International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Smart Roads, Smarter Cities: Machine Learning Integration for Dynamic Traffic Management

Cecil Johny[1] and Dr. Amrita Sharma[2]
[1]Indus University
ceciljohny.20.rs@indusuni.ac.in
[2] Indus University
amritasharma.dcs@indusuni.ac.in

Abstract— As the world's cities become more urbanised, traffic congestion becomes a major problem. Conventional approaches are unable to deliver timely insights, which impedes the application of efficient congestion control strategies. This study presents a novel machine learning-based traffic congestion control system that combines a Euclidean distance tracker with the YOLO (You Only Look Once) object recognition framework. As cities struggle with the intricacies of increasing traffic, the need for intelligent technologies capable of real-time vehicle surveillance and congestion analytics is highlighted. To address this, the suggested solution goes beyond traditional constraints by using machine learning to accurately detect and track automobiles in urban environments. Utilizing the YOLO object detection framework, which is renowned for its speed and accuracy, the study builds on prior research in computer vision and transportation engineering. By connecting object detections between frames, the Euclidean Distance Tracker improves performance and allows a continuous comprehension of vehicle motions. The system's effectiveness in real-world circumstances is demonstrated by the results, which offer high accuracy across a range of vehicle classes. A major advancement in the development of urban mobility has been made with the integration of YOLO and the Euclidean Distance Tracker, which offers a viable solution for intelligent traffic management.

Keywords— Urbanization, Traffic congestion Machine learning ,Intelligent transport systems, YOLO (You Only Look Once),object detection, Euclidean Distance Tracker, Real-time vehicle tracking, Adaptive traffic control

I. INTRODUCTION

Urbanization's continuous growth has created previously unheard-of difficulties for traffic management, with congestion becoming a major problem in today's cities. For most individuals, traffic congestion has become a major issue since it causes air pollution, noise, and time wastage. Because the current traffic signal system follows a predetermined time length schedule, it is insufficient to manage the problematic traffic congestions. With the advent of the internet of things, new models of intelligent traffic light systems have been introduced recently. These models use a variety of approaches, including radiofrequency identification, ultrasonic modelling, and predictive modeling[27]. Addressing this challenge requires innovative approaches that harness the power of advanced technologies. This research introduces a novel system for traffic congestion control through the integration of machine learning, specifically employing the YOLO (You Only Look Once) object detection framework and a Euclidean Distance Tracker. The requirement for intelligent systems with real-time vehicle tracking, detection, and congestion analytics is growing as cities struggle to handle the complexity of additional vehicles on the road.

The urgent need for precise and effective traffic control techniques that can adjust to changing urban surroundings is what motivated this work. It is frequently not possible to obtain real-time insights into traffic conditions using traditional approaches, which makes it more difficult to put responsive congestion control measures into place. By using machine learning to precisely identify and track automobiles as they travel through urban thoroughfares, the suggested system seeks to get beyond these constraints. The system provides a comprehensive solution for traffic flow monitoring and management by fusing the tracking capabilities of the Euclidean Distance Tracker with the effectiveness of YOLO for real-time object detection.

The basis for this research was established by previous research in the domains of transportation engineering, machine learning, and computer vision. The foundation for identifying and categorizing different kinds of vehicles is the YOLO object detection framework, which is well-known for its quickness and precision. By linking object detections from successive frames, the Euclidean Distance Tracker improves the system's performance and allows for a continuous comprehension of vehicle motions.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

In order to create more responsive and effective urban landscapes, machine learning integration is becoming increasingly important as cities want to be resilient and adaptive in the face of changing traffic patterns[26]. Thus, this research highlights the groundbreaking potential of machine learning in reducing the problems brought on by modern urbanization, in addition to advancing our technological grasp of intelligent traffic solutions. Our goal is to make a comprehensive contribution to the field by pushing the boundaries of intelligent transport systems and shaping the direction that urban mobility will take in the future.

