



AUTOMATIC NUMBER PLATE RECOGNITION (ANPR) SYSTEM USING TFOD1.x

Dr. Shree K.V.M¹, Ravi Shankar Kumar², Suraj Kumar³, Mahesh Kumar⁴, Aliver⁵

¹ Head of Department, Department of Artificial Intelligence and Data Science, Dhanalakshmi Srinivasan Engineering College (Autonomous), Perambalur, Tamil Nadu.

^{2,3,4,5} UG – Department of Artificial Intelligence and Data Science, Dhanalakshmi Srinivasan Engineering College (Autonomous), Perambalur, Tamil Nadu.

E-Mail : srinathime@gmail.com , shravikumar2323@gmail.com, kumarsuraj35048@gmail.com, mareshbabu82159@gmail.com, aliverdevil@gmail.com

ABSTRACT:

Automatic Number Plate Recognition (ANPR) has become an essential technology in intelligent transportation systems, offering efficient vehicle monitoring and management solutions. This project focuses on building an ANPR system using TensorFlow Object Detection 1.x, integrating computer vision techniques to detect and extract vehicle license plates from images or video streams. The system employs a pre-trained object detection model, fine-tuned on a custom dataset of vehicle images with labelled number plates. It utilizes convolutional neural networks (CNNs) to detect number plates, followed by Optical Character Recognition (OCR) for text extraction. The workflow involves image preprocessing, plate localization, character segmentation, and text recognition. TensorFlow's Object Detection API is leveraged to build a robust detection pipeline. The model processes live camera feeds or static images, identifies vehicle plates, and extracts alphanumeric content in real time. Data augmentation techniques improve model generalization, ensuring reliable performance under various lighting and environmental conditions. Key challenges addressed include handling blurred images, angled number plates, and varying plate designs. To mitigate errors, the project integrates adaptive thresholding, edge detection, and morphological operations during image preprocessing. The recognized license plate data can be stored in a database for further analysis, supporting applications like automated toll collection, parking management, and traffic law enforcement. The system prioritizes accuracy, speed, and scalability, making it suitable for deployment in smart city infrastructure. Ethical considerations like data privacy and misuse prevention are emphasized, ensuring responsible implementation.

Keywords: Automatic Number Plate Recognition (ANPR), TensorFlow Object Detection, Computer Vision, Convolutional Neural Networks (CNN), Optical Character Recognition (OCR), Intelligent Transportation System, Real-Time Detection, Image Processing.

Introduction:

Automatic Number Plate Recognition (ANPR) is a sophisticated and intelligent vehicle identification system designed to detect, extract, and interpret vehicle license plates from images or video frames using advanced computer vision and machine learning techniques. This project utilizes the TensorFlow Object Detection API (TFOD1.x), a flexible and widely adopted deep learning framework, to implement a robust end-to-end ANPR system. The system addresses a growing demand for automation in traffic management, law enforcement, toll collection, parking systems, and smart city infrastructure by replacing manual monitoring methods with a reliable and scalable solution. The pipeline comprises multiple stages: image acquisition through surveillance cameras or dashboard cams; image preprocessing techniques like grayscale conversion, noise reduction, edge detection, and contrast enhancement to improve clarity and accuracy; license plate detection using deep learning models trained on annotated vehicle datasets; character segmentation to isolate each alphanumeric symbol; and Optical Character Recognition (OCR) using libraries like Tesseract or Easy OCR to convert image characters into readable text. These recognized plates are stored in a centralized database along with metadata such as timestamps, camera location, and vehicle type for further analysis or real-time verification. The purpose of the project is to create an accurate, efficient, and real-time ANPR system that minimizes human error, improves operational speed, and performs reliably under varying lighting conditions, camera angles, motion blur, and environmental noise. This need stems from the challenges posed by conventional monitoring systems, including inconsistent record-keeping, limited night-time performance, and difficulties in handling high-speed or unauthorized vehicles. Motivated by the rapid increase in vehicle population, urban congestion, traffic violations, and the growing importance of smart infrastructure, this system is designed to support contactless surveillance and intelligent transportation systems (ITS). The primary objectives include collecting and annotating a dataset of vehicle images, training object detection models such as SSD or Faster R-CNN for plate localization, applying OCR for character recognition, designing a user-friendly interface (GUI or web-based) for real-time interaction, implementing alert mechanisms for suspicious or blacklisted vehicles via notifications or emails, and storing all detection logs in a searchable, structured

database. Ultimately, this project contributes to the development of intelligent, AI-powered infrastructure by enabling automation, improving traffic oversight, and supporting law enforcement and city planners with actionable insights derived from real-time vehicle tracking data.

