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# A Hybrid Artificial Intelligence-Based Approach for Accurate Number Plate Preprocessing and Recognition

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## Abstract

Number plate recognition is an important component of smart transportation systems as it plays a significant role in automated traffic management, law enforcement, and road safety. In order to achieve accurate and effective recognition under various types of settings, this paper provides a thorough analysis of number plate preprocessing and recognition algorithms. Our system leverages computer vision and object detection techniques to accurately identify vehicles and extract their license plates. To ensure precise number plate recognition, we employ methods such as skew correction, noise reduction, grayscale conversion, and optical character recognition. Common issues with number plate recognition like slanted orientations and varying lighting conditions are addressed. Through the integration of these techniques, our system achieves a recognition accuracy of 98.1%, outperforming several existing approaches. Our approach attempts to offer insights into enhancing the accuracy and robustness of number plate recognition systems by assessing current approaches and their effectiveness.

**Categories:** Image Processing and Analysis, Computer Vision, Machine Learning (ML)
**Keywords:** computer vision, object detection, number plate recognition, image preprocessing, ocr, smart transportation systems

## Introduction

The increasing need for efficient traffic management and law enforcement has driven significant interest in automated number plate recognition (ANPR) systems [1]. These systems play a vital role in enabling smart transportation applications such as automated toll collection, parking management, and violation detection. Despite considerable technological advancements, ANPR continues to face challenges in real-world environments, particularly when dealing with low-resolution images, poor lighting conditions, occlusions, and skewed license plate orientations.

Preprocessing techniques - such as image enhancement, noise reduction, and skew correction - are critical in addressing these challenges. By preparing images for accurate character segmentation and recognition, preprocessing directly influences the performance and reliability of the overall system. In particular, robust preprocessing is essential for achieving high recognition accuracy across varied number plate styles, lighting conditions, and imaging angles [2].

This study is motivated by the need to reduce manual intervention in traffic monitoring systems and to improve the accuracy and reliability of automated number plate recognition. Recognition errors can lead to missed violations, misidentification, and diminished trust in automated enforcement systems. Therefore, it is essential to evaluate the interplay between preprocessing methods and optical character recognition (OCR) accuracy in ANPR pipelines.

The aim of this research is to conduct a comprehensive analysis of preprocessing and recognition methods for number plate recognition. The work focuses on assessing the effectiveness of various image enhancement and noise reduction techniques, followed by manual character-level annotation to isolate license plate characters. A custom OCR model is trained on annotated images to recognize alphanumeric characters with high accuracy. Through this approach, we seek to identify the strengths and limitations of current techniques and propose improvements that enhance system robustness and adaptability to real-world conditions.

## Materials And Methods

### Related works

Due to the difficulties presented by different license plate designs, changing climatic conditions, and fluctuating image quality, the field of number plate recognition has made significant strides. To develop reliable and effective solutions, researchers have used leading machine learning models as well as

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conventional image processing techniques.

To manage license plates with different designs from various nations, an effective approach for ANPR is set out. This system recognizes characters using You Only Look Once Version 3 Spatial Pyramid Pooling (YOLOv3-SPP), detects license plates using a small YOLOv3 network, and extracts the right character sequence using a layout detection technique. The system's versatility is demonstrated by its ability to handle single-line and double-line plates without the need for dataset-specific preprocessing. The technique has been tested on license plates from 17 different nations and has proven to be very accurate and cross-country applicable, making it a standard for international ANPR solutions [3]. The primary objective of MATLAB-implemented research is on number plate recognition's simplicity and efficiency. The system successfully tackles issues like blurriness and low visibility by investigating preprocessing, feature extraction, and character recognition techniques. It is appropriate for a variety of applications due to its modular design, which guarantees computational efficiency [4]. Modern number plate recognition systems now rely heavily on Convolutional Neural Networks (CNNs). In one study, CNNs are used for both character recognition and license plate detection in a two-stage system. The system's high accuracy during testing on Moroccan license plates shows that it is more successful than conventional techniques. The method improves accuracy and economy by combining CNN with wavelet decomposition, making it especially appropriate for applications involving autonomous vehicles [5].

