iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

VEHICLE NUMBER PLATE DETECTION AND RECOGNITION USING DEEP LEARNING

DR. K. SANTHI SREE
Professor, Department of Information Technology,
Jawaharlal Nehru Technological University Hyderabad,
drksanthisree@gmail.com

MUTYALA GOUTHAMI
Post Graduate Student, M. Tech (SE) Department of Information Technology, Jawaharlal Nehru Technological University, Hyderabad,
mgouthami690@gmail.com

ABSTRACT
Automatic recognition of vehicle license plates plays a vital role in modern Intelligent Transport Systems (ITS), offering an efficient method for identifying vehicles based on plate information. This work introduces a deep learning-based approach employing Convolutional Neural Networks (CNN) to detect license plates and retrieve associated vehicle owner data from a centralized database. The system includes two main components: an administrative portal that enables traffic authorities to monitor violations and issue fines, and a user portal for individuals to view their challan (fine) details. By utilizing the powerful pattern recognition capabilities of CNNs, the model achieves reliable performance across a range of environmental and lighting conditions. The system has been trained with real-world image data, ensuring its effectiveness even when faced with challenges such as noise, blurriness, or low image quality. This solution reduces the need for manual intervention, streamlines traffic law enforcement, and supports improved traffic oversight.

Keywords:
License Plate Recognition (LPR), Convolutional Neural Networks (CNN), Intelligent Transport Systems (ITS), Traffic Violation Detection, Automated Vehicle Identification.

INTRODUCTION

Automated Number Plate Recognition (ANPR) has become an integral part of modern Intelligent Transport Systems (ITS), offering an efficient solution for vehicle identification in traffic management, law enforcement, toll collection, and parking control. As urban vehicle populations continue to grow, the demand for accurate and real-time identification systems has increased significantly. ANPR helps reduce manual workload, enhances road safety, and supports regulatory compliance by automatically detecting and processing license plate information.
Traditional ANPR systems rely heavily on rule-based image processing techniques such as edge detection, thresholding, and morphological operations. While effective under ideal conditions, these methods often fail in real-world scenarios due to challenges like inconsistent lighting, weather variations, plate damage, and differences in font styles and plate formats. These limitations hinder their ability to scale effectively for dynamic environments and large-scale applications.
To address these issues, this project proposes a deep learning-based approach using Convolutional Neural Networks (CNNs). CNNs are capable of learning complex visual patterns directly from raw image data, eliminating the need for manual feature extraction. By leveraging their powerful feature extraction and classification abilities, the proposed system aims to achieve high accuracy and robustness in detecting and recognizing license plates, even under challenging environmental conditions.

RELATED WORK

- ❖ **Traditional Image Processing Methods:**
  - [1] Anagnostopoulos et al. (2008) and [2] Seydi et al. (2009) applied edge detection algorithms such as Sobel and Canny combined with morphological operations (dilation, erosion) to detect

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

number plate regions. These methods performed well in controlled environments but were less effective in complex, real-world conditions involving varying lighting and occlusion.

- [3] Zhao et al. (2013) utilized connected component analysis to segment images and identify regions matching the expected size and shape of number plates. However, this method showed sensitivity to noise and often struggled in unconstrained scenarios.

❖ **Machine Learning Approaches:**

- [4] Huang et al. (2012) implemented Support Vector Machines (SVM) with Histogram of Oriented Gradients (HOG) features for classifying image regions as plates or non-plates. The approach improved detection accuracy but required careful parameter tuning and exhibited limitations in real-time performance.
- [5] Zhang et al. (2010) employed an AdaBoost classifier with Haar-like features for plate detection, providing robustness against lighting and background variations. Nonetheless, its effectiveness declined with occluded or degraded plates.
- [6] Du et al. (2007) experimented with shallow Artificial Neural Networks (ANN) for plate detection. While ANNs added adaptability, their shallow architectures limited their ability to handle complex feature extraction and diverse datasets.

