Traffic Management System Based On Image Processing and AI

1st Abdul Aziz
Computer Science Department
Chandigarh University
Mohali, India
abdulaziz99289@gmail.com

2nd Anmol Aneja
Computer Science Department
Chandigarh University
Mohali, India
anmolaneja47@gmail.com

3rd Rishab Tiwari
Computer Science Department
Chandigarh University
Mohali,India
iamrishabtiwari@gmail.com

4th Prince Verma
Computer Science Department
Chandigarh University
Mohali, India
2002princeharshverma@gmail.com

5th Er. Khushwant
Computer Science Department
Chandigarh University
Mohali, India
khushwant.e14423@cumail.in

***Abstract*—In today's modern world there are a lot of factors which are responsible for the increase in the pollution level in the atmosphere, and one such reason is traffic congestion, and not only it contributes in the increase in pollution level but it also plays a vital role in the increase of noise pollution. To tackle this issue, machine learning and Artificial Intelligence can be used to develop effective traffic management systems that will not only reduce the traffic congestion but also eventually lead to a decrease in the level of carbon footprints. This review paper analyses the latest developments in AI for the improvement of traffic management and providing in depth knowledge of technologies, difficulties and future scope in this field. We study in detail about key AI techniques such as Machine learning, image processing, integration of IOT and further discuss their usage in traffic surveillance so that we can achieve the end results that we are targeting. This review paper also highlights the benefits of an AI powered traffic management system, such as reducing congestion on roads, improving vehicle as well as human safety, and also tackling the privacy and ethical concerns. The old school system of management has become a huge task in today's modern world, and automating the system can really reduce the workload of government and human operators. It also paves the way for making insightful decisions which results in the reducing the effects of accidents and chronic traffic jams on raod-ways. This review paper outlines an ideal way of monitoring real time traffic using image processing and Artificial Intelligence.**

***Index Terms*—insert, style, formatting, component, roadways**

I. Introduction

A long-term challenge in the transportation engineering has been monitoring it efficiently. A majority of traffic control centers are still totally operated by human operators, who have the burden to manually monitor the traffic flow and incidents occurring on the roads, and this whole process consumes a lot of time and a large amount of labor to be executed. Humans are prone to errors and fatigue, and this may result in an inconsistency of the outcomes. In order to the reducet he workload placed on human operators and raises output efficacy, automated traffic monitoring solutions need to beput to use, consisting of modern technology. It is important to note that vision-based cameras are commonly used for traffic surveillance by the Traffic Management Centers, but they require human supervision, and it's tough to always keep an eye on the traffic, parked cars, and count the vehicles accurately. And hence these TMC have been working to automate their systems. AI powered traffic monitoring systems not only have the capacity the to the manage the traffic efficiently, but also the monitor the roads actively to reduce the unfortunate disasters. An AI-powered traffic management system can easily identify the movement of any vehicle present on the road and manage the traffic accordingly in an efficient way, and also lower down the number of road disasters. It can also easily spot any rash driving behavior such sudden lane changing and over speeding. In recent times there has been a lot of research on traffic monitoring based on machine and deep learning. There is a lot of limitations when we involve human coordinators in tasks such as calculating vehicles or measuringthe traffic density, and thus it becomes a necessity to include Artificial intelligence in our systems.

II. Background

In urban areas traffic congestion has been always a general/common issue, causing a loss in both economic and environmental terms. The Traditional traffic management systems have not been able to keep up with the growing needs of urban areas, to address that challenge Artificial Intelligence (AI)has emerged as a game changer offering efficient solutionsto manage the traffic, reducing carbon footprints, and also at the same promoting safety protocols.