A deep learning-based pipeline is used to identify and detect license plates from live CCTV footage. After identifying the vehicle using the YOLO object detection method, the system locates the license plate and uses OCR to recognize the characters. The method uses preprocessing methods such bilateral filtering, grayscale conversion, and Canny edge detection for character segmentation to increase robustness [6]. One important study tackles the intrinsic heterogeneity in Indian number plates, focusing on variations in letter spacing, font style, and size. YOLOv5, a model that is known for its ability to detect smaller objects more effectively than earlier versions, is used for number plate detection in the proposed system, which begins with image acquisition through CCTV cameras. Google Tesseract OCR is used to segment and recognize the characters on the observed plates. This combination guarantees an efficient framework that can be implemented in the real world [7]. Another method combines an OCR model for identifying alphanumeric characters on low-quality number plates with Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) for image improvement. With an average recognition accuracy of 85%, this technique greatly increases the system's accuracy. Adaptive classification for reliable recognition, contour detection for plate localization, and residual learning for image reconstruction are important elements [8].

Without the need for prior knowledge of pre-processing and post-processing criteria, an end-to-end YOLO-based pipeline was used for license plate identification, recognition, and vehicle detection. While YOLOv4 is used in the later stages of the pipeline with data augmentation techniques to improve recognition accuracy, YOLOv2 is integrated for initial vehicle detection. The system maintains real-time performance on low-end GPUs. A fully automated, rule-independent ANPR framework and unique data augmentation techniques for creating license plate image synthesis are few important contributions [9]. A CNN-based OCR model for character recognition and YOLOv3 for Region of Interest (ROI) identification is suggested in an ANPR system that uses a dual deep learning method. After identifying the ROI, preprocessing is done to improve the image prior to CNN classification. To improve performance, motion deblur is applied with a Weiner filter. To determine car registration information, the system compares the retrieved characters with the Regional Transport Office database [10]. For efficient number plate recognition, a four-stage pipeline has also been proposed. After preprocessing to improve image quality, the pipeline performs morphological operations to precisely extract the license plate region. Individual characters are segmented using the bounding box method and subsequently identified by template matching. With an extraction accuracy of 97.5%, segmentation accuracy of 96.67%, and recognition accuracy of 94.17% on a dataset of 120 images, this method demonstrated remarkable performance [11].

In another study, problems unique to Indian number plates - like different lighting conditions, noisy images, and skewed plates - are addressed by using sophisticated image processing techniques. The system uses contour tracing, Gaussian smoothing, and Gaussian thresholding for character recognition and preprocessing. Even in non-standard circumstances, the K-Nearest Neighbors (KNN) algorithm produces high detection as well as identification accuracy [12]. An additional study evaluates ANPR systems for detecting auto theft, emphasizing problems brought on by low image quality. Before using detection algorithms, the study highlights the value of preprocessing methods such motion blur reduction and image sharpening to improve recognition accuracy. In order to ensure dependability in practical situations, the job tackles a crucial component of ANPR systems [13]. Four distinct deep learning models - CNN, MobileNet, Inception V3, and ResNet50 - have been assessed for character recognition, while novel techniques have been presented for the phases of plate extraction, preprocessing and segmentation to increase efficiency. CNN performs better than the other models, according to experimental results. The system is made to withstand challenging circumstances such as dim lighting, haziness, and skewed license plates [14].

## Proposed method

Figure 1 describes the number plate recognition system that minimizes human error by utilizing advanced technology. At its core, a rigorously trained neural network model forms the backbone of this system. Its main responsibility is to process and analyze license plates images, and this requires constant model parameter adjustment to guarantee optimal performance and accuracy.

