Intelligent Traffic Analysis: Determination of Macro Traffic Parameters Using Object Detection and Tracking

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(2024)

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A thesis submitted to the National University of Sciences and Technology, Islamabad, in partial fulfillment of the requirements for the degree of

Master of Science in

Transportation Engineering

Thesis Supervisor: Dr. Sameer-ud-Din (P.E.)

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National University of Sciences & Technology (NUST)

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DEDICATION

"To my caring parents and siblings, and my inspirational brother Fawad Ali, without whom this wouldn't be possible."

ACKNOWLEDGEMENTS

First, I would like to thank ALLAH for blessing me with completing this thesis. Then, praises are also addressed to our Prophet Muhammad ﷺ who has guided us to a better life today. I greatly appreciate my supervisor Dr. Sameer-ud-Din (P.E.), whose guidance, support, encouragement, and motivation have been impressive throughout this research work. Along with other co-supervisors, I would especially thank my fellow students and staff of NUST, who consistently supported and guided me whenever I needed them.

ABSTRACT

Urbanization and increasing traffic volumes have intensified congestion, highlighting the need for intelligent transportation solutions. Traditional traffic data collection methods are often inaccurate and inefficient. This thesis proposes an advanced traffic analysis system using YOLOv8 for object detection and DeepSORT for tracking to estimate traffic parameters like volume, density, and speed from video inputs. A dataset of 20,000 images across seven vehicle classes (Car, Bike, Bus, Truck, Hiace/Van, Tractor, and Rickshaw) was annotated using Roboflow. The YOLOv8 model demonstrated high precision and recall, with a mAP@0.5 of 0.88 and a mAP@0.5:0.95 of 0.64. DeepSORT effectively tracked moving objects, maintaining unique ID's across frames for accurate traffic parameter estimation. The developed API integrates detection and tracking data from video streams, providing precise traffic volume, density, and speed estimates. Tests on video clips yielded accurate traffic volume estimates of 992, 6,397, and 2,879 vehicles per hour for the G10-F10 and Srinagar Highway F-9 intersection. It also determined traffic densities of 21.94, 19.81, and 31.25 pcu/mile/lane and speeds of 27.46, 53.81, and 31.82 mph for the same locations. This research showcases the potential of real-time YOLOv8 and DeepSORT for traffic analysis. Future improvements could include expanding the dataset, fine-tuning the model, integrating additional data sources, and applying the system to real-world traffic monitoring. The proposed system offers valuable insights for traffic control and urban planning, providing a foundation for enhancing transportation infrastructure's safety and efficiency.

Keywords: Intelligent Transportation System, Ramp Metering, Deep Learning,

YOLOV8, Deep SORT**,** Macro traffic parameters.

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CHAPTER 1: INTRODUCTION

Effective urban traffic management is crucial due to rapid urbanization and technological advancements. With rising populations and explaining urban areas, managing the complex highway networks in bustling cities becomes increasingly challenging. Over the past decade, Pakistan has seen significant traffic growth, with freight increasing by 10.6% and passenger traffic by 4.4% (National Highway Authority, n.d.). Highways now handle approximately 96% of freight and 92% of passenger traffic (The Pakistan Credit Rating Agency Limited, n.d.). Consequently, effective traffic data collection solutions are essential to ensure smooth traffic flow amidst this evolving landscape.

Traffic congestion in developing and developed countries has expanded dramatically because of urbanization, population, and growth in vehicle usage. The motorisation rates in developing countries are rising by approximately 10 percent a year (Thondoo et al., 2020). This is because the rates of growth of congestion are slow in developed countries because of improved transport infrastructure; however, some densely populated though developed metropolitan areas are experiencing problems attributable to high car ownership. According to EU's "Statistical Pocketbook 2021" EU countries have already reached the pre-COVID-19 pandemic level of road traffic. Hence, it is quite vivid to witness a relatively steadfast growth in traffic(Directorate-General for Mobility and Transport (European Commission), 2021). In the same way, major South Asian countries have witnessed steep traffic growth, and the areas considered the most crowded places in the world are cities. Several South Asian cities are ranked among the top 10 most congested this year, and the traffic continues to rise yearly, according to TomTom Traffic Index (TomTom International BV., 2023).

In response to this growing congestion, traffic control and data acquisition in developing countries depend on traditional mechanisms like traffic signals and manual traffic control from the traffic police. In contrast, nowadays, the utilization of advanced smart traffic control appears in cities that integrate CCTV cameras and AI to control traffic signals and digital traffic signs (Naz & Hoque, 2023). In South Asian countries, traffic management varies, in which the use of ITS is limited to electronic toll collection and e-challans (Pathak et al., 2021). The use of ITS in urban traffic management systems has become common in developed countries. They use real-time data for AIS, AI, IoT, and actual traffic data to accumulate for better traffic flow, manage incidents, and minimize congestion (Fhwa, 2023). Modern developed countries use the most advanced monitoring systems; among them, traffic can be detected with the help of inductive loop sensors, radar, and video images. These methods offer reliable and timely information on traffic stream, speed, and class of vehicles on the road (The Intelligent Transportation Society of America, 2024). In developing countries, traffic data collection is less systematic and may sometimes involve manual daily estimates or simple electronic devices. Despite this, there is a growing popularity of the use of data from mobile phones and GPS data to obtain traffic data more efficiently(Tsumura et al., 2022).

Today, there is a fast-growing traffic stream in developing and developed countries, especially in South Asia, so applying effective traffic management approaches and suitable methods to collect traffic flow data is critical. As this approach provides a closer and more timely solution to traffic data collection, this study would benefit the development of traffic control applications, especially where traditional methods are incapable.

Population growth and increased car ownership have decreased the level of service, contributing to congestion. High urbanization and urban development have also increased peak-time travel demand on existing road networks. This high demand strains the existing infrastructure due to limited Right of Way (ROW), resulting in increased travel time, carbon emissions, and delays. Enhancing road infrastructure is a traditional but costly solution. A more advanced and cost-effective approach incorporates IoT for traffic data collection and machine learning for traffic management. This efficient method can resolve congestion issues and reduce travel time delays in real-time.

It is crucial to efficiently measure and analyze macro traffic parameters such as volume, density, and speed as vehicle volume rises. These indicators are vital for urban planning, infrastructure development, and traffic management, including assessing the volume-capacity ratio, estimating the origin-destination (OD) matrix, optimizing traffic signals, and identifying bottleneck roads (Z. Zhang et al., 2020). The increasing traffic underscores the persistent need for effective data collection and traffic flow management.

Traffic volume, a crucial metric for assessing road usage and identifying peak hours, is "the count of vehicles passing a particular point within a given time-period" (Garber N. J & Hoel L. A, 2017). Traditional methods relied on manual monitoring using tally counters or visual observation, leading to delays and inaccuracies (Teodorovič Dušanand Vukadinovič, 1998). While inductive loop detectors and automatic traffic counters are accurate, they are expensive, lack real-time analysis, and often produce limited data requiring further processing.

Traffic density, representing the number of cars per unit length on a road segment, indicates congestion levels, with higher density leading to reduced traffic speeds and longer travel times. Techniques for computing density include spot speed studies, manual traffic counts, and detectors such as radar or lidar sensors (Kara M. Kockelman et al., 2013). These methods are labour-intensive, error-prone, and offer only partial accuracy.

Traffic Speed, a fundamental metric, measures the average velocity of vehicles on a road section. Accurately calculating speed is essential for implementing congestion-alleviating solutions and identifying bottlenecks. Conventional methods like floating car techniques and roadside sensors share similar drawbacks with volume and density measurements.

Integrating artificial intelligence (AI) and computer vision techniques has transformed the process of determining macro traffic parameters. Researchers now seek more precise, real-time, affordable, and automated solutions for measuring these parameters. Intelligent transportation systems (ITS) technologies aim to address the challenges of traffic data collection (Stathopoulos & Karlaftis, 2003). Deep learning, a subset of machine learning, has attracted significant attention in both academic and commercial circles. As described in "Traffic Flow Prediction with Big Data: A Deep Learning Approach", it has been successfully applied in classification, prediction, dimensionality reduction, object detection, and motion modelling (Lv et al., 2014).

Object detection plays a fundamental role in identifying and categorizing vehicles in traffic engineering. In contrast, object tracking ensures continuous vehicle identification over time and space, enabling traffic volume estimation. It can calculate traffic density, and evaluating space-mean speed allows for assessing traffic speed by delineating regions of interest (Redmon et al., 2016). This approach significantly advances over traditional methods, offering enhanced accuracy and efficiency.

This study differentiates itself from previous research in the traffic engineering domain by leveraging deep learning and computer vision to provide a more comprehensive and integrated traffic management system (TMS). We aim to test our model in various scenarios to demonstrate its effectiveness and robustness. Specifically, we will examine urban and suburban environments, times of day, and weather conditions to ensure our model's adaptability and reliability.

The objective is to create a real-time traffic data collection platform in Pakistan under various scenarios. This platform will aid in urban traffic flow optimization, traffic signal optimization, congestion management, and real-time optimization of travel time delays caused by abrupt and abnormal changes in demand during peak occasions, such as public gatherings or events.

One novel aspect of our study is its focus on real-time data processing and analysis. Unlike traditional methods, often involving significant data collection and interpretation delays, our approach enables immediate insights into traffic conditions. This real-time capability is essential for effective traffic management, allowing for prompt responses to congestion, accidents, and other traffic-related issues.

Additionally, our research addresses the challenge of scalability. Previous studies have often been limited to specific regions or small-scale implementations. In contrast, our model is designed to be scalable and capable of handling large datasets and expansive geographic areas. This scalability ensures that our TMS can be applied to various cities and regions, providing a versatile solution to traffic management.

Another key innovation in our study is the integration of multiple traffic parameters into a single cohesive system. While past research has often focused on parameters such as traffic volume or speed, our approach combines these elements to provide a holistic view of traffic dynamics. This integrated perspective is crucial for developing effective traffic management strategies that consider all aspects of traffic flow.

This study aims to demonstrate the practical application of AI-driven methods in determining macro traffic parameters. It seeks to provide valuable insights into traffic dynamics to help policymakers, traffic engineers, and urban planners make informed decisions for enhancing traffic management systems by analyzing real-world traffic video data.

Furthermore, this study also aims to incorporate predictive analytics into our model. This system can forecast future traffic patterns and identify potential issues before they arise by analyzing historical traffic data and current conditions. This proactive approach to traffic management can significantly reduce congestion and improve overall traffic flow.

In summary, this study represents a significant advancement in traffic engineering by integrating AI and computer vision to create a real-time, scalable, comprehensive traffic management system. It aims to provide a robust and adaptable solution for modern urban traffic challenges by addressing the limitations of previous research and focusing on novel aspects such as predictive analytics and user feedback. This research can transform traffic management practices, leading to more efficient and sustainable urban transportation systems.

To collect real-time traffic data and validate the proposed macro traffic parameters, we selected several signalized intersections in Islamabad, such as G10–F10, F-9 intersection, and Kashmir Highway, as case studies (Figure 1). These busy routes and signals are ideal for testing due to their high traffic volume and diverse patterns.

AI-based object detection methods and tracking algorithms measure flow parameters and optimize the signalized network. This study uses the YOLOv8 object detection model and DeepSORT tracking algorithms to measure traffic flow parameters from video data. This data can be used for real-time optimization, ramp metering, adaptive signal control, and congestion management.

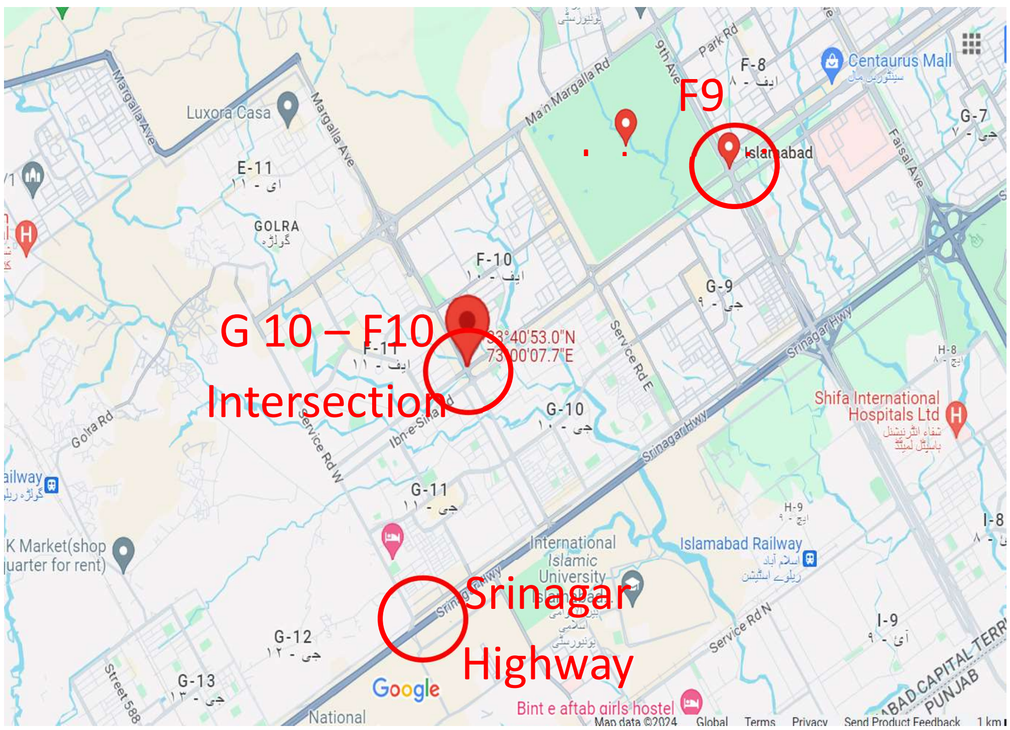

Figure 1 : Study Area Locations marked on Google Earth Map

Table 1: Table showing Study areas along with their GPS Co-ordinates

Location ID	Location Name	Co – ordinates
01	G10 – F10 Intersection	33.681383°, 73.002125°
02	F9 Intersection	33.698262°, 73.037441°
03	Srinagar Highway	33.663394°, 73.006953°

This thesis is structured as follows: Chapter 2 reviews the literature on traffic parameter estimation and the use of AI in traffic analysis. Chapter 3 details the methodology, including data collection, detection model formulation, and algorithms for estimating traffic volume, density, and speed. Chapter 4 presents and discusses the results of the analysis. Chapter 5 concludes the thesis and suggests future research avenues.

