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The implementation and result of a vehicle detection and smart traffic management system using IoT

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Abstract

One of the most important parts of a smart city is its traffic management system. Road congestion is a common problem in major cities due to the increasing number of people living there and the ease with which they can move about. This article presents a smart traffic management system that utilises the Internet of Things (IoT) to address many road traffic management concerns and assist authorities with effective planning. An algorithm is developed to effectively handle different traffic scenarios, and a hybrid method is used to optimise road traffic flow. The system operates the traffic lights after receiving data on the density of traffic from a) cameras and b) sensors. In order to reduce traffic congestion, another AI-based system is used to foretell future traffic densities. Furthermore, radio frequency identification tags are also used to provide higher priority during traffic congestion to emergency vehicles like fire brigade vehicles and ambulances. Additionally, smoke detectors are integrated into this system to identify the occurrence of a fire on the road. An optimised traffic flow and the ability to link nearby rescue departments to a central server are two features that the prototype features to prove the efficacy of the suggested traffic management system. Even better, it gleans valuable data displayed graphically, which could aid authorities with future road planning.

Keywords: IoT, smart city, smart traffic management, traffic congestion, traffic signal management

Introduction

The integration of Machine Learning (ML) and the Internet of Things (IoT) is revolutionizing Smart Traffic Management (STM) in response to rapid urbanization and increasing vehicle densities. This connection enables real-time investigation, prediction, and optimization of traffic patterns, aiming to reduce commuting times, improve road safety, and minimize congestion. IoT devices, such as cameras, GPS trackers, and sensors, collect crucial data on traffic volume, vehicle location, motion, and environmental factors. A paradigm shift towards smarter, more efficient, and environmentally friendly urban transportation solutions is imminent due to the combination of these technologies. The Android app uses advanced cloud APIs, IoT, machine learning, and cloud computing to provide precise real-time traffic statistics. The system's highly optimized system relies on crowdsourcing data from users' locations, with TensorFlow's sophisticated training methods making it the backbone of the application.

The adaptability of the Android-based real-time traffic data engine makes it an ideal fit for consumers. The app gathers location-based crowdsourced data, evaluates and uses this data to ensure accuracy. The app also has state-of-the-art cloud computing capabilities, allowing it to handle massive data sets with ease. This technology guarantees the system's ability to process large amounts of traffic data quickly and accurately., The convergence of ML and IoT is revolutionizing Smart Traffic Management, enabling cities to address issues presented by conventional traffic management systems and create smarter, more efficient, and environmentally friendly urban transportation solutions.

Literature review

Developing nations are what India is. As a nation develops, the number of personal automobiles also increases. Congestion in major cities has increased as a result of this. Therefore, an improved mechanism for managing traffic is required. Making a traffic system that changes based on the current lane traffic situation is the main goal of this project. As a rule, we keep all lanes' average waiting times constant.

By tracking the amount of traffic in each lane, this effort aims to reduce the average waiting time. The data will be sent to a central system over the internet, and that system will use the dumped software to determine the signal timing. In order to facilitate lane changes during congestion, this proposal also proposes installing congestion lights at already established junctions. In addition to helping with pollution and traffic congestion reduction, the system is effective in emergencies.

The book discusses the chronic issue of traffic congestion in Indian cities, highlighting issues with signal failures, inadequate law enforcement, and poor traffic management methods. Traffic jams cause physical and mental exhaustion, slow down freight trucks, and extend queues at checkpoints and toll booths. They also lead to 40% more pollution from automobiles due to increased fuel consumption and carbon dioxide emissions. The book proposes a technological solution using the Internet of Things to reduce travel and waiting times, focusing on reducing the sub-risks to mankind.

Traffic congestion in metropolitan areas leads to increased travel time, fuel consumption, and environmental pollution. Traditional traffic management systems struggle to adapt to changing circumstances in real-time. This study focuses on using AI to improve traffic flow and reduce congestion. AI-powered traffic management models are created using computer vision, neural networks, and machine learning. These models are trained using large amounts of traffic data and tested in virtual settings. The report examines real-life examples of cities using AI in traffic systems and highlights the pros and cons of this approach. The research shows that AI-powered traffic management significantly improves traffic flow, decreases congestion, and offers a scalable solution to contemporary city design problems.

