Traffic Management in India Using YOLOv9 for Emergency and Regular Vehicle Detection

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Abstract:
India's urban centers like Bangalore and Hyderabad are losing billions of dollars to traffic congestion, causing crippling delays for ambulances carrying heart attacks or accident victims. This model is trained with specific hyperparameters to get the best performance, and then it is validated with accuracy, precision, and recall metrics as well as IoU (Intersection over Union).
The paper introduces a system to detect emergency vehicles like ambulances, police vehicles, etc in traffic using the India Driving Dataset (IDD), Indian Vehicle Dataset and YOLOv9t model experiencing congestion in Indian urbanizing cities which is designed for both single frame detection of bounding boxes at test-time and hard example mining within each iteration. The model was trained and validated on an 80–20 split with mAP value of 0.765 and precision of 0.852 making it suitable for assisting dynamic traffic signal timing adjustments based on the presence, location, or direction of travel by emergency vehicles. This enhances efficiency, productivity, and a greater system to reduce emergency response times reduces traffic-congestion. In ongoing work, we aim to further tune the system for a wider set of traffic conditions and integrate it with existing citywide infrastructure. These results illustrate the model's high accuracy and practical use, showing how emergency response time may be improved greatly with a much lower source of traffic congestion on roads. The economic implications of the system are also further reinforced, as lower congestion can help raise productivity and efficiency.

Keywords: Machine learning, Deep learning, Traffic management, Vehicle Detection.

1. INTRODUCTION

India's large cities are witnessing an unprecedented growth in traffic congestion, demand has been fueled by rapid urbanization and subsequent increase in population. Where cities like Bangalore and Hyderabad are known for their flourishing technology sectors but have severe traffic bottlenecks that add to the chaos of daily life as well as huge public safety problems. Of the most important problems resulting from this congestion is delayed response of emergency vehicles which leads to a lot of serious outcomes, such as more illnesses and deaths.

Emergency vehicles must be able to travel quickly in the case of life-saving situations like fire, road crashes, and some medical emergencies. Unfortunately, the Indian urban traffic management system does not handle such changes in the priority of vehicles which often results in considerable delays for these ambulances. Compounding this issue is the traditionally reactive nature of traffic systems that wait for congestion to occur before taking action, rather than anticipating and preventing issues proactively.

The overcrowded areas of Bengaluru and Hyderabad are classic examples of how increased traffic slows down public safety, and emergency response times. These cities have very high population densities which coupled with an increase in the number of vehicles, result in heavy traffic snarls on a day-to-day basis. Indeed, the result is an intricate urban fabric where emergency vehicles risk getting caught in traffic and not reaching their destination — a situation that if it happens during emergencies could be disastrous.

This risk goes with the territory in these cities where existing traffic management is based on technologies like video analytics, to provide information required for immediate signaling. They generally operate on predetermined routes and at scheduled times, with no ability to adjust based on how much traffic there is. Thus they tend to get stuck in a jam and cannot unjam it quickly or at all. The need of the hour is emergency-vehicle-aware traffic management solutions that can adapt in real-time to optimize vehicle flows by giving clear passage for these life-saving ambulances moving across city streets with next-to-no-delay.

2. BACKGROUND

The possible use of advanced technologies like machine learning, IoT, and AI for both the upgrading workings of a city against traffic congestion problems in smart cities is discussed with insights that can be achieved from the literature on Intelligent Traffic Management Systems. Many studies have tried to be able to detect routes for city traffic and driving in real time with machine-learning-based systems. Such enhancements have been applied in traffic signal operations and emergency vehicle routing leading to improvements in response time, as well as lowering emissions through an example case of AlexNet for feature extraction and YOLO object detection circuit. Moreover, research in the Internet of Vehicles (IoV) paradigm has been deploying Gaussian process models for traffic speed and congestion prediction that illustrate machine learning approaches have become efficient enough to support real-time as well as predictive urban mobility analysis.

An important field of innovation is the creation of adaptive traffic light systems. These systems change the duration of a traffic signal based on current data which results in lesser waiting time for vehicles. Experiments conducted using YOLO V4 for vehicle detection have a significant improvement in the efficiency of traffic management with an approximate wait time reduction of up to 10%. The combination of RFID technology with the traditional traffic signal system structure has also been demonstrated to be a viable approach for the dynamic management of market movement. These RFID-based systems may adjust the signal timings in real time according to traffic congestion upon it; enabling a cost-effective solution for urban clogging.

