Automatic Number Plate Recognition in Hazy Conditions

Gaurav Bansal, Lakshay Joshi, Manas Gupta, Pankaj Dahiya
Department of Electronics and Communications Engineering
Delhi Technological University
Delhi, India
gauravbansal0209@gmail.com, lakshayjoshi15@gmail.com, guptamanas95@gmail.com, pankajdahiya@dtu.ac.in

***Abstract*—This study explores automatic number plate recognition (ANPR) in hazy conditions, emphasizing the critical role of dehazing methods in enhancing model accuracy and resilience, especially in challenging weather scenarios like winter. Through a systematic evaluation of ANPR techniques, the study identifies effective dehazing strategies tailored to address specific environmental obstacles, underscoring the significance of customized approaches for optimal performance. By integrating the dark channel prior technique, the model's robustness in adverse weather conditions is significantly improved, laying the foundation for future advancements in ANPR technology through targeted research on hardware optimization and enhanced dehazing methodologies.**

Keywords— image processing, number plate detection, CNN based OCR, de-hazing, dark channel prior, haar cascade classifier

I. INTRODUCTION

In smart traffic systems, ANPR technology plays a central role in automatically recognizing vehicles using their license plates. ANPR utilizes image processing and optical character recognition (OCR) to retrieve license plate data from captured vehicle pictures. The process involves pre-processing for image enhancement, followed by identification of region-of-interest to isolate the number plate. Character segmentation separates individual characters, and finally, advanced OCR techniques using convolutional neural networks (CNNs) perform recognition of characters. It offers a multi-faceted approach, improving efficiency and accuracy in various domains. Law enforcement utilizes it for stolen vehicle checks and traffic violation enforcement. Traffic management is improved by ANPR's capability to continuously monitor traffic flow, allowing for better control of congestion. Additionally, ANPR automates toll collection and simplifies parking systems.

Recent advancements have seen the development of diverse frameworks that leverage multiple machine learning and image processing techniques for detection and recognition of license plate. A visual data processing method for Indian license plate extraction and recognition in a variety of circumstances, including a noisy environment, poor light, an unusual license plate, and a cross-angled scenario, was given by Ravi Kiran et al. [1]. They employed a number of methods for the pre-processing, including morphological transformation (erosion and dilation), gaussian thresholding, and gaussian smoothing. Contours and the KNN (K-nearest neighnor) technique were utilized for recognizing characters during segmentation.

The framework proposed by Simmani et al. [2] leverages the two-dimensional wavelet transform for vertical edge extraction from input images. This technique is based on the fact that a high count of vertical edges aids in locating the number plate. A deep convolutional neural network (DCNN) classifier is implemented to recognize the characters. The suggested approach, according to the author, can resolve several commonly faced problems with character and license plate recognition.

Anuj S. et al. [3] proposed a license plate identification method that involves first converting color (RGB) images to grayscale images, then segmenting characters using pixel contrast and edge scissoring and finally recognizing characters using OCR. According to the author, this approach can eliminate several preprocessing chores like contrast enhancement, histogram equalization, noise filtering, and so on.

X. Ascar et al. [4] proposed a license plate detection method that combines binary image processing and kernel density functions. This method works by first multiplying the original image with a binary version of itself. This highlights areas that are expected to contain the license plate due to the high contrast between characters and background. Finally, the resulting binary image is filtered using a kernel density function to further refine the detection process.

Shobayo et al. [5] developed an internet-of-things (IoT) system for automatic license plate recognition. This system leverages a high-resolution sensor to capture clear images of vehicles. To identify the license plate number, the system utilizes image processing techniques to locate, isolate, and recognize the characters. The implementation relies on OpenCV, a popular computer vision library, along with various IoT devices like a Raspberry Pi equipped with high-quality sensors and additional components.

Dilshad et al. [6] proposed a system that first preprocesses the input image to improve quality and reduce noise. Next, it extracts potential license plate regions using morphological operations. Next, techniques like connected component analysis are used to isolate individual characters on the license plate. Finally, recognizing characters employs template matching to identify segments by comparing them to a database. However, the system faces challenges like broken plates or visually similar characters. Additionally, complex images or challenging conditions can decrease accuracy and increase processing time.

