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## rCounting the Future: Deep Learning-Based Electric Vehicle Estimation from Video Surveillance

<sup>1</sup>Ms. Gitanjalee Salunkhe, <sup>2</sup>Ms. Jyoti Kengale, <sup>3</sup>Ms. Sanika Chavan, <sup>4</sup>Ms. Gouri Dhampalwar, <sup>5</sup>Ms. Anushka Chaudhari

<sup>1,2</sup>Assistant Professor MKSSS Cummins College, Pune, India

<sup>3, 4, 5</sup> Undergraduate Student MKSSS Cummins College Pune, India

E m a i l : <sup>1</sup> gitanjalee.salunkhe@cumminscollege.in, <sup>2</sup> jyoti.langhi@cumminscollege.in,

<sup>3</sup> sanikachavan3268@gmail.com, <sup>4</sup> dhampalwargouri@gmail.com, <sup>5</sup> anushkachaudhari0@gmail.com

Peer Review Information	Abstract
<p><i>Submission: 21 Oct 2025</i></p> <p><i>Revision: 18 Nov 2025</i></p> <p><i>Acceptance: 05 Dec 2025</i></p> <p><b>Keywords</b></p> <p><i>YOLO Model, Vehicle Detection, Deep Learning, Plate Detection, HSV Thresholding.</i></p>	<p>Research and policymaking activity on sustainable transportation thrust the importance of electric vehicle (EV) existence and distribution within urban environments. A computer vision framework presented in this study enables video surveillance data to determine EV counts within particular geographical locations. The methodology uses YOLOv11 license plate recognition together with YOLOv5 object detection to explore electric vehicle plates during examination and vehicle identification processes. A precise vehicle and license plate cropping process maintains accuracy. Processed information is applied to the recognition of electric versus non-electric vehicles. The system proves efficiency by using video surveillance from public roads to identify vehicles, recognize their license plates, and count electric vehicles. An intricate two-stage system, "search" and "identify" phases, ensures proper vehicle and license plate cutting. Further processing of the data completes the identification of conventional and electric vehicles. The system shows its functionality by using public road video footage to identify cars and extract license plates before counting electric vehicles. The investigation demonstrates that deep learning enables both traffic monitoring through analysis and environmental assessment.</p>

### 1. Introduction

Green transportation usage, together with worldwide efforts to lower carbon emissions created electric cars (EVs) to be key components supporting city transportation sustainability. A correct estimation of electric vehicles within specific areas helps both evaluate environmentally friendly vehicles adoption trends while providing foundation for organizing infrastructure like charging locations and road regulations and tax exemptions. The proposed method combines automated video surveillance technology with real-time data processing to count electric vehicles in a

particular area, which surpasses existing methods based on manual surveys and static counts and registration data records.

The methodology combines deep learning computer vision models for detecting electric vehicles by recognizing their appearance and their associated license plates. The system follows a three-step process.

#### A. Vehicle Detection and Cropping from Surveillance Video:

The first operation evaluates real-time traffic feed from city surveillance cameras that simultaneously contains moving vehicles with

static cars. The YOLOv5 model identifies various vehicle types such as cars and trucks in addition to buses and motorbikes. The detection filtering process uses an Intersection over Union (IoU) threshold to eliminate duplicate frames while maintaining detection uniqueness. Each specific vehicle gains its own region of interest (ROI) from the frames which are afterward extracted. The cropped images from this process will be stored for the number plate detection phase since they have no active bounding box zones.

#### B. License Plate Extraction:

The procedure relocates and picks out license plates from the extracted vehicle pictures. To detect vehicle license plates with high accuracy the system employs a YOLOv11 model specifically trained for this purpose. The detection process uses bounding boxes to isolate plates after which the saved images support downstream OCR or database matching tasks.

All detected license plates receive annotations directly on their corresponding original vehicle images in order to preserve traceability for visual inspections.

#### C. EV Classification via HSV Thresholding:

The evaluation process for determining vehicle type as EV depends on analyzing the visual features in the number plates. The license plates of electric vehicles in India are typically marked with green color. The system identifies green-colored plates by implementing HSV (Hue, Saturation, Value) color thresholding on detected plate images. The analysis system uses HSV color filters to determine which plates qualify for counting, and it then determines the amount of EVs found in the monitored area.

