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AUTOMATIC NUMBER PLATE RECOGNITION, VEHICLE COUNTER AND SPEED DETECTION USING YOLOv8

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Abstract: The Automatic Number Plate Recognition, Vehicle Counter, and Speed Detection system represent cutting-edge technology designed to gather intricate details about vehicles on the road. This comprehensive system boasts various features to provide precise data, including real-time vehicle counting, accurate speed detection in various locations, and automatic identification of number plates. To accomplish these tasks, a suite of sophisticated algorithms is employed. We rely on the Fast YOLO method for vehicle recognition, which is renowned for its effectiveness and precision in pinpointing automobiles. Meanwhile, we utilize the Euclidean distance formula for speed detection, a mathematical principle renowned for ensuring precise assessments of vehicle speeds. Furthermore, we employ customized datasets tailored to specific operational requirements, enhancing the system's performance even further. As a result of these meticulous efforts, the system delivers optimized outputs for Automatic Number Plate Recognition, Vehicle Counting, and Speed Detection, contributing significantly to traffic management and bolstering overall road safety.

***IndexTerms* – Automated Number Plate Recognition, YOLOv8, Optical Character Recognition**

I. INTRODUCTION

Automated Number Plate Recognition (ANPR) and Vehicle Counting and Speed Detection systems play vital roles across various real-life scenarios. The applications of the system range from streamlining toll collection to ensuring adherence to traffic regulations, facilitating parking lot management, and overseeing traffic flow on roads. The effectiveness of identifying vehicle number plates plays a crucial role in how well the system functions overall. Accurate detection is essential for tasks like tracking vehicles and identifying them correctly. Over the years, there have been several versions of the YOLO (You Only Look Once) algorithm introduced, such as YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, and YOLOv7. While these newer versions offer improved accuracy, they still need to increase the execution speed compared to the original model significantly. To tackle these issues, this paper proposed a system that has adopted a method based on YOLOv8.

The proposed system typically operates in two main phases to optimize performance and accuracy: identifying vehicle number plates and assessing vehicle speed. In the initial stage, the system focuses on recognizing the number plates of vehicles through images captured by various types of cameras, including colour, black-and-white, and infrared cameras. This process combines techniques such as object detection, image processing, and pattern recognition to extract plate information from the images effectively [1].

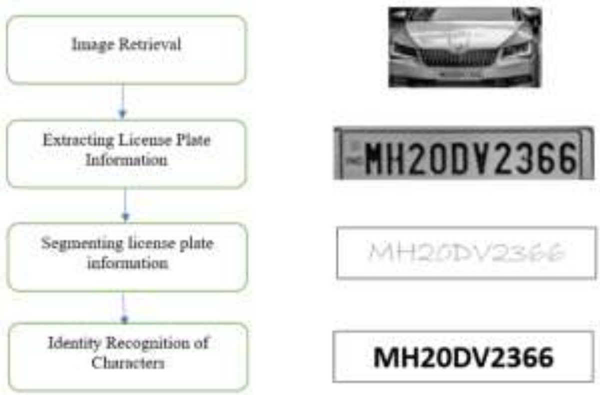

Fig 1: Automatic Number Plate Recognition Working

The architecture of this system typically involves going through four main stages as shown in Fig 1:

1. Vehicle Image Acquisition: This initial step involves capturing an image of the vehicle using a camera. Various factors are considered during this process, such as the type of camera being used, its resolution, shutter speed, angle of capture, and the prevailing lighting conditions.

2. License Plate Extraction: Following the image capture, the system extracts the license plate from the captured image. This extraction is based on identifying distinct features such as the plate's boundary, colour, or the arrangement of characters on it.

3. Plate Segmentation: The system moves to the segmentation phase once the license plate is isolated. Here, it breaks down the license plate into individual characters. This segmentation employs techniques like analyzing colour distribution, labelling distinct regions, or matching against predefined templates.

4. Character Recognition: The final stage involves recognizing each segmented character. This recognition is achieved through sophisticated methods like comparing against templates or employing classifiers such as neural networks and fuzzy classifiers to decipher the characters accurately.