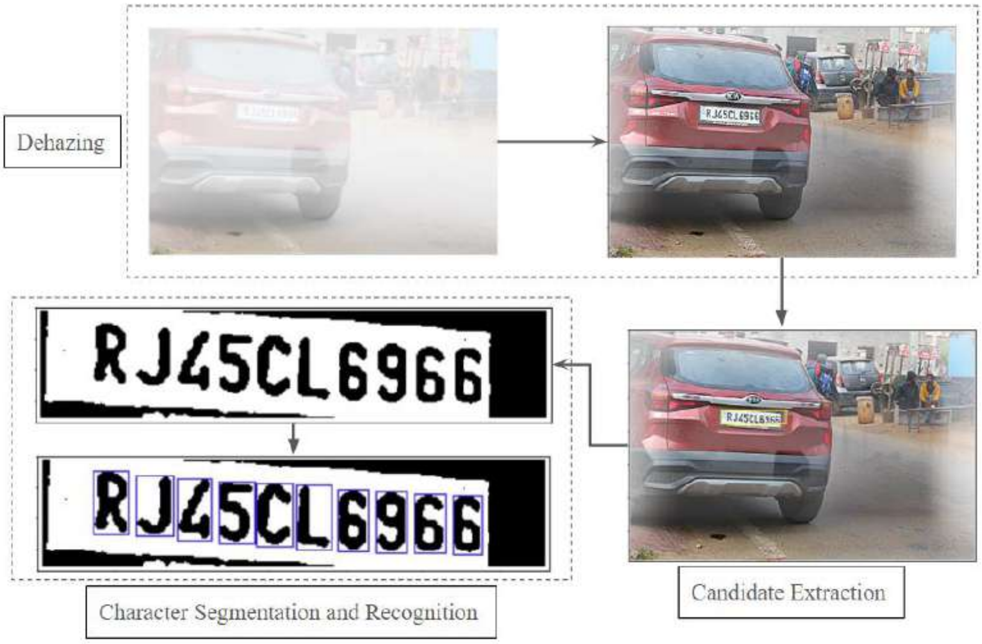

Fig. 1. Number plate recognition system in hazy conditions

Fei Xie et al. [7] introduced a number plate recognition system that utilizes a hybrid model. This model leverages a Back-Propagation Neural Network for classification purposes, coupled with an efficient feature extraction strategy to achieve accurate recognition. The authors asserts that their approach can solve the issues of dim lighting and complex backgrounds. The car's image has been strengthened through pre-processing, and once the license plate has been located, a feature extraction model is created. Lastly, characters are recognized through the use of a backpropagation neural network model.

In order to achieve effective plate recognition, Amruta et al. [8] developed a system that incorporated texture-analysis methods, methods based on picture global attributes, and hybrid methods that merged several techniques. For character extraction and segmentation, methods based on histograms, morphology, and linked component analysis algorithms were applied. However, drawbacks were encountered, such as limitations of binarization algorithms on plates with spots, character mislabeling leading to information loss, and inapplicability of some techniques for real-time processing when multiple plates are present in frames.

Several prior studies have investigated techniques for removing haze from images. Building on the observation of outdoor image statistics, He et al. [9] introduced a novel approach to image dehazing, leveraging a technique called the dark channel prior. This method's drawback is that when scene elements lack shadows and have light levels comparable to the ambient light, the dark channel prior becomes erratic. In such cases, the method underestimates the transmission for these objects.

A unique deep learning strategy for single picture dehazing is presented by Cai et al. [10], building on conventional haze characteristics and dehazing algorithms. Unlike traditional CNNs, their approach uses a special trainable end-to-end mechanism to estimate transmission in medium. This system incorporates specialized layers made for non-linear regression and feature extraction.

Despite advancements in ALPR, existing systems struggle with adverse weather, especially India's hazy winter. This dissertation proposes a novel ANPR system optimized for extremely hazy conditions by leveraging and fine-tuning existing best practices.

