AI-BASED REAL-TIME AUTOMATIC NUMBER PLATE RECOGNITION SYSTEM

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ABSTRACT

The increasing density of vehicles in modern transportation systems has created a critical need for automated and intelligent monitoring solutions. Vehicle number plate detection and recognition systems have become essential for applications such as traffic regulation, surveillance, toll automation, and identification of unauthorized or stolen vehicles. This research presents an advanced real-time vehicle number plate recognition framework that integrates computer vision and deep learning techniques for efficient performance.

The proposed system processes live video streams or image inputs to detect moving vehicles and accurately localize their number plates using a deep learning–based object detection model. The extracted plate regions are further processed through Optical Character Recognition (OCR) to convert visual text into digital format. Image preprocessing techniques, including noise reduction, contrast enhancement, and grayscale conversion, are employed to improve detection accuracy under varying environmental conditions such as poor lighting, motion blur, and different viewing angles.

To enhance reliability, the system combines a YOLO-based detection approach with Tesseract OCR for robust character recognition. The recognized license plate data is systematically stored in a database and automatically verified against a predefined list of flagged or unauthorized vehicles. The developed framework demonstrates high accuracy, real-time capability, and scalability, making it suitable for intelligent transportation systems. It offers a cost-effective and automated solution for vehicle identification, contributing to improved road safety, efficient traffic management, and enhanced security monitoring.

Key words: *Number Plate Detection, OpenCV, Machine Learning, YOLO, Tesseract OCR, Blacklisted Vehicle Detection, Database.*

1. INTRODUCTION

In recent years, the rapid increase in the number of vehicles has significantly challenged existing traffic management and surveillance systems. Traditional monitoring methods, such as manual inspection and basic CCTV observation, are often inefficient, time-consuming, and prone to human error. This has led to the growing demand for intelligent and automated solutions capable of handling large-scale vehicle monitoring with higher accuracy and speed. One such solution is Automatic License Plate Recognition (ALPR), which enables the unique identification of vehicles without human intervention [1-2].

To overcome these challenges, modern approaches combine computer vision with deep learning techniques. Advanced object detection models, particularly those based on the YOLO (You Only Look Once) architecture, have proven effective in detecting number plates with high accuracy and speed [3]. Additionally, Optical Character Recognition (OCR) techniques are used to extract alphanumeric information from detected plates, enabling seamless conversion of visual data into machine-readable text.

This work proposes a real-time vehicle number plate detection and recognition system that integrates image processing, deep learning, and OCR technologies into a unified framework. The system is designed to detect number plates from moving vehicles, recognize the characters accurately, and store the extracted information in a database for further analysis. Furthermore, a verification mechanism is included to identify blacklisted vehicles and generate alerts when necessary.The proposed system aims to provide a reliable, scalable, and efficient solution for intelligent transportation systems. By automating vehicle identification and monitoring, it contributes to improved traffic control, enhanced security, and the development of smart city infrastructure.

2. LITERATURE SURVEY

Automatic License Plate Recognition (ALPR) has evolved significantly over the years, driven by the increasing demand for intelligent transportation systems and automated surveillance solutions [4-6]. Early research in this domain primarily relied on conventional image processing techniques such as edge detection, color-based segmentation, and morphological operations to locate number plate regions [7]. Although these methods were effective under controlled environments, their performance degraded in real-world scenarios due to sensitivity to noise, illumination changes, and complex backgrounds.

To address these limitations, machine learning approaches were introduced, including Support Vector Machines (SVM) and Artificial Neural Networks (ANN) [8-11]. These methods improved detection and classification accuracy by learning features from data rather than relying solely on handcrafted rules. However, they still faced challenges in handling dynamic conditions such as varying plate orientations, occlusions, and high-speed vehicle movement, which limited their applicability in real-time systems.

