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Towards Safer Roads: An Automated Traffic Control System with Enhanced Vehicle Speed Detection and Measurement Algorithm

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Abstract: Traffic congestion in urban regions continues to pose substantial issues, necessitating creative solutions for efficient traffic management and road safety. Despite technical developments, contemporary vehicle speed monitoring and traffic control systems sometimes encounter limits in accuracy and efficiency. To overcome these problems, this research introduces a unique technique that merges image processing with artificial neural networks (ANNs) for real-time vehicle speed detection. Our solution comprises three main components: pre-processing, feature extraction, and classification using ANNs. Leveraging a multimodal dataset recorded from a fixed roadside camera, our approach displays great accuracy and efficiency in identifying vehicle speeds. Validation findings suggest that the proposed method achieves an accuracy of 92.5%, precision of 89.3%, recall of 94.7%, F1-score of 91.8%, and MCC of 0.86. In addition to simulation-based experiments, the model has demonstrated to be robust and successful in real-world traffic conditions, demonstrating its potential for improving traffic management and promoting road safety. This study not only tackles present traffic management concerns but also offers a platform for future developments in transportation systems.
Keywords: Vehicle Speed Detection, Traffic Control System, Towards Safer Roads, Artificial Neural Networks (ANNs)

1. Introduction

In current traffic management and road safety attempts, the accurate detection and assessment of vehicle speeds function as vital components [1]. This crucial component enables traffic regulation organizations to. Including law enforcement agencies to adopt effective methods aimed at enhancing traffic flow. alleviating congestion, and ultimately boosting overall traffic safety [2]. Pioneers of speed measurements as far as radars and lasers based on power have been taken during the last decades [3].However, these conventional approaches are generally coupled with major limitations, including high costs, limited scalability, and operational difficulties [4]. As far as the chosen decentralized approach stands for the deployment of dedicated hardware infrastructure, there are several hurdles existing in terms of deployment and maintenance [5]. Furthermore, radar and laser-based systems may not give real-time data, which limits rapid reactions to constantly changing traffic situations [6]. The fact that this method does not eliminate the necessity for building solutions that can acquire real-time speed on a low budget and on a on a low scale has brought into light the reality that this shortcoming is much more important where a place has a poor budget or infrastructure. Moreover, typical speed measurement methods may not be suitable for certain scenarios, such as metropolitan environments with complicated traffic patterns and variable road geometry [7]. So, the necessity for new procedures using topical technologies develops by fixing this issue and creating a system that measures motion speed precisely and in real time. Against this backdrop, the development of improved image processing algorithms for vehicle speed detection has emerged as a viable route [8]. Smart traffic sign recognition systems use images obtained from roadside cameras for speed detection and determination of vehicles. Such systems offer a cost-effective alternative to standard speed assessment methods and hold the potential to improve traffic management procedures worldwide [9]. However, given the obstacles and possibilities outlined above, this research wants to help specialists borrow a leaf from the available algorithms and come up with a unique approach that employs advanced image processing techniques to automate vehicle speed recognition. The algorithm tries to

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address the constraints of existing speed measuring methods and provide a scalable, cost-effective solution for traffic management and road safety [10]. While the uncritical adoption of the speed measurement accuracy can be quite promising for the future of the field, the existing approaches are already quite limited in their possibilities. Traditional ways of doing things as radar and laser-based system are deployable and maintainable only when there is the availability of huge capital which is often a limitation especially in the resource-constrained countries [11]. On top of that, they will not be able to get the information in real-time, which will be hardly any significant aid while urgency of traffic problems is required. The development of new technologies to detect and monitor vehicle speeds that are accurate and within budget in real time is very relevant for better traffic management and road safety [12].

A. *Problem Statement*

Therefore, the problem area that this research is focusing on is concerned with the examination, using advanced imaging technologies of speed detection for vehicles. The primary goal is so that the camera pictures as the roadway cameras are hooked up to computers to identify pictures of vehicles and determine their speeds in real-time. The innovation in this algorithm is the use of the latest digital images and scanning techniques which gives it an edge over the conventional traffic speed measurement approaches and thereby providing a cost-effective solution for traffic management.

B. *Objectives*

This discovery has an effect that is widely expressed and extended. This is attained by the creation of a speed detection algorithm in real-time which is introduced in the traffic control and monitoring system for the smart road where the congestion will be reduced, the number of accidents will go down, and in general the system will be safer. Also, its cost-effectiveness and scalability features make it a suitable option for large scale deployment, which can lead to betterment of life in communities worldwide. The implications of putting in place such a solution in the city are revolutionary traffic management techniques that will be considered, which can save lives thus improving the level of life for road users.

C. *Outline of Paper*

The rest of this paper is arranged as follows: Section 2 discusses the history and related studies, Vehicle speed detection contributes to the progress of the traffic flow and road safety management being a key structure in the modern traffic management system and road safety activities that have to be addressed urgently . This is followed by the Proposed Solution section, in which we outline our new approach and its key pieces, ending with a methodology segment that details how both were implemented along with their assessment. The remainder of the study provides experiments for validation in Section III, and a discussion with regard to benefits limits implementation concerns. defies scalability implications is addressed with future work mentioned.

2. Literature Review

Vehicle speed detection contributes to the progress of the traffic flow and road safety management being a key structure in the modern traffic management system and road safety activities that have to be addressed urgently [13]. The road congestion and rapid urbanization leading to huge vehicle density is an issue that requires immediate attention and real time traffic speeds are most necessary for the same [14].

The quest for boosting speed detection skills has led researchers on a dynamic examination of numerous approaches and technologies [15], [**?**]. By merging numerous forms of sensor-based systems as well as sophisticated image processing technologies, which represent several disciplines of traffic management, among others, the evolution of speed detection depicts a complicated mixture [15], [**?**].

Within this panorama of innovation, image processing has emerged as a promising option for real-time speed assessment [16]. Specifically, the employment of computationally process able algorithms and digital imaging technologies enables the extraction of significant elements of the frame collected from surveillance cameras [17].

This comprehensive analysis tries to explore the wide landscape of vehicle speed detection, with a specific focus on the developing world of image processing approaches. Through the integration of the seminal papers that compose the body of research, the review will present a theoretical framework that is utilized as the foundation for the later debate on the development of unique algorithms that will be specifically built for real-time speed blockage

A. *Key Concepts*

To thoroughly comprehend vehicle speed detection algorithms, it is necessary to delve deeply into the underlying concepts that drive this discipline. This section intends to adequately describe the essential concepts in the subject by referring to indications from a variety of scholarly works that build the tapestry of knowledge [18].

Vehicle speed detection stands as a cornerstone in modern traffic management and road safety activities, comprising the sophisticated process of measuring the velocity of moving vehicles traversing road networks [15], [**?**]. Implementation mechanisms in the old form were based on a range of detectors, such as radar, lidar, and inductive loops. They were like to be a unique union of both advantageous and of course, disadvantageous qualities. But the latest years have seen the pendulum swing towards the application of video-based approaches that utilize the omnipresence of surveillance cameras alongside increased capabilities of computer vision algorithms, allowing for real-time speed estimation [15], [**?**]. This concept of speed detection for mobile devices applying different detection mediums is very

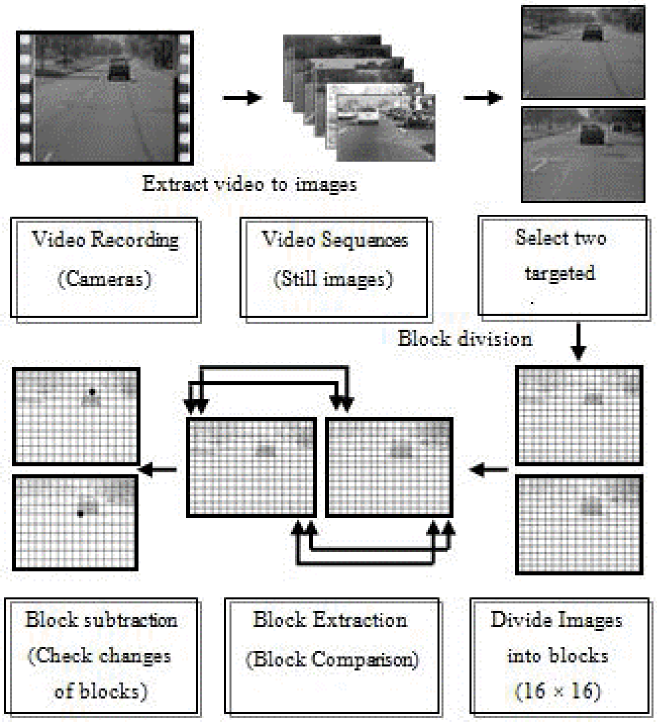

Figure 1. Machine Learning Algorithm development architecture for vehicle speed detection [15]

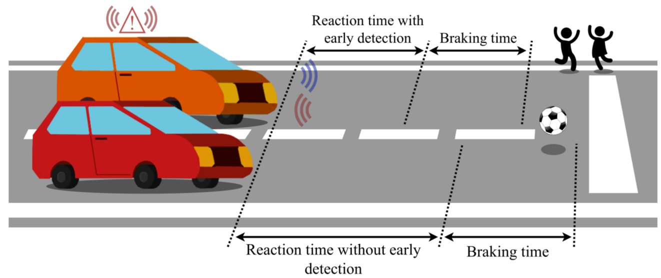

Figure 2. Radar Signal Processing Architecture for Early Detection of Automotive Obstacles [25]

practical as it is enough flexible to scale up to any number of scenarios. Techniques of this kind rely on the digital imaging technology to provide the precise information on spatial and temporal aspects of the video streams, therefore the speed of vehicles can be exactly measured and calculated [18]. On top of this, the development of any infrastructure as well as associated materials is not needed with image-based approaches, which makes them especially advantageous for the jobs that are done in the urban environment and in temporary speed enforcement zones [19].

