Smart Traffic Management Systems: An Overview of AI and IoT Integration

Abstract:

Urban traffic congestion remains a significant challenge, often worsened by conventional traffic lights that operate on fixed schedules without adapting to real-time traffic conditions. While recent smart traffic systems using Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) technologies have made notable progress, many are limited to basic scenarios, overlook pedestrian needs, or fail to prioritize emergency vehicles effectively.

In this study, we propose a cost-effective, intelligent traffic light control system that combines the YOLOv4 object detection model with a hybrid scheduling algorithm based on Shortest Job First (SJF) and Round-Robin (RR) strategies. The system captures real-time vehicle counts through cameras and uses these insights to dynamically allocate green light durations, minimizing overall waiting time while ensuring fairness across all directions.

We trained the model on Kaggle traffic image datasets, using a twelve-step moving average for preprocessing. The model achieved over 60% mAP@0.5 and around 45–50% mAP@0.5:0.95, with precision above 50% and recall up to 65%. Detection accuracy was 100% for motorbikes and about 70% for cars, police cars, and rickshaws. Misclassifications occurred mainly in rare classes like ambulances and garbage vans, suggesting a need for better class balance.

Overall, this research presents a scalable and adaptable solution for modern traffic management that enhances traffic flow, reduces delays, and supports the development of smarter, more responsive urban transportation infrastructure.

Introduction:

The increasing urbanization and growth in vehicle populations have led to significant challenges in traffic management, including congestion, pollution, and safety issues. To address these challenges, smart traffic management systems have emerged as a promising solution, leveraging technologies such as Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT). These systems aim to optimize traffic flow, reduce congestion, and promote sustainable urban development.

Predictive modeling has become base of modern traffic management systems. By analyzing historical and real-time data, these models can predict congestion levels and optimize traffic signal timings.

A smart traffic light system utilizing infrared sensors and microcontrollers to dynamically adjust traffic signal timings based on vehicle density is proposed **[1].** Similarly, a traffic control system employing Raspberry Pi and PIR sensors to optimize traffic flow at simple intersections was designed **[2].** However, both approaches were limited to single-lane scenarios and lacked comprehensive traffic modeling for performance evaluation.

Machine learning has been widely applied in intelligent traffic light control systems. A model utilizing deep reinforcement learning to optimize traffic light timings at isolated intersections significantly reduced vehicle and pedestrian delays by dynamically adjusting green light intervals [3]. Furthermore, an intelligent traffic light model based on reinforcement learning was developed to optimize traffic signals across multiple intersections. However, this approach primarily focused on vehicle movement and did not account for pedestrian delays **[4].**

Artificial Intelligence, particularly Deep Reinforcement Learning (DRL), has revolutionized traffic light control systems. DRL enables real-time decision-making by processing data from various sources, such as vehicle positions, speeds, and pedestrian movements. A study combining Visible Light Communication (VLC) and DRL demonstrated significant improvements in traffic flow and pedestrian safety **[5].** The system uses VLC to transmit real-time data, which is then processed by DRL agents to dynamically adjust traffic light phases. This approach not only reduces congestion but also prevents cascading gridlocks by rerouting traffic effectively.

The Internet of Things (IoT) plays a pivotal role in smart traffic management by enabling real-time data collection and analysis. IoT devices, such as smart cameras and sensors, are strategically deployed at intersections to monitor traffic conditions, vehicle counts, and pedestrian movements. This data is then transmitted to a central control unit, which uses sophisticated algorithms to dynamically modify traffic signal timings. For instance, a study proposed an IoT-based smart traffic management system that uses image processing and automated street lighting to optimize energy consumption and reduce congestion **[6]**. The system not only improves traffic efficiency but also contributes to sustainable urban development by reducing energy waste.

Traditional fixed traffic light controllers, which operate on predetermined schedules, are often inefficient and contribute to increased congestion and emissions. In contrast, smart traffic light systems adapt to real-time conditions, reducing unnecessary stops and idling times. A study focusing on the implementation of smart traffic lights in Pasir Gudang highlighted the potential of these systems to reduce carbon emissions and support low-carbon smart city initiatives **[7].** By dynamically adjusting traffic signal durations, the system minimizes fuel consumption and lowers greenhouse gas emissions, aligning with global sustainability goals.

