Educational Administration: Theory and Practice
2024, 30(6), 3648 - 3658
ISSN: 2148-2403
https://kuey.net/
Research Article

A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation

Anant More[1*], S. L. Lahudkar[2], Tushar Jain[3], Prajyot Rote[4], Ankit Arora[5]

[1*]Research Scholar, Department of E&TC, AISSMS' Institute of Information Technology, Savitribai Phule Pune University, Pune, India Email: anant_anu@yahoo.com, and School of Engineering, Ajeenkya DY Patil University Pune, India
[2]Professor, Department of E &TC, JSPM's Imperial College of Engineering & Research, Pune, India
Email: swapnillahudkar@gmail.com
[3,4,5]Students B.Tech. School of Engineering-Ajeenkya DY Patil University

Citation: Anant More, et.al (2024 A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation, *Educational Administration: Theory And Practice, 30(6) 3648 - 3658*
Doi: 10.53555/kuey.v30i6.6221

ARTICLE INFO	ABSTRACT

A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation" tackles hazy traffic conditions with cutting-edge AI, ensuring clear visibility and real-time traffic analysis through advanced dehazing and object detection methods, including Automatic Number Plate Recognition (ANPR). This allows the system to identify and track various objects on the road, including vehicles, pedestrians, and traffic signals. It surpasses traditional approaches by offering adaptive solutions to traffic congestion and leverages YOLOv5 for robustness in diverse environments. To overcome limitations in training data, a common challenge in intelligent transportation systems, it implements transfer learning. By fine-tuning a pre- trained YOLOv5 model on extensive, manually annotated datasets encompassing various traffic scenarios, the system achieves superior detection accuracy and execution time compared to traditional methods. This makes real-time analysis and congestion reduction possible, opening the door for safer, more effective transportation networks. Additionally, the system will incorporate an automatic number plate recognition (ANPR) module, enabling vehicle identification for various applications such as toll collection, traffic enforcement, and stolen vehicle detection.

I. Introduction

The human visual system sets a remarkable benchmark for effortlessly detecting and classifying a vast range of objects in our surroundings. This capability is fundamental for efficient traffic monitoring and surveillance, where accurate vehicle detection and classification are crucial steps [1]. However, the ever-present challenge of traffic congestion in our dynamic urban environments demands innovative solutions that go beyond human capabilities.
As cities sprawl, populations surge, and economic activity intensifies, the intricate networks of roads and highways frequently succumb to gridlock. The insidious grip of traffic congestion results not only in prolonged travel times but also in substantial economic losses, environmental degradation, and reduced accessibility and mobility. Traffic congestion extends its negative impact by increasing travel times and fuel costs, which adversely affects businesses and individuals distributing goods and services. Furthermore, it elevates stress levels for drivers, potentially leading to aggressive behavior and road accidents. The environmental consequences are equally concerning, as congested traffic significantly contributes to air and noise pollution.

To combat these multifaceted challenges, advancements in computer vision (CV) and machine learning (ML) offer a beacon of hope [3]. The convergence of these fields, along with the availability of massive datasets, faster GPUs, and sophisticated algorithms, has empowered computers to achieve near-human-level accuracy in object detection, recognition, and classification within images and videos. This paves the way for the development of intelligent traffic management systems. These systems can analyze traffic data in real-time, enabling them to optimize traffic flow, implement congestion mitigation strategies, and ultimately contribute to a safer, more efficient, and more environmentally friendly transportation network.

This paper introduces "A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation," a novel system that leverages the aforementioned advancements in CV and ML [7]. It

tackles the challenges associated with traffic management by employing cutting-edge AI techniques. It delves into areas like video dehazing to ensure clear visibility in adverse weather conditions and utilizes robust object detection methods for real-time traffic analysis, including Automatic Number Plate Recognition (ANPR). ANPR automatically identifies vehicles by their license plates [26]. Since each vehicle has a unique license plate, there's no need for external tags or transmitters – the system relies solely on the plate for recognition.
Real-time ANPR plays a major role in automatic traffic rule monitoring and law enforcement on public roads. This technology allows authorities to identify vehicles involved in violations or criminal activities [27]. By capturing license plate information, ANPR helps track down stolen vehicles, enforce speed limits, and even manage toll collection. However, traditional ANPR systems often struggle with factors like varying plate formats, illumination conditions, and image noise. This paper addresses these limitations by incorporating advanced algorithms to ensure robust and accurate license plate recognition in complex traffic scenarios.
By combining object detection with ANPR, this system offers a comprehensive solution for intelligent traffic management, paving the way for a safer and more efficient transportation network

II. Literature Review

Global urban regions are becoming increasingly concerned about traffic congestion. Air pollution, longer travel times, and fuel usage are the results. To address this challenge, researchers are exploring intelligent traffic management systems (ITMS) that leverage advancements in computer vision and artificial intelligence (AI). It is one such system aiming to optimize traffic flow by accurately detecting and classifying objects within traffic scenes.