## 2. Literature Review

Automatic number plate recognition (ANPR) from video streaming is a key technology for traffic management, security, and law enforcement. Unlike still-image systems, video-based ANPR must handle challenges such as motion blur, varying lighting, and low resolution, making accurate and real-time recognition more complex. [1] discusses a deep learning-based ANPR pipeline that accurately recognizes number plates from various Asian and European countries, improving vehicle access control accuracy. The ANPR pipeline achieved up to 98% single-character recognition accuracy with deep learning. [2] The CNN-based approach is the most suitable for recognizing Indian license plates from live stream videos, with high accuracy in traffic management and speed control. [3] YOLO-EV: Real-Time Electric

Vehicle Detection Using YOLO. The main objective is to enhance real-time EV detection for smart traffic and charging infrastructure. It adapts YOLOv7 for EV-specific detection, optimizing speed/accuracy trade-offs. Datasets used are the Curated dataset with EVs (e.g., Tesla, BYD) and ICE vehicles, emphasizing hard cases (e.g., partial occlusion, low-light). Innovations used are EV-Specific Heads: Modified detection heads to recognize EV features (charging ports, smooth grilles). It uses lightweight LSTMs to track EVs across frames in video streams. And Edge Deployment: Quantization/pruning for real-time performance on edge devices (e.g., Jetson Xavier). It shows ~95% mAP on a custom EV test set and around ~40 FPS on a Tesla V100 GPU. But it struggles with rare EV models due to training data bias. Also involves a high computational cost for 4K video streams. [4] Automatic Number Plate Recognition (ANPR) Using Machine Learning: The main objective is robust license plate detection and recognition in varied conditions. It uses YOLOv5 for locating license plates, a hybrid model (CNN + LSTM) for character recognition. It performs preprocessing: Adaptive thresholding for low-light/glare correction and perspective transformation for skewed plates. It uses a dataset that includes regional variations (e.g., Indian license plates). It shows ~98% accuracy on clean plates and around ~85% accuracy in challenging conditions (rain, dirt). But performance drops with non-standard fonts or decorative frames also require region-specific retraining. [5] Real-time object detection, tracking, and monitoring framework for security surveillance systems: This paper proposes a framework for real-time security surveillance using object detection and tracking and focuses on improving accuracy and efficiency in monitoring systems. The methodologies used deep learning (YOLO/SSD) and tracking (e.g., SORT, DeepSORT). [6] Recognition of Vehicle License Plates from a Video Sequence: It presents a method for detecting and recognizing license plates from video feeds. The main emphasis is on real-time processing and accuracy in dynamic conditions. It uses Traditional image processing (edge detection, OCR) + motion tracking. Real-time but less robust than modern DL. It is mainly used for traffic monitoring, toll systems. Early real-time LPR solution, but it is outdated for modern high-resolution videos. [7] Recognition of Indian License Plate Number from Live Stream Videos: It mainly focuses on Indian license plate recognition in live video streams and addresses challenges like varying fonts, lighting, and

regional plate formats. It combines traditional methods (morphological ops) with ML (e.g., SVM, CNN). Targets real-time but may face latency in complex scenarios. Adoption of end-to-end DL (e.g., YOLO + OCR) may increase accuracy. [8] Efficient Vehicle Detection and Classification Algorithm Using Faster R-CNN Models: It discusses vehicle detection and fine-grained classification (e.g., sedans, trucks, buses) using Faster R-CNN. It uses region-based CNN for high-precision localization and optimized anchor boxes and feature extraction for traffic scenarios. It provides High accuracy in complex environments (e.g., occlusions, varying lighting). Also, its modular design allows integration with traffic management systems. It has a Slower inference speed compared to one-stage detectors (e.g., YOLO). And it is

computationally heavy for edge devices. The main applications focused on are Smart traffic monitoring, toll automation, and urban planning. [9]V2X-Enabled ANPR for Smart Cities: Automatic Number Plate Recognition (ANPR) integrated with Vehicle-to-Everything (V2X) communication. It combines deep learning-based ANPR (e.g., YOLO + OCR) with V2X protocols (DSRC/5G). Leverages edge computing for real-time processing. It enables dynamic traffic updates (e.g., stolen vehicle alerts, toll evasion) and scalability for smart city infrastructure (IoT-enabled cameras, connected vehicles). But limitations are it requires V2X-equipped vehicles and city-wide IoT deployment. Applications considered are Smart cities, connected traffic systems, and automated law enforcement.

