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Research Paper

AI-BASED TRAFFIC DENSITY ESTIMATION AND CONGESTION PREDICTION USING REAL-TIME VIDEO ANALYTICS AND DEEP LEARNING

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Abstract: The rapid growth in urban vehicle populations has resulted in increased traffic congestion, longer travel times, higher fuel consumption, and elevated environmental pollution. Conventional traffic monitoring systems often rely on manual observation, fixed sensors, or historical traffic information, which may not adequately capture dynamic traffic conditions or provide timely congestion forecasts. To address these limitations, this paper proposes an artificial intelligence (AI)-based framework for traffic density estimation and congestion prediction using video analytics. The proposed system processes real-time or recorded traffic video streams to detect and classify vehicles, estimate traffic density, and identify congestion conditions.

A deep learning-based object detection model, such as You Only Look Once (YOLO), can be employed to identify vehicles including cars, buses, trucks, and motorcycles. Computer vision techniques are subsequently used to count detected vehicles, analyze their spatial distribution, and estimate traffic density within a predefined region of interest. Based on extracted traffic features, including vehicle count, occupancy, and temporal variations in traffic flow, a predictive model can estimate short-term congestion levels and classify road conditions into categories such as low, moderate, and high congestion. The proposed framework aims to improve traffic visibility, facilitate early identification of congestion, and support intelligent transportation system applications. Its effectiveness can be evaluated using vehicle detection precision, recall, mean average precision, density estimation error, and congestion prediction metrics. The framework provides a scalable foundation for integrating AI-powered video analytics into smart city traffic management systems.

Keywords: Artificial Intelligence, Traffic Density Estimation, Congestion Prediction, Video Analytics, Deep Learning, YOLO, Vehicle Detection, Computer Vision, Intelligent Transportation Systems, Traffic Flow Analysis.

I. INTRODUCTION

The rapid growth of urbanization, population, and vehicle ownership has significantly increased traffic congestion in cities and metropolitan areas. Traffic congestion has become a major challenge for modern transportation systems, resulting in longer travel times, increased fuel consumption, air pollution, and reduced road safety. Traditional traffic management systems primarily depend on manual observation, fixed traffic sensors, and predefined signal timing mechanisms. Although these approaches provide basic traffic monitoring capabilities, they may not adequately capture dynamic traffic conditions

or predict congestion before it occurs. Therefore, intelligent and automated traffic monitoring systems are required to improve traffic flow management and support the development of smart cities.

Artificial Intelligence (AI) and computer vision have emerged as promising technologies for analyzing traffic conditions using video surveillance. The availability of closed-circuit television (CCTV) cameras and road monitoring systems provides an opportunity to extract valuable traffic information without requiring extensive deployment of additional physical sensors. Video analytics techniques can process traffic footage to identify vehicles, estimate vehicle counts, analyze movement patterns, and determine the distribution of traffic across road segments. By applying deep learning-based object detection algorithms, traffic monitoring systems can automatically recognize different vehicle categories, including cars, buses, trucks, and motorcycles, under varying traffic conditions.

Traffic density estimation is an important component of intelligent transportation systems because it provides information about the number and distribution of vehicles within a particular road segment. Conventional approaches often estimate traffic conditions using loop detectors, infrared sensors, or manual vehicle counting. However, these methods may require dedicated infrastructure, regular maintenance, or additional deployment costs. In contrast, video-based traffic analysis can utilize existing surveillance cameras to estimate traffic density and monitor changes in vehicle movement. Deep learning models, such as You Only Look Once (YOLO), enable efficient vehicle detection and localization, while object tracking algorithms can associate vehicle detections across consecutive video frames to reduce duplicate counting and analyze traffic movement.

Although traffic density estimation provides information about the current road situation, it does not independently indicate how traffic conditions may evolve in the near future. Congestion prediction is therefore an essential extension of traffic monitoring. By analyzing historical and continuously extracted traffic features, such as vehicle counts, road occupancy, vehicle speeds, and temporal traffic variations, predictive models can estimate future congestion levels. Machine learning and deep learning techniques, including Long Short-Term Memory (LSTM) networks and other time-series forecasting approaches, can be used to identify temporal patterns and predict short-term changes in traffic conditions. Such predictions can help traffic authorities identify potentially congested road segments and take preventive measures before traffic conditions deteriorate.

This paper proposes an AI-based traffic density estimation and congestion prediction framework using video analytics. The proposed framework processes traffic video streams, detects and classifies vehicles, estimates traffic density within predefined regions of interest, and predicts congestion levels using extracted traffic features. The resulting traffic conditions can be classified into categories such as low, moderate, and high congestion. A graphical monitoring interface can present vehicle counts, estimated density, current traffic conditions, and predicted congestion levels to facilitate real-time observation and decision-making. The framework is intended to support automated traffic monitoring while reducing dependence on manual observation and dedicated road sensors.