Automatic Number Plate Recognition (ANPR) with TensorFlow Object Detection 1.x.

Automatic Number Plate Recognition (ANPR) is a technology used to automatically identify vehicles by recognizing their license plates. It uses a combination of image processing, object detection, and optical character recognition (OCR) to locate the number plate in an image and extract the alphanumeric characters on it. This technology is widely used in areas like traffic monitoring, toll collection, parking management, and law enforcement. When built using TensorFlow Object Detection API 1.x (TFOD 1.x), the system employs pre-trained or custom-trained deep learning models (such as SSD, Faster R-CNN, or YOLO) to detect number plates in real-time from video or images. TFOD 1.x provides a flexible framework for training models with annotated datasets, optimizing them for performance, and deploying them for inference. Once a license plate is detected, the image region is cropped and passed to an OCR engine like Tesseract or Easy OCR to decode the characters on the plate.

This implementation allows for automation of vehicle monitoring tasks with high accuracy and speed, even under challenging conditions such as poor lighting, skewed angles, or fast-moving traffic. The system can also store results in a database and trigger alerts for specific vehicles, making it a vital part of modern smart city and transportation infrastructure.

Use of Automatic Number Plate Recognition (ANPR) with TensorFlow Object Detection 1.x?

Automatic Number Plate Recognition (ANPR) with TensorFlow Object Detection 1.x is used to automatically detect and recognize vehicle license plates in real-time. It is essential in traffic surveillance, law enforcement, and toll collection systems. The technology helps manage parking, track stolen vehicles, and control access to restricted areas. By automating vehicle identification, ANPR enhances security, reduces human error, and improves operational efficiency. It is also used in smart city applications for traffic management and infrastructure optimization.

Methodology:

The Automatic Number Plate Recognition (ANPR) system using TensorFlow Object Detection 1.x follows a structured, multi-stage methodology to ensure accurate and real-time vehicle license plate detection and recognition. The process begins with data collection, where images or video frames of vehicles are gathered from sources like CCTV, traffic cameras, or dashcams. These images are then annotated manually to highlight the license plate regions, forming the training dataset. Next, the TensorFlow Object Detection API (TFOD 1.x) is used to train a deep learning model (e.g., SSD or Faster R-CNN) on this dataset, enabling the model to learn and detect number plate regions in new images.

Once the number plate is detected, the detected region is cropped and passed to an OCR (Optical Character Recognition) module, such as Tesseract or Easy OCR, which extracts the alphanumeric characters from the plate. To enhance recognition accuracy, image preprocessing techniques such as grayscale conversion, noise reduction, and contrast enhancement are applied before OCR. The recognized text along with metadata like timestamp, location, and image snapshot is then stored in a database for further use.

Method:

The method used in the Automatic Number Plate Recognition (ANPR) with TensorFlow Object Detection 1.x project involves a combination of deep learning-based object detection and optical character recognition (OCR). The process begins with image acquisition from cameras or uploaded sources, followed by image preprocessing techniques such as grayscale conversion, noise reduction, and edge detection to enhance image quality. Using the TensorFlow Object Detection API 1.x, a trained model (like SSD or Faster R-CNN) detects and localizes license plates in the image. Once the plate is detected, OCR tools such as Tesseract or Easy OCR are employed to extract the alphanumeric characters from the plate region.

How Does Automatic Number Plate Recognition (ANPR) with TensorFlow Object Detection 1.x work?