II. METHODOLOGY

The process of number plate recognition is divided into 4 steps (Fig. 1): The first stage involves preprocessing the captured image to eliminate haze and noise. This is followed by extraction of the number plate region itself. Next, the system separates each letter and number on the license plate. Finally, the system performs character recognition to identify the alphanumeric sequence. A detailed explanation of the specific methodologies employed at each stage is provided in the subsequent subsections.

1. Image Pre-processing

1.1. Calculating degree of haziness

The Laplacian operator highlights regions of rapid intensity change. The Laplacian variance method [11] calculates variance of Laplacian operator across the entire image. By quantifying the variance of the Laplacian operator's output, the Laplacian variance method provides a numerical measure of image sharpness or haziness.

1.2. Haze Filtering

In the initial step, the hazy pictures are dehazed using the technique of haze removal in a single image using dark channel prior along with guided image filtering [9,12].

The mathematical analysis for this is as follows:

$$\boldsymbol{I}(i) = \boldsymbol{J}(i)\boldsymbol{t}(i) + \boldsymbol{A}(1 - \boldsymbol{t}(i)) \tag{1}$$

- I*(i)*: This represents the pixel intensity at location 'i' in the hazy picture.
- J*(i)*: This represents the scene radiance intensity at location 'i' in the absence of haze.

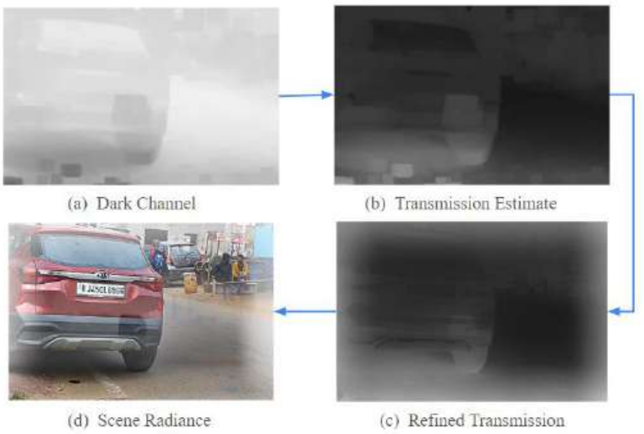

Fig. 2. Car plate image dehazing using dark channel prior

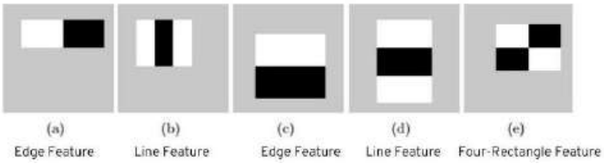

Fig. 3. Classification of features in Haar Cascade Classifiers

- t*(i)*: This term represents the transmission map at location 'i'. This map describes how much light is able to reach the camera sensor from the scene, with a value of 1 indicating no haze and 0 indicating complete blockage by haze.
- A: This represents the global atmospheric light. This is the constant color cast introduced by the haze particles throughout the image.
- *J(i)*t*(i)*: This represents the direct attenuated radiance. It describes the amount of scene radiance (*J(i)*) that reaches the camera sensor after being attenuated (weakened) by the haze along the path (*t(i)*).
- A(1 - t*(i)*): This represents the airlight. It describes the contribution of the ambient scattered light in the atmosphere (*A*) that reaches the camera without being reflected by any object in the scene. This term increases as the transmission (t*(i)*) decreases.

The pixels exhibiting less intensities in one or more color channel tend to be brightened due to the airlight term (*A(1-t(i))*) in hazy images. By analyzing the distribution of these dark pixel intensities, DCP based methods can estimate the transmission map (*t(i)*) and recover the scene radiance (*J(i)*) which leads to a dehazed image. (Fig. 2)

1.3. Noise Removal

A median blur filter was applied to eliminate salt-and-pepper noise from the image. While this filter can slightly blur colors, it effectively removes noise at low intensity settings. In this case, a 3x3 kernel size was used for the filter.

