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An Intelligent Traffic Management of Vehicles using Deep Learning Approach in Smart Cities

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Abstract—**Smart traffic management of automobiles has been one of the utmost sought-after issues in the academic community due to the ever-increasing pace of urbanization and civilization over the last several centuries. Vehicle dissection, traffic density appraisal, and vehicle tracing are the three main components of smart traffic management. This problem becomes more difficult to resolve when there are occlusions, background clutter, and fluctuations in traffic density. In light of this need, we explore a deeper learning approach based on R-CNNs for faster vehicle segmentation in this study. There is adaptive backdrop modeling in the computational framework. It solves problems with lighting and shadows as well. The use of topological active net deformable models allows for segmentation that is more precise. The deformations mentioned can be accomplished with the aid of topological and stretched topological active nets. Minimizing energy allows for mesh deformation. Using a tweaked version of the stretched topological active net improves the segmentation accuracy to 98.3%. The investigational findings show that this framework is better than other methods.**

Keywords—traffic control, vehicle segmentation, deep learning, smart cities, R-Cnns.

I. Introduction

One of the powerful research applications in the intelligent transportation system (ITS) that provides information to prevent or minimize traffic congestion is the vehicle adhoc network. The most important VANET standards are IEEE 802.11, the dedicated short-range communication (DSRC) protocol, and WAVE. Disputes in traffic management for smart cities center on congestion, energy usage, pollution emissions, and delays caused by traffic. Intelligent parking, intelligent vehicle routing, and intelligent traffic prediction are all things that traffic management must implement [1].

We must overcome the increasing death rate from vehicle accidents in recent years if we want to preserve lives. The main causes of road accidents include human mistake, inadequate infrastructure, environmental conditions, and mechanical failures in roadways. One of the problems with the transportation system that needs fixing is traffic congestion. Congestion, accidents, and pollution have all increased in tandem with the rapid population growth in recent decades.

Traffic accidents occur as a result of sloppy planning, lax enforcement, outdated infrastructure, and malfunctioning signals. The immediate consequence of reducing road deaths in cities, highways, and other urban areas is the improvement of transportation safety [2]. Various technologically exciting alert systems, digital maps, and traffic monitoring and directing are all part of road ammunition. When it comes to collision warning systems, active safety features are an important component.

Multiple Internet of Things devices are connected wirelessly. If the number of devices connected to the internet were to increase, additional bandwidth would be necessary. The ability to manage the network's devices and traffic will be critical as the Internet of Things (IoT) expands. Internet of Things (IoT) devices can have a greater impact on bandwidth requirements as the number of devices grows. Improved bandwidth requirements are a direct result of the exponential growth in data associated with Internet of Things (IoT) devices as a result of ongoing technological advancements. Users won't experience any issues with bandwidth. The availability of fast and reliable wireless networks (Wi-Fi) is the primary obstacle to the efficient implementation of Internet of Things (IoT) technologies. An further critical component of IT traffic is the increasing speed of broadband. Compared to IP video and audio, the network requirements are substantially higher [3]. Distributing available bandwidth in a heavily populated network is no easy task. More people are using broadband and more people are using bandwidth-intensive apps and content as a result of improvements to broadband speed. Broadband speeds around the world are continuing to rise, and between 2018 and 2023, they will more than double, going from 45.9 Mbps to 110.4 Mbps.

Internet of Things (IoT) is responsible for the communication between various devices. The IoT-traffic on the roads has skyrocketed alongside the proliferation of smartphones, and numerous studies have sought to improve the end user's connection experience. When it comes to dynamic bandwidth negotiation, the traffic prediction component is vital [4]. Two separate parts of the procedure are generally sampled and forecasted. The accuracy of traffic forecasts is critical to the smooth operation of any system. It is crucial to have traffic forecast in order to utilize network resources properly. The ability to accurately estimate traffic at end points is crucial for many network operations, including congestion management, induction control, bandwidth assignment, and application detection. As a result, resources can be distributed effectively, guaranteeing consistent service quality. As network complexity and traffic grow, it becomes more difficult to prevent and detect abuses. With this, we can determine whether the traffic projection is adequate. When it comes to wireless sensor networks, the power supply is king when it comes to service quality. To make these nodes faster and use energy efficiently, an accurate traffic forecast is required. Increases in both traffic and computing demands lead to higher power usage [5].