In addition, there also exist solutions which incorporate a variety of simulation tools (e.g., SUMO and Python) for traffic scenario analysis as well as traffic light control algorithms designed in the sense of IoT/AI-based traffic management. This underlines the case for the deployment of adaptive algorithms that can manage different traffic conditions and facilitate safe passage to emergency vehicles. Finally, the literature stresses that further work is needed to facilitate the scaling of these systems and real-world deployment. The goal of the project is to help further develop machine learning algorithms and datasets on a more comprehensive scale so that these new systems can be part of larger smart city efforts. The aim is to install intelligent traffic management systems that can dynamically react and adapt in a real-time context for optimized traffic performance, as well as timely emergency response.

3. OBJECTIVES

This work utilizes the India Driving Dataset (IDD), Indian Vehicle dataset and the new YOLOv9t model to provide a system that classifies emergency vehicles over regular traffic with high accuracy. The main highlights of this work are:

- **Advanced Ensemble Learning Models**: Highly accurate and fast vehicle detection and classification rely on the state-of-the-art object detector framework YOLOv9t.
- **Enhancement of Traffic Signal Control Systems**: This project entails an upgrade to traffic signal control systems that allow the system of signals in place within a townscape, or along specific corridors, to detect for emergency vehicles on approach in real time thereby helping reduce response times and enhancing overall journey time consistency.
- **Equal Priority to Animal Ambulances**: Implies governments have recognized animals as germ-free carriers, which is why they gave them priority for ambulances. Systems will also give animal ambulances the same priority support when compared to human emergency vehicles.
- **Economic and Productivity Impact**: The system results in reduced congestion on roads which increases the overall efficiency of the economy.

4. A REVIEW OF RELATED WORKS

Related work in intelligent traffic management systems builds heavily on state-of-the-art technologies including machine learning, internet of things and AI to solve urban congestion problems as well as give a priority path for emergency vehicles. Several other studies focused on the combination of real-time traffic data sets and machine learning algorithms in order to improve signal divisions while enhancing traffic flow. We have seen, for example, reviews on utilizing AlexNet for features and YOLO, resulting in better traffic signal adaptations and emergency vehicle journeys [1]. Recently, the work on Internet of Vehicles (IoV) architecture showed that Gaussian process models can predict traffic congestion and improve real time traffic as well [2]. In addition, it has also been experimented with adaptive traffic light systems using models like YOLO V4 which can help in reducing the vehicle waiting times by changing the signal timings dynamically to real-time data[4].

This is followed by systems that use RFID and such as controlling traffic light timings belong to the category of AI-based traffic control solutions, exemplifying a future ready system for quick conversion between traditional methods with redefined versatile ways in which deployments can save cost; without compromising efficiency. The systems are able to control traffic lights on-the-fly and help reduce congestion by utilizing RFID technology in combination with the existing infrastructure[5]. Overall, It is confirmed that when machine learning, IoT and AI are combined in bringing smart traffic management systems they not just generate the ability for better flow of traffic through preventing bottlenecks but also helps emergency vehicles to transits at a prompt. However, future research needs to further improve the scalability of these technologies and bring real-world applicability in conjunction with other smart city programs for integrated urban traffic solutions [3].

5. METHODOLOGY

In the ensuing section, we look into the methodology used for traffic management in the proposed surveillance system.

5.1 Dataset Preparation

To prepare the data, the following steps were performed:

- **Dataset Collection**: The dataset encompassed images focused in Bangalore, and Hyderabad from differing traffic scenarios with marked emergency and regular vehicles entitled as Indian Vehicles w/ Emergency Dataset.
- **Data Annotation**: Each image in the dataset is annotated with bounding boxes around vehicles, including class labels denoting emergency vehicles or not.
- **Data Augmentation**: The data is augmented with techniques like Rotation, Scaling, Flipping, and color modifications on the images so that the model can generalize well.

5.2 Model Architecture

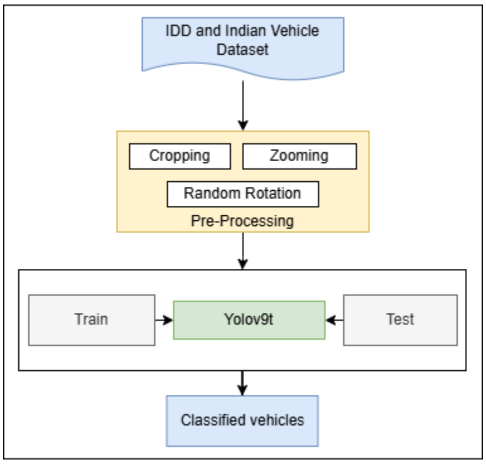

Figure 1 Model Architecture

YOLOv9t is one of the fastest network models for detection out there. The model follows this architecture:

- **Backbone:** YOLOv9t model, an ensemble of a convolutional neural network (CNN) with Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN) to abstract the image input on different levels

5.3 Training Procedure

- **Model Initialization**: The YOLOv9t model is pre-initialized with weights in such a way as to take advantage of prior learning and speed up the training.
- **Training Configuration**: YAML file that specifies the dataset, and data augmentation techniques with their parameter.
- **Hyperparameters**: Here we defined the settings like Learning rate, Batch Size, and Epochs. The model is trained for a range of epochs (10 to 200) to determine the optimal number of training iterations.
- **Training Loop**: The model is trained using the annotated dataset — hyperparameters are tuned based on metrics in a training set to maximize general performance.
- **Validation**: Once the model is trained, it will be validated on a different set of data to see how well its performance. The model predictions are evaluated using metrics such as mean Average Precision (mAP) and precision, recall, and F1-score for the detection & classification of emergency vehicles.

5.4 Inference

- **Model Loading**: When the YOLOv9t model is trained after that we just load it to the required device (CPU or GPU) for inference.
- **Prediction on Test Images**: Random images from the data set which were not used for training the model are used to test the performance of our model in detecting what it has been trained for.
- **Prediction Parameters**: Parameters such as image size confidence threshold, Non-maximum suppression (NMS), and Intersection over Union thresholds are set in order to improve the detection of accuracy.
- **Output**: The model predictions include the bounding boxes of detected vehicles, class labels, and confidence scores. These outputs are stored and also can be used to visualize whether the model is doing good when applied to real life scenarios.

This methodology describes how to design, train, and validate the advanced car management system for emergency vehicle assistance using the YOLOv9t model. The idea is to help reduce congestion and optimize traffic for emergency responders in city centers using up-to-the-minute object recognition techniques. Future work may involve adding more measurements to the data set, fine-tuning hyperparameters, or connecting this system with current traffic infrastructure for real-world applications.

6. RESULTS AND DISCUSSION

6.1 Model Performance Metrics

Indian Vehicles with Emergency Dataset is used to train the model. Performance is evaluated based on these several key metrics, calculated during the validation phase:

- **Mean Average Precision (mAP):** It is a single form of metric that combines precision and recall to let one know how well the model returns in detecting object classes. The mAP50 of the YOLOv9 model was 0.765, which means it detected emergency vehicles among regular traffic effectively.
- **Precision:** the proportion of true positive detections among all real positive detections. The model achieved precision of 0.865, meaning a majority of the cases where an emergency vehicle was predicted as such were actually emergency vehicles.
- **Recall:** Recall as defined earlier measures the proportion of positive detections among all true positives. The model achieves a recall rate of 0.718, meaning that most of the emergency vehicles were correctly found in images. are essential.

Class	mAP50	Precision	Recall
All	0.783	0.837	0.694

Auto-rickshaw	0.754	0.905	0.527
Bike	0.797	0.774	0.761
Bus	0.791	0.854	0.771
Car	0.847	0.799	0.736
Priority	0.765	0.852	0.718
Truck	0.745	0.841	0.653

