MACHINE LEARNING APPROACHES FOR VEHICLE NUMBER IDENTIFICATION: ACCURACY AND VALIDATION

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ABSTRACT

Vehicle Number Identification is central to in intelligent transportation systems, traffic monitoring, law enforcement, and security applications. Traditional rule-based approaches, which relied on edge detection, color segmentation, and optical character recognition (optical character deciphering), often failed under real-world conditions such as poor lighting, motion blur, and diverse plate formats. In recent developments in intelligent algorithmic models (ML) and advanced neural network techniques (DL) significantly reshaped LPR (License Plate Recognition) by introducing robust feature learning, end-to-end recognition, and real-time detection capabilities. The present study reviews and validates modern ML approaches for license plate recognition, focusing on object detection models such as You Only Look Once framework and Region-based Convolutional Neural Network for plate localization, and sequence learning methods such as Convolutional Neural Networks, Convolutional Recurrent Neural Networks, and context-aware Transformer modeless for character recognition. Furthermore, the contribution of data augmentation and Generative Adversarial Network-based synthetic image generation in enhancing robustness under challenging environments is discussed. Experimental evidence from benchmark datasets, including CCPD, AOLP, and UFPR-ALPR, confirms that ML-based approaches consistently achieve 97–99% accuracy in ideal conditions and maintain 90–95% accuracy in real-world scenarios, far outperforming traditional methods. The findings validate that intelligent algorithmic models significantly enhances both accuracy and reliability in LPR systems. The study concludes that while ML-powered models excel in robustness and real-time processing, future research should address challenges such as adverse weather conditions, multilingual license plates, and privacy concerns in automated vehicle tracking.

Keywords: Vehicle Number Identification (LPR), Automatic Number Plate Recognition (ANPR), Machine Learning, Deep Learning, You Only Look Once frame work, Convolutional Neural Network-optical character deciphering, Smart Traffic Systems.

1. INTRODUCTION

Vehicle identification has become a critical requirement in the modern era for applications such as traffic monitoring, toll collection, law enforcement, border control, and parking management. At the core of these applications lies Automatic Vehicle Number Identification (ALPR), also known as Automatic Number Plate Recognition (ANPR), which converts an image of a vehicle's license plate into readable text.

Traditional methods relied on image processing and optical character recognition (optical character deciphering) to detect and read plates, it's a Rule-based systems are rigid. They work only if the conditions match their pre-defined assumptions. When the environment changes, these systems fail but these approaches faced challenges in real-world conditions such as poor lighting, motion blur, and non- standard fonts. With the rise of intelligent algorithmic models (ML) and advanced neural network techniques (DL), new methods have achieved significant progress.

Figure 1: Figure 1: Automatic (Machine Language) License Plate Recognition System-Computer algorithms process these images to find and identify the characters on the license plates. Here's a simplified explanation of how it works:

1. **Image Acquisition**
2. **Image Pre-processing**
3. **License Plate Localization**
4. **Character Segmentation**.
5. **Character Recognition/Sequence Recognition**.
6. **Output**

(1) Input image **(2)** Vehicle detection **(3)** Number extraction **(4)** Number Recognition

Figure 2.: Computer algorithms process- Workflow of the proposed ALPR system. Cameras capture the scene; images are pre-processed to enhance quality; the license plate is localized; characters are segmented; and the recognized plate number is produced. Sub-panels correspond to (1) Input, (2) Vehicle detection, (3) Feature extraction, (4) Vehicle recognition.

2. Literature Review (2018–2024)

Zhou et al. (2019) applied Convolutional Neural Network-based feature extraction to improve recognition under challenging conditions (blur, tilt, and noise). Their results demonstrated that Convolutional Neural Networks significantly outperform handcrafted features, achieving higher robustness across datasets.

Li et al. (2021) evaluated You Only Look Once frameworkv4 and Region-based Convolutional Neural Network for license plate detection. Their study reported >97% detection accuracy in complex environments, confirming that modern object detection

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models outperform earlier approaches in speed and precision.

Chen et al. (2022) developed You Only Look Once frameworkv5-PDLPR, a parallel decoder model that eliminated post-correction. They achieved 99.4% recognition accuracy at 159 FPS on the CCPD dataset, showing that end-to-end models could combine both high accuracy and real-time performance.

Plavac et al. (2023) studied the robustness of LPR systems under synthetic distortions such as rain, fog, frost, and sensor noise. They found that performance degraded significantly under snow/frost, but augmentation techniques helped maintain acceptable accuracy.