CHAPTER 2: LITERATURE REVIEW

Given the rapidly evolving landscape of transportation and urban planning, the significance of efficient traffic analysis techniques has become paramount. Cities are encountering growing challenges in managing their traffic networks, ensuring public safety, and optimizing vehicle flow as the global urban population expands. Leveraging cutting-edge technologies like object detection, deep learning, computer vision, and counting techniques, intelligent traffic analysis has emerged as a viable solution to address these problems/issues. This literature review focuses on "Intelligent Traffic Analysis: Determination of Macro Traffic Parameters," specifically emphasizing traffic density, speed, and volume.

Researchers are currently exploring innovative approaches to predict, estimate, and determine macroscopic traffic flow parameters within the domain of intelligent transportation systems to facilitate the effective management of urban traffic. (Stathopoulos & Karlaftis, 2003) developed flexible multivariate time-series state space models, utilizing 3-minute volume data from arterial roads near downtown Athens through inductive loop detectors. The objective was to enable early and accurate traffic flow predictions to alleviate congestion. These models harness data from upstream detectors to enhance predictions for downstream locations. Comparative analysis between multivariate and univariate time series models demonstrated the superior prediction accuracy of the former. (Bar-Gera, 2007) utilized cell phone activities to measure traffic speeds and travel time, and the results were compared with the conventional method of magnetic loop detectors commonly used for traffic speed and travel time measurement. The findings suggested comparable outcomes between the two models.

(Min & Wynter, 2011) derived correlations between time and space to forecast traffic flow in urban areas over real-time. These correlations enabled predictions of traffic speed and volume within 5-minute intervals, extending up to 1 hour in advance. Furthermore, in traffic volume estimation, the annual average daily traffic of trucks was estimated using fuzzy C-means algorithms based on short-term traffic counts. This technique demonstrated its accuracy in traffic volume estimation, particularly when short-term traffic counts were conducted over 72 hours on weekdays (Rossi et al., 2012).

In the context of congested urban roads, the methods outlined above for determining traffic flow parameters are complex, especially with big data involvement in such scenarios, intensifying the need for more flexible, efficient, and manageable methods for traffic data collection and management. A Deep Learning Approach emphasizes the importance of accurate and timely traffic flow information. With traditional methods employing shallow prediction models, there is a significant opportunity to leverage deeper architectural models using the extensive available data. Based on deep learning (Lv et al., 2014), the autoencoder model utilizes both time and space correlations, providing an efficient method for traffic flow predictions in high-traffic concentrations.

(Z. Zhang et al., 2020) employed an innovative approach to network-wide traffic flow estimation through a geometric matrix completion model, integrating flow records with crowdsourcing data. The study also introduced a spatial smoothing index to access the volume estimate challenge for each road section. Multiple tests have consistently shown that this method outperforms benchmark models, and a robust correlation exists between estimation accuracy and the spatial smoothing index.

(Wang et al., 2022)introduced the Smart Road Stud (SRS), which employed an anisotropic magneto-resistant (AMR) sensor to measure traffic volume. The method utilizes the sensor's capability to detect changes in Magnetic Field Intensity (MFI) caused by passing vehicles. A two-step technique for monitoring traffic volume in two adjacent lanes effectively retrieves these disturbance signals, even during brief vehicle temporal headways, ensuring accuracy of over 97%. The compact size, low power consumption, and resilience to environment changes make the AMR sensor a critical tool for traffic control.

(Törő et al., 2017) proposed the use of multi-sensor object detection and tracking on highway scenes using radar measurements. This approach utilized a Bayesian framework, employing the random finite set-based Bernoulli filter as the estimation algorithm. Utilizing low-cost traffic sensors, like mounted cameras, computer vision, and AI-based object detection models such as YOLO (you only look once), can yield cost-effective and efficient measurements of traffic flow parameters. YOLO formulates the spatially separated bounding boxes and related class probabilities as a regression problem, enabling real-time processing capabilities. The architecture's unification allows for speedy processing, with the smaller iteration, Fast YOLO, handling images at 155 frames per second and the base YOLO model managing 45 frames per second (Redmon et al., 2016). Despite its rapid speed, YOLO maintains commendable accuracy, frequently surpassing other detection systems.

The YOLO algorithm and its advanced variants, based on convolutional neural networks, demonstrate continual progress in computer vision and artificial intelligence. These developments have significant implications for traffic analysis, enhancing the precision and effectiveness of object detection, a critical element of intelligent traffic analysis. (Jiang et al., 2021)conducted a review if the initial five iterations of YOLO (v1 – v5) and concluded that while these versions exhibit certain modifications, they maintain shared characteristics, rendering them comparable. The first five versions of YOLO retain considerable potential for further improvement, particularly in the context of practical implementations.

The rise of computer vision techniques and the abundance of video image data have broadened the scope of applications for on-road vehicle detection algorithms. However, the diverse nature of on-road driving environments possesses certain challenges. (Z. Yang & Pun-Cheng, 2018)emphasized the merits and constraints of vehicle detection approaches across different environmental conditions, including backpropagation neural networks, artificial neural networks, genetic algorithms, and support vector machines for motion-based vehicle detection. This investigation underscored the necessity for universal methods for vehicle detection across diverse environments, considering that each technique is tailored to specific environmental conditions.

(Azimjonov & Özmen, 2021) applied the YOLO object detection model for vehicle detection, training it on a custom dataset of 7216 images and 123831 object patterns. The addition of a novel bounding box-based vehicle tracking algorithm, employing nine machine learning-based classifiers and a CNN-based classifier, significantly increased the classification accuracy of YOLO from 57% to 95%.

This approach demonstrates the significance of precise vehicle detection and tracking in real-time traffic flow monitoring. In a subsequent study by (Azimjonov & Özmen, 2022), a bounding box tracking algorithm was utilized to predict observed vehicles that are occluded or have disappeared. The algorithm incorporated a shaking filter and a voting approach to mitigate camera shaking effects, reducing misdetection and misclassification.

Results revealed that the proposed algorithm outperformed the Kalman filter-based tracker by approximately 7%, enhancing traffic analysis accuracy. (Ashraf et al., 2023) leveraged the Hybrid Vehicle Detection Network (HVD-Net) for vehicle tracking and speed estimation, combining convolutional neural networks of detection and Simple Online Realtime Tracker (SORT) for tracking. The system also introduced mechanisms to estimate vehicle speed based on geometric projections of vehicles in consecutive frames.

To address challenges in occluded and complex environments, (Lin et al., 2023)used roadside LiDAR sensors and integrated a decision tree with the bagging algorithm for traffic object classification. An improved Hungarian algorithm with the Kalman filter was also utilized to predict vehicle paths, considering occlusion conditions. The evaluation of this framework demonstrated exceptional accuracy in detection (99.50%) and tracking (97%), surpassing state-of-the-art algorithms.

Traffic density estimation is an important parameter for predicting congestion on urban roads. Efficient congestion detection enhances safety and comfort while traveling on congested roads. (Zeroual et al., 2019) proposed a novel piecewise switched linear traffic model (PWSL)-based observer to estimate unmeasured traffic density, reducing the need for expensive sensor installations and measurement devices. The study also introduced a method for monitoring traffic congestion using a generalized likelihood ratio (GLR) test, validated with traffic data from California freeways, demonstrating the effectiveness of the proposed method.

(Pereira et al., 2022) introduced a kinetic compartmental approach to evaluate the suitability of a traffic flow model in modelling measurements derived from trajectory data. This approach treats vehicle transfers as chemical reactions and road cells as compartments, creating a discrete dynamical system where vehicle density is a reactant concentration. This method optimizes parameter estimation and enhances density measurement accuracy by effectively replicating the complexity of traffic patterns.

In their recent review, (Premaratne et al., 2023)emphasized the remarkable success of deep learning-based neural network approaches, particularly YOLO, in vehicle detection, classification, and counting, leading to more accurate traffic analysis. This study also highlighted persistent challenges, particularly in low-light conditions and nighttime classification, including the need for further exploration in these areas.

The capabilities of such technologies have been improved a lot due to the development of new algorithms of deep learning and computer vision that make it possible to solve these problems using methods and algorithms that are more effective, scalable, and capable of functioning in real-time and performing under different conditions. When designing a vehicle monitoring system, working on pedestrian tracking, or even industry automation, utilizing the advanced detection and tracking method is crucial to creating an intelligent system to deal with real-life issues seamlessly.

(Singh et al., 2023) used a computer vision approach to identify and count vehicles, highlighting the importance of computer vision in intelligent transportation systems. (Singh et al., 2023) used YOLO in object detection, OpenCV has been used in real-time video processing, and blob tracking technologies in detecting, tracking, and counting vehicles. It is especially useful to identify and count vehicles in the traffic where accurate traffic detection and counting play an essential role in planning and managing the traffic. (Vellaidurai & Rathinam, 2024) optimized the YOLOv5 for detecting and classifying vehicles in adverse traffic conditions and introduced the OYOLOV5 model, which integrates ResNet-50 for feature extraction and a Feature Pyramid Network (FPN) to enhance multi-scale object detection. The accuracy improvement under the rain, snow, and fog has achieved through the integration of Fuzzy C-Means clustering for the anchor box optimization. The (Vellaidurai & Rathinam, 2024) proves that OYOLOV5 is more accurate and faster than classical YOLO models, which makes it possible to use the technology in autonomous vehicles in difficult weather conditions. (Coifman et al., n.d.). Also, it described implementing a feature-based tracking system for real-time vehicle identification and traffic monitoring. Unlike common frameworks with problems with detection in conditions of partial occlusion or changes in lighting, it identifies separate marks characteristic of vehicles rather than the cars themselves. The system is not affected by light variation and congestion, which are characteristic of most urban traffic environments. Several machine learning and deep learning strategies were considered (Kamkar & Safabakhsh, 2016), and special attention was given to studies illustrating how changes in the environment, which commonly affect the detection, classification, and count of vehicles, have been dealt with. (Kamkar & Safabakhsh, 2016) compares the earlier models with more recent developments such as YOLO and Faster R-CNN and shows substantial improvement in precision-recall across all the conditions for the most recent models compared to the earlier ones. (L. Yang et al., 2023) developed a system based on deep learning for detecting objects at intersections with the help of trajectory prediction model, which points out the chances of collision at intersections, emphasizing the accurate detection and prediction in controlling traffic mishaps and managing the places prone to traffic congestion.

(Thonhofer et al., 2017) introduced the approach incorporating feeds from real-time traffic and predictive models that enable the system to adapt to flow, speed, and other parameters actively. It’s a new approach for estimating model parameters, increasing the accuracy of traffic forecasts, and controlling actions' adaptivity. This simulation model is valid for the conditions of traffic disruption in urban areas. (Stocker et al., 2016) proposed road-pavement vibration measurement in conjunction with supervised machine-learning techniques for detecting and identifying vehicles. The paper looks at how vibrations from passing vehicles can be analyzed and recognized to reflect the kind of vehicle, including cars, trucks, and buses. The results can be widely used in smart transportation systems where ordinary sensors cannot be applied successfully. (Nieto et al., 2016) focused on optimizing the detection of vehicles in Advanced Driver Assistance Systems (ADAS), comparing different optimization approaches with several goals concerning the speed and accuracy of the vehicle detection algorithm for real-world driving. (Nieto et al., 2016) evaluated how various factors such as environmental conditions, occlusion, and sensor noise ought to affect the detection performance.