One of the critical challenges in urban traffic management is ensuring the smooth passage of emergency vehicles. Smart traffic systems address this issue by integrating priority modes and rerouting strategies. For example, a study employing YOLOv4 for object detection and DRL for traffic light control demonstrated the ability to prioritize emergency vehicles and reduce their travel times **[8][9].** The system uses real-time monitoring and dynamic rerouting to create efficient paths for emergency vehicles, ensuring timely responses and enhancing public safety.

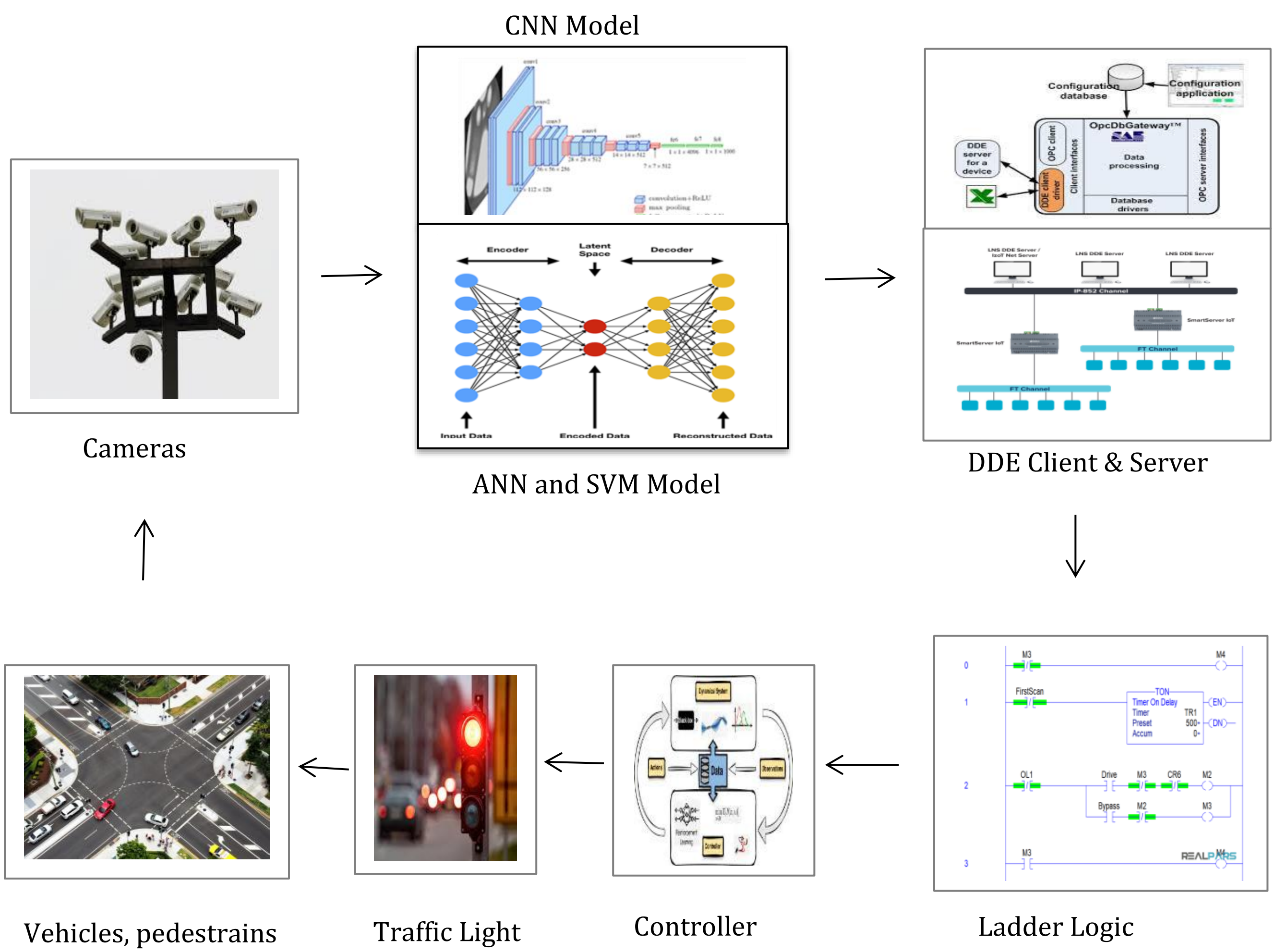

Figure 1. Operations of smart Traffic Light Control System

Literature Review:

The rapid increase in urban traffic congestion has necessitated the development of intelligent traffic management solutions, including smart traffic light systems. Traditional traffic light systems operate on fixed timing cycles, which often fail to adapt to fluctuating traffic conditions, leading to inefficiencies such as increased vehicle waiting times, congestion, and fuel consumption. Smart traffic light systems leverage advanced technologies, including machine learning, artificial intelligence, and cyber-physical systems, to enhance traffic management and reduce delays.

A study utilizing the CN+ dataset from Bremen, Germany, demonstrated the effectiveness of machine learning techniques in predicting congestion levels at intersections **[10].** The study employed advanced feature selection methods, such as Dual Importance Intersection Feature Selection (DIFS), which combines Random Forest (RF) and Chi-square analysis, to identify critical factors influencing congestion. The model achieved remarkable accuracy, with F1 and Quadratic Weighted Kappa (QWK) scores reaching 100%, making it a robust tool for sustainable urban traffic management.

Another study highlighted the integration of predictive models with IoT technologies to streamline traffic flows and prioritize pedestrians. By analyzing traffic queues and pedestrian waiting times, the system dynamically adjusts traffic signals to minimize congestion and reduce emissions **[11].** This approach not only improves traffic efficiency but also contributes to better air quality by reducing vehicle idling times.

Another innovative application of DRL is the development of a Dynamic and Intelligent Traffic Light Control System (DITLCS), which operates in three modes: Fair Mode (FM), Priority Mode (PM), and Emergency Mode (EM) **[12].** This system prioritizes emergency vehicles and adapts to real-time traffic conditions, ensuring efficient traffic flow and minimizing delays. The integration of fuzzy inference systems further enhances the decision-making process by selecting the most appropriate mode based on traffic dynamics.

A more integrated approach was presented, involving an adaptive and dynamic smart traffic light system for efficient traffic management in urban settings **[13].** Their system incorporated real-time data analytics and deep learning techniques to improve traffic flow by considering both regular and emergency vehicles. The model demonstrated superior performance in reducing congestion and enhancing road safety.

Another significant contribution was made by proposing a cyber-physical system for smart traffic light control. Their approach categorized traffic volume into four levels—low, medium, high, and very high—using traffic detection cameras and machine learning algorithms such as convolutional neural networks (CNNs), artificial neural networks (ANNs), and support vector machines (SVMs) **[14].** The study found that their dynamic traffic interval technique reduced vehicle waiting times by 12% to 27% and pedestrian delays by 9% to 23% compared to traditional traffic light systems.

On a more advanced note, one study looked into predicting traffic flow for smart traffic lights using machine learning, where the model performed exceptionally well, forecasting congestion patterns and making proactive adjustments to traffic signals **[18].** This study made it possible to optimize traffic flow more effectively, reducing congestion before it happens.Another contribution combined machine learning and IoT to design an adaptive traffic-management system specifically for smart cities **[19].** By adjusting to real-time traffic conditions, this system contributed not only to smoother traffic but also to environmental sustainability, thanks to better handling of emissions and energy use.

In yet another innovative approach, edge computing was integrated with machine learning to create a low-latency solution for smart traffic management. This system processes data at the "edge," reducing response times and optimizing traffic flow in real-time, which is crucial for large-scale, urban deployments **[20].**Additionally, deep learning agents have been employed for traffic signal control, with models that continuously adapt to changing traffic conditions, making it possible to optimize traffic signal timings on the fly **[21].**

A simulation study conducted in Dubai employed YOLO-based algorithms for real-time traffic monitoring, helping to optimize traffic flow while also prioritizing emergency vehicles. This study demonstrated that AI-based solutions could significantly reduce congestion and improve public safety **[22].**Moreover, machine learning algorithms have been used to design a system that handles traffic queues more effectively, adjusting signal phases dynamically based on real-time data, which further improves traffic management **[23].**