The article proposes using the ant colony optimization method in a distributed multi-agent architecture to address urban traffic route planning. The research suggests that using IoT technology and advanced AI approaches can transform traffic management, addressing the issue of traffic congestion in metropolitan areas. Traditional methods, such as road development and network indicators, have limitations due to complex transportation networks. The proliferation of IoT devices offers new possibilities for efficient traffic analysis based on massive amounts of unpredictable data. However, current systems only account for local occurrences, reducing efficiency. A new approach is multi-agent systems, which use dispersed agents spread across junctions to handle traffic in its entirety. Artificial intelligence methods like fuzzy logic, evolutionary algorithms, neural networks, and reinforcement learning can be used for traffic management, such as the artificial bee colony algorithm for optimized signal timings and artificial neural networks for reliable traffic pattern forecasting.

The paper proposes an IoT-based traffic regulating paradigm for intelligent transportation systems (ITS) to improve road awareness and responsiveness. It suggests that ITS can help determine the best global control approach for vehicle-to-everything (V2X) equipped cars during times of traffic congestion. The best control systems consider possible crowded road segments due to congestion propagation. The research investigates the effect of route choice behavior on system performance using V2X-supported cars. Simulation findings show that by regulating cars, the best control tactics can significantly enhance transportation system performance and reduce congestion. This approach could drive ITS development towards automation and worldwide control.

Materials and Methods

Methodology for Vehicle Detection

To train a deep learning model, ‗N‘annotated images $\{x_1, x_2, \ldots, x_N\}$ are given, and for i^{th} image x_i, there are M_i objects belonging to C categories:

$$y_i = \{(c_1^i, b_1^i), (c_2^i, b_2^i), \ldots, (c_{M_i}^i, b_{M_i}^i)\ \}$$

Where $c^i(c^i \in C)$ and b^i signify categorical and spatial labels of the j^{th} object in x_i, respectively. For x_i, the prediction shares the same format as y_i:

$$y_{pred}^i = \{(c_{pred1}^i, b_{pred1}^i), (c_{pred2}^i, b_{pred2}^i), \ldots\}$$

Over C+1 categories, a multi-class classification model is trained, where C refers to actual classes and one background.

Data collection

Standard datasets such as PASCAL VOC 2007, 2012, and MS COCO 2014 are not recommended for training the vehicle detection model [98]. Not every kind of vehicle is included in these databases. Just two category labels, "car" and "bus," make up PASCAL VOC 2007 and 2012. The 2014 MS COCO is divided into three categories: cars, buses, and trucks. For this reason, we have amassed four distinct datasets for our experiments: the FLIR thermal dataset, the FLIR RGB dataset, the MB7500 dataset, and the KITTI dataset.

Data annotation

The act of classifying and labelling data is known as data annotation. All of the pictures in this project have been labelled with six different types of vehicles: bikes, scooters, light trucks, buses, and big trucks.

Data augmentation

The variety of the data used to train models may be enhanced by data augmentation as well. In order to make the dataset more balanced, three modifications were used: horizontal flip, rotation, and Gaussian noise.

Analysis and results of vehicle detection

All three models have been implemented in Python using the TensorFlow API. Table 1 details the machine's experimental platform setup. With a batch size of 24, the model requires an input size of 300 X 300. The IoU threshold is 0.6 and the learning rate is 0.0002. Table 1 compares the FLIR dataset's thermal photos to RGB ones of the same scene, illustrating the difference. There is no need to worry about lighting or weather affecting the quality of thermal pictures since they are generated by measuring heat reflected by a subject. As a result, objects are more discernible in thermal photos compared to RGB ones.

Table 1: Experimental Platform Configuration

Computing Machine	Configuration
Operating System	Windows 10
GPU	NVIDIA GEFORCE GTX (4GB)
RAM	8 GB
Processor	Intel Core i5
GPU acceleration library	CUDA, CUDNN

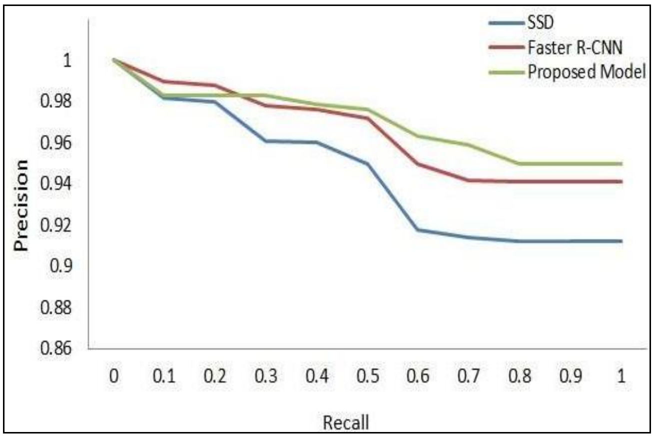

Fig 1: Precision vs. Recall Curve of SSD, Faster R-CNN, and Proposed model on FLIR Thermal dataset