III. OBJECTIVE

This paper reviews how AI helps control traffic. We look at how machine learning, computer vision, and the Internet of Things (IoT) are used in traffic management. We also talk about the good things and the problems that come with these systems, and how they might change cities. As more andmore vehicles are being used, it's become really importantto manage traffic properly. Sadly, when traffic isn't managed well, it can lead to accidents and even deaths. In India in 2021, there were over 400,000 accidents, and nearly 154,000 of them resulted in deaths. In India, roads are the cheapest wayto get around, so we need a good way to organize traffic. In thepast, people-controlled traffic with traffic lights in some places,but there aren't enough people to manage all the traffic on the roads. In 2017, there were about 200 million registered vehicles, but only about 72,000 traffic police to manage them all. According to data, cities like Mumbai have really bad traffic jams. On August 10, 2022, Mumbai had its worst traffic jam ever.

IV. Literature Review

A- Deep Learning Methods for Traffic Monitoring Traffic monitoring systems usually use two main methods: a three- step approach and a one-step method. Willis et al. studied how to spot traffic jams by means of deep neural networks and traffic images. They used a special network trained with Google Net to do this. Another team, Chakraborty et al., used deep learning and YOLO algorithms to analyze traffic images in different settings. Morris et al. created a way to measure traffic queues at intersections using video feeds. They used techniques like clustering and background removal to detect cars. Fouladgar et al developed a decentralized system where each part of the system predicted traffic congestion based on nearby areas. This system could handle different traffic patterns and was designed to grow as needed. Ma et al. suggested a deep learning model to analyze traffic data over time and space. They used neural networks to spot patterns and predict traffic jams. Wang et al. did something similar, using different model to forecast traffic speeds and find congestion spots on city roads. Carli et al. proposed a way to study city traffic using GPS data. We also talk about a video-based system for monitoring congestion, which is cheaper but not as precise as GPS. Since traffic jams are common in cities, it's important to find ways to design better transportation systems. In the field of intelligent transportation systems, there are popular methods for detecting objects like cars. We mention some of them, like Mask R-CNN and YOLO. But there's a newer one called Center Net that hasn't been used much in this field yet. Center Net is fast and efficient, making it great for real-time detection. The authors ofthis study tried using Center Net for counting objects in traffic, which could lead to more research in this area.

B-Traffic Analysis using Image processing-based camera system: Most methods for counting cars in traffic scenes fall into two main types: detection instance counters and density estimators. Detection instance counters find each car individ- ually before counting them, which can be tricky because it means looking at every single pixel in the image. Density estimators, on the other hand, estimate the overall density of cars in an area and then count them. They're not as versatile as detection instance counters, but they don't need as much training data. Some researchers, like Chiu et al., have developed systems that can spot, track, and count cars in traffic pictures automatically. They use algorithms to figure out if a car is moving or stationary and then count them based on their shape. Others, like Zhuang et al., use statistical methods with traffic cameras to count cars and estimate traffic flow. They've come up with different techniques, like using Gaussian models or origin-destination matrices. Mundhenk et al. took a different approach by using a deep neural network called ResCeption to count cars from overhead images. This network is good at spotting and categorizing cars quickly and accurately. Compared to other methods, it's better at getting precise car counts.

V. EXISTING APPROACHES

In recent years, plenty of vision-based approaches to keeping track of traffic are being examined. We undertake an initial glance at many works covering anomaly detection, overcrowding prediction, and traffic counting.

A. Machine Learning for Traffic Prediction In order for authorities to predict traffic congestion and make more effective traffic management plans, machine learning algorithms play a vital role in traffic forecasting. The implementation made use of multiple machine learning techniques, such as neural networks, decision trees, and ensemble methods, in traffic prediction models is covered in this section.

B. Computer Vision for Traffic Surveillance Through the analysis of video feeds, computer vision technologies allow for real-time surveillance of traffic situations. We explore the application of object detection methods, convolutional neural networks (CNNs), and video analytics in traffic surveillance and examine their potential to enhance incident detection and traffic management.

C. IoT Integration for Traffic Control This gathering of measurements emerges from a variety sensors, including traffic lights, environmental sensors, and vehicle detectors, through the help of Internet of Things (IoT) based devices. This section investigates how IoT technology can be incorporated into traffic management systems to improve overall traffic flow, optimize signal timings, and lessen congestion.

