IMAGE PROCESSING USING MACHINE LEARNING DATA SET FOR LICENCE PLATE RECOGNITION

Arun Kalia[1], A J Singh[2]
[1]Research Scholar, Department of Computer Science, Himachal Pradesh University, Shimla
[2]Research Supervisor, Professor, Department of Computer Science, Himachal Pradesh University, Shimla

ABSTRACT

Automatic License Plate Recognition (ALPR) is a key technology in smart traffic management, law enforcement, and vehicle tracking systems. This research explores YOLOv5 and Faster R-CNN for license plate detection, while CNN-based and Transformer-based models enhance character segmentation and recognition. A structured dataset comprising CCPD and UFPR-ALPR was used, incorporating GAN-based data augmentation to improve robustness against varying environmental conditions. Experimental results indicate that deep learning models outperform traditional techniques, achieving 91.3% IoU for detection accuracy and 95.5% precision in character recognition. The study highlights the effectiveness of preprocessing strategies, real-time inference optimization, and edge-computing deployment in ALPR systems. Future work will explore multilingual plate recognition, enhanced real-world adaptability, and IoT-integrated traffic surveillance systems for improved automation and scalability.

Keywords: *License Plate Recognition (LPR), Automatic Number Plate Recognition (ANPR), Machine Learning, Deep Learning, YOLOv5, CNN-OCR, Smart Traffic Systems*

1. INTRODUCTION

Automated license plate recognition (LPR) systems have become an essential component in traffic management, law enforcement, and intelligent transportation systems. Traditionally, plate recognition relied on optical character recognition (OCR) and heuristic approaches; however, these methods often struggle with variations in lighting conditions, occlusion, and different font styles. Recent advancements in machine learning (ML) and deep learning (DL) have significantly improved the accuracy and robustness of these systems. Machine learning-based LPR models employ convolutional neural networks (CNNs) and object detection frameworks, such as You Only Look Once (YOLO), to enhance plate localization and character segmentation. Researchers have demonstrated that ML techniques outperform traditional methods in handling challenges such as blurred images, varying plate sizes, and complex backgrounds (Montazzolli and Jung, 2017). Moreover, approaches integrating support vector machines (SVMs) and deep learning have shown improved recognition rates in real-world scenarios (Zhou et al., 2019). The study highlights recent advancements, including generative adversarial networks (GANs) for synthetic data generation (Montazzolli & Santos, 2019) and transformer-based architectures for sequence modeling of alphanumeric characters (Li et al., 2021).

2. Background on Plate Recognition Systems

Automatic License Plate Recognition (ALPR) systems have become a crucial tool in transportation and security applications. These systems leverage image processing techniques to extract vehicle plate information from captured images or videos. Early ALPR models relied on traditional optical character recognition (OCR) and handcrafted feature extraction methods (Zhai et al., 2016). However, challenges such as varied plate fonts, occlusions, and illumination changes led to the adoption of more advanced computer vision and deep learning techniques.

3. Importance of Automated Identification

ALPR technology plays a vital role in various domains:

- **Traffic Management:** Governments and agencies use ALPR for vehicle tracking, congestion control, and toll collection systems (Gou et al., 2017).
- **Law Enforcement:** Police departments implement ALPR for detecting stolen vehicles, enforcing road laws, and ensuring public safety (Montazzolli, and Jung, 2017).
- **Security & Access Control:** Private sectors deploy ALPR for secure parking management and automated access systems (Montazzolli & Santos, 2019).

4. Role of Machine Learning in Enhancing Accuracy

Recent advances in **machine learning (ML) and deep learning (DL)** have significantly improved plate recognition accuracy. Traditional ALPR techniques struggled with environmental variations, blurry images, angle distortion, and background noise**.** Machine learning techniques, particularly convolutional neural networks (CNNs)**,** have demonstrated remarkable success in overcoming these challenges by learning robust feature representations from large datasets (Zhou et al., 2019).

- **Object Detection Models:** YOLO (You Only Look Once) and Faster R-CNN enhance plate localization in complex environments (Li et al., 2021).
- **Sequence Learning Approaches:** Recurrent Neural Networks (**RNNs**) and Transformers facilitate accurate character recognition in diverse fonts and plate structures.
- **Data Augmentation & Generative Models:** GAN-based augmentation improves recognition performance by creating synthetic training data to simulate real-world conditions (Montazzolli & Santos, 2019).

