# Vehicle Surveillance Optimization via Deep Learning Methods


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***Abstract*—**The increase in number of vehicles on the road is being observed day by day, and the responsibilities that should be upheld by vehicle owners are frequently neglected. To ensure that the rules defined by the RTO are adhered to by every vehicle owner, the "Vehicle Surveillance System using deep learning" is proposed. This system is designed to capture vehicle data through web-app, with the identification of vehicles being achieved through the recognition of their number plates, and the extraction of characters from the plates. Once the vehicle's number plate is recognized, the vehicle's information and owner's details will be verified with RTO data using Ap- plication programming interface(API). If any unfulfilled criteria are identified by the system, a notification will be generated. Vehicle detection is carried out using the Common Objects in Context Single Shot MultiBox Detection (COCOSSD) model, while the Russian model is utilized for number plate recognition. The extraction of characters from the number plate is executed through Optical Character Recognition (OCR), which includes character extraction and segmentation.



***Index Terms*—**Vehicle Compliance, Real-Time Monitoring, Number Plate Recognition, Character Extraction, COCOSSD Model, Russian Model, Optical Character Recognition (OCR), Application Programming Interface (API), etc


## I. Introduction

Two-wheelers and four-wheelers are among the many types of vehicles that are present on the road, therefore problems like unpaid penalties and expired insurance frequently come up. Due to the wide variety of vehicles on the road, including both two- and four-wheelers, problems like unpaid fines and expired insurance frequently occur. Establishing a trustworthy system for recognising and classifying these cars is essential. This identification procedure includes both the vehicle recognition and the character extraction from the licence plate. Once the data on the number plate is identified, further steps are taken to confirm whether the car has any unpaid fines, expired insurance, or other problems. The first stage in this sequence is the identification of a car's licence plate. his process starts with identifying the car's license plate and usually involves four distinct phases in number plate recognition algorithms, including image preprocessing, character segmentation, optical character recognition (OCR), and post-processing for verification and validation.[1]

i) Vehicle image capture
ii) Number plate detection
iii) Character segmentation
iv) Character recognition

Once the vehicle has been identified, the gathered information can be used for any necessary post-processing tasks, such as updating records for parking management and toll collecting systems or verifying against databases for law enforcement. Strong algorithms and top-notch imaging systems are essential for character identification since the effectiveness of the number plate recognition and character segmentation processes greatly influences the accuracy of character identification. Furthermore, these systems now function much better thanks to developments in deep learning approaches, which allow for more precise and effective detection even in difficult situations like dim lighting or bad weather. See Fig. 1 for a visual representation of the Number Plate Recognition System's fundamental functions.

The study paper discusses many ways for detecting automobiles and then recognising licence plates. The majority of these Automatic Number Plate Recognition (ANPR) systems rely on well-established approaches, such as CNN integrated with TensorFlow [5], YOLO [2], Faster R-CNN [3], OpenCV [4], and K-Means in conjunction with CNN [1]. Notably, these

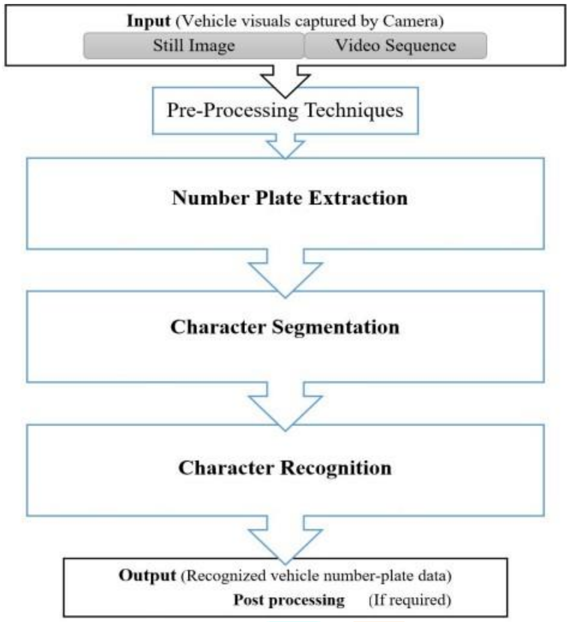


Fig. 1. Basic Flow of Number Plate Recognition [15]

