AI-Based ANPR SystemforIntelligent Vehicle Speed Detection

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Abstract:Vehicleoverspeeding is one of the major causes of road accidents, making automated and reliable speed monitoring systems essential for modern traffic management. This paper presents an AI-based Automatic Number Plate Recognition (ANPR) system for intelligent vehicle speed detection using a dual-camera approach. The proposed system captures vehicle images at two fixed checkpoints and calculates the average speed based on the time difference and known distance between the cameras. Deep learning models are employed to detect vehicles and localize number plates, while an optical character recognition (OCR) pipeline is used to extract license plate information. To improve recognition accuracy under real-world conditions, image preprocessing techniques such as contrast enhancement and adaptive thresholding are applied before OCR. The system supports multiple vehicle categories with predefined speed limits and automatically identifies overspeed violations. A web-based interface is developed to store records, visualize data, and generate downloadable PDF evidence reports for detected violations. Experimental evaluation conducted on real vehicle samples demonstrates improved plate recognition accuracy and reliable speed estimation compared to conventional approaches reported in existing literature. The proposed system offers a practical and scalable solution for intelligent traffic speed monitoring applications.

Keywords: Automatic Number Plate Recognition (ANPR), Vehicle Speed Detection, Average Speed Enforcement, Deep Learning, YOLO, Optical Character Recognition, Intelligent Traffic Monitoring.

I. INTRODUCTION

Road traffic accidents caused by overspeeding are still a critical issue in every part of the world. There is an increasing need for automated and reliable speed monitoring systems. Traditional speed enforcement methods using radar guns and single-point speed cameras are instantaneous in measurement but most often fail to capture driving behavior over distance. In this regard, these methods may not represent actual sustained overspeeding in urban and highway environments.

Recent development in the sectors of artificial intelligence and computer vision has populated the development of intelligent traffic monitoring capable of analyzing vehicle motion with visual information. ANPR has emerged as one of the key technologies in this domain, which uniquely identifies vehicles using license plate information. This allows the average speed of a vehicle across multiple checkpoints to be determined by combining ANPR with time-based measurement, hence producing a more reliable alternative to the conventional spot-speed detection systems.

There are a few existing researches on car detection and speed measurement through a single camera, optical flow technology,

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or geometric calibration algorithms. These methods are extremely dependent on camera angle and geometry calibration accuracy. The main goal of point-to-point average speed measurement systems is to minimize reliance on geometric calculations by leveraging a certain distance along with a timestamp.

In this work, an AI-based ANPR system for intelligent vehicle speed detection is presented using a dual-camera framework. The proposed system captures vehicle images at two fixed locations, extracts license plate information using deep learning–based detection and OCR techniques, and computes the average speed based on the time difference between detections. To improve number plate recognition accuracy under varying lighting and image quality conditions, image preprocessing techniques are applied prior to OCR. The system also categorizes vehicles based on type and applies corresponding speed limits to identify violations automatically.

A full end-to-end system is also designed with a web-based platform to provide storage for the records of the detection process, system output visualization, and the creation of a downloadable evidence report system. Experiments conducted with real car models indicate that the presented system has the ability to provide foolproof plate recognition and accurate speed measurement capabilities.

II. RELATED WORK

Automatic Number Plate Recognition (ANPR) and computer vision-based speed measurement of vehicles have gained significant attention over the past few years because of their practical usage in intelligent transportation systems. Previously, the main tools used for vehicle speed measurement were sensors based on radar technology and inductive loop sensors. These systems are able to detect the speed of the vehicle accurately; however, the results are not customizable.

With developments in computer vision technologies, many research works have been conducted for estimating vehicle speeds using cameras. Studies employing single cameras typically make use of optical flows, perspective projections, or homographies for transforming speeds. Even though hardware complexity has been reduced, highly calibrated cameras, specific points of view, and controlled settings remain crucial for an increased level of accuracy. Even minor variations in camera tilt or lighting conditions can influence the calculation.

These shortcomings could be overcome by the average speed enforcement system involving multiple cameras. Here, the vehicles are detected at two or more locations, and the average speed is derived based on the time difference with the known spacing between the locations. This approach has been adopted in several real-world traffic enforcement systems, as it provides a more reliable representation of vehicle behavior over a distance rather than at a single point.

