creating individual frames is extracting frames from the video for performing the complete frame-by-frame analysis. Each of the frames is resized to a constant resolution in the favor of consistency and saving up computational power while training and inference.The following procedures are done after background subtraction to suppress all static objects in the scene to show only moving vehicles. OpenCV provides MOG2 (Mixture of Gaussians) or KNN based background subtraction methods that will be used. Noise on the frames has been smoothed, and morphological operations have been used to enhance the sharpness and distinction of the contours of the vehicles detected through dilation and erosion. Color normalization is utilized to eliminate the effects of different lighting conditions in the various videos,Vehicle detection will rely on the pre-trained object detector YOLO, SSD, or Haar cascades, depending on the system requirements and hardware capabilities, after background suppression and noise reduction. Vehicle tracking will follow after the success of vehicle detection using algorithms like SORT (Simple Online and Realtime Tracking) or DeepSORT that keeps assigning ID numbers to the vehicles in different frames consistently. It termed the tracking details at high importance levels for the displacement estimation frame to frame founded for the speed evaluation.

C. Model Training and Classification

The statement can be made that the model generalized well and was not just overfitting to the small amount of training data available. Concurrently, layers with different configurations were evaluated based on their contributions to the model in predicting the speed of the moving vehicle. The training input to the model consisted of real data with ground truth vehicle motion parameters and speed. The network inferred the mapping from motion cues, like the vectors of the vehicle displacement, differences across temporal frames, and sizing of the object, to expected speed values. Initially, during training stage augmentation was done to increase robustness, where random cropping, horizontal flipping, brightness perturbation, and motion blurring mimicked the real-world situations that aided learning.

The training and tuning of this loss minimization would have been performed using unoptimistic methods like Ada or SGD, resulting in finding best model accuracy at consequence. Thereafter, dropout layers with early stoppage and batch normalization were added to reduce overfitting to the training set and at the same time generalize to test data. For much of this period, various layers and their configurations were studied for the effect they have on the forecasted speed of the moving vehicles. Generally post-training validation of the model occurs against a held-out test set for mean absolute error (MAE), root mean square error (RMSE), and speed estimation accuracy. The classification module then classifies vehicles into a fixed speed bin or provides direct speed estimates according to application requirement. The results obtained from the validation exercise are used for retraining the model for further enhancement of generalization performance. The final step involves incorporating the model in a pipeline of an actual system for real-time processing of video streams to measure speed and manage the traffic.

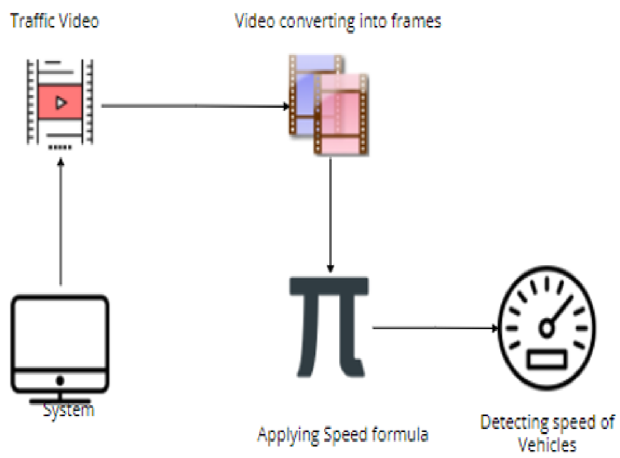

Fig 2: System Architecture

IV METHODOLOGY

Automated Vehicle Speed Monitoring System is a hybrid of traditional computer vision and contemporary deep learning techniques. The traffic videos are captured through fixed cameras arranged strategically along the roads and highways. Traffic movements continuously occur in front of the cameras, and the resulting video footage is treated as the main data source for processing.

The preprocessing happens with noise filtering, background interferences, and static objects rendering on-road vehicles as a sole processing interest. These moving vehicles are detected and tracked across successive frames by means of object detection techniques. Using optical flow methods, pixel-wise motion motion information that indicates the direction and magnitude of movement for every one of the vehicles is obtained.