Another contribution proposed a cyber-physical system that integrates traffic sensors and machine learning for real-time, adaptive traffic signal control. This dynamic system reduces waiting times for vehicles and pedestrians by adjusting signal timings based on live traffic data **[24].**Fusion-based approaches combining machine learning models have also been explored to manage congestion in smart cities. This study showed that by combining various algorithms, traffic congestion can be better controlled, ensuring smoother routes and fewer delays for commuters **[25].**

Lastly, an intelligent traffic solution developed for green and sustainable cities used machine learning to prioritize environmental sustainability. This solution focused on reducing vehicle idling time and promoting greener transportation options, aligning well with the goals of eco-friendly urban planning **[26].**Finally, to address the growing concern of security in smart traffic systems, blockchain technologies have been applied to ensure traffic lights and signal systems are protected from cyber threats. Using machine learning and blockchain together, researchers have developed a system that can detect anomalies and safeguard the entire traffic management process **[27].**

Table 1:Summary of Research Papers on Smart Traffic Light Systems Using Machine Learning:

Title	Year	Results	Datasets
Edge ML Technique for Smart Traffic Management in Intelligent Transportation Systems**[20]**	2024	The Edge ML technique for smart traffic management demonstrated promising results, achieving an accuracy of **92%** in vehicle detection and a processing speed of **37.9 frames per second (FPS)** using a pruned YOLOv3 model combined with DeepSORT	• COCO dataset used in this work consists of 80 different classes with 3,30,000 images.
Deep Learning Agent for Traffic Signal Control**[21]**	2024	There was a **70.97% reduction in average delay**, showing significantly improved traffic flow.	• Traffic Images Datasets from Kaggle
Anomaly detection in Smart Traffic Light system using blockchain: Securing through proof of stake and machine learning**[27]**	2024	This integration improved data integrity and security, leading to increased detection accuracy from 48% to 94%, thereby bolstering the reliability and resilience of smart city traffic management infrastructures.	• Synthetic traffic data
Adaptive and dynamic smart traffic light system for efficient traffic management**[13]**	2024	There was a **33.82%** reduction in queue occupancy rates, indicating more efficient traffic management.	• **simulated dataset** reflecting traffic conditions at the El-Hidhab Setif city intersection
IoT-driven traffic signal optimization and smart street lighting system Learning Approaches**[6]**	2024	Achieved enhanced traffic prediction accuracy and optimized signal control, leading to improved traffic flow and reduced congestion	• Real-time traffic data collected from IoT sensors deployed at various intersections, including vehicle counts, speeds, and congestion levels.
Smart Traffic Control System for Dubai: A Simulation Study Using YOLO Algorithms**[22]**	2023	ML algorithms like YOLO improved traffic flow and reduced congestion in simulations.	• Dubai Traffic Images dataset using YOLO Algorithm

Cyber-Physical System for Smart Traffic Light Control**[24]**	2023	Based on the simulation results, there was a 20.11% to 26.67% reduction in the overall vehicle waiting time for an intersection compared to the fixed-time traffic light system.	• 1200 data samples to predict the green light timing for detected traffic conditions
Intelligent Traffic Light Solution for Green and Sustainable Smart City**[25]**	2023	Intelligent traffic light system successfully detected and counted vehicles in real-time using image processing techniques.	• AI City Challenge Dataset (NVIDIA)
Cyber-Physical System for Smart Traffic Light Control. Sensors**[14]**	2023	The dynamic traffic interval technique led to a **12% to 27%** reduction in vehicle waiting times compared to fixed-time and semi-dynamic control methods.	• Traffic detection cameras,
Design and Implementation of an ML and IoT Based Adaptive Traffic-Management System for Smart Cities**[19]**	2022	The algorithm achieved AuC metrics higher than 0.80 for wheat disease detection.	• Datasets(Vehicle Data,Road Data,Traffic Light)
An intelligent IoT Enabled Traffic queue handling System Using Machine Learning Algorithm**[23]**	2022	IoT and ML-based traffic management reduced congestion and fatalities.	• DBSCAN clustering algorithm For Traffic light based on traffic congestion image datasets.
Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques**[25]**	2022	The accuracies and miss rates of the ANN, SVM, and fusion-based FITCCS-VN are 94%/6%, 90.3%/9.7%, and 95%,/5%, respectively.	• prelabelled VN dataset is selected
Traffic Flow Prediction for Smart Traffic Lights Using ML Algorithms**[18]**	2022	MLP-NN achieved the best traffic flow prediction with an R-Squared of 0.93.	• Road Traffic Prediction Dataset from Huawei Munich Research Center