Recent research has increasingly adopted deep learning–based object detection models for vehicle and license plate detection. The YOLO family of algorithms has been widely used due to its real-time performance and high detection accuracy. These models enable simultaneous detection of vehicles and number plates in complex traffic scenes. However, accurate license plate recognition remains challenging under conditions such as motion blur, low illumination, occlusion, and low-resolution inputs.

For license plate text extraction, traditional OCR engines such as Tesseract have been employed in many studies. Although effective for clean images, their performance degrades when plate images are noisy or distorted. More recent works have introduced deep learning–based OCR frameworks, such as EasyOCR, which demonstrate improved robustness under real-world conditions. Several studies emphasize the importance of image preprocessing, including contrast enhancement and thresholding, to improve OCR performance.

Tracking-based approaches, such as SORT and Deep SORT, have also been explored to associate vehicle detections across frames or camera views. These methods improve vehicle matching accuracy, particularly in multi-camera environments. However, tracking-based systems often require continuous video streams and higher computational resources.

Despite these advancements, many existing studies focus either on vehicle detection or speed estimation as isolated problems. Fewer works provide a complete end-to-end system that integrates ANPR, average-speed calculation, violation detection, and evidence generation within a unified framework. Moreover, limited attention has been given to practical challenges such as handling low-quality images or generating structured violation reports for enforcement purposes.

In contrast, the proposed work focuses on a practical and integrated ANPR-based vehicle speed detection system using a dual-camera approach. By combining deep learning–based detection, robust OCR preprocessing, and average-speed calculation, the system addresses several limitations observed in existing approaches and provides a deployable solution for intelligent traffic monitoring applications.

Existing studies have demonstrated promising results in vehicle detection, license plate recognition, and speed estimation. However, many approaches address these components independently and often require specialized hardware, extensive calibration procedures, or high computational resources. In contrast, the proposed system focuses on integrating these functionalities within a practical and cost-effective framework suitable for real world deployment.

III. LITERATURE SURVEY

This section explains the important research and technologies that are related to our project.Our project makes extensive use of Automatic Number Plate Recognition, vehicle detection, OCR, and an average speed calculation system. For understanding how these systems work, previous research papers, tools, and popular frameworks were studied. The information from these studies helped us design and improve our own AI-based vehicle speed detection system.

The first important technology we studied is the YOLO (You Only Look Once) object detection model. YOLO is one of the fastest and most accurate detection algorithms. It can detect objects like cars and number plates in a single step. The latest version, YOLOv8, is even better in accuracy and speed. Because of this, YOLOv8 is widely used in many real-time vehicle detection projects. In our project too, YOLO helps in identifying the vehicle and capturing the number plate area more clearly.

Different OCR tools were reviewed to read the text on the number plate. Tesseract OCR is an extremely popular OCR engine, maintained by Google.It works well on clean and clear images. But when the plates are blurred or light is low, Tesseract makes mistakes. To solve this, researchers recommend preprocessing like noise removal and sharpening.

Another advanced OCR tool is EasyOCR, which uses deep learning. EasyOCR works better on real-world images that have shadows, angles, or low brightness. It supports many languages and gives more accurate results than classical OCR. Many modern ANPR systems use EasyOCR, and our project also follows this idea for better accuracy.

In vehicle tracking, we studied two important algorithms: SORT and Deep SORT. SORT is a simple and fast method that helps track objects from one frame to another. Deep SORT is an improved version that uses deep learning to track vehicles even when they disappear for a second or when two vehicles overlap. These tracking systems are useful when building multi-camera setups like average-speed detection.

Several survey papers on ANPR explain the common steps involved: detecting the plate, cropping it, reading the text, and cleaning the result. These surveys also list many challenges such as plate tilt, motion blur, night images, and weather problems. These issues helped us understand why real-life ANPR is difficult and why deep learning is important.

We also studied OpenALPR, a popular open-source ANPR system used in parking lots and police enforcement. It shows how ANPR is used in real life and what kind of accuracy and speed is expected in production systems. This gave us a good idea of how to design our system.Then, we went over average-speed enforcement systems that work by placing two cameras a fixed distance apart and calculate speed by the time between them.

Transport departments in many countries use such systems. Their documents explain calibration, evidence handling, and legal rules. This matches exactly what our project aims to do.Some research papers focus on single-camera speed detection, but the problem is that single-camera systems need very accurate calibration and angle correction. Small mistakes can change the speed calculation. Because of this, two-camera systems (like ours) are more reliable.

