REDVET - Revista electrónica de Veterinaria - ISSN 1695-7504
Vol 25, No. 1 (2024)
http://www.veterinaria.org
Article Received: November 2023 Revised: December 2023 Accepted: January 2024

Estimating Traffic Density In Real-Time Using Enhanced Deep Learning Model

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ABSTRACT
In the field of transportation where cars are becoming more and more common metropolitan areas are experiencing an increase in traffic congestion. Using advanced technologies in Intelligent Transport Systems (ITS) has emerged as a viable solution to address this. ITS essentials like vehicle detection and counting help with traffic control and urban planning. Using current developments in Deep Learning (DL), especially with regard to the You Only Look Once (YOLO) model. By utilising object identification capabilities, the model precisely counts cars inside designated locations helping to identify congested zones and peak traffic hours. This work provides a real-time traffic density estimation technique. The work optimises the YOLOv8 model for better performance and uses the COCO benchmark dataset for vehicle detection. Through comprehensive performance evaluation including learning curve analysis, confusion matrix assessment and performance metrics evaluation the model demonstrates high accuracy and generalization capability. Inference and generalisation on test data demonstrate real-world applicability and demonstrate the model's efficacy in real-world circumstances. Inference and generalisation on test data demonstrate real-world applicability and demonstrate the model's efficacy in real-world circumstances.

Keywords: *Intelligent Transportation System; YOLO; Traffic Density; Deep Learning; Vehicle recognition.*

1. Introduction

Today's fast-paced world depends heavily on transportation for day-to-day activities. Over 1.45 billion cars are expected to be on the road by the end of 2023 with roughly 1.1 billion of those being passenger cars according to current estimates. As a result, urban regions will most likely experience an increase in traffic issues. Traffic congestion is a major problem that causes delays, discomfort and a poorer standard of living for commuters in many urban areas [2]. ITS is an advanced technology that integrates computers, information, communications and other advances which applies them to the transportation industry to provide transportation using advanced data communication technologies. Vehicle recognition and counting are the main parts of an ITS [3,4].

To improve traffic light signal effectiveness and lessen traffic congestion, engineers and researchers are developing intelligent traffic systems. Numerous scientific and experimental investigations have been carried out to tackle these concerns. Moreover, additional information sources such as video surveillance make it possible to build vehicle monitoring and counting systems more effectively. New and improved techniques for counting and keeping an eye on cars on the streets have been made possible by recent advancements in this field. For instance, researchers have developed new deep learning algorithms [5] by using object detection can accurately recognise and count autos in real time even in challenging environments.

Finding an object's position and class in a picture or video stream is called object detection. Bounding boxes surrounding each item are included in its output along with confidence scores and class labels [6]. When precise shape details are not needed this method works well for locating items within a scene. YOLO, SSDs and RCNNs are some of the top models for this purpose. Right now, YOLO models are superior than other models in achieving the right balance between speed and accuracy especially in real-time detection circumstances [7]. YOLO which stands for "You Only Look Once" transforms computer vision object detection by providing a quick and efficient method. It treats detection as a one-step activity that combines object location and classification which simplifies it in a unique way. YOLO can process photos and videos in real-time with great accuracy which is further improved by the most recent version YOLOv8. This YOLOv8 skillfully addresses issues with object detection and image segmentation. Because of its real-time capabilities YOLO is an excellent option for applications that require accurate and quick object detection [8].

Using YOLO's real-time detection capabilities this study focuses on the estimation of traffic density which is an essential part of traffic and urban management [9]. The objective is to measure traffic density by counting the number of cars in a certain area within each frame. This useful information supports urban planning by helping to identify congested areas and times of high traffic [11]. With the help of this project the study hope to create a whole toolkit that will improve traffic management and city development initiatives by offering in-depth insights into research flow and trends.

The following is the format of the remaining portions of the paper: Section 2 offers an extensive review of the literature. Section 3 provides an illustration of the proposed methodology. In Section 4, the experiment's findings are displayed. Lastly, Section 5 provides the conclusion.

