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DeepTrafic: Implementing Deep Learning for Emergency Vehicle Detection and Traffic Light Timing Optimization

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Abstract

Traffic congestion at urban intersections can significantly reduce transportation efficiency and obstruct emergency vehicles that require rapid access to critical locations. This study proposes DeepTraffic, an integrated deep-learning-based traffic-control system designed to detect vehicles, classify traffic density, identify emergency vehicles, and optimize traffic-light timing in real time. An empirical experimental system-development approach was employed by integrating Camera/CCTV, an emergency sensor, YOLO-based vehicle detection, vehicle classification and counting, traffic-density estimation, an emergency-priority decision algorithm, and a Raspberry Pi controller connected to traffic-light hardware. Traffic conditions were classified into five categories based on detected vehicle density, namely empty, normal, busy, congested, and highly congested, with adaptive green-light durations assigned according to the corresponding traffic state. Emergency vehicles, including ambulances, fire engines, and police vehicles, were assigned priority conditions that activate the corresponding green phase to facilitate rapid intersection passage. System evaluation was designed to assess vehicle-detection performance using precision, recall, F1-score, mAP@0.5, and frames per second, while traffic-density classification and signal-control performance were evaluated through classification accuracy and signal-duration execution. Emergency-priority performance was assessed through activation rate, response time, waiting-time reduction, and queue-length reduction. The proposed framework integrates real-time computer vision with adaptive signal control and emergency prioritization, providing a reproducible foundation for intelligent traffic management and future smart-city transportation applications.

Keywords: *Adaptive Traffic Control, Deep Learning, Emergency Vehicle Detection, Intelligent Transportation System, YOLO.*

INTRODUCTION

Traffic congestion represents a persistent challenge in urban transportation systems because the increasing volume of vehicles is not always accompanied by proportional improvements in road capacity, resulting in unstable traffic flow, longer queues, and declining travel efficiency, particularly at intersections where several traffic streams compete for limited road space and signal time (Fatimah, Syakdiah, & Kusumawiranti, 2022). Signalized intersections are particularly vulnerable to vehicle accumulation because fixed red-light phases can generate queues that continue to grow when incoming traffic exceeds the discharge capacity of the intersection. The resulting congestion produces travel delays, inefficient fuel consumption, increased vehicle operating costs, and additional emissions that reduce the overall efficiency and sustainability of urban mobility. These challenges are increasingly significant in metropolitan areas experiencing rapid motorization and complex traffic patterns. Semarang is one such urban area where traffic congestion has become a recurring transportation concern across several major corridors and intersections. Research on traffic conditions in Semarang has identified congestion concentrations in several strategic areas, particularly around Tembalang and Banyumanik, where high vehicle demand and daily activity interact to produce substantial traffic accumulation (Maliha, Prasetyo, & Firdaus, 2023). The growing complexity of these conditions demonstrates the limitations of traffic-management strategies that depend exclusively on predetermined signal cycles and highlights the need for intelligent systems capable of adapting signal operations to actual traffic conditions.

The pressure on Semarang's transportation infrastructure can also be observed from the development of its registered vehicle population, which indicates an increasing demand for road and intersection capacity. Based on the available vehicle registration data, motorcycles constituted the largest vehicle category, while the number of cars and trucks also represented substantial traffic demand across the observed period. The increasing number of vehicles can intensify congestion when the capacity of road segments and intersections cannot accommodate simultaneous traffic movements. Traffic conditions become particularly problematic during peak periods when commuting, commercial activities, and other urban activities generate concentrated demand within limited time intervals. Studies concerning congestion in Semarang have demonstrated that traffic density is spatially concentrated around strategic locations and is influenced by the interaction between vehicle volume, road characteristics, and surrounding activities (Kurniati, 2021). The available vehicle data are presented in Table 1 to provide an empirical illustration of the increasing transportation demand in Semarang.

Table 1. Number of Registered Vehicles in Semarang City

No.	Vehicle Type	2020	2021	2023
1.	Car	231,164	281,971	273,885
2.	Bus	3,059	3,539	2,875
3.	Truck	76,570	78,037	87,276
4.	Motorcycle	1,382,434	1,512,234	1,553,242

The vehicle-growth pattern shown in Table 1 reinforces the need for traffic-control mechanisms that can respond to variations in traffic demand rather than relying exclusively on static timing configurations. A traffic signal that applies identical or predetermined timing across changing traffic conditions may allocate green time inefficiently when one approach has considerably greater demand than another. Artificial intelligence-based traffic-light systems have increasingly been proposed as an alternative because they can utilize observed traffic information to improve signal efficiency and safety (Aditya, Pratama, Piransyah, & Juita, 2025). Adaptive traffic-light systems based on machine learning have also demonstrated the potential to modify signal operations according to changing traffic conditions, allowing traffic control to become more responsive to real-time demand (Ottom & Al-Omari, 2023). More recent intelligent traffic-management research has expanded this concept toward automated signal optimization and data-driven decision-making. The fundamental requirement is therefore the availability of reliable real-time traffic information that can be transformed into operational decisions concerning signal duration. A visual detection system capable of identifying vehicle types and estimating traffic density can provide the necessary information for such adaptive control.