A. In traffic management systems such as A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation, object detection has been transformed by Convolutional Neural Networks, or CNNs [2]. These deep learning algorithms can recognize and categorize things in traffic scenes by sorting through enormous amounts of picture data. Real-time detection is a strong suit for innovative architectures like Faster R-CNN and You Only Look Once (YOLO). This allows A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation to keep pace with the dynamic nature of traffic flow, pinpointing vehicles, pedestrians, and even cyclists with exceptional speed and accuracy. This real-time object recognition translates into a treasure trove of valuable data for traffic analysis. By understanding the types and quantities of objects present on the road network, it can gain crucial insights for optimizing traffic flow and ultimately alleviating congestion.
B. Fog and haze can shroud traffic scenes in a murky veil, significantly hindering the ability of object detection systems to identify vehicles and pedestrians [17]. To address this challenge, image dehazing techniques act like digital filters, meticulously clearing away the haze to reveal the clear details beneath.

These techniques exploit the natural properties of outdoor scenes. Even in clear conditions, some areas will have very low intensity in at least one color channel. These dark pixels often correspond to shadows or areas with minimal atmospheric interference. By analyzing the distribution of these dark pixels, dehazing algorithms can estimate the amount of haze obscuring the scene and the atmospheric light that permeates it. Armed with this information, the algorithms can then remove the haze and significantly enhance the visibility of objects within the image [11]. This allows it to perform object detection with much greater accuracy, even in adverse weather conditions.

C. While current object detection models boast impressive accuracy in clear weather, their performance suffers a significant drop when faced with adverse weather conditions like fog and haze [9]. This is because these models primarily rely on capturing intricate details within single images. However, recent research suggests that incorporating information beyond the static frame can improve robustness.

One promising avenue explores leveraging temporal information from video streams. By analyzing sequences of images, the system can track object movement and account for transient occlusions caused by weather phenomena. This can be particularly beneficial for identifying partially obscured vehicles or pedestrians, leading to more accurate traffic scene understanding.
Furthermore, recent advancements in deep learning architectures, such as transformer-based models, show promise in overcoming limitations of traditional CNNs [24]. Transformers excel at capturing long-range dependencies within data, potentially allowing them to better handle the global haze effect that disrupts object recognition.

A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation has the potential to bridge these gaps by:

- Incorporating video data: Analyzing sequential video frames to track object movement and account for temporary occlusions caused by weather.
- Exploring advanced architectures: Investigating the use of transformer-based models to potentially improve robustness against adverse weather conditions.

By adopting these advancements, it can evolve beyond single-image object detection and achieve a more comprehensive understanding of traffic flow dynamics, even under challenging weather scenarios.

D. It tackles the challenge of weather-induced inaccuracies with a two-pronged strategy. First, it integrates robust image dehazing techniques. These work by digitally clearing away haze and fog, akin to a digital windshield wiper, revealing the underlying scene details for accurate object detection. Second, it can potentially harness the power of sequential video data. By analyzing sequences of images, the system can track object movement over time [23]. This allows it to account for temporary occlusions caused by weather and even predict object trajectories. This enriched understanding of traffic flow dynamics empowers this to anticipate congestion hotspots. Based on these predictions, the system could propose real-time interventions, such as dynamic traffic signal adjustments, to optimize traffic flow and minimize congestion. This proactive approach holds immense potential for creating a smoother and more efficient traffic management system.