systems all follow a similar sequence of activities, which includes character recognition, licence plate recognition, vehicle identification, and character segmentation, even if their methodologies differ. This standardised sequence of processes emphasises the common aims shared by various systems: reliably identifying cars and extracting relevant information from licence plates.Furthermore, ANPR systems' performance has been greatly improved by developments in machine learning algorithms, especially in deep learning frameworks like TensorFlow and YOLO. This has made detection faster and more accurate in a variety of real-world circumstances. The resilience and dependability of these systems are further enhanced by the use of computer vision techniques like feature extraction and pattern recognition, which makes them essential tools in contemporary traffic management and law enforcement applications.

## II. Literature Survey

### A. Vehicle Tracking and Surveillance

Many techniques have been put forth in the field of vehicle tracking and surveillance to improve the precision and effectiveness of real-time monitoring. A prominent work, designated as Paper [1], presents an automatic car monitoring system that makes use of cutting-edge deep learning models such as YOLO and the IMAGEAI framework. This research also highlights the importance of data gathering and annotation, which is necessary to train the models. The findings show an impressive 98.5% accuracy in automobile detection, 97% accuracy in number plate detection, and 96.7% accuracy in optical character recognition.

In a similar spirit, Paper [2] investigates vehicle recognition and tracking using OpenCV, the CAMSHIFT algorithm, and Gaussian background modelling. This method's ability to follow cars precisely—even when they overlap—is one of its most amazing qualities. It shows how well the CAMSHIFT algorithm handles occlusions and deformations.

An alternative method for the real-time identification of vehicle number plates using security cameras is presented in another research, Paper [6], which makes use of Faster R-CNN. In order to improve accuracy, this study integrates sophisticated machine learning models with optical character recognition (OCR) techniques. The result is a remarkable 91 % accuracy in number plate detection and car owner information retrieval.

Moreover, Paper [7] concentrates on integrating the YOLO method for licence plate recognition and real-time vehicle identification. Convolutional neural networks (CNNs), optical character recognition (OCR), and transfer learning are among the strategies that are used in this study. This study goes beyond licence plate recognition to include the identification of helmet-less motorbike riders from CCTV footage.

It is noteworthy, therefore, that although this section is not a paper in the conventional sense, it does offer crucial background information for the real-world implementations of the research covered in the assessed articles by describing the advantages of video-based vehicle identification technologies over conventional approaches.

### B. License Plate Detection and OCR

Numerous research works have significantly improved the accuracy and productivity in the fields of optical character recognition (OCR) and licence plate recognition. In Paper [3], computer vision technologies and convolutional neural networks (CNNs) with TensorFlow are used to perform real-time licence plate identification. The input layers, convolutional layers, activation layers, pooling layers, and fully linked layers that make up the network architecture are all highlighted by the research. A high accuracy of between 70% and 99% is obtained by training the model with 25,000 steps and eight batches. The research also sheds light on the existence of car licence plates in photos, which are shown by green boxes when effective detection is achieved.

The main emphasis of Paper [5] is optical character recognition (OCR) for number plate recognition. The paper goes into detail on the sequential steps, which begin with picture capture, continue with processing, and end with character recognition. In this study, OCR using Template Matching, adaptive thresholding, binary image processing, character segmentation, and feature extraction are introduced. The work is noteworthy for its comparison of character segmentation and clustering methodologies, which shows that character segmentation consistently performs better than clustering, with an 82 % recognition rate for characters in different shapes and dimensions.

Moreover, a novel method for high-accuracy real-time automobile licence plate identification based on convolutional neural networks (CNNs) is presented in Paper [4]. This approach presents the MD-YOLO framework, which makes use of a quick intersection over union evaluation procedure and accurate rotation angle prediction. To demonstrate better performance, the study assesses and contrasts the End-To-End Model with the Split Training Model (ALMD-YOLO). Here, the focus is on how crucial it is to anticipate multi-directional licence plate rotation angles precisely, as any departure from the actual angle has a substantial effect on the overlap between anticipated bounding boxes and ground truth.