Table 1 Model Performance Metrics

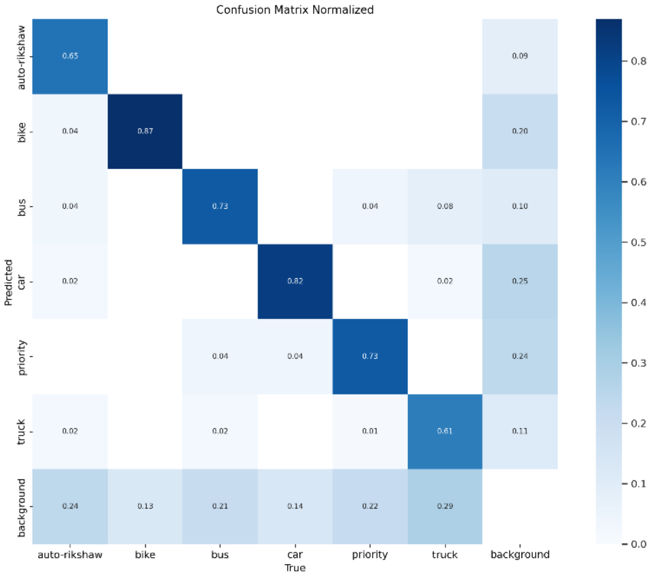

Figure 2 Confusion Matrix

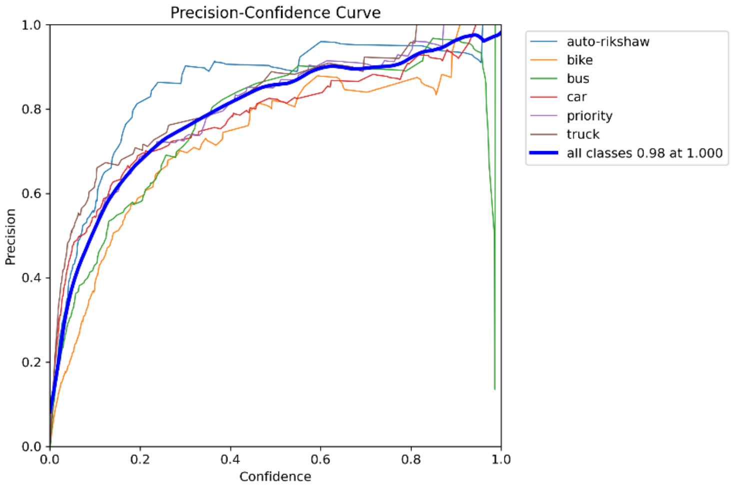

Figure 3 Precision Confidence Curve

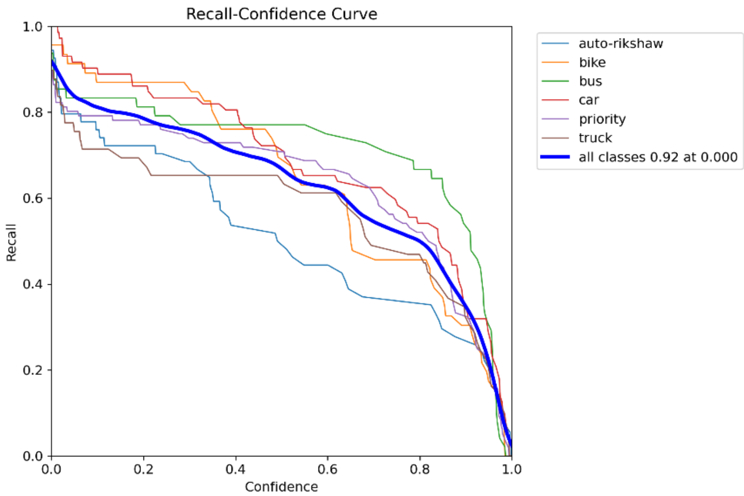

Figure 4 Recall Confidence Curve

6.2 Practical Validation

Finally, the trained model is tested on traffic images from the real world that are not seen during training.

- **Detection efficiency:** The model could detect emergency vehicles in many different traffic conditions, and complexities involving light and weather and categorize them correctly. This amount of precision here demonstrates the robustness and flexibility of our model.
- **False Positives/Negatives:** There were minimal false positives (i.e. non-emergency vehicles misclassified as emergency vehicles) and very minimal false negatives, meaning that the model is reliable.