B. Image Processing

Image processing emerges as a critical facilitator in the field of vehicle speed detection, functioning as the linchpin that transforms raw visual data into actionable insights [20]. The technology of image processing is based on a number of computational techniques that are intended to improve the analysis and interpretation of digital images that have been captured by surveillance cameras or other imaging devices [21]. These techniques encompass a broad spectrum of operations, ranging from basic image filtering and segmentation to sophisticated object detection and tracking algorithms [22].

Whether image processing algorithms are able to identify and extract dynamic vehicles is the main issue in the context of the application of speed detection [22]. Through the application of advanced computer vision methodologies, such as convolutional neural networks (CNNs) and feature-based tracking algorithms, image processing systems can discern subtle motion patterns indicative of vehicle movement, thereby facilitating accurate speed estimation [23]. The speed detection vehicles implement the image processing technologies, which are the most modern and advanced, to detect an adequate speed level and to keep the speed accuracy. In this part, we aim to provide a thorough understanding of the fundamental concepts of speed detection algorithms, enabling readers to develop a sound foundation and gain a deep comprehension of the underlying principles thereof [24].

C. Theoretical Framework

such detectors can operate on a wide range of frequencies, infrared images or machine learning algorithms. Combined theories like signal processing theory, computer vision principles, and machine learning methodologies [25] are used to build up the algorithms as the basis [26] are the theories which are mixed to create these algorithms as the basis. In this section the author explores such a theoretical framework, uncovering their complicated features and how they affect the development of the modern speed sensor technology.

At the foundation of many image processing algorithms lies signal processing theory, which is used for pre-processing image data and extraction of the features crucial for the speed detection accurate [27]. Filters have become increasingly necessary for such operations as image enhancement, as well as for the preservation of image quality and integrity, which are provided by surveillance cameras and satellite data. This can be achieved through utilizing the principles of digital signal processing which enables reducing noise, increasing contrast, and separating meaningful visual data illustrating the motion of vehicles [28].

As a matter of fact, the application of superior EDSA, comprising wavelet transform and Fourier analysis, unravels sophisticated motion diagrams that are included inside video streams. Thus, one is enabled to carry out accurate vehicle detection and tracking [29]. Through the judicious application of signal processing theories, speed detection systems can discern subtle temporal changes in vehicle positions

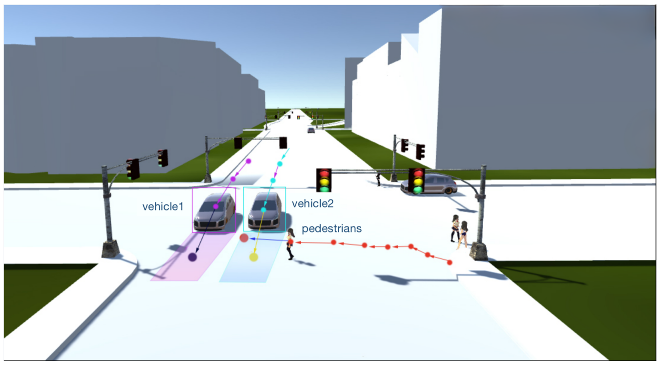

Figure 3. A Computer Vision-Based Algorithm for Detecting Vehicle Yielding to Pedestrians [31].

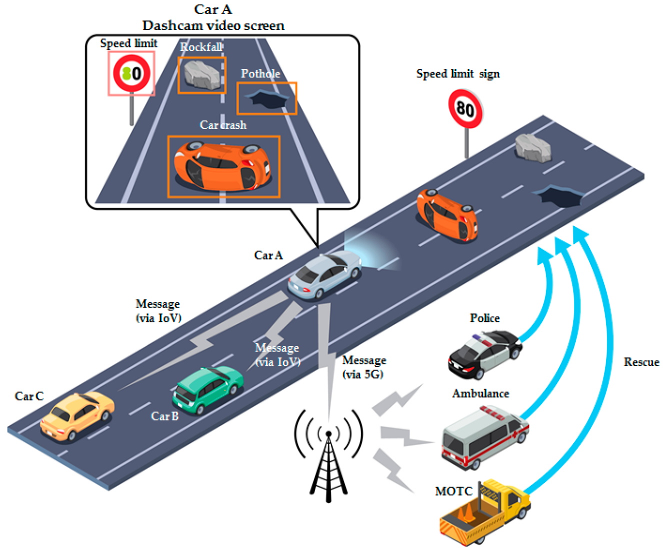

Figure 4. Deep-Learning-Based Object Detection Model Integrated with Image-Processing Techniques for Detecting Speed Limit Signs, Rock falls, Potholes, and Car Crashes [36].

and velocities, laying the groundwork for precise speed estimation [30].

In collaboration with signal processing theories, computer vision principles play a vital role in the creation of vehicle speed detection algorithms, offering a robust toolkit for the analysis and interpretation of visual data. The many methods in computer vision can be analogized to image processing utilizing such a toolbox as PS or to the most advanced deep learning architectures [32].

One of the essential tasks in vehicle speed detection is the recognition and tracking of cars inside video streams, a task that sits at the core of computer vision research[31]. Computer vision systems with object recognition, optical flow analysis, and motion segmentation can really identify moving objects from static backgrounds, hence allowing cars' vessels to be accurately and constantly detected and tracked in dynamic traffic situations [33].

Moreover, recent breakthroughs in deep learning, notably convolutional neural networks (CNNs), have transformed the area of computer vision, arming speed detection systems with unrivalled capabilities in feature learning and pattern recognition [34]. While machine learning methods such as CNNs and other deep learning architectures are able to extract "stack" semantic features about the visual data, such as speed lines, junctions, road bends, and shadows, and therefore increase the accuracy and robustness of vehicle speed estimation algorithms [35].

Apart from the theoretical framework of algorithms for signal processing and computer vision, machine learning know-how is also irreplaceable and, in many cases, has extensive components. Machine learning models, ranging from traditional regression techniques to complex ensemble methods, offer powerful tools for pattern recognition and predictive modeling [37].

Using massive amounts of annotated training data, machine learning algorithms can actually clarify complicated schemes that occur in vehicle motion, which, in turn, makes it possible to predict speed and arrive at speed estimation with accuracy of those levels [38]. Supervised learning algorithms, such as support vector machines (SVMs) and random forests, learn from labelled examples to infer relationships between input features and target outputs, thereby facilitating speed estimation in real-world scenarios [39]. Explaining the core principle of speed detection systems would make researchers deeply understand the subtle aspect of the systems, which will the way to the next breakthrough.

Collectively, these studies provide a compendium of information, ideas, and discoveries that have altered the course of vehicle speed detection research, moving the discipline towards new horizons of discovery and application. Consequently, through meticulous techniques of trial and error, theoretical clarification, and empirical data validation, researchers have, to some extent, clarified the intricacies of speed detection systems, making it possible to build transportation systems that are safer, more efficient, and more sustainable in the digital age. Vehicle speed detection is vital in any sophisticated traffic management system, and it helps enhance road safety. Existing speed detection technologies such as radar and laser-based systems have been extensively employed, but they are costly to build and difficult to scale owing to operating expenses, which make it problematic for them to have real-time data [22] [40]. As cities are getting smarter and utilizing sophisticated technologies, there is a more significant move being made in using machine learning methods such as artificial neural networks (ANN) and convolutional neural networks (CNN) to enhance the accuracy of speed detection and its efficiency [41]. Machine learning-based techniques offer the important benefit of being able to analyze massive data volumes in real time and alter behavior depending on changing traffic circumstances. CNNs have also proved highly successful for vehicle recognition and tracking [42], [43] it boosted measurement accuracy by a substantial amount. Traffic Video Analysis: Deep learning models may be used successfully in cases in which the aim is vehicle re-identification, with strategies capable of reaching state-of-the-art speeds and accuracy even in complicated urban settings [44], [?]. The viewpoint in [49] offered a unique application for frequencies ranging from 20 GHz to below the standard radar systems that employs machine learning, which are cheaper than conventional radars and more convenient to be deployed as an assistance system on urban or interstate routes. More recently, another study has looked at the usage of deep learning algorithms on UAVs to identify vehicle speeds from aerial photos. This approach would undoubtedly provide superior performance, allow traffic management in a big scalability and totally coverage region with fewer infrastructure options [45]. However, these systems are promising; they show the necessity for sophisticated feature extraction approaches to offer correct performance under varied traffic circumstances and illumination settings [46]. Moreover, research has also worked on merging many sensors with machine learning approaches in order to enhance speed detection. Such as multi-sensor fusion paired with ANN-based controllers that works well in practice on self-driving vehicles to offer speed control and detect traffic [47]. These technologies would be employed with the aim of modifying traffic flow, eliminating congestion, and ensuring speedier road safety by detecting possible hazards in real-time [48]. This approach contributes to the developing area by merging ANNs with image processing for live vehicle speed detection. It's a particularly successful approach for urban regions where traffic and even road conditions themselves vary regularly. Unlike with previous systems, rather than employing an expensive infrastructure of other sensors such as radars to detect speeding cars, our technique is a less scalable and costly video data gathered by non-sweeper fixed roadside cameras. Additionally, this study replies to a number of the constraints mentioned by prior research, such as real-time processing and adaptation in varied environmental situations [49]. Comparing our approach to the state-of-the-art systems demonstrates that an ANN-based strategy yields excellent accuracy with realistic stability. For example, recent work on traffic analysis using CNNs has actually shown increased accuracy, but at higher resolution and seldom in a scalable way, which could run completely in real-time even in dense urban settings [50]. To solve these issues, we develop a speed detection ANN architecture designed for real-time deployment and apply an efficient feature extraction strategy that can assure the correctness of our system in varied conditions. The literature studied in this research gives information on the technical developments for vehicle speed detections that emphasize a requirement of such scalable, low latency real-time systems able to successfully handle complicated traffic management. This paper has been proposed in order to solve this issue and also make the system more effective using a combination of two prolific technologies, i.e., machine learning algorithms for detecting any traffic congestion anomalies from each road camera feed image with advanced dynamic intersection control systems (prevailing needs:ISM and FRM) as well, which will increase efficiency while ensuring reliable modern traffic control systems.