This paper's latter sections explore the methods used, the experimental outcomes from both static images and real-time video streams, and a thorough analysis of the system's advantages and disadvantages. The research presented here adds to the growing body of knowledge on intelligent transport systems by shedding light on how machine learning can be used to manage traffic congestion. The incorporation of cutting-edge technologies into traffic management systems is a crucial step towards building smarter, more adaptable cities as urbanization continues its unstoppable upward trajectory.

II. RELATED WORK

In [1] two distinct approaches for vehicle identification and categorization are used. In the first approach, a Support Vector Machine (SVM) classifier is coupled with a Mixture of Gaussian (MoG) classifier. Only the quicker Recurrent Convolutional Neural Network (RCNN) is used in the other technique. Nonetheless, a sizable portion of automobiles remained undiscovered. In [2], experts created a traffic congestion status perception model by using Random Forest Classification algorithm of machine learning. The RFC has an 87.5% prediction accuracy, good efficiency, and great robustness. Furthermore, the generalization error is brief and effectively predictable. This research has limits since more reliable and accurate results could be obtained using different machine learning techniques.

A system for detecting traffic congestion on roads utilizing an opinion poll, Webcam and Global Positioning System was created by the authors in [3]. The movement patterns of the vehicle were retrieved using the sliding window approach and fed into a J48 and Artificial Neural Network (ANN). With an accuracy of 91.29%, the J48 model outperforms the suggested FITCCS-VN that makes use of machine learning techniques.

The authors of [4] developed a traffic monitoring system based on unmanned aerial vehicles (UAVs) using a convolutional neural network (CNN). Using traffic images captured by the UAV's camera, the system demonstrated an accuracy rate of 91.67% under the given traffic conditions.

In[5], the model automatically detects and classifies automobiles using a K-nearest neighbor classifier. Windows and other hollow sections of the vehicle are built to identify it as a car or motorcycle for feature extraction purposes. Conditions with high traffic and wider perspectives are not compatible with this model.

The authors of [6] created a Long Short-Term Memory and convolutional neural network framework-based data-fusion-based TCCS. Spatial data was classified using CNN. For historical data, LSTM exhibited an accuracy and miss rate of 92.3% and 7.7%, respectively, although ML techniques might provide superior outcomes.

Convolutional neural networks have been employed by the YOLO method in [7]–[9] for object detection. It uses a single image to create a single neural network. picture from a crossroads By applying object identification and image processing, real-time traffic density is computed using CCTV cameras as an input. Vehicles are categorized into various classes, which include trucks, cars, bicycles, and buses. Each class's vehicle count is used to determine the traffic density. This density is used by the signal switching algorithm to calculate when each lane's green signal will occur. The red signal timings will show this. The green signal timing is restricted to the greatest and lowest value to prevent lane starvation. This algorithm's inability to recognize small objects is a concern.

The authors of[10] described how to use a convolutional neural network (CNN) to categorize automobiles. A dataset of aerial images is used. The suggested model uses motion changes, feature matching, and heat maps to first identify whether or not there are any vehicles in the region. Subsequently, AlexNet and the Inception-v3 classification layer are used for the classification.

In [11], traffic optimization is achieved by using a genetic algorithm. Factors such as traffic phase, cycle, and traffic light green time are employed as chromosomes. To optimize traffic signal control, a fitness function is employed to minimize the number of cars in queue or the overall network wait time. GA has been employed in the study in [12] to identify alternate routes that aid with easing traffic congestion. The best outcome was found after 40 generations in less than 2 seconds, according to the results.

The authors of[13] provide a Yolov5-based real-time vehicle detection system. The attention mechanism and the novel idea of ghost convolution are added to the current model to make it better. The YOLO model's effectiveness in object detection models is demonstrated by the testing results.

In[14], a novel method for detecting and categorizing cars combines Long Short-Term Memory (LSTM) and You Only Look Once (YOLO). During the pre-processing phase, the images are divided into binary labels in order to lower the model's complexity. Additionally, the bounding boxes are tallied for the detected vehicles, and they are divided into lightweight and heavy-weight categories.