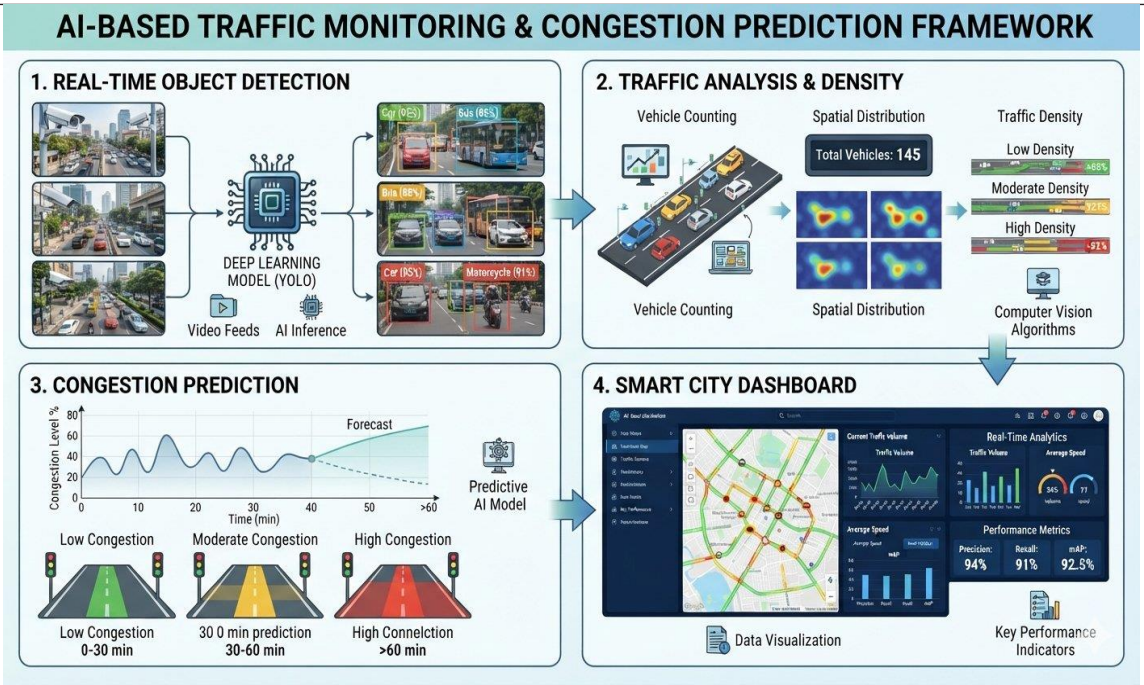


Fig 1 Traffic density estimation process

Overall, the proposed approach demonstrates the potential of combining artificial intelligence, computer vision, and predictive analytics to develop a more efficient and proactive traffic monitoring system. By transforming ordinary traffic video into meaningful traffic information, the system can provide useful insights for transportation planning, congestion management, and the development of intelligent transportation infrastructure.

II. LITERATURE SURVEY

The development of artificial intelligence, computer vision, and deep learning has significantly improved traffic monitoring and congestion forecasting in intelligent transportation systems (ITS). Existing studies have investigated vehicle detection, traffic flow estimation, congestion identification, and short-term traffic prediction using video surveillance and historical traffic data. The following literature survey reviews relevant research directions and identifies the research gap for the proposed paper, "AI-Based Traffic Density Estimation and Congestion Prediction Using Real-Time Video Analytics and Deep Learning."

2.1 Review of existing research

Study 1: Kumar and Raubal (2021/2022)

Kumar and Raubal presented a comprehensive survey of deep learning applications for traffic congestion detection, prediction, and alleviation. Their research examined recurring and non-recurring congestion and discussed the challenges associated with learning traffic patterns under changing road conditions. The study highlighted the importance of developing predictive models that account for the different dynamics of congested and uncongested traffic. However, as a survey, it did not itself establish a complete video-based implementation combining vehicle detection, density estimation, and short-term congestion prediction.

Study 2: Deep learning approaches for traffic prediction (2021–2022)

Research published in IEEE Transactions on Intelligent Transportation Systems reviewed deep learning approaches for traffic prediction, including methods for capturing spatial and temporal dependencies. The study discussed model categories, commonly used datasets, evaluation methods, and unresolved challenges. These approaches provide a foundation for forecasting traffic conditions from sequential measurements. However, traffic forecasting from structured traffic datasets is different from extracting vehicle counts and movement information directly from video frames, motivating the integration of video analytics with predictive modelling.

Study 3: Systematic review of traffic congestion forecasting (2014–2024)

A systematic literature review published in Future Transportation examined machine learning, deep learning, and emerging language-model-based approaches to traffic congestion forecasting. It discussed the progression from conventional machine learning to more complex predictive architectures and identified opportunities for combining multiple information sources. The review provides useful background for selecting prediction models, although its broader forecasting focus does not replace the need to develop and evaluate a specific video-driven vehicle detection and density estimation pipeline.