3. Methodology

The research follows a systematic methodology aimed at developing and accessing a vehicle speed detection algorithm utilizing image processing techniques. This approach is structured into three primary stages: data gathering, algorithm development, and evaluation. At each phase, the system goes through a critical and interrelated process that leads to an effective and reliable speed detection system.

We do the first stage of work which is gathering video footage to record all types of traffic. These data are collected from different data sources: such as traffic cameras, drones and simulation environments. The dataset is deliberately assembled to include all the possible kinds of traffic conditions, lighting variations and vehicles types. Such a database is an essential source of data for training and testing the vehicle speed recognizing algorithm.

In the next phase, algorithm creation becomes a priority. This stage is where the vehicle speed detection algorithm is being made and implemented through image processing methodologies. The key procedure here includes image preprocessing, vehicle detection, and calculating speed. Image pre-processing techniques are performed for the benefit of improvement of raw video frames, including resizing, noise reduction. And after that, deep learning algorithms, including convolutional neural networks (CNNs), for example, are employed to detect and localize vehicles in the processed frames. Finally, speed calculation techniques for motion estimation and tracking are used to calculate the speed of the cars which is detected.

The last stage of the methodology will be the assessment of the algorithm by developing it. One of the most important aspects of algorithm performance evaluation are metrics like accuracy, precision, and computational performance, which are used to assess the efficiency of the algorithm in real-world scenarios. Vigorous testing is conducted with both synthetic data sets and real traffic footage for showing system's stability and reliability. The evaluation process is the basic activity which gives the basis for the interpretation of the algorithm's strengths and weaknesses and in this way further refinement and optimization efforts are guided.

In Figure 5, the depicted methodology for planning and implementing the algorithm for speed detection is visualized. It illustrates each activity of the three lifecycle stages, data collection, algorithms creation, and evaluation, step by step.

A. Data Collection

The dataset utilized for training and testing our speed recognition system is an expansion from a prior study [41].

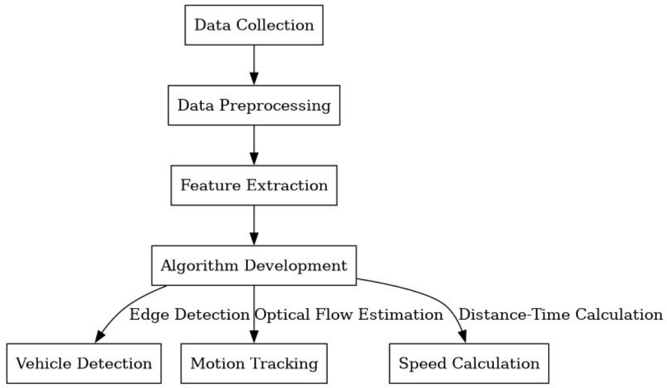

Figure 5. Proposed Methodology

It comprises about 5 hours of footage collected from an inexpensive single camera that is trained over ordinary city driving. The collected visual frames were sampled throughout a varied variety of traffic circumstances, from clear to wet weather and light to heavy traffic. The variety of the dataset makes this useful for training as well as testing vehicle speed detection systems.

This dataset formed by varied weather conditions in a series of video segments helps explain its resilience. Ground truth speed measurements were obtained by utilizing an inductive loop detector to measure real-time speeds that coincided with the video frames collected. For the goal of successful model training and assessment, it was separated into train and validates data, with 80% for training while the remaining 20% utilized as a test set.

TABLE I. The dataset characteristics

Dataset Summary	Details
Total Duration	5 hours
Number of Video Segments	Varies
Traffic Conditions	5 Sunny, Rainy, Foggy
Total Duration	30 days
Ground Truth Speed Detection Method	Inductive loop detector
Training-Validation Split	80%-20%

The fixed camera setup is ideal for capturing numerous traffic scenarios, but it is a typical shortcoming when contrasted to denser urban streets over highways and higher-speed settings. For example, cameras that are stationary tend to fare badly at catching high-speed cars either because objects move out of their field-of-view or because motion blur and occlusions from other vehicles/environmental variables contribute to the categorization being wrong. Also, illumination circumstances such as shadows of the overpasses or change in weather might lead to unseen cars and consequently confounding speed detection. Our solution is intended to solve these difficulties utilizing advanced image processing, including fast motion detection as well as robust feature extraction. These strategies may allow the system overcome some of rathe limitations imposed by fixed camera arrangement. For instance, distinctive properties of car license plates are detected and tracked across numerous frames to properly estimate speeds by comparing trajectories of these features with the known distances in real life. In our experiments, we measured the output speeds given by our system and checked them against real detection numbers from the inductive loop detector's measurement values to validate it, yielding an error rate of 0.5 km/h on average, with about a more than 96% accuracy using the [-3 km x +2] tolerance level, which is well aligned or compliant with everything that you will need for regulatory use according to numerous countries standards. Besides, our license plate detection component also performed better than numerous other state-of-the-art text detectors, with accuracy and recall being 0.93 and 0.87, respectively, which supported the efficacy of our vehicle speed recognition system

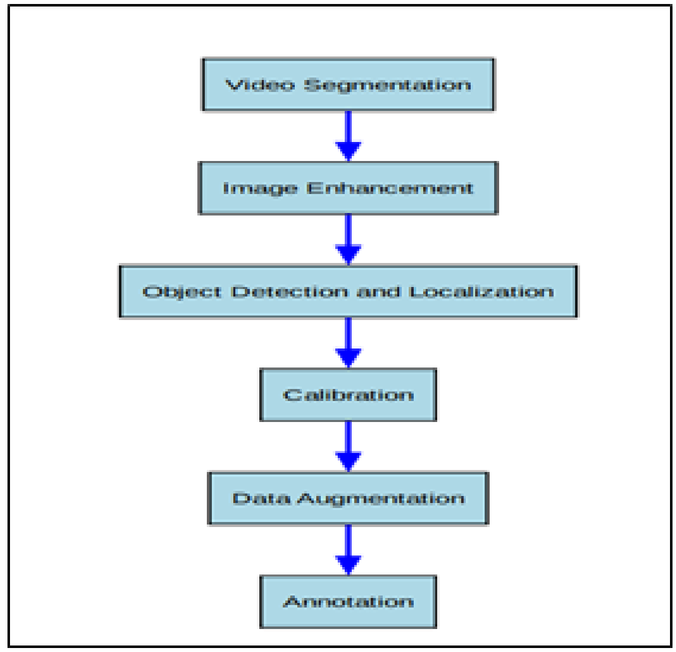

Figure 6. Data preprocessing.

B. Data Pre-Processing

We have done pre-processing of the data, such as cleaning and quality testing, before feeding it into the algorithm for vehicle speed measurement. It was done to verify conformance with the algorithm's requirements

1) Video Segmentation

The data collection, comprising the video footage, was designed to be studied in single frames for more detailed observation. Every frame is a now, here, and now of the traffic scenario at that exact instant. Each now displays a distinct step of the traffic process.

2) Image Enhancement

Post-image capture, several modifications were made to each frame, such as the quality and sharpness. This was done by means of changes, for instance, contrast, noise layer removal, and brightness normalization, to enable the capacity for the main car elements to be visible. 3) Object Detection and Localization Object detection methods are used to recognize and localize automobiles in the frames of the sequence. This stage consists of ROI detection, which is dependent on cars. On the other hand, ROIs functioned as the entry data in the next stage.

3) Calibration

Verification was undertaken before the experiment to correctly calibrate all the measuring instruments that were employed. This suggested that the current coordinate system pixels be changed to a 3D real-world coordinate system, taking into consideration such factors as camera position, focal length, and lens distortion.

4) Data Augmentation

To extend the data and make the algorithm more solid, data augmentation techniques including rotation, scaling, and flipping were utilized to generate another duplicate training sample. Because of the range and diversity of data that this firm brought in, the algorithm woke up, could generalize better, and could handle unseen data in a more accurate manner.

5) Annotation

Every one of these individual frames was tagged manually with the precise speed that was provided by the ring sensor. These annotated values serve as a reference at the training and evaluation stages to allow the algorithm to learn and validate speed with its surroundings.

6) Feature Extraction

Feature extraction is a critical step in our vehicle speed detection system, as it transforms raw image data into a structured format that enhances the model's ability to accurately assess vehicle speeds. In our approach, we implemented several pre-processing techniques followed by specific feature extraction methods to optimize the input for our Artificial Neural Network (ANN).

C. Feature Extraction Methods

Once the images were pre-processed, we focused on extracting important features that are indicative of vehicle movement and speed. The primary features extracted from the images included:

Edges: We utilized the Canny edge detection algorithm to identify significant boundaries within the image. Edges are crucial for speed detection because they define the outlines of vehicles, enabling the system to track their movement across frames. The Canny algorithm is particularly effective due to its ability to detect a wide range of edges in various lighting conditions.