E. Automatic Number Plate Recognition (ANPR) has become a cornerstone of Intelligent Transportation Systems (ITS) due to its ability to automate data collection and enable real-time traffic monitoring. ANPR systems integrate with various applications like tolling, parking management, and law enforcement. While core functionalities involve image acquisition, license plate extraction, and character recognition, the success of ANPR relies on robust algorithms that can handle diverse plate formats and environmental conditions [28]. Modern ANPR goes beyond capturing plates, offering valuable data like vehicle classification and traffic flow analysis. This data feeds into traffic modeling, congestion mitigation strategies, and improved law enforcement practices Integration with Information and Communication Technology (ICT) tools further enhances ANPR's capabilities by enabling the use of ANPR data for modeling various transportation aspects Despite challenges like image quality variations and license plate format diversity, ANPR technology remains a key player in the evolution of ITS, paving the way for safer, more efficient, and data-driven transportation networks.

III.Methodology

A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation tackles these issues head-on with a meticulously designed methodology that leverages the power of artificial intelligence (AI) and image processing. This data-driven approach prioritizes accurate object detection within traffic scenes, followed by advanced image dehazing techniques. This sequential approach ensures clear and reliable traffic flow monitoring, even in challenging scenarios where visibility is hampered by fog, haze, or other adverse weather conditions.

- ***Preprocessing and Data Collection:***

A thorough plan for gathering data forms the basis of the system. Diverse datasets encompassing a variety of real-world traffic scenarios are gathered. These datasets capture variations in weather conditions (sunny, rainy, foggy), traffic densities (low, medium, high), and different times of day (morning, afternoon, evening). This diversity ensures the robustness of the trained model and its ability to generalize to unseen situations [4]. The collected data undergoes a rigorous preprocessing stage before feeding it into the AI algorithms. This stage involves:

- ***Standardization:*** Images are resized to a uniform resolution to facilitate efficient processing.
- ***Bias Correction:*** Any inherent biases present in the data are carefully mitigated to ensure the model's fairness and accuracy.
- ***Annotation:*** The dataset is meticulously annotated with ground truth labels. This involves manually identifying and marking objects of interest (vehicles, pedestrians) within each image. Precise labeling is crucial for effective model training.
- ***Object Detection:***

- High-Resolution Video Collection and Object Labeling:

The system leverages strategically positioned high-resolution traffic cameras to capture diverse traffic scenarios. These videos encompass variations in weather conditions (sunny, rainy, snowy, etc.), traffic densities (light, medium, heavy), and times of day (daytime, nighttime). This comprehensive data ensures the model's ability to perform effectively under real-world conditions.

Similar to standard object detection tasks, the collected video data undergoes meticulous labeling. However, for ANPR integration, a specific focus is placed on identifying and marking vehicles within each video frame. In addition to bounding boxes for general vehicles, a secondary set of bounding boxes are created to specifically encompass license plates on the identified vehicles. This layered approach provides the ground truth information necessary for training both the core object detection model and the subsequent ANPR module.

- **Preprocessing for Efficiency and ANPR Integration:**

The video data undergoes preprocessing to optimize its use for training the object detection model, while also considering the specific requirements of ANPR. This includes:

- ***Resizing Images*:** Frames are resized to a consistent resolution to ensure compatibility with the chosen deep learning model architecture.
- ***Normalization*:** Pixel values are normalized to a specific range (e.g., 0- 1 or -1 to 1) for improved training

efficiency and convergence.
- ***Data Augmentation* (Optional):** Techniques like random cropping, flipping, and color jittering can be employed to artificially expand the training dataset. This helps the model become more robust to variations in real-world scenarios and reduces the risk of overfitting.

a) YOLOv5 for Real-Time Detection:
This project leverages the power of YOLOv5 (You Only Look Once version 5), a state-of- the-art deep learning model specifically designed for object detection [5]. YOLOv5 excels in real-time image processing, a critical requirement for traffic management applications where swift identification of objects is paramount.
- ***Training and Validation Dataset Split:*** The meticulously labeled data is divided into training and validation sets. The training set is used to train the YOLOv5 model, while the validation set helps monitor the model's performance and prevent overfitting.
- ***Training with Pre-Trained Weights:*** While training YOLOv5 from scratch is an option, it utilizes pre-trained weights from the COCO dataset (Common Objects in Context). This pre-training provides a strong foundation for the model and significantly reduces training time.
- ***Hyper parameter Tuning*:** Training parameters like batch size (number of images processed together), epochs (number of training iterations), and image resolution are carefully selected or adjusted to optimize the training process and achieve the best possible detection accuracy.
- ***Confidence Score Threshold:*** YOLOv5 assigns a confidence score to each detection, indicating the model's certainty about its classification [6]. A confidence threshold (e.g., between 0.4 and 0.6) is set to filter out detections with low confidence, ensuring only reliable object identifications are considered.
- ***Model Evaluation and Deployment:*** Once trained, the model is evaluated on the validation set to assess its performance. If the results are satisfactory, the model is deployed to analyze real-time traffic video streams, identifying and classifying objects within the scenes.