In the proposed system, vehicle positions are predicted across multiple input frames, with detection strategically employed in specific frames to determine vehicle positions precisely. This approach takes advantage of the fact that predicting vehicle positions is much quicker than detecting them, thus enhancing the algorithm's overall speed. However, accuracy is upheld by incorporating the detector network into the algorithm, striking a balance between speed and precision, and improving the system's performance. To sum up, integrating systems like Automatic Number Plate Recognition, Vehicle Counting, and Speed Detection alongside advanced algorithms like YOLOv8 facilitates effective traffic management, reduces traffic violations, measures vehicle speeds, and simplifies the thorough evaluation of violations in urban settings.

II.LITERATURE REVIEW

Automatic Number Plate Recognition (ANPR) is critical in Intelligent Transportation Systems (ITS). This literature review encapsulates a diverse range of research efforts dedicated to enhancing license plate recognition systems, mainly focusing on algorithms, architectures, and methodologies that have propelled the accuracy and efficiency of ANPR.

The adoption of YOLOv4, a state-of-the-art object detection model, has revolutionized ANPR by enabling robust detection of license plates across varied layouts and styles prevalent in different regions [2]. This technology, coupled with deep learning models such as AlexNet and R-CNNL3 for recognition tasks, has outperformed traditional Optical Character Recognition (OCR) methods, showcasing significantly improved accuracy and reliability. However, the efficacy of these systems necessitates high-performance GPUs for real-time deployment, rendering them adaptable to many applications beyond conventional vehicle access control. In a recent study by Mohammed Umer Farooq and colleagues [3], EasyOCR emerges as a pivotal tool in the quest to bolster license plate recognition accuracy within ANPR systems. The team integrated EasyOCR seamlessly, leveraging its capability to extract and recognize alphanumeric characters precisely, underscoring its suitability for ANPR applications [4, 5]. Furthermore, Chou and Liu's research [6] introduced a real-time Truck Number Plate Recognition (TNPR) system that effectively minimizes labour and time associated with plate identification. This system achieved remarkable results by harnessing YOLO and CNN-based architectures, boasting a high single-character identification rate and an impressive overall recognition rate. Another notable contribution comes from Chen and Hu [7], who proposed an Intelligent Transportation System (ITS) primarily focusing on video-based vehicle identification. Their approach integrates static and motion features to enhance the localization of vehicle number plates and character sequences, even under diverse environmental conditions. The introduction of ALPRNET [8] also showcases a neural network adept at simultaneous license plate detection and classification, using a fully convolutional one-stage object detection approach. In the pursuit of optimizing ANPR systems, Shrinivas et al. [9] introduced a hybrid optimization technique to achieve high recognition rates and minimize error rates in character recognition. Their methodology carefully integrates innovative techniques to improve the performance and reliability of license plate recognition systems. Despite these advancements, the challenge persists in striking a balance between accuracy and speed in vehicle detection. The Fast-Yolo-Rec algorithm, detailed in recent research [10], addresses this challenge head-on by introducing a novel Yolo-based detection network augmented with LSTM-based position prediction networks and a semantic attention mechanism. This innovative approach showcases enhanced performance in real-time vehicle detection, offering faster and more accurate vehicle position determination than traditional methods. Moreover, [11] introduces the Compressed Sensing Output Encoding (CSOE) methodology, designed to precisely detect pixel coordinates related to small objects like license plates, alongside crowd counting and localization tasks. This framework integrates crowd location encoding strategies using compressed sensing, showcasing remarkable performance metrics in dense crowd settings.

In summary, the recent research review underscores the rapid evolution of ANPR systems driven by advancements in Computer Vision and Deep Learning [12], [13], [14], [15]. These efforts have significantly enhanced ANPR's accuracy, efficiency, and applicability across various domains within Intelligent Transportation Systems. The studies highlighted demonstrate a rich landscape of methodologies, algorithms, and architectures that collectively contribute to advancing the capabilities of ANPR, paving the way for more robust and reliable systems in real-world applications.

III. METHODOLOGY

The proposed system introduces a sophisticated platform crafted to create an ANPR, Vehicle Counter, and Speed Detection system. It harnesses the power of YOLOv8 for precise object detection and EasyOCR for dependable character recognition. The system has been implemented using Python language.