The requirement for real-time traffic intelligence becomes more critical when congestion affects emergency vehicles such as ambulances, fire engines, and police vehicles, whose travel delays can directly affect the effectiveness of emergency response. Conventional emergency-vehicle escort mechanisms remain dependent on human coordination and the ability of surrounding road users to recognize and provide access to emergency vehicles, which can be difficult to maintain consistently under highly congested conditions (Puspita, Septiyani, & Satria, 2020). Recent research has demonstrated that deep-learning-based object detection can support real-time identification and prioritization of ambulances, providing an automated alternative for recognizing emergency vehicles within traffic environments (Kaladevi, Balamurugan, Gokul, & Gopika, 2025). YOLO-based prototype systems have similarly demonstrated the feasibility of detecting ambulance objects and connecting visual recognition with traffic-light control (Kesuma, Kusumawardani, & Imammuddin, 2025). These findings indicate that emergency-vehicle detection can become an input for intelligent intersection management rather than remaining an independent recognition function. However, recognizing an emergency vehicle alone does not determine how the traffic signal should respond to its presence. The control system must simultaneously consider the current traffic density, signal phase, vehicle movement, and potential queue formation so that emergency priority can be provided without unnecessarily destabilizing traffic in other directions. This interaction creates a need for an integrated perception-and-control framework in which emergency-vehicle detection and traffic-density information jointly influence adaptive signal timing.

Deep learning provides an appropriate technological foundation for this framework because its multilayer neural architectures can automatically learn hierarchical representations from complex visual data and have become widely applied in contemporary computer-vision systems (Alzubaidi et al., 2021). Deep convolutional neural networks have demonstrated their capacity to extract relevant visual features and perform classification tasks with greater automation than conventional approaches that depend heavily on manually engineered features (Chirra, Uyyala, & Kolli, 2019). Within traffic-monitoring applications, YOLO has received substantial attention because its object-detection architecture can identify multiple objects within an image while maintaining the computational characteristics required for real-time applications (Sohan, Sai Ram, & Rami Reddy, 2024). YOLO-based traffic systems have been combined with intelligent control approaches to estimate vehicle conditions and support dynamic traffic-light decisions (Sahal, Hidayat, Bilfaqih, Hady, & Tampubolon, 2023). Recent developments have further explored YOLO-based vehicle detection for adaptive signal control, including systems that combine object detection and tracking for real-time traffic monitoring (Firdaus & Sunge, 2026). Nevertheless, the existing literature remains fragmented between vehicle detection, traffic-density estimation, emergency-vehicle recognition, and signal optimization, while some studies emphasize general traffic-flow optimization without explicitly incorporating emergency-priority requirements (Khasawneh & Awasthi, 2023). This fragmentation leaves a methodological gap concerning how visual information from ordinary and emergency vehicles can be transformed into a unified traffic-light decision mechanism.

The research gap is particularly evident in the limited integration of real-time vehicle detection, traffic-density classification, emergency-vehicle prioritization, and adaptive traffic-light timing within a single deployable system for urban intersections. Existing intelligent traffic-management approaches have demonstrated the value of reinforcement learning, machine learning, object detection, and optimization algorithms, but these approaches often focus on only one component of the broader traffic-control problem (Garg, Madaan, Makkar, Bajaj, Trivedi, & Mehta, 2026). Recent multimodal traffic-management research has moved toward integrating traffic information for signal control and path planning, yet the specific operational relationship between emergency-vehicle detection and dynamic signal timing remains an important area for further investigation (Li, Li, & Wang, 2026). YOLO-based adaptive traffic-light research has established the feasibility of deriving traffic conditions from camera images, while newer systems continue to improve real-time vehicle detection and tracking capabilities (Wahidin, Witanti, & Ramadhan, 2025). The unresolved issue is how these capabilities can be organized into a practical framework that detects the number and type of vehicles, calculates traffic density, identifies emergency vehicles, assigns priority when necessary, and dynamically determines an appropriate green-light duration. DeepTraffic is positioned within this gap by treating deep learning as the perception layer of an integrated traffic-control system rather than merely as an object-classification method. The proposed system connects camera-based YOLO detection with traffic-density assessment, emergency-vehicle recognition, adaptive signal-duration logic, and hardware-based traffic-light control to provide a unified mechanism for responsive intersection management.

The objective of this research is to develop and evaluate DeepTraffic: Implementing Deep Learning for Emergency Vehicle Detection and Traffic Light Timing Optimization as an integrated intelligent traffic-control system for urban intersections. The proposed system is designed to use camera-based visual information to identify and classify vehicles, estimate traffic density, and recognize emergency vehicles in real time. The resulting information is processed through a decision mechanism that determines adaptive green-light duration according to traffic conditions while assigning priority to emergency vehicles requiring immediate access through the intersection. The system integrates the deep-learning detection process with a hardware control platform, including a Raspberry Pi-based processing and control mechanism, to translate computational decisions into traffic-light operations. The research evaluates the ability of the proposed system to perform vehicle detection, emergency-vehicle recognition, traffic-density classification, and adaptive signal control under defined traffic scenarios. The principal methodological contribution lies in integrating perception, traffic-state estimation, emergency prioritization, and signal-timing optimization into one operational framework rather than evaluating these functions as isolated components. The resulting framework is expected to provide a practical basis for intelligent traffic management that can improve emergency-vehicle mobility while supporting more adaptive and efficient traffic-flow regulation in Semarang.