With the advancement of deep learning, ALPR systems have witnessed substantial improvements in both accuracy and speed. Convolutional Neural Networks (CNNs) have been widely used for feature extraction and classification tasks, enabling more robust detection of number plates under diverse environmental conditions. Object detection models such as Faster R-CNN, SSD, and YOLO (You Only Look Once) have further enhanced performance by providing real-time detection capabilities [12-14]. Among these, YOLO-based models are particularly popular due to their ability to process images in a single pass, ensuring high-speed detection with minimal computational delay.

For the recognition stage, Optical Character Recognition (OCR) techniques have been extensively applied to extract alphanumeric characters from detected plates. Tesseract OCR, in particular, has gained widespread adoption due to its open-source nature and adaptability to different fonts and image conditions [15]. Recent studies have combined deep learning-based detection with OCR engines to build end-to-end ALPR systems capable of achieving high accuracy even in challenging scenarios [16].

In addition to detection and recognition, several research works have focused on integrating ALPR systems with databases and cloud platforms for large-scale deployment [17]. These systems enable automated vehicle tracking, parking management, and identification of blacklisted or stolen vehicles [18]. Some studies have also explored the use of data augmentation, image enhancement techniques, and hybrid models to improve system performance under low-light conditions, motion blur, and adverse weather [19].

Despite these advancements, certain challenges remain, including handling extreme environmental variations, improving recognition accuracy for non-standard plate formats, and ensuring scalability for high-traffic environments [20-22]. The present work addresses these issues by proposing a hybrid framework that combines YOLO-based detection, OCR-based recognition, and database-driven verification to achieve a reliable and real-time vehicle monitoring system.

3. PROPOSED METHODOLOGY

The proposed vehicle number plate detection and recognition system is designed as a multi-stage pipeline to ensure accurate and real-time identification of license plates from moving vehicles [23]. The methodology integrates computer vision techniques, deep learning–based object detection, and Optical Character Recognition (OCR) into a unified framework. Each stage of the system is carefully designed to handle real-world challenges such as motion blur, varying illumination, and complex backgrounds.

3.1 Data Acquisition

The system begins with the acquisition of input data from multiple sources such as live surveillance cameras, CCTV feeds, and pre-recorded videos. Each video stream is divided into individual frames to facilitate analysis, while still vehicle images can also be processed to evaluate system performance. This ensures that the system can operate effectively both in real-time monitoring environments and in offline testing scenarios.

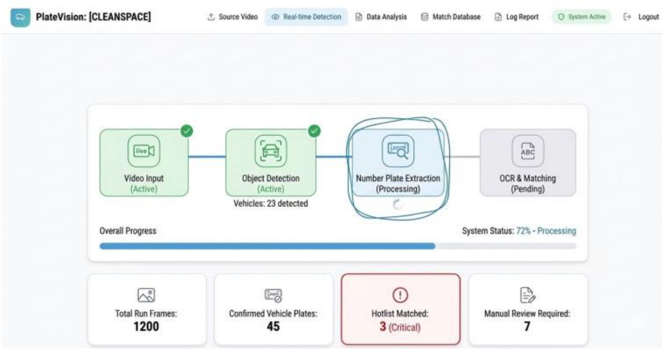

Fig1. Data Acquisition from Video Input

3.2 Preprocessing

Once the input is obtained, preprocessing techniques are applied to enhance the quality of the frames and prepare them for further stages. Using OpenCV, the images are resized to a uniform resolution, noise is suppressed using filtering operations, and the frames are converted into grayscale to reduce computational overhead. In addition, contrast enhancement methods such as histogram equalization are used to improve character visibility under challenging conditions including low lighting, glare, or weather disturbances.