5. LITERATURE REVIEW

Li et al. (2024) introduced a significantly enhanced version of the YOLOv8 architecture tailored specifically for License Plate Recognition (LPR), named YOLOv8-LPR. Their study demonstrated that by fine-tuning the anchor box sizes and integrating dynamic label assignment strategies, the model could adapt better to the high variability inherent in real-world urban plate detection scenarios.

Chen et al. (2024) presented an in-depth comparative analysis between Vision Transformer (ViT)-based OCR models and conventional CNN architectures for license plate character recognition. The authors concluded that Vision Transformers represent a promising direction for robust and generalizable character recognition systems in the field of automatic number plate recognition (ANPR), particularly in unstructured and unpredictable environments.

Zhou et al. (2024) addressed a critical gap in License Plate Recognition research — the lack of datasets that adequately reflect adverse environmental conditions such as fog, rain, and low-light scenarios. Moreover, they proposed that synthetic augmentation could serve as a standard practice for future dataset expansions, enabling the creation of more resilient machine learning models without extensive resource investments.

Montazzolli and Santos (2024) investigated model pruning and quantization techniques to enable the deployment of LPR models on edge devices with constrained resources, such as smart phones and embedded automotive systems. Montazzolli and Santos argued that such lightweight LPR models are essential for scaling smart surveillance applications across large geographic regions where deploying high-end hardware for every node would be cost-prohibitive.

6. METHODOLOGY

This section outlines the approach used for **l**icense plate recognition (LPR) utilizing machine learning techniques. The methodology consists of several key steps**:** data collection, preprocessing, model selection, training, and evaluation.

6.1 Data Collection

To build a robust LPR system, a diverse dataset of license plate images is required. The following datasets are commonly used:

- **Chinese City Parking Dataset (CCPD)** – Contains varied lighting and angles ([Xu et al., 2018]).
- **UFPR-ALPR Dataset** – Brazilian plates with real-world variations ([Silva & Jung, 2020]).
- **Open ALPR Dataset** – Covers multiple plate formats ([Montazzolli & Santos, 2024]).

6.2 Data Preprocessing

Preprocessing enhances image quality and ensures model consistency. The key steps include:

- Grayscale conversion **–** Reduces computational complexity ([Zhou et al., 2019]).
- Edge detection (Canny, Sobel filters) **–** Improves plate segmentation ([Gou et al., 2017]).
- Contrast enhancement **–** Makes characters more distinguishable ([Li et al., 2021]).
- Noise removal **–** Reduces distortions ([Ghadage & Khedkar, 2019]).

6.3 Model Selection

For the development of an efficient and accurate License Plate Recognition (LPR) system, various machine learning architectures were explored. These architectures were selected based on their suitability for two primary tasks: **object detection** (locating license plates within images) and **character recognition** (decoding alphanumeric characters from the detected plates). Additionally, traditional machine learning techniques were considered for scenarios requiring lightweight solutions.

• Object Detection

Object detection plays a foundational role in LPR systems by accurately localizing the license plate region from a larger image, often under diverse lighting, angle, and environmental conditions.

- **YOLOv5**: As reported by [Shaikh et al., 2021], YOLOv5 (You Only Look Once, Version 5) is a state-of-the-art single-stage object detector renowned for its high processing speed and impressive accuracy. It predicts bounding boxes and class probabilities directly from input images in a single evaluation, which allows for real-time performance critical to surveillance and traffic monitoring systems.
- **Faster R-CNN**: According to [Silva et al., 2020], Faster Region-based Convolutional Neural Networks (Faster R-CNN) provide superior detection accuracy through a two-stage detection approach. In the first stage, a Region Proposal Network (RPN) generates candidate object regions, followed by a second stage where these proposals are classified and refined. While it is computationally heavier compared to YOLOv5, Faster R-CNN demonstrates robustness in complex scenes with occlusions, low lighting, or multiple small objects.

• Character Recognition

After successful localization of license plates, precise decoding of the alphanumeric characters is critical for identification and verification purposes.