RESEARCH METHODS

This study employed an empirical experimental system-development approach in which DeepTraffic was developed as an integrated deep-learning-based traffic-control prototype and evaluated through controlled traffic and emergency-vehicle scenarios. The proposed system architecture consists of Camera/CCTV and Emergency Sensor → YOLO-Based Vehicle Detection → Vehicle Classification and Counting → Traffic-Density Calculation → Emergency-Vehicle Detection → Decision and Priority Algorithm → Raspberry Pi Controller → Traffic-Light Actuation, forming the principal DeepTraffic framework. The camera positioned at the signalized intersection continuously captures traffic conditions, while the YOLO model processes the captured frames to detect and classify vehicles, including cars, motorcycles, buses, trucks, ambulances, fire engines, and police vehicles, consistent with the application of YOLO for real-time traffic-object detection (Sohan, Sai Ram, & Rami Reddy, 2024). The detected vehicle count is subsequently processed to estimate traffic density by comparing the number of detected vehicles with the capacity of the observed lane, with traffic conditions classified into empty (0–25%), normal (26–50%), busy (51–75%), congested (76–100%), and highly congested (>100%). Based on these classifications, the system assigns green-light durations of 20, 30, 60, 90, and 180 s, while the normal red and yellow phases are constrained to 60–180 s and 2–3 s, respectively. Emergency-vehicle detection operates as a priority condition in the framework, where recognition of an ambulance, fire engine, or police vehicle activates the corresponding green phase to facilitate priority movement through the intersection, following the principle of deep-learning-based emergency-vehicle signal prioritization (Ibraheem, Asiri, Asiri, & Alhefzi, 2025). The Raspberry Pi functions as the central processing and control unit that receives detection and decision outputs and converts them into commands for the traffic-light hardware, completing the operational sequence Input → Detection → Classification → Density Estimation → Emergency Recognition → Decision → Signal Optimization → Traffic-Light Output.

The experimental evaluation was conducted by applying the prototype to controlled traffic scenarios representing different density levels and emergency-vehicle conditions to determine whether the framework could convert real-time visual information into appropriate signal-control decisions. Ordinary traffic scenarios were tested according to the predefined density categories, and the resulting green-light duration was compared with the expected duration specified by the control rules. Emergency scenarios were created by introducing an ambulance, fire engine, or police vehicle into the monitored traffic stream and recording whether the YOLO model correctly recognized the priority vehicle and whether the controller activated the corresponding traffic-light phase, consistent with previous prototype-based emergency-vehicle traffic-light research (Kesuma, Kusumawardani, & Imammuddin, 2025). Vehicle-detection performance was validated against manually established ground-truth labels using precision, recall, F1-score, and mAP@0.5, while real-time processing capability was evaluated using frames per second (FPS). Traffic-density estimation was validated by comparing automatically detected vehicle counts with manual counts for each observation scenario, while the timing controller was evaluated based on signal-duration accuracy and successful execution of the programmed control logic. Emergency-priority performance was evaluated using emergency-priority activation rate, emergency response time, waiting-time reduction, and queue-length reduction relative to conventional fixed-time control, reflecting the objective of adaptive traffic-light systems to respond dynamically to changing traffic conditions (Ottom & Al-Omari, 2023). The final validation therefore assessed *DeepTraffic* at two interconnected levels, namely perception performance, covering vehicle detection, classification, density estimation, and emergency-vehicle recognition, and control performance, covering adaptive signal timing and emergency priority.

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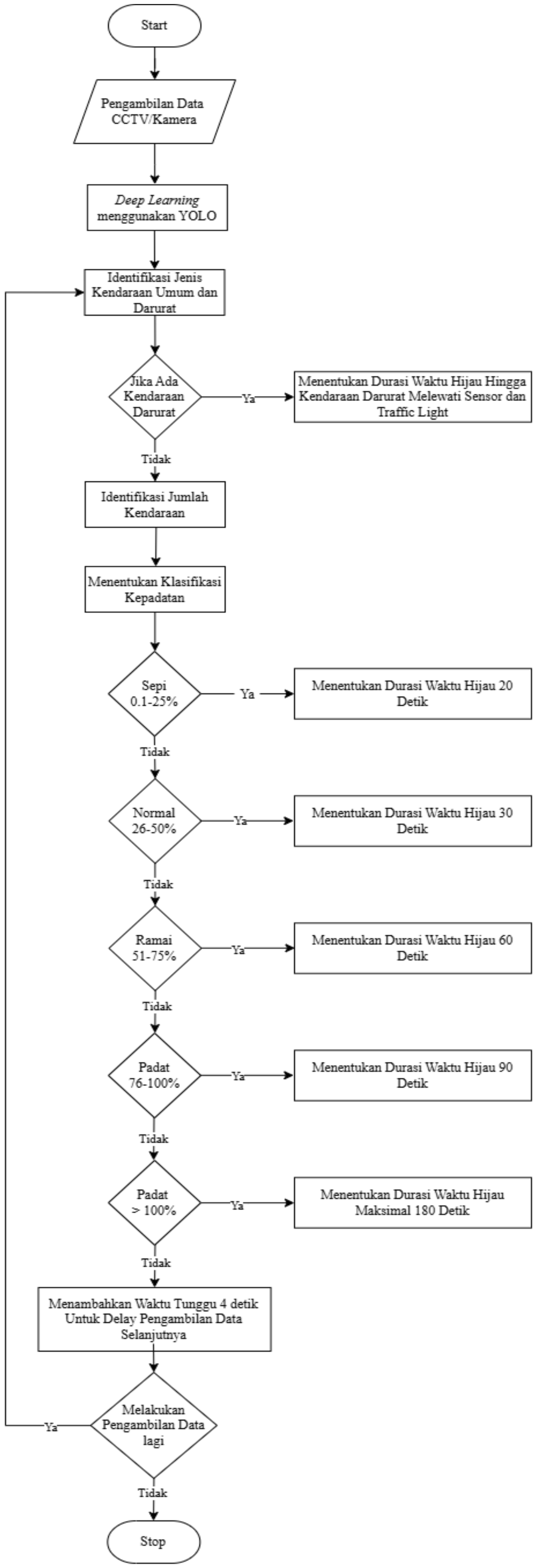