We look into a faster R-CNN based DL-strategy to vehicle dissection in this study. There are four steps to resolve this issue: (a) Optimization of results with extended topological active nets, (b) R-CNN initial refinement, (c) R-CNN based subnet operation for faster results, and (d) adaptable background model for faster results. One use of adaptive background modeling is the adaptive gain function. To fix problems with light and shadow, the gain function is used. In many cases, the topological active net deformable model improves segmentation accuracy [6]. When it comes to picture surfaces, deformable models provide a range of curvatures. Several forces, taking items of interest into account, achieve the smoothness from deformation. With this, it's easier to place items on the image's 2D surface mesh. The goal of minimizing energy is to distort the mesh. This method improves segmentation boundaries by combining the effects of all models. Type I and Type II mistakes are also included. When compared to other approaches, this one offers superior segmentation performance. Benchmarked datasets provide justification for the experimental hypothesis. Various sets of image datasets get respectable results when using the model.

The next steps outline the organization of this study. Section 2 presents the literature review. Sec 3 provides a comprehensive analysis of the computational approach. Sec 4 displays the outcomes of the simulation. Sec 5 concludes the whole thing.

II. Literature Review

Traffic signal control systems have long piqued the curiosity of researchers. Different traffic light control methods are the focus of studies on this subject. An urban traffic control system named SCATS was introduced in [7]. In the Sydney control room, there are a number of little computers that make up the system. In particular, it is a smart transportation system that uses sensors installed at traffic lights to identify vehicles in each lane and controls the timing of those lights in real time. To identify whether cars are around, this system employs induction loops. Not only is this control mechanism expensive to acquire and set up, but it also necessitates human intervention to remotely operate the system, making it vulnerable to interruptions caused by improper maintenance.

With the use of Internet of Things (IoT) technology, authors of [8] suggested a system that uses infrared (IR) sensors to measure traffic density and determine when the lights should be turned on and off dynamically. Their proposed method takes into account a certain threshold distance at which the sensor, via IoT technologies, identifies any vehicle that is within this distance. It becomes green when no one is using the other roadways. Their suggested approach is useful during off-peak time and conserves power during off-peak time, and the Internet of Things can assist with accessing components from far away. Their study has a major flaw: it doesn't take peak hours into account, which is crucial for traffic system regulation since that's when the majority of vehicles are on the road.

The durations of the traffic light signals were in [9], based on the discrete values of the activities. After gathering sensor data, they partitioned the entire junction into smaller grids. Finding out how long the green and red lights lasted from the data collected by these sensors is no easy task. The primary reason these algorithms perform poorly during peak traffic situations is that they do not take into account how the current phase time affects future traffic. Problems involving discrete states, as opposed to continuous ones, such traffic flows, are more suited to value-based approaches.

In order to use Q-learning in the continuous action domain, authors of [10], expanded on the concept. Despite the fact that their suggested approach might find policies with performance that could compete with established scheduling algorithms because of environmental dynamics, updating the policy required a full state sequence. A key consideration for continuous traffic flow is the complexity of the training process's convergence, but policy-based approaches are capable of handling continuous states. There is a lot of bias and volatility in this strategy as well. A decentralized and completely scalable MARL method for the advanced actor-critic (A2C) deep RL agent in the ATSC was proposed [11]. Additionally, they suggested two ways—the spatial discount factor and the fingerprint of nearby agents—to boost learning by making it more observable and easier for each local agent to learn. Their research proved that, when compared to competing decentralized MARL algorithms, the suggested approach was superior. Using prior research from several universities, Nicira Networks initially developed SDN. Its goal is to separate the control and data planes while allowing users to openly operate the hardware of the network, bringing devices and applications closer together. They utilize SDN to solve the mobility issue. The design specifications of OpenFlow have made it the most used SDN protocol at the moment [12].