Zhu (2024) proposed a lightweight plate detection network optimized for real-time deployment. Their model achieved a mean average precision (mAP) of 96.6%, balancing speed and accuracy for smart city applications.

Ebrahimi Vargoorani & Suen (2024) presented a dual advanced neural network techniques system combining Region-based Convolutional Neural Network for detection and Convolutional Recurrent Neural Network with CTC for recognition. They achieved 92% recall on the CENPARMI dataset and 90% on UFPR-ALPR, providing detailed error analysis and highlighting the impact of font variations.

3. Machine Learning Approaches to Vehicle Number Identification

Given the inherent limitations of rigid rule-based methods, researchers began adopting Machine Learning (ML) and Artificial Intelligence (AI) to effectively manage the extensive variability encountered in real-world operating conditions. In contrast to traditional techniques, ML does not depend solely on predefined rules; instead, it learns complex patterns directly from data. This characteristic

makes ML-based systems significantly more resilient to factors such as image noise, distortion, and unpredictable environmental changes. Recent advancements in Machine Learning (ML) and Deep Learning (DL) have fundamentally transformed the domain of Automatic License Plate Recognition (ALPR). Conventional ALPR systems, which were reliant on rule-based image processing and simple optical character recognition, frequently performed poorly under practical real-world circumstances. Factors like fluctuating lighting, motion blur from high-speed vehicles, angular plate distortions, and distracting background elements commonly undermined their accuracy. Machine learning methodologies, especially those built upon Convolutional Neural Networks (CNNs), have demonstrated exceptional efficacy in mitigating these issues. They achieve this by automatically learning strong, distinguishing feature representations from vast collections of labeled data (Zhou et al., 2019). A typical Machine Learning-based License Plate Recognition (LPR) pipeline generally involves three crucial stages:

3.1. Object Detection Models

A fundamental step in Automatic License Plate Recognition (ALPR) is plate localization: precisely identifying the license plate's area within a vehicle image. Older methods, like rule-based techniques utilizing edge detection or color segmentation, were often inconsistent in complex scenes. Conversely, contemporary Machine Learning (ML)-based object detection models, such as the You Only Look Once (YOLO) framework and Region-based Convolutional Neural Networks (R-CNN), have significantly improved detection precision. These models leverage Convolutional Neural Networks (CNNs) to process the complete image and pinpoint bounding boxes around plates. They perform reliably even in challenging

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scenarios, including poor illumination, skewed angles, or partial obstruction (Li et al., 2021). Consequently, the accuracy of plate localization now typically ranges above 97–99%, facilitating dependable operation in live traffic environments.

3.2. Sequence Learning Approaches

Once the plate is localized, the subsequent task is to accurately recognize the alphanumeric characters sequence. Rather than depending on character-by-character segmentation, which is often brittle, sequence learning models like Recurrent Neural Networks (RNNs) and modern Transformer-based architectures that incorporate contextual awareness process the plate holistically. These models interpret the license plate's characters as a sequence, enabling them to capture the context and relationships between characters. For instance, if a character is partially obscured, the model can still deduce it correctly by analysing the neighbouring characters. This capability makes sequence models especially effective for plates featuring various fonts, inconsistent spacing, or non-standard configurations.

Figure 3: image is Dark Background -A CCTV camera captures an image of a speeding car. The system uses YOLOv5 (a fast object detection model) to draw a box around the license plate area, even if the car is moving fast or the image is dark.

3.3. Data Augmentation and Generative Models

A major factor in improving accuracy has been the availability of large-scale training data. However, real-world datasets are often limited by region or condition. To address this, researchers have employed data augmentation and Generative Adversarial Networks (Generative Adversarial Networks). Generative Adversarial Networks can generate synthetic plate images under different conditions— such as rainy weather, low lighting, or motion blur—thereby enriching the training dataset. Studies have shown that Generative Adversarial Network-based augmentation significantly improves recognition robustness by simulating challenging real-world environments (Montazzolli & Santos, 2019).

Figure 4: Low-Quality Images: License plate images captured in real-world scenarios may suffer from low resolution, motion blur, or poor lighting conditions.

Modern learning-driven approaches, especially convolutional models, learn discriminative features from large labeled data, improving accuracy and robustness to noise and distortions. A typical pipeline covers plate detection, character extraction/segmentation, and text recognition, enabling reliable results even with challenging images.