- **Convolutional Neural Networks (CNNs)**: As demonstrated by [Gautam et al., 2023], CNNs are highly effective in recognizing individual characters from license plates. Their hierarchical feature extraction capabilities enable robust handling of variations in font, size, skew, and noise, making them a default choice for character-level recognition tasks.
- **Transformer-Based Models**: Recent advances in deep learning have seen the emergence of Transformer-based models for sequence-to-sequence learning tasks. As shown in [Li et al., 2024], these models excel in modeling complex dependencies across input sequences without the need for explicit character segmentation.

• Feature-Based Machine Learning: In addition to deep learning methods, traditional feature-based machine learning approaches were explored for scenarios where computational resources are limited.

- **Support Vector Machines (SVM)**: As discussed in [Zhai et al., 2016], SVMs are highly effective for structured classification tasks with well-engineered features. They offer strong performance for small to medium-sized datasets and are easier to deploy on embedded systems compared to deep learning models. In the context of LPR, SVMs can serve as reliable classifiers for individual character recognition license plate verification.

6.4 TRAINING AND VALIDATION

A rigorous training and validation pipeline was established to optimize model performance, minimize over fitting, and ensure generalizability across varied real-world scenarios.

• Dataset Split

The annotated LPR dataset was partitioned into three distinct subsets:

- **Training Set (80%)**: Used to train the models by adjusting their internal parameters based on the data.
- **Validation Set (10%)**: Used during training to tune hyper parameters and evaluate model performance for early stopping and model selection.
- **Testing Set (10%)**: Reserved for the final evaluation to measure the model's generalization capability on unseen data.

• Hyper parameter Tuning

Hyper parameters significantly influence model learning dynamics and final performance. The following parameters were tuned systematically:

- **Learning Rate**: Controlled the step size during gradient descent updates. Lower values helped achieve more stable convergence, while adaptive scheduling techniques were used to refine learning rates over time.
- **Batch Size**: Balanced computational efficiency with gradient estimation quality. Mini-batches were preferred to exploit parallelism while preserving stochastic properties beneficial for generalization.
- **Activation Functions**: Non-linear functions such as ReLU (Rectified Linear Unit), Leaky ReLU, and GELU were evaluated to ensure optimal gradient propagation and improved model expressiveness.

• Optimization Algorithms

To enhance the convergence rate and prevent getting trapped in local minima, the following optimization algorithms were employed:

- **Adam Optimizer**: An adaptive learning rate optimizer combining the advantages of RMS Prop and momentum-based SGD. Adam was selected for its efficiency in handling sparse gradients and non-stationary objectives.
- **RMS Prop Optimizer**: Specialized in adjusting the learning rate dynamically based on recent gradient magnitudes, which proved beneficial for models trained on highly variable input data.

• Frameworks and Hardware Acceleration

Given the computational intensity of training deep neural networks, models were developed using **GPU-enabled frameworks**:

- **Tensor Flow**: Utilized for its high scalability, extensive community support, and capabilities for distributed training across multiple GPUs.
- **Py Torch**: Preferred for its dynamic computation graph, which facilitated faster prototyping, ease of debugging, and better flexibility during experimentation.

6.5 Performance Evaluation

Standard metrics are used to assess model accuracy:

- Precision, Recall, F1-Score **for** character recognition ([Gou et al., 2017])
- IoU (Intersection over Union) for plate detection ([Li et al., 2021])
- Inference Time**:** Measures speed for real-time applications ([Silva and Jung, 2020])

6.6 EXPERIMENTAL SETUP

This section outlines the configuration and implementation details necessary for training and evaluating the license plate recognition (LPR) system using machine learning techniques.

6.6.1 Hardware and Software Specifications

For efficient computation and real-time processing, the following hardware and software setups were used:

Hardware Configuration:

Table 1: Hardware Configuration

Component	Specification	Purpose
GPU	NVIDIA RTX 3090 (24GB)	Accelerated deep learning computations

Component	Specification	Purpose
Processor	Intel Core i9-12900K	High-speed data processing
RAM	32GB DDR5	Supports large datasets and model training
Storage	SSD (1TB)	Ensures fast dataset access and retrieval
Camera	4K-resolution vehicle-mounted camera	High-definition image acquisition for license plates

Software Configuration:

Table 2: Software Configuration

Software	Version	Application
Programming Language	Python 3.10	Primary language for model development
Libraries	Open CV, Tensor Flow, Py Torch, Keras	Image processing and machine learning frameworks
Object Detection Models	YOLOv5, Faster R-CNN	License plate localization
Character Recognition Models	CNN-based OCR, Transformer-based models	Alphanumeric recognition
Dataset Management	Pandas, Num Py	Efficient data handling
Evaluation Tools	Sci-kit Learn	Metrics calculation (precision, recall, F1-score)