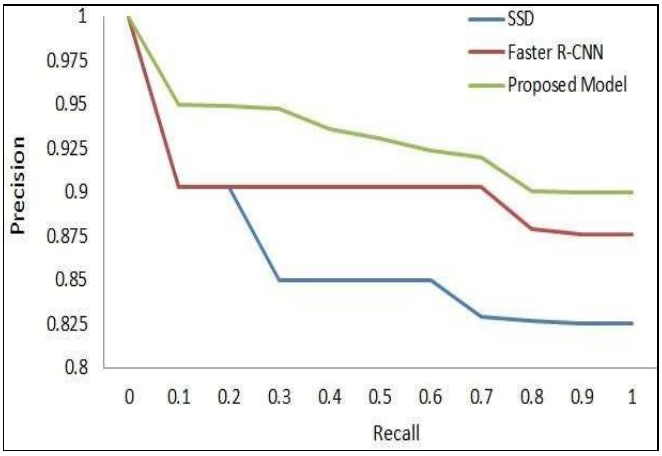

Fig 2: Precision vs. Recall Curve of SSD, Faster R-CNN, and Proposed model on FLIR RGB dataset

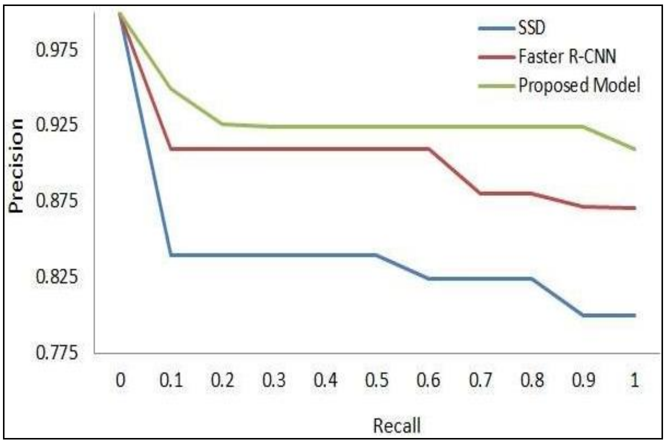

Fig 3: Precision vs. Recall Curve of SSD, Faster R-CNN, and Proposed model on MB7500 dataset

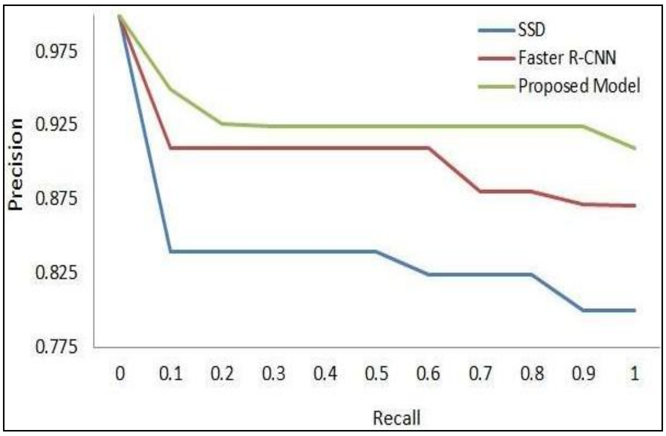

Fig 4: Precision vs. Recall Curve of SSD, Faster R-CNN, and Proposed model on the KITTI dataset

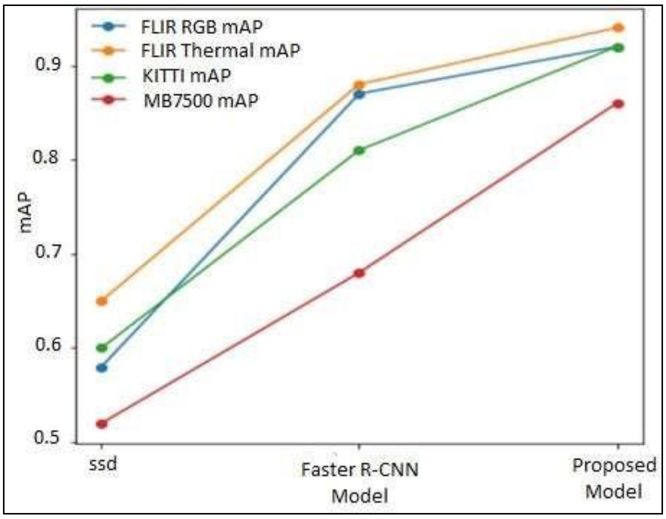

Fig 5: mAP of SSD, Faster R-CNN, and Proposed Ensemble on FLIR RGB, Thermal, KITTI, and MB7500 dataset