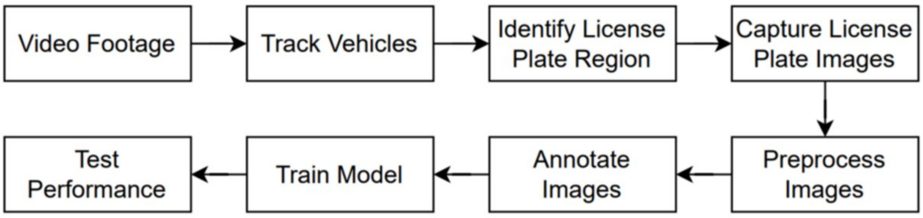


**FIGURE 1: Workflow of the system**

The first step in the procedure is gathering video footage from security cameras or other recording equipment that shows the movement of cars in different settings in real time. The following actions are based on this video footage. Vehicle recognition is performed by first applying a YOLOv8 object detection model, trained on multiple vehicle classes, to localize vehicles within each video frame. These detections are then associated across consecutive frames using a tracking algorithm, ensuring consistent identification and filtering out irrelevant regions.

The tracking algorithm used is Deep Simple Online and Realtime Tracking (DeepSORT), an algorithm commonly used for tracking objects. It combines the YOLO object detection model with an advanced tracking algorithm that leverages both motion and appearance features to maintain accurate tracking. A pre-trained CNN is employed to extract appearance features, while a Kalman filter is used for motion tracking, predicting the location of objects in the next frame based on their past movements. The Hungarian algorithm then matches new detections with existing tracks by considering both appearance and motion similarity, ensuring efficient and reliable tracking in real-time applications.

Isolating the license plate region is the next step after the vehicles have been tracked. This is accomplished by using a YOLOv8 model, which has been trained to detect the license plate region and is capable of accurately locating and extracting the license plate region of the tracked vehicle. Once the detected license plates are extracted, they can be thoroughly examined. To improve their quality and recognition accuracy, these collected images are preprocessed. Once preprocessed, the images are annotated with their corresponding license plate characters. This annotation process is crucial for creating a high-quality dataset that can be used to train an object detection model that can accurately predict the license plate characters.

Through iterative optimization to attain high accuracy, a YOLOv8 model is trained on the annotated license plate images and the model learns to recognize and interpret the characters. Lastly, a distinct validation dataset is used to thoroughly test the trained model's performance. The model's performance is assessed using metrics like accuracy, precision, and recall, and any necessary modifications are performed to further improve the model.

Figure 2 shows the preprocessing steps involved to improve the quality of images so that model learns properly.

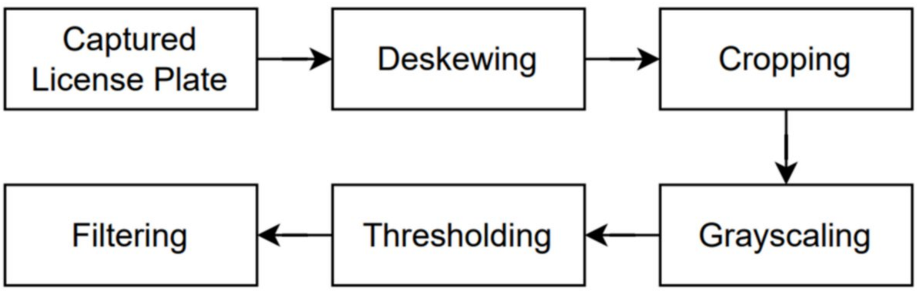


**FIGURE 2: Preprocessing steps**

In order to improve image quality and create ideal conditions for character recognition, preprocessing is an essential step in the license plate recognition system. The process begins with the captured license plate images, which often contain distortions and noise due to variations in lighting, angles, and environmental conditions. A number of preprocessing methods are used to improve the quality and readability of the license plate images in order to overcome these difficulties.

Deskewing is the first stage, which involves correcting any angular distortions in the captured image. Cameras placed at angles other than perpendicular to the license plate or motion of the vehicle can produce skewed images. Deskewing makes sure the lettering on the license plate is horizontally aligned, which makes further processing steps easier. Following deskewing, the system performs cropping, which isolates the ROI - the license plate itself. This stage removes unnecessary background noise and concentrates processing on the relevant part of the image.

