Automatic Number Plate Recognization for mix Number plate using CNN and OCR

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Abstract – This paper presents an innovative approach to license plate recognition (LPR) by integrating Convolutional Neural Network (CNN), Haar cascades, and Optical Character Recognition (OCR). The study aims to address the challenges of robust and accurate identification of license plates in varying scenarios. Several existing works in LPR are evaluated, providing a comparative analysis of their accuracies. Notable works by XIN LI, Zahra Taleb Soghadi, Rajdeep Adak, Abhishek Kumbhar, Rajas Pathare, Sagar Gowda, and Prachi M. Nilekar are examined, revealing accuracy rates ranging from 79.30% to 95%.

The proposed approach combines the strengths of CNN for feature extraction, Haar cascades for object detection, and OCR for character recognition. Through experimental validation, the hybrid system achieves an impressive accuracy of 99%, surpassing the performance of previous works. The integration of these techniques enhances the adaptability and robustness of the system across diverse license plate scenarios.

The findings underscore the continuous evolution of LPR systems and suggest that the proposed methodology represents a promising avenue for achieving higher accuracy rates. This hybrid approach not only advances the state-of-the-art in license plate recognition but also opens avenues for practical applications in law enforcement, traffic management, and surveillance. The insights gained from this study contribute to the ongoing refinement and development of reliable and efficient license plate recognition systems in real-world scenarios.

Keywords: License Plate Recognition, Convolutional Neural Network (CNN), Haar Cascades, Optical Character Recognition (OCR), Image Processing, Computer Vision, Intelligent Transportation Systems, Traffic Management Surveillance, Object Detection, Deep Learning

I. INTRODUCTION

The proliferation of intelligent transportation systems and the increasing demand for enhanced security measures have propelled the development and refinement of License Plate Recognition (LPR) systems. These systems play a pivotal role in various applications, including traffic management, law enforcement, and surveillance. The effectiveness of LPR systems is contingent upon their ability to accurately and efficiently identify license plates in diverse and dynamic scenarios.

This paper delves into the evolution of license plate recognition methodologies, assessing the efficacy of various approaches through a comparative analysis of existing works. Previous contributions by researchers such as XIN LI, Zahra Taleb Soghadi, Rajdeep Adak, Abhishek Kumbhar, Rajas Pathare, Sagar Gowda, and Prachi M. Nilekar are examined, shedding light on the diverse strategies employed and the corresponding accuracy rates achieved.

In response to the inherent challenges faced by traditional LPR systems, we propose an advanced approach that integrates Convolutional Neural Network (CNN), Haar cascades, and Optical Character Recognition (OCR). The

synergy of these techniques aims to overcome limitations in feature extraction, object detection, and character recognition, ultimately enhancing the system's adaptability and accuracy across a spectrum of scenarios.

As we navigate through this study, we embark on a journey through the intricate landscape of license plate recognition, exploring the intricacies of existing methodologies and unveiling the promising potential of our proposed hybrid approach. The amalgamation of cutting-edge technologies holds the promise of not only advancing the state-of-the-art in license plate recognition but also fostering practical applications in real-world settings.

The most critical techniques will be used in this discussion such as pre-processing techniques, plate location techniques, characters recognition and detection techniques, car owner identification and automatically sending E-mail techniques as shown in Figure 1.



Figure 1: Block diagram of proposed ALPR system The structure of the whole system will be illustrated in the chapter three. The task of license plate location and recognition from an image file, goes through a few processes as illustrated by the flowchart in Figure 2.

