Advancements and Challenges: A Comprehensive Review of GAN-based Models for the Mitigation of Small Dataset and Texture Sticking Issues in Fake License Plate Recognition

Dhuha Habeeb
Department of Electrical Engineering, Universiti Tenaga Nasional, Malaysia | Iraq University College, Basrah, Iraq
dhuha.hahu@gmail.com (corresponding author)

A. H. Alhassani
Iraq University College, Basrah, Iraq
hadi.alhassani@iuc.edu.iq

Lili N. Abdullah
Universiti Putra Malaysia, Malaysia
liyana@upm.edu.my

Chen Soong Der
Universiti Tenaga Nasional, Malaysia
chensoong@uniten.edu.my

Loway Kauzm Qata Alasadi
Iraq University College, Basrah, Iraq
lowaykaqa@gmail.com

Received: 31 August 2024 | Revised: 18 September 2024 and 24 September 2024 | Accepted: 28 September 2024

 DOI: https://doi.org/10.48084/etasr.8870

ABSTRACT

This review paper critically examines the recent advancements in refining Generative Adversarial Networks (GANs) to address the challenges posed by small datasets and the persisting issue of texture sticking in the domain of fake license plate recognition. Recognizing the limitations posed by insufficient data, the survey begins with an exploration of various GAN architectures, including pix2pix_GAN, CycleGAN, and SRGAN, that have been employed to synthesize diverse and realistic license plate images. Notable achievements include high accuracy in License Plate Character Recognition (LPCR), advancements in generating new format license plates, and improvements in license plate detection using YOLO. The second focal point of this review centers on mitigating the texture sticking problem, a crucial concern in GAN-generated content. Recent enhancements, such as the integration of StyleGAN2-ADA and StyleGAN3, aim to address challenges related to texture dynamics during video generation. Additionally, adaptive data augmentation mechanisms have been introduced to stabilize GAN training, particularly when confronted with limited datasets. The synthesis of these findings provides a comprehensive overview of the evolving landscape in mitigating challenges associated with small datasets and texture sticking in fake license plate recognition. The review not only underscores the progress made but also identifies emerging trends and areas for future exploration. These insights are vital for researchers, practitioners, and policymakers aiming to bolster the effectiveness and reliability of GAN-based models in the critical domain of license plate recognition.

Keywords-License Plate Recognition (LPR); GAN; StyleGAN2-ADA

I. INTRODUCTION

In the rapidly evolving landscape of Artificial Intelligence (AI) [1], Generative Adversarial Networks (GANs) [2] have emerged as a transformative force, pushing the boundaries of machine intelligence by enabling the creation of fake data with human-like characteristics. At the forefront of this intersection between AI and GANs lies License Plate Recognition (LPR) [3], a pivotal technology with profound implications for various industries. Designed to automatically capture, process, and interpret license plate information from vehicles, LPR systems contribute to enhance efficiency in law enforcement, traffic management, parking systems, and electronic toll collection. This review focuses on the role of GANs [2] in addressing critical challenges faced by LPR systems. The significance of LPR lies in its ability to streamline and enhance various aspects of our interconnected society. Law enforcement agencies utilize LPR to swiftly identify and track vehicles associated with criminal activities, contributing significantly to public safety. In urban environments, traffic management benefits from LPR systems to monitor and regulate the flow of vehicles, reducing congestion and improving overall efficiency [5]. Parking facilities leverage LPR for seamless access control and payment processing, optimizing the parking experience for users. However, the effectiveness of LPR systems is contingent on overcoming challenges such as small datasets and the persistent issue of texture sticking [6]. This review explores how GANs, through adversarial training, can be employed to generate fake license plate images, thereby augmenting existing datasets and addressing the limitations of small datasets. By training a generator to produce realistic license plate variations and a discriminator to distinguish between real and fake data, GANs play a crucial role in mitigating texture sticking issues, ensuring the adaptability and robustness of LPR [7] systems to diverse real-world scenarios. The mitigation of small dataset and texture sticking issues in LPR involves a multifaceted approach, combining data augmentation with GANs, refining GAN architectures for texture diversity, incorporating domain adaptation techniques, exploring dynamic GAN models, and implementing adaptive training mechanisms. These strategies collectively enhance the robustness and effectiveness of LPR systems in handling variations encountered in real-world LPR scenarios.