(H. Yang & Qu, 2018) presented an algorithm called the background subtraction model with low-rank decomposition for real-time vehicle detection and counting in complex traffic conditions. The approach concerns the isolation of the moving objects from the background and the problems such as dynamic backgrounds, different levels of illumination, and necessary shadows. This paper proves this method to be efficient for areas with high traffic and complicated roads and applicable to real-time traffic control. (Bhat et al., 2024) carried out a full system with the developed YOLOv3 model in real-time vehicle and license plate detection combined with the air quality index that is taken at strategic positions by sensors, with the aim that the system can monitor the emissions from vehicles and their impacts on the local air quality. The use of Django for the web-based front end enables further real-time monitoring and data visualization for security officials, thus providing a pragmatic solution to air pollution in controlled environments.

There is a considerable evolution of traffic management and control due to the integration of AI technology. AI-driven systems can now process data in real-time, enabling adaptive traffic signal controls, dynamic routing guidance, and efficient congestion management. These systems can use machine learning techniques to predict traffic patterns, optimize signal timings, and control vehicle flow within an urban network. The advancements in artificial intelligence, such as deep learning and neural networks, have considerably enhanced the precision and scalability of these models, allowing them to handle complex and high-density environments. These AI-based approaches improve traffic efficiency while contributing to emission reductions and overall urban mobility improvements.

(Chavhan & Venkataram, 2020) introduces a prediction-based metropolitan area's vehicle movement optimization framework. To monitor congestion levels ahead of time by applying learning algorithms based on acquired assumptions regarding historical data for road user information, (Chavhan & Venkataram, 2020) adopt machine learning tools that use past traffic patterns alongside instant inputs to forecast future breakdowns and flexibly adapt their timing accordingly before they happen. (CHANGXI et al., 2020) presents a combined model using genetic algorithms and artificial neural networks for short-term traffic flow prediction. The (CHANGXI et al., 2020) have improved forecasting accuracy by incorporating exponential smoothing techniques into their model, underscoring the significance of adaptive models in detecting abrupt changes in traffic flow during peak hours or special events. (LUO, 2020) investigate a Bayesian network-based approach for short-term traffic flow prediction, which employs quantile regression to capture uncertainty in traffic data.

The study deals with irregularity and unpredictability of traffic, making it possible to give accurate estimates under various conditions related to road capacity. Using quantile regression, the model can generate probabilistic forecasts representing different potential scenarios rather than giving one fixed forecast. (Khan & Thakur, 2024) propose a machine learning framework for managing dynamic urban traffic. This system proposal uses reinforcement learning and real-time data on public transport to optimize signal timing and thus reduce congestion on roads. Continuous learning from historical patterns in traffic and subsequent adjustment of controls helps adapt to changing circumstances relating to motor vehicle movement over time. (R. Li et al., 2023) explores improving traffic control using information from license plate recognition (LPR) systems. The research uses LPR technology to gather up-to-the-minute details about vehicles on the road. This data helps to fine-tune traffic lights and navigation systems. By combining LPR information with traffic patterns, the system can spot likely traffic jams before they happen and adjust controls ahead of time.

(W. Zhang et al., 2023) analyze the traffic flow dynamics and merging behavior on Chinese expressways, focusing on asymmetric traffic flow characteristics at merge zones. (W. Zhang et al., 2023) explores the impact of driver behavior and conditions variations on the flow efficiency. Field data and simulation models are employed to deepen understanding of various operational features of these zones that result from different forms of traffic. Thus, the study provides insights that could be utilized in efficient design and control strategies for the expressway merging areas. (Shen et al.,

2015) aims to study how the gap acceptance model can determine the capacities of freeway merge areas under varying traffic flow conditions. A more practical model for capacity estimation is suggested by considering random vehicle arrivals and diverse driver behaviors, among other variables. The results show that traditional models underestimate these variables' impacts, implying improved designs, especially during complex situations in traffic simulations and merge areas. (Yu et al., 2023) focuses on the relevance of trajectory data with extensive scale for application in resolving large city traffic issues and fine-grained traffic flow analysis. As the dataset of this study includes detailed movement patterns over a wide range of road networks, it provides a fresh look at traffic flow analysis, urbanity planning, and real-time traffic prediction. (T. Li et al., 2024) presents the development of an enhanced surveillance system that utilizes the orientation of the cameras by predicting traffic data with an online learning model. It uses multiple correlation and multi-level predictions to increase the efficiency of real-time traffic monitoring. The proposed system has aimed to be highly adaptive, which means that the efficiency of traffic surveillance and management can be increased in different conditions of the urban environment.

Using the speed-flow-density relationship, outflow traffic from Kuala Lumpur is examined by (Mustapha & Nik Hashim, 2016). The study also analyses some of the parameters affecting traffic congestion and suggests ways to increase the outflow rate. Hence, to apply and incorporate actual data and traffic simulation results into formulating policies and designing infrastructure in the National Capital. The problem of data occlusion is tackled by (Ngeni et al., 2024) in the context of traffic monitoring through computer vision. To address this problem, computer vision is integrated with DeepSORT–a deep learning-based tracking algorithm to enhance the accuracy of object detection and inter-object tracking in complicated urban traffic conditions. The approach improves the reliability of vision systems, thus improving the probability of collecting accurate and consistent traffic information.

The dynamic landscape of intelligent traffic analysis, driven by cutting-edge technologies such as deep learning, computer vision, and object detection, has introduced new prospects. However, this evolution has revealed a significant research gap. Despite notable advancements in traffic analysis methodologies, the current literature review emphasizes the necessity for unified and comprehensive traffic analysis solutions. These solutions should encompass real-time traffic prediction, efficient vehicle detection under various environmental conditions, and precise traffic density estimation. While individual studies have addressed certain aspects of these challenges, there remains a scarcity of research consolidating these diverse elements into a cohesive framework.

YOLO stands out in real-time object detection because it's fast and accurate. It uses deep learning to do this. Most object detection methods first suggest regions and then classify them. But YOLO detects objects in one go, which makes it efficient. YOLOv8 builds on earlier versions by making some key changes. It's better at pulling out features and uses computer power more. These upgrades have made YOLOv8 even more powerful than before.

In the YOLO family, the real-time object detection model for computer vision tasks with the highest accuracy and speed is YOLOv8. In general, YOLOv8 (Wang et al., 2022)offers a quicker and more robust network architecture that provides a better feature integration approach, more precise object detection performance, a more robust loss function, and an improved label assignment and model training efficiency.

YOLOv8 is the fastest and most accurate real-time object detection model for computer vision tasks in the YOLO family.

YOLOv8 marks a step forward in deep-learning models to detect objects building on what YOLOv5 could do. It brings in new network improvements and uses C2F modules to boost performance. YOLOv8 includes CSP modules, which cut down on parameters and floating-point operations without losing accuracy. It also has a new anchor box generator that adapts to how big objects are in the dataset. We chose to use YOLOv8 because of its better object detection and recognition results. YOLOv8 is the best version of the YOLO family in object detection. It offers higher mean average precision and faster detection times on the COCO dataset.

YOLOv8's network architecture has three main parts: a backbone network, a neck, and a head. The backbone network pulls out feature maps from the input image. The neck blends information from different scales to make detection better. The head processes these features to create bounding box predictions and class probabilities. YOLOv8 uses CSPDarknet53 as its backbone network, which plays a big role in making it perform better.

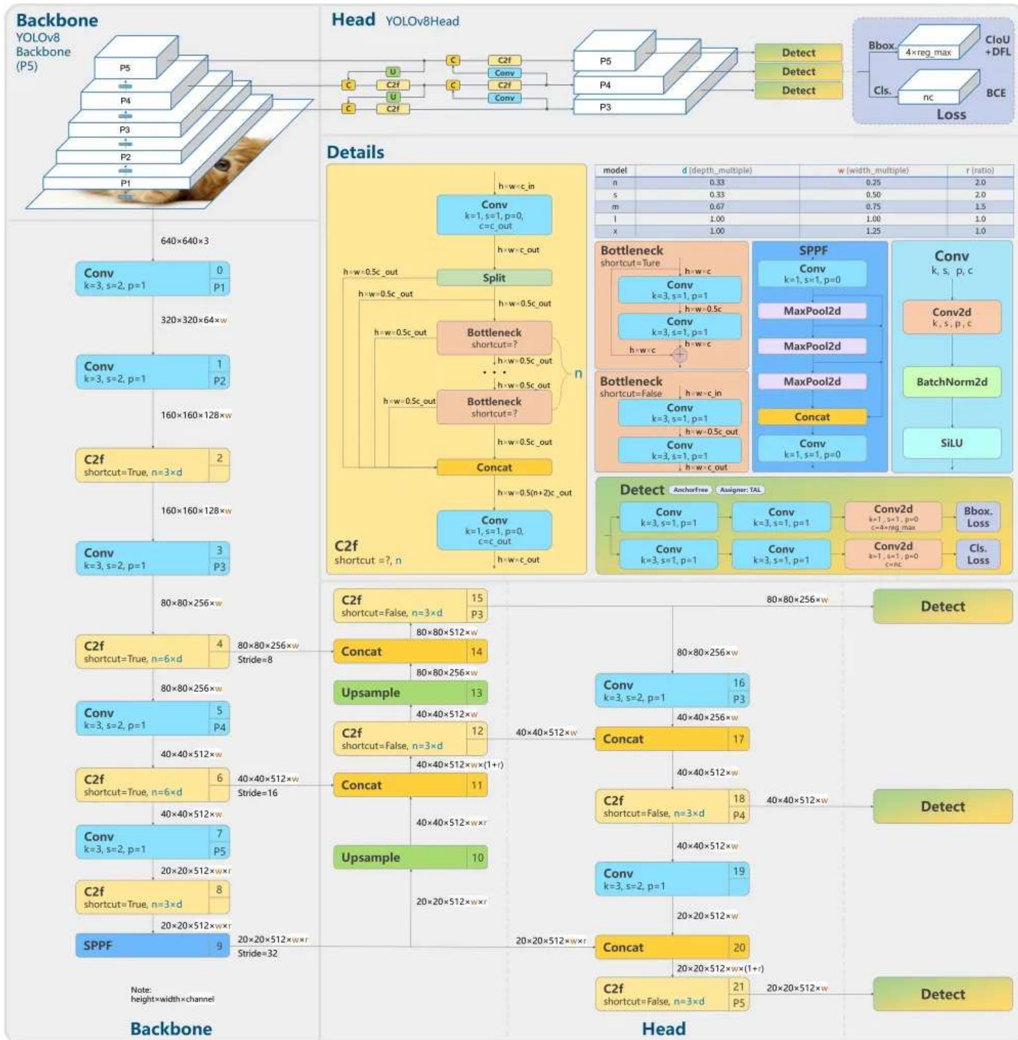

Figure 2: Model Architecture of YOLOv8
(https://blog.roboflow.com/whats-new-in-yolov8/)

Key features of YOLOv8 model are given as:

3.1.1. Anchor-Free Detection:

YOLOv8 doesn't use anchors. It directly determines the centre of objects instead of offsets and difference from its previous anchor frames. This way, it needs fewer box predictions, which makes the Non-Maximum Suppression (NMS) faster. NMS is a tricky step after inference to filter through possible detections.

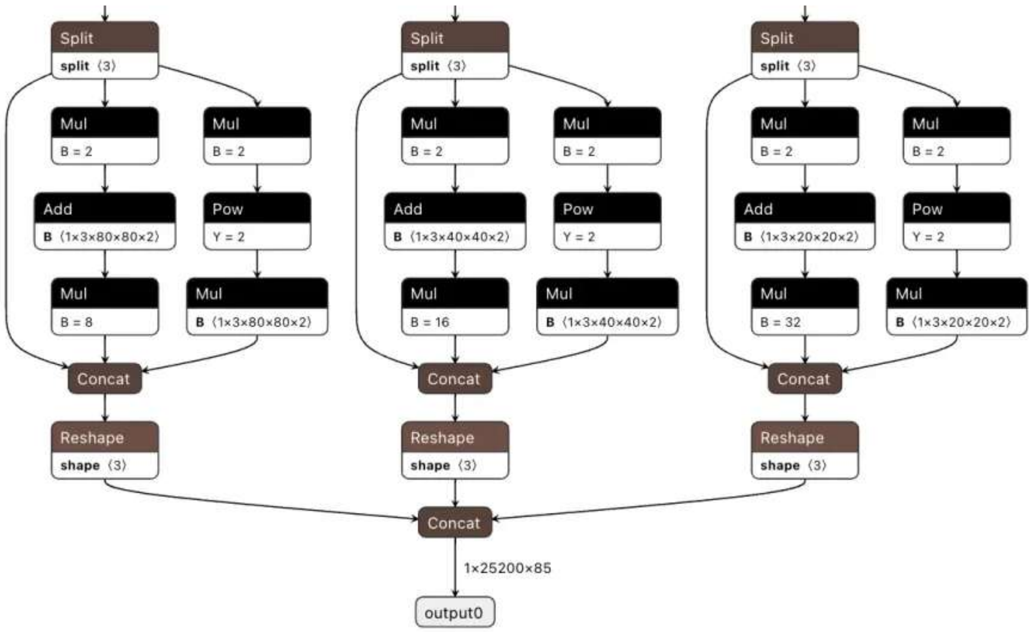

Figure 3: Detection head of YOLOv5 (offsets from known anchor boxes) (https://blog.roboflow.com/whats-new-in-yolov8/)