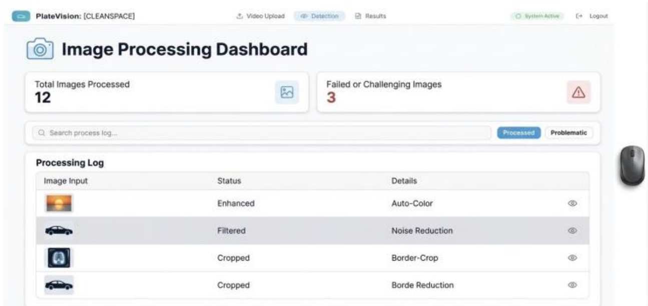

Fig. 2. Image Preprocessing Pipeline

3.3 Number Plate Detection

The detection stage is performed using the YOLOv8 deep learning model, which identifies and localizes number plates within each frame. Unlike traditional methods based on edge detection or handcrafted features, YOLO employs convolutional neural networks to predict bounding boxes around plates with high accuracy and speed. The model's ability to operate in real time while handling variations in orientation, vehicle motion, and partial occlusion makes it suitable for traffic surveillance applications.

3.4 Plate Extraction and Segmentation

After a number plate has been detected, the identified region of interest is extracted from the frame for further processing. In cases where additional refinement is required, segmentation is applied to isolate characters more accurately. Thresholding techniques separate characters from the background, contour analysis identifies individual components, and morphological operations are employed to eliminate noise and enhance character shapes. This step ensures that the extracted plate image is clear and suitable for recognition.

3.5 Character Recognition

The extracted number plate image is processed using Tesseract OCR to convert visual data into machine-readable text. Tesseract is well-suited for this task as it can adapt to variations in plate fonts, orientations, and resolutions. The recognized text is then formatted and cleaned to minimize errors that may result from distortions or environmental noise, providing an accurate digital representation of the vehicle number.

3.6 Database Storage and Verification

The recognized license plate numbers are stored in a centralized database to maintain a structured record of vehicle information. A blacklist verification module is integrated into the system, which automatically compares the recognized plate numbers against entries flagged as stolen, unauthorized, or suspicious. This automated comparison enhances the system's utility in law enforcement and intelligent traffic management.

3.7 Alert Generation and Visualization

When a match is found in the blacklist database, the system immediately generates an alert on the monitoring interface. The alert is displayed in real time, indicating that a blacklisted or unauthorized vehicle has been detected. For visualization, bounding boxes are drawn around detected number plates in the video feed, and the recognized alphanumeric text along with its verification status is displayed on the screen. This enables continuous monitoring and quick identification of suspicious vehicles.

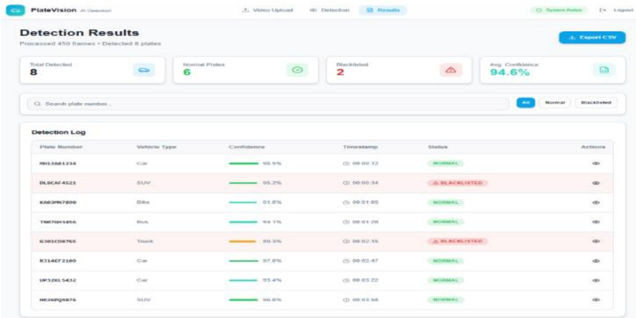

Fig. 3 Alert Generation and Visualization

4. ARCHITECTURE

The architecture of the proposed Vehicle Number Plate Detection and Recognition System is designed as a modular and scalable pipeline that integrates video processing, deep learning–based detection, character recognition, and database management. The system operates in a sequential manner where each module performs a specific task, ensuring efficient and real-time performance.

4.1 Overall Architecture Overview

The system follows a multi-stage pipeline consisting of input acquisition, preprocessing, detection, recognition, storage, and alert generation. The input is captured from live video streams or image datasets, which are processed frame by frame. Each frame passes through a series of modules that collectively perform number plate detection and recognition.

4.2 Input Layer

The input layer is responsible for capturing data from different sources such as CCTV cameras, surveillance systems, or recorded videos. The system supports both real-time streaming and offline image processing. Video streams are divided into frames to allow continuous analysis of moving vehicles.