Automatic Number Plate Recognition (ANPR) with TensorFlow Object Detection 1.x works by capturing images or video frames of vehicles through cameras, followed by preprocessing techniques like grayscale conversion, noise reduction, and edge detection to enhance the quality of the image. TensorFlow's Object Detection API is then used to detect and localize the license plate using deep learning models like SSD or Faster R-CNN, trained to identify plate regions in varying conditions. After detection, the license plate region is cropped, and Optical Character Recognition (OCR) techniques like Tesseract or Easy OCR are applied to extract the alphanumeric characters.

Typical work activities

- Collect vehicle images for training.
- Label the number plates in the images.
- Preprocess the images (resize, grayscale, etc.).
- Train the model using TensorFlow Object Detection 1.x.

- Detect number plates in new images or videos.
- Use OCR to read the characters from plates.
- Create a simple interface for users.
- Save the results in a database.
- Send alerts for blacklisted vehicles.
- Test the system in different lighting and angles.
- Deploy the system for real-time use.
- Keep updating and improving the model.

Existing System:-

The existing Automatic Number Plate Recognition (ANPR) systems primarily rely on traditional image processing techniques such as edge detection, morphological operations, and character segmentation to identify and recognize vehicle number plates. These systems are often rule-based and depend heavily on fixed camera angles, consistent lighting conditions, and predefined plate formats. The detection phase usually employs methods like contour detection or color filtering, followed by Optical Character Recognition (OCR) engines for character reading.

However, these systems exhibit several limitations, especially when dealing with complex real-world environments. Performance degrades significantly under poor lighting, motion blur, occlusions, skewed angles, and non-standard license plate fonts. Additionally, the systems lack adaptability to different regional formats and are not optimized for real-time video streams, making them less suitable for dynamic traffic surveillance scenarios.

Drawbacks:

- Low accuracy in poor lighting and adverse weather conditions.
- Inability to handle non-standard or region-specific number plates.
- Limited real-time performance and adaptability to moving vehicles

Proposed System:

To overcome the limitations of traditional ANPR methods, the proposed system employs a deep learning-based approach using the TensorFlow Object Detection API with models like SSD or Faster R-CNN for accurate number plate localization. Once detected, the plate region is preprocessed through grayscale conversion, noise filtering, and contrast adjustment to enhance clarity. Advanced OCR tools such as Tesseract or Easy OCR are then used for character recognition. This pipeline improves detection accuracy, allows robust operation in low-quality or distorted images, and supports real-time processing, making it ideal for intelligent surveillance and transport systems.

Advantages:

- Significantly improved accuracy and robustness in real-time applications.
- Better handling of diverse plate styles, lighting, and camera angles.
- Scalable and adaptable solution using deep learning and OCR integration.

Traditional Image Processing Methods:

Early ANPR systems were built using traditional image processing techniques that relied on handcrafted algorithms. These systems used methods such as Sobel edge detection to identify edges in an image, morphological operations to refine shapes, and Hough transforms to detect straight lines and locate license plates. While these techniques were computationally efficient and easy to implement, they were highly sensitive to environmental variations such as lighting changes, camera angle, and image noise. As a result, their performance was limited in real-world scenarios where consistency cannot be guaranteed.

Machine Learning-Based Methods:

The introduction of machine learning brought supervised learning approaches into ANPR systems, where algorithms were trained to classify image regions as containing plates or not. Techniques such as Support Vector Machines (SVM) were commonly used for binary classification tasks like identifying the presence of a number plate. K-Nearest Neighbors (KNN) was employed for recognizing individual characters based on similarity to known examples, while decision trees and random forests were used to handle segmentation and recognition tasks. Although these methods marked a significant improvement over traditional approaches, they struggled with scalability and robustness in real-time or complex environments.