Methodology:

For this study we worked with openly available traffic-camera image sets hosted on Kaggle. These collections consist of annotated frames captured from multiple urban intersections and are commonly used for short-term traffic-flow forecasting and signal-timing optimisation. Each frame is stamped with the capture time and tagged with vehicle counts (cars, buses, motorbikes, etc.).

Raw camera feeds occasionally include corrupted frames or blank images, typically the result of momentary sensor outages. Instead of replacing the missing counts with global means—an approach that can introduce unrealistic spikes—we apply a twelve-step moving average drawn from the preceding hour of valid observations. This smooths abrupt discontinuities while respecting local traffic trends. After cleaning, the dataset is partitioned chronologically: the first 75 percent of frames form the training set and the remaining 25 percent are reserved for testing.

In this paper, we propose a dynamic traffic light system with a switching mechanism that is based on the shortest job first (SJF) and round-robin algorithm. The proposed mechanism initially uses the optimized YOLO mechanism to compute the number of vehicles waiting in each lane. The traffic light is turned green in the lane with the least number of cars. This is done to avoid a large waiting time. It is known that implementing SJF technique gives the least overall waiting time. However, the road (or lane) with a larger number of vehicles can suffer from starvation of green signals if only the road with the smallest count of vehicles is given priority. Hence, we implement the round-robin approach among all the traffic signal directions to address the problem.

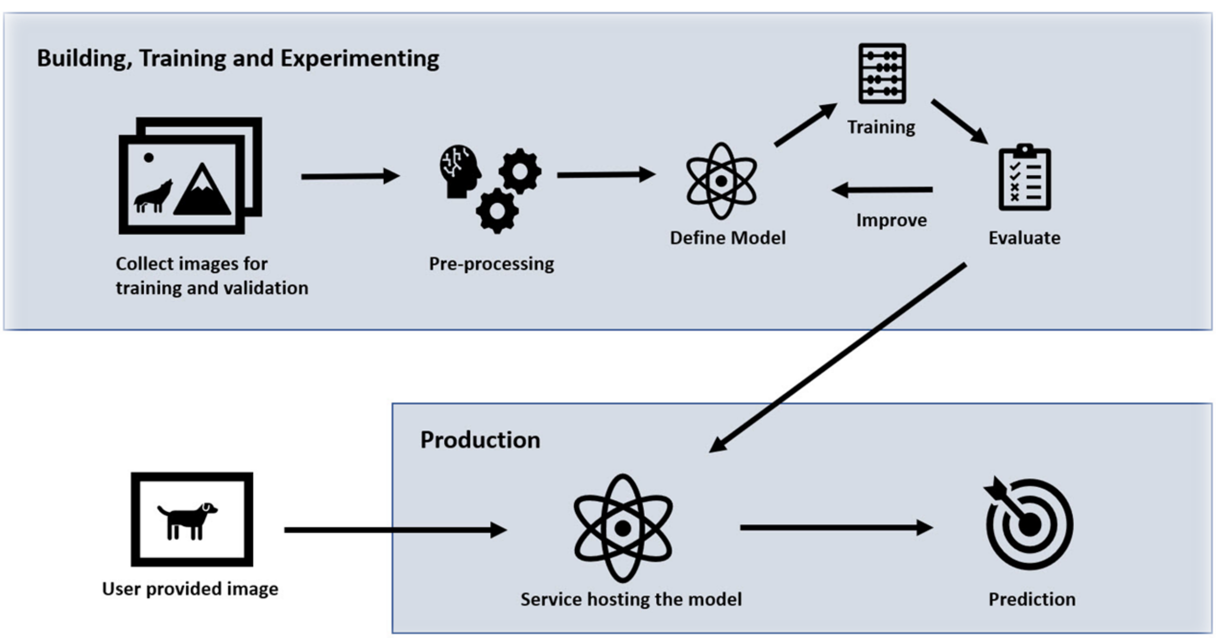

Figure 2. Flowchart of proposed method.