2. Detection of Region of Interest

This step involves detection and cropping of the number plate region from the input picture. Haar cascade classifiers [13] are a type of machine learning algorithm designed for detection of objects in images. They operate by analyzing features like edges, corners, and textures to identify candidate regions

TABLE I. COMPARISON BETWEEN CNN MODELS

Characteristics	***Model 1***	***Model 2***
Batch size	96	256
Image size	96 * 96	40 * 32
Epochs	25	25
Accuracy	96.9%	64.5%
Total Images	35490	35490
Images used for Training	18132	17390
Images used for Testing	7090	7453
Images used for Validation	10268	10647

containing the target object. (Fig. 3) In this case, a pre-trained haar classifier was leveraged which is specifically designed to recognize Indian license plates. The classifier systematically scans the image at various scales and locations, discarding areas unlikely to contain a license plate. This multi-stage filtering approach makes haar cascades computationally efficient.

3. Character Segmentation

Before feeding the image into the character segmentation algorithm, it undergoes several steps. First, it's converted to grayscale to simplify the image data. Then, Otsu's dynamic thresholding [14] is employed to find the optimal value for the characters separation (foreground) against the background of the plate. Finally, erosion and dilation techniques are used to refine the characters by shrinking and expanding white regions in the image, respectively, potentially enhancing features like edges. Once the pre-processing is complete, individual characters need to be separated from the entire license plate image. This is achieved by identifying the contours, which are basically the boundaries that enclose each character shape. With the utilization of contour bounding rectangles, these contours are analyzed to isolate each character from the background, effectively dividing the license plate into individual character images for further processing.

4. Optical Character Recognition using CNN model

The approach to image classification relies on a convolutional neural network (CNN) architecture [15-16]. The ability of CNNs to automatically capture hierarchical features in images makes them a efficient tool for this field.

4.1. Model Architecture:

The model leverages a hierarchical structure of convolutional layers, layers of pooling, and fully connected layers to learn and extract relevant features from input images. Using the TensorFlow Keras API, it is constructed as a sequential model. This architecture comprises a series of convolutional layers with increasing depth, interspersed

TABLE II. COMPARISON OF PERFORMANCE METRICS ON BOTH DATASETS

Performance Metrics	**Techniques Used**	Haze-Free Dataset	Hazy Dataset
Plate Extraction Rate	Haar Cascade Classifier	93.47 %	79.06 %
	Canny Edge Detection	87.88 %	65.98 %
Character Segmentation Rate	Mathematical Morphology and Contour Bounding	89.53 %	44.11 %
	Vertical Histogram	82.04 %	39.05 %
Character Recognition Accuracy	CNN based OCR Model	92.80 %	62.19 %

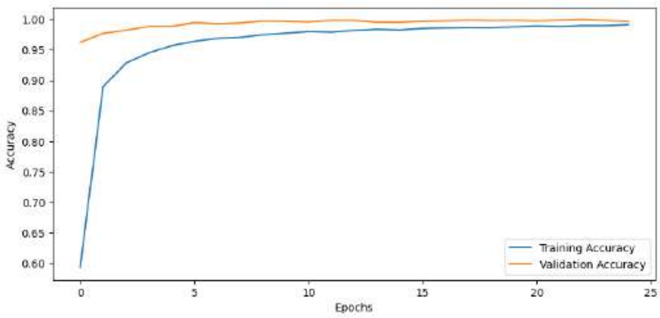

Fig. 4. Training and Validation accuracy with increasing epochs for Model 1

with max-pooling layers for spatial downsampling. It is made to progressively find intricate features from input pictures. The network then employs a flattening layer to convert the two-dimensional feature maps generated by the convolutional layers into a one-dimensional vector that is fed into dense layers for the classification task. It concludes with a softmax layer to produce class probabilities.

4.2. Data Augmentation:

To mitigate overfitting and improve generalization, data augmentation is used, incorporating random transformations like rotation, zooming, and horizontal flipping that helps enhance dataset variety and bolster the model's capacity to generalize to new, unique data.

4.3. Preprocessing:

Prior to entering the CNN layers, the input images undergo rescaling to normalize pixel values between 0 and 1. This step ensures a consistent input range and facilitates convergence during training.

4.4. Training and Evaluation:

The model is trained over 25 cycles using a training dataset [19] and validated using a separate validation dataset. A custom callback function is implemented to monitor the training progress. The training is halted if both training and validation accuracies surpass a predefined threshold, indicating the model's convergence. Multiple approaches to the model were tried and tested (Fig. 4 and 5), and the comparison between the 2 best models is shown in Table 1.