II. LPR CHALLENGES

The continued development of LPR systems is marked by advancements in computer vision, AI, and data processing technologies. As technology progresses, addressing challenges and ethical considerations will be essential for the responsible and effective deployment of LPR systems [8, 9]. Training GANs with small datasets presents several challenges. The limited diversity in a small dataset may result in fake samples that fail to capture the richness and variability of real-world data. Overfitting becomes a significant concern, as GANs may learn specific details of the small dataset but struggle to generalize to unseen examples. Mode collapse, where the generator produces a restricted set of samples repeatedly, is exacerbated by the insufficient variety in a small dataset, hindering the model's ability to represent diverse data distributions effectively. Training instability is prevalent with small datasets, causing fluctuations in generator and discriminator dynamics and impeding convergence to a stable and realistic output. Capturing high-level features becomes challenging, as the small dataset may lack examples to adequately represent intricate patterns and complexities. Data augmentation, a common solution, has limited effectiveness when the original dataset is small, potentially failing to introduce significant new information for improved generalization. Hyperparameter sensitivity is heightened, making it difficult to find optimal settings for effective GAN training [10]. The resource intensiveness of GANs, especially in deep architectures [11], exacerbates the risk of overfitting and convergence issues with small datasets [12]. Evaluating GAN performance with small datasets is also problematic, as conventional metrics may not reliably indicate the model's quality. Addressing these challenges requires careful consideration of techniques like transfer learning, regularization methods, and architectural adjustments, as well as acquiring or generating additional diverse data to enhance training effectiveness.

The texture sticking problem in fake LPR arises when generative models, like GANs, produce fake license plate images that exhibit repetitive or overemphasized textures. This issue occurs due to the difficulty in capturing the diverse and nuanced textures present in real license plates. As a result, the fake license plates may lack the authentic variability found in genuine plates, making them visually distinguishable as generated or fake by recognition systems. Overcoming the this problem involves refining the training process, adjusting model architectures, and incorporating more comprehensive and diverse datasets to ensure the generated license plates closely resemble the complexities of real-world counterparts [13]

III. GENERATIVE ADVERSARIAL NETWORKS

GANs have been extensively applied in the domain of license plate generation due to their ability to generate realistic and diverse images. These networks consist of two main components: the generator and the discriminator. The generator aims to produce fake data, while the discriminator tries to distinguish between real and fake data. Through adversarial training, both components improve iteratively, resulting in the generation of high-quality fake data. GANs have been employed for tasks such as license plate synthesis, augmentation, and anonymization. A comprehensive review of GAN architectures commonly used for license plate generation follows.

- **Deep Convolutional GANs (DCGANs):** DCGANs have emerged as a popular approach for generating fake license plates with high fidelity and realism [14]. These networks consist of a generator and a discriminator, both built using convolutional layers. The generator takes random noise vectors as input and progressively upsamples them through convolutional layers to produce fake license plate images. Meanwhile, the discriminator is trained to distinguish between real and fake license plates by downsampling the input images and extracting features for classification. Through adversarial training, where the generator aims to fool the discriminator and the discriminator aims to correctly classify real and fake images, both networks improve iteratively. This process results in the generation of increasingly realistic license plates. DCGANs can also be utilized for data augmentation in license plate datasets by generating fake plates to increase dataset diversity. Additionally, they can be adapted for style transfer tasks, enabling the transformation of license plates between different styles while preserving key characteristics. Moreover, DCGANs can be modified for conditional generation, allowing for the generation of license plates with specific attributes or styles by conditioning the generator on relevant input information, such as region or font type. Overall, DCGANs offer a versatile and effective framework for generating fake license plates with various styles, attributes, and levels of realism. Authors in [15] introduced a modification to enhance stability and address training convergence issues by replacing the generator and discriminator networks' fully connected layers with two convolutional layers. Several improvements were proposed, including replacing the pooling layers in the discriminator network with strided convolutions, incorporating batch normalization in both the generator and discriminator networks, utilizing ReLU activation functions in all generator layers except the output layer, which adopts the tanh activation function. Furthermore, the discriminator network employs LeakyReLU activation functions to mitigate gradient sparsity. These enhancements aim to promote stable training and improve convergence in DCGANs [16].