Table 2: Comparative analysis of SSD, Faster R-CNN, and Proposed Ensemble based upon mAP on FLIR, KITTI, and MB7500

Model	Dataset	mAP	CY	TW	LV	HV	TR	BU
SSD	FLIR RGB	0.58	0.65	0.54	0.64	0.55	0.58	0.5
	FLIR Thermal	0.65	0.7	0.64	0.61	0.58	0.81	0.55
	KITTI	0.60	0.55	0.51	0.51	0.59	0.46	0.93
	MB7500	0.52	0.52	0.47	0.59	0.41	0.57	0.56
Faster R-	FLIR RGB	0.87	0.94	0.87	0.8	0.94	1	0.67
CNN	FLIR Thermal	0.88	0.96	0.91	0.86	0.87	0.86	0.8
	KITTI	0.81	0.75	0.75	0.84	0.89	0.77	0.85
	MB7500	0.68	0.68	0.6	0.59	0.94	0.6	0.67
Proposed	FLIR RGB	0.92	0.94	0.93	0.91	0.91	1	0.83
Ensemble	FLIR Thermal	0.94	0.95	0.96	0.89	0.97	1	0.9
	KITTI	0.92	0.85	0.87	0.96	0.92	0.97	0.98
	MB7500	0.86	0.89	0.8	0.96	0.94	0.78	0.78

The planned study is compared to previous research in Table 3. The majority of the research has focused on visible image vehicle detection [221]. The research here suggests and tests a set of deep neural networks using both visual and thermal pictures. Results for both picture kinds are encouraging for the suggested approach.

Table 3: Comparison of the proposed model with existing methods

Technique/Reference	Image Type	Accuracy
Nam's Approach	Visible Images	92.7
Nam's Approach	Thermal Images	65.8
CNN-based Ensemble	Visible Images	93.2
ShuffleDet	Visible Images	62.89
ECNN-SVM	Visible Images	93.63
LittleYOLO-SPP	Visible Images	77.44
Proposed Model	Visible Images	92
Proposed Model	Thermal Images	94

One hundred individuals were surveyed by us. We got the following results from our survey that asked participants about their familiarity with the term "Smarttraffic Management System Using Iot." —

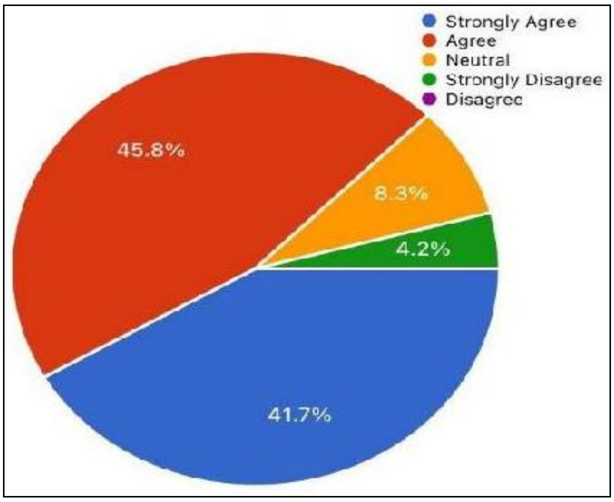

Fig 6: Figure showing the smart traffic systems will help in smoother traffic operations

Inference: In this case, 4.2% of people strongly opposed, 8.3% were unsure, 45.8% agreed, and 41.7% were very much in agreement.

Analysis: Smart traffic systems would aid in more efficient traffic operations, according to the majority of respondents, whereas the minority of respondents strongly disagreed.

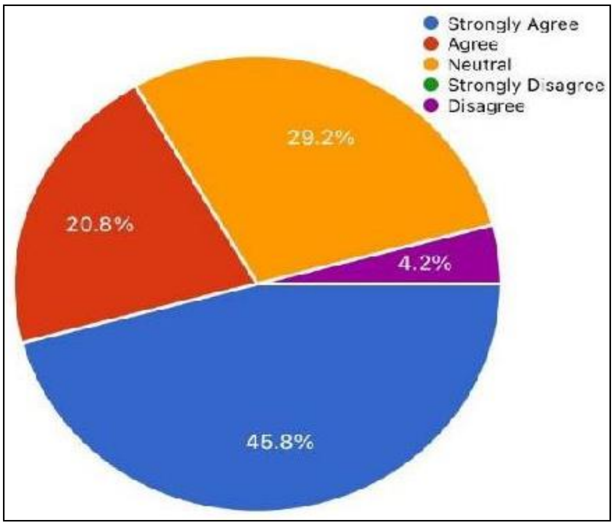

Fig 7: Figure showing the AI smart traffic system camera, crime rates come down by capturing through AI detection mode

Inference: In this case, 45.8% of respondents were in agreement, 20.8% were in agreement, 29.2% were neutral, and 4.2% were in disagreement.