Once the license plate region is extracted and aligned, grayscaling is applied. Converting the image from full color to grayscale lowers data complexity, while maintaining the key properties needed for identification. By displaying intensity changes in a single channel, grayscaling streamlines additional image analysis and facilitates character recognition on the license plate.

Thresholding is done after grayscaling, with a special focus on OTSU Thresholding, a technique in image processing named after Nobuyuki Otsu, who first described the method [15]. This technique automatically analyzes the image's pixel intensity distribution to establish the ideal threshold value. By binarizing the image, OTSU Thresholding distinguishes the foreground (characters) from the background. The end effect is a clear black-and-white picture with the text standing out against a consistent background. This method dynamically adjusts to the intensity profile of the image, making it very useful for managing varying lighting conditions. OTSU Thresholding was chosen after manual binary thresholding was attempted but failed to produce results as good as OTSU.

Filtering is the last phase, which improves the image's clarity and eliminates noise. Character edges were preserved while imperfections were refined down using popular filtering methods including mean filtering, median filtering, and Gaussian blur.

This preprocessing pipeline makes sure that the license plate characters are distinct and prepared for recognition, which is essential for achieving high accuracy in subsequent steps of segmentation and character recognition within the license plate recognition system.

## Results And Discussion

### License plate preprocessing

To enhance the quality of the isolated license plate region and to improve the recognition accuracy, the following series of preprocessing steps are performed:

1) Deskewing: When the extracted license plate image appears skewed due to camera angle or vehicle orientation, a deskewing process is applied to realign it. In this process, Harris Corner Detection is used to identify the four corner points of the plate region. These corner coordinates are then analyzed using Principal Component Analysis to estimate the dominant orientation and an affine transformation is then applied to align the plate horizontally, ensuring uniformity in orientation. This correction enhances the accuracy of subsequent recognition tasks by providing a consistently aligned input for processing. Deskewing significantly improved the alignment of the license plate image, as shown in Figure *3*.


**FIGURE 3: Deskewing result: (a) Actual license plate image; (b) Deskewed license plate image**

2) Cropping: Post-deskewing, unnecessary regions surrounding the license plate are removed to isolate the relevant area, which contains only the license plate. Contour detection, which uses techniques such as the canny edge detector and contour area filtering, is used to determine the precise boundaries of the license plate. The cropping process yielded tightly bounded images of license plates, eliminating unwanted background regions. Figure *4* demonstrates the comparison between deskewed and cropped image.


**FIGURE 4: Cropping result: (a) Deskewed license plate image; (b) Cropped license plate region**

3) Grayscaling: The cropped license plate images are then converted to grayscale using an OpenCV image processing function, to reduce computational complexity and focus on intensity variations. Grayscaling transforms the image into a single channel, emphasizing structural features essential for character recognition. Figure *5* illustrates the transformation from cropped image to grayscale image.


**FIGURE 5: Grayscaling result: (a) Cropped license plate image; (b) Grayscaled license plate image**

4) OTSU Thresholding: To further enhance the grayscale images, OTSU's thresholding method is applied. This adaptive thresholding technique determines an optimal threshold value to binarize the image, effectively separating the foreground (characters) from the background. The binarized images showed clear delineation of license plate characters, as seen in Figure *6*, enabling accurate character segmentation.


**FIGURE 6: OTSU Thresholding result: (a) Grayscaled license plate image; (b) OTSU thresholded license plate image**

5) Filtering Techniques: In an effort to refine the binarized images, we explored three filtering techniques:

• Mean Filtering: Averages neighboring pixel values to reduce noise.

• Median Filtering: Removes salt-and-pepper noise by replacing each pixel with the median value of its neighbors.

• Gaussian Blur Filtering: Smooths the image by applying a Gaussian kernel, preserving edges.

Figure *7* showcases the effects of each filtering method on OTSU-thresholded images.

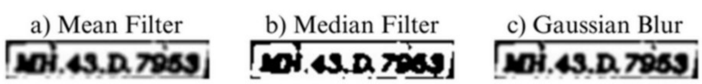


**FIGURE 7: Results of the filtering techniques on the grayscaled image**

While these filters effectively reduced noise, they also introduced excessive blurring, particularly for smaller or thinner characters, thereby reducing recognition accuracy. Based on empirical results, OTSU thresholding and filtering techniques were excluded from the final preprocessing pipeline.