D. Faster R-CNN A method for detecting objects in images, known as Faster RCNN, operates in two main steps. It uses both local consensus network rpn and network discovery to achieve it. The RPN predicts both the boundaries of objects and their corresponding scores at various locations simultaneously. Faster RCNN leverages the advanced region suggestions provided by the RPN's comprehensive training to make accurate object predictions. Compared to the previous Fast RCNN method, Faster RCNN excels in recognition of objects employing the more robust RPN in lieu of the selective search methodology. Each image is initially split by the procedure into portions that are easier to manage. Thus following this, these sections undergo a series of convolution filters to extract important features. These features are then fed into a classifier, which evaluates the likelihood of objects being present in each area of the image.The model is trained with a focus on recognizing pedestrians, cyclists, buses, trucks, and cars. This focused training improves its accuracy

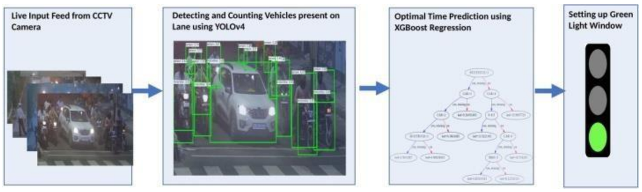

Fig. 1. YOLO: Capturing Traffic Congestion

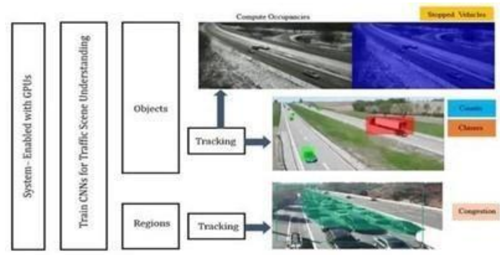

Fig. 2. Visual Representation Of Traffic Congestion

in making predictions, particularly when analyzing videos captured by traffic cameras.

E. Mask R-CNN Faster R-CNN is an expansion of Mask R-CNN, which stands for Mask-region based Convolution Neural Network [13]. Faster R-CNN can perform jobs that Mask R-CNN can as well, but it also adds superior masks and divides the region of interest pixel-by-pixel. This study's model, which is built on the Feature Pyramid Network (FPN), runs on the resnet101 backbone. ResNet101 acted as the model's feature extractor in this instance. The typical feature extraction pyramid was enhanced by the addition of a second pyramid that extracted higher level characteristics from the first pyramid and subsequently passed them over to lower tiers while employing FPN. This made it possible for features at any level to access both higher- and lower-level characters. In this investigation, 50 validation steps were used, and the minimum detection confidence rate was set at 90%. Each image was cropped to the shape of a square using an image centric training technique. When the photos passed via the backbone network, they were changed from 1024 px by 1024 px by 3 (RGB) to a feature map with the dimensions32 px by 32 px by 2048. Each of our batches had a single image and a total of 200 trained Regions of Interest (ROIs)for each image. The model was trained on an NVIDIA GTX 1080Ti GPU with a learning rate of 0.001 and a batch size of 1. Throughout the iteration, a continuous learning rate was applied. Similarly, a learning momentum of 0.9 and a weight decay of 0.0001 were applied. The model took roughly 3hours to train in total using a sample dataset.

F. YOLO: You Only Look Once (YOLO) is a cutting- edge object detection technique that revolutionizes traditional algorithms by examining the image only once to identify objects. Unlike conventional methods that repeatedly analyze an image at various scales and locations, YOLOv4, utilized in this research, efficiently performs vehicle detection, counts, and queue formation comparisons in traffic scenarios. YOLO streamlines object detection by employing a single CNN to predict multiple bounding boxes and their associated class probabilities simultaneously. This approach drastically reduces processing time, with typical YOLO model builds taking between 20 to 30 hours, utilizing similar hardwareresources as Mask R-CNN for training.