In [15] [16], the Q-learning technique was used for function approximation-based traffic signal control. An approximate state action-value function is constructed using a feedforward neural network that has been trained by backpropagation. The longest queue first strategy was tested on a grid with five intersections. The longest queue first strategy was outperformed by Q-learning using a function approximation method.[25]

[11] uses fuzzy logic and contrasts it with the Webster model. [25]The quantity of lanes, cars, and green lights are considered as variables for making decisions. The outcomes demonstrate that the flexibility of fuzzy logic has lowered typical waiting times by 50%. Fuzzy input parameters in [17], [18] include the quantity of cars gathered and the traffic volume on the arrival and queue sides of the intersection.

When the classification framework was used for vehicle identification, it was discovered to operate well (a significant number of positive samples were accurately detected). Image recognition has made extensive use of the HOG feature in conjunction with the SVM classifier [19], and pedestrian identification has been greatly successful with this combination.

The online integrated estimation of important model variables and traffic flow parameters is one of the traffic state estimator's most novel features. Prediction using the Gaussian process is non-parametric. A multi-output Gaussian process was applied to the complex spatiotemporal patterns of partial traffic acceleration data in [20][25]. Guitar is a geographical routing system based on intersections, specifically crafted to identify resilient routes tailored for effective navigation in urban environments. Utilizing the Global Positioning System (GPS) and considering street density and orientation, [21] employs an optimization approach in the vehicle routing system. The findings indicate that the predictive accuracy of the combined model surpasses that of a single Support Vector Machine (SVM) model, particularly in situations where traffic flow speed is relatively low and undergoes significant fluctuations. Bus trip timings were forecast using Support Vector Machines (SVM) with a decay factor to switch the weights between old and new data. The test results demonstrate that the SVM with the adaptive algorithm and decay factor performs better in terms of prediction accuracy and dynamic performance than other existing algorithms.

To better predict Traffic, the author in[22] combines three sets of weather-related parameters with machine learning techniques. Three machine learning techniques are used in this study: ANN, SVM, and KNN. It can be challenging to select the optimal ML model for a particular set of data, though. This study demonstrates the impact of choosing each essential element of three machine learning algorithms on prediction accuracy. KNN performs better than SVM and ANN.

Based on past traffic data, the author suggested an Artificial Neural Network (ANN) in [23] to predict short-term traffic flow. The features that are considered include traffic volume, speed, density, and the time of day and week. The speed of each type of vehicle is employed as a separate input variable in this study as opposed to previous research in the literature that used the average traffic flow speed as an input variable. The findings show that the Artificial Neural Network performs reliably even when the TFP time interval is increased from five to fifteen minutes, and it generates acceptable outcomes even when the individual vehicle speeds are taken into account as input variables.

III. METHODOLOGY

This comprehensive methodology encompasses the configuration of the YOLO model, integration of the Euclidean Distance Tracker, real-time video and static image processing, and the logic for vehicle counting and classification.

A. Data Collection and Preprocessing

Gathering a dataset of pictures and videos featuring different kinds of cars in various driving scenarios is the first step . To make sure they are appropriate for input into the YOLOv8 model, the photos and videos undergo pre-processing. This involves normalizing the pixel values, scaling the photos and videos to the appropriate dimensions, and enriching the data to make it more expansive and diverse.

B. YOLO Architecture

After receiving an image as input, the YOLO algorithm employs a basic deep convolutional neural network to identify objects in the image. By inserting a temporary average pooling and fully connected layer, ImageNet is used to pre-train the model's first 20 convolution layers. Then, as other studies have shown that incorporating convolution and

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

connected layers into a pre-trained network enhances performance, this pre-trained model is transformed to conduct detection. The last fully connected layer of YOLO predicts bounding box coordinates as well as class probabilities. An input image is divided into a S × S grid by YOLO.