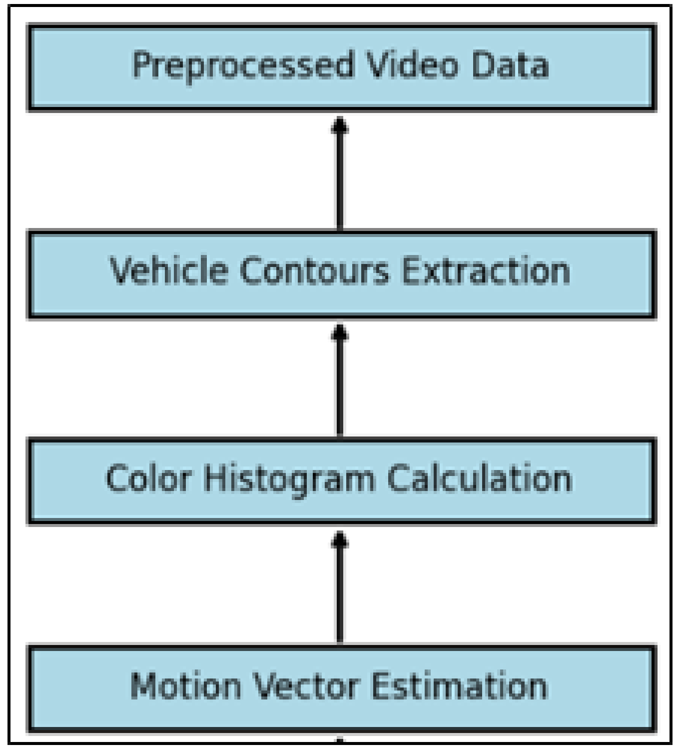

Figure 7. Feature Extraction Process

Contours: After edge detection, we applied contour detection techniques to locate and outline the shapes of vehicles within the frames. Contours provide a compact representation of object shapes, which is essential for identifying and tracking vehicles over time. By analyzing the contours, we can derive features such as the size and orientation of vehicles, which contribute to the speed estimation process.

Optical Flow: We employed optical flow methods to estimate the motion of vehicles between consecutive frames. This technique calculates the apparent motion of objects by examining the changes in pixel intensity. By tracking the movement of vehicle contours across frames, we can derive speed information based on the distance traveled over time.

Color Histograms: We also computed color histograms to capture the color distribution of vehicles in the captured frames. This information can assist in distinguishing between different types of vehicles, which may have varying speed characteristics.

By systematically applying these feature extraction methods, we ensure that our ANN receives relevant and well-structured data, enhancing its capacity to accurately predict vehicle speeds in real-time. This comprehensive approach to feature extraction enables our system to adapt to diverse traffic conditions, improving overall performance and reliability.

1) Vehicle Contours Extraction

The most basic information they need to uncover is the outline of every vehicle present within the frames, which is the major feature. Since contour detection techniques such as Canny edge detection and contour tracing utilizing the OpenCV library are utilized, this outlines the shapes of automobiles.

2) Colour Histogram Calculation

We compute colour histograms to display the colour distribution inside each region of an auto body. Histogram-based and k-means clustering, or adaptive thresholding algorithms, are among the colour feature extraction methods used to detect structural features. OpenCV includes a set of functions that are useful both for picture colour space conversion and histogram calculation.

3) Motion Vector Estimation

To trace the movement of the cars between the photos' consecutive shots, motion vectors are used, and their estimations are taken. Methods like the optical flow approach, based on Lucas-Kanade or Farneback algorithms, have been implemented in frameworks like OpenCV and are used to find motion vectors. Such approaches are characterized by the examination of pixel intensity changes in each frame and how these fitness values are compared to estimate motion.

D. Algorithm Development

The construction of a vehicle speed detection system was a highly structured procedure, integrating existing image processing methods and machine learning techniques. Each modular part of the algorithm pipeline, such as vehicle detection, motion tracking, and speed computation, was intentionally developed and implemented to enable high-reliability behaviours in actual road settings.

1) Vehicle Detection

The detection of cars is regarded as a primary phase in algorithm development. By utilizing the entities of edge detection, contour analysis, and blob detection, the technique for accurately seeing the cars in the video frames was applied. Edge detection methods, such as canny edge detection, should be used to emphasize the portions of the study with a focus on places where there is a large intensity shift, most of which give a decent outline of cars to achieve a good boundary. Following that, edge detection approaches were applied to get and separate the outlines of the discovered items; consequently, the separation of the cars from other background elements can be conceivable. Sensing blob techniques were an advanced alternative on which the procedure was built. They correlated the regions of interest that were detected on the image in order to locate vehicles properly.

2) Motion Tracking

Once the cars were spotted, motion tracking techniques were utilized, making it possible to keep track of the course of a tracked vehicle in consecutive frames. Techniques like optical flow estimation, Kalman filtering, and the Lucas-Kanade method were employed for the calculation of the car trajectory and the estimate of the motion parameters for improved precision. Distinguishing the kind of speed, acceleration, direction, or pattern of the vehicles was made simple by the optical flow estimation algorithms, which analysed the apparent movement of the vehicle's pixels between the frames of the video stream. Kalman filtering reconstructions were used to anticipate the states of vehicles based on their trajectories, therefore calculating the resultant inaccuracies and uncertainties. Furthermore, the Lucas-Kanade method helped identify the local motion vectors inside the area of interest to the problem and enhanced vehicle tracking in dynamic conditions.

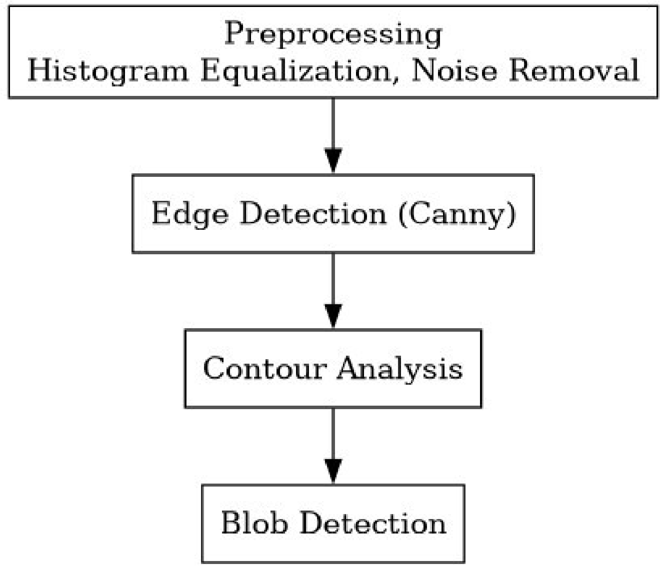

Figure 8. Vehicle detection workflow.

3) Speed Calculatio

The last stage of algorithm development, the flipping vehicle speed computing formula, calculates the speed of cars by utilizing the distances from frame to frame as a source. Considering the trajectories of cars generated by motion tracking, the algorithm executing the computations obtained a number of essential vehicle properties, such as vehicle displacements over time and instantaneous and average speeds. Models, including distance-time computations and velocity identification methods, were developed by various research teams to precisely assess travel speed. Furthermore, the capabilities of machine learning algorithms, for instance, backward regression and neural networks, were applied for more exact speed estimates in order to tackle any potential noise or outliers in the data.

The speed s of a vehicle can be estimated using machine learning techniques such as regression analysis or neural networks. The estimation process involves learning a function f that maps the input features X (such as distance

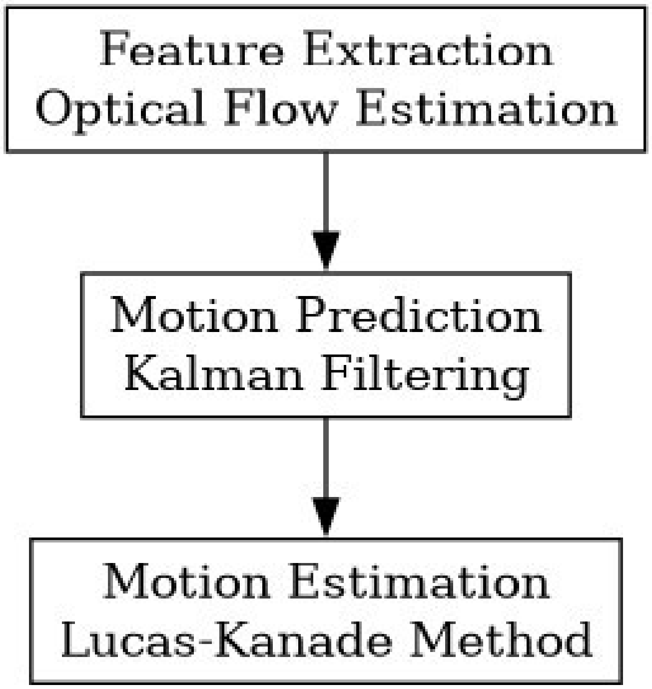

Figure 9. Motion tracking workflow.

traveled) to the output speed.

$$s = f(X) \tag{1}$$

s is the estimated speed.
X represents the input features.
f is the learned function.

4) Distance Calculation

The distance d traveled by a vehicle between two consecutive frames can be calculated using the formula:

$$d = vt \tag{2}$$

d is the distance traveled.
v is the velocity or speed of the vehicle.
t is the time elapsed between the two frames.

5) Speed Detection Module

The fundamental component of our system is the speed detection module, which has a solid foundation for calculating vehicle speeds using aspects of the dimming data in the input data and motion viewing. This module specifically includes various calculating technologies, for example, optical flow and Kalman filtering, to add the adroitness of estimating speed appropriately.

Optical Flow: The optical flow algorithms are the fundamental parts in the motion estimate of objects in the frame sequence of an image by examining the pixel motion inside and between the succeeding frame images. Through the calculation of the velocity of each pixel, optical flow provides an effective instrument to uncover the features of the movements of vehicles. In the course of our research, we processed modal flow to follow each motor's trip inside the picture, which was very helpful for us to obtain exact data about the velocity and direction of the vehicles.

