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Overcoming Blurred Vision: A YOLO-NAS and Cycle GAN-based Approach for Accurate ANPR in Challenging Images

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Abstract
This paper introduces a novel two-stage methodology to enhance the accuracy of Number Plate Recognition (NPR) systems, particularly in challenging scenarios characterized by blurred images. The proposed approach integrates the You Only Look One Network Architecture (YOLO-NAS) for precise vehicle detection and Generative Adversarial Networks (CYCLE GANs) for effective de-blurring of license plates. In the first stage, YOLO-NAS ensures accurate identification of vehicles even in the presence of image blur. The second stage employs a specially crafted CYCLE GAN architecture to de-blur license plates, preserving critical details for accurate character recognition. This integrated method not only overcomes the limitations of traditional NPR systems but also sets a new standard for accuracy and reliability in challenging conditions. The proposed solution holds significant potential for diverse applications, including toll roads, parking areas, and restricted zones, marking a transformative leap in addressing blurred vision challenges and enhancing the efficiency of NPR systems in real-world scenarios.

Keywords: CYCLE GAN, NPR, CNN, YOLO-NAS and OCR

1. Introduction

In the dynamic landscape of modern society, the omnipresence of vehicles has propelled the need for robust and efficient identification systems. At the forefront of this technological frontier stands Automatic Number Plate Recognition (ANPR), a pivotal component in traffic management, law enforcement, and security applications. However, the accuracy of ANPR systems can be significantly compromised when faced with the challenge of blurry images caused by factors such as motion, low light conditions, or considerable distances[1].

The necessity to incorporate vehicles into information systems appears to have been prompted by the development of information technologies. This can be achieved through the investigation of substantial data provided by vehicles for factual and informational intentions, whether conducted manually or by an intelligent system capable of identifying vehicles by their licence plates in the physical world and redirecting the data to a theoretical framework.

Moreover, as the number of vehicles on the road continues to rise, it appears that automated systems employing cutting-edge technologies like cameras, sensors, and machine learning algorithms are required to manage and monitor parking lots more effectively[2]. These types of systems may be utilised to monitor the quantity of vehicles. Moreover, the integration of vehicle information systems may provide traffic management with useful information, such as current traffic patterns, degrees of overload, and accident detection. The optimised data can be utilised to assess traffic flow, enhance road safety, and decrease commuters' travel duration. In general, the progressions in information technologies have created novel prospects for the integration of vehicles into information systems, thereby potentially exerting a substantial influence across diverse domains and sectors of employment.

The primary features of an advanced number plate recognition system that is combined with vehicle detection are character decomposition and number plate area detection[3]. At the end of the license plate identification process, the detected image of the license plate is improved the quality and then is segmented by character. Through this process, superfluous data is excluded in order to exclusively collect the necessary information for character identification.

In recent years, license plate recognition systems have grown in popularity and adoption due to developments in machine learning and computer vision technologies. These systems take pictures of licence plates using cameras and sophisticated software, extract the characters, and turn into readable text that computers can read. Subsequently, the gathered data may be employed to automate an assortment of procedures, including but not limited to vehicular tracing and identification, traffic regulation enforcement, and parking violation monitoring.

The suggested technique may be used for parking lots, toll highways, and other restricted zones. The process commences with an NPR system utilizing a camera or an alternative video device to capture the license plate image. Better evidence is available to support informed decision-making in situations where high-definition pictures are obtained by advanced camera systems. However, budgetary restrictions sometimes force the adoption of less expensive sensors, which might provide problems for large-scale applications. The presence of insufficient lighting and lower sensor quality can introduce image noise, impacting both Intelligence, Surveillance & Reconnaissance (ISR) missions and commercial industries[4]. To address this, image enhancement algorithms, particularly those incorporating CYCLE GAN-based approaches for blurry images, such as the proposed method, should be considered.

The captured video image undergoes a series of image processing techniques to pinpoint the license plate location and enhance the overall image quality. A CYCLE GAN-based approach is employed for image enhancement, ensuring effective deblurring in scenarios where image quality is compromised. Character recognition, facilitated by the Improved Convolutional Neural Network (ICNN), is subsequently executed after successfully identifying the license plates. This system proves beneficial in various sectors, including parking management, law enforcement agencies, and transportation industries. Through the identification and continuous monitoring of vehicles, the NPR system contributes to automating toll collection processes, bolstering the security of restricted areas, and optimizing traffic flow. By adopting a CYCLE GAN-based approach for image enhancement, the system addresses the challenges posed by blurry images, ensuring that accurate information is obtained for effective decision-making in real-world applications. The following is the format of the paper: The literature review is summarized in Sec-II and other authors' findings to be examined; Sec-III describes the research methodology and proposed work; Sec-IV delves into the mathematical modelling of the proposed CYCLE GAN model; and Sec-V presents the results, concluding with a discussion of the findings.