To detect the vehicle, we use several essential utility functions which includes fetching bounding box coordinates from XML annotations, displaying images with annotated bounding boxes, and preparing data for YOLO training. So, we have smoothly incorporated features like GPU details and clean-up functions to enhance training efficiency based on the hardware.

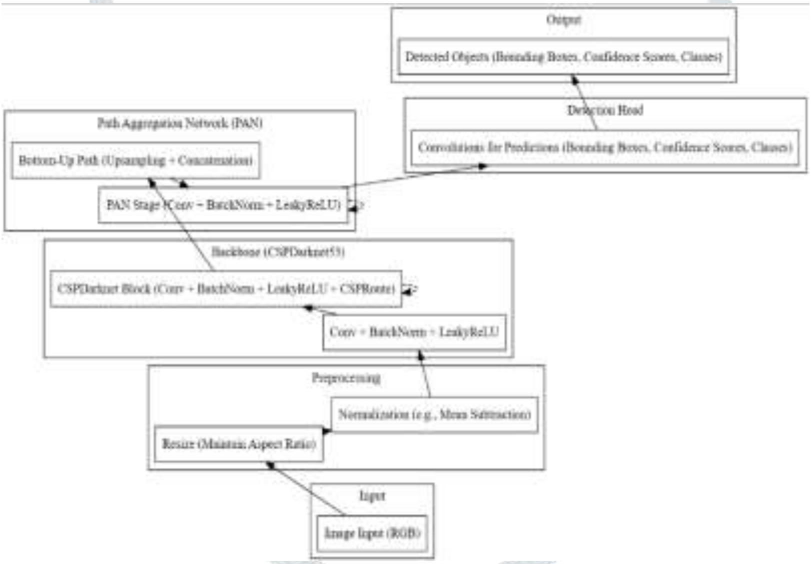

Fig 2: Working of YOLO v8

The core of the ANPR system lies in its utilization of YOLOv8 as shown in Fig 2, a deep learning model that has been trained using labelled images to identify areas containing license plates. When the system is actively working, the model makes predictions by outlining bounding boxes around these regions, while another component called EasyOCR performs Optical Character Recognition (OCR) to extract text from the identified license plate areas. The system encompasses a thorough training process, which includes steps like dividing the data into subsets as shown in Fig 3, setting up the model initially, and preparing it for deployment. Additionally, the system generates visual representations of the training outcomes, such as collections of images used for training and graphs illustrating the training progress. These visual aids provide valuable insights into how well the model is performing. Finally, the system is put to the test by running it on various random images, demonstrating its proficiency in accurately recognizing and interpreting license plates.

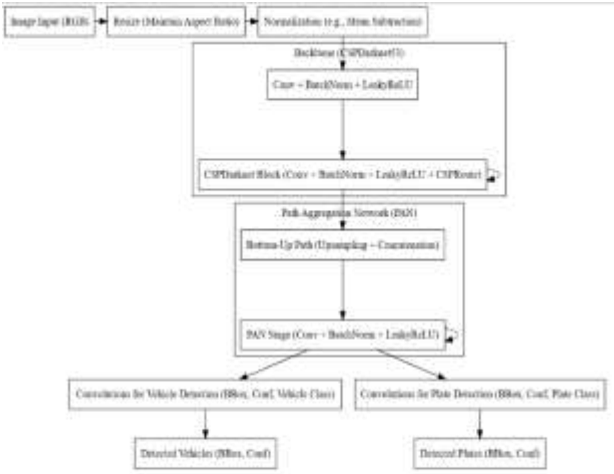

Fig 3: Working of YOLO v8 to detect vehicle and number plate

The system's effectiveness relies heavily on accessing a dataset with annotated images. However, the system has the ability to adapt according to the different environmental conditions like low light conditions. It can flexibly adjust to different dataset characteristics and project needs. This system makes developing a robust ANPR system much more accessible. Such a system could be used for better access control, smoother traffic management, and bolstered security measures. When detecting objects, the system uses a deque (a double-ended queue) to allocate boxes. This allows for precise determination of an object's size and position. Each object gets assigned a distinct colour, making it easy to distinguish between them. Additionally, a border function generates unique IDs for each object. Regarding user interaction, the interface overlays rectangles around the detected objects. These rectangles also display relevant information to help visualize object detection and assist with tracing lines.