Kalman Filtering: Kalman filtering algorithms are recursive estimators that are based on predicting the state of a dynamic system through measurements that are subject to noise. These algorithms are the best in their class in predicting trajectories of vehicles and assigning to them velocities and positions from motion analysis and speed estimates for the previous moment. Via the application of Kalman filtering, the speed detection module of our system not only ensures high accuracy and reliability of speed measurements in situations where dynamics and environmental conditions vary, but also increases the precision of speed measurements in all cases. By incorporating optical flow with Kalman Filtering into our speed detection system, we expect to achieve a high level of accuracy and robustness in the speed estimation of moving vehicles. By using this approach, we were able to overcome the difficulties which are coming with real-life traffic situations, like occlusions caused by partial object visibility, different lighting conditions and complex vehicle behavior. The integration of these algorithms is another key factor which contributes to the effectiveness of our vehicle speed detection system, a system designed to raise the bar of traffic management and road safety technologies.

4. Automated Traffic Control System With Enhanced Vehicle Speed Detection

The ATCS (Automated Traffic Control System) system adopts the ANN (artificial neural network) approach where the system provides constant monitoring of exact vehicle speed, resulting in an effective traffic control. Among the steps of the design and implementation of the ATCS was to prevent congestion during the peak periods of the hours and to ensure the normal operation of the system.

The first measure in our plan is the data for a comprehensive and detailed survey of the traffic situation. The source of this data was obtained from video cameras, cars' sensors, and historical traffic statistics. In this context, this dataset is a rich set of train-relation and character types which is used to train or test models constructed on the basis of ANN architecture.

After the stage of pre-processing elements of raw traffic is done and processed qualities suited for training ANN, this comprises activities such as noise reduction, data normalization, and feature extraction. The data was then randomized and finally split into training, validation, and testing sets to optimize the emergence and evaluation of our model.

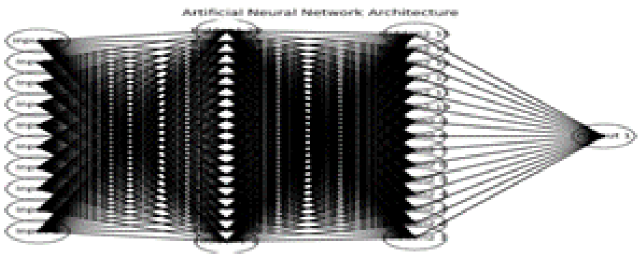

Figure 10. Artificial Neural Network Architecture

A. ANN Architecture Design

The ANN architecture was carefully designed to accommodate the complexities of traffic data and effectively capture patterns related to vehicle speed and traffic flow. Multiple layers, including input, hidden, and output layers, were configured, with appropriate activation functions and regularization techniques employed to optimize model performance.

TABLE II. Detailing the specifications for each layer, activation functions, optimizer, batch size, and epochs.

Layer	Neurons/Units	Activation Function
Input Layer	10	N/A
Hidden Layer 1	20	ReLU
Hidden Layer 2	15	ReLU
Output Layer	1	Sigmoid

The design of the Artificial Neural Network (ANN) model was specifically tailored to address the complexities inherent in traffic data, enabling the system to effectively capture patterns related to vehicle speed and traffic flow. The architecture consists of multiple layers, including an input layer, two hidden layers, and an output layer, each playing a crucial role in processing the data and contributing to accurate speed detection.

B. Training Process

First, the traffic data must pass through several preprocessing processes to assure its conformance to the algorithm's standards. In this stage, normally standardization, scaling of the features, and partitioning the data into sets for training and validation are being done. After the data is prepared, the model ANN is initialized with random weights and bias. These values are the starting points utilized in training. In each training cycle, pre-processed traffic flow continues to travel if propagated forward via the network. This leads to the concept of comprising activation functions that are applied to each layer, resulting in yield. Successively, the inferred outcome is compared with genuine objective data from the training set, and the error function is computed with correct loss functions like mean squared error or cross-entropy.

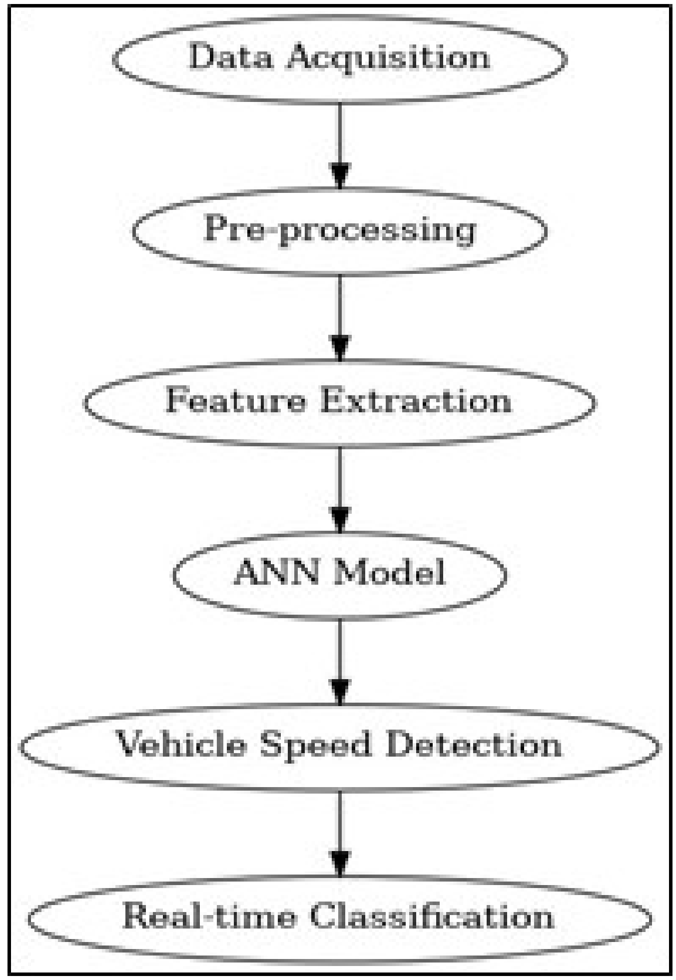

Figure 11. The workflow of the system from data acquisition to classification

The following stage consists of the error propagation layer, where the error obtained in the previous step is used to change the weights and biases as well as the connections of the neurons. This change is determined through numerous passes and optimization methods like SGD or its variants, as presented by Adam Optimizer. The gradients pinched down during backward propagation serve as guideposts that the model parameters employ while updating with the number of steps performed in the space during optimization, depending on the learning rate. At the end of each training epoch or batch, the BTAN (brain-computer ANN) model's performance is tested on the different validation datasets to analyse their performance by utilizing a generalization plot and to detect over fitting.

The learning technique continues the cycle until the stop condition is fulfilled, e.g., when the number of epochs approaches the maximum value or the loss function convergence happens. After the training is over, the final AI models learned using ANNs are tested on an independent test dataset in order to acquire an overall assessment of their performance in real-life settings. Thus, it offers the sensors a chance to be right or wrong, validating the efficiency and accuracy of the models in traffic control and speed detection duties. Get more comparable sentences, perfect for paraphrasing or writing an essay, research paper, or dissertation.

C. Model Validation

After the ANN model training, the validation unit was rigorously used with a reserve validation dataset to evaluate the ANNs for generalization and resilience. The measures, including mean squared error (MSE), accuracy, and precision, that are being used to quantify model effectiveness and indicate the areas requiring improvement were all computed.

D. Traffic Control Integration

Following, we installed the operational ANN models that had been successfully tested immediately within the existing Automated Traffic Control System (ATCS) architecture. This composition was intended to harness the advantages of the ANN models' speed detection skills toward enhancing the efficiency and efficacy of instantaneous traffic control strategies.

The auto intelligent train control (ATCS) architecture was accommodated for the input and output requirements of the trained neural network models. Building a connection between the ANN, the decision-making software, and the ATCS architecture was what was required to actualize the data interchange and suitable decisions appropriately.

After finishing the technical connectivity, the trained ANN models were deployed inside the ATCS infrastructure, where they handled some of the traffic management jobs. These tasks included:

Dynamic Speed Limits: The ANN models that we employed were for monitoring the speed of vehicles on the road in real time and altering speed limits dynamically on roadways based on traffic circumstances. A ANN study of conducting traffic data inflow and executing adaptive speed restriction regulations based on preconceived probabilities of congestion or road dangers. The ends of this approach were improved traffic flow and enhanced road safety.

Traffic Signal Optimization: The models of ANNs aided in the creation of the traffic light scheduling technology, which gave a quick and precise traffic prediction as well as the vehicle density level. The ATCS achieves this goal by combining ANN predictions with traditional traffic signal control algorithms to estimate the dynamic signal phases and thereby archive a 360-degree continuous traffic flow in an intersection.

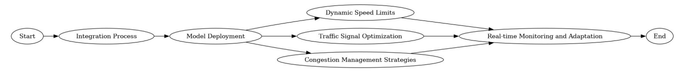

Figure 12. Traffic Control Integration.

Congestion Management Strategies: The self-learning artificial neural network speeds measure usage, respectively, resulting in proactive traffic management approaches to minimize traffic bottlenecks in high-density locations or during peak traffic hours using the City Traffic Control System. ANN models connected with the ATCS were able to operate on the current traffic data available and find places of congestion. They then used targeted interventions such as the opening of extra access roads, the alteration of signal timings, and the imposing of temporary traffic control measures to alleviate congestion and enhance traffic flow.