In practice, the trained model would sit inside an intelligent signal controller fed by live counts from lane-level vehicle sensors. These per-interval counts build a dataset identical in structure to the one described earlier, letting us retrain or fine-tune the model for each junction. At runtime the model ingests a window of recent counts and outputs a traffic-flow estimate for the next interval. That forecast, in turn, drives the timing plan: either an operator adjusts the signal phases manually, or an embedded algorithm computes the optimal green, amber and red durations automatically. Communication between signals and a central hub can be wireless, or all calculations can reside in the roadside controller itself. A block diagram and a street-level view of this architecture are presented in Figure 3

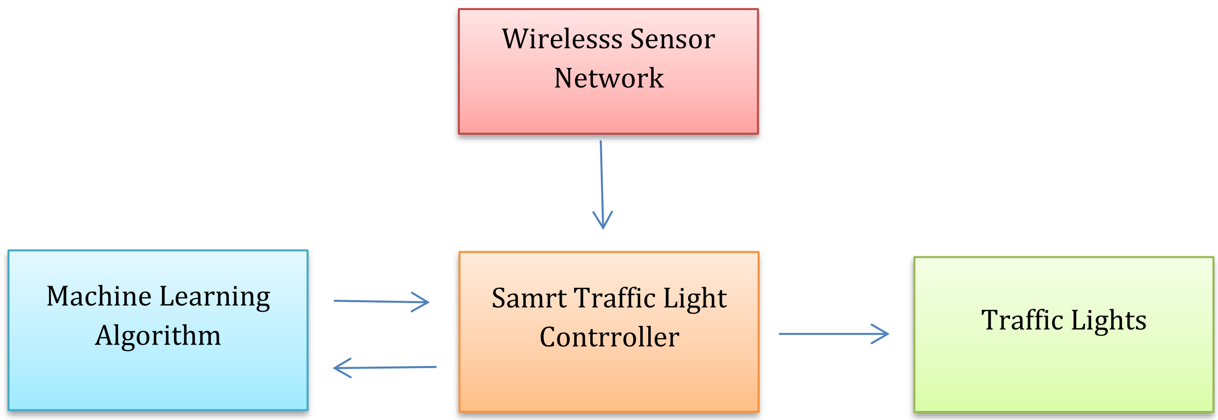

Figure 3. Proposed usage block diagram

Results and Discussion :

Training box loss measures how well the model draws bounding boxes around traffic objects; its downward trend shows increasing accuracy. Training class loss evaluates category predictions (e.g., car versus background) and likewise declines, indicating better classification. Training DFL (Distribution Focal Loss) tracks feature learning inside each box and falls steadily, reflecting richer feature representation. Precision on the evaluation set represents the proportion of detected cars that are truly cars; despite some bumps it stays above 50 percent, which is acceptable. Recall gauges the fraction of all real cars that the model detects; it rises gradually, so the model is spotting more genuine cars as training proceeds. Mean Average Precision at 0.5 IoU (mAP 50) improves progressively, confirming overall accuracy gains, and the stricter mAP 50-95 metric also climbs, signaling robustness across IoU thresholds. On unseen validation images, box-loss trends downward—in spite of noise—implying good generalization; validation class loss decreases steadily as category predictions sharpen, and validation DFL loss drops as the model continues to capture discriminative features in new data.