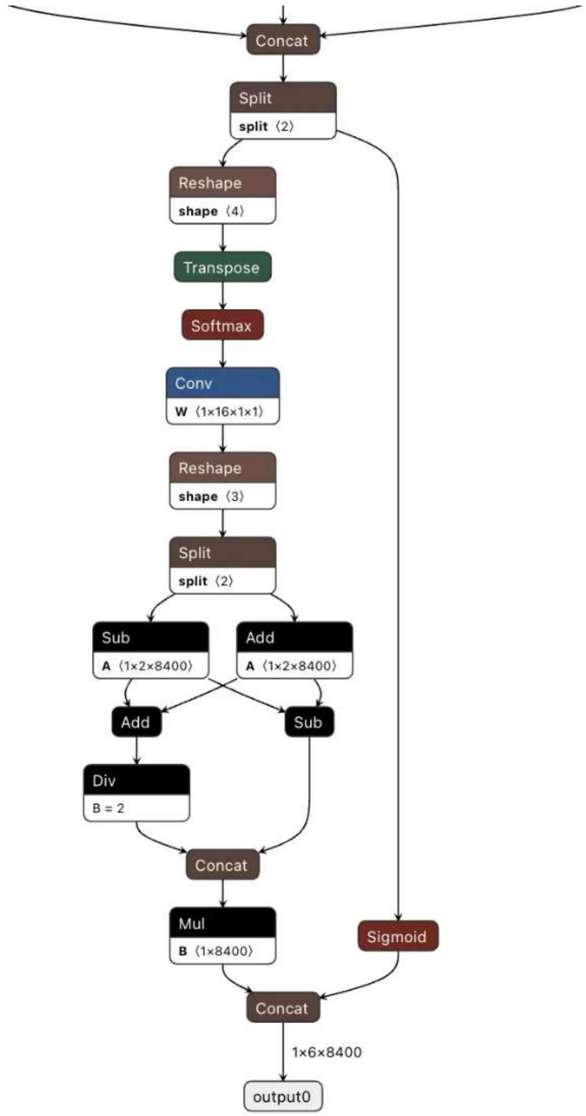

Figure 4: Detection head of YOLOv8 (anchor free detection)
(https://blog.roboflow.com/whats-new-in-yolov8/)

3.1.2. Mosaic Augmentation:

YOLOv8 changes images on the fly during training. Each round shows the model's different versions of the given images. One way it does this is by putting four images together into one. This makes the model learn to spot objects in new places when they're hidden and against different backgrounds. However, this method can worsen the model, so it's better to turn it off for the last ten training rounds.

3.1.3. YOLOv8 Accuracy test:

To assess the performance of YOLOv8, the Roboflow dataset domain used 100 sample data sets of Roboflow Universe intending to determine the extent to which models perform optimally in unforeseen settings. All the datasets are trained for 100 epochs. The results are shown in Figure 05 below, which depicts the higher accuracies of YOLOv8 than YOLOv5 and YOLOv7.

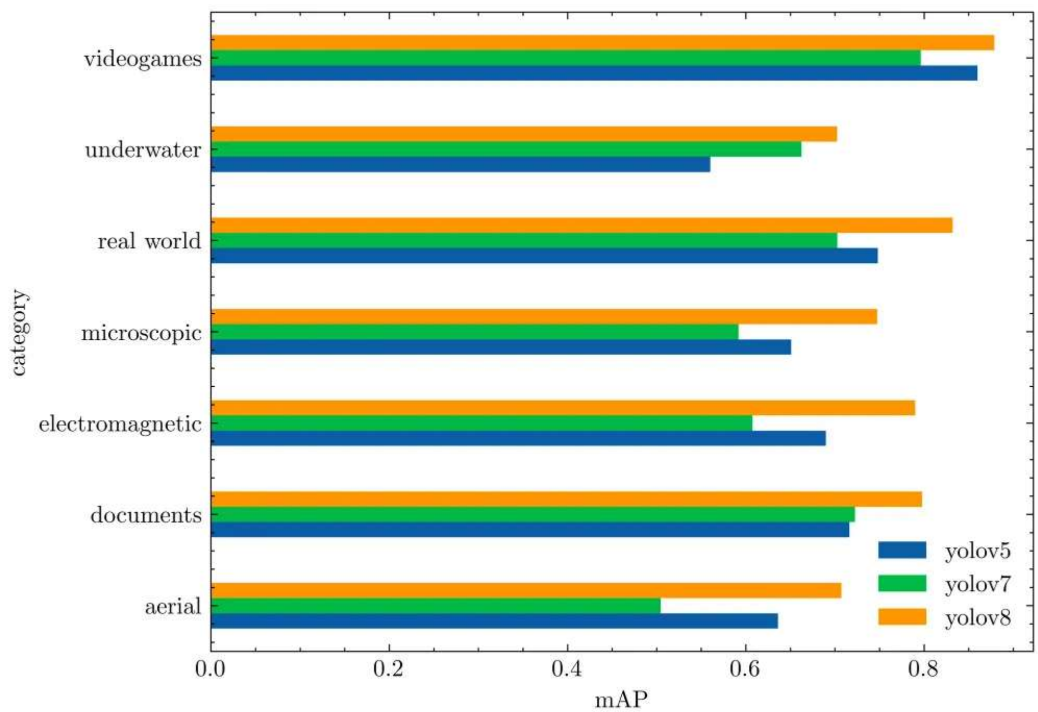

Figure 5: Average mAP@50 against different categories of dataset (https://blog.roboflow.com/whats-new-in-yolov8/)

The SORT algorithm uses the Hungarian algorithm to measure correlation, and a Kalman filter to correct for frame-to-frame correlation is a useful method for object tracking at high frame rates. However, because it ignores the appearance attributes of detected targets, it only works well when target state estimation uncertainty is modest. Additionally, SORT tends to remove targets that do not match in a sequence of frames, which might result in ID switching—a problem in which the assigned IDs can frequently change.

Deep SORT is an object tracking algorithm that was derived from the SORT, which stands for Simple Online and real-time tracking with a Deep Association Metric. It incorporates deep learning for object appearance tracking. On the object position, SORT uses Kalman filtering and the Hungarian algorithm for prediction and matching but performs the identity switches in crowded scenes. DeepSORT solves this issue by applying a deep convolutional neural network (CNN) for the appearance features of the detected objects to achieve increased generalization capability in tracking the specified object.

The Deep SORT (Du et al. 2023) approach uses a ReID model to add appearance information to extract feature embeddings. Since their look can more accurately identify targets, this results in a 45% reduction in ID switching. Additionally, Deep SORT enhances SORT's matching mechanism by incorporating a Matching Cascade technique, which resolves the issue of matching targets obscured for some time by giving track matching to frequently appearing targets priority over long-term occluded targets. Moreover, IoU matching is performed to unmatched tracks and detection targets to mitigate alterations resulting from apparent mutations or partial occlusion in the final matching stage. Deep SORT borrows the ReID model to increase tracking accuracy by requiring a well-distinguishing feature embedding from the object detection network's output for computing similarity. Deep SORT is a more reliable and precise object-tracking method that enhances SORT's matching mechanism by incorporating appearance data.

Architecture Overview: YOLOv8 consists of three main components: Backbone, Neck, and Head.

a) Backbone (CSPDarknet53): The backbone network captures feature maps from input images. Based on the CSPDarknet53 Convolutional Neural Network (CNN), it uses Cross Stage Partial (CSP) connections to divide and process feature maps efficiently, reducing computational effort while maintaining performance. It extracts features ranging from low-level details like edges to high-level aspects such as object parts and shapes.

b) Neck: This layer integrates features from different scales, enhancing the model's sensitivity to objects of varying sizes. It employs Path Aggregation Network (PAN) and Feature Pyramid Network (FPN) methods to analyze feature maps from multiple layers. This multi-scale feature fusion improves object detection across various sizes.

c) Head: The head generates the final outputs, including bounding boxes and class probability distributions. It processes feature aggregates from the neck to determine object locations and class types, providing coordinates and probability scores for each detected object.

Key Features of YOLOv8: YOLOv8 stands out with anchor-free detection, mosaic augmentation, and efficient feature extraction.

Traffic speed, density, and volume estimation are important metrics in traffic management and transportation planning. The advent of artificial intelligence (AI) and deep learning techniques has improved these estimates' accuracy and automation. AI-based systems that detect or track vehicles could process real-time data from various sensors, including cameras and LiDAR. To identify patterns in traffic flow, spatial and time-related aspects must be assessed using techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or a combination thereof. Calculating these figures will aid in optimizing traffic flows, reducing congestion, and enhancing safety measures. Recent advancements have sought to exploit deep learning models such as YOLO (You Only Look Once) and other object detection frameworks that improve detection robustness even under complex dynamic traffic conditions. These AI-driven solutions are revolutionizing traditional traffic monitoring systems by providing scalable real-time insights that can adjust according to different road conditions and traffic scenarios.

A spatio-temporal generative inference network for predicting long-term highway traffic speeds by capturing both spatial linkages between road segments and temporal patterns in traffic flow is used by (Zou et al., 2023) that combines graph neural networks (GNNs) with generative models to deal with missing data and fluctuating traffic conditions. The spatiotemporal approach has better forecast quality for speed variations over longer periods than the traditional ones. (Rani et al., 2024) proposes the LV-YOLO deep learning-based framework, which enhances logistic vehicle speed detection and counting using the YOLOv5 network. Specifically designed for highway surveillance, it leverages a U-net-powered segmentation layer for improved object isolation and accuracy. The boxy vehicles dataset trains the LV-YOLO system, which achieves high mean average precision (mAP) while keeping inference time low. With truck detection, speed estimation, and vehicle counting in one pipeline, this method surpasses conventional algorithms in effectiveness and efficiency, making its suitability in real-time traffic monitoring within logistics highly relevant. The traffic speed is estimated from probe data of GPS and vehicle detectors using deep convolutional networks (CNNs) by (Rempe et al., 2022), which efficiently learns spatial features from road networks when processing sequential information of a probe input to predict traffic speeds accurately. Instead of relying on infrastructure sensors that are in traditional methods, this model takes advantage of crowd-sourced information, thus making it easily adaptable and inexpensive for large-scale deployment. A symbolic regression algorithm for predicting traffic speed in highway operations is presented by (LINCHAO et al., 2017), which is unlike conventional machine learning models, symbolic regression provides more transparent and human-understandable results, making it easier to diagnose and adjust predictions. A review paper by (Fernández Llorca et al., 2021) examines different vision-based vehicle speed estimation approaches using camera image and video data. (Fernández Llorca et al., 2021) divide available methods into feature-, model-, and deep learning-based types, along with their comprehensive comparison based on strengths and weaknesses, among other things. The survey shows recent developments in deep learning models like YOLO and Faster R-CNN, which have greatly enhanced the accuracy and efficiency of speed measurement. Through quantitative data collection from different road segments, (Kutela et al., 2024) examine contexts, including road width, signage, and infrastructures associated with high speeding. The results suggest that specific measures should be taken concerning road planning and legislation to reduce speeding hazards.

(Gholami et al., 2016) estimated the volumes of turning movements at intersections using actuated traffic signal information in combination with AI algorithms. Analyzing signal timings and vehicle detection data from road-embedded sensors predicts turning volumes accurately. It aims to show how using artificial intelligence (AI) in the existing traffic infrastructure can help us understand our traffic better without additional cost. (Shaygan et al., 2022) provides a comprehensive review of recent developments in AI-based models for predicting traffic, focusing on emerging approaches such as graph neural networks, reinforcement learning, and hybrid models. (Shaygan et al., 2022) analyze how effective different methods are in predicting varying environments, such as urban or highway areas, by speed, density, and volume. Moreover, this review identifies major obstacles like multi-source data amalgamation and demands for explainable AI while suggesting prospects for future work. The potential of combining aerial imagery with sparse ground-based data for traffic volume prediction is investigated by (Ganji et al., 2022) to predict traffic volume from aerial imagery while correcting for gaps and inconsistencies in road count data. In addition, (Ganji et al., 2022) propose a multimodal framework merging visual features from the images with numerical data, which improves the model's prediction accuracy. (Zhao et al., 2019) describes several ways of estimating queue length and traffic volume using probe vehicle trajectories. The study employs vehicle GPS data to model intersection traffic behaviours, emphasizing how queue lengths influence overall traffic flow. The proposed methods use machine learning algorithms to analyze the trajectory data, providing real-time estimates that can be integrated into traffic management systems. Computer vision techniques are used by (S. Li et al., 2020) to count vehicles and estimate traffic flow parameters in crowded situations. Accurate detection and counting of vehicles are done even under highly congested circumstances using the combined approach of deep learning and traditional image processing techniques. Considering this study, their algorithms face challenges such as partial occlusion or varying illumination conditions that threaten their robustness.