- **Conditional GANs (cGANs):** cGANs have found application in generating MNIST digits with specific attributes or characteristics [2]. In cGANs, both the generator and discriminator are conditioned on additional information, such as class labels or attributes related to the license plates. This conditioning allows for more control over the generated outputs, enabling the generation of license plates with desired styles, formats, or regional variations. For instance, the generator can be conditioned on attributes like the font type, color scheme, or region-specific features of the license plate. By conditioning the discriminator as well, cGANs [17] ensure that the generated license plates not only resemble real plates but also adhere to the specified attributes. This approach is particularly useful in scenarios where the generated license plates need to meet specific requirements, such as for training data augmentation or generating fake datasets for testing and evaluation. Overall, cGANs offer a flexible framework for conditional generation of license plates tailored to various applications and specifications.
- **CycleGAN:** CycleGAN [18-20] has been applied to license plates for image-to-image translation tasks without the need for paired training data. CycleGAN can be utilized to perform style transfer, transforming license plates from one style or format to another while preserving important features. For example, it can convert license plates from one country's format to another, e.g. transforming European-style plates to North American-style plates. This process is achieved by training two generators and two discriminators simultaneously, with one generator focusing on translating license plates from the source domain to the target domain, and the other focusing on the reverse translation. Through adversarial training and cycle consistency loss, CycleGAN ensures that the translated license plates maintain consistency and realism across both domains. This enables the generation of diverse license plate styles and formats, making CycleGAN a valuable tool for tasks such as data augmentation, style transfer, and license plate synthesis [21]. A robust model for license plate recognition in unconstrained environments was presented in [22]. The proposed model is based on an Xception CNN module for feature extraction and a 2D-attention-based RNN module for sequence decoding. To address the shortage or imbalance of real training data, CycleGAN was tailored to generate fake LP images with different deformation styles and a more balanced distribution of region codes, offering a simple yet effective means to complement available real data. Extensive experimental results indicated the superiority of CycleGANs, particularly when dealing with distorted license plates or limited training data.
- **Super-Resolution Generative Adversarial Network (SRGAN):** SRGANs [23, 24] have been applied to license plates for enhancing image resolution and improving image quality. IN SRGANs, the generator aims to produce high-resolution images from low-resolution inputs, while the discriminator distinguishes between real high-resolution images and those generated by the generator. SRGANs can be used to upscale low-resolution license plate images, resulting in sharper and clearer representations. This can be particularly useful for scenarios where license plate images are captured under challenging conditions, such as low-light environments or long distances. By leveraging adversarial training, SRGANs are capable of generating high-quality, realistic license plate images with improved resolution, contributing to better accuracy in license plate recognition systems. Overall, SRGANs offer a valuable tool for enhancing the visual quality and resolution of license plate images, thereby improving the performance of license plate recognition algorithms. Authors in [23] proposed a method to enhance the quality of vehicle license plate images in smart surveillance environments. Their approach focused on increasing image resolution and removing motion blur, addressing challenges in efficient vehicle management. They introduced SRGAN-LP, a solution designed to intelligently deblur images, outperforming existing methods both qualitatively and quantitatively.

Table I shows the general workflow for creating license plates using GANs, mentioning image resizing and normalization to a consistent format along with architecture selection.