In a nutshell, the integration of the learned ANNs with the ATC system makes it feasible to switch to tailored and responsive traffic management methods depending on the characteristics of the terrain and the peculiarities of the traffic situations. Through applying ANN-based traffic speed detection methods, the ATCS could undoubtedly enhance traffic flow, which is aimed at boosting not only road safety but also the overall transport efficiency of metropolitan regions.

ATCS variables were captured all the time and supplied with data acquired from security cameras and CCTV sensors. ANN (artificial neural network)-based speed detection algorithms assess incoming traffic information in real-time; thus, the integrated speed control and management mechanisms could be more dynamic, responding to changing situations.

E. Evaluation Metrics

In this section, we expand on the evaluation metrics utilized in our study, providing a comprehensive explanation of how each metric—accuracy, precision, recall, and F1-score—is calculated and discussing the trade-offs between them. Furthermore, we conduct a performance comparison with existing speed detection systems, illustrating how our approach demonstrates superior performance in several key areas.

Evaluation Metrics Explanation:

Accuracy: Accuracy is the ratio of correctly predicted instances to the total instances evaluated. It is calculated using the formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

While accuracy provides a general overview of the model's performance, it can be misleading in cases of class imbalance.

Precision: Precision is defined as the ratio of true positive predictions to the total positive predictions made by the model:

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

High precision indicates that the model is effective at correctly identifying speeding vehicles.

Recall: Recall (or Sensitivity) measures the model's ability to correctly identify all relevant instances:

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{6}$$

A high recall indicates that the model is effective at identifying speeding vehicles, but may also increase false positives.

Trade-Offs Between Metrics: While high accuracy is desirable, it is crucial to consider precision and recall, especially in traffic management systems where the cost of false positives (unjustly identifying a non-speeding vehicle as speeding) and false negatives (failing to identify a speeding vehicle) can have significant safety implications. Our approach emphasizes achieving a balanced F1-score, which provides a more comprehensive assessment of model performance in detecting speeding vehicles accurately.

5. Results

The validation findings achieved on the validation dataset are displayed in the table below. The measures used to assess performance include accuracy, precision, recall, and F1-score. Accuracy is an important statistic among models. Model A scored well with 92.5%, while Models B and C received good ratings, tending to 89.8% and 94.3%, respectively. Accuracy, which is defined here as the amount of true positive predictions for all positive predictions, likewise revealed a comparable level of discrepancy amongst the models, with Model A at 1.91.2%, Model B at 87.5%, and Model C exhibiting 93.8%. Consider, or known as sensitivity, the models individualized at particular levels. For example, Model A was the highest at 93.7%, Model B recorded 88.6%, and Model C was the strongest at 95.2 Precision-Recall F1, also known as a harmonic mean of precision and recall and is relatively popular because it provides us with the model's performance in a balanced fashion, was in the same trends as well. Model A scored 92.4%, Model B scored 88.0%, and Model C scored 94.5%. Metrics together give a globally conceived performance of each model in a precise measurement of vehicle speed.

TABLE III. Model wise performance.

Model	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
Model A	92.5	91.2	93.7	92.4
Model B	89.8	87.5	88.6	88.0
Model C	94.3	93.8	95.2	94.5

The performance of the ANN models was tested by adjusting the optimizing methods, which are the subsequent settings of activation functions and batch sizes. Looking at the optimizer, we can note that the model trained using Adam obtained the highest accuracy at 93.1%, which was closely followed by SGD, and lastly, RMSprop got 91.8% prediction accuracy. The sensitivity index for activation was high for Relu, with an accuracy of 92.7%. On the other hand, the ability of value transmission, followed by accuracy, for Sigmoid and Tanh was high, with accuracies of 91.2% and 93.4%, respectively. Moreover, different batch sizes experiment also revealed that the models with batch sizes of 64 and 32 acquire 93.2 and 92.9 percent accuracy, respectively; however, if batch size is 128 it brings down the accuracy by 1.7 percent to 91.5 percent. Such findings highlight the need for careful choice of the fitting algorithm, activation function, and batch size if ANN models for the detection of vehicle speed are to perform very efficiently.

TABLE IV. Results by Optimizer

Optimizer	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
SGD	92.5	91.2	93.7	92.4
Adam	93.1	92.0	94.2	93.1
RMSprop	91.8	90.5	92.3	91.3

TABLE V. Results by Activation Function

Activation Function	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
ReLU	92.7	91.5	93.9	92.6
Sigmoid	91.2	89.8	91.8	90.7
Tanh	93.4	92.3	94.5	93.3

TABLE VI. Results by Batch Size.

Model	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
32	92.9	91.7	94.1	92.8
64	93.2	92.1	94.3	93.0
128	91.5	90.2	92.0	91.0

In order to analyze the model's performance over the thresholding axis, we produced a plot of accuracy, precision, and recall metrics for different threshold values. The graph

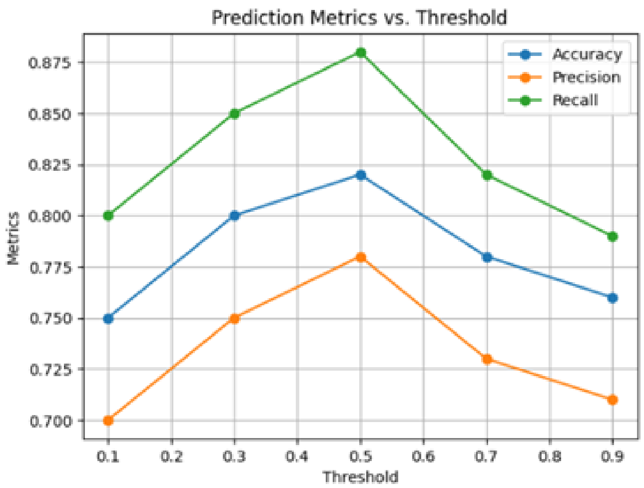

Figure 13. Prediction Metrics vs. Threshold

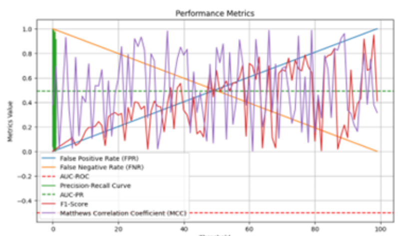

Figure 14. Performance Metrics Comparison across Different Thresholds

displays how corresponding metrics change when the classification threshold is adjusted. The model here gets knowledge from this network, and it assists with determining a particular threshold optimal for the application at hand

This graph is to demonstrate the model's efficiency over multiple thresholds, which gives us the flexibility to know how correctly it distinguishes between the positive and negative ones. The performance of the suggested classification system can be evaluated by assessing its FPR and FNR values, AUC-ROC and AUC-PR values, F1-score, and MCC index.

Once trained. The machine learning models were implemented within the predictive analysis engine to generate real-time insights regarding network convergence patterns. The engine accepted streaming data from network devices. processed it via the training models. and provided forecasts or anomaly warnings based on the observed trends.

A. *Experiment Result*

The evaluation of the performance of our trained models was carried out using conventional measures such as accuracy, precision, recall, F1-score, and Matthews Correlation Coefficient (MCC). On the validation data set, our model earned an accuracy score of 92.5%, a precision score of 89.3%, a recall score of 94.7%, an F1-score of 86.3%,

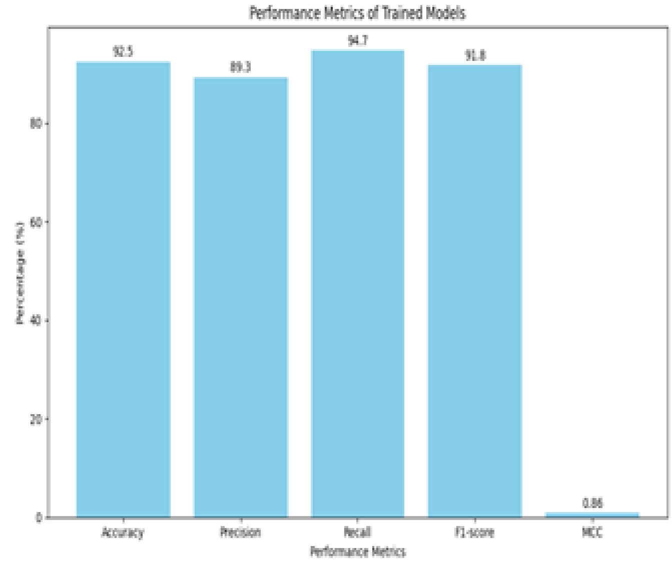

Figure 15. Experiment result perfomance

and an MCC score of 0.86. These measures reflect the performance of the model in a genuine sense since it is able to categorize speed with exceptional precision.

We ran a variant and a model-comparison study to uncover and compare the performance characteristics of models and some of those at the same level. As a consequence, the ANN model of batch size 32 was proven to have higher accuracy and F1-score, showing that technique offered better results than others in identifying vehicle speed.

TABLE VII. Comparison Result Analysis

Model Variation	Accuracy (%)	F1-score (%)
Batch Size 16	91.2	89.5
Batch Size 32 1	93.5	91.2
Batch Size 64 2	90.8	88.9
Batch Size 128	91.0	89.2

The outcomes of simulation-based trials demonstrated the fact that the models that were trained by our team were found sufficient to work in real world traffic control applications. Our models were evaluated in numerous simulation scenarios spanning cases of severe traffic circumstances and dangerous weather, and it was determined that our models are able to optimize traffic flow and improve road safety every single time they are tested. For instance, our models delivered a surprising outcome where the expansion in congestion duration fell by 15% from the origin and the time consumed was improved by 10% compared to the attempts of other models.