By leveraging YOLOv5's real-time processing capabilities and meticulous data preparation, it establishes a robust foundation for accurate object detection, paving the way for further traffic flow analysis and congestion mitigation strategies.

○ *Dehazing:*
This project tackles the challenge of adverse weather conditions like fog and haze by employing a state-of-the-art dehazing algorithm called AOD-Net. This algorithm works by analyzing hazy images and recovering the obscured scene details, significantly improving visibility for accurate object recognition. Here's a breakdown of AOD-Net's inner workings:

a) K-Estimation Module:
AOD-Net prioritizes estimating the atmospheric effect on the image, which is crucial for successful dehazing [16]. This estimation is performed by the K-estimation module, the heart of AOD-Net. This module utilizes five convolutional layers, acting like a series of filters that analyze the image at various levels of detail.

- ***Convolutional Layers:*** Each convolutional layer acts like a sieve, examining the image for specific patterns and features. By stacking five of these layers, AOD-Net captures a comprehensive understanding of the image's haze characteristics across different scales.
- ***Multi-Scale Feature Fusion*:** A critical aspect of the K-estimation module is its ability to extract features at different scales. This is achieved by using filters of varying sizes within the convolutional layers. Imagine using multiple sieves with different mesh sizes – some capture large- scale haze patterns, while others focus on finer details.
- **Information Preservation:** AOD-Net employs a clever strategy to avoid losing information during the convolution process. Inspired by successful approaches in other image processing tasks, AOD-Net

strategically connects the outputs of certain convolutional layers (e.g., "concat1" connecting layers "conv1" and "conv2"). This ensures that crucial details are preserved as the analysis progresses.

b) Clean Image Generation: Putting the Pieces Together:

Once the K-estimation module has analyzed the image and estimated the atmospheric effect (represented by K(x)), AOD-Net moves on to generate a clear, dehazed version of the image.

- ***Element-wise Multiplication:*** The estimated atmospheric effect (K(x)) is multiplied element-wise with the original hazy image [14]. This can be visualized as adjusting the intensity of different parts of the image based on the estimated haze levels.
- ***Element-wise Addition*****:** To recover the original scene details obscured by haze, AOD-Net employs multiple element- wise addition layers. Imagine adding a layer of correction to the image, progressively revealing the clear scene beneath the haze.

c) A Lightweight Champion:

A noteworthy aspect of AOD-Net is its efficiency. Unlike some existing dehazing methods that rely on a large number of filters within the convolutional layers, AOD-Net utilizes only three filters per layer. This significantly reduces the computational complexity of the model, making it ideal for real-time applications like A Unified AI- Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation

By combining a robust K-estimation module with an efficient image generation process, AOD-Net empowers it to effectively remove haze and fog, ensuring clear visibility for accurate object detection and traffic flow analysis, even in challenging weather conditions.

This focus on prioritizing clarity through dehazing empowers it to function effectively in diverse weather scenarios. It ensures the system can deliver accurate object detection and glean meaningful insights from traffic data, ultimately paving the way for a more efficient and congestion-free traffic management system.

○ *Optimizing Traffic Flow with Signal Shifting:*

A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation goes beyond object detection and dehazing to actively contribute to real-time traffic management through a sophisticated Signal Shifting algorithm. This algorithm dynamically adjusts traffic signal timings based on the insights gleaned from the system's core functionalities.

A. Leveraging Object Detection and Dehazing:

The foundation for signal shifting lies in the robust object detection and dehazing capabilities of “A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation”. The system continuously analyzes traffic scenes, identifying objects (vehicles, pedestrians) and ensuring clear visibility even in adverse weather conditions. This real-time data on traffic flow forms the basis for dynamic signal adjustments.