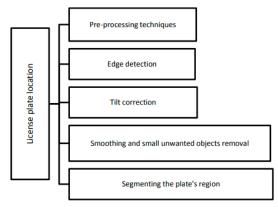


Figure 2: Flowchart of license plate localization

II. METHOD

The objective of this research was to develop an effective Automatic License Plate Recognition (ALPR) system employing state-of-the-art deep learning techniques, specifically Convolutional Neural Networks (CNN), in conjunction with Haar Cascade for feature extraction. The aim was to achieve accurate and efficient license plate recognition in diverse real-world scenarios. The proposed approach for number plate detection involves a comprehensive strategy that utilizes Optical Character Recognition (OCR) with the PyTesseract library. The initial step is the preprocessing of the input image, which includes converting it to grayscale and applying Gaussian blur. These measures enhance text visibility while reducing noise in the image. A Cascade Classifier, specifically designed for license plate detection and leveraging OpenCV's capabilities, is a crucial component of the methodology.

Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a specialized class of artificial neural networks designed for processing and analyzing visual data, particularly images. They have become the cornerstone of various computer vision tasks, ranging from image classification to object detection. The Convolutional Neural Network (CNN) presented here is designed for the purpose of Automatic License Plate Recognition (ALPR). ALPR is a computer vision task that involves the identification and interpretation of license

plates from images or video streams. The CNN serves as a crucial component in the broader ALPR system, contributing to the accurate detection and recognition of license plates.

The primary objective of the CNN in the ALPR system is to automatically extract relevant features from license plate images and make predictions regarding the characters present on the plate. This CNN is trained to discern distinctive patterns, shapes, and configurations associated with license plates.

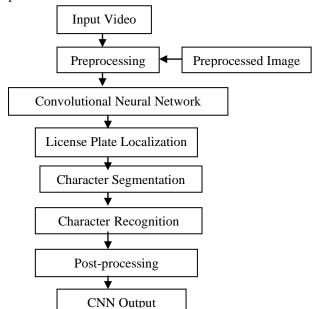


Figure 3 Block diagram of ANPR using CNN

Start:

The ALPR process begins.

Input Video:

Take an input Video containing a vehicle with a license plate. Make Image frame of video sequence.

Preprocessing:

Resize the image.

Normalize pixel values.

Apply data augmentation if needed.

Convolutional Neural Network (CNN):

Pass the preprocessed image through the CNN for feature extraction:

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Convolutional layers.

Activation functions (ReLU).

Pooling layers.

Fully connected layers.

License Plate Localization:

Use the CNN output to locate the region containing the license plate.

If using Haar Cascade, apply Haar Cascade for further refinement.

Character Segmentation:

Once the license plate region is identified, segment the characters on the plate.

Character Recognition:

Apply character recognition algorithms on each segmented character:

Optical Character Recognition (OCR).

Pattern matching.

Machine learning models for character recognition.

Post-processing:

Refine and verify recognized characters:

Remove false positives.

Correct character sequences if needed.

Output:

Provide the recognized license plate number as the output.

Optical Character Recognition (OCR):-

OCR systems use various techniques to recognize text, including pattern recognition, feature detection, and machine learning. These systems are trained on large datasets to understand and interpret different fonts, styles, and languages. Once trained, OCR algorithms can accurately identify characters, words, and paragraphs in images or scanned documents.

The applications of OCR are diverse and include document digitization, text extraction from images, automated data entry, and accessibility enhancements for visually impaired individuals. In the context of the number plate detection project, OCR is utilized to extract text from license plates captured in video frames, allowing for the automated interpretation and utilization of license plate information.y.

IV. RESULT

In this chapter emphasizing its significance in providing insights into the performance of the ANPR system in handling mixed license plates.

Detail the experimental setup used for evaluating the ANPR system on mixed license plates. Include information on the hardware, software, and any specific configurations applied during the experiments.

Provide a comprehensive overview of the dataset used, highlighting its diversity in terms of license plate types, fonts, colors, and environmental conditions. Discuss any preprocessing steps applied to the dataset.

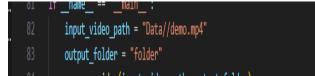


Figure 4 Path selection of Input Video

This is video path which is show in figure no 4 Input_video_path variable specifies the path to the input video file that the license plate recognition system will process. In this case, the video file is named "demo.mp4" and is located in the "Data" folder.