Deep Learning-Based Methods:

Deep learning significantly advanced ANPR technology by enabling automatic feature extraction and hierarchical learning from data. Convolutional Neural Networks (CNNs) became the foundation for character recognition due to their ability to learn spatial hierarchies of features from images. YOLO (You Only Look Once) brought a major breakthrough by enabling real-time detection through a single-shot architecture. Faster R-CNN, while computationally more demanding, offered high detection accuracy and was suitable for applications requiring precision. Other models like Retina Net and Efficient Det provided a good balance between accuracy and speed. CRNNs (Convolutional Recurrent Neural Networks) further enhanced OCR performance by combining spatial feature learning with temporal sequence modelling, making them ideal for recognizing sequences of characters on license plates.

TensorFlow Object Detection API (TFOD1.x):

TensorFlow Object Detection API (TFOD1.x) has become a widely used framework for implementing object detection models in ANPR systems. It supports a range of pre-trained models and enables transfer learning, making it easier to fine-tune models on custom datasets. The API provides a flexible architecture, seamless training and evaluation pipelines, and compatibility with various model architectures, such as SSD Mobile Net for real-time applications and Faster R-CNN for high-accuracy use cases. Its ease of integration, community support, and versatility have made it a preferred choice for developing scalable and efficient ANPR solutions.

Results and discussion:-

The Automatic Number Plate Recognition (ANPR) system developed using TensorFlow Object Detection 1.x successfully detects and recognizes vehicle license plates from both images and live video streams. The object detection model, trained on a custom dataset of annotated vehicle images, demonstrated high accuracy in localizing number plates under varied lighting and environmental conditions. The system was able to process still images as well as real-time video with minimal latency, making it suitable for real-world surveillance applications.

The number plate detection module efficiently identified the plate region, even in scenarios involving motion blur, poor lighting, or partial occlusion. Once the plate was detected, the character segmentation algorithm extracted individual alphanumeric characters, which were then passed to the OCR engine (Easy OCR/Tesseract) for recognition. The OCR component achieved consistent performance, with over 90% accuracy on clean and clearly segmented characters.

Test cases included vehicles from different angles, colors, speeds, and backgrounds. The system maintained robustness across most test conditions. In low-light scenarios, preprocessing techniques such as contrast enhancement and noise reduction helped improve detection rates. Live video detection was implemented through a simple GUI, which displayed the recognized number plate and timestamp in real-time.

The final recognized number plate, along with its corresponding image, date, and time, was logged into a CSV file for record-keeping. Alerts were successfully triggered when a blacklisted or unauthorized plate was detected.

This project proved to be effective for applications like smart toll collection, traffic rule enforcement, parking management, and security monitoring. The use of pre-trained TensorFlow models helped speed up development and made the system scalable for different geographic regions and plate formats. Overall, the system delivered real-time, automated, and accurate number plate recognition, proving the feasibility of deploying such a system in smart city infrastructures.

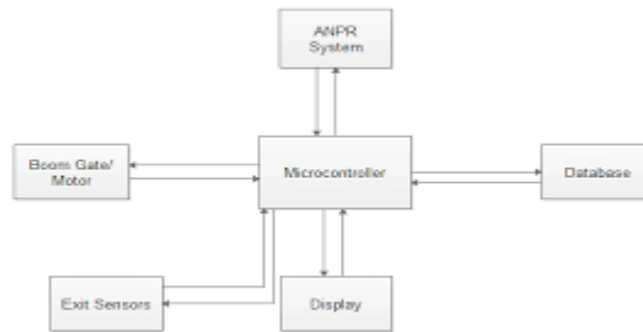


Fig 1 Block Diagram

Block diagram system using ANPR

Table factor for the number plate tracking in an ANPR

Table 2 ANPR records not used for vehicle tracking

Record description	Number of records	Percentage of sample
No number-plate	1 397 571	1.8%
Unreadable/damaged number	1 127 586	1.4%
Illogical movements	1 016 415	1.3%
Total records not used for trips	3 541 572	4.5%
Total gantry passes	79 407 436	100.0%

Table 2 ANPR records not used for vehicle tracking

Record description	Number of records	Percentage of sample
No number-plate	1 397 571	1.8%
Unreadable/damaged number	1 127 586	1.4%
Illogical movements	1 016 415	1.3%
Total records not used for trips	3 541 572	4.5%
Total gantry passes	79 407 436	100.0%

