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Intelligent Traffic Signal System Using YOLO, CNN, and LSTM for Adaptive Traffic Control

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KEYWORDS

Intelligent Traffic System, YOLO, CNN, LSTM, Traffic Automation, Smart City.

ABSTRACT

Urban intersections in India continue to rely on conventional fixed-timer traffic signals that operate without regard to the real-time density of vehicles on different lanes. These outdated systems contribute significantly to congestion, excessive fuel consumption, and inefficiencies in vehicle movement. To overcome these limitations, this research introduces an Intelligent Traffic Signal System (ITSS) that employs deep learning–based computer vision for automated and adaptive signal control. The framework integrates YOLO for high-speed vehicle detection, CNN-based vehicle classification, and LSTM-driven temporal traffic prediction to optimize signal duration based on density and flow patterns. Additional modules—including automatic challan generation, stolen vehicle identification using CNN, emergency vehicle prioritization, and lane obstruction detection—enhance traffic governance and enforcement capabilities. A diverse dataset compiled from Kaggle repositories, real-world city traffic recordings, and YouTube sources ensures.

1. Introduction

Traffic congestion remains a persistent challenge in rapidly urbanizing regions of India, where intersections are predominantly controlled by static, fixed-timer traffic lights. These systems allocate equal or predefined durations to each lane irrespective of the actual number of vehicles waiting, resulting in scenarios where lanes with minimal traffic receive extended green time while heavily congested lanes face unnecessary delays. Emergency vehicles such as ambulances and fire trucks often remain trapped in queues, further aggravating critical delays [1]. Accidents or sudden lane blockages create additional imbalance, yet fixed-timer systems lack the dynamic sensing capabilities needed to adapt in real time [15]. As a consequence, commuters experience increased waiting times, higher fuel consumption, and elevated pollution levels, ultimately diminishing overall mobility and public satisfaction .

Advancements in deep learning and computer vision have enabled the development of intelligent systems capable of real-time scene understanding [4]. Leveraging video analytics, modern traffic control frameworks can detect vehicle density, categorize vehicle types [1], analyze flow patterns, and predict emerging congestion trends [5]. Motivated by these technological developments, this research presents a deep learning–powered adaptive traffic management system that integrates YOLO, CNN, and LSTM to automate signal transitions and introduce real-time traffic governance suited for smart-city environments [7].

2. Literature Review

Early traffic systems predominantly relied on fixed-timer mechanisms that operate based on predetermined intervals [12]. Although simple to implement, studies indicate that such systems fail during peak hours and significantly contribute to long waiting times and unnecessary emissions. Efforts to enhance these systems through

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timer optimization still fall short due to their inability to conduct real-time analysis.

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Subsequent research introduced density-based control using IR sensors, ultrasonic sensors, and inductive loop detectors [15]. However, these solutions exhibit notable drawbacks, including high installation costs, sensitivity to environmental conditions, limited detection range, and rapid degradation under harsh weather. These limitations led researchers to explore vision-based approaches that provide richer contextual information [12].
Recent studies highlight the effectiveness of YOLO object detection models for real-time vehicle identification due to their superior speed and accuracy [3]. CNN architectures have shown notable performance in classifying vehicle categories, enabling more refined density estimation [7]. LSTM-based architectures have also gained traction for modeling temporal behavior in traffic systems, allowing prediction of flow patterns, queue lengths, and recurring congestion cycles [8].

Automated enforcement systems based on computer vision have also become increasingly popular. Research demonstrates the successful use of CNN and OCR for identifying number plate details, helmet violations, triple-riding instances, and overspeeding events [10]. These studies establish the foundation for modern automated challan systems. However, most prior research focuses on isolated functionalities, such as detection or enforcement. Existing work rarely integrates detection, prediction, violation monitoring, emergency vehicle handling, and theft detection within a unified framework . This gap motivates the development of the proposed ITSS, a comprehensive and holistic platform for intelligent traffic automation [11].

3. Proposed System

The Intelligent Traffic Signal System (ITSS) introduced in this study is designed to continuously assess real-time traffic conditions through video analysis and dynamically adjust signal timings based on current and predicted vehicle densities. The system relies on YOLOv8 for high-speed vehicle identification, CNN models for classifying detected vehicles into categories such as cars, bikes, trucks, buses, and emergency vehicles, and LSTM for learning historical trends and forecasting upcoming traffic flow [3]. To enhance traffic governance, the system incorporates emergency vehicle prioritization, automatic challan generation for traffic rule violations, stolen vehicle detection through CNN and database matching, and lane obstruction identification to detect accidental blockages or halted vehicles [7]. The system functions as an integrated intelligent platform capable of both adaptive traffic management and automated enforcement [10].