The authors of [13] tackle the problem of failed or delayed handoffs in IEEE 802.11 networks that are based on software-defined networking. This research shows that SDN can improve network efficiency and traffic control by incorporating ML approaches. It demonstrates how software-defined networking (SDN) can improve network security while decreasing resource usage with the help of lightweight SAVI implementations. In order to optimize traffic and intelligently govern networks, they also investigate how SDN can be integrated with big data and artificial intelligence. The study aims the potential advantages of utilizing SDN and AI to improve traffic efficiency and achieve intelligent network control. In their study, authors [14] examine how failover affects both traditional and software-defined networks. As compared to traditional networks, SDN-based network management is more resilient and better able to handle interruptions. Management of networks using software-defined networking (SDN) in conjunction with load balancing and failover techniques is investigated.

III. Proposed Methodology

Using a Faster R-CNN based DL-ensemble method, this part highlights smart traffic vehicle supervision. Vehicle segmentation at various backdrop levels is fundamental to the traffic management research topic. To that end, we investigate Faster R-CNN, a system for intelligent traffic analysis. Data pertaining to decision-making processes is derived from segmentation operations on several smart traffic analytics strategic domains.

A. Dataset description

Various traffic circumstances are taken into consideration when preparing the datasets. Vehicle objects with several classes are initially taken into consideration. The dataset incorporates multiple difficulty elements, like traffic bottlenecks and overlapping automobiles. In general, two types of traffic scenes—high density and low density—are considered while creating datasets [15]. In the former, several objects are contained within a single image, whereas in the latter, each image only contains one class with no overlap. Images from both scenarios are separated into separate datasets for improved training. From a variety of less congested locations, we analyze the high density traffic scenarios. One thousand photos are created for six different types of vehicles.

B. Proposed method

Next, we will give you the rundown on the suggested technique, which is dubbed Fast R-CNN. Figure 1 shows the four steps of the approach, which are noted below.

(a) Optimization of results with extended topological active nets, (b) R-CNN initial refinement, (c) R-CNN based subnet operation for faster results, and (d) adaptable background model for faster results.

Using traffic video as input, adaptive backdrop modeling is employed to generate the background. In order to create a background model, the video frames are examined. Discovering the optimal background estimate is the goal at hand. This reduces the effects of lighting and shadow changes on the foreground model. At the outset, a small number of frames are initialized, and further updates are performed continuously. To get the foreground image, you have to go to the next series of frames. When setting up the backdrop model, the pixel values from the first frame are taken into account.