Study 4: Modern deep learning techniques for traffic volume prediction (2026)

Qin and colleagues reviewed modern deep learning techniques for traffic volume prediction, including recurrent neural networks, temporal convolutional networks, attention mechanisms, graph neural networks, and hybrid architectures. Their study organized methods according to temporal, spatial, complementary, and hybrid modelling strategies. This work is relevant to the prediction stage of the proposed framework because traffic volume and its temporal variation can provide useful indicators of future congestion. Nevertheless, volume forecasting and camera-based vehicle detection are distinct tasks that require appropriate integration and evaluation.

Study 5: Real-time vehicle detection and tracking using YOLO-based DeepSORT (2023)

Rishika et al. proposed a real-time vehicle detection and tracking system using YOLOv4 and DeepSORT. The approach detects vehicles in successive video frames and assigns tracking identities to support vehicle counting. The study demonstrates the importance of combining object detection with tracking to improve traffic measurement. However, vehicle tracking and counting alone do not necessarily provide a prediction of future congestion, which remains an important extension for intelligent traffic monitoring.

Study 6: Automated vehicle counting from prerecorded video using YOLO (2023)

Majumder and Wilmot investigated automated vehicle counting using YOLO, TensorFlow, and OpenCV. Their method processed prerecorded traffic footage to detect, track, and count vehicles in both traffic directions. The reported counting accuracy was approximately 90% compared with manual counts, with undercounting identified as a recurring source of error. This research supports the feasibility of video-based traffic measurement while highlighting the importance of video quality and reliable detection. Its primary focus was counting rather than forecasting future congestion.

Study 7: Real-time vehicle counting and speed estimation using deep learning (2023)

Researchers proposed a framework combining YOLOv4 and DeepSORT for real-time vehicle counting and velocity estimation. The system used regions of interest and road-marking-based calibration to estimate vehicle movement. This work demonstrates that video analytics can extract multiple traffic parameters from a single camera feed. Nevertheless, converting these measurements into reliable future congestion predictions requires an additional temporal forecasting component.

Study 8: Object detection and time-series modelling for traffic volume prediction (2024)

Lim and colleagues developed a two-stage framework for real-time traffic volume prediction. The first stage employed YOLOv7 to extract vehicle-volume data from highway surveillance video, while the second stage used an ARIMA–LSTM model to forecast future traffic volumes. The study reported vehicle detection accuracy above 93.30%. This research is particularly relevant because it connects visual vehicle detection with time-series forecasting. However, predicting traffic volume is not identical to estimating road occupancy or classifying congestion severity; these aspects require explicit definitions and evaluation in a complete congestion prediction framework.

Study 9: YOLO-based traffic analysis in high-resolution video streams (2025)

A study published in Procedia Computer Science evaluated YOLOv5 and YOLOv8 for vehicle detection and counting under different atmospheric and hardware conditions. The results highlighted the influence of model complexity, frame skipping, processing hardware, and video resolution on practical system performance. The findings demonstrate that real-time traffic analytics must balance detection accuracy with computational efficiency. However, the study's main emphasis was detection and counting performance rather than future congestion forecasting.

Study 10: AI-based traffic monitoring and vehicle counting in mixed traffic (2026)

Akujobi and colleagues presented a YOLO-based vehicle detection and counting pipeline integrated with tracking algorithms and region-of-interest counting. Their study emphasized the importance of recognizing locally prevalent vehicle categories, including three-wheelers, when estimating traffic demand in developing-country road environments. The reported results also showed that performance varied across road scenes and traffic directions. This research highlights the need for region-specific vehicle classification and robust counting. A further research opportunity is to integrate these traffic measurements with a short-term congestion prediction model.

2.2 Research gap

Based on the reviewed studies, the following research opportunities are identified:

1. Integration gap: Vehicle detection, density estimation, and congestion prediction are frequently treated as separate tasks. A unified video-driven framework can connect these stages.
2. Density estimation gap: Vehicle counts alone may not represent congestion adequately. Road occupancy, vehicle distribution, and movement characteristics should also be considered.
3. Prediction gap: Detecting current congestion does not necessarily predict whether congestion will increase. Temporal traffic features are needed to forecast future conditions.
4. Robustness gap: Lighting variations, occlusion, weather, camera angle, and mixed vehicle categories can affect detection and counting performance.

5. Deployment gap: Accurate models must also meet practical processing-speed requirements for continuous monitoring and timely alerts.