As discussed above, the current research on intelligent traffic analysis shows a significant focus on applying new technologies, including deep learning, computer vision, and AI algorithms, to compute gross traffic parameters, density, volume, and speed. Previous research works have used time series models, sensor information, and neural networks for traffic management and control. Some of the recent achievements include object detection models like YOLO and tracking algorithm such as Deep SORT, which have helped improve the real-time detection, classification, and tracking of vehicles even in a cluttered environment. However, most of these solutions are developed to work in certain environments or with only certain classes of vehicles. The problem remains unsolved in general or in other complex conditions, for instance, in the South Asian region, and many sorts of heterogeneity and occlusion hinder traditional techniques. So, this research proposed the most updated custom YOLOv8 model from scratch designed for driving in the South Asia traffic context, bearing in mind all the kinds of vehicles such as cars, buses, trucks, and smaller unique types such as HiAce and rickshaws. Deep SORT integration to the model improves the tracking mechanism of the model, which helps estimate traffic volume, density, and speed in real time. Also, developing an API that can provide these metrics in real-time adds real-life relevance to your solution in rural and urban regions.

CHAPTER 3: METHODOLOGY

The proposed model for determining macro traffic flow parameters involves labelling images in the training dataset based on vehicle type. It is focused on classes of vehicles that are either abundant (cars, buses) or specific to traffic in Pakistan (rickshaws, bikes, tractors). This classification aids in traffic data collection for urban, suburban, and rural areas in Pakistan.

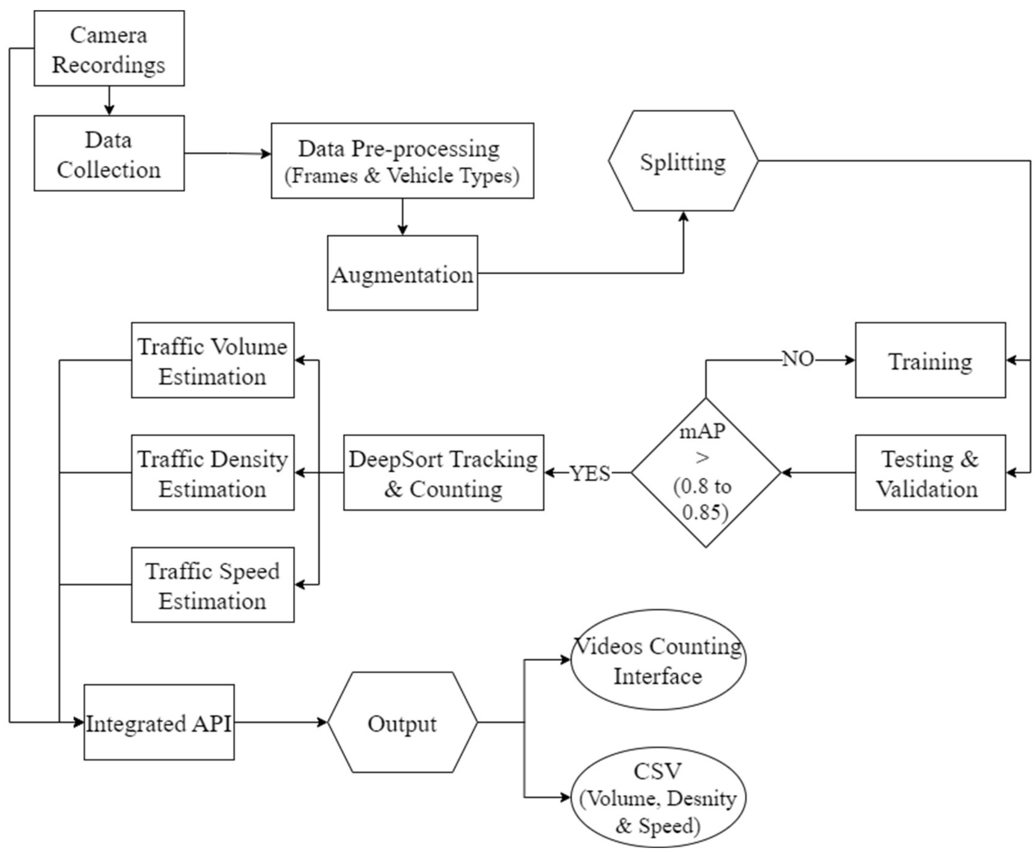

Figure 6: Framework of the proposed methodology

3.1. Data Collection

The object detection and tracking system primarily focuses on data collection. Data was gathered from various traffic cameras in different locations and times to ensure variation. This diversity is crucial for the model's functionality in multiple contexts and lighting conditions.

Videos were collected from urban, suburban, and rural locations and converted into frames at a rate of 30 fps. It is extracted every 450th frame (one image every 15 seconds) for urban areas with high traffic volume, every 900th frame (one image every 30 seconds) for moderate traffic flows, and every 1800th frame (one image every 60 seconds) for rural areas. All frames are sorted from the video dataset, removing duplicate frames of identical vehicles and frames without vehicles.

3.1.1. Dataset Composition:

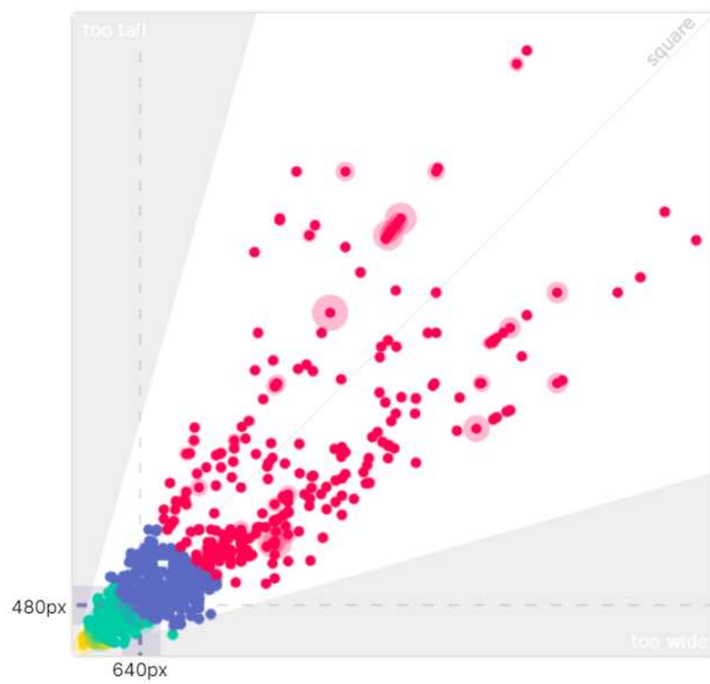

Figure 7: Distribution of images based on its image ratio

3.1.2. Data Annotation:

The dataset contains 9,559 annotated images, totalling 16,471 annotations. Each image has an average of 1.7 annotations, achieved by drawing bounding boxes around vehicles and labelling them by class. Figure 8's histogram displays the distribution of annotations per image, with the X-axis representing the annotation count and the Y-axis representing the number of pictures with that count.

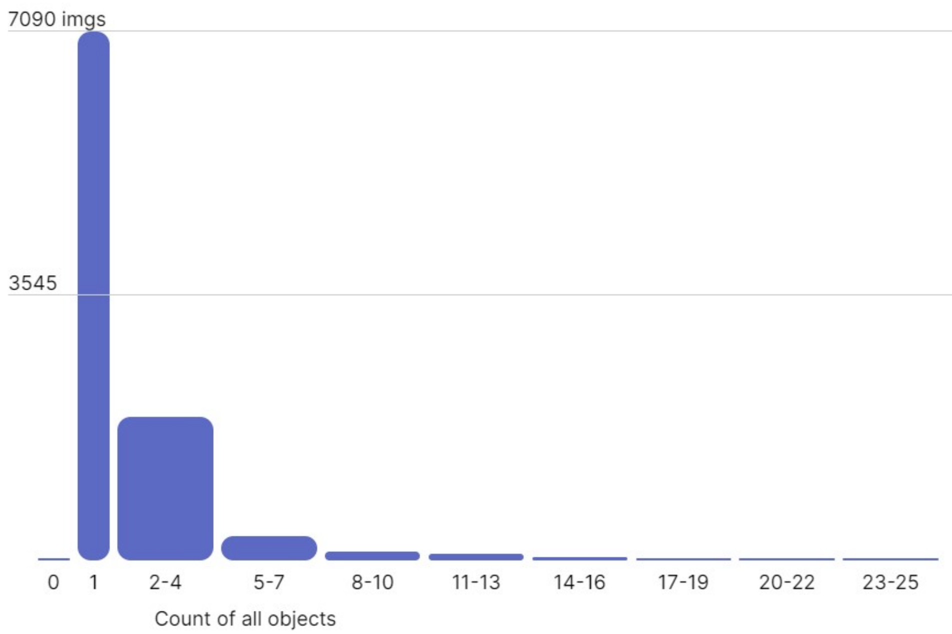

Figure 8: Histogram showing the number of annotations(count) of objects against the images

Most classes have balanced annotations, except for bikes, which are under-represented compared to the other six classes, as shown in Figure 9. We intentionally kept bike annotations low because the bikes in our dataset have similar dimensions and styles, with minimal variability in size and shape. This limited number of annotations is sufficient for precise model training, as an excess could lead to classification errors.

Figure 9: Number of annotations for each class of vehicles

3.1.3. Data Preprocessing & Augmentation:

Preprocessing transforms raw data into a structured format to ensure uniformity. It removes noise, corrupt, and irrelevant frames from the dataset. Since we manually handled this preprocessing before annotation, we applied auto-orientation to the frames and resized each to 640 x 640 pixels for consistency.

Data augmentation involves generating new data from existing images using techniques such as de-texturizing, de-colorization, flipping, rotation, and sharpening. This process enriches the dataset and improves model robustness. In this study, we augmented the dataset by rotating images between -24° and +24° and adding 7% noise around the bounding boxes. This increased the dataset from 9,559 to 22,939 images and enhanced the model's performance under varying conditions.

The dataset was divided into three subsets: 75% for training, 15% for testing, and 10% for validation. This distribution provides sufficient data for model training while retaining separate samples for testing and parameter adjustment. Figure 10 illustrates examples of annotated image batches used for model training.

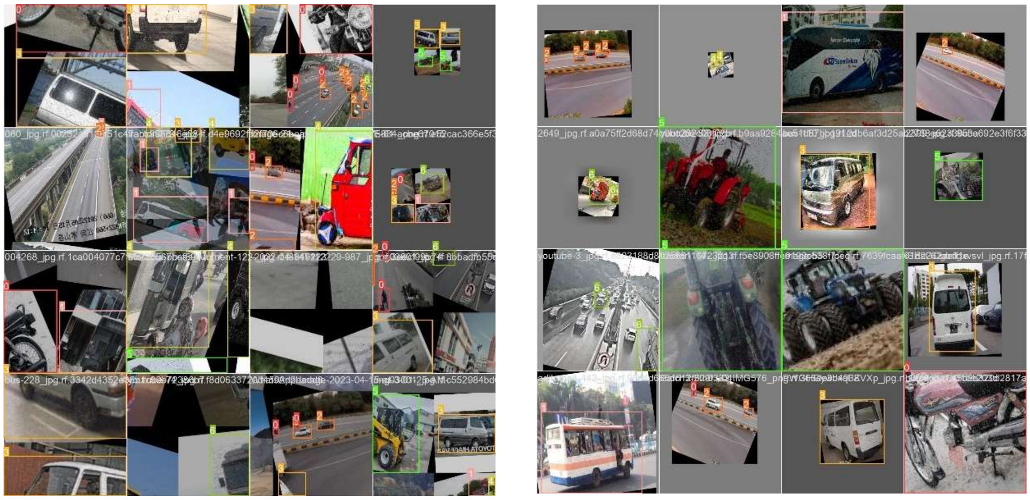

Figure 10: Image annotation with a batch size of 16 for the training of model

3.2. Model Training and Object Detection:

This study focuses on object detection, which is essential for accurately identifying and localizing vehicles in traffic video data. YOLOv8 was chosen for its effective architecture and features.

a) Model Training: Training, the YOLOv8 model, involves several steps: data preprocessing, hyperparameter tuning, setting up the training pipeline, and model validation.

b) Data Preprocessing: Images are rescaled to 640x640 to match YOLOv8's input size, standardizing the data and speeding up processing. Pixels are normalized between 0 and 1, and annotations are formatted for YOLO, including class labels and bounding box coordinates.

c) Hyperparameter Optimization: Tuning hyperparameters is crucial for optimizing model performance. Key hyperparameters for this model are detailed in Table 2.