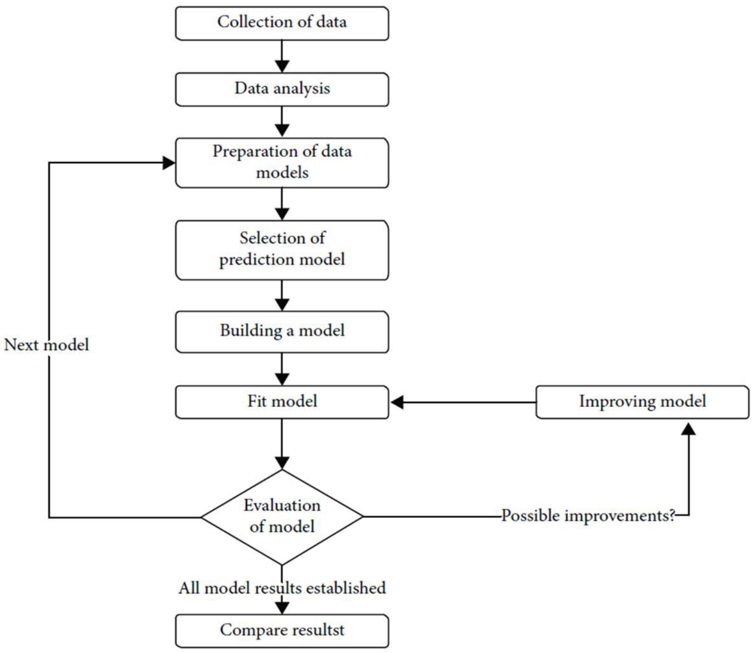

Fig. 1. The proposed model Architechture

In this case, the sinusoidal function's inflection point is handled by the Gain and _ parameters. With each frame, the background model is refreshed. When we remove the background from every scene, we get to the things in the foreground, since we consider the background to be adaptable. Following the implementation of adaptive background model based reduction, the fundamental Faster R-CNN architecture utilized throughout this study is introduced. Starting with the design of Faster R-CNN in Ref.5, we take into account a variation-based baseline.

C. Training process

Now let's take a quick look at the training procedure. The Faster R-CNN algorithm is used to train the data that has been annotated and enhanced. Lots of parameters are utilized for training, such as batch size, number of epochs required, and image resolution. The network is trained from the beginning, which means that the weights are initialized at random. Here, we may train the model with the originally trained COCO weights, which saves a lot of time and reduces computation. Using a Faster R-CNN with transfer learning that was taught originally yields the best weight values. To train the bespoke datasets mentioned, the Chaudhuri datasets are utilized as a benchmark. Here, the batch sizes under consideration. In addition, the epochs are now 100, 200, 300, 400, and 500. A range of 0.4 to 0.6 is used for the confidence levels. Objects in datasets are detected using the best weights. The evaluation pictures with bounding boxes and confidence values, as well as the anticipated labels, are also acquired.

D. Evaluation criteria

Important metrics for smart city evaluations include: investment efficacy, information flow solidity, infrastructure services, the intrinsic excellence of community benefits, and key process indicators that align with multiple community priorities across neighborhoods. In the "Experiments and results" section, we cover the several assessment measures that were utilized in this study to measure how well our strategy worked. The effectiveness and robustness of the suggested method can be determined with the aid of these metrics. In this case, recall values between 0 and 1 are used to calculate mean average precision (mAP). In addition, we also conduct a comparison study of the outcomes.

IV. RESULTS AND DISCUSSIONS

An in-depth analysis of the outcomes of the simulation is offered here. With a T4GPU, an IntelXeon CPU, and 64GB of RAM, we ran extensive experiments in Google Colab. In this study, the simulation tool employed was Python version 3.11.5. A number of cutting-edge detectors are tested to determine how well vehicle detection methods work. Taking accuracy and execution times into account, we also conduct other comparisons with the specified method. The COCO and DAWN datasets are used to train all of the techniques.

The COCO dataset uses real-world settings to detect and segment items. Images of one hundred distinct object kinds with three million instance labels make up the dataset. We use some YOLOv5 semantics. The aforementioned method, taking into account variations in luminance, accurately detects all cars. We compare the stated strategy to fourteen others, as shown in Table 1, to further establish its superiority. This section provides a concise summary of several key points. In terms of mAP values, the computational structure that is stated offers the optimum performance for photos with varying resolutions.In this case, COCO datasets show promise for the detection of various items. Included in this category are automobiles of varied dimensions. Figure 2 displays all of the outcomes. The performance of the procedure in question is studied and investigated using the DAWN dataset. 2000 images with various versions make up the DAWN dataset.

TABLE I. PERFORMANCE EVALUATION OF THE PROPOSED MODEL

Model	Inputsize	Multiscale	mAp(%)
CNN	512X512	False	49.1
R-CNN	512X512	False	48.23
VGGNet-16	800X800	False	43
ResNet-50	800X800	False	51.23
Proposed method	512X512	False	59.10

Fig. 2. Vehicle detection results of COCO dataset

It displays a wide range of traffic scenarios under various climates. Taking into account noteworthy observations, Figure 3 displays pretty detailed results. Every possible type of weather, including wet days, typical dry days, and snowy days, can be accommodated by the described strategy. The findings are compared to those in Table 2. Here are a few points to note. Has the most status in a fog. With regard to a wide variety of settings, we now offer some more findings from our study. This research delves into every state-of-the-art object detecting approach. This section provides a concise summary of the findings. We look into the BIT-Vehicle and UADETRAC datasets. Various datasets are examined, each with its own unique set of variables pertaining to road conditions, weather, and complicated background information.