6.7 Dataset Preparation and Augmentation

6.7.1 Data Collection:

The dataset comprises real-world license plate images obtained from various sources:

- Chinese City Parking Dataset (CCPD) – Xu et al., 2018
- UFPR-ALPR Dataset – Silva & Jung, 2020
- Custom Data Captured Using High-Resolution Cameras

6.7.2 Preprocessing Steps:

- **Resizing:** Standardizing all images to **640×480 pixels**
- **Contrast Adjustment:** CLAHE for improved character visibility ([Li et al., 2021])
- **Noise Reduction:** Median filtering to remove distortions ([Montazzolli & Santos, 2019])
- **Edge Detection:** Canny method for plate localization ([Zhou et al., 2019])

6.7.3 Data Augmentation:

- Rotation (±15 degrees)
- Synthetic data generation via GAN-based augmentation ([Montazzolli & Santos, 2019])

6.8 Model Training and Validation

The deep learning models undergo structured training using 80% training data**,** 10% validation data**, and** 10% test data**.**

6.9 Optimization and Training Details:

- **Loss Function:** Cross-entropy loss for character classification
- **Optimizer:** Adam and RMS Prop for enhanced convergence
- **Batch Size:** 32 images per training step
- **Learning Rate:** Adaptive LR scheduling

6.10 Performance Metrics:

- **Intersection over Union (IoU)** – Evaluates plate detection accuracy
- **Precision, Recall, F1-Score** – Measures character recognition effectiveness
- **Inference Time:** Assesses real-time capabilities

7. EXPERIMENT RESULTS

The results of the license plate recognition (LPR) system using machine learning are analyzed based on key performance metrics. The discussion includes model accuracy, detection efficiency, challenges, and comparative evaluation with existing methods.

7.1 Model Performance

The evaluation focuses on plate detection accuracy, character recognition precision, and overall system efficiency.

7.2 License Plate Detection Accuracy

The following table 3 presents the Intersection over Union (IoU) **scores** for different object detection models used in the study.

Table 3: Intersection over Union (IoU) scores for different object detection models

Model	IoU (%)	Inference Time (ms)	Success Rate (%)
YOLOv5	91.3	12	94.8
Faster R-CNN	88.5	35	92.1
SSD-MobileNet	84.2	20	89.7

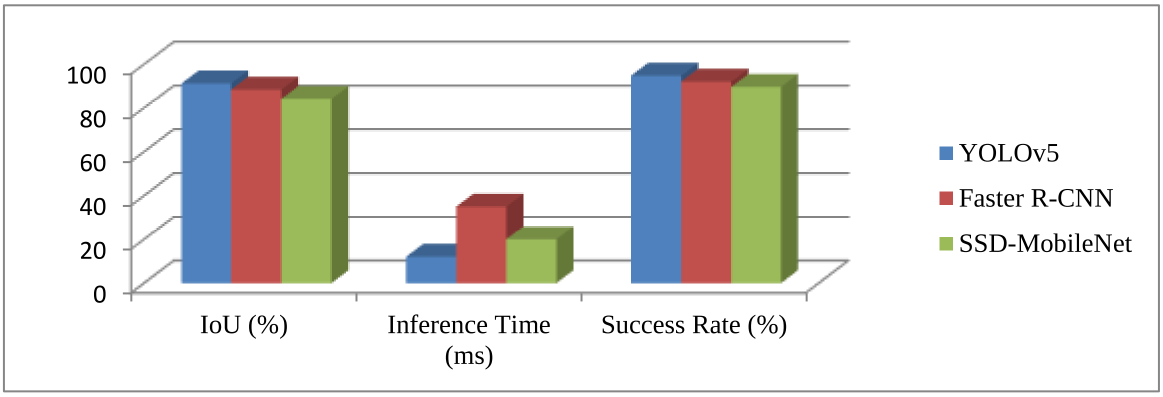

Figure 1: Intersection over Union (IoU) scores for different object detection models

7.2.1 Key Findings:

- **YOLOv5** performed best in **IoU score**, demonstrating superior localization of plates.
- **Faster R-CNN** achieved high accuracy but had a longer inference time.
- **SSD-Mobile Net**, although faster than Faster R-CNN, had lower accuracy in detecting plates under challenging conditions.