Table 2: Tuned Hyperparameters for training object detection model for YOLOv8

Parameter	**Value**
Dataset Type	High point videos
Classes	07
Labels	[‘Bike’, ‘Bus’, ‘Car’, ‘Hiace’, ‘Rickshaw’, ‘Tractor’, ‘Truck’]
Epochs	204
Batch Size	16
Weight Decay	0.001
Warmup Epochs	5
Patience	50
Image Size	640×640
Iou threshold	0.7
Maximum detections	300
Initial and Final learning rate	0.0001 & 0.01

The YOLOv8 custom object detection model was developed using categorical cross-entropy loss with 0.1 label smoothing and 0.001 weight decay to minimize loss and prevent overfitting. The model was trained for 204 epochs using a batch size 16 and an initial learning rate of 0.0001, which increased to 0.01 after 5 warm-up epochs. Hyperparameters were optimized based on prior studies and experimentation. The training was stopped if there were no mean Average Precision (mAP) improvements for 50 consecutive epochs. To enhance the model’s detection capabilities in congested traffic, we set the maximum detections to 300 vehicles per frame. We adjusted the

Intersection over Union (IoU) threshold to 0.7 for better alignment between predicted and actual bounding boxes.

3.2.1. Training Pipeline:

a) Initialization: Set model parameters as described and use a pre-trained weight file for transfer learning.

b) Forward Pass: Pass 16 images through the model to obtain predictions, including bounding boxes and class probabilities.

c) Loss Calculation: Compute loss using the predefined function, which includes bounding box regression, objectness score, and class probabilities.

d) Backward Pass: Apply automatic differentiation to compute gradients of the loss function concerning model weights.

e) Weight Update: Use the Adam optimizer to update model weights.

f) Validation: Periodically assess model performance and adjust hyperparameters as needed.

3.2.2. Validation and Evaluation:

a) Validation involves assessing the model's performance on a separate dataset not used during training. Key metrics include:

b) Mean Average Precision (mAP): Measures the model’s precision and recall, evaluating object detection performance.

c) Precision and Recall: Precision shows the accuracy of optimistic predictions, while recall indicates the percentage of true positives detected out of all actual positives.

d) F1 Score: Combines precision and recall into a single metric to judge overall model performance.

3.3. Traffic Volume Estimation

The first step in estimating traffic volume involves detecting and locating vehicles in video footage, using the YOLOv8 model for object detection and the DeepSORT algorithm for tracking. YOLOv8 scans each video frame, identifies vehicles, and labels them with a class (e.g., car, bus, bike) and a confidence level indicating the likelihood of correct detection.

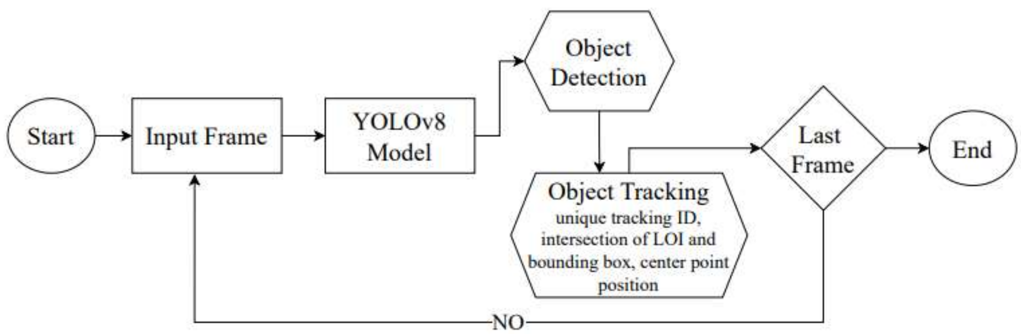

Figure 11: Methodological flow chart of Object detection, tracking and counting

The object detection model is integrated with DeepSORT, which assigns an ID to each detected vehicle and tracks it throughout the video. DeepSORT uses motion and appearance information to maintain accurate tracks, updating them with new detections and creating new tracks for previously undetected vehicles. Tracks are closed if a vehicle is not detected in subsequent frames, ensuring that only active tracks are counted.

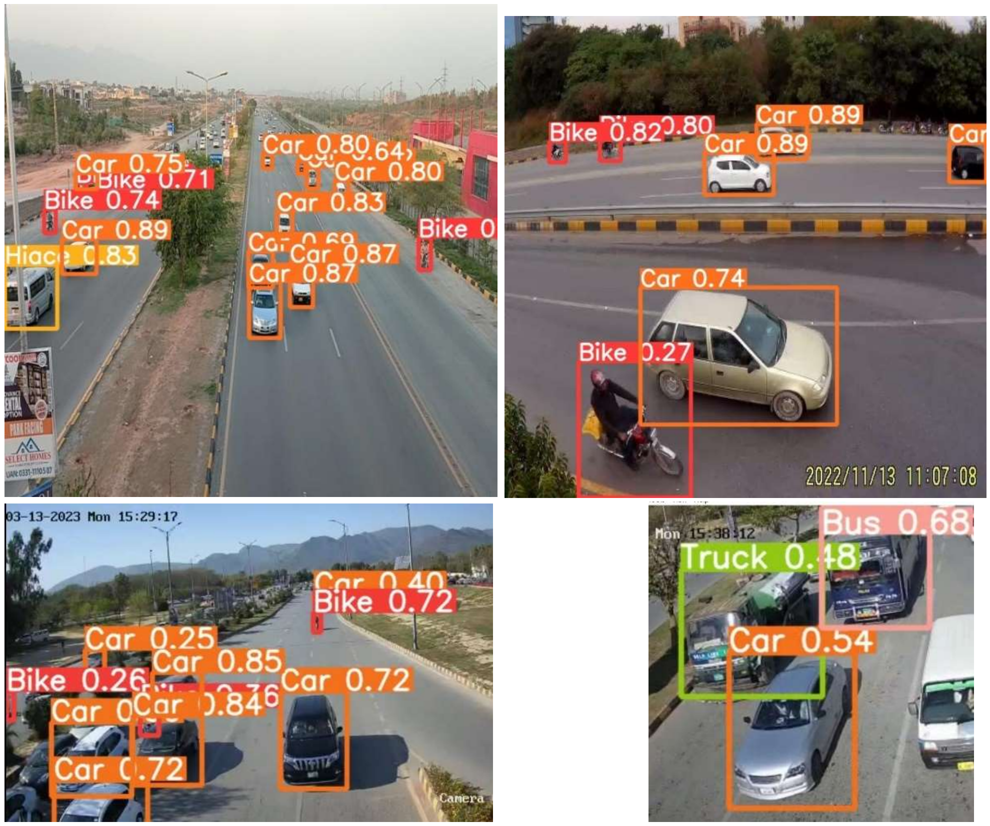

Figure 12: Images showing object detection from different input videos

3.3.1. Line of interest (LOI):

The Line of Interest (LOI) is a virtual line or area within the video frame where vehicles are counted. The LOI is strategically placed to ensure vehicles cross it at a 90-degree angle, maximizing detection accuracy. When a vehicle's bounding box intersects the LOI for two consecutive frames, it is counted as crossing the line. The system tracks the IDs of detected vehicles to prevent multiple counts of the exact vehicle.

```
def find_time(cap):
    fps = cap.get(cv2.CAP_PROP_FPS)
    totalNoFrames = cap.get(cv2.CAP_PROP_FRAME_COUNT)
    durationInSeconds = totalNoFrames // fps
    durationInHours=durationInSeconds/(60*60)
    return durationInHours
traffic_volume = counter.display_total()/durationInHours
```

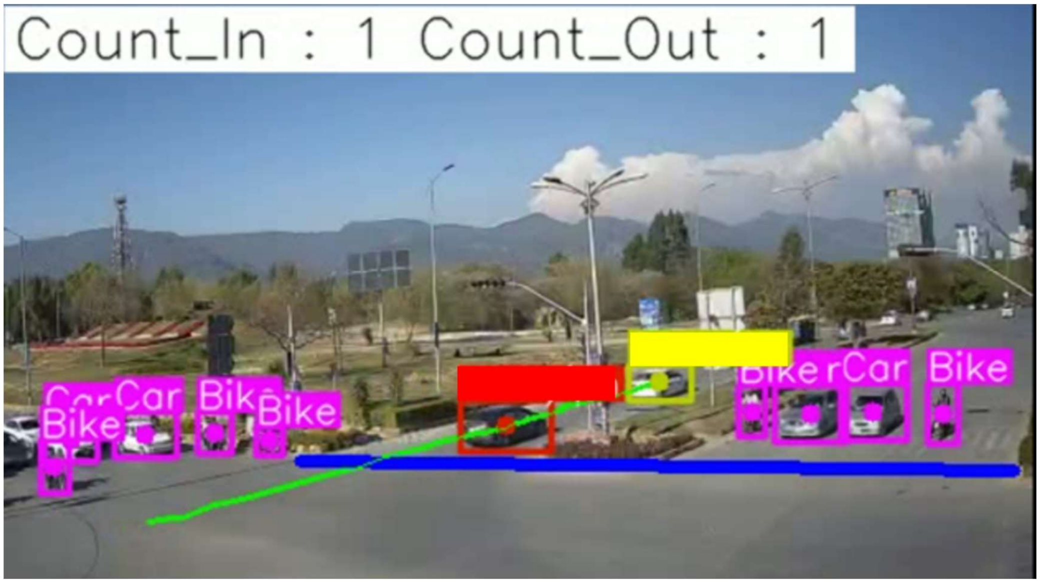

Figure 13: Example image showing of vehicle tracking, counting and LOI

3.4. Traffic Density Estimation:

Traffic density measures the number of vehicles in a specific area over time, indicating traffic flow and congestion levels. The Area of Interest (AOI) is defined within the video frame, and vehicles are counted as they enter this area. The AOI is typically rectangular and large enough to capture traffic flow without occlusion or overlaps. Vehicle counts within the AOI are used to calculate traffic density, with the final density output averaged over each frame to reduce short-term variations.

Figure 14: Image from an output video showing area of interest for traffic density estimation

```
line_pts = [region_points[0], region_points[3]] #Short
len_dist_1 = calculate_distance(region_points[0], region_points[1])
len_dist_2 = calculate_distance(region_points[3], region_points[2])
if len_dist_1>=len_dist_2:
    length = len_dist_1
else:
    length = len_dist_2
print(length)
traffic_density = counter.display_total()/(NumberOfLines*length)
```

3.5. Traffic Speed Estimation:

Speed estimation involves calculating the average speed of vehicles along a road segment or at an intersection. After detecting and tracking vehicles, the distance covered between frames is calculated using the coordinates of the bounding boxes. The time interval between frames, derived from the video frame rate, allows the conversion of the distance into speed using appropriate conversion factors. Once the coordinates for detection vehicles are extracted in each frame, the distance measured between two frames is calculated using the following formula,

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Where d is distance covered between two frames and (x_1, y_1) , (x_2, y_2), are the extracted coordinated of bounding boxes between two frames.

Then the time interval between frames is calculated using frame rate of the input video as $t = \frac{1}{fps}$ (fps is a frame rate of input video) and the "t" is in pixels per second, then converted to kmph of mph using conversion factors. The conversion factor is attained using distances calculated and incorporated into the video. For example, if the length of a road segment in the video corresponds to the size of real-world measurements, it will be used to calibrate pixel measurements for real-world units.

3.6. Model Implementation:

An API was created to serve the trained YOLOv8 and DeepSORT models with traffic video inputs. This API accepts video inputs and returns traffic flow, density, and mean speed. The API consists of an input handler, detection module, tracking module, parameter estimation module, and an output handler that produces a CSV file and output video.

3.6.1. Hardware Setup:

a) High-performance GPU for model training and execution.

b) High-resolution cameras for capturing traffic videos.

3.6.2. Software Setup:

a) Linux-based systems like Ubuntu for stability and performance.

b) Deep learning frameworks like PyTorch or TensorFlow.

c) API frameworks like Flask or FastAPI.

The final step involves integrating hardware and software, deploying the system at a traffic monitoring site, calibrating parameters based on traffic conditions, and testing the system's effectiveness by comparing estimated traffic parameters with actual values.

CHAPTER 4: RESULTS AND DISCUSSION

The proposed study was conducted at the G10 – F10, F-9 intersection, and Kashmir Highway to determine macro traffic parameters. Outcomes were evaluated based on the model's mean average precision and compared with manual counts. This chapter presents the results obtained from applying the intelligent traffic analysis system. It concludes with a detailed discussion of traffic volume, density, and speed estimation results, explaining the developed methodology's efficiency.

4.1. Training, Testing and Validation:

This study tested the YOLOv8 model for object detection and the Deep SORT algorithm for tracking after multiple training and testing phases. During training, we recorded the model's convergence against each epoch. In testing, interference was recorded against each image in the test dataset—validation involved determining parameters like the confusion matrix, F1 curves, and P curves.

4.1.1. Training Results:

The model was trained on a dataset of 17,205 annotated images (augmented and preprocessed), which is 75% of the total dataset across seven classes: Car, Bike, Bus, Truck, Hiace/Van, Tractor, and Rickshaw. Training lasted for 205 epochs with a batch size of 16. Figure 15 shows the convergence of this model in each epoch against reductions in box loss, class loss, and defocus loss.