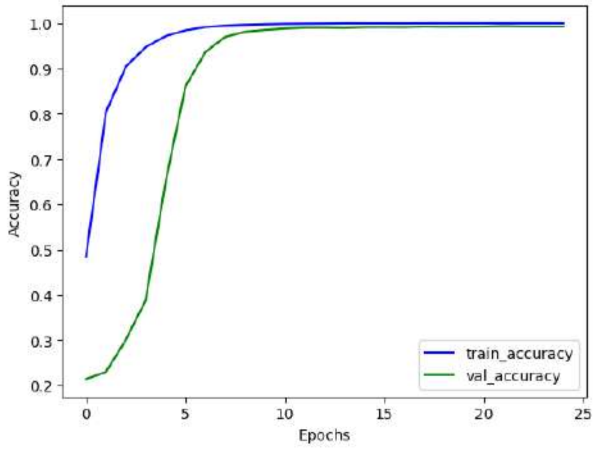

Fig. 5. Training and Validation accuracy with increasing epochs for Model 2

III. RESULTS

The approach in this paper focuses on calculating accuracy based on proper identification of the number plate region, proper character segmentation, and analyzing the visual resemblance between characters predicted with the actual characters. The performance of this approach was evaluated using a diverse dataset of Indian number plates collected from various regions [18]. The accuracies of the following sub processes were calculated on a dataset of 250+ images each of haze-free and hazy images:

- Extraction rate - percentage of images where the number plate is successfully being detected
- Segmentation rate - percentage of images where the characters are successfully being distinguished
- Character Recognition rate - comparing predicted characters with the actual characters on the plate.

The average blur value calculated using Laplacian Variance method comes out to be **5159.08**. Using color attenuation prior (CAP) [17], the average blur value comes down to **0.79**, whereas dark channel prior brings it down to **0.35**. The performance metrics achieved by utilizing few of the best methods for each sub process are summarized in Table 2.

IV. CONCLUSION

This study comprehensively explored Automatic number plate recognition (ANPR) methods specifically designed for hazy car images. A systematic evaluation of prominent ANPR techniques was conducted, identifying the most effective ones for dehazing car images and recording their performance at each stage. This analysis established robust benchmarks for comparison and underscored the importance of tailoring ANPR approaches to address specific environmental challenges. By integrating the dark channel prior technique for dehazing, the model's resilience and accuracy in adverse weather conditions was significantly enhanced, particularly during winter.

However, further research is needed to address some limitations. Hardware constraints currently hinder the efficiency of model training. Additionally, the dehazing process itself presents an opportunity for improvement. The model's character segmentation on hazy images suffers due to these limitations. Future research efforts focused on advanced hardware and improved dehazing techniques have the potential to advance the efficiency of ANPR technology, especially for handling challenging weather conditions.

REFERENCES

[1] Ravi Kiran Varma, Srikanth Ganta, B. Hari Krishna, S.V.S.R.K. Praveen, A novel method for Indian vehicle registration Number Plate Detection and recognition using image processing techniques detection and recognition using image processing techniques, in: *International Conference on Computational Intelligence and Data Science (ICCIDS 2019)* vol. 167, Elsevier, Procedia Computer Science,2020, pp. 2623–2633.

[2] Ibtissam Slimani, Abdelmoghit Zaarane, Wahban Al Okaishi, Issam Atouf, Abdellatif Hamdoun, “An Automated License Plate Detection and Recognition System Based on Wavelet Decomposition and CNN” *Array* vol. 8, Elsevier, 2020, pp. 1–7.

[3] Tote, Anuj S., Sujit S. Pardeshi, and Abhishek D. Patange. "Automatic number plate detection using TensorFlow in Indian scenario: An optical character recognition approach." *Materials Today: Proceedings* 72 (2023): 1073-1078.

[4] X. Ascar Davix, C. Seldev Christopher, D. Judson, Detection of the vehicle License Plate using a kernel density with default search radius algorithm filter, in: *International Journal of Light and Electron Optics, Optik*, Elsevier, 2018, pp. 1–8, 2020.