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OpenCV is another important library studied. It provides many functions for image processing like filtering, edge detection, cropping, and resizing. These functions are needed before passing the plate image into an OCR engine.Camera calibration papers help in measuring real-world distances from images. Even though our project uses a fixed known distance between two cameras, understanding calibration gives better clarity about how professional speed systems work.

We also checked papers on vehicle re-identification (Re-ID). This technology is used to match the same vehicle between different cameras, even if the number plate is not clear. Re-ID uses the shape, color, and features of the vehicle for matching. Several tutorials and GitHub projects helped us understand how YOLO can be trained specifically for plate detection. These practical guides helped us when designing our detection pipeline.

We looked into ReportLab, a Python library that produces PDFs, in order to create the reports. This library enables the addition of text, tables, images, and timestamps to a PDF file. ReportLab was utilised in our project to create a violation report that included entry and exit photos.Finally, we studied about privacy and ethics in ANPR. Since number plates are personal information, systems must follow rules such as secure storage, limited access, and data protection. This helped us design the system with admin-only access.

IV. SYSTEM DESIGN AND ARCHITECTURE

The proposed system aims to develop an end-to-end AI-driven vehicle speed detection system using computer vision and deep learning concepts, and the use of web platforms. In this approach, the main systems and methodologies deployed are modular and utilized to develop systems that are easy to implement and use in real-life traffic systems. The method implemented here uses two fixed cameras marked as Camera A and Camera B located a fixed distance apart.

At the data acquisition layer, cameras continuously capture vehicle images at both checkpoints. When a vehicle passes Camera A, an entry image is captured and forwarded to the processing module. Similarly, when the same vehicle reaches Camera B, an exit image is captured. Each captured frame is time-stamped to enable accurate speed calculation.

The processing layer is responsible for vehicle detection, license plate localization, and text extraction. A deep learning–based object detection model is used to identify the vehicle and localize the number plate region within the image. Once the number plate region is detected, it is cropped and passed through an image preprocessing pipeline. This preprocessing stage includes contrast enhancement, noise reduction, and adaptive thresholding to improve the quality of the plate image before text recognition.

The optical character recognition (OCR) component extracts alphanumeric characters from the preprocessed image of the number plate. The extracted plate number acts as an identifier linking entry and exit points of the vehicle coming from both camera stations. The component classifies the type of vehicle for appropriate speed limits based on categories of cars, bikes, buses, and trucks.

In the speed calculation component, it determines the average speed using the known distance between the two cameras and the known time difference. When it is detected that the calculated speed is breaching the known speed limit based on its type, it is classified as speed violation.

The data management layer is responsible for storing all car information, such as timings, plate numbers, car type, speed values, and images captured. The web-based application layer, built using Django framework technology, is used as an interface through which system events can be monitored. Using this interface, system events can be accessed by authorized personnel. They can view logs of detection events, analyze violative events, and generate PDF reports.
On the whole, the architectural design of the system guarantees perfect compatibility of the AI-based detection method with web-based data management and reporting. Thus, this system can be applicable in intelligent traffic monitoring and enforcement.