## 2.6 Gap in Literature

**Table 1:** Comparison of Previous Work

Paper	Strengths	Limitations
Abba et al. (2024)	Broad applicability	Not optimized for LPR
Tsai et al. (2009)	Foundational LPR work	Outdated (no DL)
Avale & Bari (2019)	Tailored for Indian plates	Region-locked
Khan et al. (2022)	End-to-end DL pipeline	Requires a large dataset
Prabhu et al. (2017)	Early Indian LPR solution	Low accuracy in complex scenes
YOLO-EV (2023)	<b>Real-time EV detection</b>	Limited to EVs
Pujar & Kulkarni (2023)	Simple ML implementation	Poor scalability
EL Mallahi et al. (2024)	High-precision classification	Slow (Faster R- CNN)
Chen et al. (2024)	<b>V2X integration</b> (future-proof)	Needs smart city infra
Pradeep Avale & Bari (2019)	Balanced accuracy/speed	Outperformed by newer DL methods

## 3. Proposed System

The suggested system uses a multi-stage computer vision pipeline to estimate the

number of electric vehicles (EVs) in an area. YOLOv5 is used to identify and crop vehicle frames in traffic videos. To identify license

plates, they are further examined using a specially trained YOLO model. To determine green pixel ratios, the plates are sharpened and converted to the HSV color space. Dynamic and automated EV estimation is made possible by identifying plates with the highest green intensity as EVs.

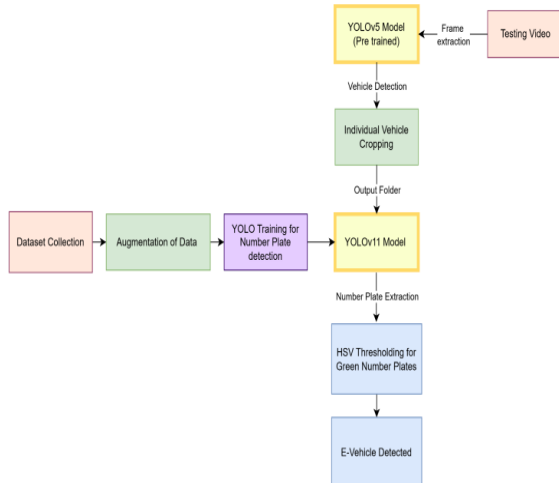


Figure 1: Flow Diagram

### 3.1 Vehicle Detection Model

We used a two-stage computer vision pipeline utilizing cutting-edge object detection frameworks to recognize and separate cars from unprocessed surveillance footage.

#### 3.1.1 Model Selection & Configuration:

To identify four pertinent vehicle classes—cars, motorcycles, buses, and trucks—we pretrained the YOLOv5s (You Only Look Once) model on the COCO dataset. For real-time inference on high-resolution video streams, this option provides the best possible balance between speed and detection accuracy.

#### 3.1.2 Video Processing for Testing:

In order to optimize resource usage, the system was built to process input video frames at predetermined intervals of two seconds (based on frame rate), as opposed to analyzing each frame individually. The YOLOv5 model processes each chosen frame and provides bounding boxes for every vehicle that is detected.

#### Duplicate Elimination using IoU:

An Intersection over Union (IoU) threshold of 0.5 was used to prevent counting the same vehicle more than once across frames. Only non-overlapping (unique) bounding boxes were regarded as new vehicles after being compared to previously observed ones.



Figure 2: Vehicle detection

#### 3.1.3 Vehicle Cropping:

To maintain image clarity, the corresponding area of each newly detected vehicle was cropped in the frame before annotation. For use in number plate recognition and EV classification, these cropped car photos were methodically saved for later processing.