### *C. Models Accuracy Summary*

Every paper displays the number plate detection model's accuracy. A wide range of accuracy, from 70% to 99%, is demonstrated by the Convolutional Neural Network (CNN), underscoring its versatility and promise for high precision [3,4,7]. The efficacy of OpenCV in successfully detecting number plates is demonstrated by its 91% accuracy rate when combined with Optical Character Recognition (OCR) [2]. Easy-OCR performs admirably in difficult situations like fuzzy photos, even with its reasonable 82% accuracy. However, the remarkable accuracy rate of 98.5% displayed by the YOLO model combined with IMAGEAI highlights its applicability for accurate and effective number plate identification in real-world surveillance settings [1].

## III. Methodology

A structured implementation process is provided by the deep learning-based Vehicle Surveillance System approach.It starts with a webcam taking pictures of vehicles in real time. Next, it uses the COCOSSD model to detect vehicles. The system then uses the Easy-OCR to extract characters from the observed number plate and a Russian model for accurate number plate identification. After that, to decide whether to send notifications to the right department or the car owner, the system compares the retrieved data with a database of vehicle details. Notably, COCOSSD was selected for vehicle detection due to its ability to identify clearly visible cars and licence plates. The methods used in the Real Time Vehicle Compliance Monitoring System are derived from a survey of carried literature. The following order must be followed for the system to be implemented effectively. The techniques applied in the Real-Time Vehicle Compliance Monitoring System are derived from a thorough examination of existing literature. This ensures that the approach is founded on established practices and findings from research. To effectively implement the system, it is imperative to follow a specific sequence: firstly, capturing real-time images using a webcam; then, employing the COCOSSD model for vehicle detection; subsequently, utilizing Easy-OCR for extracting characters from license plates; employing a specialized Russian model for accurate identification of number plates; and lastly, comparing the obtained data with the vehicle details database to make informed decisions regarding notifications. Such a structured approach guarantees the smooth integration and operation of the Vehicle Surveillance System for monitoring vehicle compliance in real-time.

i) Real-time Image Capture: Utilizing a webcam, images of vehicles are captured in real-time.
ii) Vehicle Detection: Employing the COCOSSD model, vehicles are detected within the captured images.
iii) Number Plate Recognition: Once vehicles are identified, the Russian Model is employed to recognize the number plates.
iv) Character Recognition: Easy-OCR is utilized to extract and recognize characters from the detected number plates.
v) Data Verification: The vehicle details are cross-referenced with RTO data to determine the necessity of sending notifications to either a specific department or the vehicle owner.

### *A. Data Acquisition:*

The license plate (LP) images can be captured using any resolution camera. High resolution images are suggested for accurate results. Pictures are captured from the front and rear of the cars at a distance of up to three meters (about two meters). Pictures are gathered for the model's testing from a variety of locations, including parks, camps, and streets. Nevertheless, the license plate can always be directly scanned. For the time being, only the English (LP) images are applicable. A license plate from a two-wheeled or four-wheeled vehicle is possible.

### *B. Preprocessing:*

The colored license plate is converted during image processing from BGR (Blue-Green-Red) to grayscale color space, which is commonly referred to as BGR2GRAY. In many digital systems, images are represented using the BGR color model. This model uses three color channels—blue, green, and red, respectively—to represent each pixel in an image. The methodical process of converting a multi-channel BGR representation to a single-channel grayscale representation is known as the BGR2GRAY conversion technique. Images in grayscale display pixel intensity values between 0 (black) and 255 (white), along with various shades of gray. Furthermore, Gaussian blur, a well-known method in digital image processing, is applied. This technique is well-known for its effectiveness in tasks involving noise reduction and image smoothing. Fundamentally, Gaussian blur is the result of convolutioning an image through a matrix called a Gaussian kernel, whose components are dictated by the Gaussian distribution.