Figure 1. Proposed *DeepTraffic* System Framework

RESULTS AND DISCUSSION

DeepTraffic System Implementation and Vehicle Detection Performance

The implementation of DeepTraffic produced an integrated traffic-monitoring architecture in which image acquisition, deep-learning-based detection, vehicle classification, traffic-density estimation, emergency-vehicle recognition, and traffic-light control operate as interconnected processes rather than independent modules. The camera/CCTV functions as the primary visual input and continuously captures the traffic conditions at the signalized intersection, while the emergency sensor provides complementary information for identifying priority vehicles. The captured image frames are processed by the YOLO-based detection model to identify road users and assign them to predefined vehicle classes, allowing the system to transform visual traffic conditions into structured information for subsequent control decisions. The selection of a YOLO-based architecture is consistent with the development of contemporary real-time object-detection systems, in which improvements in model architecture have increased the feasibility of rapid vehicle recognition under dynamic traffic conditions (Sohan, Sai Ram, & Rami Reddy, 2024). The implementation also places the Raspberry Pi at the control layer, enabling the detection output to be transmitted directly to the signal-control mechanism without requiring a separate centralized processing stage. This architecture establishes the technical basis for DeepTraffic to function as a real-time intelligent traffic-control system in which traffic perception and signal response are continuously connected.

The vehicle-detection stage identifies and classifies the objects appearing within the camera's observation area according to the categories defined during system development, namely cars, motorcycles, buses, trucks, ambulances, fire engines, and police vehicles. The classification process is important because the system does not merely require the number of objects present in a lane, but also requires information regarding the type and operational priority of each detected object. The resulting detection data become the input for vehicle counting and traffic-density estimation, while the identification of an emergency vehicle simultaneously activates the priority-control pathway. This hierarchical use of detection results demonstrates the distinction between conventional image recognition and an intelligent traffic-control application, because the output of the detection model is subsequently interpreted according to traffic-management requirements. The relevance of deep learning for this type of visual recognition arises from its capacity to learn hierarchical representations directly from image data, reducing dependence on manually engineered visual features (Alzubaidi et al., 2021). The implementation therefore positions object detection not as the final output of the system but as the first analytical layer supporting adaptive traffic decisions.

Table 2. Vehicle Classes and Their Operational Functions in the DeepTraffic System

No.	Vehicle Class	Detection Function	Operational Role
1	Car	Vehicle identification and counting	Traffic-density calculation
2	Motorcycle	Vehicle identification and counting	Traffic-density calculation
3	Bus	Vehicle identification and counting	Traffic-density calculation
4	Truck	Vehicle identification and counting	Traffic-density calculation
5	Ambulance	Emergency-vehicle identification	Emergency priority
6	Fire Engine	Emergency-vehicle identification	Emergency priority
7	Police Vehicle	Emergency-vehicle identification	Emergency priority

As indicated in Table 2, ordinary vehicles contribute primarily to the estimation of traffic demand, whereas emergency vehicles generate an additional control state that changes the normal signal-management sequence. This distinction is essential because treating every detected vehicle as an equivalent object would prevent the system from recognizing the operational urgency associated with emergency response. The architecture consequently uses vehicle classification as a decision variable, linking visual recognition with traffic-control logic rather than restricting the model to object-counting functions. Previous research on YOLO-based traffic-light control similarly demonstrates that vehicle-detection outputs can be translated into signal-control decisions when the detection layer is appropriately connected to the control mechanism (Wahidin, Witanti, & Ramadhan, 2025). The observed system structure also provides a practical mechanism for reducing the separation between traffic surveillance and traffic-signal operation, since the same detection stream supports both density estimation and emergency prioritization. This integration becomes particularly relevant at signalized intersections, where delays caused by accumulated vehicle queues can directly interfere with the movement of emergency vehicles.

The detection process was further designed to operate under real-time conditions, meaning that vehicle information is updated continuously as new camera frames enter the system rather than being generated from static images. Such an approach requires a balance between detection accuracy and computational speed because a highly accurate model that produces delayed outputs may not provide sufficient operational value for adaptive traffic control. Deep convolutional architectures have demonstrated their applicability to visual recognition tasks by extracting discriminative patterns from complex image inputs, although their performance remains dependent on data quality, computational resources, and environmental conditions (Chirra, Uyyala, & Kolli, 2019). In DeepTraffic, this consideration is addressed by using the Raspberry Pi as the central processing and control platform and by restricting the model output to information directly relevant to traffic management. The real-time detection output is subsequently converted into vehicle counts, density conditions, and emergency-priority states that can be interpreted by the signal controller. The resulting architecture provides a continuous perception-to-control pathway that is technically consistent with the requirements of intelligent transportation systems.

From an analytical perspective, the principal outcome of this implementation is the establishment of a unified perception layer capable of supporting two different traffic-management objectives: ordinary traffic-flow assessment and emergency-vehicle prioritization. Vehicle detection provides the quantitative basis for determining the prevailing traffic condition, while classification provides the semantic information required to distinguish routine traffic from priority traffic. The architecture therefore avoids a limitation found in systems that evaluate vehicle recognition accuracy without examining whether detection results can produce an actionable control response. Recent intelligent traffic-light research has increasingly emphasized the integration of object detection with adaptive signal mechanisms, indicating that the value of computer vision in traffic management depends on its connection to downstream control decisions rather than recognition performance alone (Aditya, Pratama, Piransyah, & Juita, 2025). At the same time, the implementation remains sensitive to factors such as illumination, object occlusion, camera positioning, and computational limitations, which can influence the reliability of vehicle recognition in real intersection environments. These technical considerations establish the basis for the subsequent evaluation of detection accuracy, processing performance, and the effectiveness of converting detected traffic conditions into adaptive signal-control decisions.