G. CenterNet: CenterNet is an advanced object detection framework that operates with reduced computational costs while achieving superior precision and recall scores. Unlike its predecessor, CornerNet, which relies on pairs of corner key points for object detection, CenterNet identifies objects as triplets, enhancing its ability to capture a more comprehensive perspective of objects within images. By leveraging central key points in addition to corner key points, CenterNet gains a deeper understanding of object positioning and classifica- tion, leading to more accurate detections. The architecture of CenterNet involves generating corner key point heatmaps and a central key point heat map using a CNN backbone. This design, incorporating cascade corner pooling and center pooling modules, enhances the model's ability to recognize visual patterns and accurately locate objects' central regions. Ultimately, CenterNet predicts bounding boxes based on de- tected corners and embeddings, leveraging central key points to refine and establish final bounding box predictions. This innovative approach makes CenterNet a robust single-stage detector, combining the benefits of RoI pooling with enhanced object analysis capabilities for efficient object detection in complex traffic environments.

H. Detection of Stationary Vehicles The methodology pro- posed for identifying stationary or immobilized vehicles is illustrated in Figure 5. Initially, a pre-trained YOLO model designed for vehicle detection is employed to initiate the process. Subsequently, detections are refined by tracing the trajectory of each vehicle across traffic scenes using the Intersection over Union (IOU) technique. This tracking data is then utilized to delineate specific travel directions (such as east, west, north, or south), classify the type of roadway under observation (e.g., intersection or highway), and estimate the speed at which the tracked vehicles are moving. After the tracking phase, distinct travel directions, road types, and estimated vehicle speeds are identified. The model can flag a vehicle as stationary on certain road types if its speed remains below a predetermined threshold for a spec-ified duration of time. This comprehensive approach ensures accurate detection and classification of stationary vehicles, enhancing the overall effectiveness of traffic monitoring and management systems.

VI. RESULT AND DISCUSSION

Here, we present the outcomes of our evaluation regarding the traffic backlogs detection, Anomaly detection system, and Automatic vehicle counts.

A. Traffic Queues Detection To assess the performance of

Fig. 3. Traffic Queue Detection

Traffic queues detection, we utilized 1000 traffic camera images, comprising 500 congested scenes and 500 uncongested scenes. Our evaluation involved comparing the performance of Mask R-CNN with a traditional YOLO framework. We employed standard performance metrics such as precision, recall, and accuracy, represented by Equations (1), (2), and (3) respectively. Additionally, we conducted a real-time implementation of Mask R-CNN at an intersection, showcasing its effectiveness in detecting traffic queues. The amount of waiting time at an intersection was measured using the Mask R-CNN framework. The beginning and end of queues are clearly depicted by the heat map. Both the AM and PM peak hours may be seen on the intersection's heat map.

B. Vehicle Count The integration of Intelligent Transportation Systems (ITS) has revolutionized vehicle counting methods, moving from traditional loop detectors to advanced vision-based systems. While loop detectors offer precise traffic counts, they struggle with vehicle type identification and can be intrusive. In contrast, vision-based systems, being non-intrusive, can accurately count various vehicle types with high confidence levels. Accurate vehicle counts are crucial for Traffic Management Centers (TMCs) and transportation organizations, enabling them to optimize daily operations, calculate journey times, and make informed traffic projections. This data is instrumental in making strategic decisions to improve traffic flow on different road segments. This study aims to develop a single-view vehicle counting system capable of automatically counting and categorizing vehicles passing through a road segment. Utilizing object detectors and trackers, vehicles are accurately located to generate precise vehicle counts. Equation (4) defines the Intersection over Union (IOU) threshold set at 0.5 for the trackers, ensuring accurate vehicle tracking and preventing duplicate counts.

C. Autonomous Vehicles The fusion of autonomous vehicles and AI-driven traffic management technologies holds immense potential for revolutionizing urban mobility. This section delves into the capabilities of AI in orchestrating self-driving vehicles and its profound impact on traffic control systems.