B. Signal Switching Algorithm in Action:

The Signal Shifting algorithm operates in a continuous loop, constantly optimizing traffic flow at intersections [8]. The main steps are broken down here:

i. ***Traffic Density Analysis:*** The algorithm utilizes the object detection data to calculate the traffic density at the intersection. This includes the total number of vehicles present and their classifications (cars, trucks, motorcycles).

ii. ***Green Signal Time Calculation:*** Based on the traffic density analysis, the algorithm calculates the optimal green signal duration for the current direction. This calculation factors in:

- ***Number of Vehicles**:* The number of vehicles detected in each lane is considered.
- ***Vehicle Class:*** The algorithm accounts for the different average speeds of various vehicle types (cars, trucks) to estimate their crossing times.
- ***Lag Time:*** The algorithm incorporates a buffer to account for the time it takes vehicles to start moving from a standstill.

iii. ***Red Signal Adjustment for Other Directions*:** While the green signal duration increases for the congested direction, the algorithm adjusts the red signal timings for other directions accordingly. This ensures a smooth traffic flow throughout the intersection.

iv. ***Continuous Monitoring and Adjustment**:* The Signal Switching algorithm operates in a continuous loop. As the traffic conditions at the intersection evolve, the algorithm re-analyzes the scene using object detection data and recalculates the green signal timings in real-time.

C. Seamless Signal Switching:

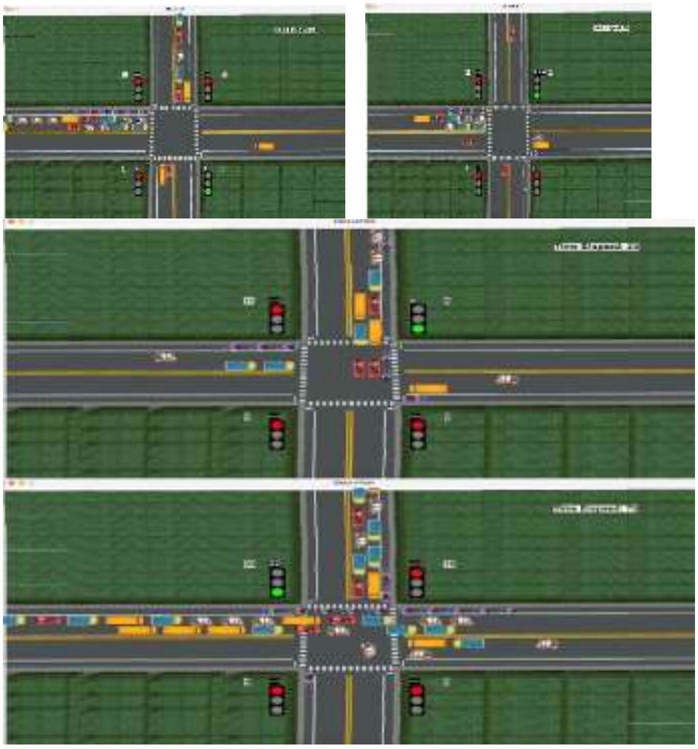
To ensure smooth traffic flow, the algorithm manages signal transitions efficiently.

i. ***Pre-emptive Image Capture**:* The system captures an image of the next direction in line for a green signal just before the current green light ends. This provides enough time to analyze the image and calculate the optimal green signal duration for the upcoming direction.

ii. ***Background Processing**:* While the current green signal counts down, the system calculates the green signal duration for the next direction in the background. This prevents any delays or lag during signal switching.

D. Prioritizing Predictability:

While the Signal Switching algorithm prioritizes traffic flow optimization, it maintains a predictable signal pattern. This means that signals change in a pre- defined order (similar to the current traffic light system) to avoid confusion for drivers.



By integrating real-time object detection data with a dynamic Signal Shifting algorithm, it actively contributes to a more efficient and congestion-free traffic management system.