Figure 3: Unique Vehicle Cropping

#### 3.1.4 Visualization and Monitoring:

Matplotlib and OpenCV were used to display intermediate results, like cropped car photos and frames with bounding boxes annotated. This helped with real-time pipeline logic validation and detection efficacy monitoring.

#### 3.1.5 Output Summary:

After finishing, the system produced an output summary that included the total number of frames processed, the number of distinct vehicles found, and the total number of cropped vehicle photos saved to the disk. The following license plate detection model used these cropped outputs as its input.

### 3.2 Data Collection

Open-source platforms, Roboflow and Kaggle to create a reliable and comprehensive dataset for license plate detection on the unique cropped

vehicles. The first set includes 731 photos from Roboflow, which feature a variety of vehicle views in various lighting and environmental settings. The second set, which has 210 photos taken from Kaggle, has more generalization abilities and added more variability.

Merging datasets from both the open-source platforms created a final dataset of 941 images on the Roboflow platform. The dataset is split into training, validation, and testing in a ratio of 70:20:10, containing 662, 187, and 92 images, respectively. Bounding boxes were created around vehicle license plates to aid in precise detection, and auto-labeling was done using Roboflow's integrated labeling interface. Data annotation resulted in YOLOv5-compatible TXT files along with corresponding images for smooth adoption within the object detection pipeline operation. The curated dataset with an extensive vehicle range made precise training and validation operations for the YOLO number plate recognition model.



Figure4: Dataset for Vehicle Detection

### 3.3 Number Plate Detection Model

A main component of electric vehicle detection is the Number Plate Detection Model, which accurately recognizes and extracts license plates from photos of all the vehicles using object detection algorithms. The model deploys YOLOv11 architecture for better real-time object detection due to its position as the modern version of the You Only Look Once (YOLO) family. The YOLOv11 model is designed and optimized for object detection, including identifying license plates on vehicles, as it is part

of the Ultralytics object detection framework. It guarantees accurate segmentation and localization of license plates by leveraging advanced features, like the C3k2 block and the Spatial Pyramid Pooling Fast (SPPF) block

#### 3.3.1 Model Selection and Architecture:

The creation of YOLOv11 came about due to the system's capability to do fast real-time processing while multitasking on other object detection that need to be performed. The model successfully implements a convolutional neural network(CNN) backbone| YOLOv11, which is well known for giving fast detections in addition to high precision on difficult targets like license plates that are present in all vehicle images. With specially tailored data, the model can locate license plates even in harsh environmental conditions.

#### 3.3.2 Preprocessing and Input Pipeline:

The model takes the input as cropped vehicle photos that were taken from a sequence of video frames taken during the vehicle detection stage. YOLOv11 reduces computational complexity and guarantees that the model can concentrate its resources on detecting number plates; these images only focus on the vehicle region. The preprocessing pipeline ensures precise and effective detection by optimizing the images for YOLOv11's input requirements.

#### 3.3.3 Detection Mechanism and Bounding Box Regression:

The vehicle detection phase creates an output folder that contains cropped vehicle photos in video frames, and this is the input to the model. The YOLOv11 model functions optimally by detecting number plates through images that show only vehicle regions while reducing complexity in processing. The preprocessing pipeline ensures YOLOv11 receives perfect input that enables the detection system to achieve its most effective results. The model is trained over 100 epochs with an input image size of 640\*640 pixels.

### 3.4 Plate Cropping and Output Generation:

After the completion of the prediction, the model extracts the identified number plates from the initial image. The precise cropping method extracts the bounding box area that contains license plates with high precision. The processed license plates are saved to a particular output directory to serve as input for electric vehicle detection through HSV thresholding.

#### 3.4.1 Bounding Box Visualization and Annotated Output:

Visual validation of model detections happens when the system creates bounding boxes that surround recognized license plates present in original car images. The transparency box detections offer easy visual confirmation because they use clear blue hues for enhanced clarity. The images with annotated plates exhibit bounding boxes for identified plates, which are saved to separate folders for future evaluation.