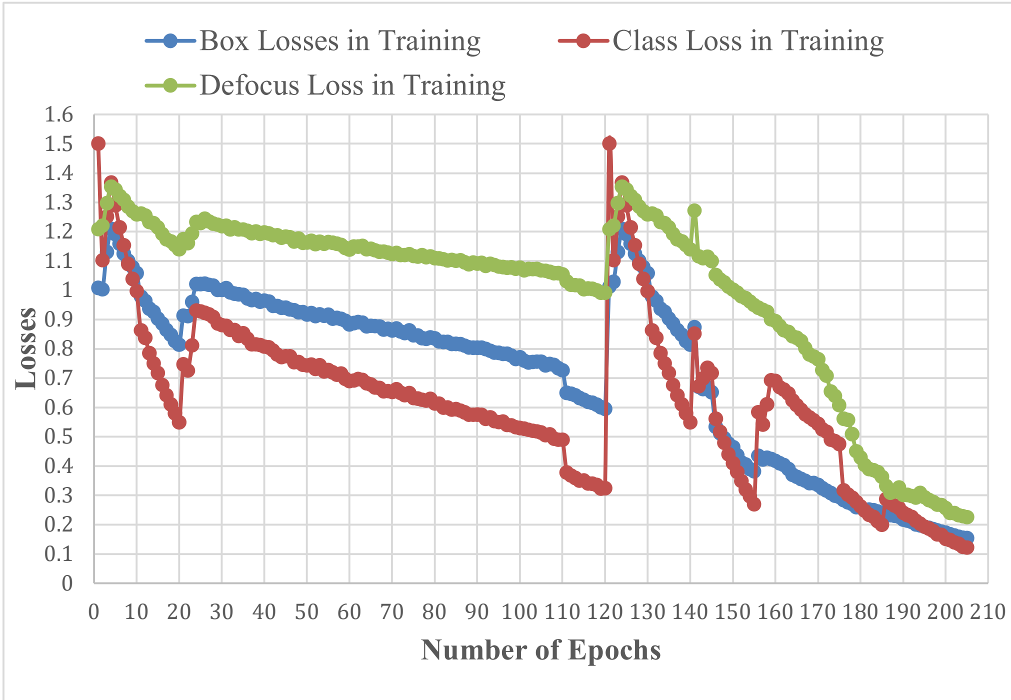

Figure 15: Box loss, Class loss & Defocus loss in model training

Losses decreased for up to 20 epochs, indicating the start of training and better model fitting. Afterward, there was a uniform trend until 120 epochs, where a rise in the curve indicated the inclusion of novel batches. Subsequently, there was a steady trend in loss reduction. Box loss (0.1544), class loss (0.12206), and defocus loss (0.22658) values indicate accurate object identification and exemplary performance in blurry scenarios. The model's precision is 0.8723, and recall is 0.80187, as shown in Figure 16, indicating it correctly identifies 87.23% of its predictions as relevant objects and successfully detects 80.187% of all relevant objects.

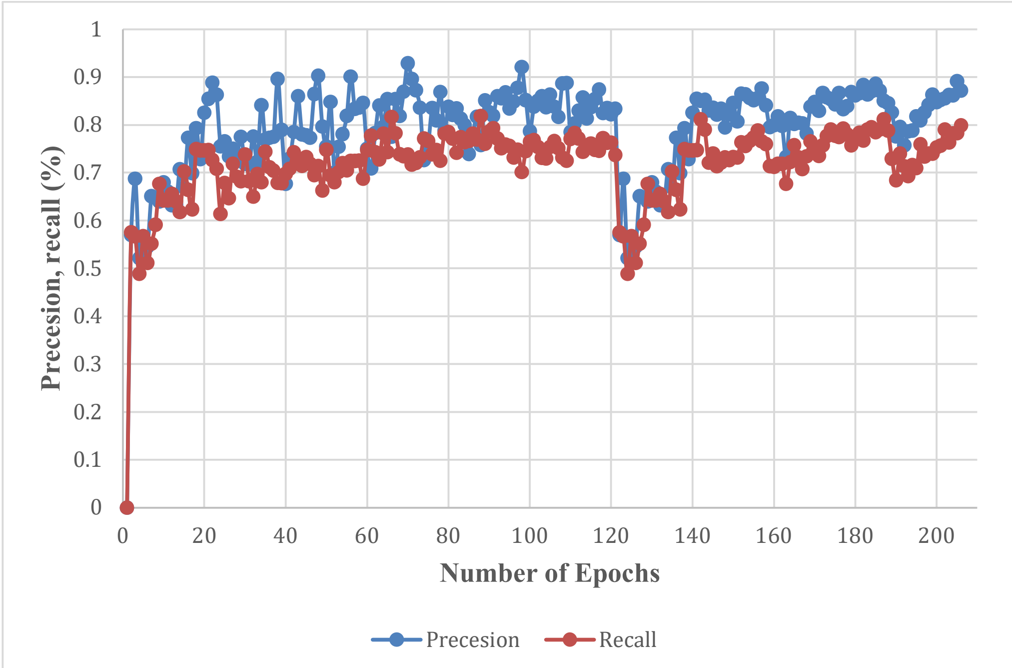

Figure 16: Behavior of model's precision and recall during training

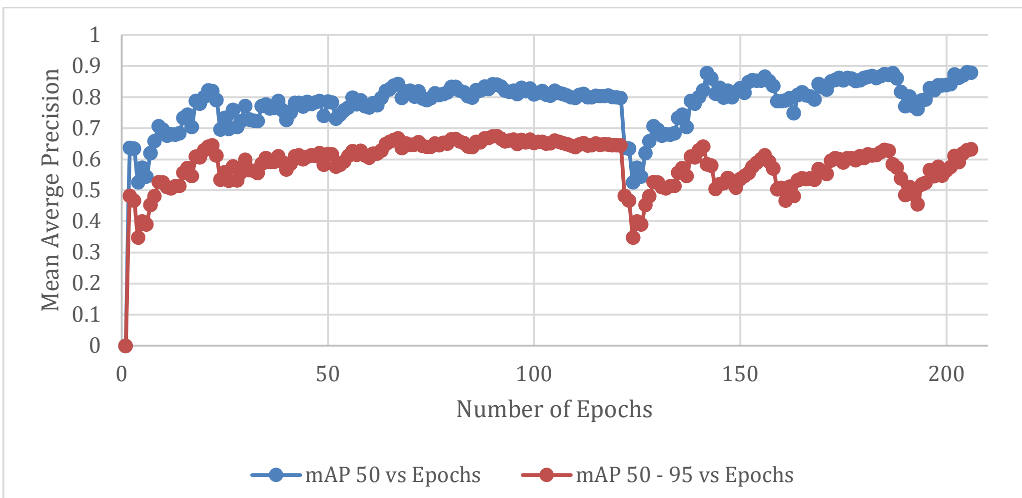

Figure 17: Mean Average Precision of Model against each Epoch during training

4.1.2. Validation Results:

Model Validation was done on a dataset of 2,300 annotated images (augmented and preprocessed), which is 10% of the total dataset across seven classes. Validation involved extracting the confusion matrix, F1 score, and precision-recall curves. The confusion matrix (Figure 18) shows 72% true predictions for bikes, 78% for passenger cars and tractors, 79% for buses and trucks, 89% for Hiace, and 85% for rickshaws.

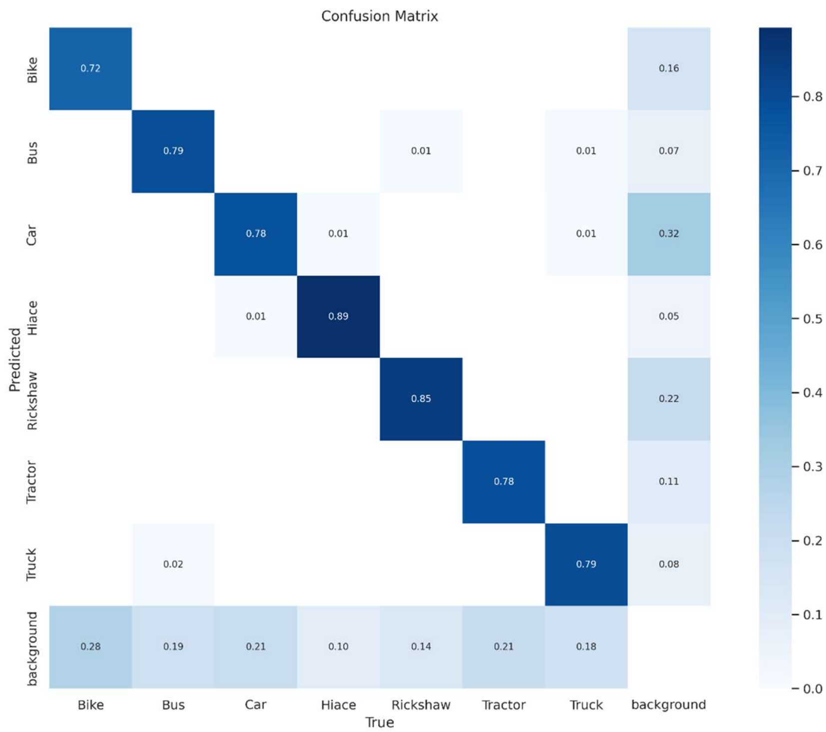

Figure 18: Confusion Matrix of custom Object detection model

Overall, the true results for each class are high, indicating efficient model performance. The F1 confidence curve (Figure 19) shows the model is optimized for a confidence threshold of 83% against an F1 score of 0.314. The precision-confidence curve (Figure 20) and the precision-recall curve (Figure 21) further validate the model's performance.

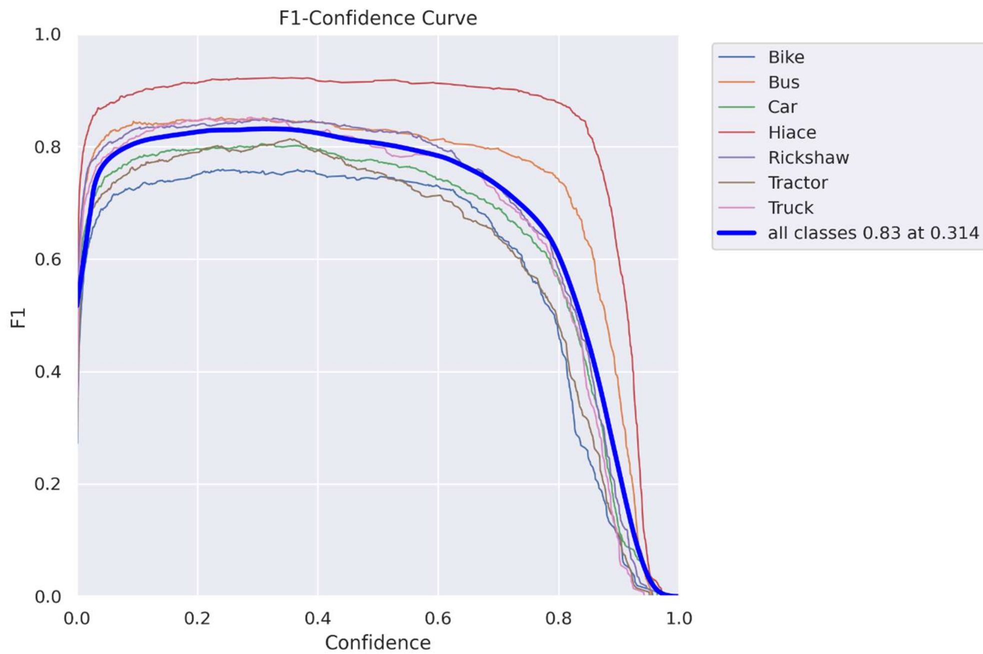

Figure 19: F1 – Confidence Curve for Object Detection Model

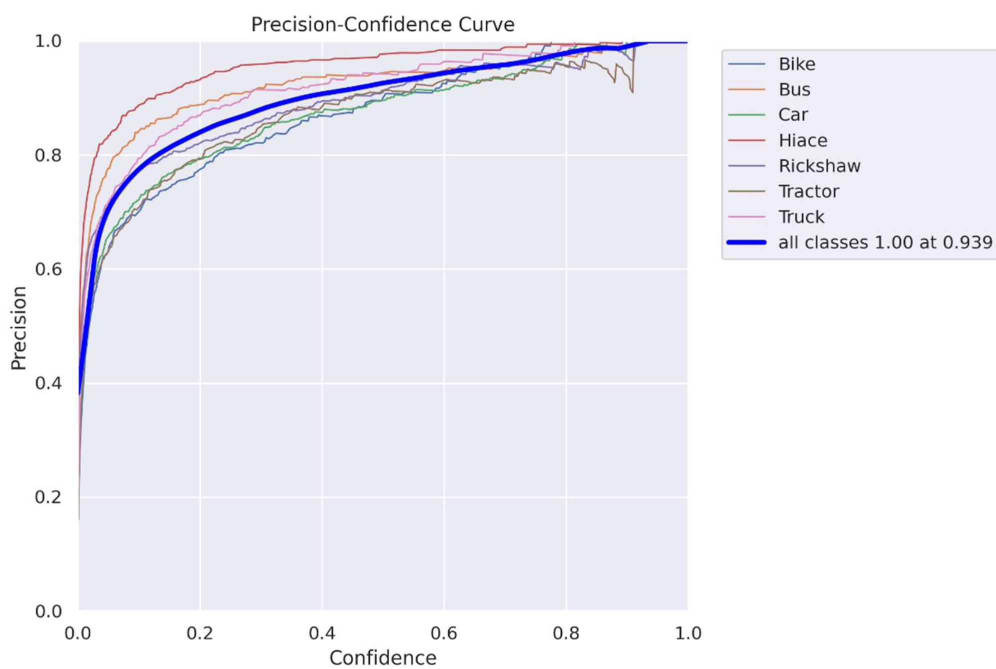

Figure 20: Precision – Confidence Curve of object detection model

The precision Recall curve (PR Curve) is a plot to measure the performance of any machine learning model using precision and recall, which is a performance measure that estimates the proficiency of a classification model. The precision-recall tradeoff is the plot of precision against recall at varying threshold Levels. This curve measures both the recall and the precision, where precision means low false positives, and recall means low false negatives. The higher area under the precision-recall curve of this model indicates high precision and recall, as shown in Figure 21.