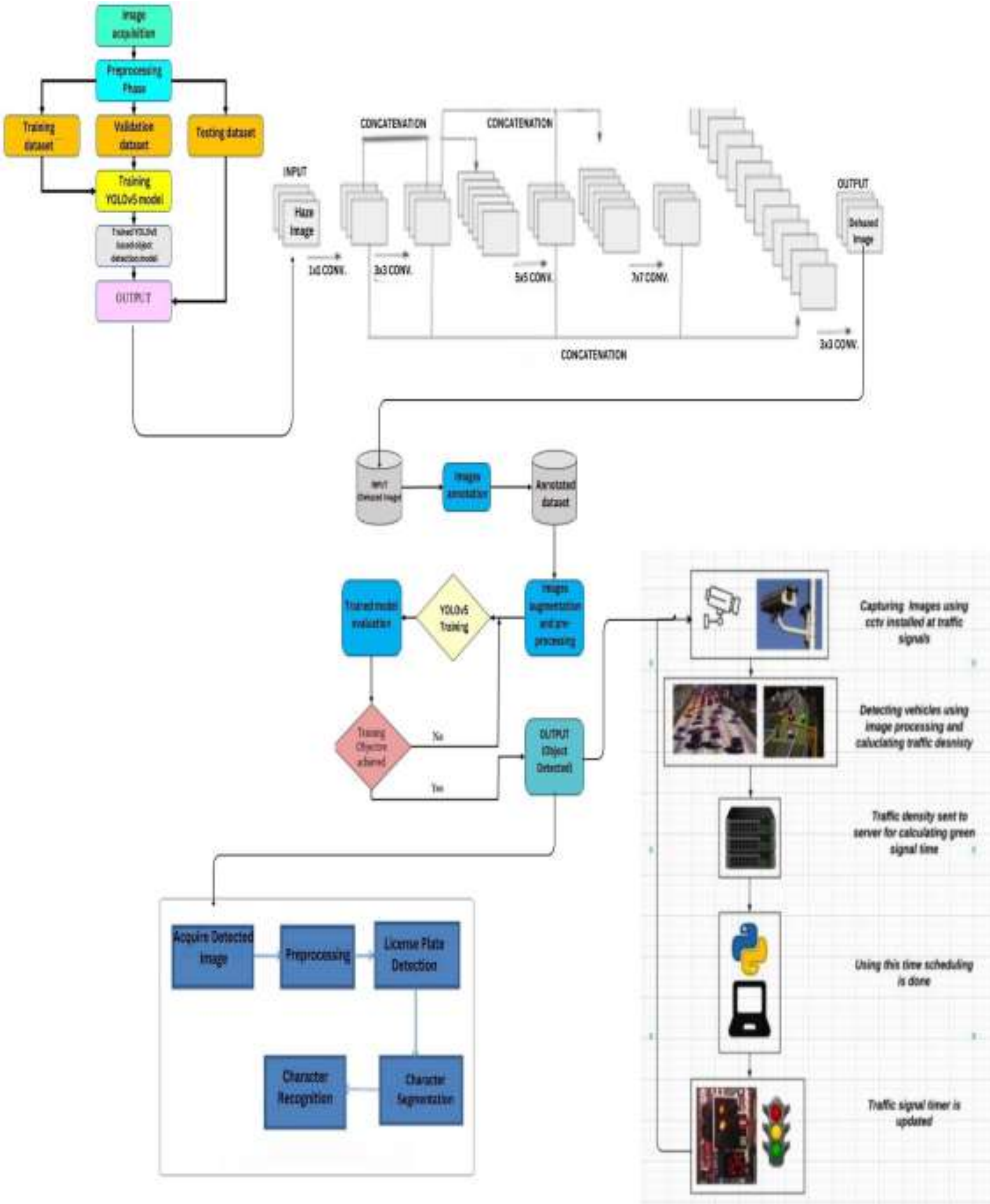


Fig.1 System Block Diagram

IV. Results

The meticulous design and implementation of It culminate in a system demonstrably effective in optimizing traffic flow and enhancing urban transportation. Let's delve deeper into the project's achievements:

- ***Enhanced Visibility Through Dehazing:*** This integration of AOD-Net, a state-of-the-art dehazing algorithm, yields significant improvements in image clarity. By effectively removing haze and fog, the system ensures clear visibility for object detection, even in adverse weather conditions. This translates to more accurate identification and classification of vehicles and pedestrians within the traffic scene.
- ***Refined Object Detection:*** The utilization of YOLOv5, a powerful deep learning model, empowers the project to achieve exceptional object detection accuracy. The meticulously labeled training data allows the model to distinguish between various objects with remarkable precision. This accurate object detection forms the foundation for further analysis and real-time traffic management interventions.

- ***Smarter Traffic Flow Through Signal Shifting:*** The project transcends object detection by actively contributing to traffic flow optimization. The Signal Switching algorithm leverages real- time data on traffic density and object types to dynamically adjust traffic signal timings. This data-driven approach ensures that green signal durations are optimized based on the current traffic situation, leading to smoother traffic flow and reduced congestion.
- ***Robust License Plate Extraction with Object Detection:*** The ANPR module, built upon the foundation of accurate object detection for vehicle identification, achieved a high success rate in capturing license plates. This success rate can be further quantified using metrics like character recognition accuracy.