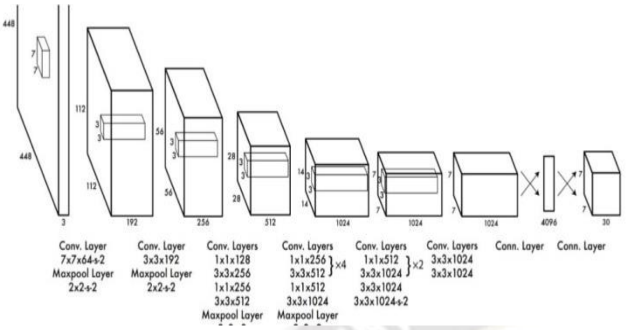

Fig 1. YOLO architecture[24]

A grid cell is responsible for detecting an object whose centre lies inside it. For every grid cell, the anticipated B bounding boxes and confidence scores for those boxes are provided. These confidence ratings reflect the correctness of the projected box as well as the model's degree of confidence that the box contains an object. YOLO produces multiple bounding box predictions for every grid cell. During training, we only want one bounding box predictor to be in charge of each item. YOLO assigns a predictor as "responsible" for an object prediction based on whose prediction has the higher current IOU with the ground truth. The bounding box predictors consequently grow more specialised. Each predictor improves the recall score overall by improving its capacity to forecast particular object sizes, aspect ratios, or classes. One important technique in the YOLO models (NMS) is non-maximum suppression. NMS is a post-processing technique that improves the accuracy and efficiency of object detection. In object detection, it is common custom to create many bounding boxes for a single object in an image. Even though some of these bounding boxes may overlap or be in different places, they all represent the same item. NMS is used to identify and remove erroneous or superfluous bounding boxes from the image, as well as to extract a single bounding box for each item.

C. Euclidean Distance Tracker

The Euclidean Distance Tracker in the provided code serves as a crucial component for object tracking across consecutive frames in a video stream. In this implementation, the tracker functions by associating each detected object with a unique identifier based on its position, specifically the center coordinates of the bounding box. For each frame, the tracker calculates the Euclidean distance between the current object's center and the centers of previously tracked objects. If the distance is below a certain threshold, the tracker updates the object's position and maintains its identifier, ensuring continuity in tracking. This mechanism effectively handles scenarios where objects persist in the video stream, allowing the system to recognize and follow their trajectories. Additionally, the tracker aids in preventing duplicate identifications of the same object, contributing to the accuracy and efficiency of the overall object detection and tracking process. The Euclidean Distance Tracker thus plays a pivotal role in providing seamless and consistent tracking of objects, enhancing the robustness of the system for real-world applications such as traffic monitoring and vehicle counting.

D. Real-time video processing

The code provided performs real-time video processing by employing the Euclidean Distance Tracker and the YOLO object recognition model to analyze video frames in a dynamic and continuous manner. With the use of the OpenCV library, frames are taken, scaled, and input into the YOLO model for real-time object recognition; the Euclidean Distance Tracker makes sure that objects are tracked smoothly between frames. With the help of this real-time processing capacity, traffic scenarios may be monitored in real time, enabling accurate vehicle counts and classification. The system is a useful tool for intelligent traffic management and surveillance applications in real-world settings because of its effectiveness in processing changing scenarios and its capacity to deliver rapid insights.

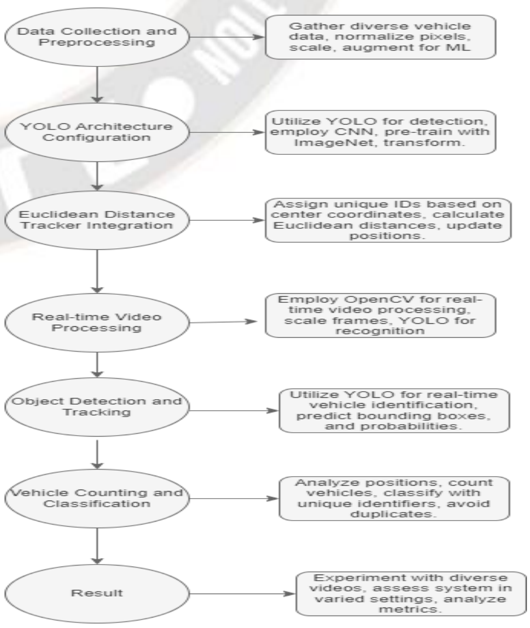

Fig. 2 Flow of the system.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

E. Object detection and tracking

Object detection and tracking in the provided code involve utilizing the YOLO model for real-time identification of vehicles in urban traffic scenarios. YOLO efficiently predicts bounding boxes and class probabilities, enabling simultaneous detection of multiple objects. Subsequently, the Euclidean Distance Tracker ensures seamless tracking by assigning unique identifiers to detected objects based on their center coordinates. This tracker employs Euclidean distance calculations to match objects across frames, preventing duplicates and ensuring continuous tracking. Together, these components create a robust system for real-time object monitoring and tracking, forming the basis for effective traffic management and vehicle counting in dynamic urban environments.