2. Literature Review

[6] To detect the blur kernel, the author set up a novel approach based on sparse representation. They

determine the angle of the kernel by looking at the restored image's sparse representation coefficients, based on the discovery that the recovered image has the maximum sparse representation when the kernel angle matches the genuine motion angle. Next, they used the Fourier domain Radon transform to determine the motion kernel's length. Even in cases when a person cannot recognise the licence plate, their system can effectively manage huge motion blur. Authro assess their method using real-world photographs and compare it to several well-liked, cutting-edge blind image deblurring techniques. The advantage of our suggested technique in terms of resilience and efficacy is shown by the experimental findings.

[7] Deep networks were originally designed for unsupervised feature learning, but the author provides a unique approach to low-level vision issues that effectively adapts them to the tasks of image denoising and blind inpainting. Using an alternate training approach, the deep networks are pre-trained using denoising auto-encoders. Their method's image denoising function is comparable to that of KSVD, a well-liked sparse coding method. The experiment results demonstrate that the proposed method performs well for both blind in painting and picture denoising. They also suggest that the more effective DA training approach may improve the results of unsupervised feature learning.

[5] The author proposed a unique regularised approach for estimating a blur kernel from a single blurred image by regularising the sparsity characteristic of natural photographs. Moreover, this method may recover valuable salient edges for kernel estimation by adding an adaptive structure map during the deblurring phase. Lastly, we provide an effective method that can solve the suggested model effectively. The efficiency of the suggested approach is shown by extensive trials compared with the most advanced blind deblurring techniques.

[8] First, the study's author shows how cutting-edge, contemporary kernel estimation methods based on the 0 gradient prior may be altered to continue working well even in the face of high noise levels.

They then demonstrated how denoising the fuzzy picture beforehand may greatly enhance a quick non-blind deconvolution technique. Results from the suggested method are comparable to those from far more computationally intensive techniques.

[9] Author proposes method for recovering motion-blurred photographs. Image restoration is crucial for criminal identification, since blurred photos from hit-and-run situations might obscure human faces or vehicle number plates.

Understanding the point spread function (PSF) is crucial for restoring motion blurred pictures. Motion blur PSF parameters include blur direction and blur duration. A technique was provided to determine PSF parameters from blurred and noisy pictures using the log spectrum.

These settings restore pictures. Experiments show effective picture restoration from images with significant natural and artificial blur.

[10] The study proposes a revolutionary way to improve licence plate numbers in actual traffic recordings. A high-resolution picture of the number plate is created by combining diverse, noisy, and subpixel-shifted data. A stepwise nonconvexity optimisation approach estimates the superresolved picture as a Markov random field from observations. A discontinuity adaptive regularizer enhances readability by preserving edges in the rebuilt number plate. The suggested technique is shown to be resilient to possible inaccuracies in motion and blur estimations via experimental findings on many traffic sequences. The approach is computationally efficient since all operations are performed locally in the picture domain.

[11] This paper presents an approach that focuses on restoring images with super resolution. The system

is based on the blur licence plate. Utilizing the LBP feature in conjunction with fuzzy logic, the image recognition and restoration process is enhanced. Simultaneously, striving to achieve optimal results in order to enhance the recognition rate of licence plates.

[12] The author identifies several factors that contribute to the primary challenge in text extraction from images: variation in font size, misalignment of text, and variation in font colour. A novel hybrid method for character recognition and segmentation is presented here. Designing and implementing algorithms for the recognition of Indian license plates is the purpose of this project. This study presents a stable approach for the location of licence plates, their segmentation, and the Cycle GAN of the characters found on the located plate. Due to the fact that text regions in license plate images consist primarily of repeated vertical strokes (edges), adjacent edges of a segment are connected once the group of edges has been identified. Existing methods are less effective when it comes to inclined or curved characters compared to the suggested approach. The outcomes of experiments show that the method under consideration enhances both the efficiency and resilience of license plate recognition.