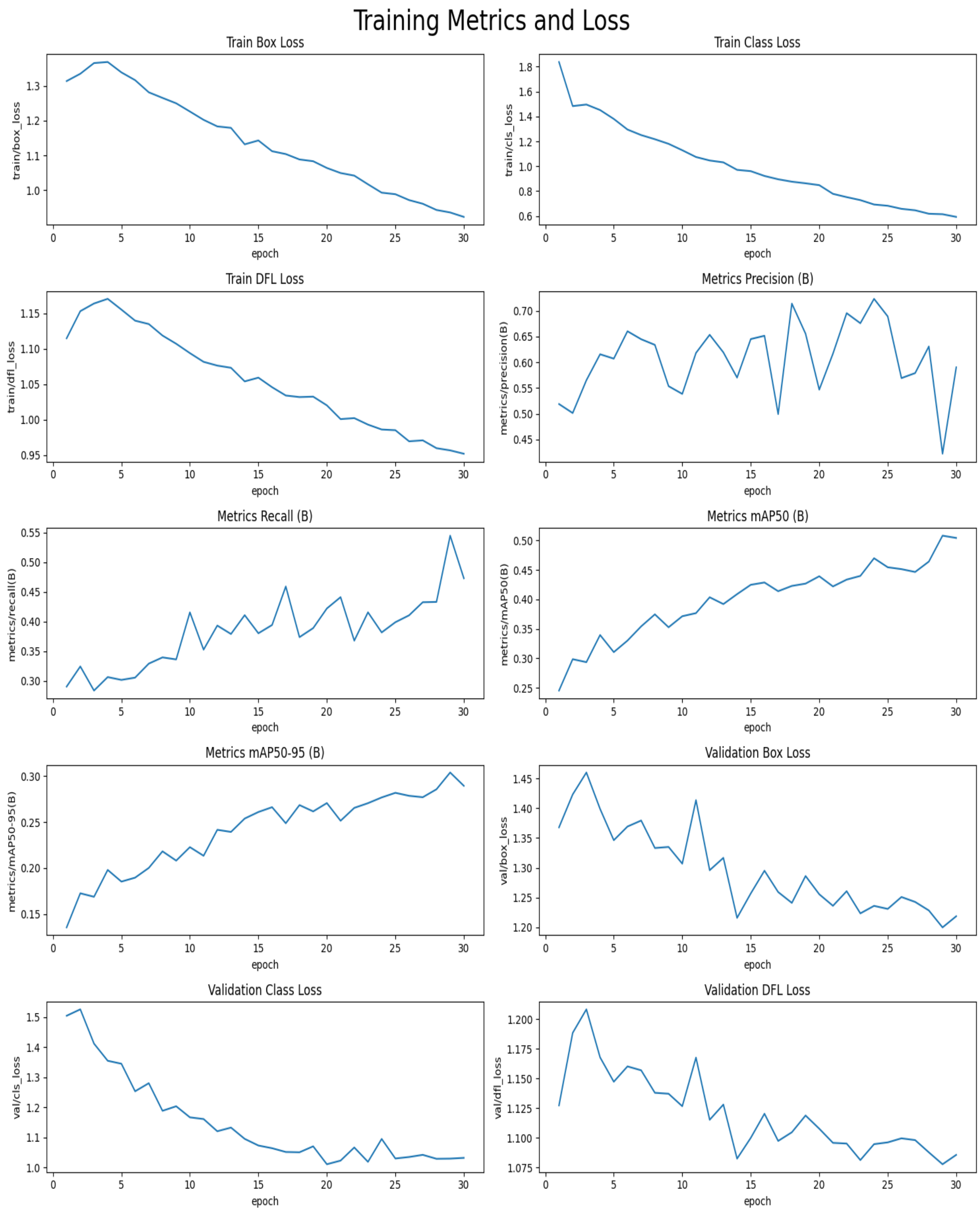

Figure 4. Model Training Performance Visualization

The confusion matrix for the multi-class vehicle detector maps actual classes (columns) against the model's guesses (rows), with each cell holding a frequency from 0 to 1. Dark diagonal cells signal correct hits, and here the model nails motorbikes every time (1.00) while cars, police cars and rickshaws post solid scores of roughly 0.70. Trouble spots emerge for ambulances, army vehicles and human haulers, which are frequently mis-labelled, and for a broad "background" class that the network often mistakes for real vehicles such as bicycles, buses and cars—evidence it sometimes hallucinates objects where none exist. Size-and-shape cousins—minibuses, minivans and vans—are also mixed up, an understandable error given their similar rooflines. In short, performance is strong on common, visually distinct categories but weaker on rare or look-alike classes; supplementing the dataset or re-balancing under-represented labels should help the model better recognise ambulances, garbage vans and other seldom-seen vehicles.