TABLE II. COMPARISON OF MODELS ON DAWN DATASETS

Model	Fog	Rail	Snow	Dryday
CNN	25	21.52	39.34	24.14
R-CNN	27.56	22.4	29.19	18
VGGNet-16	23.89	28.41	34.56	24.56
ResNet-50	29.1	27.56	33.62	24.61
Proposed method	32.14	45.55	46.31	26.62

Fig. 3. Vechile detection results on DAWN datasets

TABLE III. PERFORMANCE METRICS

Dataset	Acc(%)	Sp(%)	Se(%)	Pe(%)	F1
HDD	98.3	98.2	96.7	97.2	97.4
LDD	96.7	97.4	96.8	97.3	96.8
COCO	97.2	97.5	97.6	96.43	97.4
DAWN	97.3	97.6	97.2	97.3	98.65

Between the actual values and the expected bounding box adjustment, there is a smooth L1 loss, which is the localization loss. In bounding-box regression, the coordinate-correction transformation is the same as R-CNN. How likely it is that an object is included within the bounding box is represented by the confidence loss. The predicted and ground truth bounding boxes are used in the logistic regression procedure to determine it. In Table 3, you can see the findings reinforced by the values of specificity (SP), accuracy (Acc), sensitivity (Se), precision (Pe), and F1-score (F1). To further emphasize the importance of the results, Figure 4 shows how our method compares to others using the structural similarity-index, spatial-overlap distance, and hausdroff distance metrics.

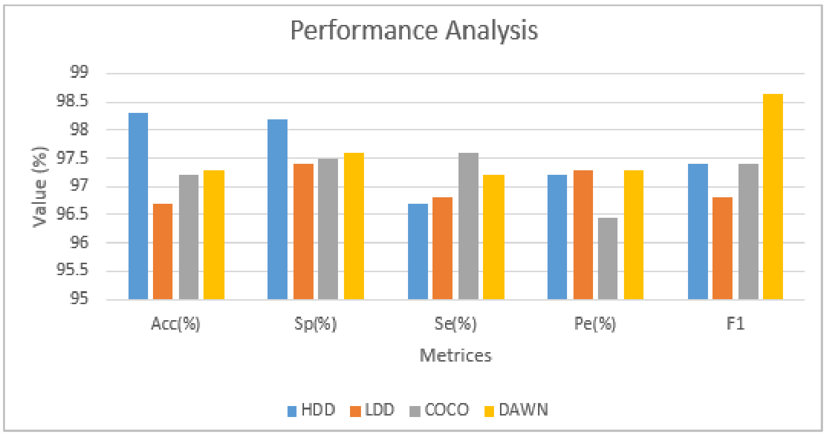

Fig. 4. Performance metrics of the proposed models with different dataset

V. CONCLUSIONS AND FUTURE WORKS

This study investigates the use of a faster R-CNN based DL-strategy to intelligent traffic management of cars. This subject has proven to be extremely challenging in the subject of artificial intelligence and computer-vision. This challenge gets even more complex when there are occlusions, backdrop clutter, and traffic with density changes. Optimization of results with extended topological active nets, faster R-CNN initial refinement, faster R-CNN based subnet operation, and optimization with an adaptive background model are the four stages that make up the computational paradigm. A key component of this system is adaptive background modeling. Also handled are matters pertaining to light and shadow. Deforming the mesh aids in reducing energy use. Using a tweaked version of the protracted topological active net improves the segmentation accuracy. Investigational outcomes establish the method's superiority over alternative approaches. Various performance indicators were used to accomplish this, including F1, Acc, Sp, Se, and TypeI &TypeII mistakes. When we compare our method's performance to that of other approaches using metrics like structural similarity-index, spatial-overlap distance, and hausdroff distance, the results become even more noteworthy.

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