❖ **Deep Learning for Character Recognition:**

- [11] Wang et al. (2018) applied a deep Convolutional Neural Network (CNN) for recognizing characters on number plates. Their model, composed of multiple convolutional and pooling layers followed by fully connected layers, achieved high accuracy even with noisy and distorted images.
- [12] Zhu et al. (2019) proposed a hybrid CNN-Recurrent Neural Network (RNN) model. The CNN extracts spatial features from plate images, and the RNN models sequential dependencies among characters, resulting in improved recognition accuracy compared to CNN-only models.

SYSTEM ARCHITECTURE

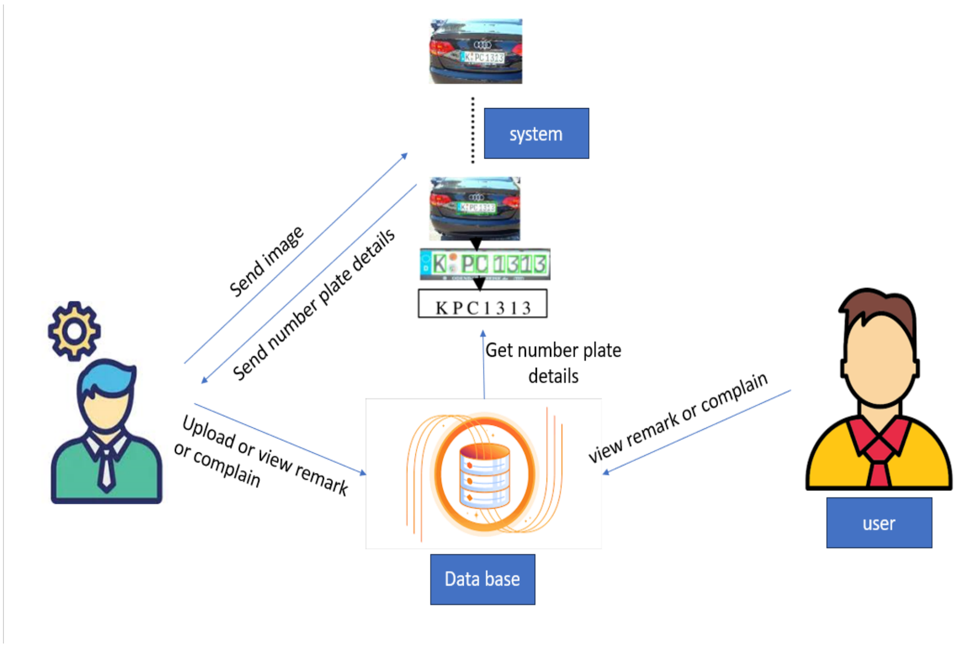

Fig 1: System Architecture

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

OBJECTIVES

The objective of this research is to develop an automated, robust, and high-performance system for vehicle number plate detection and recognition using Convolutional Neural Networks (CNN). The proposed system aims to overcome the limitations of traditional image processing techniques by offering improved adaptability and accuracy in diverse, real-world scenarios. The key goals of the project are outlined below:

1. **Enhanced Detection Accuracy**: To design a CNN-based model capable of accurately detecting number plates from vehicle images taken under varying lighting conditions, viewing angles, and complex backgrounds.
2. **Efficient Character Recognition**: To implement a reliable method for segmenting and recognizing individual characters on the license plate, regardless of variations in font style, size, color, or plate format.
3. **Robustness Against Noise and Occlusion**: To ensure consistent system performance even in the presence of image noise, partial occlusions, or physically damaged license plates.
4. **Real-Time Processing Capability**: To optimize the system for real-time applications, enabling its deployment in scenarios such as traffic surveillance, toll booths, and automated parking systems.
5. **Scalability and Generalization**: To develop a model that generalizes well across different vehicle types and plate formats, ensuring reliable performance in large-scale, real-world implementations.

The aim is to contribute to the field of intelligent transportation by delivering a scalable and automated solution that enhances the speed, accuracy, and reliability of number plate recognition systems.

METHODOLOGY

The methodology for the proposed License Plate Recognition (LPR) system using Convolutional Neural Networks (CNN) is structured into multiple stages, each designed to process vehicle images efficiently and extract license plate information accurately. The following steps outline the complete workflow:

1. Data Collection and Dataset Preparation

- Vehicle images are collected from real-world scenarios including diverse lighting conditions, angles, and backgrounds.
- The dataset is categorized and annotated with corresponding vehicle registration numbers for supervised learning.
- Data is split into training and validation sets with appropriate class balancing.