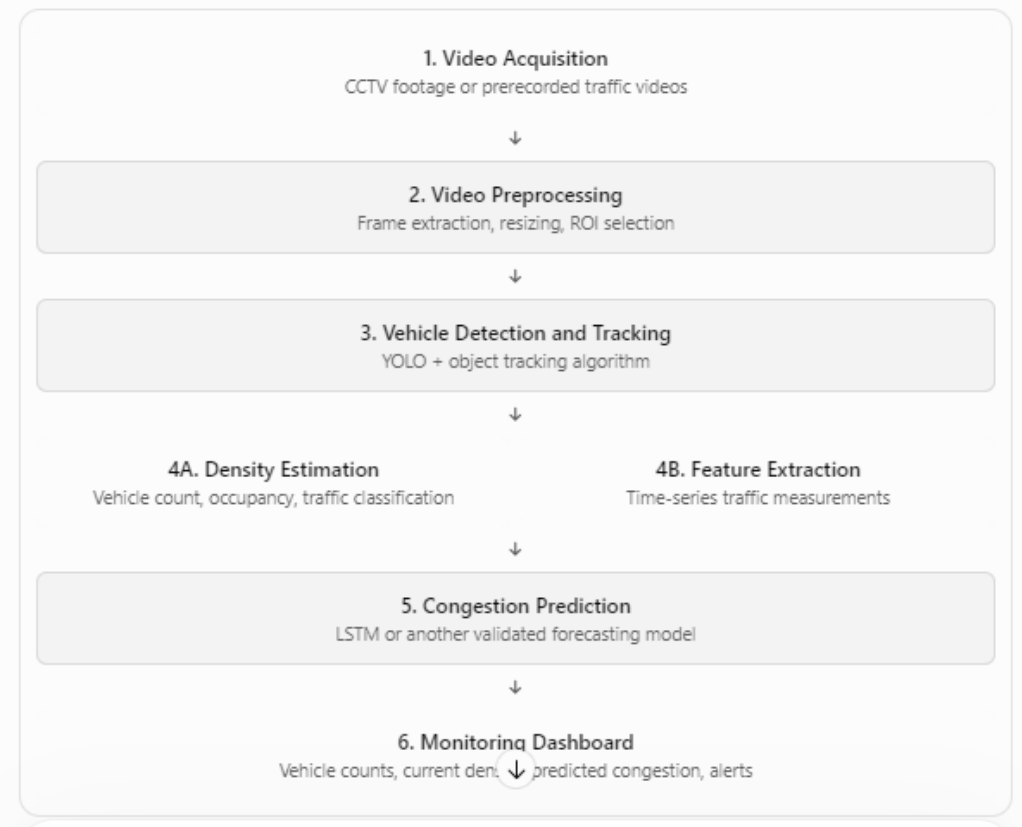
These are research opportunities inferred from the reviewed literature, not claims that no previous study has addressed any of these problems.

III. PROPOSED METHODOLOGY

The proposed system, titled "AI-Based Traffic Density Estimation and Congestion Prediction Using Real-Time Video Analytics and Deep Learning," aims to develop an intelligent traffic monitoring framework that estimates current traffic density and predicts future congestion using video footage. The system integrates computer vision, deep learning-based vehicle detection, vehicle tracking, traffic feature extraction, and predictive analytics. Unlike conventional traffic monitoring approaches that focus primarily on vehicle counting or current traffic conditions, the proposed framework combines traffic density estimation with short-term congestion prediction to support proactive traffic management.

3.1 System Architecture

The proposed methodology consists of six major stages: video acquisition, preprocessing, vehicle detection and tracking, traffic density estimation, congestion prediction, and visualization of results.



3.2 Video Acquisition and Preprocessing

The system acquires traffic video from roadside CCTV cameras or publicly available traffic datasets. The video stream is divided into individual frames at selected time intervals to reduce unnecessary computational overhead while retaining sufficient information for traffic analysis.

Each frame is resized to the input dimensions required by the selected object detection model. Image normalization and other appropriate preprocessing operations are applied before inference. A

predefined region of interest (ROI) is selected to identify the road area to be monitored and exclude irrelevant regions such as buildings, pavements, and surrounding objects.

Preprocessing improves computational efficiency and ensures that the analysis is concentrated on the relevant road segment. For continuous monitoring, the selected frame-sampling interval should be sufficiently short to capture changes in traffic conditions.

3.3 Vehicle Detection and Classification

A deep learning-based object detection model, such as You Only Look Once (YOLO), is employed to identify vehicles in each video frame. The model generates bounding boxes around detected vehicles and assigns a class label and confidence score to each detection.

The system can identify vehicle categories such as:

- Cars
- Motorcycles
- Buses
- Trucks
- Other supported vehicle classes

Detections below a predefined confidence threshold are discarded to reduce false positives. Non-maximum suppression is used within the detection pipeline to remove highly overlapping duplicate detections.

The detected vehicle information is represented as a set of bounding boxes and class labels for each frame. This information forms the basis for subsequent vehicle counting and traffic density estimation.