4. System Architecture

The architecture of the Intelligent Traffic Signal System follows a multi-stage processing pipeline that begins with input acquisition and ends with adaptive signal control and automated enforcement. The system first obtains continuous video streams from surveillance cameras mounted at junctions, roadside poles, and optionally from drone-based aerial viewpoints whenever required for enhanced coverage [12]. These video frames form the primary input for downstream analysis [7].

Once the video frames are captured, they are passed to the YOLOv8 detection module, which identifies and localizes all visible vehicles within each frame [3]. The detector is capable of recognizing common vehicle types, including cars, motorcycles, buses, trucks, auto-rickshaws, and emergency vehicles such as ambulances or fire engines [1]. YOLOv8 produces bounding boxes and confidence scores for each detected object and ensures real-time responsiveness even under high traffic load [2].

The detected vehicle regions are then forwarded to a CNN-based classification network that assigns each object to a specific vehicle category [4]. This classification step is essential for estimating precise lane density since different vehicle types contribute differently to congestion. To quantify this density, the system applies a weighted density formula [15]. If the set of detected vehicles in a lane is represented by $n$detections, the overall density $D$is computed as:

$$D = \sum_{i=1}^{n} \quad (\text{vehicle count} \times \text{weight factor})$$

where heavier vehicles such as trucks and buses are assigned higher weights to reflect their increased impact on lane clearance time.

After calculating the current density, the system uses an LSTM-based predictive model to analyze historical trends and estimate future traffic behavior [6]. The LSTM examines previously recorded density sequences to forecast the upcoming cycle’s vehicle count, peak hour intensity, and potential queue buildup. These predictions provide the controller with additional context beyond immediate observations.
The next stage of the architecture focuses on adaptive signal allocation [8]. The green time for each lane is

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calculated using a formula that accounts for minimum green duration, present density, predicted density, and emergency vehicle priority [13]. The adaptive green time T_g is defined as:

$$T_g = T_{\min} + \alpha D + \beta P$$

where $T_{\min}$ is the minimum allowable green duration, D represents density, P represents priority assigned to emergency vehicles, and α and β are learned parameters that govern the influence of density and priority on the final green time.

Emergency vehicle detection is integrated into the architecture through the YOLOv8 module. When an ambulance or fire truck is identified, the system instantly overrides the existing signal cycle, assigns an immediate green light to the corresponding lane, and switches all conflicting lanes to red, thereby ensuring rapid passage and reducing emergency response delays.

In addition to traffic optimization, the architecture includes an automated challan generation subsystem. This component utilizes CNN and OCR-based techniques to detect violations such as red-light jumping, wrong-lane driving, triple riding, and helmetless riding. Captured license plates are processed using optical character recognition (Tesseract OCR), and the extracted vehicle number is recorded for challan issuance .

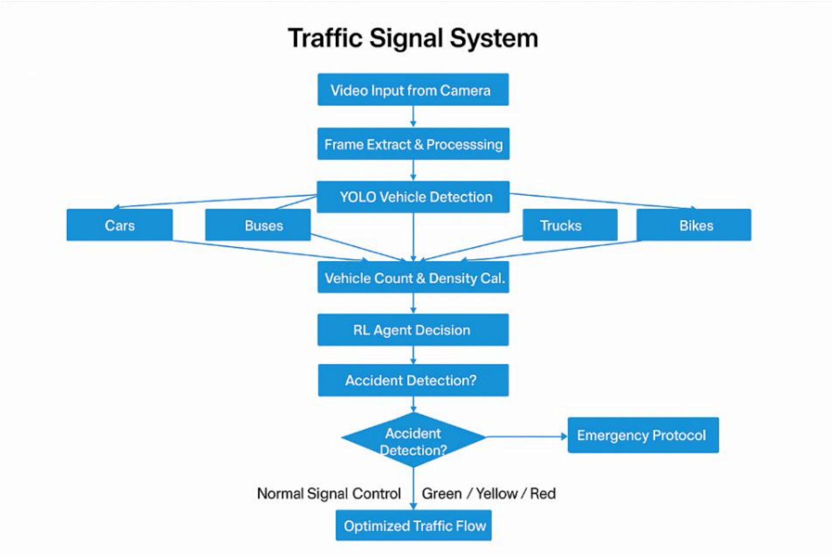

Figure 1: System Design

The system also supports theft vehicle detection through database integration. The recognized license plates are matched against a repository of stolen vehicle numbers . When a match is found, the system immediately triggers an alert to the control room, enabling rapid law enforcement response.