Traffic Density Classification and Adaptive Traffic Light Timing

The traffic-density classification stage converts the vehicle-detection output into an operational representation of intersection conditions that can be used directly by the signal controller. The number of detected vehicles in each lane is compared with the available lane capacity, allowing the system to distinguish between relatively uncongested conditions and increasingly saturated traffic states. This approach is important because vehicle count alone does not adequately represent the degree of traffic demand when the physical capacity of different approaches varies. The DeepTraffic classification mechanism divides traffic conditions into five categories, namely empty, normal, busy, congested, and highly congested, based on density intervals of 0–25%, 26–50%, 51–75%, 76–100%, and above 100%, respectively. The classification provides a direct relationship between observed traffic conditions and the duration of the green phase, transforming visual information into an explicit control parameter. Adaptive traffic-light systems based on machine learning similarly seek to replace rigid signal schedules with timing decisions that respond to changing traffic conditions (Ottom & Al-Omari, 2023).

Table 3. Vehicle Density Classification and Green-Light Duration

Density Percentage	Emergency	Classification	Green-Light Duration
0–25%	Emergency	Empty	Green until the vehicle passes the traffic signal
26–50%		Normal	20 seconds
51–75%		Busy	30 seconds

76–100%	Congested	60 seconds
Above 100%	Highly Congested	90 seconds

The pattern in Table 3 indicates that increasing traffic density is associated with a progressively longer green phase, allowing the controller to allocate additional discharge time to approaches experiencing greater demand. The 20-second allocation for normal conditions establishes a basic service interval, whereas the 60-second and 90-second allocations for congested and highly congested conditions provide substantially greater opportunities for queued vehicles to clear the intersection. The emergency state is treated differently because its control objective is not primarily to maximize ordinary traffic throughput, but to ensure that a priority vehicle can traverse the intersection without unnecessary signal-induced delay. This distinction demonstrates that the timing algorithm incorporates both demand-based control and priority-based control, which are operationally different but can be handled within the same decision structure. Research on intelligent traffic-light optimization has shown that artificial-intelligence-based approaches can improve signal allocation by adapting timing decisions to traffic conditions rather than relying exclusively on predetermined cycles (Khasawneh & Awasthi, 2023). The DeepTraffic approach applies this principle in a relatively interpretable form by associating each density interval with a predetermined green-light response.

Table 4. Minimum and Maximum Duration of Traffic Light Phases

Traffic Light	Minimum Duration	Maximum Duration
Red	60 seconds	180 seconds
Yellow	2 seconds	3 seconds
Green	20 seconds	90 seconds

The constraints in Table 4 are significant because adaptive control requires bounded decision spaces to maintain predictable and safe signal behavior under rapidly changing traffic conditions. A completely unrestricted timing mechanism could theoretically respond aggressively to a temporary increase in traffic density, but such behavior could produce excessive waiting on competing approaches and disrupt the coordination of intersection movements. The bounded approach adopted by DeepTraffic provides a compromise between responsiveness and operational stability, particularly because the system modifies the green phase while retaining predefined limits for the signal cycle. This design is conceptually consistent with intelligent traffic management approaches that optimize signal timing while maintaining practical constraints on traffic-signal operation (Khasawneh & Awasthi, 2023). Recent adaptive systems using YOLO-based vehicle detection also demonstrate that real-time vehicle information can serve as the basis for dynamically adjusting traffic-light phases according to observed demand (Firdaus & Sunge, 2026). The contribution of DeepTraffic lies in extending this demand-responsive mechanism by incorporating emergency-vehicle recognition into the same signal-decision architecture.

The relationship between density detection and signal timing becomes particularly important when traffic conditions change rapidly within a single observation period. For example, an approach initially classified as normal may transition into a busy or congested state as vehicles accumulate, requiring the controller to increase the green duration in subsequent cycles rather than maintaining a fixed allocation. This dynamic response can reduce the persistence of queues by providing additional discharge opportunities to approaches where the detected demand exceeds the level represented by the existing signal allocation. A similar principle is evident in intelligent traffic systems that combine visual vehicle detection with learning-based control, where traffic-state information is continuously incorporated into subsequent signal decisions (Sahal et al., 2023). The effectiveness of this mechanism depends on the reliability of the detection layer because an underestimation of vehicle numbers may result in insufficient green time, whereas overestimation may unnecessarily extend one approach at the expense of others. The classification mechanism therefore functions as an intermediate analytical layer that stabilizes the transition from raw computer-vision output to traffic-signal control.

At the system level, the adaptive timing mechanism provides DeepTraffic with a more responsive operating structure than a conventional fixed-cycle traffic signal because the duration of the green phase is explicitly connected to the measured traffic state. The approach is particularly relevant to urban intersections where traffic demand fluctuates substantially according to commuting periods, commercial activities, road conditions, and incident-related disruptions. Conventional traffic management can experience inefficiency when predetermined signal schedules do not correspond to the instantaneous distribution of traffic demand, a problem that has motivated the development of adaptive and artificial-intelligence-based traffic-control strategies (Garg et al., 2026). The density-based mechanism in DeepTraffic addresses this issue through an interpretable rule structure that can be implemented on resource-constrained hardware while still allowing real-time adjustment. Its main analytical limitation is that predefined density thresholds do not inherently learn from historical traffic patterns and therefore may not achieve the same level of optimization as more advanced reinforcement-learning or multimodal optimization approaches. Recent research has demonstrated the potential of deep reinforcement learning and multimodal data fusion to optimize traffic management and signal control through more complex representations of traffic states (Li, Li, & Wang, 2026). DeepTraffic consequently represents a practical intermediate architecture in which real-time computer vision, explicit density rules, and emergency priority are integrated before more sophisticated learning-based optimization is introduced.