V. WORKFLOW

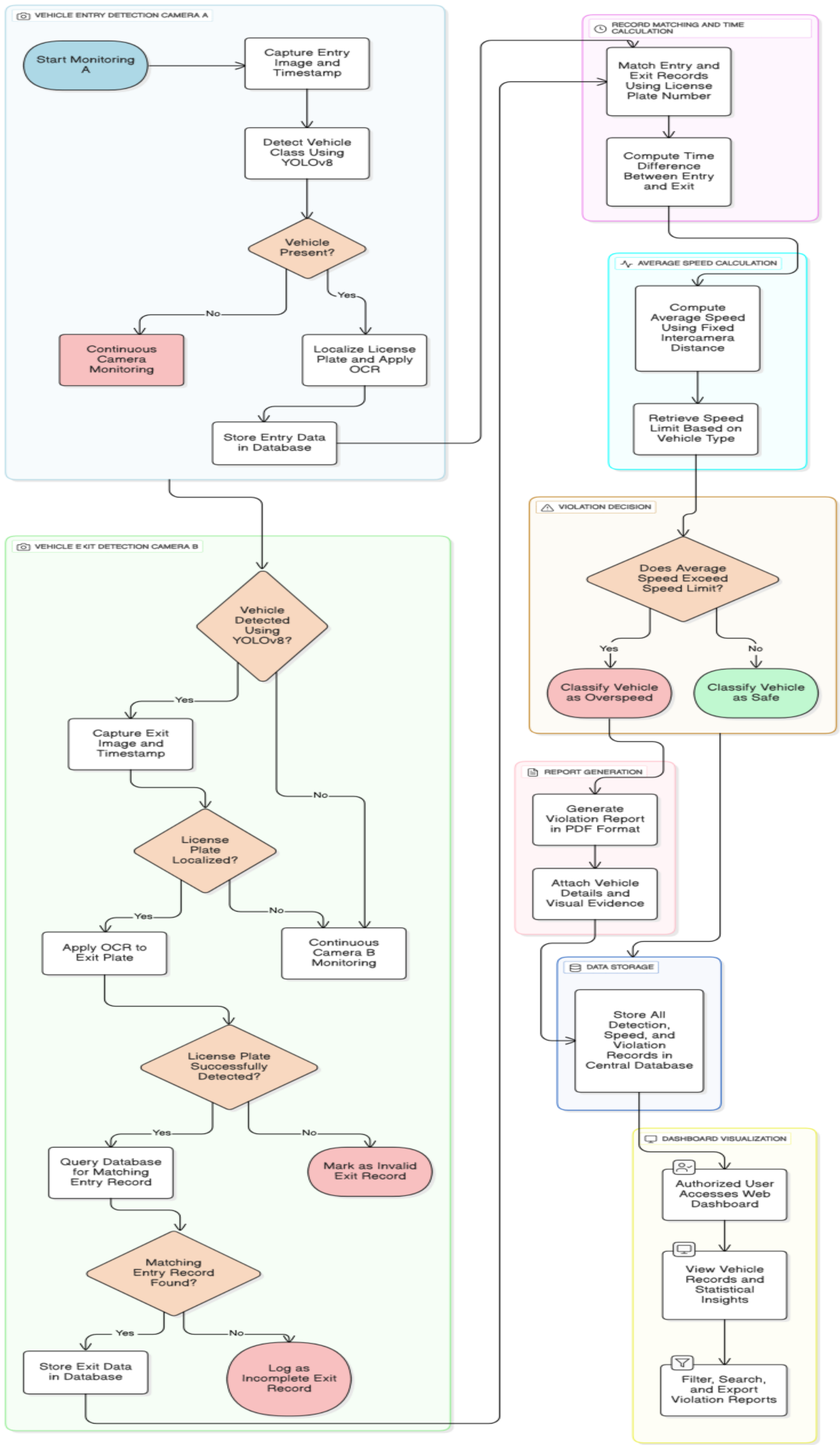

Fig. 1(a): Workflow of The Proposed AI-Based ANPR System

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VI. IMPLEMENTATION

The proposed system for vehicle speed detection is developed with a modular and scalable approach as an integrated framework with computer vision-based approaches using deep learning along with a web-based application setup.

A. Data Acquisition and Camera Functionality:

There are two fixed cameras named Camera A and Camera B. They are mounted at designated points on both sides of the road, at a known interval. The pictures of cars are taken by Camera A at entry points, and by Camera B at exit points. Each picture is labeled with timestamps to enable the accurate calculation of car speeds. The processing is done per picture frame and not per video.

B. Vehicle and License Plate Detection :

To identify cars and locate license plates in taken pictures, deep learning-based object detection is utilized. Because of its real-time performance and detection accuracy, a YOLO-based model is employed. The identified vehicle is categorized into pre-established groups, such as truck, bus, bike, or car. After being cropped from the identified bounding boxes, license plate regions are sent for additional processing.

C. Image Preprocessing and OCR:

To improve license plate recognition accuracy under varying lighting conditions and image quality, an image preprocessing pipeline is applied before OCR. This pipeline includes contrast enhancement, noise reduction, resizing, and adaptive thresholding. These preprocessing steps enhance character visibility and reduce background interference. Optical Character Recognition is then performed using a deep learning–based OCR engine to extract alphanumeric characters from the license plate region.

D. Record Matching and Speed Calculation:

The plate number extracted is a token that is used for linking entry and exit points for images captured by the two cameras. The time difference is calculated from entry to exit once a plate number has been found. The speed of the vehicle is calculated using the time difference and the known separation of the cameras. Speed limits, which depend on the type of vehicles, are introduced to check whether the calculated speed is above the limit.