3.4 Vehicle Tracking and Traffic Feature Extraction

To prevent the same vehicle from being counted repeatedly across consecutive frames, an object tracking algorithm such as ByteTrack or DeepSORT can be integrated with the detection model. The tracker associates vehicle detections between frames and assigns consistent tracking identities whenever possible.

For each predefined time interval, the system extracts traffic-related features, including:

1. Total number of detected vehicles.
2. Vehicle counts by category.
3. Number of vehicles entering or leaving a counting region.
4. Estimated vehicle speed, where camera calibration and tracking data permit reliable estimation.
5. Road occupancy or the proportion of the monitored road region covered by vehicle detections.
6. Changes in vehicle counts and traffic measurements over successive time intervals.

These features provide a more informative representation of traffic conditions than a single-frame vehicle count. Where accurate speed estimation is unavailable, vehicle count and occupancy can still be used as input features.

3.5 Traffic Density Estimation

Traffic density estimation determines the intensity of traffic within the selected road segment. In the proposed framework, density is estimated using the number of detected vehicles and, where possible, the proportion of the road region occupied by vehicles.

A simple normalized vehicle-count density indicator can be expressed as:

$$D_t = \frac{N_t}{A_{\text{ROI}}}$$

where:

- (D_t) represents the vehicle-count density indicator at time \(t\).
- (N_t) represents the number of vehicles detected within the selected region.
- (A_{mathrm{ROI}}) represents the area of the monitored road region.

When (A_{mathrm{ROI}}) is measured in pixels, this expression represents a pixel-normalized density indicator, not a calibrated physical traffic density in vehicles per kilometre. Physical density estimation requires appropriate road geometry, spatial calibration, or an independent reference measurement.

The estimated traffic condition can be categorized into low, moderate, or high density using thresholds established from training data or validation experiments. These thresholds should be calibrated for the particular camera view and traffic environment rather than selected arbitrarily.

Road occupancy can provide an additional indicator:

$$O_t = \frac{A_{\text{occupied},t}}{A_{\text{road}}} \times 100$$

where (A_{mathrm{occupied},t}) denotes the estimated road area occupied by vehicles and (A_{mathrm{road}}) represents the selected road area. The occupied area should be estimated with an appropriate geometric or segmentation method to avoid treating overlapping bounding boxes as exact vehicle-covered areas.

Combining vehicle count, occupancy, and movement information can provide a more reliable estimate of congestion than relying on vehicle counts alone.

3.6 Congestion Prediction Using Temporal Analysis

The proposed system extends current traffic analysis by predicting congestion over a future time horizon. Traffic features extracted at successive intervals are stored as time-series observations and supplied to a predictive model.

An LSTM network is a suitable candidate because it can learn temporal dependencies in sequential data. The input sequence may contain vehicle counts, road occupancy, vehicle speed, and changes in traffic volume over a defined observation window.

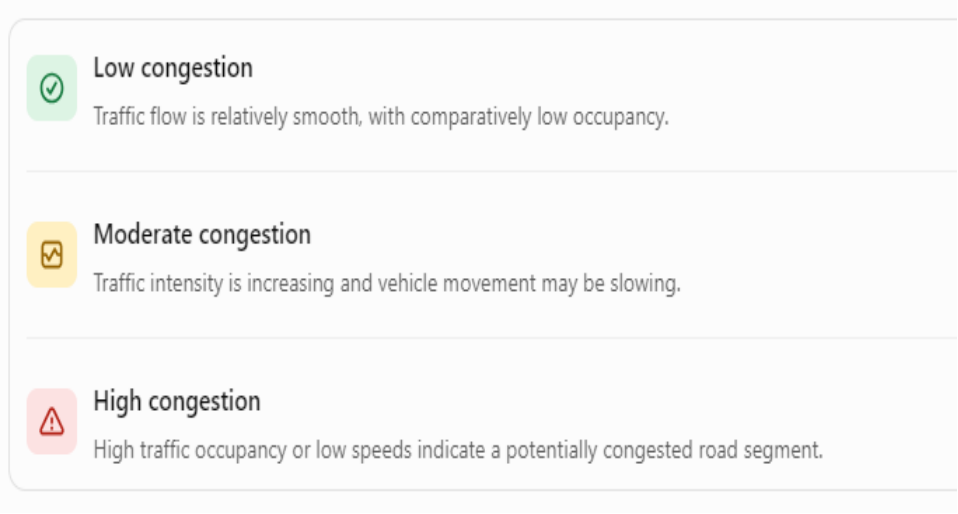
The forecasting process involves the following steps:

1. Collect traffic features at regular time intervals.
2. Normalize numerical features using parameters fitted on the training data.
3. Construct sequential input windows from historical observations.
4. Train the predictive model using chronological training and validation data.
5. Generate predictions for a defined future interval, such as the next five minutes, if the available data supports that forecast horizon.