### *C. Model Integration for Vehicle Surveillance System/ Model Implementation:*

i) COCOSSD: One well-known deep learning model for real-time object detection in photos is COCO-SSD. With great accuracy and speed, COCO-SSD provides a single-shot detection framework that can recognize multiple objects in images. identifying a specific vehicle type, such as a two- or four-wheeled vehicle, in this way. A

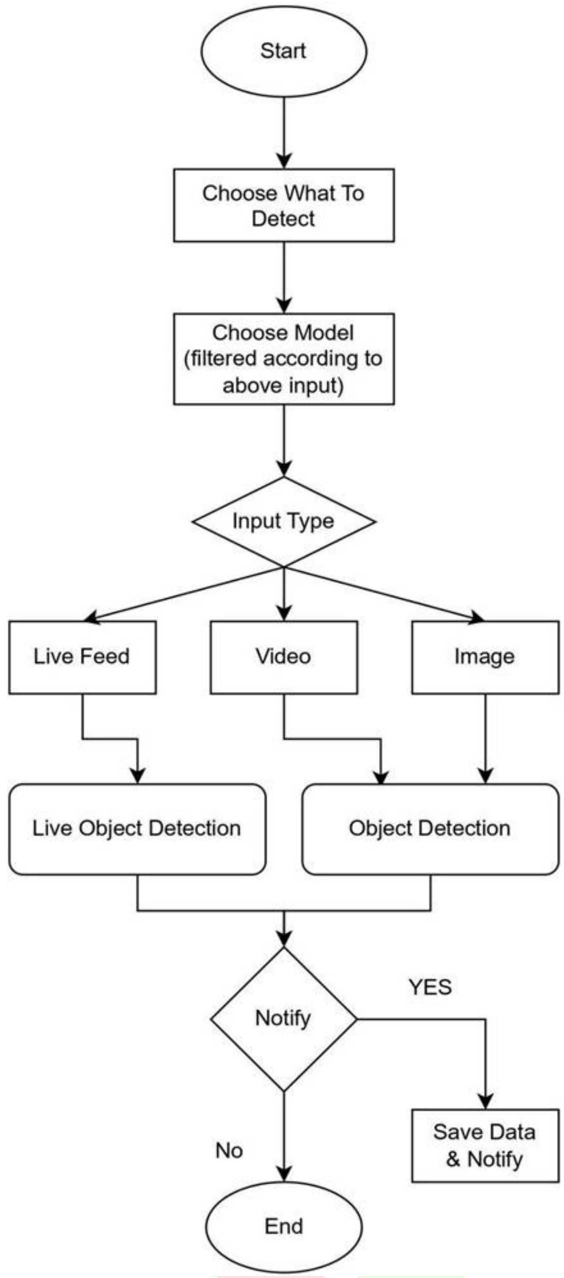


Fig. 2. Flow of Vehicle Surveillance System using deep learning

deep convolutional neural network (CNN) architecture serves as the foundation for COCO-SSD and is intended to effectively extract features from input images. The feature extractor, or backbone network, is in charge of processing input images and obtaining hierarchical features that record both high-level and low-level data. In order to enhance object detection capabilities for a range of object sizes and capture multi-scale features, COCO-SSD frequently integrates a Feature Pyramid Network (FPN) atop the backbone network. FPN aggregates data from various backbone network scales to create a hierarchical pyramid of feature maps. This allows the model to handle scale variations and detect objects at different resolutions. Multiple prediction heads, each responsible for predicting bounding box coordinates and class probabilities for objects at a given scale, are a part of COCO-SSD and are affixed to various levels of the feature pyramid.

ii) Russian Model: The Russian model plays a crucial role in our system as it is the most suitable model for swiftly identifying number plates when a video frame is passed through it. With this model, we can accurately crop the number plate region from the frame and subsequently feed it to our Optical Character Recognition (OCR) system for seamless text extraction.