#### 3.4.2 Real-Time Display and Feedback Loop:

The original images with bounding boxes surrounding the detected plates are shown in real-time along with the model's detection results using OpenCV. Such dynamic evaluation enables instant model performance evaluation, which helps detect potential problems to solve, such as false positives and missed detections. The model receives iterative accuracy improvements through an evaluation process that runs continuously.

#### 3.4.3 Detection Metrics and Performance Evaluation:

The detection concludes by showing output information about plate counts with their detection confidence levels and the total number of padded license plates the model stores in its performance summary. The detection model's operational effectiveness becomes measurable through these performance indicators, which also help identify sections that require further improvement. The detection capabilities of the model are presented thoroughly to users through the system while maintaining records of unique plate identification counts.

#### 3.4.4 Performance

Testing confirmed the exceptional value of the YOLOv11-based detection model through outstanding performance on essential evaluation criteria. The model achieved a precision level of 97% while confirming the accuracy of nearly every prediction made, and an 81% recall, which indicated the model found most genuine objects. The model achieved outstanding accuracy by obtaining 84% mean average precision when assessing locations and classifications of objects at the 50% overlap threshold. Under challenging circumstances with overlap threshold settings between 50% and 95% the model produced stable results that reached approximately 63% accuracy.

The technical capabilities of the model become clear through this outcome because it demonstrates readiness in solving practical operational hurdles while offering deployment reliability. Monitoring operations need to

incorporate tested metrics that evaluate vehicle tracking methods under diverse environmental conditions.

```
'metrics/precision(B)': np.float64(0.9653572413983014)
'metrics/recall(B)': np.float64(0.8138176276352553)
'metrics/mAP50(B)': np.float64(0.8424029424545734),
```

Figure 5: Metrics of Number Plate Detection



Figure 6: Number Plate Detection

#### 3.5 Electric Vehicle Detection using Green Plate Identification:

Using computer vision techniques, the Electric Vehicle (EV) Detection Model recognizes electric vehicles by their distinctive green license plates. Many nations have required EVs to have green license plates in order to make it easier to identify eco-friendly automobiles. This detection system distinguishes EVs from conventional vehicles by specifically identifying vehicles based on the ratio of green color present in the license plate.

##### 3.5.1 Image Enhancement and Preprocessing:

The PIL library provides image processing functions to sharpen images, which makes license plate numbers more distinguishable and visible for detection. The program performs this transformation because OpenCV operates better with the BGR color format rather than RGB.

##### 3.5.2 Green Ratio Calculation for Detection:

The identification of green pixels within specified HSV color parameters generates the green ratio for each picture. Analysis of the plate origin from electric vehicles depends on calculating the proportion between green pixels and the entire picture area. The upper HSV threshold value is set to [30, 30, 30], and the lower HSV threshold value is set to [95, 255, 255].

### 3.5.3 Dynamic EV Identification and Visualization:

The final output shows the detected green plates of all the electric vehicles with their green ratios. The identification of green pixels within specified HSV color parameters generates the green ratio for each picture. The green ratio is a value between 0 and 1 that shows the proportion of green pixels within the license plate area

### Results

The comprehensive results of our electric vehicle (EV) identification methods are shown in this part, ranging from the final EV calculation based on license plate color classification to vehicle recognition in video surveillance. To give a thorough grasp of our procedure, each stage is backed up by data-driven observations and visual examples.

#### 4.1 Unique Vehicle Detection and Cropping from Surveillance Footage

The initial stage concentrated on identifying and separating distinct cars from live traffic surveillance footage. Both stationary and driving cars on city streets were shown in these videos. To identify common vehicle classes, including cars, buses, trucks, and motorbikes, we used a pre-trained YOLOv5 model.

We used a filtering method based on intersection over union (IoU) to avoid multiple detections of the same vehicle. By doing this, duplication from the same car showing up in more than one frame was prevented, and only unique vehicles were counted.

Once detected, the corresponding regions of interest (ROIs) were cropped from the frames to create clear images of individual vehicles. Care was taken to ensure that bounding box annotations were not present in the cropped images, as these would interfere with downstream processing.



Figure 7: Sample detections with bounding boxes on traffic video frames.