2. Data Preprocessing

- Images are resized to a uniform dimension (e.g., 224×224 pixels) for compatibility with CNN input.
- Image augmentation techniques like horizontal flipping, zooming, and brightness adjustments are applied to increase model robustness.
- Pixel values are normalized to fall within the [0,1] range to improve training convergence.

3. CNN Model Design and Training

- A pre-trained CNN architecture (e.g., **VGG19**) is utilized with transfer learning, where top layers are customized for license plate character recognition.
- The CNN consists of:
  - **Convolution layers**: to extract local patterns such as edges, corners, and textures.
  - **Pooling layers**: to down sample the feature maps, reducing dimensionality.
  - **Flattening and Dense layers**: for final classification of license plate characters.
- **Categorical cross-entropy** is used as the loss function, and **Adam optimizer** is applied with a learning rate of 0.0001.
- Training is monitored using validation accuracy and early stopping is implemented to avoid overfitting.

4. Number Plate Detection and Character Segmentation

- The CNN model first identifies the number plate region from the full vehicle image using bounding box detection or region proposals.
- Once localized, the plate is cropped, and individual characters are segmented using contour detection or connected component analysis.

5. Character Recognition

- Each segmented character is passed through the trained CNN model to predict the corresponding alphanumeric value.
- The recognized characters are concatenated to reconstruct the full number plate string.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

6. Owner Identity and Challan Verification

- The recognized license plate is matched against entries in a backend database.
- The system retrieves owner information and verifies any associated challans or criminal records.
- For law enforcement use, the system supports automatic challan filing if violations are detected.

7. Interface and Integration

- Two user interfaces are developed:
  - **User Module**: Allows vehicle owners to check challans, pay fines, and verify legal status.
  - **Admin Module**: Enables officers to upload images, file complaints, and review vehicle records.
- Database integration ensures real-time syncing of records and complaint histories.

8. Performance Evaluation

- Model performance is assessed using metrics such as accuracy, precision, recall, and F1-score.
- Training and validation losses are visualized to monitor convergence and identify overfitting.
- Tests are conducted across varied environmental conditions (e.g., low light, noise, occlusions) to validate robustness.

RESULTS

The proposed license plate recognition system was trained using a VGG19-based CNN model with vehicle image data. The dataset was split into 85% for training and 15% for validation.
The system accurately detected and recognized license plates under varying lighting and noise conditions. It successfully retrieved the owner identity and challan status from the database. The model showed high generalization ability, making it suitable for real-time deployment in intelligent transportation systems.