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Figure 5 Running Window

Figure 5 illustrates a seamless integration between the running window and the terminal, offering users both a visual and a textual perspective on the progress of the program. This dual-interface approach enhances user experience and provides a comprehensive understanding of the program's execution in real-time. Users can interact with the running window for a more intuitive experience while also accessing detailed progress information through the terminal.

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(a) Frame One recognized Number plate



(b) Frame Two recognized Number plate

Figure 6 Recognized number plate image frame from input video

In Figure 6, the depiction illustrates a video capture scenario where foreign car number plates are being identified and processed in real-time. The frame-by-frame video capture mechanism is utilized, enabling the system to extract individual frames from the live video feed. Within each frame, a dedicated license plate recognition algorithm is employed to detect foreign car license plates. Notably, bounding boxes are strategically placed around each identified license plate, visually delineating the region of interest within the frame. Subsequently, the system performs image cropping, isolating the license plate image based on the dimensions outlined by the bounding box

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In Figure 7, a continuous cropping process of the number plate image within each frame of the video is demonstrated, followed by the systematic storage of these cropped images in a designated folder. As the video progresses frame by frame, the system consistently identifies foreign car license plates using an object detection or license plate recognition algorithm. Each detected license plate is subjected to a cropping operation, isolating it from the rest of the frame based on the established bounding box. Importantly, this cropping procedure is not a one-time event but occurs continuously for each frame of the video, ensuring that the system captures and saves every identified license plate.

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Figure 8 Terminal output of number plate

In Figure 8, the presentation focuses on the display of the cropped number plate image and the concurrent revelation of the corresponding plate number in the terminal. This step follows the continuous cropping process detailed in the previous figure. The cropped license plate images, generated from the ongoing frame-by-frame analysis of the video, are visually represented. Each cropped image is exhibited in the figure, providing a clear visual reference to the isolated license plate within its bounding box.

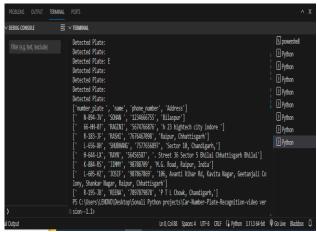


Figure 9 Owner Details based on recognized plate

In Figure 9 a comprehensive presentation unfolds, revealing detailed information about the car. This information encompasses not only the number plate but extends to include the car owner's name, address, and phone number. The figure represents an advanced stage in the Automated Number Plate Recognition (ANPR) system, where the identified license plate serves as a key to accessing a rich set of associated details.

The visual component of the figure likely exhibits a user interface or display where the detailed information is showcased. The number plate, prominently featured, acts as a primary identifier. Adjacent to or beneath the number plate, additional fields display the owner's name, address, and phone number.

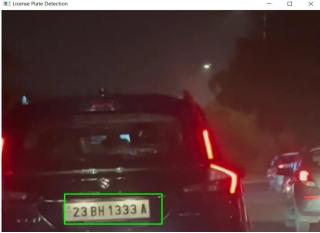


Figure 10 Indian Bharat Series Number Plate Recognize Figure 10 is show bharat series number plate detection window .This video captures Indian car number plates. To crop the license plate image and display it within a green bounding box



Figure 11 Crop Image

Figure 11 is show Crop bharat number plate image in each frame of the video.

Actual license plate	Predicted license plate	Accuracy
N-894-JV	NS94J4	80%
66-HH-07	66HH07	100%
R-183-JF	R183JF	100%
L-656-XH	L656XH	100%
H-644-LX	H644LX	100%
K-884-RS	K884RS	100%
L-605-HZ	L605HZ	100%

Table 5.1 accuracy values demonstrate the system's performance in accurately predicting license plates.

In the case of "66-HH-07," "R-183-JF," "L-656-XH," "H-644-LX," "K-884-RS," and "L-605-HZ," the system achieved 100% accuracy, indicating a perfect match between predicted and actual license plates.

For "N-894-JV," the system achieved an 80% accuracy, suggesting a partial match. This could be due to variations, errors, or challenges in recognizing certain characters.