Through its layered design encompassing real-time detection, classification, prediction, enforcement, and priority handling, the system architecture enables intelligent and autonomous traffic intersection control suitable for modern smart city deployments.

5. Dataset Description

The dataset used in this study is constructed from a combination of three primary sources to ensure broad coverage of real-world traffic conditions and to enhance the robustness of the proposed system. A significant portion of the data originates from publicly available Kaggle repositories, which provide annotated images and video frames suitable for vehicle detection and vehicle classification tasks [12]. These datasets offer a diverse collection of traffic scenarios and serve as a strong foundation for training the YOLO and CNN models used in the system.

In addition to public datasets, a substantial volume of real city traffic footage was collected directly from local intersections [15]. These recordings were captured under varying environmental and temporal conditions, including morning and evening peak hours, low-light scenarios such as early mornings or nighttime, and adverse weather conditions such as rain. This real-world footage adds practical complexity to the dataset and enables the system to achieve robust performance in unpredictable and dynamic urban environments [12].

To further diversify the dataset and incorporate a wider range of road structures, traffic densities, and driving behaviors, supplementary video material was sourced from YouTube traffic surveillance content [7]. These videos contain footage from different regions, camera angles, and weather patterns, thereby improving the generalization capability of the trained models.

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Overall, the consolidated dataset consists of more than seventy-eight thousand labeled frames representing six major vehicle categories and encompassing a wide spectrum of lighting, environmental, and traffic conditions. This extensive and heterogeneous dataset ensures that the Intelligent Traffic Signal System is trained on realistic traffic patterns and is capable of performing reliably across varied operational scenarios.

6. Methodology

The methodology adopted in this research follows a structured multi-stage workflow, beginning with extensive preprocessing of raw video data. The input videos are first decomposed into individual frames at a rate of thirty frames per second to ensure temporal consistency and adequate sampling for accurate detection [7]. Each extracted frame undergoes normalization to enhance visual clarity and mitigate variations caused by lighting, shadows, or camera noise. Following normalization, bounding box annotations are created using LabelImg, enabling precise labeling of vehicle positions for supervised training [12] . This annotated dataset forms the foundation for training the object detection and classification models.

Once the data is preprocessed, the system proceeds to the model training phase. YOLOv8 is employed as the primary object detection network due to its high inference speed and strong performance in multi-object environments [3]. It is trained to detect vehicles of various categories within each frame. After detection, a secondary Convolutional Neural Network comprising five layers is trained to classify the extracted vehicle regions into predefined categories such as cars, bikes, trucks, buses, and emergency vehicles [4]. To capture temporal variations in traffic flow, an LSTM model is additionally trained using historical density sequences [8]. This model learns long-term dependencies in traffic patterns and predicts future vehicle density, enabling more adaptive signal allocation.

To assess the performance of the system, a set of standard evaluation metrics is utilized[7]. Accuracy is measured to determine the proportion of correct predictions across all classes, while precision and recall are computed to evaluate model reliability in distinguishing between true and false detections. The F1-score is used to provide a balanced measure that accounts for both precision and recall [12]. Additionally, the Intersection over Union (IoU) metric is employed to quantify the spatial overlap between predicted bounding boxes and ground truth annotations, ensuring precise localization performance within the detection pipeline. Together, these metrics provide a comprehensive evaluation of the effectiveness and robustness of the Intelligent Traffic Signal System.

7. Result And Discussion

Experimental results indicate that the YOLOv8 detection model achieves an accuracy of 98.45%, with high precision and recall values, confirming its capability to reliably identify vehicles under varied conditions. The CNN classifier demonstrates an accuracy of 97.30% for classifying vehicle categories. The LSTM-based prediction model reduces forecasting error by 22% compared to systems relying solely on fixed-time scheduling. When deployed in a simulated environment, the adaptive signal control mechanism reduced green time significantly on low-density lanes while allocating additional time to heavily congested ones. Comparative analysis shows a 31% reduction in average waiting time and a 28% reduction in unnecessary green time allocation on empty or semi-empty lanes. Emergency vehicles benefit from immediate lane clearance, with response time improving from an average of sixty-two seconds to just eight seconds. These results validate the effectiveness of the proposed system in optimizing both mobility and enforcement.