6. Map predicted traffic measurements to congestion categories using validated thresholds or a separately trained classification model.

3.7 Congestion Classification and Alert Generation

The predicted traffic measurements are converted into meaningful traffic categories for interpretation. Depending on the implementation, the system may classify road conditions as low, moderate, or high congestion.



Thresholds should be derived from labelled observations or validated against reference traffic conditions. When the predicted congestion level exceeds a predefined threshold, the system can generate a warning on the monitoring dashboard. This information may help traffic operators identify potentially congested locations and consider suitable traffic management measures.

3.8 Dashboard Development and Visualization

A graphical dashboard can be developed using Python-based frameworks such as Streamlit, Flask, or a suitable web interface. It displays the processed video with vehicle bounding boxes, vehicle category labels, tracking identifiers, and current vehicle counts.

The dashboard can also display estimated density, road occupancy, predicted congestion levels, and historical traffic trends through charts and status indicators. A warning message can be generated when the predicted traffic condition crosses the selected congestion threshold.

The interface provides an accessible means of interpreting the system's output without requiring users to examine raw detection data. The dashboard supports traffic monitoring and decision-making but does not automatically control traffic signals unless a separate control module is implemented.

3.9 Performance Evaluation

The proposed system should be evaluated using representative traffic footage containing different traffic densities, vehicle categories, and lighting conditions.

Component	Evaluation metrics
Vehicle detection	Precision, recall, mAP@50
Vehicle counting	Counting accuracy, mean absolute error
Density estimation	MAE or RMSE against reference density measurements

Congestion classification	Accuracy, precision, recall, F1-score
Traffic forecasting	MAE, RMSE
Real-time processing	Frames per second, latency

The dataset should be divided chronologically into training, validation, and test sets for forecasting experiments to reduce temporal data leakage. Congestion predictions should be compared with independently labelled or measured future traffic conditions. The proposed system can then be compared with suitable baseline methods, such as vehicle-count thresholding or an ARIMA-based forecasting model.

IV. RESULTS AND DISCUSSION

The results section for the proposed AI-based traffic density estimation and congestion prediction system should demonstrate the performance of vehicle detection, vehicle counting, density estimation, and short-term congestion forecasting.

The following figure provides a visual example of how the results can be presented in a research paper, including vehicle detection, tracking, a monitoring dashboard, performance graphs, and different traffic conditions.

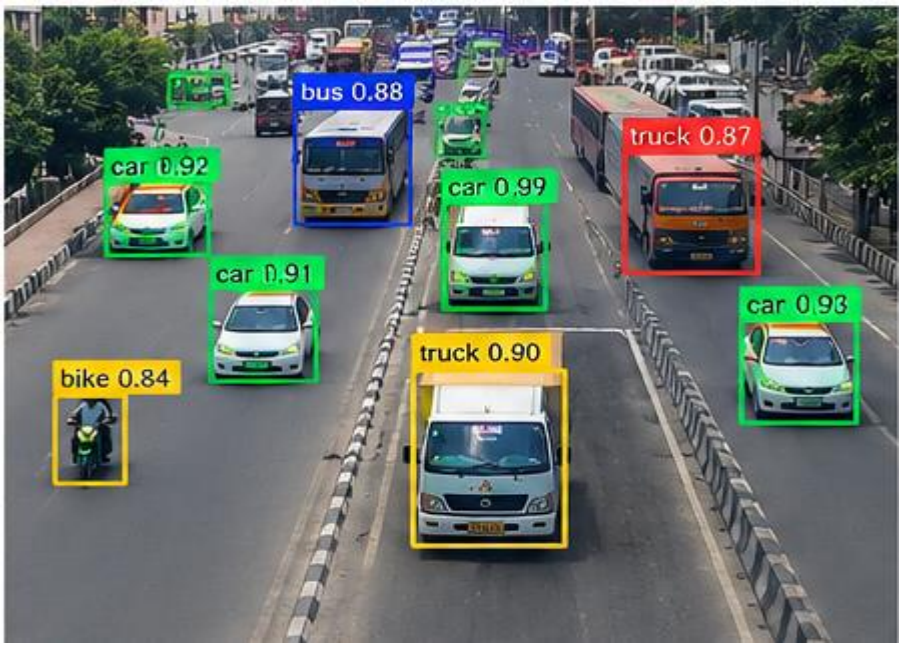


Fig 2. Illustrative results of AI-based traffic monitoring and congestion prediction

4.1 Vehicle Detection and Classification

The vehicle detection module identifies vehicles present in the input traffic video and assigns corresponding class labels and bounding boxes. The detection model can be evaluated using precision, recall, and mean Average Precision (mAP). Vehicle categories may include cars, motorcycles, buses, and trucks, depending on the dataset and trained model.