[13] The author asserts that despite the automation of the traffic management process, it remains a highly complex issue due to the wide range of plate formats, dimensions, rotations, and non-uniform illumination conditions that occur during image acquisition.

Accurate and cost-effective management of traffic rule violations is the primary aim of this endeavour. The proposed model incorporates an automated system that captures video using Arduino-based IR sensors and a camera. Number Plate Recognition and additional image manipulation techniques are presented in the project to facilitate character recognition and plate localization, thereby accelerating, and simplifying the process of number plate identification. After identifying the car number from the number plate, an SMS based module is created to notify the vehicle owners of their violation of traffic restrictions. Regional Transport Office (RTO) receives a supplementary SMS for the purpose of monitoring the report's status.

[14] According to the author, address the problem of recovering images that have been blurred owing to the relative motion of the camera and the topic of interest. This problem occurs commonly when the imaging device is in motion or is being handled manually, as well as in the context of robot vision. It is critical to understand the blurring system's point-spread function (PSF) to guarantee proper restoration of the damaged picture. The author offers a straightforward method that uses only the original blurry picture to improve motion-blurred photographs. The approach starts by detecting the point spread function (PSF) of the blur and then employs it to recover the blurred picture. Understanding that visual attributes in the direction of motion are largely impacted by blurring and are distinct from qualities in other directions is the foundation for identifying blur in this context. They emphasise the PSF correlation qualities over those of the original picture when they filter the blurry image. Exhibited are picture restoration results including both artificial and natural motion blur.

3. METHODOLOGY

Our proposed methodology is a carefully orchestrated two-stage process, leveraging the strengths of YOLO-NAS for precise vehicle detection and a custom-designed Generative Adversarial Network (GAN) for the intricate task of deblurring license plates. This combined approach aims to overcome the challenges posed by blurry images in Number Plate Recognition systems..

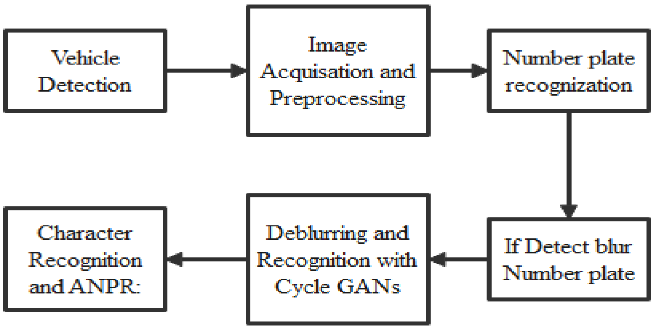


Figure 1 Proposed Frame Work

The process of the vehicle identification system is methodical and starts with taking a picture of the intended car. After being acquired, the picture is preprocessed to improve its quality. This includes duties like cropping to improve clarity and noise reduction. After that, a character recognition module receives the preprocessed picture and uses optical character recognition (OCR) methods to recognise and extract alphanumeric characters from the licence plate. The recognised number plate number is produced if the operation is successful; if not, an iterative loop is initiated by the system. In an effort to identify the licence plate, the picture is processed further and the character recognition module is repeated inside this loop. Interestingly, the procedure includes "Cycle GANs," which proposes the use of generative adversarial networks to improve picture quality in preprocessing. The purpose of this update is to enhance the character recognition module's overall performance. In order to prohibit processing of the number plate indefinitely without successful identification, an iterative loop is maintained until either the number plate is successfully recognised or a predetermined maximum number of tries is achieved.

A. Research Methodology

The proliferation of police investigation cameras necessitates effective video encoding to a significant degree. While contemporary video encoding standards have significantly enhanced the efficacy of video encoding, their intended application is not surveillance video but rather general-purpose video. Multiple vehicle detection in laptop vision applications and intelligent transportation systems may represent a challenging yet potentially fruitful endeavour. Most current strategies locate vehicles using bounding box representations and do not provide vehicle situations. Nevertheless, location information is crucial for numerous time-sensitive applications, such as motion estimation and vehicle navigation.

B. Pre-Processing

The object identification technique known as YOLO-NAS, which stands for "You Only Look Once Version-Neuronal Architecture Search," employs a single neural network in order to identify items inside an image. A convolutional neural network (CNN) architecture serves as the foundation for YOLO-NAS, which is capable of detecting objects in real time with a high degree of effectiveness. Optimisation using the Ant Bee Colony Optimization Algorithmic Rule (ABC) and the Whale Optimisation Algorithm (WOA) has the potential to enhance the performance of the YOLO-NAS network while also reducing the complexity of the computations involved. It is feasible to increase the accuracy of the detection process as well as the speed at which it is carried out by using YOLO-NAS in conjunction with ABC-WOA optimisation for the detection of license plates, vehicles, and speeds.