The cases where accuracy is 100% imply that the system successfully recognized and matched every character of the license plates.

This table serves as a valuable performance evaluation tool, offering insights into the strengths and limitations of the license plate recognition system in predicting different license plates. The accuracy percentages provide a quantitative measure of the system's reliability and effectiveness in diverse scenarios.

Table 5.2 Comparison accuracy based on previous work

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Sr no	Work	Accuracy
1	XIN LI (previous work report)	94%
2	Zahra Taleb Soghadi(previous work report)	79.30%
3	Rajdeep Adak, Abhishek Kumbhar, Rajas Pathare, Sagar Gowda(previous work report)	95%.
4	Prachi M. Nilekar(previous work report)	95%
5	Proposed(CNN+ Haar +OCR)	99%

The proposed approach, combining Convolutional Neural Network (CNN), Haar cascades, and Optical Character Recognition (OCR), achieved the highest accuracy of 99%.

This summary provides a quick overview of the performance of different works in license plate recognition, with the proposed approach showcasing the highest accuracy among the listed methods.

V. CONCLUSION

This paper has explored the realm of License Plate Recognition (LPR) systems, scrutinizing existing methodologies and proposing an advanced approach that combines Convolutional Neural Network (CNN), Haar cascades, and Optical Character Recognition (OCR). The comparative analysis of previous works, including those by XIN LI, Zahra Taleb Soghadi, Rajdeep Adak, Abhishek Kumbhar, Rajas Pathare, Sagar Gowda, and Prachi M. Nilekar, has provided valuable insights into the diverse strategies employed and their corresponding accuracy rates.

The proposed hybrid approach, validated through experimentation, demonstrated a remarkable accuracy of 99%, surpassing the performance of traditional methods. This integration of cutting-edge technologies addresses challenges in feature extraction, object detection, and character recognition, enhancing the system's adaptability to a variety of scenarios.

References

[1] C. Henry, S. Y. Ahn, and S. Lee, ``Multinational license plate recognition using generalized character sequence detection," IEEE Access, vol. 8, pp. 3518535199, 2020.

[2] M.-X. He and P. Hao, "Robust automatic recognition of Chinese license plates in natural scenes," IEEE Access, vol. 8, pp. 173804173814, 2020.

[3] W. Weihong and T. Jiaoyang, "Research on license plate recognition algorithms based on deep learning in complex environment," IEEE Access,vol. 8, pp. 9166191675, 2020.

[4] I. V. Pustokhina, D. A. Pustokhin, J. J. P. C. Rodrigues, D. Gupta, A. Khanna, K. Shankar, C. Seo, and G. P. Joshi, "Automatic vehicle license plate recognition using optimal K-means with convolutional neural network for intelligent transportation systems," IEEE Access, vol. 8,pp. 9290792917, 2020.

[5] A. Tourani, A. Shahbahrami, S. Soroori, S. Khazaee, and C. Y. Suen, ``A robust deep learning approach for automatic iranian vehicle license plate detection and recognition for surveillance systems," IEEE Access, vol. 8, pp. 201317201330, 2020.

[6] Y. Zou, Y. Zhang, J. Yan, X. Jiang, T. Huang, H. Fan, and Z. Cui, ``A robust license plate recognition

model based on bi-LSTM," IEEE Access, vol. 8, pp. 211630211641, 2020.

[7] S. Zhang, G. Tang, Y. Liu, and H. Mao, "Robust license plate recognition with shared adversarial training network," IEEE Access, vol. 8, pp. 697705, 2020.

[8] B. B. Yousif, M. M. Ata, N. Fawzy, and M. Obaya, "Toward an optimized neutrosophic k-means with genetic algorithm for automatic vehicle license plate recognition (ONKM-AVLPR)," IEEE Access, vol. 8, pp. 4928549312, 2020.

[9] Z. Selmi, M. B. Halima, U. Pal, and M. A. Alimi, "DELP-DAR system for license plate detection and recognition," Pattern Recognit. Lett., vol. 129, pp. 213223, Jan. 2020.