[5] Olamilekan Shobayo, Ayobami Olajube, Ohere Nathan, Modupe Odusami,Obinna Okoyeigbo, Development of smart plate number recognition system for fast cars with web application, *Appl. Computat. Intellig. Soft Comput*. Hindawi 2020 (2020) 1–7.

[6] Dilshad Islam, Tanjim Mahmud, Tanjia Chowdhury, An efficient automated vehicle license plate recognition system under image processing, *Indonesian Journal of Electrical Engineering and Computer Science* Vol. 29, No. 2, February 2023, pp. 1055~1062 ISSN: 2502-4752.

[7] Fei Xie, Ming Zhang, Jing Zhao, Jiquan Yang, Yijian Liu, Xinyue Yuan, A robust License Plate Detection and character recognition algorithm based on a combined feature extraction model and BPNN, *J. Adv. Transport.* Hindawi 2018 (2018) 1–14.

[8] Mhatre, A. , & Sharma, P. (2023). Deep Learning Approach for Vehicle Number Plate Recognition System with Image Enhancement Technique. *International Journal of Intelligent Systems and Applications in Engineering*, 11(1s), 251–262.

[9] Kaiming He, Jian Sun and Xiaoou Tang, "Single image haze removal using dark channel prior," *2009 IEEE Conference on Computer Vision and Pattern Recognition*, Miami, FL, 2009, pp. 1956-1963, doi: 10.1109/CVPR.2009.5206515.

[10] B. Cai, X. Xu, K. Jia, C. Qing and D. Tao, "DehazeNet: An End-to-End System for Single Image Haze Removal," in *IEEE Transactions on Image Processing*, vol. 25, no. 11, pp. 5187-5198, Nov. 2016, doi: 10.1109/TIP.2016.2598681.

[11] R. Bansal, G. Raj and T. Choudhury, "Blur image detection using Laplacian operator and Open-CV," *2016 International Conference System Modeling & Advancement in Research Trends (SMART)*, Moradabad, India, 2016, pp. 63-67, doi: 10.1109/SYSMART.2016.7894491

[12] He, Kaiming, Jian Sun, and Xiaoou Tang. "Guided image filtering." Computer Vision–ECCV 2010. *Springer Berlin Heidelberg*, 2010. 1-14.

[13] Ratna Yustiawati, Nyayu Latifah Husni, Evelina Evelina, Sabilal Rasyad, Iskandar Lutfi, Ade Silvia, Niksen Alfarizal and Adella Rialita, "Analyzing Of Different Features Using Haar Cascade Classifier," *2018 International Conference on Electrical Engineering and Computer Science* (ICECOS), Pangkal, Indonesia, 2018, pp. 129-134, doi: 10.1109/ICECOS.2018.8605266

[14] Yousefi, Jamileh. (2015). Image Binarization using Otsu Thresholding Algorithm. 10.13140/RG.2.1.4758.9284.

[15] Alkaddo, Ahmed & Albaqal, Dujan. (2022). Implementation of OCR using Convolutional Neural Network (CNN): A Survey. *Journal of Education and Science*. 31. 27-41. 10.33899/edusj.2022.133711.1236.

[16] N. Sarika, N. Sirisala and M. S. Velpuru, "CNN based Optical Character Recognition and Applications," *2021 6th International Conference on Inventive Computation Technologies (ICICT)*, Coimbatore, India, 2021, pp. 666-672, doi: 10.1109/ICICT50816.2021.9358735

[17] Zhu, Qingsong & Mai, Jiaming & Shao, Ling. (2014). Single Image Dehazing Using Color Attenuation Prior. BMVC 2014 - *Proceedings of the British Machine Vision Conference 2014*. 10.5244/C.28.114.

[18] Sharma, Divya; Sharma, Shilpa; Bhatnagar, Vaibhav (2023), “Foggy-Hazy License Plates Images”, *Mendeley Data*, V1, doi: 10.17632/p3jr4555tf.1

[19] https://www.kaggle.com/datasets/aladdinss/license-plate-digits-classification-dataset