IV. DATASET

The dataset serves as the foundation for training and evaluating GAN models for generating fake license plates. It provides the necessary real-world examples for the models to learn from, enabling them to produce realistic and diverse fake license plates that closely resemble those found in actual surveillance or recognition systems. Deepfake datasets typically consist of pairs of real and fake images or videos, with the fake content being generated with deep learning techniques. These datasets are crucial for training and evaluating deepfake detection models and understanding the capabilities and limitations of deepfake generation algorithms. Some of the most important ways to get such datasets are described below.

TABLE I. GENERAL WORKFLOW FOR CREATING LICENSE PLATES USING GANS

Reference	Architecture	Experimental Setup	Network	Resolution
[23]	SRGAN	NVIDIA GTX 1070 GPU with 12 GB memory and 24 GB RAM	Deep CNN model	64 × 64
[25]	MAC-GAN	N/A	Two NN	128 × 256
[21]	LPRGAN	AMD Ryzen 7 2700× 8 Cores 16 Threads CPU Asrock B450 Gaming K4 Motherboard Galax NVIDIA GeForce RTX 2080 Ti 11GB GDDR6 352-bit 260 Watts GPU Corsair 32GB DDR4 Memory WD Green SATA SSD 120GB Cooler Master 80PLUS Gold Full Modular 750W Power Supply	CNN	256 × 128
[4]	pix2pix_cGAN	Desktop CPU with GPU	CTC-CNN	140 × 60 and 100 × 50
[26]	StyleGan2	N/A	pix2pix	128 ×128

A. Web-Scraped Real Images

Creating a dataset of real license plate images through web scraping involves automating the process of downloading images from websites that contain relevant content. This is typically achieved using web scraping tools or libraries like BeautifulSoup, Scrapy, or Selenium. Researchers identify and specify search parameters such as keywords and website sections to target. The scraping script crawls through the selected websites, extracts image URLs, and downloads the images. After filtering out irrelevant images and cleaning the data, the images are manually annotated with metadata such as license plate region, alphanumeric characters, and vehicle type. The dataset is then organized, stored, and validated to ensure quality and compliance with ethical considerations such as copyright laws and website terms of use. Finally, documentation is provided, and the dataset may be shared with the research community for collaboration and reproducibility [27].

B. Application-Oriented License Plate (AOLP)

This dataset is a collection of license plate images specifically curated for application-driven research and development. It is tailored to address the needs of various license plate-related tasks, such as license plate detection, recognition, segmentation, and analysis. The AOLP dataset typically includes images captured in diverse real-world scenarios, including different lighting conditions, weather conditions, vehicle types, and environmental backgrounds. The benchmark database comprises 2049 images of Taiwan license plates, which are categorized into three subsets: Access Control (AC) [28] with 681 samples, traffic Law Enforcement (LE) [29] with 757 samples, and Road Patrol (RP) [30] with 611 samples. In AC scenarios, vehicles passing fixed passages at lower speeds or coming to a full stop are depicted, representing the simplest situations. These images are captured under various illuminations and weather conditions. In LE scenarios, vehicles violating traffic laws are captured by roadside cameras, resulting in backgrounds cluttered with road signs and multiple plates in a single image. RP scenarios involve cameras mounted on patrolling vehicles, resulting in images being taken from diverse viewpoints and distances [31].

C. PKU (License Plate Detection)

The PKU dataset consists of nearly 4,000 images divided into five distinct groups, denoted as G1 through G5, each depicting various scenarios [32]. For instance, G1 showcases highway scenes captured during daylight hours, featuring solitary vehicles. In contrast, G5 contains images depicting crosswalks under both daytime and nighttime conditions, presenting multiple cars and their associated license plates (LPs) [33].

D. CD-HARD

The CD-HARD dataset contains 102 images showing vehicles with angled license plates, obtained from the Cars dataset. Each image in this collection focuses solely on one vehicle and was taken during daylight. Although the dataset includes pictures from various locations worldwide, it mainly features images that appear to be captured in European settings [34].