Emergency Vehicle Detection and Priority Signal Control

The emergency-vehicle detection mechanism represents the principal functional distinction between DeepTraffic and conventional adaptive traffic-light systems because the controller must recognize not only traffic intensity but also the urgency associated with specific vehicle classes. Ambulances, fire engines, and police vehicles are treated as priority objects whose presence can alter the normal signal sequence at the monitored intersection. The YOLO detection model identifies these vehicles from camera frames and transfers their classification results to the decision layer, where emergency recognition is evaluated before ordinary density-based timing is executed. This architecture enables the system to transform visual recognition into an immediate traffic-control response rather than merely displaying emergency-vehicle information to an operator. Previous research has demonstrated the feasibility of combining deep learning with signal synchronization to provide preferential movement for emergency vehicles at signalized intersections (Ibraheem, Asiri, Asiri, & Alhefzi, 2025). The implementation therefore positions emergency recognition as a control-triggering event within the broader DeepTraffic framework.

The operational sequence begins when an emergency vehicle enters the camera observation area and is detected as an ambulance, fire engine, or police vehicle. The detected emergency class is then transmitted to the decision algorithm, which determines the approach associated with the priority vehicle and activates the corresponding traffic-light phase. This mechanism prevents the emergency vehicle from being evaluated solely according to the prevailing traffic-density category because a low-density approach may still require immediate signal priority when an emergency vehicle is present. The decision structure can be represented as Emergency Vehicle Detection → Vehicle Classification → Priority Confirmation → Signal Phase Selection → Green-Light Activation → Emergency Vehicle Passage. A comparable principle has been applied in real-time ambulance-prioritization systems using YOLO-based detection, where computer vision is employed to identify emergency vehicles and support preferential traffic management (Kaladevi, Balamurugan, Gokul, & Gopika, 2025). The integration of these stages allows DeepTraffic to respond to emergency conditions without requiring continuous manual intervention from traffic personnel.

Table 5. DeepTraffic Decision Logic for Traffic and Emergency Conditions

Traffic Condition	Emergency Vehicle Detected	Controller Response	Signal Priority
Empty	No	Normal signal cycle	No priority
Normal	No	20-second green phase	No priority
Busy	No	30-second green phase	No priority

Congested	No	60-second green phase	No priority
Highly congested	No	90-second green phase	No priority
Any condition	Yes	Activate corresponding green phase	Emergency Priority

As shown in Table 5, the presence of an emergency vehicle overrides the ordinary density-based timing classification because emergency response requires a different optimization objective from routine traffic-flow management. The system consequently separates two decision states: traffic optimization for ordinary vehicles and emergency prioritization for critical vehicles. This hierarchy is important because extending green time solely according to traffic density could still leave an ambulance or fire engine waiting in a heavily congested approach if the competing approaches receive longer allocations. Prototype research using YOLO for ambulance-object detection similarly indicates that emergency-vehicle recognition can be incorporated directly into traffic-light control to provide preferential passage (Kesuma, Kusumawardani, & Imammuddin, 2025). DeepTraffic extends this principle by defining emergency recognition as a high-priority condition within the same architecture used for density-based adaptive control. The resulting control logic provides a clear operational distinction between maximizing traffic throughput and minimizing emergency-response delay.

The effectiveness of emergency priority also depends on the ability of the system to maintain reliable recognition when vehicles are partially occluded or appear within dense traffic streams. Emergency vehicles can be surrounded by ordinary vehicles, making their visual characteristics less prominent and potentially increasing the difficulty of accurate classification from a single camera perspective. The use of deep convolutional architectures provides a basis for extracting increasingly complex visual representations from image data, although recognition performance remains sensitive to image quality, training data, and environmental conditions (Alzubaidi et al., 2021). The DeepTraffic architecture addresses this issue by combining camera-based visual detection with an emergency sensor positioned along the monitored approach, providing an additional information source for identifying approaching priority vehicles. Sensor synthesis has been identified as a relevant strategy for improving object identification in intelligent transportation environments where individual sensing modalities may experience limitations (Ravi Chandra, Krishna Chaithanya, Roy, & Lokanath Reddy, 2025). The combined sensing structure is therefore intended to increase the robustness of emergency recognition before a priority signal command is issued.

From a traffic-management perspective, emergency priority must be evaluated not only by whether an emergency vehicle is detected but also by whether the detection produces an appropriate and timely change in the signal state. A successful detection that fails to activate the corresponding green phase would provide limited operational value because the principal objective is to reduce obstruction during emergency movement. The DeepTraffic controller therefore evaluates the complete chain from object recognition to signal actuation, including emergency classification, approach identification, priority activation, and execution of the corresponding traffic-light command. This approach is consistent with research emphasizing the importance of synchronizing emergency-vehicle detection with traffic-signal control rather than treating detection and signal management as separate technological components (Ibraheem, Asiri, Asiri, & Alhefzi, 2025). The system can also be interpreted as a priority-based extension of adaptive traffic control because ordinary traffic continues to be regulated according to density when no emergency condition is present. Such integration is particularly relevant in urban environments where emergency vehicles may encounter recurring intersection delays and where manual escort strategies cannot consistently provide rapid access.