Feature Selection

The Artificial Bee Colony (ABC) method's exploration efficiency and the Whale Optimisation method's (WOA) exploitation capabilities are combined in the ABC-WOA hybrid algorithm. Feature selection is the application of this synergistic technique. Hybridizing optimization algorithms, like combining Ant Bee Colony (ABC) and Whale Optimization Algorithm (WOA), is vital for achieving superior optimization outcomes[15][16]. This approach enhances performance by synergizing the strengths of multiple algorithms, balancing exploration, and exploitation, and providing robustness across various problem types. By customizing the hybrid approach to specific problems and dynamically adapting to changing landscapes, hybridization accelerates convergence, overcomes algorithm limitations, and maximizes the chances of finding high-quality solutions. It plays a crucial role in addressing complex optimization challenges across diverse fields, ultimately advancing efficiency and effectiveness in problem-solving.

Algorithm: Hybrid ABC-WOA Optimization

Initialization: Initialize ABC and WOA populations randomly:
- ABC population: N_ABC bees
- WOA population: N_WOA whales
Repeat for a maximum of max_iterations or until termination criteria are met:
For each ABC bee in ABC population:
Employed bees explore solutions locally:
Modify the position of bee using a local search strategy.
Calculate the fitness of each employed bee.
Onlooker bees select employed bees based on fitness and perform global search:
Select employed bees probabilistically.
Apply global search strategy.
Evaluate fitness of onlooker bee.
For each WOA whale in WOA population:
Update whale position using WOA equations:
X_WOA_j = A * sin(B) * |C * X_rand - X_WOA_j| - X_WOA_j
Evaluate fitness of WOA whale.

CYCLE GANs

The goal of the generative adversarial network (GAN) design known as cycle GAN, or cycle generative adversarial network architecture, was to solve the problem of unpaired image-to-image translation.
Cycle GAN, created by researchers Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros, has shown impressive ability in converting pictures across different domains without requiring paired training samples..

Generative Adversarial Network (GAN):

Cycle GAN is based on a family of artificial intelligence models called GANs, which are a generator and a discriminator operating in a competitive environment. The discriminator attempts to discern between actual and created pictures, whilst the generator produces images that seem realistic. The generator is driven by this adversarial process to continuously enhance its capacity to generate pictures that are identical to genuine ones. [17]

Cycle-Consistency:

The unique feature of Cycle GAN is its emphasis on cycle-consistency. In unpaired image translation, where there is no direct correspondence between input and output images, ensuring consistency is challenging. Cycle-consistency enforces that translating an image from one domain to another and back should result in the original image. This constraint is achieved through the introduction of cycle-consistency loss during training, encouraging the model to produce meaningful and coherent translations[18].

Unpaired Image-to-Image Translation:

Unlike traditional GANs that require paired examples for training (input and corresponding output), Cycle GAN can learn mappings between two domains using unpaired datasets. This is particularly valuable in real-world scenarios where obtaining perfectly matched pairs for every possible translation is impractical.

Dual Generators and Discriminators:

Cycle GAN consists of two generators and two discriminators – one set for each domain being translated. The generators are responsible for transforming images from one domain to another and back, while the discriminators assess the realism of the generated images. This dual architecture allows for bidirectional translation and cycle-consistency enforcement. [2]

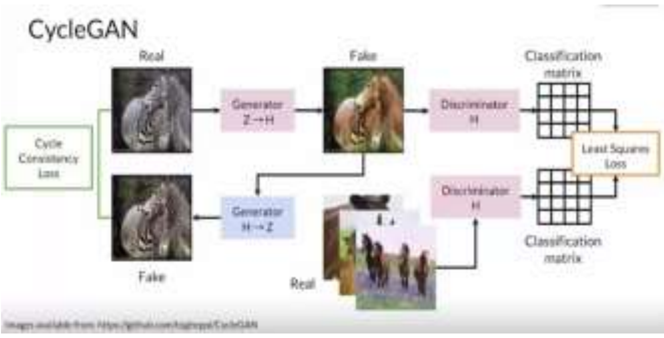


Figure 2 Cycle GAN: a GAN architecture for learning unpaired image to image transformations.

