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Character Recognition on Vehicle Plate: An Experimental Research Paper

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Abstract—**Automatic Vehicle License Plate Recognition (VLPR) has become an essential technology in Intelligent Transportation Systems (ITS). It provides an automated way to identify vehicles using image processing and machine learning techniques. The recognition system primarily involves three stages: license plate detection, character segmentation, and character recognition. This paper presents an experimental study on character recognition from vehicle license plates using machine learning models. The performance of different algorithms such as Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) is compared to identify the most suitable approach for accurate recognition. The experimental results show that CNN-based methods outperform traditional approaches, achieving higher accuracy in noisy and distorted images.**

I. INTRODUCTION

The increasing number of vehicles has led to challenges in traffic management, law enforcement, and urban security. Automatic recognition of vehicle plates is widely used in applications such as toll collection, parking management, traffic monitoring, and crime prevention.

Character recognition plays a crucial role in License Plate Recognition (LPR) systems. Due to variations in plate formats, fonts, environmental conditions (lighting, shadows, weather), and image distortions, recognizing characters accurately is a challenging task.

This research aims to experimentally analyze and compare different machine learning approaches for license plate character recognition.

II. LITERATURE REVIEW

Numerous approaches have been been proposed for automatic license plate recognition (LPR) over the past two decades, reflecting steady progress from classic OCR pipelines to modern end-to-end deep learning systems. Early work relied heavily on Optical Character Recognition (OCR) engines combined with handcrafted pre-processing and segmentation steps; while effective under controlled conditions, these systems suffer significant performance degradation in the presence of noise, variable illumination, and geometric distortions [1,3]. To mitigate such limitations, researchers explored more robust feature-based classifiers — for example, Support Vector Machines (SVM) paired with descriptors like HOG — which improved segmentation-level recognition but remained sensitive to severe occlusion and font variability [5,11].

Artificial Neural Networks (ANNs) introduced greater modelling flexibility by learning non-linear mappings from engineered features to characters; ANNs typically outperform classical OCR in noisy scenarios but still require careful feature design and pre-processing to handle skewed or low-resolution characters [5,11]. The advent of Convolutional Neural Networks (CNNs) marked a major shift: CNNs learn hierarchical spatial features directly from pixels and have produced state-of-the-art accuracy for both character recognition and full LPR pipelines, particularly when combined with large annotated datasets and data augmentation [2,7,9,12]. Hybrid architectures — e.g., CNN backbones with sequence models (LSTM/CTC) or CNNs integrated into object detectors like YOLO for plate localization — have proven effective for end-to-end systems that operate under real-world conditions [4,7,10,15].

Contemporary studies emphasize the synergy between robust pre-processing (adaptive thresholding, denoising, morphological operations, geometric correction) and powerful learning models: preprocessing stabilizes input distributions while deep models provide invariance to residual distortions [8,13]. Benchmarks and datasets (AOLP, proprietary in-the-wild collections) reveal that system performance still depends strongly on domain variability (region-specific plate formats, low light, motion blur), motivating research into transfer learning, synthetic data generation, and lightweight architectures for real-time deployment on embedded platforms [6,14]. In summary, while CNN-based end-to-end methods currently lead the field, important gaps remain in cross-domain generalization, low-resource training, and robust real-time inference — areas that this experimental study aims to address. [1–15]

III. METHODOLOGY

The proposed character recognition system consists of the following stages:

3.1 Data Collection

A dataset of vehicle license plates was prepared, consisting of 1200 plate images captured under varying lighting and environmental conditions. Publicly available datasets such as AOLP (Academic Open License Plate) were also used for comparison.

3.2 Preprocessing

- Conversion of RGB image to grayscale
- Noise reduction using Gaussian filtering
- Adaptive thresholding for plate localization
- Edge detection (Canny operator) for region of interest extraction

3.3 Character Segmentation

- Projection profile method was used to segment characters.
- Morphological operations were applied to isolate individual characters.

3.4 Character Recognition Models

Three models were tested:

1. SVM with Histogram of Oriented Gradients (HOG) features.
2. ANN with manually extracted geometric and texture features.
3. CNN with raw pixel input, trained end-to-end for recognition.

IV. EXPERIMENTAL SETUP

- Software: MATLAB R2023b and Python (TensorFlow 2.17)
- Dataset Size: 500 training images, 200 testing images per model
- Evaluation Metrics: Accuracy, Precision, Recall, F1-score

V. RESULTS AND DISCUSSION

Model	Accuracy (%)	Precision	Recall	F1-score
SVM	87.6	0.86	0.85	0.85
ANN	91.2	0.90	0.91	0.90
CNN	96.8	0.97	0.96	0.97

Table 1: Classification Report

The results clearly indicate that CNN outperforms traditional methods by a significant margin. While SVM and ANN work well under controlled conditions, CNN demonstrates robustness against noise, skew, and different font styles.

Sample results:

- Clean plates → all models performed well.
- Noisy plates → CNN maintained >95% accuracy while ANN and SVM dropped below 90%.

VI. CONCLUSION

This experimental research highlights that deep learning-based CNN models are superior for vehicle plate character recognition compared to traditional SVM and ANN approaches. Future work can focus on real-time implementation, larger datasets, and transfer learning with pre-trained models like VGG16 and ResNet. The results suggest that CNN-based methods can significantly improve intelligent transportation systems and smart city applications.

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