Figure 8: Cropped outputs of unique vehicles used for further analysis.

#### 4.2 Number Plate Detection and Cropping

Once a vehicle is detected, we then use each cropped vehicle image to identify the number plates. For this, a specially trained YOLOv11 model was employed using its improved performance on localized and smaller features, such as license plates.



Figure 9 : Bounding box overlays on vehicle crops showing number plate localization.

Each licence plate detected was cropped from the vehicle image and stored separately. To ensure transparency and traceability, the annotated images with bounding boxes showing the plate regions are also saved.

4.3 EV Estimation via HSV-Based Plate Color Classification We used HSV (Hue, Saturation, Value) thresholding to do color analysis on the cropped license plates in order to find green-colored plates, which indicates an Electric vehicle.

The HSV filtering pipeline was adjusted to accurately distinguish between green license-plates and conventional white/yellow plates. We

were able to categorize cars as either EVs or Non-EVs according to the color of their license plates.



*Figure 10: HSV thresholding visualizations differentiating green (EV) vs non-green plates.*

The approach effectively handled both moving and stationary vehicles, mitigated repeated detections through IoU-based filtering, and ensured clarity in image preprocessing for number plate analysis. The results indicate that a significant portion of vehicles captured in surveillance footage can be automatically classified as electric or non-electric based on license plate color, with minimal manual intervention.

The system detected three green license Plates from a video, with only one Electric vehicle. The result highlights the occurrence of False positives in the detection. The False positives were primarily due to the occurrence of a same vehicle in multiple frames being detected. These results could lead to overestimation of the count of E-Vehicles.

These findings highlight the potential of computer vision in supporting smart city infrastructure, offering scalable solutions for EV monitoring, traffic analytics, and policy planning. Furthermore, this analysis could be instrumental in estimating the density of EVs across different regions, which in turn can inform decisions regarding the optimal placement and number of electric vehicle charging stations needed within a given distance range.

#### 4. Discussion

For environmental policy and informing infrastructure development, the spatial distribution and density of electric vehicles (EVs) play a vital role. Surveillance data helps to estimate the number of EVs running in a particular region, with the help of that, planners can more correctly assess the demand for public and private charging stations and ensure sufficient capacity to meet future needs. This information is also important for avoiding inadequate utilization or traffic at charging points. Additionally, regions with lower EV penetration can be identified, enabling policymakers to design targeted incentive programs and awareness campaigns to promote

EV adoption. Increasing the proportion of EVs in these areas has the potential to significantly reduce vehicular emissions, thereby contributing to the improvement of air quality and lowering the Air Quality Index (AQI). Such data-driven approaches are crucial for achieving sustainable urban mobility and meeting environmental goals.

#### 5. Limitations And Future Directions

While our analysis provided valuable insights, it also faced certain limitations: Detection Challenges: Factors such as occlusion (Vehicles often get partially or fully occluded by other objects e.g., other vehicles, trees, pedestrians making detection harder), motion blur (fast moving cars appear blur in frames), varying Lighting Conditions ( shadows, nighttime degrades the detection) and weather conditions (Rain, snow, fog, or dirty lenses reduces visibility and affect detection accuracy.) posed challenges for accurate detection and localization of vehicles. The limited availability of surveillance videos featuring a large number of electric vehicles constrains the ability to thoroughly test and evaluate detection models.

#### 6. Conclusion

Previous studies have demonstrated that many existing models for automatic vehicle number plate recognition suffer from limited accuracy and suboptimal performance. The proposed system addresses these challenges by utilizing video processing techniques to identify and analyze electric vehicles in real-time. By incorporating robust image pre-processing and number plate extraction methods, emphasizing features such as a high green ratio, the system enhances detection accuracy. The machine learning algorithms, particularly pretrained YoloV5, further improves the precision of vehicle recognition from video streams. This approach not only enables efficient monitoring of electric vehicle usage but also supports data-driven planning for the deployment of public and private charging infrastructure. Moreover, it contributes to broader environmental goals by aiding in air quality management and promoting the adoption of electric vehicles, thereby advancing sustainable urban mobility.

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