F. Vehicle counting and classification

Vehicle counting and classification in the code are accomplished by analyzing the bounding box positions of detected objects. The system employs a logic that categorizes vehicles based on their position relative to predefined lines, determining their direction. Unique identifiers assigned by the Euclidean Distance Tracker aid in avoiding double counting. The code maintains separate counts for various vehicle classes, including cars, motorbikes, buses, and trucks. This integrated approach ensures accurate counting and classification, providing valuable insights into traffic patterns and contributing to the effectiveness of the intelligent traffic management system.

IV. EXPERIMENT AND RESULT ANALYSIS

This study's experimental design made use of a variety of video datasets that were taken from a traffic surveillance camera. The dataset included a variety of settings, including varied vehicle kinds, lighting conditions, and traffic density, with the goal of simulating real-world traffic scenarios. The chosen video stream offered a representative sample that could be used to evaluate the suggested real-time vehicle monitoring and counting system's generalisation potential and resilience. The application made use of the YOLO (You Only Look Once) object identification model, which was set up especially to identify different types of vehicles, such as trucks, cars, motorcycles, and buses. The Euclidean distance tracker was easily incorporated into the system to provide identified vehicles distinct identities and enable tracking of those vehicles across a series of frames.

The suggested real-time vehicle tracking and counting system's trial findings demonstrate its reliable operation and potent ability to precisely track moving vehicles. The system, which combined the Euclidean distance tracker and the YOLO (You Only Look Once) object detection model, showed remarkable accuracy in recognizing and following vehicles in a variety of traffic situations.

With classes set up specifically for cars, bikes, buses, autos, and trucks, the YOLO model was able to identify vehicles within video frames. The system's efficiency was enhanced by YOLO's real-time processing capacity, which allowed for quick and precise vehicle recognition as they moved over the surveillance area.

The Euclidean distance tracker is a crucial tool for accurately tracking vehicles, ensuring consistent counting and trajectory monitoring. Its ability to handle object identity through distance computations contributes to system stability in varying traffic densities and complex scenarios. The system successfully counts vehicles in different classes, including cars, motorbikes, buses, and trucks, providing valuable insights into traffic dynamics by distinguishing between entering and exiting vehicles.

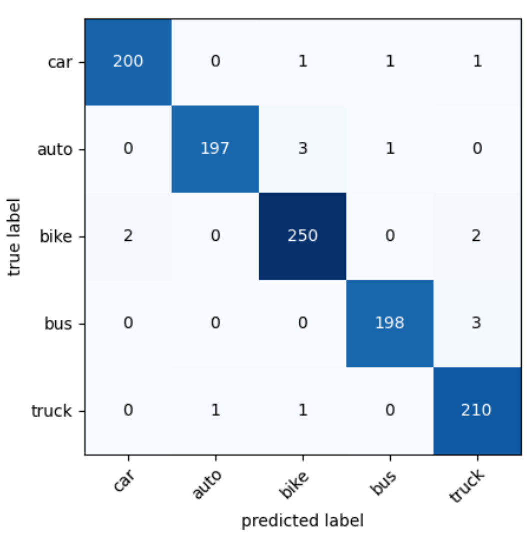

Fig 3. Confusion Matrix

Observations:

- The model exhibits high accuracy across all classes, with F1 scores ranging from 98.36% to 99.01%.
- Notably, the model performs exceptionally well in distinguishing between 'car' and 'auto,' achieving precision and recall scores above 98% for both classes.
- Class 'Truck' demonstrates high precision but slightly lower recall, indicating that while the model correctly identifies most trucks, there are

instances where it fails to capture all actual instances.