E. Dataset Issues

1) Challenges in Small Dataset

Small dataset challenges significantly hinder the development of accurate and robust fake LPR systems. Limited availability of labeled data, particularly for fake license plates, poses a major obstacle in training and evaluating recognition models. Small datasets fail to capture the diversity and complexity of real-world license plate variations, resulting in degraded model performance, including decreased accuracy, precision, and recall. Traditional machine learning and computer vision techniques are insufficient in handling small datasets and adapting to diverse license plate variations. Mitigation strategies such as data augmentation, transfer learning, and semi-supervised learning are essential to overcome these challenges, enabling the development of more effective recognition systems. However, significant research efforts are still required to address the remaining challenges and enhance the performance of fake license plate recognition in real-world scenarios.

2) Challenges in Texture Sticking

Texture sticking occurs when generating fake images and videos using deep learning models like GANs, where the generated content exhibits repetitive or unrealistic textures closely resembling those in the training data. This issue arises from the model's tendency to replicate specific texture patterns, resulting in a lack of diversity and fidelity in the generated outputs. In fake image generation, texture sticking might manifest as repeated facial features or unnatural skin textures, while in video synthesis, it could lead to repetitive background elements or unrealistic motion patterns. Mitigating texture sticking involves architectural modifications, regularization techniques, diversity-promoting objectives, data augmentation, adversarial training, and fine-tuning, aiming to enhance the diversity and realism of generated content. This problem was not mentioned in fake LPR data but was mentioned using fake human image generation.

Table II summarizes the most important works that suffered from these two problems. The table also highlights mitigation strategies and significant works that have faced these challenges, underscoring the importance of addressing these issues for the development of effective fake LPR systems.

TABLE II. MOST IMPORTANT LPR WORKS AND ISSUES THEY SUFFERED FROM

Ref	Type of characters	Year	Dataset	Dataset size	Issues	Type
[27]	Korean LP images	2020	web-scraping	159 images	Small dataset	License plate images
[22]	China LP images	2020	CLPD	1200 images	Small dataset	License plate images
[35]	Russian LP images	2021	From http://avto-nomer.ru/	First dataset: 5486 images Second dataset: 20 images	Small dataset	License plate images
[36]	China LP images	2021	CCPD	200K+ images	Small dataset	License plate images
[31]	Taiwan LP images	2022	Car plate dataset and AOLP	First dataset: 2190 Second dataset: 2049 images	Small dataset	License plate images
[21]	Thailand LP images	2023	AI Center	16,194 images	Dimension size is fixed (256 × 128 × 3). It cannot be used to create other larger or smaller sizes	License plate images
[37]	N/A	2019	FFHQ	70000	Texture sticking	Human faces image
[38]	N/A	2020	LSUN CAR and FFHQ	70000	Texture sticking	Human faces and car images
[6]	N/A	2021	METFACES FFHQ, AFHQV2, and BEACHES	1336, 70000,15803, and 20155 images	Texture sticking	Faces and animals image

V. CHALLENGES IN PERFORMANCE MEASUREMENT

Evaluating the performance of GAN models in fake LPR is carried out using multiple metrics, each addressing different aspects of image quality and model effectiveness [39]. Accuracy and precision are standard metrics and provide a basic evaluation of the model's ability to correctly identify and classify images. However, while useful, insights into the visual quality or realism of the generated images, which are crucial for effective fake LPR, are not offered by these metrics. Fidelity and diversity are essential metrics for assessing the quality of GAN-generated images. Fidelity is measured by how closely the generated images resemble real license plates, ensuring high visual quality and authenticity. Diversity is evaluated by the range of different images the GAN can produce, preventing mode collapse where the model generates similar or identical images repeatedly. High fidelity ensures that the fake license plates are convincingly realistic, while high diversity ensures robustness and adaptability to various scenarios. Balancing these two aspects is critical but challenging, as improvement in one can sometimes compromise the other.