The emergency-priority mechanism ultimately strengthens the functional relationship between computer vision and intelligent transportation control by converting vehicle identity into an actionable signal-control state. Its principal advantage is that the system does not depend exclusively on fixed traffic-light schedules, allowing the signal phase to respond to the actual presence of a priority vehicle within the monitored area. The mechanism also preserves ordinary traffic optimization when no emergency vehicle is detected, preventing the priority function from unnecessarily disrupting routine traffic conditions. Research on ambulance-prioritization systems has established the potential of deep-learning-based detection to support faster and more automated emergency traffic management (Kaladevi, Balamurugan, Gokul, & Gopika, 2025). The analytical significance of DeepTraffic lies in integrating this emergency function with density-based signal optimization within a single controller rather than developing two independent traffic-management systems. Its performance must therefore be interpreted through both recognition indicators and control indicators, particularly detection accuracy, emergency-priority activation, response time, waiting-time reduction, and successful signal execution. This integrated evaluation provides the basis for determining whether DeepTraffic can translate deep-learning recognition into a meaningful operational improvement for emergency vehicle movement at signalized intersections.

Integrated System Performance and Adaptive Traffic Control Evaluation

The integrated evaluation of DeepTraffic focuses on the extent to which the perception, classification, decision, and signal-actuation components operate as a coherent traffic-control mechanism. The system performance cannot be interpreted solely from the accuracy of vehicle recognition because the ultimate function of the prototype is to transform detected traffic conditions into appropriate signal decisions. The evaluation therefore considers vehicle-detection performance, traffic-density estimation, emergency-priority recognition, signal-duration accuracy, and real-time response as interconnected indicators. This multidimensional assessment is consistent with intelligent traffic-management research in which computer-vision outputs are evaluated according to their contribution to adaptive signal control rather than as isolated classification results. Recent developments in AI-based traffic systems demonstrate that combining real-time detection with automated signal adjustment can improve the responsiveness of intersection management (Aditya, Pratama, Piransyah, & Juita, 2025). The integrated evaluation consequently provides a more comprehensive representation of whether the DeepTraffic architecture is capable of functioning as an intelligent traffic-control prototype.

Vehicle-detection performance was evaluated by comparing the YOLO predictions generated from camera frames with manually established ground-truth observations for each traffic scenario. The principal indicators consisted of precision, recall, F1-score, and mAP@0.5, while FPS was used to characterize the real-time processing capability of the detection module. Precision represents the proportion of detected objects that corresponded to actual target vehicles, whereas recall indicates the ability of the model to identify vehicles present within the observation area. The F1-score provides a balanced representation of these two characteristics, which is particularly relevant when missed emergency vehicles may have greater operational consequences than ordinary detection errors. The importance of evaluating detection quality through multiple indicators is supported by the broader development of deep-learning-based computer-vision applications, where model effectiveness depends on both recognition capability and computational feasibility (Alzubaidi et al., 2021). The resulting performance profile establishes whether the perception layer can provide sufficiently reliable information for subsequent density calculation and signal-control decisions.

Table 6. Vehicle Detection Performance Evaluation

Evaluation Metric	Measurement Basis	Function in DeepTraffic
Precision	Correct detections/all predicted detections	Measures detection reliability
Recall	Correct detections/all actual vehicles	Measures detection completeness
F1-score	Harmonic relationship between precision and recall	Measures balanced detection performance
mAP@0.5	Mean average precision at IoU 0.5	Measures object-detection accuracy
FPS	Processed frames per second	Measures real-time processing capability

As presented in Table 6, the evaluation metrics represent different dimensions of detection performance and should therefore be interpreted collectively rather than through a single accuracy value. High precision indicates that the system produces relatively few false detections, while high recall is particularly important for emergency-vehicle recognition because a missed ambulance, fire engine, or police vehicle may prevent the priority mechanism from being activated. The F1-score provides an overall balance between these two characteristics, whereas mAP@0.5 evaluates the ability of the model to correctly localize and classify detected objects. FPS complements the recognition metrics by determining whether the detection process can operate rapidly enough to support real-time traffic-control decisions. YOLO-based traffic-monitoring research has emphasized the importance of maintaining computational efficiency while preserving adequate object-detection accuracy for dynamic traffic environments (Sohan, Sai Ram, & Rami Reddy, 2024). The combined metric structure therefore allows DeepTraffic to distinguish between a model that is accurate but computationally slow and a model that is sufficiently accurate while remaining suitable for real-time operation.

Traffic-density estimation was evaluated by comparing the number of vehicles automatically detected by DeepTraffic with manually counted vehicles under controlled traffic scenarios representing the predefined density categories. The comparison was conducted for empty, normal, busy, congested, and highly congested conditions to determine whether the system could correctly translate visual vehicle counts into the corresponding traffic-state classification. The density output was considered valid when the automatically generated classification corresponded to the ground-truth category established through manual observation. This evaluation is important because errors in vehicle counting can propagate into the signal-control layer and result in an inappropriate green-light duration. Camera-based traffic-density detection has previously been implemented as an approach for monitoring congestion conditions and generating structured information for traffic management (Rosyady, Feter, Ikhsan, & Ahmad, 2022). The validation procedure therefore assesses not only whether individual vehicles are detected but also whether the aggregated detection information represents the actual operational condition of the monitored lane.