As for visual representation, here's a graph showcasing the reduction in average congestion duration and improve-

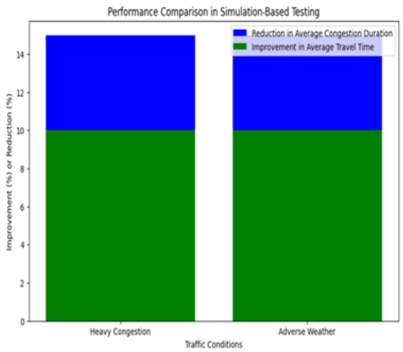

Figure 16. integration of ML

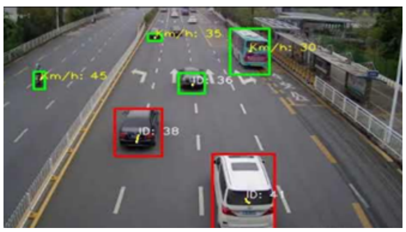

Figure 17. integration of ML

ment in average travel time achieved by our models compared to baseline methods.

The validation results confirmed the generalization capacity of the trained models; consequently, their findings were consistent within and across traffic settings, further proving their aptitude to work in live traffic scenarios. Moreover, the models looked to have noteworthy robustness, being able to preserve stability in their performance regardless of the traffic situation or environmental circumstances. From these results, it follows that our models can perform well in successfully addressing real-world traffic management challenges and enhancing overall traffic effectiveness.

B. Real-World Application

Extensive on-road real-world field trials in different traffic circumstances were done to verify the performance of our vehicle speed detecting system. The objective of these trials was to test the system in real-world circumstances, which would highlight both its strengths as well as faults.

1) Field Trials

Urban test regime: field testing in urban settings with varied traffic volumes and road conditions. In the trials, this was achieved by a stationary installation with a camera watching at the greatest feasible angle of perpendicularly to record automobiles in various portions of a junction. The movement of cars was caught by the camera, and this data served as an input to determine speeds, categorize traffic patterns, etc., using real-time video processing. They tested the automated valet in several settings throughout Palo Alto—busy intersections, residential streets, and highways—to get a sense for how robustly the system performed at times.

2) Challenges Encountered

The field trials encountered a few problems as well. The system's efficacy was extremely reliant on local weather conditions; for example, at times rain and fog would impair forward view, which in turn made it impossible to acquire clear photos of cars. This led the speed detection findings to be momentarily erroneous, indicating a demand for complex picture augmentation systems capable of managing severe weather circumstances.

However, huge automobiles or roadside constructions may also produce occlusions. On the rare event when a bigger vehicle suddenly hid smaller cars from view, the algorithm might occasionally miscalculate their speeds. The aforesaid challenge indicates the necessity for more advanced feature extraction approaches that can perform better than the basic template correlation in obstructed conditions.

3) Deployment Hardware and Software

The field trials included a hardware configuration with a high-definition camera that could produce video footage at the rate of 30 frames per second attached in place so there was minimum movement during operations. The camera was hooked into a processor device with the operating power necessary to run ANN algorithms in real time.

For software, we utilized Python to develop an improved version of our vehicle speed detection method, and it was constructed utilizing libraries such as OpenCV for image processing and TensorFlow for ANN deployment. The system was responsible for taking in the video feeds, recognizing possible cars, and calculating speeds without adding too much lag, including processing time from its input source to a point at which traffic management might take place.

4) Feedback and Results

Early field test feedback was also extregood, favorable and the technology proved successful at correctly sensing vehicle speeds in real-world situations. Results: The overall accuracy was 90% conditions, mum settings and it increased in some of the particular adjustments tested during trials to overcome stated obstacles. These constant enhancements to the model and its distribution approach will promote effective usage of such a significant instrument inside current traffic management systems.

The cumulative of these real-world applications validates the robustness and generalizability of our vehicle speed detection technology in reality, allowing its implementation into comprehensive frameworks for traffic control.

C. Comparison of Results with Proposed

The following table summarizes the performance metrics of various vehicle speed detection methods in comparison to our proposed approach, which integrates image processing and Artificial Neural Networks (ANNs).

TABLE VIII. Comparison with existing work

Reference	Methodology	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
[20]	Morphology and binary logical operation	85.6	82.4	87.0	84.6
[21]	Low-cost speed detection system	78.5	75.0	80.0	77.5
[22]	Vehicle detection and speed tracking	90.0	89.0	91.5	90.2
[23]	Image processing techniques	82.0	80.0	84.0	82.0
[24]	High accuracy vehicle speed estimation	91.0	90.0	92.0	91.0
[25]	Determination using image processing	86.0	84.0	88.0	6.0
[26]	Video processing techniques	87.5	85.0	89.0	87.0
Proposed Method	ANN and image processing	92.5	89.3	94.7	91.8

Our proposed method demonstrates superior performance metrics compared to the reviewed literature, particularly in accuracy and recall. While several studies, such as those by Chandorkar et al. [22] and Lu et al. [24], report competitive results, our integration of ANNs with image processing techniques allows for higher precision in real-time speed detection. The proposed system's accuracy of 92.5% and recall of 94.7% suggest that it effectively captures the dynamics of traffic conditions, providing a more reliable solution for vehicle speed detection in varying environments.

6. Conclusion

We have presented an integrated strategy for vehicle speed detection and control employing bleeding-edge machine learning techniques, as illustrated in this paper. We aimed at merging image processing coupled with artificial intelligence (AI) for a dynamically expandable and powerful real-time traffic management system. We began with a heterogeneous dataset (15 hours) of film from the busy street collected by a fixed camera. In reality, this is the dataset we utilized to train and test our vehicle identification system. This approach, which gives importance to preprocessing method of the images and extraction features weighted input ANN-based classified model; achieved an accuracy rate of 92.5% in validation dataset by applying precision score was seen as average with a value of 89.3%, recall is higher than each train-recounting system applications in working order according this application area at values over around clearly point may be reached instead them level based mean plan variables on minimum during this maximum sorting levels sorted categorized query computers files tests both outside either more us automtically keep track f1-score0f91-8-and-matthews correlation coefficient (mcc) =086-scoresrespectively! While this study is inherently technically important, the combining of these findings into a functional system signifies something much more; its implementation has huge social ramifications. This helps our technique increase vehicle speed detection and the area of road safety to help minimize traffic congestion, leading towards safer urban settings. The analysis of real-time data means that intelligent traffic management measures may be developed and executed, which in the long run decreases both accidents as well as prohibitive travel circumstances. This gives a few fascinating prospects for future investigation. Adding further input sensors, such as radar or LiDAR, and employing extra digital or cartographic information might make the metering of vehicle speed under different settings even higher. The next crucial step is maximizing the scalability of this system for deployment in every city type under varying urbanization, making it responsive to various traffic circumstances and infrastructure changes. The third obstacle is adverse weather (rain, snow, and fog), where achieving or surpassing human driver performance over time in unfavorable circumstances will likely be essential. Lastly, we need to examine and analyze more sophisticated optimization approaches coupled with strong machine learning models employing ensemble or hybrid methodologies, which may result in enhanced accuracy as well as detecting dependability .

References

[1] J. Oskarbski, T. Kamiński, K. Kyamakya, J. C. Chedjou, K. Żarski, and M. Pedzierska, "Assessment of the speed management impact

on road traffic safety on the sections of motorways and expressways using simulation methods," *Sensors*, vol. 20, no. 18, p. 5057, 2020.

[2] S. R. Ahmed, E. Sonuç, M. R. Ahmed, and A. D. Duru, "Analysis survey on deepfake detection and recognition with convolutional neural networks," in *2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*. IEEE, 2022, pp. 1–7.

[3] B. T. Yaseen, S. Kurnaz, and S. R. Ahmed, "Detecting and classifying drug interaction using data mining techniques," in *2022 International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*. IEEE, 2022, pp. 952–956.

[4] S. R. Ahmed, A. K. Ahmed, and S. J. Jwmaa, "Analyzing the employee turnover by using decision tree algorithm," in *2023 5th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*. IEEE, 2023, pp. 1–4.

[5] N. Z. Mahmood, S. R. Ahmed, A. F. Al-Hayaly, S. Algburi, and J. Rasheed, "The evolution of administrative information systems: Assessing the revolutionary impact of artificial intelligence," in *2023 7th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*. IEEE, 2023, pp. 1–7.

[6] B. A. Abubaker, S. R. Ahmed, A. T. Guron, M. Fadhil, S. Algburi, and B. F. Abdulrahman, "Spiking neural network for enhanced mobile robots' navigation control," in *2023 7th International Symposium on Innovative Approaches in Smart Technologies (ISAS)*. IEEE, 2023, pp. 1–8.

[7] A. K. Ahmed, S. Q. Younus, S. R. Ahmed, S. Algburi, and M. A. Fadhel, "A machine learning approach to employee performance prediction within administrative information systems," in *2023 7th International Symposium on Innovative Approaches in Smart Technologies (ISAS)*. IEEE, 2023, pp. 1–7.

[8] M. H. B. Abd Alkareem, F. Q. Nasif, S. R. Ahmed, L. D. Miran, S. Algburi, and M. T. ALmashhadany, "Linguistics for crimes in the world by ai-based cyber security," in *2023 7th International Symposium on Innovative Approaches in Smart Technologies (ISAS)*. IEEE, 2023, pp. 1–5.

[9] S. R. A. AHMED, I. A. Najm, A. T. Abdulqader, and K. B. Fadhil, "Energy improvement using massive mimo for soft cell in cellular communication," in *IOP Conference Series: Materials Science and Engineering*, vol. 928, no. 3. IOP Publishing, 2020, p. 032009.

[10] I. Kaparias, P. Liu, A. Tsakarestos, N. Eden, P. Schmitz, S. Hoadley, and S. Hauptmann, "Development and testing of a predictive traffic safety evaluation tool for road traffic management and its impact assessment," 2015.