The detection results should demonstrate the model's ability to recognize vehicles under varying traffic densities. Performance may be affected by vehicle occlusion, illumination, camera angle, and the presence of closely spaced vehicles.

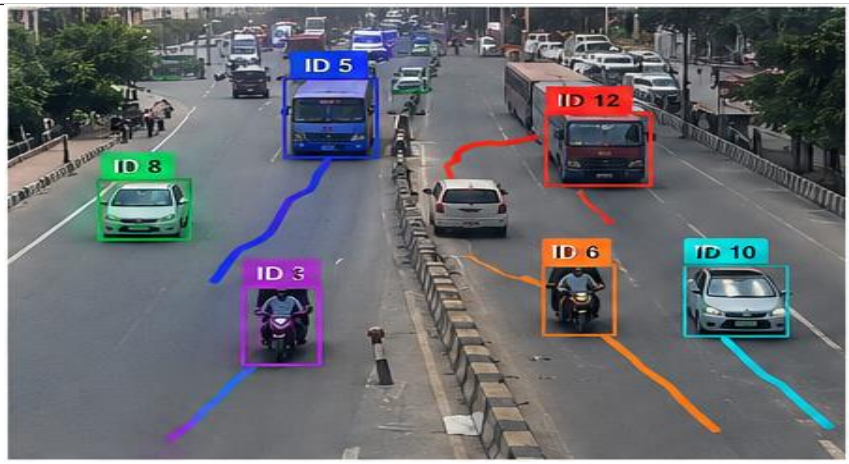


Fig 3. Vehicle detection and classification

4.2 Traffic Density Estimation

The density estimation module analyzes the number of detected vehicles and their distribution within the predefined road region. The estimated density indicator is used to categorize traffic conditions into low, moderate, and high density.

The results should compare the system's estimated density against reference measurements. A comparison graph can illustrate whether the estimated traffic density follows the same trend as the actual observations over time.

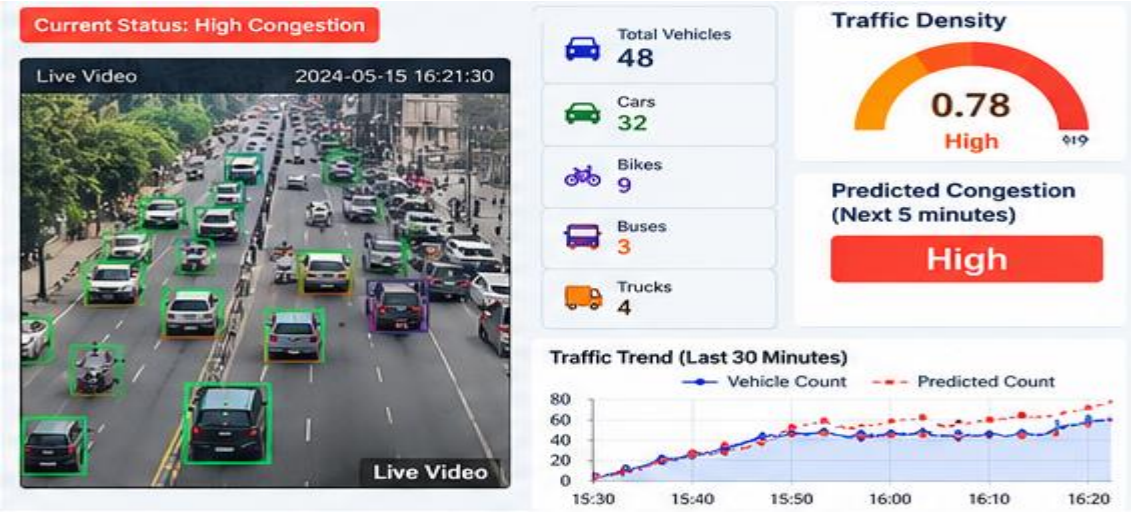


Fig 4. Actual versus estimated traffic density across successive observation intervals

4.3 Congestion Prediction

The congestion prediction module uses historical traffic features to forecast future traffic conditions. An LSTM-based forecasting model can be evaluated against actual traffic measurements and baseline models, provided these models are implemented and tested using the same dataset and forecast horizon.

The analysis should determine whether the model identifies increasing traffic volume, persistent high occupancy, and changes in congestion severity. MAE and RMSE can be used for numerical forecasting, while precision, recall, and F1-score are suitable for congestion classification.