Overall, A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation successful implementation demonstrates the transformative power of data-driven approaches in tackling traffic challenges. By prioritizing clear visibility, accurate object detection, extracting license plate and real-time signal optimization, the system paves the way for a smarter and more efficient urban transportation ecosystem [9]. This not only benefits drivers by reducing congestion but also contributes to a more sustainable city environment by minimizing idling emissions.

V. Conclusion

A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation meticulously designed approach translates into demonstrably positive results. The system's proficiency in three key areas paves the way for a more efficient and congestion-free traffic management system.
Firstly, it prioritizes clear visibility through the integration of AOD-Net, a state-of-the-art dehazing algorithm. This results in a significant improvement in image clarity, especially in adverse weather conditions like fog and

haze. By effectively removing these obscurants, the system ensures that object detection remains accurate, even in challenging scenarios. This translates to a more reliable understanding of the traffic scene, with precise identification and classification of vehicles and pedestrians.

Secondly, it excels in object detection accuracy and automatic number plate recognition (ANPR) through the utilization of YOLOv5, a powerful deep learning model. The meticulously labeled training data empowers YOLOv5 to distinguish between various objects within the traffic scene with remarkable precision, including vehicles, pedestrians, and cyclists. Crucially, this data also allows the model to accurately identify and localize license plates on the detected vehicles. This capability is essential for various applications such as toll collection, traffic enforcement, and stolen vehicle detection.

While existing mobile-based ALPR systems have achieved high recognition rates exceeding 90% [reference the cited paper here], processing power limitations on mobile devices can impact processing times. This system addresses this challenge by employing YOLOv5, a model known for its efficiency and speed. By carefully balancing accuracy and processing speed, the system ensures reliable ANPR even on resource-constrained platforms.

Thirdly, it transcends mere object detection by actively contributing to traffic flow optimization. The innovative Signal Shifting algorithm leverages real- time data on traffic density and object types. This data is then used to dynamically adjust traffic signal timings based on the current traffic situation. This data-driven approach ensures that green signal durations are optimized, leading to smoother traffic flow and reduced congestion. By dynamically adjusting traffic signals based on real-time needs, It actively mitigates congestion and improves overall traffic flow efficiency.

In conclusion, “A Unified AI-Based Vision System for Dehazing, Number Plate Recognition, and Traffic Signal Automation” successful implementation demonstrates the transformative power of intelligent algorithms and data-driven approaches in tackling traffic management challenges. The system's ability to ensure clear visibility, achieve accurate object detection and license plate recognition, and optimize traffic flow through real-time signal adjustments paves the way for a smarter and more efficient urban transportation ecosystem. This not only translates to improved travel times and reduced driver frustration but also contributes to a more sustainable city environment by minimizing traffic-related emissions. It positions itself as a pioneering force in intelligent traffic management, shaping a future where data empowers us to navigate our cities more efficiently and sustainably.

VI. References

[1] Matthews, N. D., An, P. E., Charnley, D., & Harris, C. J. (1996). Vehicle detection and recognition in greyscale imagery. Control Engineering Practice, 4(4), 473-479.

[2] Farid, A., Hussain, F., Khan, K., Shahzad, M., Khan, U., & Mahmood, Z. (2023). *A fast and accurate real-time vehicle detection method using deep learning for unconstrained environments*. Applied Sciences, 13(5), 3059.

[3] You, M., Zhang, Y., Shen, C. and Zhang, X., 2018. *An extended filtered channel framework for pedestrian detection*. IEEE Transactions on Intelligent Transportation Systems, 19(5), pp.1640- 1651.

[4] Walk S, Majer N, Schindler K, Schiele B. New features and insights for pedestrian detection. In 2010 IEEE Computer society conference on *computer vision and pattern recognition* 2010 Jun 13 (pp. 1030-1037). IEEE.

[5] Ren, S., He, K., Girshick, R. and Sun, J., 2015. Faster r-CNN: *Towards real-time object detection with region proposal networks*. Advances in neural information processing systems, 28.