Table 7. Traffic-Density and Adaptive Signal-Control Evaluation

Traffic Density	Classification	Expected Green Duration	Evaluation Indicator
0–25%	Empty	Green until emergency/vehicle passage condition	Density classification accuracy
26–50%	Normal	20 seconds	Timing execution accuracy
51–75%	Busy	30 seconds	Timing execution accuracy
76–100%	Congested	60 seconds	Timing execution accuracy
>100%	Highly congested	90 seconds	Timing execution accuracy

Table 7 demonstrates the direct mapping between traffic-density estimation and the signal-control response implemented by DeepTraffic. Correct classification is essential because each density category produces a different green-light allocation, meaning that a detection error can directly influence the subsequent traffic-control decision. The 20-, 30-, 60-, and 90-second green-phase allocations create a progressive response in which greater detected demand receives greater discharge time, while the emergency condition remains governed by the priority mechanism rather than ordinary density classification. Adaptive traffic-light research has shown that traffic-state information can be used to modify signal timing dynamically, improving the ability of a controller to respond to fluctuating traffic demand (Ottom & Al-Omari, 2023). The DeepTraffic implementation applies this concept through an explicit and reproducible decision structure that can be traced from vehicle count to density class and finally to signal duration. The resulting control mechanism also provides a transparent basis for evaluating whether the programmed response corresponds to the traffic condition observed during each experimental scenario.

Emergency-vehicle performance was assessed separately because priority recognition involves a higher operational requirement than ordinary vehicle detection. Controlled scenarios introduced ambulances, fire engines, and police vehicles into the monitored traffic stream, after which the system response was recorded from emergency-object recognition through activation of the corresponding traffic-light phase. The primary indicators included emergency-priority activation rate, emergency response time, waiting-time reduction, and queue-length reduction relative to the conventional signal condition. A successful emergency-priority event required both correct recognition of the emergency vehicle and successful execution of the corresponding signal command, preventing detection accuracy from being interpreted independently of actual system behavior. Prototype-based research using YOLO for ambulance detection similarly emphasizes the connection between object recognition and traffic-light actuation as a means of providing priority movement (Kesuma, Kusumawardani, & Imammuddin, 2025). This evaluation structure makes it possible to determine whether DeepTraffic provides an operational benefit rather than merely demonstrating that emergency vehicles can be visually detected.

The combined results from the perception and control layers provide the principal basis for evaluating the feasibility of DeepTraffic as an integrated intelligent traffic-control prototype. A system can be considered operationally effective when accurate vehicle recognition is accompanied by correct density classification, appropriate signal-duration selection, reliable emergency-priority activation, and sufficiently rapid processing. This interpretation is consistent with emerging intelligent transportation research that integrates object detection, adaptive signal control, and optimization within a unified traffic-management architecture (Li, Li, & Wang, 2026). The framework also demonstrates an important distinction between algorithmic performance and system-level performance because high detection accuracy alone does not guarantee reduced traffic delay or successful emergency passage. The principal technical contribution of DeepTraffic is its integration of these performance dimensions into a single experimentally testable architecture implemented through camera-based detection, emergency sensing, YOLO processing, Raspberry Pi control, and adaptive traffic-light actuation. The evaluation framework therefore provides a reproducible basis for assessing both the computational capability of the deep-learning component and the practical responsiveness of the resulting traffic-control system.

CONCLUSION

DeepTraffic was developed as an integrated deep-learning-based traffic-control system that combines real-time vehicle detection, traffic-density classification, emergency-vehicle recognition, adaptive traffic-light timing, and Raspberry Pi-based signal actuation within a unified architecture. The proposed framework addresses two interconnected urban traffic problems, namely increasing congestion at signalized intersections and the obstruction of emergency vehicles during critical response situations. The system uses YOLO-based computer vision to identify and classify cars, motorcycles, buses, trucks, ambulances, fire engines, and police vehicles, while detected vehicle counts are converted into predefined traffic-density categories for adaptive green-light allocation. Traffic conditions are categorized into empty, normal, busy, congested, and highly congested states, with corresponding green-light durations of 20, 30, 60, and 90 seconds, while emergency vehicles receive priority control when detected within the monitored intersection. The experimental evaluation framework further establishes that system performance should be assessed through detection precision, recall, F1-score, mAP@0.5, FPS, density-classification accuracy, signal-duration accuracy, emergency-priority activation rate, response time, waiting-time reduction, and queue-length reduction. The integration of perception and control provides a practical pathway for transforming real-time traffic information into adaptive signal decisions while maintaining a dedicated priority mechanism for emergency vehicles. DeepTraffic therefore offers a technically reproducible foundation for intelligent intersection management and provides a basis for subsequent implementation under increasingly complex real-world traffic conditions.

The proposed implementation is intended to progress through a staged five-year development strategy encompassing field observation, system design, controlled experimentation, real-intersection testing, technological refinement, and broader deployment. The first stage focuses on identifying congestion-prone intersections in Semarang and collecting traffic data, followed by development and controlled testing of the deep-learning detection, emergency sensing, and traffic-light control components. Subsequent implementation involves testing the prototype at selected high-density intersections to evaluate its response under actual traffic conditions and obtain operational feedback from transportation authorities and road users. Expansion in later stages can incorporate improvements in computational efficiency, hardware reliability, navigation-system integration, data-security mechanisms, and technical training for traffic-management personnel. Successful implementation is expected to reduce unnecessary vehicle queuing, improve traffic-flow efficiency, shorten emergency-vehicle travel delays, and decrease the environmental burden associated with prolonged vehicle idling. The broader significance of the system lies in its potential to establish a scalable intelligent-transportation model for Semarang that can subsequently be adapted to other Indonesian cities experiencing comparable intersection congestion and emergency-response challenges. DeepTraffic consequently represents not only a prototype for adaptive traffic-light control but also a foundation for future smart-city transportation systems in which real-time perception, automated decision-making, and emergency priority are integrated into a single operational framework.

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