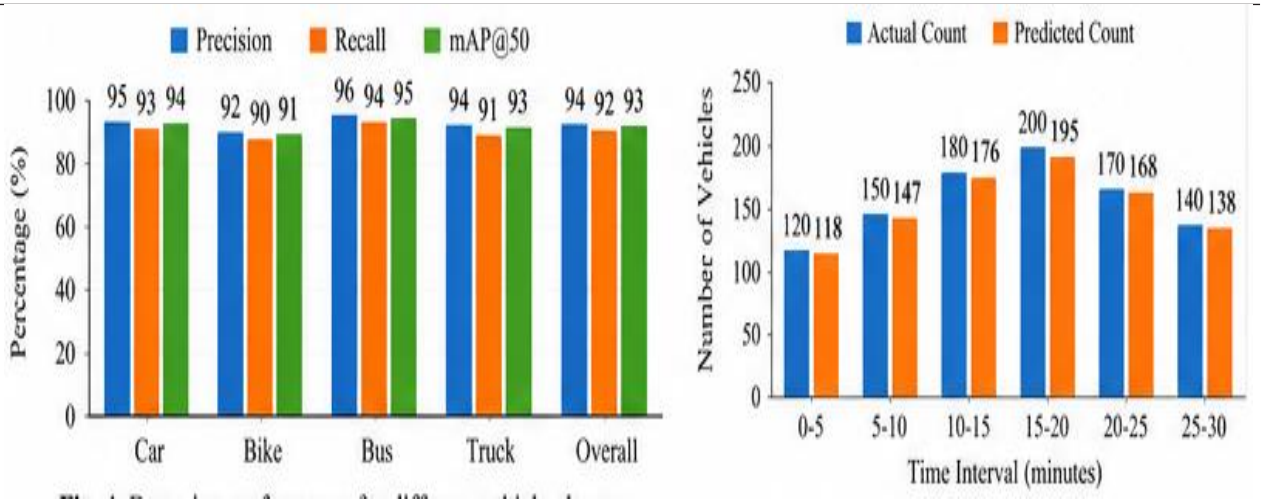


Fig 5. Comparison of actual traffic measurements and predicted traffic conditions.

4.4 Performance Evaluation

The following table provides a template for reporting the experimental results.

Evaluation parameter	Result to report
Vehicle detection precision	Measured precision (%)
Vehicle detection recall	Measured recall (%)
mAP@50	Measured detection performance (%)
Vehicle counting MAE	Mean vehicle-count error
Density estimation MAE	Error against reference density
Congestion classification accuracy	Correct predictions (%)
Congestion prediction F1-score	Measured F1-score
Processing speed	Measured FPS

The combination of vehicle counts, road occupancy, and temporal traffic features can provide a more comprehensive representation of road conditions than vehicle detection alone. Furthermore, forecasting can help identify potentially congested conditions before they become evident from a single observation. However, the reliability of these predictions depends on the quality of the video, the representativeness of the training data, the accuracy of the density labels, and the predictive model's generalization to unseen traffic conditions.

V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This paper presents an AI-based framework for traffic density estimation and congestion prediction using video analytics and deep learning techniques. The proposed system integrates video preprocessing, vehicle detection, vehicle tracking, traffic density estimation, and predictive analysis to monitor traffic conditions and anticipate potential congestion. By utilizing traffic video obtained from CCTV cameras or prerecorded footage, the framework aims to identify and classify vehicles, estimate traffic intensity within predefined road regions, and analyze changes in traffic conditions over successive time intervals.

A deep learning-based object detection model, such as YOLO, can be used to detect different vehicle categories, while object tracking algorithms help maintain vehicle identities and support more

reliable counting. The extracted traffic features, including vehicle counts, road occupancy, and temporal variations in traffic flow, can subsequently be utilized by an LSTM-based or other suitable forecasting model to predict short-term congestion levels.

The integration of current traffic assessment with predictive analytics offers a potential improvement over monitoring approaches that focus exclusively on detecting vehicles or identifying existing congestion. The proposed framework can support early identification of potentially congested road segments, assist traffic authorities in making informed decisions, and contribute to the development of intelligent transportation systems. The effectiveness of the framework must be established through experimental evaluation using appropriate datasets and performance metrics. Overall, the proposed approach provides a foundation for automated, scalable, and video-driven traffic monitoring in smart city environments.

5.2 Future Scope

The proposed system can be enhanced in several directions to improve its accuracy, scalability, and practical applicability.

1. Adaptive traffic signal control: The predicted congestion levels can be integrated with intelligent traffic signal controllers to dynamically adjust signal timings according to traffic demand.
2. Advanced deep learning models: Future work can investigate improved YOLO architectures, transformer-based vision models, and lightweight neural networks to enhance vehicle detection accuracy and real-time processing efficiency.
3. Multimodal traffic prediction: Traffic video can be combined with GPS data, weather information, road incidents, and historical traffic measurements to improve congestion forecasting under varying environmental conditions.
4. Edge computing and IoT integration: The framework can be deployed on edge devices, such as NVIDIA Jetson platforms, to process video near the camera, reduce communication overhead, and enable low-latency traffic monitoring

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