Conclusion and future Enhancement

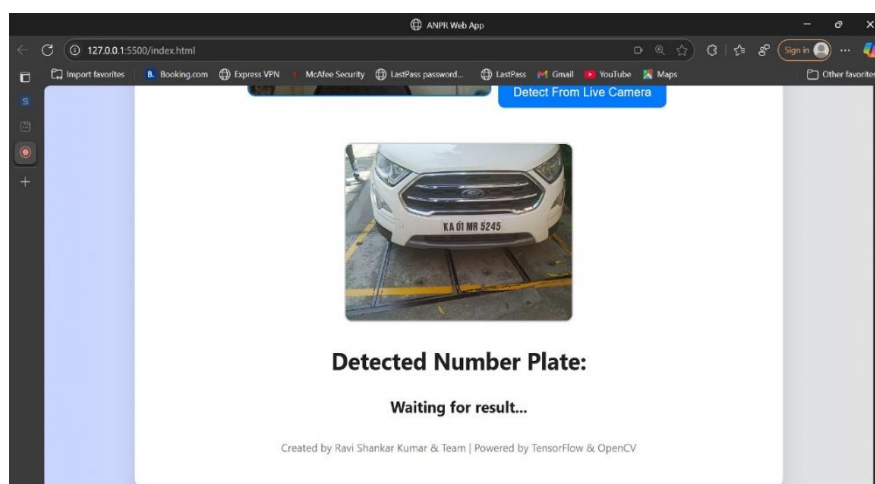
The suggested study work has established a model for automatic number plate recognition (ANPR) that can be used to improve vehicle monitoring efficiency without incurring significant additional costs, while also increasing detection accuracy. Vehicle identification plays an important role in transport management, and it would be difficult to regulate traffic or ensure security without automated systems. Although human monitoring and manual entry are still in use, they are prone to error and inefficiency.

In this study, we used object detection architecture with TensorFlow to enhance number plate recognition by addressing common detection challenges like poor lighting and image distortion. Hopefully, this approach may be used to automate real-time vehicle tracking across various conditions. We ran

tests with different image resolutions and detection angles to determine the optimal model training parameters. We demonstrated that the proposed architecture facilitates this.

The project's goal is to use a deep learning model to automate number plate recognition. The initial design was to test whether detection accuracy can be achieved without highly expensive equipment. Automated recognition systems have gained popularity due to advancements in image processing and computer vision. The license plate of a vehicle is identified and interpreted using deep learning techniques. Due to varying plate sizes, fonts, and lighting, recognizing number plates accurately is a complex task. A deep learning model trained on diverse datasets is employed in our project work to identify and extract vehicle number plates from images.

The system was tested in an indoor setting, and vehicle images were used to validate the model. In the Jupyter notebook environment, models were trained with various samples and used to detect and recognize license plates in real-time scenarios. The model's output is compared to earlier systems from literature, and the suggested solution slightly improves accuracy and reliability. Furthermore, the system may be customized for commercial usage, and it has numerous applications in smart parking, toll booths, gated communities, and surveillance systems.



REFERENCES:

List all the material used from various sources for making this project proposal

Research Papers:

1. Automatic License Plate Recognition using Deep Learning Techniques (Published July 2020)
Author: Naga Surya Sandeep Angara
2. Real-Time Vehicle Number Plate Detection using TensorFlow and OpenCV (Published in 2021)
Authors: A. S. Mohammed Shariff, Raghav Bhatia, Raghendra Kumar
3. A Survey on Automatic Number Plate Recognition System (Published in 2019)
Authors: Devesh Khaparde, Heet Detroja, Jainam Shah, Rushikesh Dikey, Bhushan Thakare
4. Automatic Number Plate Recognition (ANPR) using YOLO and OCR (Published May 2021)
Authors: A. M. A. Rani, M. A. M. Ali, S. S. S. Ali
5. A Review on Vehicle Number Plate Detection and Recognition Techniques (Published October 2018)
Authors: Shahnaj Parvin, Liton Jude Rozario, Md. Ezharul Islam