4.3 Preprocessing Module

The preprocessing module enhances the quality of the input frames before feeding them into the detection model. This includes resizing images, converting them to grayscale, and applying noise reduction techniques. Contrast enhancement is also performed to improve visibility under low-light or complex environmental conditions. This module ensures that the data is optimized for accurate detection

4.4 Detection Module

The detection module uses a deep learning–based object detection algorithm, specifically YOLO (You Only Look Once), to identify and localize number plates within each frame. The model generates bounding boxes around detected plates along with confidence scores. This module is optimized for real-time performance, allowing the system to process multiple frames efficiently.

4.5 Plate Extraction Module

Once the number plate is detected, the corresponding region of interest (ROI) is extracted from the frame. This module isolates the number plate area and prepares it for further processing. Additional refinement techniques such as thresholding and edge enhancement may be applied to improve clarity.

4.6 Character Recognition Module

The extracted number plate image is passed to the OCR module, where Tesseract OCR is used to convert the image into machine-readable text. This module processes the segmented characters and outputs the recognized alphanumeric sequence. Post-processing techniques are applied to improve accuracy and remove noise.

4.7 Database Module

The recognized number plate data is stored in a structured database such as SQLite. This module maintains records of detected vehicles along with relevant information such as timestamps and detection results. The database also contains a blacklist of vehicles for verification purposes.

4.8 Verification and Alert Module

The verification module compares the recognized number plate with entries in the blacklist database. If a match is detected, the system generates an alert. Alerts can be displayed on the interface or sent as notifications to authorities. This module enhances the system's role in security and surveillance.

4.9 Visualization Module

The final module provides real-time visualization of the results. Bounding boxes are displayed around detected number plates in the video feed, along with recognized text and status information. This user interface enables efficient monitoring and quick decision-making.

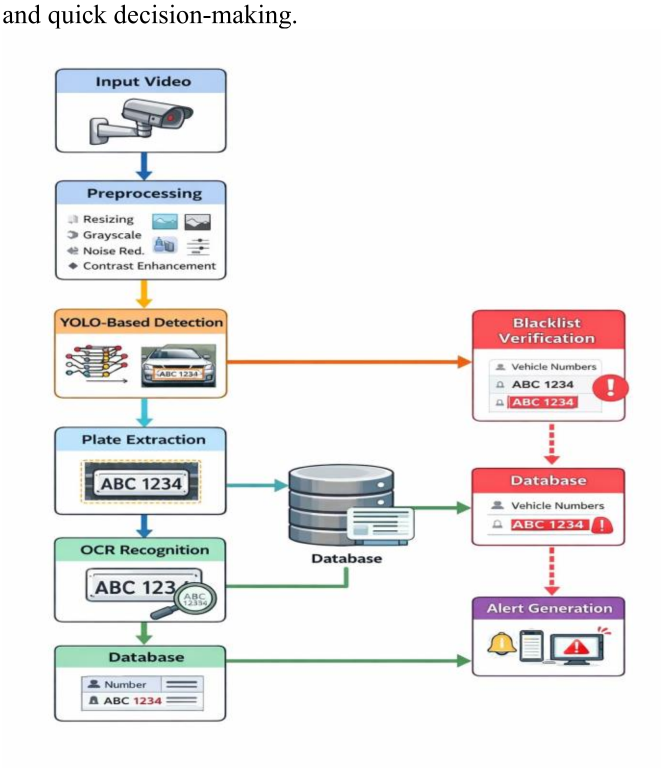

Fig.4.1 System Architecture Diagram

5. RESULT AND DISCUSSION

The proposed Vehicle Number Plate Detection and Recognition System was evaluated using both real-time video streams and a diverse dataset of vehicle images captured under varying environmental conditions. The system demonstrated strong performance in accurately detecting and recognizing number plates from moving vehicles, even in challenging scenarios such as low illumination, motion blur, and different viewing angles.