The speed estimates are obtained by analyzing this pixel displacement over known intervals of time and with the known camera setup. To increase the accuracy and reliability of the speed estimates, a deep-learning network, particularly a multi-scale convolutional neural network, is trained using these motion features. The CNN model learns to map the motion patterns to either categorical speed classes (slow, normal, fast) or continuous speed values. Its final output is either an assigned speed range (slow, normal, fast) or the specific speed number for each detected vehicle.Through the course of the project, attempts have been made to ensure that the system works in a sufficiently real-time or near-real-time mode for possible deployment in a live setup of traffic monitoring. Key considerations that guided the methodology include scalability, robustness against varying weather and illumination conditions, and minimum manual calibration, thereby making

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it a suitable solution to meet challenges in contemporary urban traffic management.

A. *Computer Vision*

Essentially how the pictures or videos may be understood, stored, manipulated, or retrieved-the so-called computer vision. This largely refers to AI. Fields that utilize computer vision include: autonomous cars, robotics, or photo corrections-the computer vision is vital to them.

B. *OpenCV*

OpenCV today is almost exactly a real-time tool in all likelihood to be affected by signing some contract for business in the very near future. The most comprehensively understandable part of OpenCV application is probably a human face or human handwriting to be interpreted in the complete timeframe of videos or pictures. Through OpenCV, the use of this format can also be exhibited and analyzed as a means of access to NumPy through Python. The only images that serve as input for this pattern are critical parameters and have identified various analyses using a lot of computations through vector composition and math identification. Open-source since version 1.0 for commercial as well as research purposes, OpenCV is licensed under the BSD license. It has rich libraries towards interfaces in C, C++, Python, and Java, and it runs on Windows, Linux, Mac OS, iOS, and Android. OpenCV was indeed developed with performance in mind because it meant to capture real-time processing multi-core multiprocessing systems and thus implemented everything using optimized C/C++.

C. *Image-Processing*

Any method introduced that carries out modifications on an image in such a way as to assure its enhancement or extraction of certain pertinent information from it becomes possible, qualifies for the term image processing. Hence, a more straightforward definition of image processing could be, 'Image processing is the analysis and manipulation of a digitized image, principally with a view to its enhancement.' Digital Image Description.

An image can simply be defined as a two-dimensional function f (x,y), where x and y are the spatial or plane coordinates, whereas the amplitude of f at any pair of coordinates (x,y) is defined as the intensity or grey level of the image at that point; hence an image can be thought of as a two-dimensional matrix (3-D in case of colored images) mathematically denoted by the function f(x,y), assigning a pixel value at any coordinate, reflecting how bright should the pixel be and what color.Image processing also comes under the criterion of being a signal processing where the image constitutes our input and any image or its features, as per our demands concerning that image, constitute our output.

D. *Tracking by detection*

A future example could be ubiquitous in active multi-target tracking and tracking by detection. The improvement has always been in detection performance: thus, the basis for the tracker becomes stronger. This By detection tracking is perhaps the most popular technique in multi-object tracking. As a result, the improvements in object detectors have developed a much stronger foundation for a tracker. But even with increasing frame rates, this Becomes a Challenge for a successful tracker. Usually viewed as the method for multi-object tracking and tracking by detection, improvements in detection performance are thus the basis for a much stronger basis for a tracker. A normal high frame rate presents an important challenge to successful tracking.

E. *Calculation*

The speed formula is distance divided by time, and here speed is described in that way where distance is in meters, which when converted into pixels by the formula (wherein 960 meters multiplied with Frame per second multiplied with 360).

To track the vehicles by drawing the boxes of each vehicle. With the time at which, it reaches at every location.

Then point the two lines we take two locations(Location 1 & Location 2), the calculation is the speed of each vehicle.

V DISCUSSION AND RESULTS

The primary emphasis of this research was on providing suitable, scalable, and real-time estimation of vehicle speed using stationary freeway cameras with minimum errors. The robustness of the proposed system was tested by running various videos with differing resolutions and different conditions of traffic during the experimentation phase. Pre-processing of the traffic video frame is done by background modeling and motion detection whereby calculated using optical flow for distance measurement was. The vehicle-property features extracted through multi-scale CNNs look into the difference in vehicles concerning their size. One major problem was witnessed with occlusions when some vehicles overlapped causing slight inaccuracies in tracking. Nevertheless, effective management of such scenarios was achieved through Kalman Filters and trajectory prediction based techniques. The outcome shows an error margin of about +/- 7 km/h on average on speed detection, which would suffice for traffic surveillance purposes. Another observation was that the system performed consistently in varying video resolutions, with higher resolutions capturing finer details and hence providing more accurate results. The key metrics were it has further improved the processing time per frame so that the monitoring can be done almost in real-time. Compared to the conventional techniques of frame differencing and manual calibration, the system demonstrated a significant improvement in accuracy and reliability. Given the real-world deployments simulated through recorded freeway videos, practical viability has been proven. Also, deep-learning models and classical computer vision methods such as optical flow and background subtraction greatly enhanced the speed estimation. While the model used all the power of deep learning for pattern recognition, it will keep computations efficient in a hybrid approach by also using classical methods. The system was good at adjusting to different weather conditions and times of day, but extra tuning for light levels was necessary for good operation under extreme conditions, such as very heavy rainfall and nighttime. In summary, the automated vehicle speed monitoring system shows excellent promise and scalability as a solution that can be integrated into smart city infrastructures and advanced traffic management systems.