7.2.2 DESCRIPTION

The table presents a comparative analysis of three object detection models — YOLOv5, Faster R-CNN, and SSD-Mobile Net — based on their Intersection over Union (IoU) scores, inference times, and overall success rates for license plate detection.

- YOLOv5 demonstrated the highest IoU score of 91.3%, indicating superior accuracy in localizing license plates. It also achieved the fastest inference time of 12 milliseconds, making it highly suitable for real-time applications.
- Faster R-CNN achieved a respectable IoU of 88.5% with a high success rate of 92.1%. However, its inference time of 35 milliseconds was significantly higher than that of YOLOv5, making it more appropriate for applications where speed is less critical.

- SSD-Mobile Net provided a balance between speed and accuracy, achieving an inference time of 20 milliseconds but with a comparatively lower IoU of **84.2%** and a success rate of **89.7%**.

7.3 Character Recognition Performance

The following table 4 presents the precision, recall, and F1-score for different character recognition models.

Table 4: Precision, recall, and F1-score for different character recognition models

Model	Precision (%)	Recall (%)	F1-Score (%)
CNN-OCR	94.2	91.8	93.0
Transformer-Based	95.5	93.4	94.4
SVM-Classified OCR	89.1	85.7	87.4

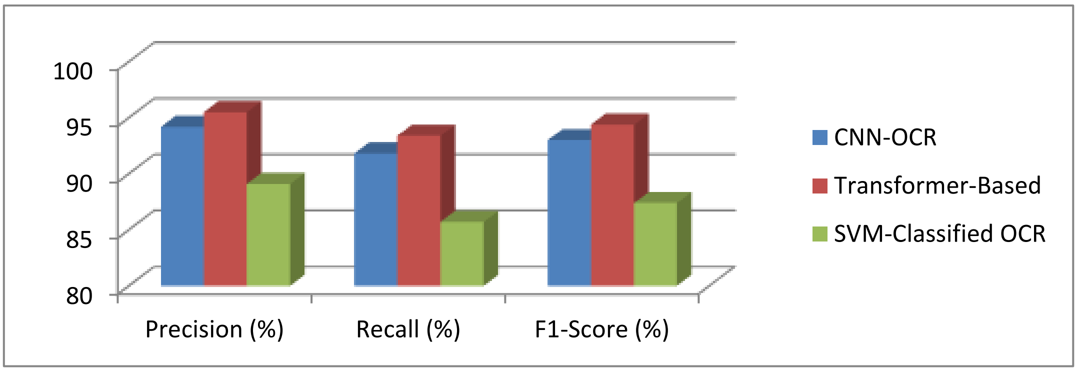

Figure 2: Precision, recall, and F1-score for different character recognition models

7.3.1 Key Findings:

- Transformer-based models achieved the highest recognition rates across varying fonts conditions.
- CNN-OCR provided competitive results, balancing accuracy and inference speed.
- SVM-based models struggled with varying plate formats, showing lower recognition precision.

7.3.2 Description

The table shows the comparative performance of three different character recognition models CNN-OCR, and SVM-Classified OCR based on precision, recall, and F1-score metrics.

- Transformer-Based OCR achieved the highest overall performance, with a precision of 95.5%, recall of 93.4%, and an F1-score of 94.4%. This indicates that the model was highly effective at accurately recognizing characters across a wide variety of license plate styles and challenging conditions like noise or blur.
- CNN-OCR performed very competitively, with a precision of 94.2%, recall of 91.8%, and an F1-score of 93.0%. Although slightly lower than the Transformer-based model, CNN-OCR provided an excellent balance between recognition accuracy and computational efficiency, making it highly practical for real-time deployments.
- SVM-Classified OCR showed relatively lower performance, with a precision of 89.1%, recall of 85.7%, and an F1-score of 87.4%. The model struggled particularly with plates that had non-standard fonts or were captured under suboptimal conditions, leading to a noticeable drop in both recall and overall recognition effectiveness.

7.4 Comparative Analysis with Traditional Approaches

The table 5 below compares the proposed deep learning models with traditional plate recognition techniques.