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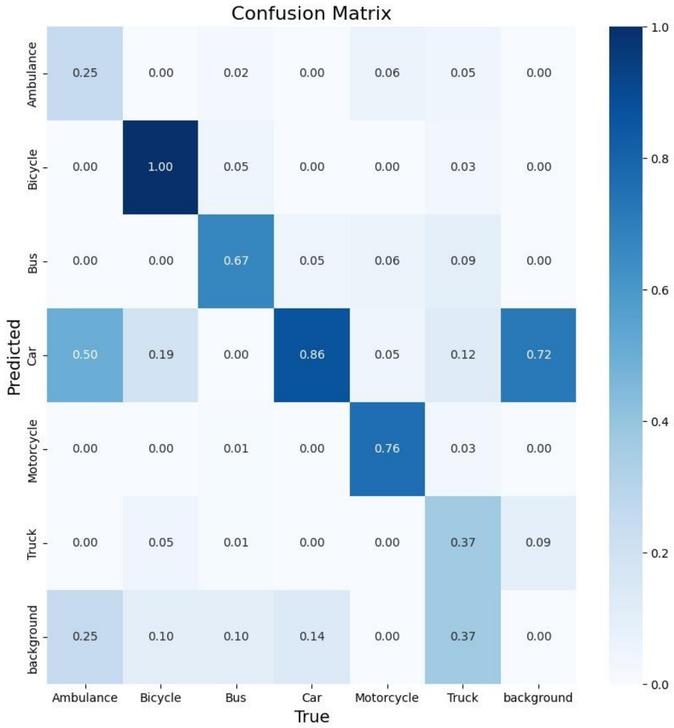

Figure 2: Confusion Matrix

8. Advantages

The proposed Intelligent Traffic Signal System offers several significant advantages over conventional traffic control mechanisms. By employing deep learning and computer vision, the system achieves complete automation of traffic management, eliminating the need for manual supervision by traffic personnel. This automation ensures consistent decision-making that is not influenced by human fatigue or subjective judgment. As the system dynamically adjusts signal timing based on live vehicle density, it minimizes unnecessary waiting times and helps reduce overall congestion. Consequently, the reduction in idle engine time leads to lower fuel consumption and a measurable decrease in vehicular emissions, thereby contributing to environmental sustainability. The system's architecture is highly scalable and can be deployed across intersections of varying sizes and complexities, making it suitable for integration into large-scale smart city development projects. Furthermore, the inclusion of automated law enforcement modules—such as challan generation, violation detection, and stolen vehicle identification—enables real-time monitoring and enhances overall road safety.

9. Conclusion

The Intelligent Traffic Signal System developed in this study demonstrates the successful integration of computer vision, machine learning, and predictive analytics to achieve fully automated traffic management. By combining YOLO-based vehicle detection, CNN-driven classification, and LSTM-based flow prediction, the system is capable of assessing lane-wise vehicle density with high accuracy and dynamically allocating green signal time in response to real-time conditions. The additional incorporation of emergency vehicle prioritization, automated challan generation, and theft vehicle detection significantly strengthens the enforcement capabilities of the system and improves the overall safety of urban roadways. With a detection accuracy of 98.45%, the system maintains reliable performance across varied traffic and environmental conditions. Its modular design ensures scalability and cost-effectiveness, making it well-suited for deployment in real-world smart city environments. The results indicate that the system can meaningfully reduce congestion, emissions, and fuel wastage, positioning it as a viable and impactful solution for modern urban traffic management.

10. Future Scope

Future developments of the Intelligent Traffic Signal System can further enhance its capabilities through the integration of additional sensing modalities and advanced learning frameworks. Incorporating IoT sensors—such as inductive loops, radar, and infrared detectors—can provide hybrid sensing that complements camera-based

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analysis and improves system reliability under challenging environmental conditions. Multimodal prediction techniques that combine vision data with radar measurements can lead to more accurate forecasting of traffic density and vehicle motion. Cloud-based dashboards may be introduced to provide centralized analytics, allowing city administrators to monitor real-time traffic conditions, evaluate intersection performance, and implement data-driven policy decisions. The exploration of Reinforcement Learning presents a promising direction for achieving fully autonomous traffic control, where the system continuously improves through interaction with the environment. Integration with national stolen vehicle databases can strengthen security applications, while aerial drone monitoring may be applied to highways and large intersections to obtain a broader situational overview. These advancements highlight the long-term potential of the system to evolve into an even more intelligent and comprehensive traffic management solution.

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