E. Violation Detection and Data Storage:

If the calculated average speed is greater than the preset speed limit, the vehicle will be identified as an overspeed case; otherwise, the case will be identified as safe. All details such as the number of the plates, type of vehicles, timings, values of the calculated speeds, violation, and images will be stored in a proper database.

F. Web Interface and Reporting:

A web-based system is developed using Django for handling system operations and visualization. Authorized users are provided with access to a dashboard for monitoring vehicle records, violation statistics, and filtering violations by various parameters. For overspeed violations, the system provides downloadable PDF reports containing details of the vehicle, overspeed details, times, and pictorial evidence taken at both checkpoints.

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VII. RESULT

The system successfully detects vehicles, recognizes their number plates, and calculates the average speed using entry and exit timestamps. Overspeeding vehicles are correctly identified and displayed on the dashboard. The PDF report generation feature provides proper documentation of each violation, including entry and exit images and calculated speed values. OCR and YOLOv8 performed well under normal daylight conditions, with accuracy improving after applying preprocessing techniques. The proposed system reduces human effort and provides an automated and low-cost method for road speed enforcement.

Although the proposed system demonstrated reliable performance during testing, the experimental evaluation was conducted using 83 vehicle samples. While the obtained results validate the feasibility of the proposed approach, a larger and more diverse dataset would provide a more comprehensive assessment of system performance under different traffic, environmental, and operational conditions. Future evaluations will focus on testing the system using larger datasets and extended real-world deployments.System performance may decrease under severe occlusion, poor weather conditions, nighttime operation, motion blur, and license plate tampering. These limitations have been acknowledged as future improvement areas.

A qualitative comparison with existing ANPR-based monitoring systems indicates that most reported approaches focus on either license plate recognition or vehicle speed estimation as independent tasks. In contrast, the proposed system integrates vehicle detection, OCRbased license plate recognition, average-speed calculation, violation classification, database management, dashboard visualization, and automated PDF report generation within a single framework. This integration improves practical deployability and operational efficiency for intelligent traffic monitoring applications.

The performance of the proposed system may decrease under challenging conditions such as heavy rain, fog, lowlight environments, severe motion blur, partial plate occlusion, and deliberate license plate tampering. Although the system performed reliably under normal daylight conditions, these scenarios remain challenging for computer vision-based monitoring systems and require further investigation.

On the whole, it is proved that the system can successfully detect cars, accurately identify license numbers, and correctly calculate the average speed of the cars.

Fig. 2(a): Web-based dashboard showing vehicle statistics and speed violation summary

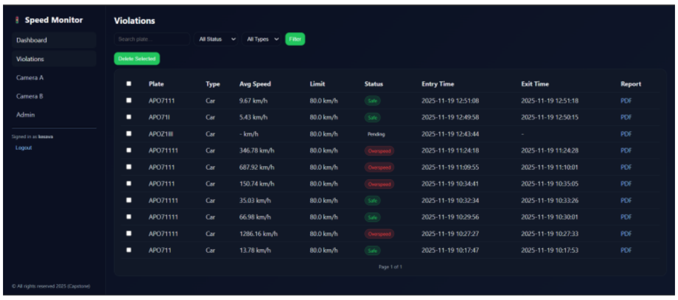

Fig. 2(b):Violation records displaying detected vehicles, speed status, and report generation

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VIII. CONCLUSION

This paper presented an AI-Based ANPR System for Intelligent Vehicle Speed Detection. The system captures vehicle images at two checkpoints, extracts license plate information using deep learning and OCR techniques, and calculates average vehicle speed based on the time difference and a fixed inter-camera distance. Vehicle type classification and speed limit checking have been applied to automatically detect speeding violations.

Experimental results demonstrate that the system performs vehicle detection reliably, license plate recognition accurately, and speed estimation correctly. The use of a two-camera average-speed approach reduces dependency on single-point measurements and improves overall accuracy. The developed web-based interface and automated report generation further demonstrate the practicality of the proposed system for real-time traffic monitoring applications.

Since vehicle license plates contain sensitive information, secure storage and controlled access mechanisms are essential. The proposed system restricts access to authorized users through an administrative interface. Data retention policies, privacy regulations, and legal compliance requirements should be considered before large-scale deployment. Additionally, deployment challenges such as camera positioning, network connectivity, maintenance, and environmental conditions must be addressed to ensure reliable operation.

Overall, the proposed approach provides an effective and deployable solution for intelligent vehicle speed monitoring and violation detection.

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