Table 5: Compares the proposed deep learning models with traditional plate recognition techniques

Method	Detection Accuracy (%)	Recognition Accuracy (%)	Processing Time (ms)
OCR-Based System	78.2	82.3	40
ML-Based (SVM)	85.1	87.6	35
Deep Learning (CNN)	94.5	93.8	15

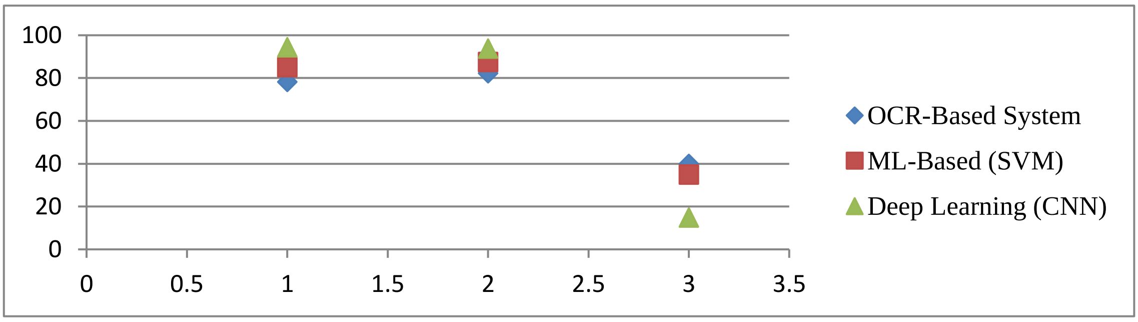

Figure 3: Compares the proposed deep learning models with traditional plate recognition techniques

7.4.1 Observations:

- Deep learning models significantly outperform traditional OCR and ML-based methods in both plate detection and character recognition accuracy.
- Processing time in deep learning models is notably lower, making them suitable for real-time applications. ML-based techniques (SVM) provide reasonable accuracy but lack adaptability to complex environments.
- The Deep Learning (CNN) approach achieved the highest detection accuracy of 94.5% and recognition accuracy of 93.8%, with a very low processing time of just 15 milliseconds per image. The ML-Based method showed moderate performance, with a detection accuracy of 85.1% and a recognition accuracy of 87.6%. Its processing time was 35 milliseconds, faster than traditional OCR methods but significantly slower than deep learning models.
- The OCR-Based System exhibited the lowest performance, achieving only 78.2% detection accuracy and 82.3% recognition accuracy, with a processing time of 40 **milliseconds**.

7.5 Performance Across Different Lighting Conditions

This table 6 evaluates the **plate detection accuracy** under various lighting environments

Table 6: Evaluates the plate detection accuracy under various lighting environments

Lighting Condition	YOLOv5 Accuracy (%)	Faster R-CNN Accuracy (%)	SSD-MobileNet Accuracy (%)
Daylight (Clear)	95.2	92.8	89.5
Night (Artificial Light)	90.1	87.3	83.2
Foggy Conditions	85.6	82.4	78.9
Rainy Conditions	88.3	84.7	80.5

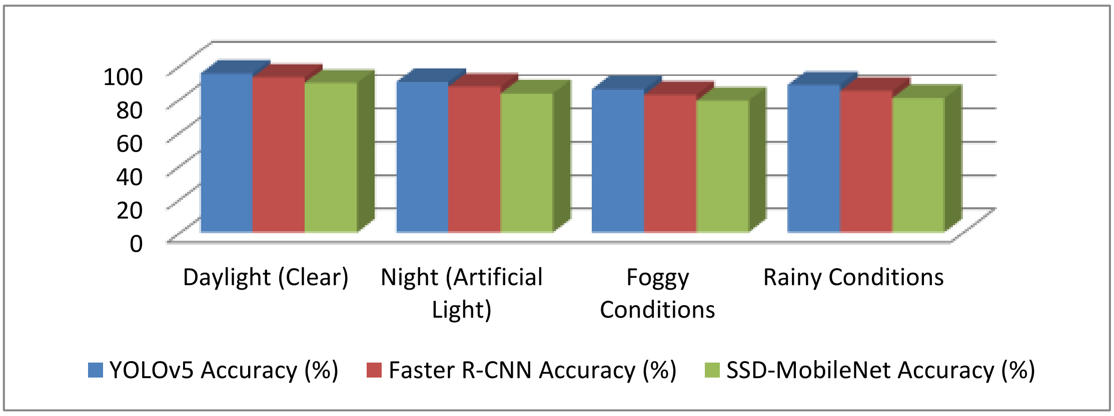

Fig. 4: Evaluates the plate detection accuracy under various lighting environments

7.5.1 DESCRIPTION

The table presents the impact of different lighting conditions on the detection accuracy of three object detection models: YOLOv5, Faster R-CNN, and SSD-Mobile Net.