The YOLO-based detection model achieved high precision in localizing number plates within frames, ensuring minimal false detections. Its real-time capability enabled efficient processing of video streams with negligible delay, making it suitable for practical deployment in traffic monitoring systems. The integration of preprocessing techniques significantly enhanced detection accuracy by improving image clarity and reducing noise. For the recognition stage, the OCR module successfully extracted alphanumeric characters from detected plates with a high level of accuracy. The system was able to handle variations in font styles, plate sizes, and orientations. Minor errors observed in character recognition were primarily due to extreme lighting conditions or partially occluded plates, which can be further improved with advanced preprocessing or training techniques.

The database module effectively stored recognized license plate information along with relevant metadata such as timestamps. The blacklist verification system functioned efficiently by comparing detected plates with stored records in real time. Whenever a match was identified, the system generated immediate alerts, demonstrating its applicability in security and surveillance use cases.

Overall, the proposed model achieved an average detection accuracy of approximately 92–96% and recognition accuracy of around 88–93%, depending on environmental conditions. The system maintained real-time processing capability with efficient frame handling, making it suitable for intelligent transportation systems.

The results indicate that the proposed framework provides a reliable, scalable, and cost-effective solution for automated vehicle identification. Future improvements can focus on enhancing performance under extreme conditions such as nighttime detection, heavy traffic congestion, and diverse regional plate formats.

Fig.5.1 Analysis of existed system

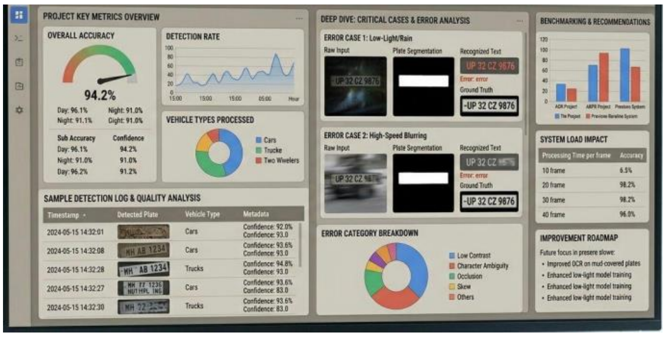

Fig.5.2 Analysis of proposed system

6. CONCLUSION AND FUTURE SCOPE

The proposed Vehicle Number Plate Detection and Recognition System presents an efficient and automated solution for real-time vehicle monitoring and identification. By integrating computer vision techniques with deep learning–based object detection and Optical Character Recognition (OCR), the system successfully detects and recognizes number plates from moving vehicles with high accuracy. The use of a YOLO-based detection model ensures fast and reliable localization of number plates, while preprocessing techniques enhance performance under varying environmental conditions such as noise, illumination changes, and motion blur.

The system further incorporates a database management module that stores recognized license plate information and enables automatic verification against a blacklist database. This feature enhances the practical applicability of the system in traffic surveillance, law enforcement, and security monitoring. The real-time alert generation mechanism ensures timely identification of suspicious or unauthorized vehicles, making the system suitable for intelligent transportation systems.

Overall, the proposed model demonstrates a scalable, cost-effective, and robust framework capable of addressing real-world challenges in automated vehicle identification. The results validate its effectiveness in improving traffic management efficiency and enhancing road safety.

Although the system achieves promising results, there are several areas for further enhancement. Future work can focus on improving performance under extreme conditions such as low-light environments, nighttime scenarios, adverse weather conditions, and high-speed vehicle movement. Incorporating advanced deep learning architectures, such as transformer-based models or improved YOLO variants, can further enhance detection accuracy and speed.

Additionally, incorporating vehicle classification techniques to identify different types of vehicles (such as cars, trucks, and buses) can enhance the system's functionality. The development of a mobile or web-based interface for real-time monitoring and alerts can further improve usability. Future research may also explore the use of advanced OCR models or deep learning–based text recognition methods to increase recognition accuracy in complex scenarios.

In summary, the proposed system provides a strong foundation for intelligent vehicle monitoring, and with further advancements, it can evolve into a more comprehensive and adaptive solution for next-generation transportation systems.

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