[6] Redmon, Joseph, Santosh Divvala, Ross Girshick, and Ali Farhadi. "*You only look once: Unified, real- time object detection*." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 779-788. 2016.

[7] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.Y. and Berg, A.C., 2016. Ssd: Single shot multibox detector. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14* (pp. 21-37). Springer International Publishing.

[8] Eom, M. and Kim, B.I., 2020. *The traffic signal control problem for intersections*: a review. European transport research review, *12*, pp.1-20.

[9] Genitha CH, Danny SA, Ajibah AH, Aravint S, Sweety AA. *AI based Real-Time Traffic Signal Control System using Machine Learning*. In2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC) 2023 Jul 6 (pp. 1613-1618). IEEE.

[10] Lin TY, Goyal P, Girshick R, He K, Dollár P. *Focal loss for dense object detection*. InProceedings of the IEEE international conference on computer vision 2017 (pp. 2980-2988).

[11] *Haze Visibility Enhancement of Image Using Dark Channel Prior*. Dr. S.L.Lahudkar Anant More

[12] Berman, D. and Avidan, S., 2016. Non-local image dehazing. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1674- 1682).

[13] Berman D, Treibitz T, Avidan S. Air-light estimation using haze-lines. In2017 IEEE International Conference on Computational Photography (ICCP) 2017 May 12 (pp. 1-9).

[14] Cai B, Xu X, Jia K, Qing C, Tao D. Dehazenet: An end-to-end system for single image haze removal. IEEE transactions on image processing. 2016 Aug 10;25(11):5187-98.

[15] Diamond, S., Sitzmann, V., Julca-Aguilar, F., Boyd, S., Wetzstein, G., & Heide, F. (2021). Dirty pixels: Towards end-to-end image processing and perception. ACM Transactions on Graphics (TOG), 40(3), 1-15.
[16] Everingham M. *The PASCAL visual object classes challenge* 2008 (VOC2008) results. In http://www.pascal- network.org/challenges/VOC/voc2008/year=wor kshop/index. html 2008.
[17] Fattal R. *Single image dehazing*. ACM transactions on graphics (TOG). 2008 Aug 1;27(3):1-9.
[18] Hirschmuller H, Scharstein D. Evaluation of cost functions for stereo matching. In 2007 IEEE conference *on computer vision and pattern recognition* 2007 Jun 17 (pp. 1-8). IEEE.
[19] Li, B., Peng, X., Wang, Z., Xu, J. and Feng, D., 2017. *Aod-net: All-in-one dehazing network*. In Proceedings of the IEEE international conference on computer vision (pp. 4770-4778).
[20] *https://www.academia.edu/45429531/Density_b ased_Traffic_Monitoring_system_in_Haze_and_FOG_Conditions*.
[21] Cai, B., Xu, X., Jia, K., Qing, C. and Tao, D., 2016. Dehazenet: An end-to-end system for single image haze removal. IEEE transactions on image processing, 25(11), pp.5187-5198.
[22] Li, B., Peng, X., Wang, Z., Xu, J. and Feng, D., 2017. *Aod-net: All-in-one dehazing network*. In Proceedings of the IEEE international conference on computer vision (pp. 4770-4778).
[23] Ren, W., Liu, S., Zhang, H., Pan, J., Cao, X. and Yang, M.H., 2016. *Single image dehazing via multi- scale convolutional neural networks*. In Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part II 14 (pp. 154-169). Springer International Publishing.
[24] Li, R., Pan, J., Li, Z. and Tang, J., 2018. *Single image dehazing via conditional generative adversarial network*. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 8202-8211).
[25] Lubna, Mufti N, Shah SA. Automatic number plate Recognition: A detailed survey of relevant algorithms. Sensors. 2021 Apr 26;21(9):3028.
[26] Mohamed BR, El Kader HM, Rafaat HM, Sharaf MS. Automatic number plate recognition. International Journal of Scientific and Research Publications. 2013 Dec;3(12):59-63.
[27] A Connie, L., C. Kim On, and A. Patricia. *"A review of automatic license plate recognition system in mobile based platform."* Journal of Telecommunication, Electronic and Computer Engineering (JTEC) 10, no. 3-2 (2018): 77-82.
[28] Kumawat, K., Jain, A. and Tiwari, N., 2024. Relevance of Automatic Number Plate Recognition Systems in Vehicle Theft Detection. Engineering Proceedings, 59(1), p.185.