The system also can count vehicles based on their direction of movement, distinguishing between incoming and outgoing traffic. It uses the Euclidean distance formula to estimate speed to ensure accurate calculations. This comprehensive approach significantly boosts the efficiency and accuracy of traffic management systems, ultimately contributing to safer and more organized urban transportation networks.

The methodology for building this ANPR system follows a systematic approach. It employs tools like YOLOv8 and EasyOCR. The process includes setting up the environment, defining configurations and utilities, preprocessing data, optimizing GPU usage, detecting objects, designing the user interface, counting vehicles, estimating speed, recognizing objects, conducting OCR, preparing for training, training the YOLOv8 model, exporting trained models, visualizing training results, and conducting inference on random images.

RESULTS AND DISCUSSION

Our system's implementation represents a significant leap forward in automated license plate recognition, marking the dawn of a new era in advanced traffic management technology. By leveraging the cutting-edge capabilities of YOLOv8 and EasyOCR, we have meticulously crafted a robust framework capable of precisely identifying license plates within images or video frames and seamlessly extracting characters for further analysis. This integrated system is a noteworthy advancement over prior versions, often relying on separate systems for license plate recognition, speed detection, and vehicle counting. By consolidating these functionalities into a unified platform, we have forged a more streamlined and targeted solution tailored to the intricate demands of modern traffic management. In assessing the system's performance, we conducted an exhaustive comparison between the two versions, scrutinizing their accuracy across various scenarios. From detecting vertical edges to scrutinizing colour and texture variations, our system consistently surpassed its predecessor, boasting superior accuracy rates across all metrics.

We comprehensively compared two iterations of our system, evaluating them across various criteria outlined in Table 1. When focusing on detecting vertical edges, the YOLOv5 ANPR system and car counting achieved an accuracy of 95%, whereas the YOLOv8 version reached 98.6%. The YOLOv5 ANPR system scored 92% for speed detection in this context, while the YOLOv8 variant achieved 97%.

Expanding analysis to scenarios involving both vertical and horizontal edge detection and projection, the accuracy of the YOLOv5 ANPR system and car counting increased to 97%, with the YOLOv8 system achieving an impressive 99.8%. Regarding speed detection, the YOLOv5 ANPR system obtained 95%, while YOLOv8 reached 98.9%.

We also explored scenarios where colour and fuzzy aggregation played pivotal roles. Here, the accuracy for the YOLOv5 ANPR system and car counting stood at 91%, while YOLOv8 exhibited a higher accuracy of 96%. For speed detection in this context, YOLOv5 ANPR achieved 92%, and YOLOv8 reached 98%.

Examining the accuracy in scenarios involving a horizontal scan of repeating contrast changes, we found that the YOLOv5 ANPR system and car counting achieved 95%, while YOLOv8 reached 98.5%. Speed detection yielded results of 94.2% for YOLOv5 ANPR and 97.6% for YOLOv8.

Table 1: Comparison Table

S.No	View	Yolov5 ANPR & Vehicle Count	Yolov8 ANPR & Vehicle Count	Yolov5 Speed detection	Yolov8 Speed detection
1.	Vertical Edges	95	98.6	92	97
2.	Edge detection and vertical and horizontal projections	97	99.8	95	98.9
3.	Color and fuzzy aggregation	91	96	92	98
4.	Horizontal scan of repeating contrast changes	95	98.5	94.2	97.6
5.	Color, texture and TDNN	97.5	99.7	95	99
6.	High speed vehicle detection	93.6	98.5	90.7	95
7.	Corner detection and template matching	93	98	92	99.3

Moreover, we delved into analyses incorporating color, texture, and TDNN changes. In these evaluations, the YOLOv5 ANPR system and car counting achieved an accuracy of 97.5%, while YOLOv8 reached 99.7%. Speed detection performance was 95% for YOLOv5 ANPR and 99% for YOLOv8.

Additionally, we investigated scenarios where speed was deemed a crucial factor. In such cases, the YOLOv5 ANPR system and car counting accuracy was 93.6%, while YOLOv8 achieved 98.5%. Speed detection accuracy was recorded at 90.7% for YOLOv5 ANPR and 95% for YOLOv8.