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2. Literature Review

Model-driven approaches comprise the majority of conventional techniques for traffic state estimation and prediction. These models were developed with the assumption of perfect conditions and ideals that perfectly describe real-world traffic flow occurrences. Yuyan et al. (2022) proposes a hybrid framework TFMDL for traffic state estimation (TSE) that combines model-driven and data-driven methods. Their approach, evaluated on the US I-405 corridor dataset, outperforms benchmark models in accuracy and data efficiency [10].
Baoling et al. (2024) propose a lightweight YOLOv8n-ShuffleNetv2-Ghost-SE model for real-time monitoring of apple fruits in smart orchards. By integrating ShuffleNetv2 and Ghost modules and employing WIoU for bounding box regression, the model achieves high precision with reduced memory and computation costs. It outperforms advanced models in terms of model size and detection speed making it suitable for deployment on edge devices [12].
Anirudh et al. (2022) review recent advances in deep learning for traffic flow prediction, highlighting the crucial role of accurate forecasts in transportation systems. The challenges prompt exploration of hybrid and unsupervised methods. The review underscores the importance of understanding model performance factors and the shift towards hybrid approaches in traffic prediction [13]. Alpamis et al. (2023) introduce an advanced real-time vehicle counting system for mitigating traffic congestion in urban areas. Utilizing YOLOv5 and DeepSort algorithms, the system achieves 98.1% accuracy in vehicle counting within 0.2408 seconds. Integrated into the Tashkent Smart City project, it operates effectively in various weather conditions and contributes to traffic management and signal optimization. The study also provides a dataset for further research and suggests future enhancements [14].
Sayed et al. (2023) explore the role of ITS in smart cities, focusing on traffic flow prediction to tackle congestion. Their study reviews ML and DL techniques in traffic forecasting, addressing challenges in their application. Through an extensive review of 40 articles, the study contributes insights into the importance of traffic forecasting for urban planning and road design, serving as a valuable resource for future research in transportation efficiency [15]. Getahun et al. (2023) propose traffic prediction models to preemptively manage elephant flows in multimedia applications, aiming to prevent network congestion. Using H2O, Deep Autoencoder, and autoML algorithms, they achieve high validation accuracies of up to 100%. Their models provide explicit explanations through Explainable Artificial Intelligence, emphasizing the importance of early detection and prevention to optimize network QoS [16].

3. Materials and Proposed Model

3.1. Materials

In this work the dataset utilized is COCO benchmark dataset for vehicle detection. This dataset is sourced from Kaggle website. The 536 training photos and 90 validation images that make up the dataset for this study are all sized evenly at 640x640 pixels. With a split ratio of about 85% for training and 15% for validation a substantial amount of data is provided for model learning while keeping a sufficient number of images for effective model validation. Sample images represented in Figure 1.

Figure 1. Sample Image on COCO Dataset

3.2. The Proposed Real-Time Traffic Density Estimation Model

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3.2.1. System Structure
Finding position and type of objects in pictures or video streams is called object detection. Bounding boxes surrounding each item class labels and confidence ratings are included in its output. When pinpointing an object in a scene without needing to know its exact shape this method works great. RCNNs, SSDs and YOLO are among of the best models for this kind of work. For the time being YOLO models are the best at striking a balance between speed and accuracy especially in situations involving real-time detection. To process each individual frame the system first extracts a series of frames from the incoming video. The sampling rate is a custom-set number of frames per second (fps). The next step involves using a convolutional neural network (CNN) model to identify items on every frame. For system development and implementation, the YOLOv8 model is employed. One of the most sophisticated and precise object identification models is this one. Ultimately the generated image is one that uses bounding boxes to pinpoint the locations of automobiles. As a result, the system is able to determine the quantity of each kind of vehicle as well as the overall volume of traffic at the intersection.

3.2.2. Model YOLOv8
The YOLOv8 model is employed in this study to construct the system. Glenn Jocher developed the research group Ultralytics which created the YOLOv8 model. Modern models like the YOLOv8 model capitalize on the popularity of earlier iterations of the YOLO concept. In order to further improve performance and versatility this model also adds new features and upgrades. YOLOv8 is a great option for a range of object recognition, picture segmentation and image classification applications because of its quick, accurate and user-friendly design. Figure 2 [1] demonstrates the YOLOv8 model's structure. There are various variations of the YOLOv8 model including YOLOv8s, YOLOv8n, YOLOv8m, YOLOv8x and YOLOv8l. The model must be trained as the initial step in the system building process. In order to build a database for the model's training and testing we gather and label data during this step.