D. 5G Connectivity The emergence of 5G technology presents a transformative opportunity to enhance the capabilities of AI-powered traffic management systems. With its ability to facilitate real-time data transfer and expedite decision-making processes, 5G holds immense potential in optimizing traffic management strategies. This section delves into the synergistic relationship between 5G connectivity and AI in revolutionizing traffic management.

VII. Conclusion

Traffic management systems powered by artificial intelligence (AI) present a viable approach for addressing the long-standing issues related to urban traffic congestion. These systems provide creative solutions that have the potential to improve urban mobility, lessen congestion, and enhance overall quality of life through the adding up of ML, CV, Internet of Things (IoT) based technologies. As this review has shown, there are many different uses of AI in traffic management, each of which has advantages, drawbacks, and potential applicationsin the future.

Congestion reduction is one of the main advantages of AI powered traffic management. Authorities can identify traffic bottlenecks and prepare preventive measures thanks to machine learning-based traffic prediction algorithms. As a result, commuters' travel times are shortened, and fuel consumption and greenhouse gas emissions are reduced. The use of AI technology into traffic management systems enables dynamic adjustment of signal timings, improving intersection safety and easing traffic flow.

The increase in safety is a significant advantage of AI in traffic management. Computer vision-based AI-driven surveillance systems are able to monitor and respond to situations in real time. Artificial intelligence (AI) improves emergency response and lowers the possibility of additional accidents by quickly identifying accidents and potential threats. This not only prevents deaths but also lowers the societal and financial consequences of road accidents.

AI helps the environment be more sustainably developed by supporting eco-friendly sources of transportation and streamlining traffic patterns. Vehicles can be rerouted using traffic optimization algorithms to ease congestion and use less fuel. AI can also promote the usage of bicycles, carpooling, and public transportation, which will lessen the carbon footprints of urban transportation networks.

But there are issues and difficulties in integrating AI into trafficcontrol systems. Due to the considerable data collection involved in these systems, privacy issues must be carefully considered. To ensure justice and accountability, algorithmic bias and transparency issues need for vigilant scrutiny. Additionally, communities must balance the advantages of using AI in traffic control against the associated expenses. This requires large infrastructure investments.

The potential for AI in traffic control is bright in the future. The fusion of AI with autonomous driving has the potentialto completely change urban transportation. Self-driving cars and AI-powered traffic control systems working together can improve energy efficiency, further reduce accidents, and improve traffic flow. By enabling real-time data transfer and quicker decision-making, which is especially important for managing the constantly-changing dynamics of urban traffic, the implementation of 5G connectivity will further improve the capabilities of AI. Finally, AI-driven traffic management systems have the potential to significantly advance the creation of smarter, moreeffective, and sustainable urban settings. Cities can fully utilizethe promise of AI to lessen traffic congestion, improve safety,and advance environmental sustainability by tackling the is-sues of privacy, ethics, and infrastructure costs. Embracingand properly controlling the revolutionary power of artificialintelligence in traffic management is the key to a future withmore efficient traffic flows and safer roads. This analysis showsthat there is countless potential for good change as cities expandand technology advances.

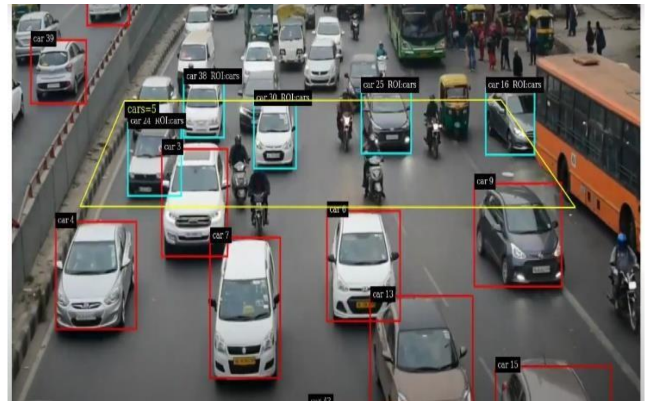

Fig 4: Computer vision Traffic Detection

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