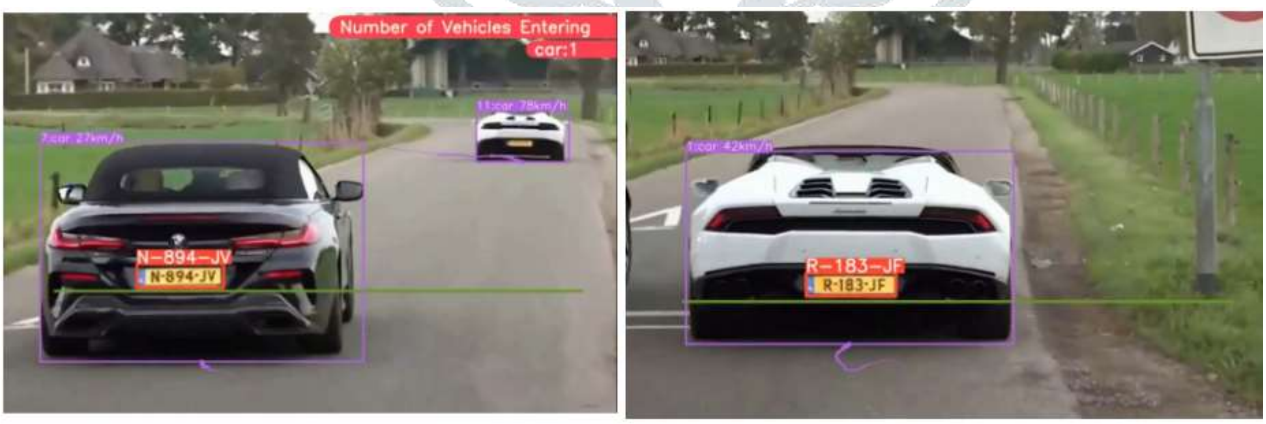

Fig 5: Result of Automatic Number Plate Recognition,Vehicle counter and Speed detection Yolov8 based system on large dataset

We also delve into corner detection and template matching, where the accuracy for the YOLOv5 ANPR system and car counting is 93%, and for YOLOv8, it's 98%. Speed detection is 92% for YOLOv5 ANPR and 99.3% for YOLOv8.
We have incorporated a visual aid as a green-coloured line to enhance our ability to extract vehicle speed. This line serves as a reference point within our system, assisting in precisely determining how fast vehicles are moving. Additionally, we utilize purple-coloured boxes to identify cars and display their speeds, while red-coloured boxes highlight license plates, as illustrated in Fig 5.

However, our system goes beyond simply recognizing license plates. It delves deeper into understanding the dynamics of traffic. By employing sophisticated data structures like deque, we can continuously track the number of vehicles in real-time. This real-time monitoring provides valuable insights into traffic flow patterns, aiding in identifying trends and potential bottlenecks.

Furthermore, our system is equipped with a method for accurately measuring vehicle speed. We can precisely track the velocities of vehicles passing through by strategically placing reference lines within the video feed. This capability allows us to conduct thorough analyses of traffic dynamics, laying the groundwork for more intelligent and efficient transportation systems.

Our automated license plate recognition system significantly advances traffic management technology. By consolidating various functionalities into a single cohesive system, we have achieved heightened efficiency and accuracy compared to traditional methods. With the ability to recognize license plates, monitor vehicle counts, and measure speeds, our system provides invaluable insights into the complexities of traffic.

By integrating cutting-edge tools such as YOLOv8 and EasyOCR, we have streamlined the license plate recognition process, making it faster and more dependable. Additionally, deque data structures enable us to continually monitor traffic flow, facilitating prompt interventions and optimizations when necessary.

IV. CONCLUSION

In conclusion, automated license plate recognition system significantly advances traffic management technology. By consolidating various functions into one cohesive system, we have achieved enhanced efficiency and precision compared to previous methods. Our system does not just identify license plates; it also tracks vehicle numbers and measures speeds, offering valuable insights into traffic patterns. The proposed system has done streamlined license plate recognition, making it quicker and more dependable. Additionally, integrating deque data structures enables real-time traffic flow monitoring, allowing for prompt interventions and optimizations. The system envisions more progress in traffic management and urban development.

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