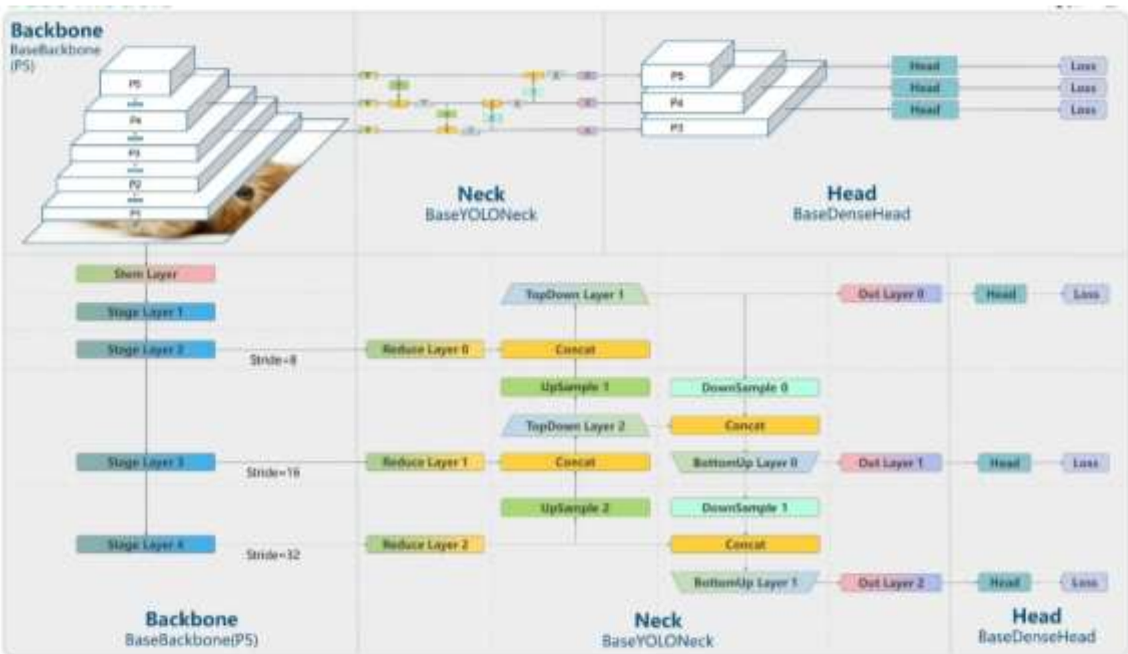

Figure 2. The Structure of YOLOv8 Model [1]

3.2.3. Fine-Tuning YOLOv8
To use transfer learning to improve our YOLOv8 object identification model specifically adjusting it to our 'Top-View Vehicle identification Image Dataset. We build upon the solid foundation already established by the YOLOv8 model. This strategy saves a significant amount of time and resources while simultaneously utilising our intended dataset to enhance the model's ability to accurately identify and detect automobiles in top-view photographs. With this training approach the model may be efficiently and effectively adjusted to the unique requirements of aerial vehicle detection.

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4. Discussion and Experimental Results

4.1. Model Performance Evaluation

This effort entails a thorough investigation and assessment of the model's performance including: Analysis of Learning Curves, Assessment of Confusion Matrix Evaluation and Performance Metrics.

4.1.1. Learning Curves Analysis

To evaluate the learning stability and efficiency we first examine the training and validation loss patterns over epochs:

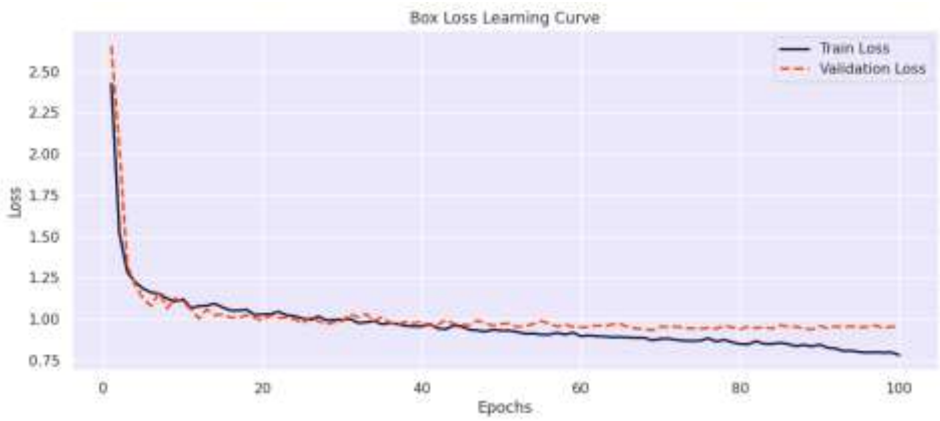

Figure 3. Box Loss Learning Curve

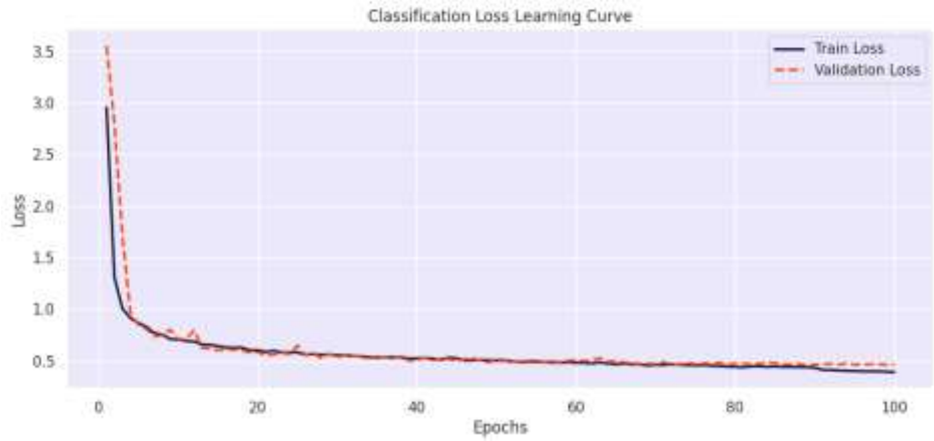

Figure 4. Classification Loss Learning Curve

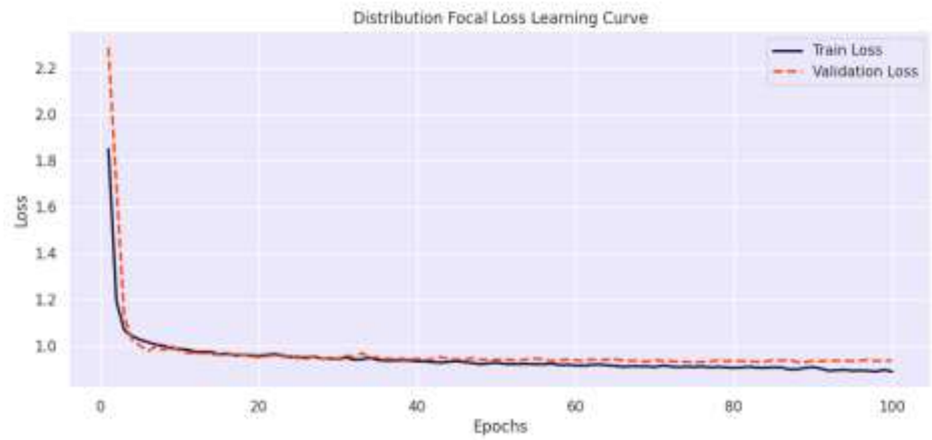

Figure 5. Distribution Focal Loss Learning Curve

As training advances the loss values for box loss, distribution focal loss and classification loss show a sharp decline in the first few epochs before levelling out. In addition to the training and validation loss lines tight alignment this trend

indicates that the model is learning efficiently without overfitting which means it is well-suited to the dataset without being unduly biased or variable.
The smoothness of the learning curve which is especially apparent in the latter epochs indicates that extra training won't significantly increase performance and that the model is getting close to equilibrium. This finding implies that 100 epochs should be enough to train this model as more training is not expected to yield meaningful improvements.