Fig .4 Count of vehiclesz

Fig 5. Count of vehicles

The benefit of the suggested real-time vehicle tracking and counting system is demonstrated by the trial findings. A complete solution for intelligent transport systems is provided by the combination of YOLO and the Euclidean distance tracker, which delivers precise and trustworthy insights into traffic patterns, congestion analysis, and urban planning. The system's ability to function well in a variety of experimental conditions highlights its potential for use in real-world traffic management situations.

V. CONCLUSION AND FUTURE ENCHANCEMENTS

In summary, this study presents a thorough approach that combines machine learning technology to address the intricate problem of urban traffic congestion. The Euclidean Distance Tracker and the YOLO object recognition framework together provide a powerful real-time traffic analytics and vehicle tracking solution. With its high efficiency and precision in counting, classifying, and recognising vehicles, the system has a lot of potential to completely transform urban traffic management. Its insights not only help to reduce traffic but also provide useful information for well-informed infrastructure construction and urban planning.

The system's future development includes incorporating data from multiple cameras for a comprehensive view of urban traffic patterns. It also needs improvements in weather and lighting adaptability, advanced preprocessing techniques, and the integration of crowdsourced data for a more nuanced understanding of traffic behaviors. Additionally, a real-time decision support system could provide actionable insights for traffic management, enhancing urban mobility and transforming intelligent transport systems.

REFERENCES

[1] Arinaldi, A., Pradana, J.A., Gurusinga, A.A. "Detection and Classification of Vehicles for Traffic Video Analytics." Procedia Computer Science, vol. 144, 2018, pp. 259-268.

[2] Liu, Y., Wu, H. "Prediction of road traffic congestion based on random forest." 10th International Symposium on Computational Intelligence and Design (ISCID), vol. 2, no. 1, 2017, pp. 361-364.

[3] T. Thianniwet, S. Phosaard, W. Pattara-Atikom " Classification of road traffic congestion levels from vehicle's moving patterns: a comparison between artificial neural network and decision tree algorithm"

[4] L. Jian, Z. Li, X. Yang, W. Wu, A. Ahmad, G. Jeon"Combining unmanned aerial vehicles with artificial-intelligence technology for traffic-congestion recognition: electronic eyes in the skies to spot clogged roads "

[5] Sarikan, S.S.; Ozbayoglu, A.M.; Zilci, O. "Automated Vehicle Classification with Image Processing and Computational Intelligence." Procedia Comput. Sci. 2017, 114, 515–522.

[6] S. Khan, S. Nazir, I. García-Magariño, A. Hussain"Deep learning-based urban big data fusion in smart cities: Towards traffic monitoring and flow-preserving fusion"Comput Electr Eng, 89 (1) (2021), pp. 1-11

[7] R. C. Gatto and C. H. Q. Forster, "Audio-Based Machine Learning Model for Traffic Congestion Detection," in IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 11, pp. 7200-7207, Nov. 2021, doi: 10.1109/TITS.2020.3003111.

[8] T. H. Nguyen and J. J. Jung, "Swarm intelligence-based green optimization framework for sustainable transportation", Sustain. Cities Soc., vol. 71, pp. 102947, April 2021.

[9] J. Withanawasam and A. Karunananda, "Multi-agent based road traffic control optimization", IEEE Conf. Intell. Transp. Syst. Proceedings ITSC, vol. 2018, pp. 977-981, 2018.

[10] Tan, Yi, et al. "Vehicle detection and classification in aerial imagery." 2018 25th IEEE International Conference on Image Processing (ICIP). IEEE, 2018.

[11] K. T. K. Teo, Kiam Beng Yeo, Shee Eng Tan, Zhan Wei Siew and Kit Guan Lim, "Design and development of portable fuzzy logic based traffic optimizer," 2013 IEEE International Conference on Consumer Electronics - China, Shenzhen, China, 2013, pp. 7-12, doi: 10.1109/ICCE-China.2013.6780856.

[12] H. Dezani, N. Marranghello and F. Damiani, "Genetic algorithm-based traffic lights timing optimization and routes definition using Petri net model of urban traffic flow", IFAC Proc., vol. 47, no. 3, pp. 11326-11331, 2014.