Cycle GAN [4] excels in situations with limited paired datasets, i.e., source and target images. Cycle GAN's ability to learn image-to-image translations without a one-to-one mapping between input and target domain motivates its use in document cleaning, where clean documents are scarce and noisy documents are prevalent. Cycle GAN uses cycle-consistency loss to avoid learning meaningful transformations in unpaired datasets. This method ensures that samples from the source distribution are obtained when an image is transformed from source to target distribution and back again. Figure 1 illustrates how Cycle GAN incorporates loss using two generators and two discriminators. The generator GB converts the picture from noisy domain A (I_A) to a clean domain B (O_B) output. Learning features to map back OB to the noisy input domain is necessary to establish a meaningful relationship between I_A and O_B. Second generator GA reverses OB into noisy image CA. The same transformation process is utilised to convert photographs from clean domain B to noisy domain A. Each discriminator necessitates two inputs, as illustrated in Figure 2: the source domain original image and a generator-generated image. In order for the discriminator to vanquish the generator by rejecting its generated images, it must differentiate between them[19]. The generator learns to create pictures like the original input while competing with the discriminator to cease rejecting them. We employ the Cycle GAN network. The generator network has two stride 2 convolutional layers, residual blocks, and two stride 1 transposed convolution layers. A discriminator network employs 70x70 Patch GANs[20] to identify authentic or false pictures with 70x70 overlapping patches.

Integration with NPR System:

The deblurred license plate images, now enhanced with preserved details, seamlessly integrate into the broader NPR system. This integration is carefully orchestrated to ensure that the deblurring process contributes to the overall accuracy of character recognition and subsequent identification processes. The NPR system benefits from the clarity achieved in the deblurring stage, resulting in a holistic and reliable approach to license plate recognition even in challenging image conditions Improved Convolutional Neural Network-based number plate Character Recognition.

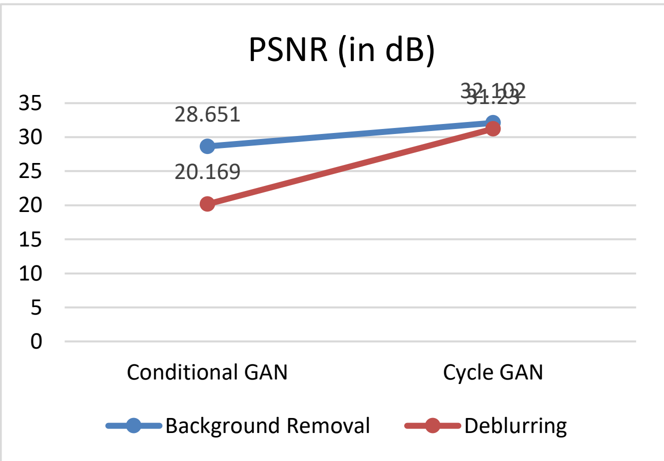
4. Results and Discussion

This segment provides a thorough synopsis of the datasets that were employed in the development of the document cleansing suite. A comprehensive description of the training methodologies employed in our experiments is furnished. Following this, a comparison is made between the outcomes of the experiments we conducted and the foundational model, Conditional GAN.

	PSNR (in dB)	
Task	**Conditional GAN**	**Cycle GAN**
Background Removal	28.651	32.102
De-blurring	20.169	31.23

Table 1 Comparing the performance of Conditional GAN and Cycle GAN based on PSNR

The dataset includes 50 purposely blurred images of vehicle number plates, capturing a wide range of real-world scenarios like motion blur, low light conditions, and varying distances. Every image is meticulously annotated with accurate bounding boxes that outline the number plates. This meticulous annotation serves as ground truth for deblurring algorithms and as valuable training data for machine learning models. This dataset is perfect for professionals looking to conduct research and development in Automatic Number Plate Recognitions systems. It provides a comprehensive collection of data that specifically focuses on addressing the challenges of image blur in vehicle identification. With this dataset, professionals can explore innovative solutions and make significant advancements in their work.



A comparison of the performance metrics, specifically the Peak Signal-to-Noise Ratio (PSNR) in decibels, for Conditional GAN and Cycle GAN, two well-known generative adversarial network (GAN) architectures, is displayed in Table 1. The evaluation is conducted on two distinct tasks – Background Removal and De-blurring. In the task of Background Removal, Cycle GAN outperforms Conditional GAN, achieving a higher PSNR of 32.102 dB compared to 28.651 dB. Similarly, in the De-blurring task, Cycle GAN demonstrates superior performance with a PSNR of 31.23 dB, surpassing Conditional GAN, which scores 20.169 dB.