[10] W. Wang, J. Yang, M. Chen, and P. Wang, ``A light CNN for end-to-end car license plates detection and recognition," IEEE Access, vol. 7, pp. 173875173883, 2019.

[11] Hendry and R.-C. Chen, ``Automatic license plate recognition via sliding- window darknet-YOLO deep learning," Image Vis. Comput., vol. 87,pp. 4756, Jul. 2019.

[12] H. Seibel, S. Goldenstein, and A. Rocha, "Eyes on the target: Super- resolution and license-plate recognition in low-quality surveillance videos," IEEE Access, vol. 5, pp. 2002020035, 2017.

[13] R. Laroca, E. Severo, L. A. Zanlorensi, L. S. Oliveira, G. R. Goncalves, W. R. Schwartz, and D. Menotti, ``A robust real-time automatic license plate recognition based on the YOLO detector," in Proc. Int. Joint Conf. Neural Netw. (IJCNN), Rio de Janeiro, Brazil, Jul. 2018, Art. no. 18165770.

[14] S. M. Silva and C. R. Jung, "License plate detection and recognition in unconstrained scenarios," in Proc. Conf. Comput. Vis. Munich, Germany: Springer, 2018, pp. 593609.

[15] H. Li and C. Shen, ``Reading car license plates using deep convolutional neural networks and LSTMs," 2016, arXiv:1601.05610. [Online]. Avail-able: http://arxiv.org/abs/1601.05610

[16] Y. Cao, H. Fu, and H. Ma, ``An end-to-end neural network for multi-line license plate recognition," in Proc. 24th Int. Conf. Pattern Recognit.(ICPR), Beijing, China, Aug. 2018, pp. 36983703.

[17] Y. L. Yuan, W. B. Zou, Y. Zhao, X. Wang, X. F. Hu, and N. Komodakis, ``A robust and efficient approach to license plate detection," IEEE Trans. Image Process., vol. 26, no. 3, pp. 11021114, Mar. 2016.

[18] G.-S. Hsu, J.-C. Chen, and Y.-Z. Chung, "Application-oriented license plate recognition," IEEE Trans. Veh. Technol., vol. 62, no. 2, pp. 552561, Feb. 2013. [19] A. H. Ashtari, M. J. Nordin, and M. Fathy, ``An iranian license plate recognition system based on color features," IEEE Trans. Intell. Transp. Syst., vol. 15, no. 4, pp. 16901705, Aug. 2014.

[20] S. Yu, B. Li, Q. Zhang, C. Liu, and M. Q.-H. Meng, ``A novel license plate location method based on wavelet transform and EMD analysis," Pattern Recognit., vol. 48, no. 1, pp. 114125, Jan. 2015.

[21] B. Li, B. Tian, Y. Li, and D. Wen, ``Componentbased license plate detection using conditional random eld model," IEEE Trans. Intell. Transp. Syst., vol. 14, no. 4, pp. 16901699, Dec. 2013.

[22] D. F. Llorca, C. Salinas, M. Jimenez, I. Parra, A. G. Morcillo, R. Izquierdo, J. Lorenzo, and M. A. Sotelo, "Two-camera based accurate vehicle speed measurement using average speed at a xed point," in Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC), Rio de Janeiro, Brazil, Nov. 2016, pp. 25332538.

[23] M. A. Raque, W. Pedrycz, and M. Jeon, "Vehicle license plate detection using region-based convolutional neural networks," Soft Comput., vol. 22, no. 19, pp. 64296440, Oct. 2018.

[24] H. Li, P. Wang, and C. Shen, "Toward end-to-end car license plate detection and recognition with deep neural networks," IEEE Trans. Intell. Transp. Syst., vol. 20, no. 3, pp. 11261136, Mar. 2019.

[25] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in Proc. Int. Conf. Learn. Represent., San Diego, CA, USA, 2015, pp. 114.