[13] Hamzenejadi, Mohammad Hossein, and Hadis Mohseni. "Fine-tuned YOLOv5 for real-time vehicle detection in UAV imagery: Architectural improvements and performance boost." Expert Systems with Applications (2023): 120845.

[14] Kumar, Sandeep, et al. "Deep Neural Network Based Vehicle Detection and Classification of Aerial Images." Intelligent Automation & Soft Computing 34.1 (2022).

[15] Y. Wang, M. Papageorgiou and A. Messmer, "Real-time freeway traffic state estimation based on extended Kalman filter: Adaptive capabilities and real data testing", Transp. Res. Part A Policy Pract., vol. 42, no. 10, pp. 1340-1358, 2008.

[16] I. Arel, C. Liu, T. Urbanik, and A. G. Kohls, “Reinforcement learning-based multi-agent system for network traffic signal control,” IET Intell. Transp. Syst., vol. 4, no. 2, pp. 128–135, 2010, doi: 10.1049/iet-its.2009.0070.

[17] S. Mehan and V. Sharma, "Development of traffic light control system based on fuzzy logic", Proc. Int. Conf. Adv. Comput Artif. Intell. ACAI 2011, pp. 162-165, 2011.

[18] N. Kumar, S. S. Rahman and N. Dhakad, "Fuzzy Inference Enabled Deep Reinforcement Learning-Based Traffic Light Control for Intelligent Transportation System", IEEE Trans. Intell Transp. Syst., vol. 22, no. 8, pp. 4919-4928, 2021.

[19] A. J. Joshi and F. Porikli, "Scene-adaptive human detection with incremental active learning" in Proc. Int. Conf. Pattern Recognition, Piscataway, NJ:IEEE, pp. 2760-2763, 2010.

[20] Y. Yuan, Z. Zhang, X T. Yang and S. Zhe, "Macroscopic traffic flow modeling with physics regularized Gaussian process: A new insight into machine learning applications in transportation", Transp. Res. Part B MethodoI., vol. 146, pp. 88-110, 2021.

[21] O. D. Jimoh, L. A. Ajao, O. O. Adeleke and S. S. Kolo, "A Vehicle Tracking System Using Greedy Forwarding Algorithms for Public Transportation in Urban Arterial", IEEE Access, vol. 8, pp. 191706-191725, 2020.

[22] Rahman, Faysal Ibna. "SHORT TERM TRAFFIC FLOW PREDICTION USING MACHINE LEARNING-KNN, SVM AND ANN WITH WEATHER INFORMATION." International Journal for Traffic & Transport Engineering 10.3 (2020).

[23] Kumar, Kranti, Manoranjan Parida, and V. K. Katiyar. "Short term traffic flow prediction for a non urban highway using artificial neural network." Procedia-Social and Behavioral Sciences 104 (2013): 755-764.

[24] Wu, Jiatu. "Complexity and Accuracy Analysis of Common Artificial Neural Networks on Pedestrian Detection." MATEC Web of Conferences, vol. 232, 2018, article number 01003, doi:10.1051/matecconf/201823201003.

[25] C. Johny and V. Dahiya, "Machine Learning Applications in Vehicular Traffic Prediction and Congestion Control: A Systematic Review," 2022 6th International Conference on Electronics, Communication and Aerospace Technology, Coimbatore, India, 2022, pp. 948-954, doi: 10.1109/ICECA55336.2022.10009384.

[26] J. Park et al., "Intelligent Vehicle Power Control Based on Machine Learning of Optimal Control Parameters and Prediction of Road Type and Traffic Congestion," in IEEE Transactions on Vehicular Technology, vol. 58, no. 9, pp. 4741-4756, Nov. 2009, doi: 10.1109/TVT.2009.2027710.

[27] Faraj, M. A., and N. W. Boskany. “Intelligent Traffic Congestion Control System Using Machine Learning and Wireless Network”. UHD Journal of Science and Technology, vol. 4, no. 2, Dec. 2020, pp. 123-31, doi:10.21928/uhdjst.v4n2y2020.pp123-131.