iii) Easy-OCR: The process of turning text-containing images into machine-readable text is known as optical character recognition (OCR), and the popular Python library EasyOCR is used for this purpose.To find text-containing regions in the input image, EasyOCR uses a text detection module. To predict bounding boxes around text regions, this module typically makes use of a convolutional neural network (CNN) architecture, such as a Single Shot Multibox Detector (SSD) or Faster R-CNN.Following the detection of text regions, EasyOCR uses a text recognition module to identify and extract the text contained in each region. To identify individual characters or words, this module usually applies a deep learning-based technique, like a recurrent neural network (RNN) or convolutional recurrent neural network (CRNN). Numerous scripts and languages are supported by EasyOCR.

### *D. Data Retrieval and Management:*

Once text extraction from the number plates is accomplished successfully, the extracted data is securely transmitted to our database system through a protected API key. This process of data retrieval facilitates access to essential information concerning the identified vehicles, encompassing details regarding Pollution Under Control (PUC) certification and insurance status. In the event of either the PUC or insurance being expired, an automated fine notification is swiftly dispatched to the owner's mobile number. Furthermore, the database undergoes an update to document these fines, thereby contributing to the maintenance of a streamlined record of violations. This comprehensive approach ensures efficient monitoring of compliance and enforcement of regulatory standards within our system.

## IV. Experimentation and Empirical Analysis

Utilizing a variety of sophisticated models, the outcomes depicted in Figure 3 are obtained, showcasing the accuracy in identifying vehicles within images through the application of the COCOSSD Model. This model, renowned for its robustness and precision, excels in its capability to discern vehicles amidst complex visual backgrounds with remarkable accuracy. Furthermore, upon successful vehicle detection, the


Fig. 3. Examined Results

Russian model seamlessly proceeds to the next step, swiftly identifying and isolating the number plate. This crucial task is executed with remarkable efficiency, underscoring the model's adeptness in discerning intricate details within the visual data. Subsequently, the Easy-OCR model, renowned for its prowess in optical character recognition, is employed to extract the characters imprinted on the number plate. Demonstrating an impressive accuracy rate ranging between 80 to 85 percent, Easy-OCR proves to be a valuable asset in the extraction process. However, it is imperative to acknowledge that despite the inherent capabilities of these pre-trained models, additional post-processing techniques are necessitated to refine and enhance the accuracy of the extracted characters. This iterative process underscores the complexity inherent in automated character extraction from visual data and underscores the ongoing efforts to optimize the performance of such models in real-world scenarios.

## V. Future Scope

Advancements in "Vehicle Management and Surveillance using deep learning" face various challenges that necessitate attention for future progress:

i) Environmental Impact: Recognition of number plates can be affected by environmental factors like sunlight intensity and fog. Focus should be on robust algorithms for accurate detection under varying conditions.
ii) Vehicle Speed: High-speed vehicles pose challenges to accurate plate detection. Research is needed for faster and efficient recognition methods, especially for fast-moving vehicles.
iii) Obstructed Plates: Vehicles with obscured or damaged plates require advanced image processing techniques for accurate recognition and adaptation to varying plate appearances.
iv) Plate Design Variability: Systems must accurately recognize diverse plate designs worldwide, requiring enhanced adaptability through comprehensive training and augmentation.
v) Night time Recognition: Research into night vision and adaptive processing techniques is necessary for improved performance in low-light conditions.
vi) IoT Integration: Leveraging IoT devices can enhance real-time data collection and decision-making for proactive vehicle management.

## Conclusion

The culmination of the "Vehicle Surveillance System using deep learning" heralds a new era in regulatory compliance and management efficiency. With a laser focus on mitigating RTO violations, this project stands as a testament to the power of advanced technology in bolstering surveillance capabilities. By seamlessly integrating deep learning algorithms, it not only extracts vehicle data with unparalleled accuracy but also elevates surveillance to an art form through meticulous post-processing techniques. In essence, this system isn't just a solution; it's a paradigm shift towards a more streamlined, data-driven approach to governance and oversight.

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