## OCR model training and testing

To perform OCR using the YOLOv8 model, we created and used a custom dataset titled Grayscaled Plates, specifically designed for license plate character detection and recognition, which has been made publicly available via Roboflow [16]. The dataset consists of 6,143 images of license plates that are entirely preprocessed using our preprocessing pipeline, preserving essential information from the original image while also reducing the file size. All images are annotated at the character level, with each character representing one of the 35 classes (digits 0-9 and letters A-Z, except the letter I). This comprehensive annotation enables the model to accurately identify and classify individual characters within license plates. We divided the dataset into train-validation-test split of 70%-15%-15%. As the model training progresses, the improvement in the model's performance metrics on the validation set, plotted over training epochs, is shown in Figure 8.

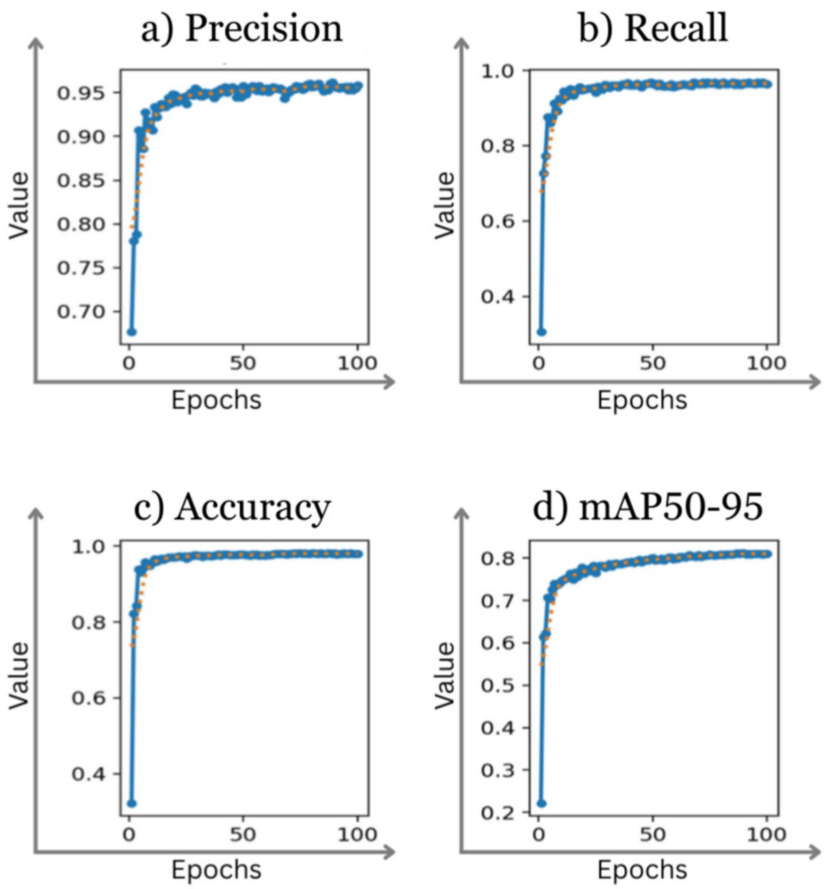


**FIGURE 8: Performance metrics (precision, recall, accuracy, mAP50-95) on validation set over training epochs**

Table 1 illustrates the performance metrics of our model with respect to precision, recall, accuracy, and mAP@0.5:0.95.

| Performance Metric | Score |
|---|---|
| Precision | 95.3% |
| Recall | 96.6% |
| Accuracy | 98.1% |
| mAP@0.5:0.95 | 81.2% |

**TABLE 1: Performance metrics for the proposed methodology**

• Precision: It measures the model's ability to correctly identify characters while minimizing false positives. A precision score of 0.953 indicates that 95.3% of the predicted characters were correct.