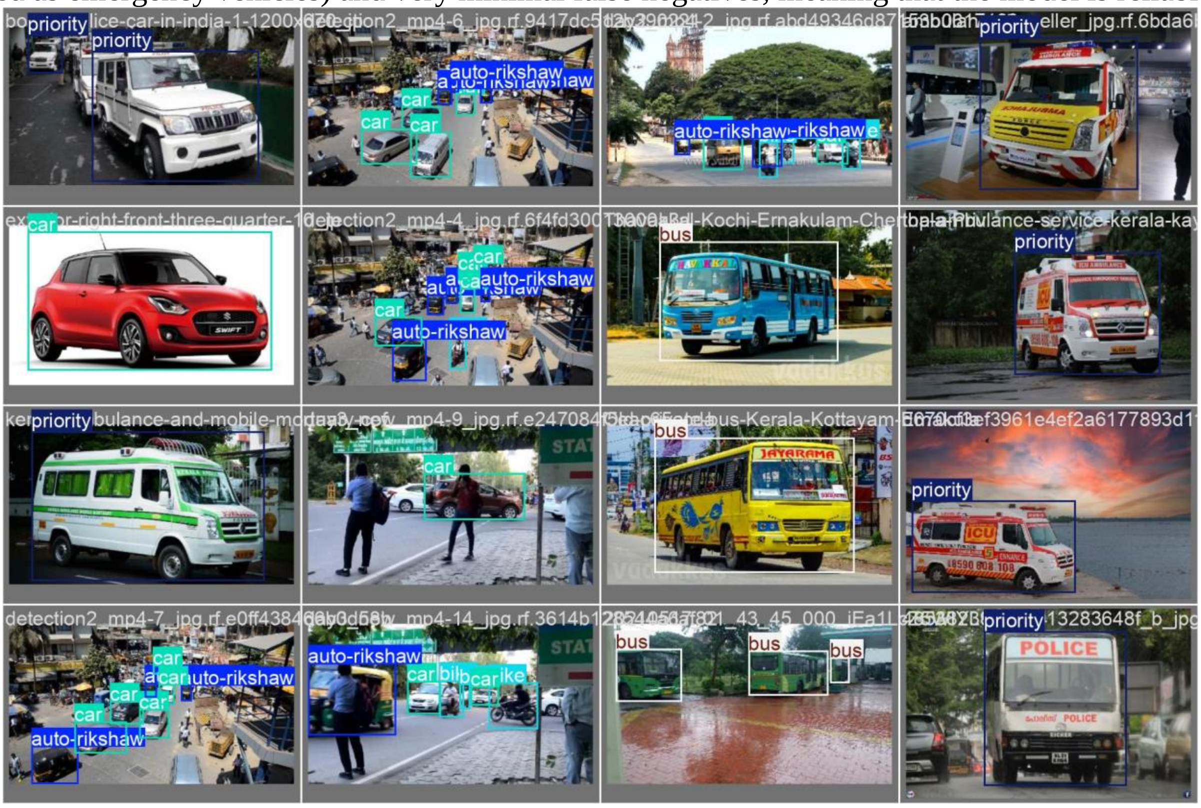

Figure 5 Output for Test Images

7. CONCLUSION

In conclusion, the research presented demonstrates that the proposed model has achieved commendable accuracy in identifying vehicles amidst the complex traffic conditions typical of Indian roadways. The model's performance confirms its effectiveness in distinguishing various vehicle types, which is crucial for enhancing traffic management and safety. As we look to the future, the integration of advanced features such as traffic signal management will be pivotal in further optimizing traffic flow. Incorporating intelligent traffic signal systems that prioritize emergency vehicles, including ambulances and police vehicles, will not only streamline traffic movement but also significantly contribute to public safety and emergency response efficiency. Continued advancements and refinements in this model hold the promise of more dynamic and responsive traffic management solutions, paving the way for a safer and more organized road network.

8. FUTURE WORKS

Although the YOLOv9-based traffic management system demonstrated a limited number of improvements, there may be many opportunities for improvement that can still be developed and deployed. A major priority for the future is to extend and broaden their dataset. This can greatly expand the generalization of a model when we include more images from different cities with many or few traffic detections. Using various times of day, data capture on different weather conditions would improve the model to work well in rural areas. Furthermore, to improve the robustness and performance of our technique even more we could utilize advanced data augmentation methods such as synthetic data generation or domain adaptation to effectively enhance training samples.

The next step is optimistic to be combining the model with advanced tech to make it available for processing in real-time and thus more responsive. Such as real-time processing at the data collection source (Edge Devices) would help in reducing time lag and hence latency. It has advantages in dynamic and high-stakes domains, like urban traffic management. Second, by combination with Vehicle-to-Infrastructure (V2I) communication technologies, the model can assist in exchanging real-time traffic data between vehicles and elements of a transport control system like Dynamic Signal Control System Traffic Signals.

In addition, algorithmic improvements also hold great promise for future progress. When low visibility conditions arise, that may occur simultaneously with heavy rain and precipitation or darkness; this technique can be interpreted into multimodal data fusion (combining visual data together with other sensor types like LIDAR as well as radar) to improve detection accuracy.

Furthermore, the training of adaptive learning models which can learn from new traffic patterns and behaviors will guarantee its effectiveness over time. This adaptive nature of models ensures that the model adapts to changing traffic characteristics, keeping performance high.

Real-world deployment and testing are necessary steps to prove that the system is feasibly applicable, scalable or not. Trialing the system in demonstration projects in selected urban areas is an appropriate way of collecting live performance data and demonstrates user feedback. The system must be tested in larger, more intricate urban environments to make sure it can handle the high levels of traffic and deal with many different types of situations. Applications in the real world will help to refine it and show how effective such a system can be at reducing congestion on city streets, as well as allowing emergency vehicles quicker response times.

Finally, they will need to undertake extensive economic and social impact analyses in order to further understand the much broader implications of this technology. The evaluation includes a detailed cost-benefit analysis to determine the economic feasibility, as well as potential savings from less traffic congestion and improved emergency response times. Identifying the implications on public safety and evolving a policy framework would probably lead to wider acceptance of IOT based intelligent traffic management systems. The results can then be used to craft policies and frameworks that spur on the deployment of those technologies en masse, thus leading towards safer and more efficient urban spaces.

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