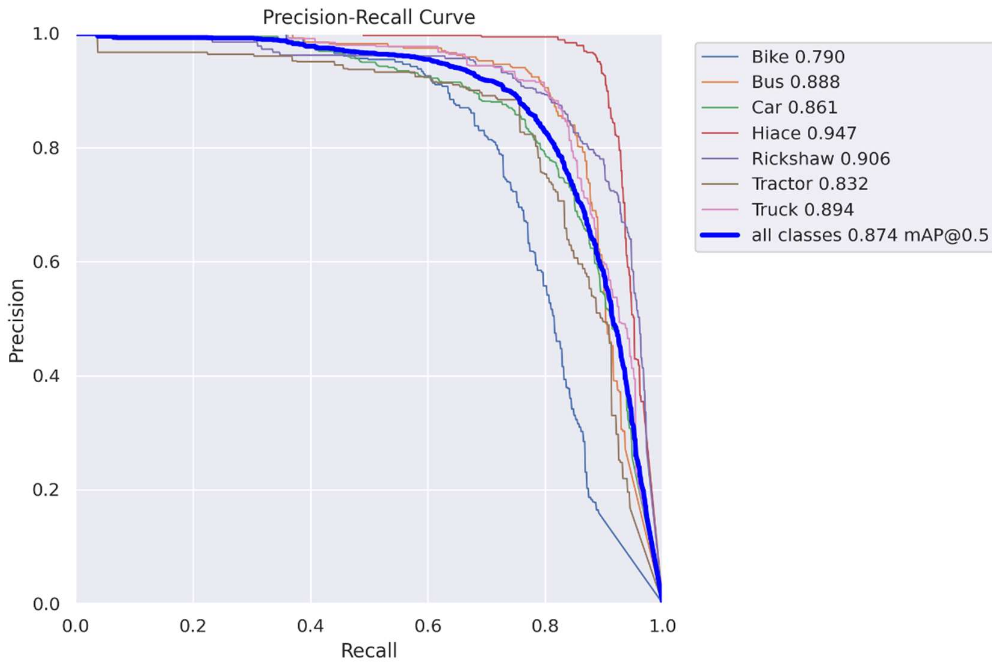

Figure 21: Precision – Recall Curve of object detection model

4.1.3. Testing Results:

The model was tested on a dataset of 3,500 images (augmented and preprocessed), which is 15% of the total dataset across seven classes. These images were not used in model training and validation. We tested the model by running inferences and checking detection against earlier annotations to predict accuracy. Testing provided a general overview of the model's reaction to new, unseen input videos of traffic.

Figure 22: Inferences on test Images showing accurate detection of Bikes, Trucks, Rickshaws, Cars and tractors

Figure 23: Inferences of test Images showing accurate detection of Bike, Cars, Trucks, Hiace, Rickshaws, Tractors and Buses

4.2. Traffic Volume Estimation:

Video cameras positioned at the three locations captured vehicle trajectories, enabling recognition of traffic patterns and prediction of traffic flow and composition. Traffic volume and vehicle counts were determined. Videos from each site, spanning one hour, were preprocessed and used as input for the YOLOV8-DeepSORT algorithm, which provided classified counts and traffic volume. The output included a video showing classified counts and a CSV file with traffic volume in vehicles per hour and passenger car units (PCUs). Passenger car equivalents and the code to extract traffic flow parameters in PCUs are given in Table 3. Comparison with manual counts showed a substantial degree of accuracy, particularly under normal daylight conditions (96% accuracy), but lower accuracy during dawn (84.83%) and dense traffic conditions (83.01%), as shown in Table 4. Traffic volume estimates from the proposed methodology and manual methods are compared in Table 5.

Table 3: Passenger Car equivalents for each class of vehicle

Vehicle Class	Passenger Car Equivalent
Car	1.00
Bus	2.50
Bike	0.30
Rickshaw	0.50
Hiace	1.50
Truck	3.00
Tractor/Trolley	3.00

Table 4: Manual Traffic counts and traffic counts based on a proposed methodology

Time & Condition	**Location**	**Vehicle Class**	**Manual Counts**	**Proposed Method**	**Percentage Error (%)**	**Overall accuracy (%)**
Sunday 1200 – 0100 hrs Sunlight	G10 – F10 Intersection	Car	663	650	1.96	96.59
		Bike	340	319	6.17	
		Bus	3	3	0.00	
		Truck	7	7	0.00	
		Tractor	1	1	0.00	
		Hiace	13	12	7.69	
		Rickshaw	0	0	-	
Monday 0800 – 0900 hrs Morning (Low light)	Srinagar Highway	Car	5100	4810	5.72	84.83
		Bike	1584	1321	16.60	
		Bus	93	79	15.05	
		Truck	84	78	7.14	
		Tractor	7	6	14.20	
		Hiace	118	99	16.10	
		Rickshaw	4	4	0.00	
Monday 1530 – 1630 hrs Sunlight (Congested Traffic Conditions)	F -9 Intersection	Car	2180	1915	12.15	83.01
		Bike	1104	807	26.90	
		Bus	94	79	15.95	
		Truck	24	21	12.50	
		Tractor	6	6	0.00	
		Hiace	60	51	15.00	
		Rickshaw	0	0	0.00	

Table 5: Manual Traffic Volume and Traffic Volume based on proposed methodology

Location	Manual Traffic Volume (Veh/hr)	Proposed Traffic Volume (Veh/hr)	Manual Traffic Volume (pcu/hr)	Proposed Traffic Volume (pcu/hr)
G10 – F10 Intersection	1027	992	816	795
Srinagar Highway	6990	6397	6260	5806
F – 9 Intersection	3468	2879	2926	2512

4.3. Traffic Density Estimation:

Traffic density, an important parameter for determining congestion and service levels, was estimated using the area of interest (AOI). Unlike traditional occupancy rate and time methods, we estimated density using the highway capacity manual definition. The AOI, drawn in a near-rectangular shape, was divided by the roadway section's width to determine the study length, which was then converted into miles. Vehicles staying in the AOI were tracked and counted, and these counts were divided by the length and number of lanes to return traffic density in PCUs per mile per lane, as shown in Table 6. The AOI's location at intersections led to higher densities due to vehicles starting to leave upon the green light. The dataset for the G10 – F10 intersection recorded on a Sunday afternoon showed lower traffic density compared to F-9 intersections recorded on a Monday.

Table 6: Traffic Density and LOS based on a proposed methodology

Location	Traffic Density (pc/mile/lane)	Level of Service
G10 – F10 Intersection	21.94	C
Srinagar Highway	19.81	C
F – 9 Intersection	31.25	D

4.4. Traffic Speed Estimation:

Traffic speed was estimated using the time difference of tracked vehicles moving from one frame to subsequent frames. We recorded the time a vehicle takes to enter and leave the AOI, extracted the distance in pixels, and converted it into miles. This method provided individual object speeds, and the average speed of each vehicle class was calculated and shown in Table 7. Although not highly accurate due to pixel-to-frame conversion, this method is efficient and non-rigorous, making it reliable for quick, less laborious average speed estimates. The overall average speed was determined using the weighted average of each vehicle class divided by the total number of vehicles.

Table 7: Average Speeds of individual classes and overall average speed of each facility

Location	Car (mph)	Bike (mph)	Bus (mph)	Truck (mph)	Tractor (mph)	Hiace (mph)	Average speed of facility (mph)
G10 – F10 Intersection	29.61	23.40	21.25	19.50	16.76	26.07	27.46
Srinagar Highway	58.34	38.76	45.85	39.20	30.28	56.12	53.81
F – 9 Intersection	34.12	23.67	22.82	21.92	17.70	31.82	30.71

The findings from this study offer significant insights for transportation policy and strategy development. The high accuracy of the YOLOv8 and Deep SORT models in estimating traffic volume, density, and speed, particularly under normal daylight conditions, underscores the potential for these intelligent traffic analysis systems to enhance traffic management. Policymakers could leverage these technologies to implement real-time traffic monitoring and control systems, optimizing traffic flow and reducing congestion. By integrating such advanced models, cities can improve traffic signal timings, dynamically manage lane usage, and deploy rapid-response measures to traffic incidents, leading to more efficient and safer road networks.

Moreover, the variability in model accuracy under different lighting and traffic conditions highlights the need for adaptive traffic management strategies. For instance, deploying additional sensors or enhancing video preprocessing techniques during low-light conditions can maintain high accuracy in traffic data collection. This adaptability is crucial for developing robust traffic policies accommodating diverse urban environments and scenarios. Furthermore, accurately estimating traffic speed and density can inform infrastructure investments, such as road expansions or creating dedicated lanes for high-occupancy vehicles and public transportation, promoting sustainable urban mobility solutions.

CHAPTER 5: CONCLUSION

This thesis unveiled a groundbreaking intelligent traffic analysis system that leverages deep learning to calculate essential macro traffic parameters. Harnessing the power of YOLOv8 for object detection and DeepSORT for tracking, the system transforms input video streams into precise estimates of traffic volume, density, and average speed.

YOLOv8, with its versatile architecture, excelled in accurately identifying multiple vehicle classes, achieving an impressive mAP@0.5 of 0.88 and mAP@0.5:0.95 of 0.64. These results underscore the model's robustness even in the most congested traffic scenarios. Complementing this, DeepSORT proved highly effective in tracking vehicles, enabling precise calculation of traffic indices. The seamless integration of these technologies offers a powerful solution for real-time traffic analysis.

Our system demonstrated exceptional accuracy in determining traffic volumes by quantifying vehicles passing through a line of interest. It maintained consistency across various samples, with only minor discrepancies in heavily occluded cases. Traffic density estimation was highly accurate, with slight deviations in overcrowded areas. The system also effectively calculated the average traffic speed from vehicle motion in video frames.

The developed API provided real-time insights into traffic volume, density, and speed, boasting low recall but high precision, making it an ideal tool for real-world traffic monitoring and control. The model's training and validation processes showcased its proficiency in image identification and data annotation, with a final loss value indicating successful convergence. Key metrics such as precision, recall, the F1 score, and mAP validated the model's capacity to address traffic challenges.

In conclusion, this study presents a state-of-the-art traffic analysis system that combines advanced deep learning techniques with practical applicability. The results highlight its potential to revolutionize traffic management, offering accurate, real-time data to significantly enhance traffic monitoring, control, and planning strategies. This intelligent system is a testament to technology's transformative power in addressing modern urban traffic challenges.

RECOMMENDATIONS

The proposed strategy offers an effective approach to the estimation of traffic flow parameters and opens new ways for practical implementation and recommendations for future research:

1. **Improvement in travel time:**

   When deployed in real time at signalized intersections, this system can determine the traffic flow parameters of each leg and turning vehicle.

2. **Ramp Metering and toll Plazas:**

   Ramp metering is the system of signals installed in interstate arterials on ramps that uses traffic signals to regulate the inflow and outflow of vehicles on ramps. This model can be integrated into a time ramp metering system, increasing the system's effectiveness and reducing the risk of freeway crashes by alerting the vehicles entering the highway through the ramp about the other vehicles' speed and lane.

   The system, if deployed on toll plazas, can help in the decision-making of exact capacity enhancements using real-time traffic demand and queue lengths of toll plazas.

3. **Congestion management:**

   An advanced congestion management system can be implemented by incorporating this model.

4. **Integration with other traffic data sources:**

   If this model is combined with other forms of data like GPS data, sensor data, and past records of traffic flow, then a more detailed analysis can be made.

5. **Realtime System Deployment:**

   Testing in real-life traffic will give mechanisms for understanding real-life opportunities for using this system.

6. **Extension to Additional Traffic Parameters:**

   Diversification of the system to forecast other traffic characteristics, including more robust vehicle classification, lane occupancy, and traffic congestion, will be useful to give a more comprehensive picture of the traffic situation in real-time.

7. **Scalability and Performance Optimization**:

   On this premise, ensuring that the system can handle large volumes of data in the real-time environment is vital.

8. **Integration with Autonomous Vehicles**:

   Explore synergies with autonomous vehicle systems by incorporating the proposed strategy into connected environments. Collaborating with autonomous systems can optimize traffic flow and coordination, enhancing the strategy's impact.

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