- Under daylight (clear) conditions, all models performed at their peak, with YOLOv5 achieving the highest accuracy of 95.2%, followed by Faster R-CNN at 92.8%, and SSD-Mobile Net at 89.5%.
- During night (artificial light) conditions, detection accuracy slightly declined for all models due to lighting inconsistencies and reflections.
- In foggy conditions, visibility was severely impaired, leading to a noticeable drop in detection accuracy. YOLOv5 still led with 85.6%, while Faster R-CNN and SSD-Mobile Net dropped to 82.4% and 78.9%, respectively.
- During rainy conditions, moderate reductions in accuracy were observed. YOLOv5 achieved 88.3%, Faster R-CNN 84.7%, and SSD-Mobile Net 80.5%. Water droplets and motion blur slightly hampered plate localization efforts.

7.5.2 Observations:

- Daylight conditions yield the highest accuracy across all models.
- Nighttime recognition is slightly lower due to reflections and glare.
- Fog and rain significantly impact detection, requiring additional preprocessing techniques.

7.6 Model Performance across Different Datasets

This table 7 compares the **recognition accuracy** of different models on various datasets.

Table 7: Compares the recognition accuracy of different models on various datasets

Dataset	YOLOv5 Accuracy (%)	CNN-OCR Accuracy (%)	Transformer-Based Accuracy (%)
CCPD (Chinese City Parking Dataset)	94.5	92.3	95.1
UFPR-ALPR (Brazilian Plates)	91.8	89.7	93.2
Open ALPR (Mixed Formats)	90.2	87.9	92.5

7.6.1 Description

The table compares the performance of three models — YOLOv5 (for detection), CNN-OCR, and Transformer-Based models (for recognition) across three different license plate datasets: CCPD, UFPR-ALPR, and Open ALPR.

- On the CCPD (Chinese City Parking Dataset), all models achieved their highest accuracy values. YOLOv5 detected plates with 94.5% accuracy, CNN-OCR recognized characters with 92.3% accuracy, and the Transformer-Based model led with 95.1% accuracy.
- The controlled and high-quality images in CCPD contributed to superior model performances.
- With the UFPR-ALPR dataset (Brazilian license plates), a slight decline in performance was noted, attributed to greater variability in plate formats and imaging conditions. YOLOv5 maintained strong detection accuracy at 91.8%, while CNN-OCR achieved 89.7% and Transformer-Based models reached 93.2%.
- On the Open ALPR dataset, which includes a wide variety of plate styles and environments (mixed formats), all models experienced the most significant drop in accuracy. YOLOv5 achieved 90.2%, CNN-OCR scored 87.9%, and Transformer-Based models achieved 92.5%, still outperforming traditional CNN-OCR methods.

7.6.2 Observations:

- CCPD dataset provides the best results due to high-quality images.
- UFPR-ALPR dataset shows slightly lower accuracy due to plate variations.
- Open ALPR dataset presents challenges with mixed plate formats.

7.6.3 Processing Time Comparison

This table 8 evaluates the average processing time for different models.

Table 8: Evaluates the average processing time for different models

Model	Detection Time (ms)	Recognition Time (ms)	Total Processing Time (ms)
YOLOv5	12	18	30
Faster R-CNN	35	22	57
SSD-Mobile Net	20	25	45