Analysis: Here, the majority of respondents were in agreement, with a small minority expressing disagreement, that the use of AI smart traffic system cameras reduces crime rates via the use of AI detection mode.

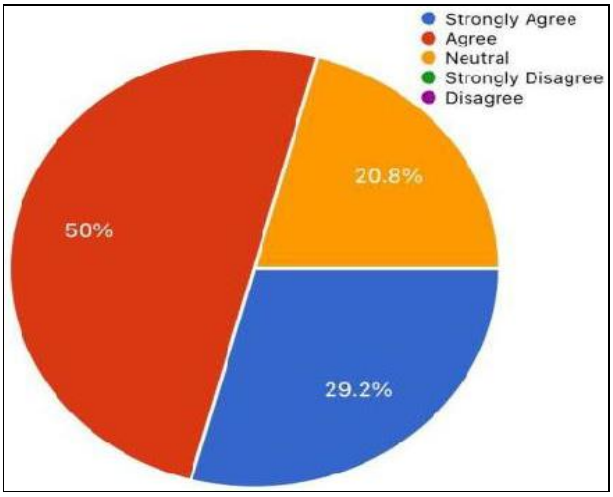

Fig 8: Figure showing the AI detection camera's, it can capture traffic violators easily

Inference: In this case, 29.2% of respondents were in complete agreement, 50% were in agreement, and 20.8% were unsure.

Analysis: Here, the majority of respondents agreed while the minority were unsure that AI detection cameras can readily catch traffic offenders.

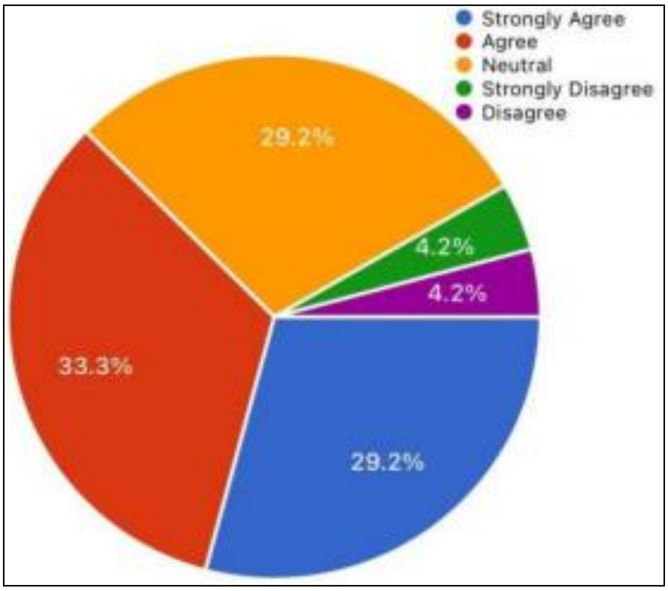

Fig 9: Figure showing the time to reach particular destinations at main junction road to divert traffic by getting information from cloud

Here, 29.2% of voters were in complete agreement, 33.3% were in partial agreement, 29.2% were undecided, and 4.2% were in strong disagreement. Time to reach certain locations at key junction road to redirect traffic by collecting information from the cloud: most respondents strongly agreed or were indifferent on the matter, while few strongly objected or disagreed.

Conclusion

The study uses open-source datasets to identify and categorize automobiles, train two deep learning architectures, and implement an ensemble learning-based hybrid model. The model outperforms base estimators in accuracy and traffic density estimation. It also produces superior density estimation results. Emergency vehicles are identified using radio frequency identification (RFID) and siren sounds from an open-source library. Three fully connected neural network (CNN) and RNN-based deep learning models are applied, and an ensemble model is applied. The ensemble model outperforms individual models, but RNN is not as effective as the ensemble model. An adaptive neuro-fuzzy inference system is used to optimize green light, considering traffic rate at intersections, density at the present lane, and the neighboring lane as input parameters. The system optimizes the green light by identifying the next necessary green signal at each stage. The results are compared with fixed timers and fuzzy logic controllers, reducing waiting time for cars. However, the research study has some drawbacks, such as the lack of integration for modules such as vehicle identification, emergency vehicle detection, and signal optimization. The ensemble method is suggested for identifying vehicles, while base estimators require less time.

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