4.1.2. Confusion Matrix Evaluation

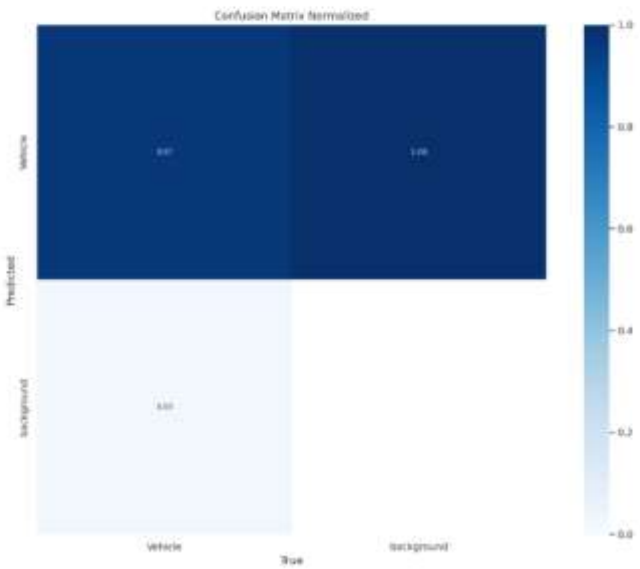

Figure 6. Confusion Matrix

Our YOLOv8 car detection model's confusion matrix demonstrates exceptional accuracy. The model has a 97% success rate in recognising the presence of a vehicle indicating strong detection skills. However, the model only misses 3% of real-world cases when it is unable to recognise a car suggesting that there is still opportunity to improve the accuracy of false negatives.

4.1.3. Performance Metrics Assessment

Table 1. Model Evaluation

Metrics	Metric Value
Precision	0.916
Recall	0.938
mAP50	0.975
mAP50-95	0.742
Fitness	0.765

The validation set yields outstanding results for the YOLOv8 model. With a precision of 91.6% it shows that most of the model's predictions are accurate. The model's 93.8% recall score indicates that it can locate the majority of the pertinent examples inside the dataset. The mean Average Precision (mAP) of the model is 97.5% at 50% Intersection over Union (IoU) which indicates a high degree of accuracy in identifying items that significantly overlap the ground truth. The model retains a strong mean absolute performance of 74.2% even when the IoU threshold range is increased from 50% to 95%. Finally the model's efficacy in object identification tasks is confirmed by the fitness score of 76.5% which shows a decent balance between precision, recall and the IoU of the predictions.

4.2. Model Inference & Generalization Assessment

In three separate steps the model's capacity to draw generalisations will be thoroughly evaluated. The validation set images will be used for first inference to assess the model's performance on data that it has seen but not had much training on. Next the model's generalization will be tested further by conducting inference on an unseen test image. This step will help understand how the model behaves with completely new data which is crucial for gauging its real-world applicability and robustness.

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4.2.1. Inference on Validation Set Images
Using a random selection of images from the validation dataset in this section analyse model predictions. Using a random sample of images taken from the validation dataset evaluate the model's predictions.

Figure 7. Balidation set Inferences

4.2.2. Inference on an Unseen Test Image
Currently using the most improved iteration of our refined model to see how well it generalizes. Here will test it on the same picture that was previously examined on the COCO dataset using the pre-trained YOLOv8 model:

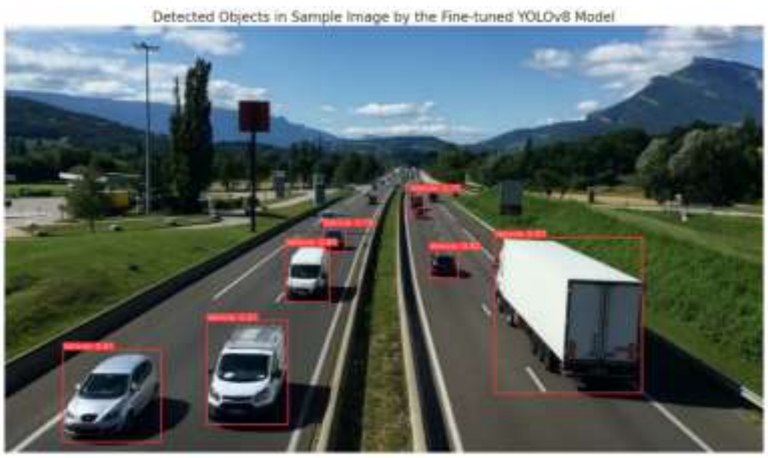

Figure 8. Detected Objects in Sample Image by the Fine-Tuned YOLOv8 Model

When we contrast the image above which had in step 2 it becomes clear why fine-tuning the YOLOv8 model for a particular purpose is advantageous. The graphic above demonstrates how the refined model using a dataset unique to each vehicle has successfully identified and categorized a number of vehicles including the truck that was previously overlooked. This enhancement demonstrates the model's improved capacity to identify features unique to cars improving recall and precision in vehicle detection.