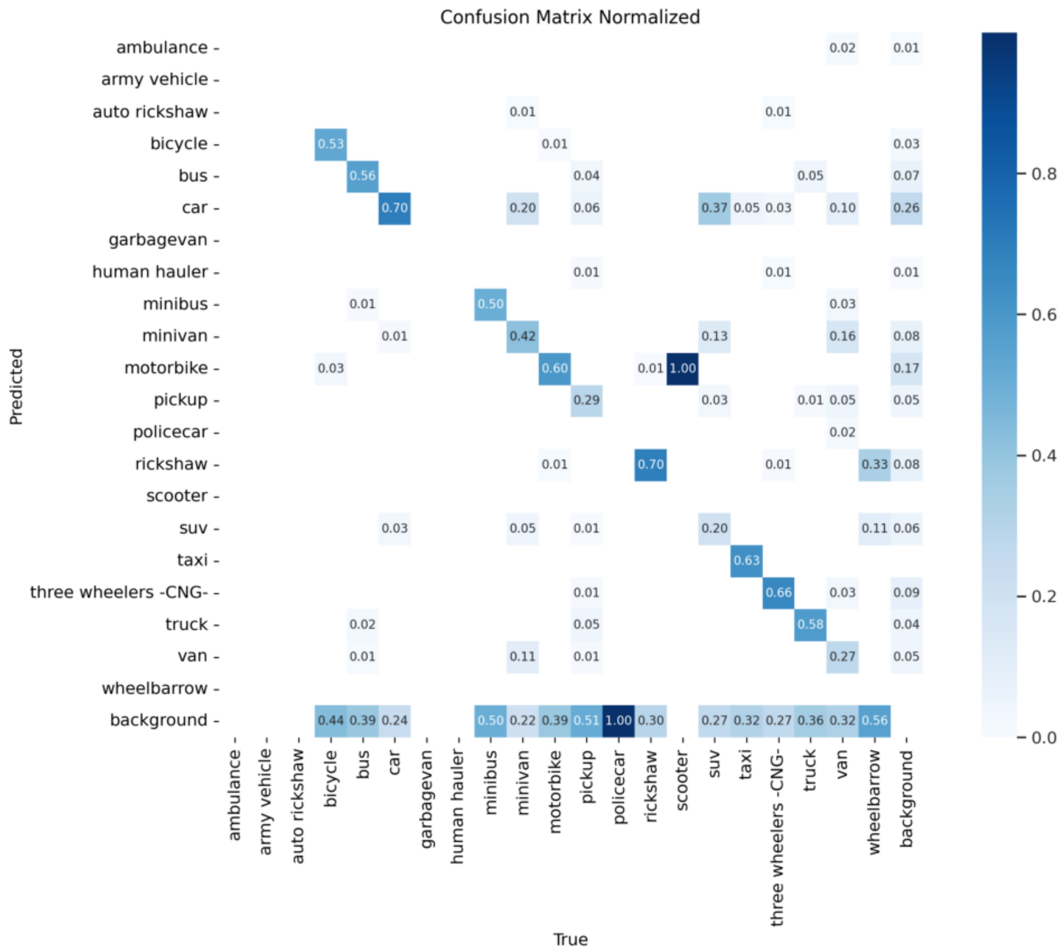

Figure 5. Confusion Matrix for Multi-Class Vehicle Detection

Conclusion:

In this work we built a simple but useful smart-traffic-light setup. We started with free traffic-camera pictures from Kaggle. Each image was already marked with the kinds of vehicles in it. We cleaned the data with a rolling average, put the numbers on the same 0-to-1 scale, and kept the first 75 % of the days for training while saving the last 25 % to test how well we did.YOLO counted the cars in real time. To choose which lane gets the green light, we mixed “shortest-job-first” (so the lane with fewer cars goes first) with a round-robin turn-taking rule so no lane is ignored.

Even with this light setup the results looked good. The training mistakes went down, precision and recall went up, and the mAP scores climbed. In plain terms, the model got better at spotting and counting common vehicles. The confusion matrix showed it does great on cars, bikes, and rickshaws but still mixes up rare ones like ambulances. That tells us we need more examples of those. In short, the result was a lean, low-cost smart traffic-light demo that already cuts waiting and can only improve with more varied images, a slightly smarter model, and on-street trials.

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