• Recall: It quantifies the model's ability to detect all relevant characters in the images, minimizing false negatives. A recall score of 0.966 means that 96.6% of the actual characters were successfully detected.

• Accuracy: Accuracy measures the overall effectiveness of the model by evaluating the proportion of correct predictions (both true positives and true negatives) out of the total number of predictions. An accuracy score of 0.981 indicates that 98.1% of the predictions were correct.

• mAP@0.5-0.95: The mAP@0.5:0.95 is a stricter metric that evaluates the model's performance across multiple Intersection over Union (IoU) thresholds, ranging from 0.5 to 0.95 in increments of 0.05. A score of 81.2% demonstrates the model's robustness and its ability to perform well under varying thresholds, reflecting its ability to handle both clear and challenging cases.

Table *2* shows the comparison of accuracy of our system with other existing systems.

| Method | Accuracy |
|---|---|
| ESRGAN-enhanced OCR [8] | 85% |
| YOLOv4 [9] | 90.3% |
| CNN-based OCR model [10] | 91.5% |
| MATLAB software [11] | 94.17% |
| K-Nearest Neighbor [12] | 96.22% |
| Our YOLOv8-based hybrid system | 98.1% |

**TABLE 2: Comparative analysis of recognition accuracy between the proposed license plate recognition system and existing methods**

ESRGAN, Enhanced Super-Resolution Generative Adversarial Network; OCR, Optical Character Recognition; YOLO, You Only Look Once; CNN, Convolutional Neural Network

We tested the model's performance once it had been successfully trained and validated. The OCR model result, when applied to the preprocessed license plate image, is shown in Figure *9*. The model accurately predicted all characters present on the plate, demonstrating its effectiveness in recognizing license plate characters with high precision. This result further reinforces the reliability and accuracy of our approach in real-world scenarios.


**FIGURE 9: Result of the OCR model**

OCR, Optical Character Recognition

## Conclusions

With an emphasis on overcoming obstacles including distortions, noise, and changes in lighting, our approach provided a thorough examination of preprocessing and recognition methods for vehicle number plates. By implementing methods like deskewing, cropping, grayscaling, and OTSU thresholding, the proposed system significantly enhanced the clarity and accuracy of number plate recognition. Vehicle number plates were successfully isolated and processed in real-world situations through the incorporation of complex algorithms like DeepSORT for vehicle tracking and YOLOv8 for license plate region detection and license plate character identification. The proposed system achieves a recognition accuracy of 98.1%, surpassing several existing methods, demonstrating that robust detection and identification models in combination with rigorous preprocessing can produce excellent accuracy and reliability in many different kinds of environmental settings. This comprehensive strategy highlights the system's potential for automating essential tasks in traffic management and law enforcement, ensuring adaptability and ease of deployment in dynamic, real-world scenarios and creating the way for more efficient and effective intelligent transportation systems.

Future work can focus on building domain-adaptation and synthetic-data pipelines to make the system more versatile. This includes handling multiple languages and scripts, different font styles and sizes, and diverse plate layouts. Realistic synthetic data and augmentations such as dirt, reflections, occlusion, and blur can help the model generalize better across regions and conditions. Another improvement could be adding a confidence level and uncertainty estimation alongside a human-in-the-loop active-learning workflow. Low-confidence detections would be sent for manual verification and those verified examples would be fed back to periodically retrain the system, reducing errors over time while keeping annotation cost low.

# Additional Information

## Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

**Concept and design:** Ananth Balvalli, Aashish Bathe, Shruti Dalvi, Prashansa Erande, Jyoti More

**Acquisition, analysis, or interpretation of data:** Ananth Balvalli, Aashish Bathe, Shruti Dalvi, Prashansa Erande, Jyoti More

**Drafting of the manuscript:** Ananth Balvalli, Aashish Bathe, Shruti Dalvi, Prashansa Erande, Jyoti More

**Critical review of the manuscript for important intellectual content:** Ananth Balvalli, Aashish Bathe, Shruti Dalvi, Prashansa Erande, Jyoti More

**Supervision:** Jyoti More

## Disclosures

**Human subjects:** All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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