4.2.3. Real-Time Traffic Intensity Estimation
The enhanced vehicle recognition model is employed to assess the traffic density. This stage is crucial to demonstrate that the model can generalise and perform correctly on movies that haven't been viewed previously that is on videos that weren't part of the training or validation sets. Our goal is to measure the amount of traffic by counting cars frame by frame inside predefined boundaries on the driving lanes. The study will show the number of vehicles as well as the

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traffic intensity classifying it as "Heavy" or "Smooth" according to a preset threshold. Understanding traffic flow and count is crucial for both urban planning and traffic management. A selection of photos from the Real-Time Traffic Intensity Estimation video are shown below.

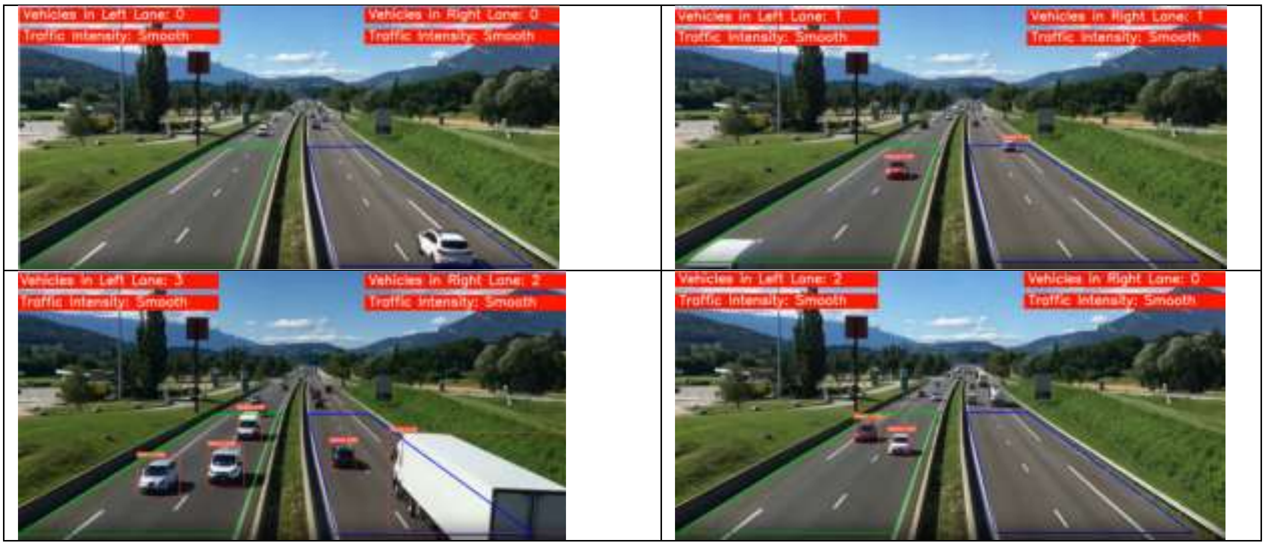

Figure 9. Real-Time Traffic Intensity Estimation

5. Conclusion

The possibility of using cutting-edge DL approaches particularly the YOLOv8 model for real-time traffic density estimation has been shown by this research. Through efficient vehicle counts in designated zones the suggested method provides significant perspectives for traffic control and urban planning projects. The model's accuracy and capacity for generalisation are validated by the thorough assessment of its performance which includes learning curve analysis, confusion matrix assessment and performance metrics evaluation.

Additionally, the production of the specialised vehicle dataset and the process of fine-tuning the model highlight how important it is to tailor the model for certain applications. The YOLOv8 model is improved in terms of recall and precision especially when it comes to recognising different kinds of vehicles from the air.

Inference and generalisation on test data demonstrate the practical applicability of the suggested method and demonstrate its efficacy in real-world circumstances. The model's usefulness is further increased by the incorporation of a real-time traffic intensity assessment algorithm which offers practical advice for urban planning and traffic management.

This research advances ITS by offering a dependable and effective way to estimate traffic density in real time. The refined model's cross-platform deployment readiness guarantees its adaptability and accessibility opening the door for broad acceptance and implementation in diverse transportation infrastructure contexts.

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