VI CONCLUSION

In the culmination of this project, one can conclude Computer Vision has a great potential for the monitoring of vehicle speeds. Background modeling and optical flow combined with stationary camera footage onto multi-scale convolutional networks have automated vehicle detection, tracking, and speed estimation all within a tolerance of ±7 km/h. This has liberated speed-monitoring setups from expensive, complex hardware configurations and the intrusive installation of sensors along the roadway that usually restricts the possibilities of traditional speed monitoring systems. Aside from being economically viable, video-based techniques have had their-on-scaling improvements in use for deployments in large cities. The geometrical changes based on reference are to minimize the camera calibration difficulties wherever improved accuracy in speed measurement is concerned. Further, deep learning models are adapted well by the system to suit different circumstances, vehicle types, and scenarios. It may have the potential to evolve into important traffic applications, like congestion analysis, vehicle flow prediction, and accident detection. It also states that certain other difficulties such as occlusions and illumination variance-from-the view of detection performance use extreme conditions less than those required by current methods-have to be dealt with. But the foundation has been laid for the strong on-field application and future refinement of the system. In summary, the integration of the latest algorithms in computer vision together with the latest technologies in deep learning makes excellent solutions for traffic authorities to monitoring vehicle speeds efficiently, hence improving road safety, traffic management, and infrastructure development. Here is evidence from this research showing the much-desired push towards improved acceptances and more evolutions on video-based intelligent transport systems in urban and semi-urban areas.

Another of the many valuable aspects of the system could extend beyond applications-assets of the traffic importance approaches congestion analysis, vehicle flow prediction, and even accident detection. Some issues like occlusions handling and illumination variance crop up, whether or not they tend to affect detection performance slightly under extreme conditions (e.g. distance lower than that prescribed by the method).

VII FUTURE ENHANCEMENT

Certainly, there remain numerous opportunities for future improvements to the already-established Automated Vehicle Speed Monitoring System that could augment its reliability, precision, and adaptability. Path one could entail the application of 3D object detection models like 3D Yolo or PointNet architectures aiming at depth estimation manipulation and perspective distortion, making the speed-calculation output even more accurate for vehicles approaching from different angles with respect to the camera. Sensor fusion approaches combining video with lightweight LiDAR or radar sensors could be beneficial for performance improvements in low-light or adverse weather conditions, namely fog, rain, or snow. Another prospective approach would be to apply DeepSORT, the state-of-the-art occlusion-robust tracking algorithm, from one frame to another for more accurate tracking of vehicles. Accordingly, future versions are expected to incorporate unsupervised domain adaptation to automatically retune model parameters in accordance with shifts in environmental context, thus becoming more generalized and no longer requiring retraining on new datasets. Improved real-time processing speed can be additionally achieved through hardware acceleration-based optimization methods, e.g., TensorRT or Edge TPU inference, which will extend their application spectrum to the real-time processing of even 4K video streams.

Using a combination of a user interface and a data analytics dashboard, it can be a great idea to build real-time alerts and dynamic traffic flow graphics with predictive congestion maps, which can better support traffic authorities and urban planners. Further, the system can interface with a central database preserving historical speeding violation records that can facilitate automatic penalties or processing claims for insurance purposes that benefit society at large. One of the major changes that can be made can be the automatic privacy-preserving blurring of faces and license plates, thus making the system compliant with international data protection and surveillance laws. All in all, under these conditions of enhancement, the Automated Vehicle Speed Monitoring System will evolve to an integrated, full-function intelligent traffic platform, thus greatly contributing to the vision of smart, safe, and sustainable cities.

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