These PSNR values serve as quantitative indicators of the quality and fidelity of image generation, with higher values representing improved image quality.

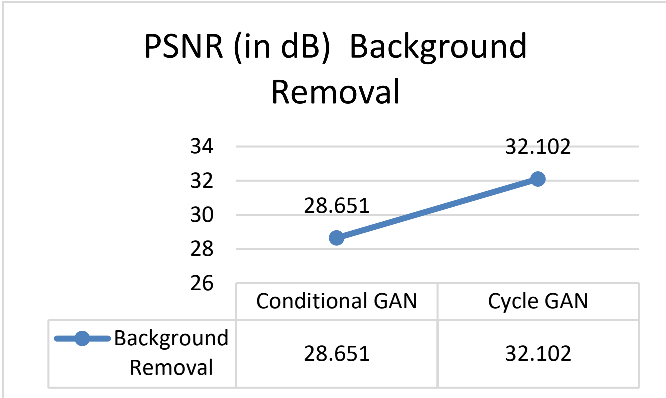


Figure 3 PSNR Comparison Graph OF Back Ground Removal

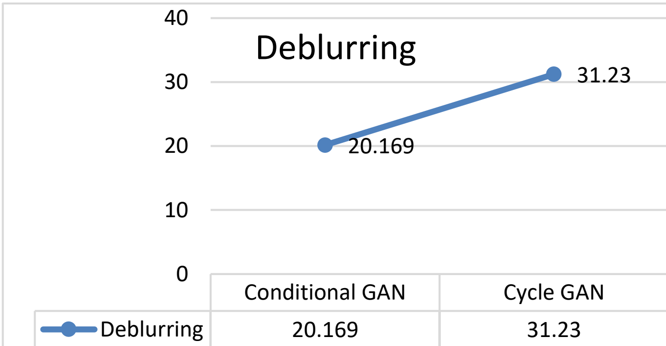


Figure 4 PSNR Comparison Graph OF Deblurring

To visually depict the comparative performance, a line graph has been plotted using the PSNR values obtained for Background Removal and De-blurring tasks for both Conditional GAN and Cycle GAN. The graph clearly illustrates the superiority of Cycle GAN over Conditional GAN in both tasks, with consistently higher PSNR values. This visual representation provides a comprehensive overview of the relative performance of these GAN architectures, aiding in the interpretation of their effectiveness in the specific image generation tasks of Background Removal and De-blurring.

Figure 5 Comparison

The dataset under consideration comprises 50 intentionally blurred images of vehicle number plates, meticulously curated to encompass various real-world scenarios, including motion blur, low light conditions, and diverse distances. Each image is intricately annotated with precise bounding boxes outlining the number plates, establishing a reliable ground truth for the evaluation of deblurring algorithms and serving as invaluable training data for machine learning models. This dataset provides a focused and comprehensive resource for professionals engaged in research and development in Number Plate Recognition systems, particularly addressing the challenges posed by image blur in the context of vehicle identification.

5. CONCLUSION

In conclusion, this paper introduces a pioneering two-stage methodology that combines the strengths of You Only Look One Network Architecture (YOLO-NAS) and Generative Adversarial Networks (CYCLE GANs) to address the pressing challenges of Number Plate Recognition (NPR) systems in scenarios marked by image blur. The first stage, utilizing YOLO-NAS, focuses on precise vehicle detection within blurry images, ensuring that even faintly visible vehicles are accurately identified. Subsequently, the second stage employs a specially crafted CYCLE GAN architecture to effectively de-blur license plates, preserving critical details for accurate character recognition.

This integrated approach not only surpasses the limitations of traditional NPR systems but also sets a new standard for accuracy and reliability in challenging conditions. The successful combination of YOLO-NAS and CYCLE GANs signifies a transformative leap in overcoming blurred vision challenges, offering enhanced performance and efficiency for NPR systems, particularly in real-world scenarios such as toll roads, parking areas, and restricted zones.

By paving the way for improved character recognition, our proposed method opens new horizons for the future of NPR systems across diverse domains. The significance of this research extends beyond the realm of traditional methods, presenting a robust solution for applications where image blur poses a significant hurdle. The integration of cutting-edge technologies showcased in this paper positions NPR systems to achieve unprecedented accuracy and efficiency, contributing to the evolution of OCR technology in real-world settings.

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