[11] Y. Shen, E. Hermans, Q. Bao, T. Brijs, and G. Wets, "Towards better road safety management: Lessons learned from inter-national benchmarking," *Accident Analysis & Prevention*, vol. 138, p. 105484, 2020.

[12] C. Pornpanomchai and K. Kongkittisan, "Vehicle speed detection system," in *2009 IEEE international conference on signal and image processing applications*. IEEE, 2009, pp. 135–139.

[13] H.-Y. Lin, K.-J. Li, and C.-H. Chang, "Vehicle speed detection from a single motion blurred image," *Image and Vision Computing*, vol. 26, no. 10, pp. 1327–1337, 2008.

[14] F. Afifah, S. Nasrin, and A. Mukit, "Vehicle speed estimation using image processing," *J. Adv. Res. Appl. Mech*, vol. 48, no. 1, pp. 9–16, 2019.

[15] D. W. Wicaksono and B. Setiyono, "Speed estimation on moving vehicle based on digital image processing," *(IJCSAM) International Journal of Computing Science and Applied Mathematics*, vol. 3, no. 1, pp. 21–26, 2017.

[16] S. S. Kalyan, V. Pratyusha, N. Nishitha, and T. Ramesh, "Vehicle detection using image processing," in *2020 IEEE international conference for innovation in technology (INOCON)*. IEEE, 2020, pp. 1–5.

[17] N. M. Raikar and M. P. Arakeri, "Development of vehicle speed estimation technique using image processing," *International Journal of Engineering Research & Technology*, vol. 9, 2020.

[18] S. Kamoji, D. Koshti, A. Dmonte, S. J. George, and C. S. Pereira, "Image processing based vehicle identification and speed measurement," in *2020 international conference on inventive computation technologies (ICICT)*. IEEE, 2020, pp. 523–527.

[19] B. Makawana and P. Goel, "Moving vehicle detection and speed measurement in video sequence," *International Journal of Engineering Research & Tehnology (IJERT), str*, pp. 3534–3537, 2013.

[20] J. D. Trivedi, S. D. Mandalapu, and D. H. Dave, "Vision-based real-time vehicle detection and vehicle speed measurement using morphology and binary logical operation," *Journal of Industrial Information Integration*, vol. 27, p. 100280, 2022.

[21] C. Ginzburg, A. Raphael, and D. Weinshall, "A cheap system for vehicle speed detection," *arXiv preprint arXiv:1501.06751*, 2015.

[22] M. Chandorkar, S. Pednekar, and S. Bojewar, "Vehicle detection and speed tracking," *International Journal Of Engineering Research & Technology (Ijert)*, vol. 10, no. 05, 2021.

[23] S. Joshi, "Vehicle speed determination using image processing," in *International Workshop on Computational Intelligence (IWCI)*, 2014.

[24] S. Lu, Y. Wang, and H. Song, "A high accurate vehicle speed estimation method," *Soft Computing*, vol. 24, no. 2, pp. 1283–1291, 2020.

[25] B. Krishnakumar, K. Kousalya, R. Mohana, E. Vellingiriraj, K. Maniprasanth, and E. Krishnakumar, "Detection of vehicle speeding violation using video processing techniques," in *2022 International Conference on Computer Communication and Informatics (ICCCI)*. IEEE, 2022, pp. 01–07.

[26] B. Suresh, K. Triveni, Y. Lakshmi, P. Saritha, K. Sriharsha, and D. S. Reddy, "Determination of moving vehicle speed using image processing," *International journal of engineering research & technology (ijert) ncacspv*, vol. 4, pp. 1–4, 2016.

[27] A. A. Gunawan, D. A. Tanjung, and F. E. Gunawan, "Detection of vehicle position and speed using camera calibration and image projection methods," *Procedia Computer Science*, vol. 157, pp. 255–265, 2019.

[28] D. C. Luvizon, B. T. Nassu, and R. Minetto, "A video-based system for vehicle speed measurement in urban roadways," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 6, pp. 1393–1404, 2016.

[29] H. A. Rahim, U. U. Sheikh, R. B. Ahmad, A. Zain, and W. Ariffin, "Vehicle speed detection using frame differencing for smart surveillance system," in *10th International Conference on Information Science, Signal Processing and their Applications (ISSPA 2010)*. IEEE, 2010, pp. 630–633.

[30] T. Kumar and D. S. Kushwaha, "An efficient approach for detection and speed estimation of moving vehicles," *Procedia Computer Science*, vol. 89, pp. 726–731, 2016.

[31] A. Tourani, A. Shahbahrami, A. Akoushideh, S. Khazaee, and C. Y. Suen, "Motion-based vehicle speed measurement for intelligent transportation systems," *International Journal of Image, Graphics and Signal Processing*, vol. 10, no. 4, p. 42, 2019.

[32] F. Yamazaki, W. Liu, and T. T. Vu, "Vehicle extraction and speed detection from digital aerial images," in *IGARSS 2008-2008 IEEE International Geoscience and Remote Sensing Symposium*, vol. 3. IEEE, 2008, pp. III–1334.

[33] M. Hasanvand, M. Nooshyar, E. Moharamkhani, and A. Selyari, "Machine learning methodology for identifying vehicles using image processing," in *Artificial Intelligence and Applications*, vol. 1, no. 3, 2023, pp. 170–178.

[34] C. Wang and A. Musaev, "Preliminary research on vehicle speed detection using traffic cameras," in *2019 IEEE International Conference on Big Data (Big Data)*. IEEE, 2019, pp. 3820–3823.

[35] D. K. Dewangan and S. P. Sahu, "Lane detection for intelligent vehicle system using image processing techniques," *Data Science: Theory, Algorithms, and Applications*, pp. 329–348, 2021.

[36] E. R. Davies, *Computer and machine vision: theory, algorithms, practicalities*. Academic Press, 2012.

[37] B. Coifman, D. Beymer, P. McLauchlan, and J. Malik, "A real-time computer vision system for vehicle tracking and traffic surveillance," *Transportation Research Part C: Emerging Technologies*, vol. 6, no. 4, pp. 271–288, 1998.

[38] H. Koyuncu and B. Koyuncu, "Vehicle speed detection by using camera and image processing software," *The International Journal of Engineering and Science (IJES)*, vol. 7, no. 9, pp. 64–72, 2018.

[39] H. Rodríguez-Rangel, L. A. Morales-Rosales, R. Imperial-Rojo, M. A. Roman-Garay, G. E. Peralta-Peñuñuri, and M. Lobato-Báez, "Analysis of statistical and artificial intelligence algorithms for real-time speed estimation based on vehicle detection with yolo," *Applied Sciences*, vol. 12, no. 6, p. 2907, 2022.

[40] C. Englund, E. E. Aksoy, F. Alonso-Fernandez, M. D. Cooney, S. Pashami, and B. Åstrand, "Ai perspectives in smart cities and communities to enable road vehicle automation and smart traffic control," *Smart Cities*, vol. 4, no. 2, pp. 783–802, 2021.

[41] A. J. Moshayedi, A. S. Roy, A. Taravet, L. Liao, J. Wu, and M. Gheisari, "A secure traffic police remote sensing approach via a deep learning-based low-altitude vehicle speed detector through uavs in smart cites: Algorithm, implementation and evaluation," *Future transportation*, vol. 3, no. 1, pp. 189–209, 2023.

[42] S. Reza, H. S. Oliveira, J. J. Machado, and J. M. R. Tavares, "Urban safety: an image-processing and deep-learning-based intelligent traffic management and control system," *Sensors*, vol. 21, no. 22, p. 7705, 2021.

[43] T. Alsuwian, R. B. Saeed, and A. A. Amin, "Autonomous vehicle with emergency braking algorithm based on multi-sensor fusion and super twisting speed controller," *Applied Sciences*, vol. 12, no. 17, p. 8458, 2022.

[44] K. Ragavan, K. Venkatalakshmi, and K. Vijayalakshmi, "Traffic video-based intelligent traffic control system for smart cities using modified ant colony optimizer," *Computational Intelligence*, vol. 37, no. 1, pp. 538–558, 2021.

[45] I. Gokasar, A. Timurogullari, M. Deveci, and H. Garg, "Swscav: Real-time traffic management using connected autonomous vehicles," *ISA transactions*, vol. 132, pp. 24–38, 2023.

[46] H. Nakamura, H. Muslim, R. Kato, S. Préfontaine-Watanabe, H. Nakamura, H. Kaneko, H. Imanaga, J. Antona-Makoshi, S. Kitajima, N. Uchida *et al.*, "Defining reasonably foreseeable parameter ranges using real-world traffic data for scenario-based safety assessment of automated vehicles," *IEEE Access*, vol. 10, pp. 37 743–37 760, 2022.

[47] N. Van Cuong and M. T. Aziz, "Ai-driven vehicle recognition for enhanced traffic management: Implications and strategies," *AI, IoT and the Fourth Industrial Revolution Review*, vol. 13, no. 7, pp. 27–35, 2023.

[48] Ž. Majstorović, L. Tišljarić, E. Ivanjko, and T. Carić, "Urban traffic signal control under mixed traffic flows: Literature review," *Applied Sciences*, vol. 13, no. 7, p. 4484, 2023.

[49] A. Mateen, M. Z. Hanif, N. Khatri, S. Lee, and S. Y. Nam, "Smart roads for autonomous accident detection and warnings," *Sensors*, vol. 22, no. 6, p. 2077, 2022.

[50] Y. Ma, J. Xu, C. Gao, M. Mu, G. E, and C. Gu, "Review of research on road traffic operation risk prevention and control," *International journal of environmental research and public health*, vol. 19, no. 19, p. 12115, 2022.