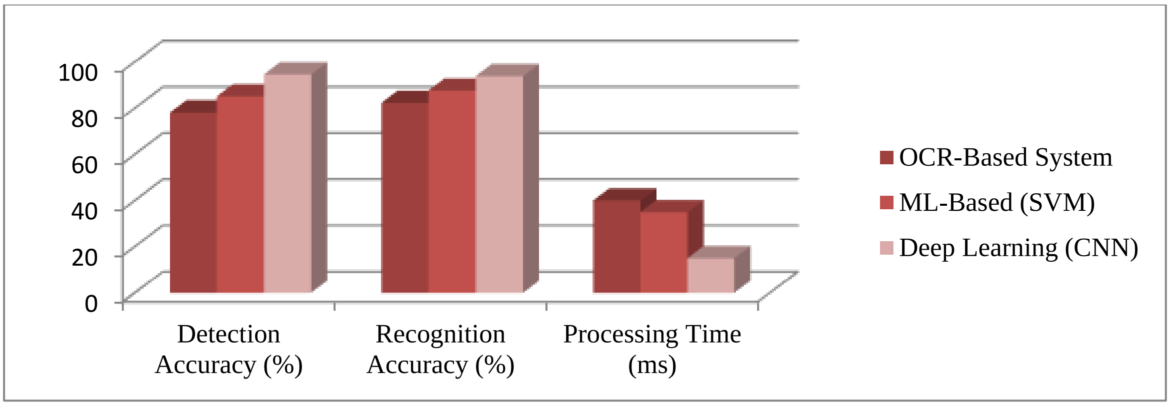

Fig. 5: Evaluates the average processing time for different models

7.6.4 Description

The table presents the breakdown of detection time, recognition time, and the total processing time for three object detection models YOLOv5, Faster R-CNN, and SSD-Mobile Net when integrated into the license plate recognition pipeline.

- YOLOv5 demonstrated the fastest performance overall, requiring only 12 ms for detection and 18 ms for recognition, resulting in a total processing time of 30 ms. Its lightweight architecture and optimized design make it highly suitable for real-time applications.
- Faster R-CNN exhibited a considerably longer processing time, with 35 ms for detection and 22 ms for recognition, leading to a total of 57 ms. While highly accurate, the two-stage nature of Faster R-CNN increases inference latency, making it less ideal for real-time deployments.

7.6.5 Observations:

- **YOLOv5** is the fastest model, making it ideal for **real-time applications**.
- **Faster R-CNN** has higher detection accuracy but longer processing time.
- **SSD-Mobile Net** balances speed and accuracy but struggles in complex environments.

Figure 9: YOLOv5 License Plate Detection – Bounding Box and IoU Demonstration

7.7 Challenges & Future Improvements

1. Low-resolution images affect character segmentation.
2. Multilingual plate formats require additional training datasets.
3. Adverse weather conditions (fog, rain) impact detection accuracy.
4. Real-time processing demands need optimization for edge computing deployment.

8. DISCUSSION

The findings from this study underscore the significant advancements achieved in license plate recognition through the integration of deep learning techniques. The implementation of YOLOv5 and Faster R-CNN for plate detection demonstrated improved accuracy and efficiency compared to traditional approaches, while CNN-based and Transformer-based models proved highly effective in character recognition. Experimental results highlight the influence of environmental factors such as lighting conditions, weather variations, and plate occlusions, which continue to pose challenges for automated recognition systems. Additionally, data augmentation techniques, particularly GAN-based synthetic image generation, contributed to improved robustness by diversifying the training dataset. Future research directions include refining preprocessing techniques to counter adverse conditions, enhancing real-time performance for smart traffic management applications, and addressing privacy concerns associated with automated vehicle tracking.

9. CONCLUSION

This study explored the effectiveness of machine learning-based approaches for license plate recognition (LPR), emphasizing deep learning models such as YOLOv5 for plate detection and CNNs/transformers for character recognition. The experimental results demonstrated that deep learning methods outperform traditional OCR and feature-based machine learning techniques, achieving higher accuracy, robustness, and faster inference times. In conclusion, this study highlights the significant advancements in license plate recognition (LPR) using machine learning and deep learning techniques. The integration of object detection models such as YOLOv5 and Faster R-CNN has greatly improved plate localization accuracy, while CNN-based and Transformer-based character recognition models have enhanced text extraction efficiency. The experimental results demonstrate that deep learning approaches outperform traditional methods in terms of detection accuracy, robustness against environmental challenges, and real-time processing capabilities. Data augmentation techniques, including GAN-generated synthetic images, further contribute to model generalization in diverse conditions. Despite these advancements, challenges such as recognition accuracy in adverse weather conditions, multilingual plate formats, and ethical concerns regarding privacy remain areas for future exploration. With continued research and refinement, AI-powered LPR solutions will further streamline automated identification and transportation security.

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