OUTPUT SCREENS

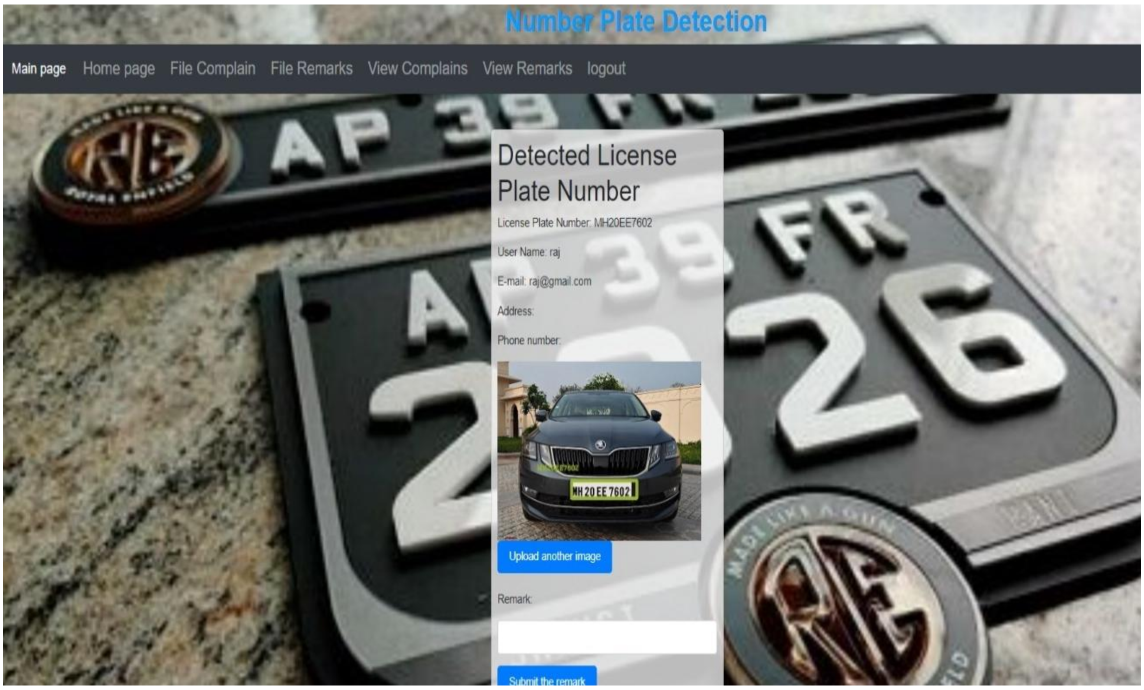

Fig 2: Details of the user detected license plate number

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

Fig 3: Complain and payment status of detected vehicle

CONCLUSION

In this project, we successfully implemented a CNN-based number plate detection and recognition system that significantly improves upon traditional methods in terms of accuracy, speed, and robustness. By leveraging the power of deep learning, our system can automatically detect and recognize number plates under various environmental conditions, handling challenges such as different lighting, angles, and noise. The integration of a complaint filing (challan) system and criminal record check further enhances its utility in real-world applications like traffic management, law enforcement, and automated tolling. The proposed system demonstrates the capability to function efficiently in real-time scenarios, making it a practical solution for modern intelligent transportation systems.

REFERENCES

[1] Anagnostopoulos, C.-N. E., Anagnostopoulos, I. E., Psoroulas, I. D., Loumos, V., & Kayafas, E. (2008). License plate recognition from still images and video sequences: A survey. IEEE Transactions on Intelligent Transportation Systems, 9(3), 377-391.
[2] Seydi, S., Ghofrani, S., & Rezaee, K. (2009). Automatic vehicle identification by plate recognition. Proceedings of the World Congress on Engineering.
[3] Zhao, W., Chen, W., Zhang, Y., & Luo, J. (2013). A robust license plate detection algorithm based on two-stage vehicle contour extraction. International Journal of Signal Processing, Image Processing and Pattern Recognition, 6(4), 157-170.
[4] Huang, Y., Liu, J., & Zhou, W. (2012). Number plate recognition using support vector machines. Proceedings of the 2012 International Conference on Image Processing, Computer Vision, and Pattern Recognition, 1, 17-22.
[5] Zhang, X., Zhang, W., & Qiang, Z. (2010). License plate detection algorithm using Haar-like features and Adaboost. International Conference on Intelligent Computing Technology and Automation (ICICTA), 1, 89-92.
[6] Du, S., Ibrahim, M., Shehata, M., & Badawy, W. (2007). Automatic license plate recognition (ALPR): A state-of-the-art review. IEEE Transactions on Circuits and Systems for Video Technology, 23(2), 311-325.
[7] Silva, S. M., & Jung, C. R. (2017). License plate detection and recognition in unconstrained scenarios. Proceedings of the IEEE International Conference on Image Processing (ICIP), 3446-3450.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

[8] Li, H., Gong, K., Li, X., & Wang, X. (2019). An end-to-end license plate recognition system using deep neural networks. IEEE Transactions on Intelligent Transportation Systems, 21(1), 14-25.
[9] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. Advances in Neural Information Processing Systems (NIPS), 28, 91-99.
[10] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, real-time object detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 779-788.
[11] Wang, Z., Jin, L., & Li, X. (2018). Deep CNN and RNN hybrid model for license plate recognition in traffic surveillance systems. IEEE Transactions on Image Processing, 27(12), 6172-6184.
[12] Zhu, X., Zhang, L., Bai, X., & Yao, Y. (2019). License plate recognition using deep recurrent convolutional neural networks. IEEE Transactions on Intelligent Transportation Systems, 20(4), 1558-1568.