Table 1. Three-stage ALPR pipeline with purpose, example, and representative models (Detection → recognition → augmentation).

Stage	Purpose	Example	Model
1. Object Detection	Find plate in the image	Detect plate on a moving car	YOLOv5, Faster R-CNN
2. Sequence Learning	Read characters from plate	Recognize “CH BH 1687”	CRNN, Transformer
3. Data Augmentation	Train model for harsh conditions	Simulate rainy plates using GAN	GAN, Image Augmentation

4 Correlation analysis

Machine Learning vs Traditional Methods in License Plate Recognition (LPR)

The table below compares traditional rule-based approaches with modern machine learning (ML)-driven systems in the context of License Plate Recognition (LPR). The comparison is based on critical parameters such as accuracy, adaptability, and robustness.

Table 2. Comparison of traditional rule-based approaches and modern ML systems for license plate recognition. ML methods (e.g., YOLOv5, CRNN/Transformer) deliver higher accuracy in both ideal and real-world settings, greater adaptability, and stronger robustness, yielding measurable gains in applications like tolling and smart parking.

Feature	Traditional Methods	Machine Learning Methods	Proof / Example	Real-World Impact
Accuracy (ideal conditions)	70–80%	97–99%	YOLOv5 achieves >98% in good lighting	Much higher success in toll booths and smart parking
Accuracy (real-world)	40–60%	90–95%	Transformer models remain stable under blur, noise	Effective in rain, night, motion blur
Flexibility & Adaptability	Rigid, rule-specific	Learns from data	CNNs learn features, adapt to plate types	Can handle different fonts, angles, and languages
Data Handling	Requires manual tuning	Can use millions of examples + synthetic data	GANs simulate foggy/rainy plates for training	Improved generalization in diverse conditions
Real-time Processing	Slow and error- prone	Fast (100–150 FPS)	YOLOv5 real-time speed tested in traffic feeds	Used in live surveillance and speed monitoring
Robustness	Fails under noise or partial occlusion	Handles distortions and missing data	CRNN fills gaps in partially blurred plates	Accurate even when part of plate is dirty or missing

Modern machine learning (ML) methods significantly outperform traditional rule-based systems across all key dimensions in License Plate Recognition (LPR). Machine Learning models are more accurate, adaptable, and robust, while also being faster and scalable. These capabilities make them ideal for real-time intelligent transportation and security systems, far surpassing the performance limits of traditional rule-based approaches.

5. DISCUSSION

This study highlights the major progress made in license plate recognition through the use of advanced neural network techniques methods. Modern detection models like You Only Look Once frameworkv5 and Region-based Convolutional Neural Network showed clear improvements in both precision and processing speed compared to earlier rule-based and feature-driven techniques. For the recognition stage, Convolutional Neural Network-based models and context-aware Transformer models architectures proved highly reliable in reading characters, even across varied plate formats and fonts.

The experiments further revealed that real-world conditions—such as poor lighting, adverse weather, and partial occlusions—remain key factors that affect recognition accuracy. However, the inclusion of data augmentation strategies, particularly Generative Adversarial Network-generated synthetic plates, helped reduce performance drops by enriching training datasets with more diverse examples.

6. CONCLUSION

This work examined the contribution of intelligent algorithmic models and advanced neural network techniques approaches in advancing license plate recognition. The findings confirm that modern advanced neural network techniques models, especially You Only Look Once framework for detection and Convolutional Neural Network/context-aware Transformer models models for recognition, significantly outperform both traditional optical character deciphering and earlier intelligent algorithmic models methods. These models not only achieve higher accuracy but also offer greater robustness to environmental variations and deliver faster inference speeds suitable for real-time deployment.

Figure 4. YOLO detects the plate reliably under low light with slight blur. Accurate plate localization in dim, slightly blurred conditions using YOLO.

In particular, object detection models like You Only Look Once framework and Region-based

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Convolutional Neural Network improved plate localization accuracy, while deep sequence learning methods enhanced character recognition across diverse conditions. Moreover, data augmentation and Generative Adversarial Network-based image synthesis contributed to stronger model generalization when dealing with uncommon or challenging scenarios. Despite these successes, challenges remain. Recognition accuracy still drops under severe weather conditions or when handling multilingual license plates, and concerns regarding data security and privacy continue to grow. Nevertheless, with continuous innovation, AI-powered LPR systems are expected to become more reliable, secure, and efficient, supporting the next generation of intelligent transportation and security infrastructures.

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