Issues arise from the lack of standardized benchmark datasets for fair comparison of GAN models in fake license plate recognition [32]. Without common datasets, comparing the performance of different models becomes difficult, as each study may use different data sources with varying characteristics. This lack of standardization can lead to biased evaluations and hinder the reproducibility of results, making it challenging to establish a clear benchmark for assessing model performance. Maintaining consistency in evaluation methods across different studies presents significant challenges. Variability in data preprocessing, training protocols, and metric implementations can lead to inconsistent results, making it difficult to compare findings reliably. This inconsistency can obscure the true performance of GAN models, as minor differences in experimental setups can produce significant variations in reported outcomes. Assessing the performance of GAN models in real-world scenarios versus controlled environments is fraught with difficulties [40, 41]. Systematic testing under ideal conditions is allowed by controlled environments, but the variability and complexity of real-world situations, such as different lighting conditions, angles, and occlusions, are not captured. Real-world testing is resource-intensive and logistically challenging, yet it is essential for understanding how GAN models perform in practical applications and for ensuring their robustness and reliability in diverse, uncontrolled settings.

VI. EVALUATION AND COMPARATIVE ANALYSIS

To conduct a detailed comparative analysis of various GAN enhancements addressing small dataset and texture sticking challenges in fake LPR, researchers begin by identifying a range of proposed enhancements in the literature, encompassing novel architectures, loss functions, regularization techniques, and training methodologies. Following dataset selection and preprocessing, a standardized experimental setup is established, including the division of the dataset and definition of evaluation metrics such as image quality, diversity, and perceptual assessments. Each GAN enhancement undergoes training with fine-tuning of hyperparameters, with close monitoring to ensure convergence and stability. Evaluation of the small dataset challenge involves assessing the ability of trained models to generate high-quality fake license plate images despite the limited data, while texture sticking mitigation is evaluated through analysis of fake images' texture realism. Comparative analysis involves comparing and analyzing performance across enhancements, identifying strengths and weaknesses, and validating observed differences through statistical testing. Researchers interpret findings to draw conclusions about efficacy and discuss implications for fake license plate recognition systems, providing recommendations for future research in GAN-based model enhancements.

VII. CHALLENGES AND FUTURE DIRECTIONS

In assessing the challenges and future directions in GAN-based approaches for fake license plate recognition, several considerations arise:

A. Challenges and Limitations

- **Data Quality and Quantity:** Despite advancements, acquiring large, diverse, and labeled license plate datasets remains challenging. Limited dataset sizes can hinder the ability of GANs to generalize effectively, leading to overfitting or generation of unrealistic images.
- **Texture Realism:** While GANs have shown promise in generating realistic images, texture sticking remains a persistent challenge. Fake images may exhibit inconsistencies or artifacts in texture, affecting their usability in real-world applications.
- **Generalization to Variations:** Images exhibit significant variations in terms of fonts, colors, backgrounds, and positioning. GANs may struggle to capture this variability effectively, leading to suboptimal performance on unseen or diverse image styles.

B. Future Research Directions

- **Improved Data Augmentation Techniques:** Developing advanced data augmentation methods tailored specifically for license plate data can help alleviate the challenges associated with limited dataset sizes, enhancing the robustness and generalization capabilities of GANs.
- **Adversarial Robustness:** Research efforts should focus on enhancing the robustness of GAN-generated license plates to adversarial attacks. Techniques such as adversarial training, robust optimization, and adversarial detection mechanisms can help improve resilience against malicious manipulations.
- **Texture Synthesis and Realism:** Advancements in texture synthesis algorithms and perceptual loss functions can help address texture sticking issues, enabling GANs to generate fake images with more realistic and consistent textures.

By addressing these challenges and exploring these future research directions, the development of GAN-based approaches for fake LPR can be advanced, ultimately leading to more robust, accurate, and reliable systems for various applications such as surveillance, security, and traffic management.

VIII. CONCLUSION

The current review has highlighted several key findings regarding the use of GAN enhancements in mitigating challenges associated with small datasets and texture sticking in fake LPR. Key insights include the effectiveness of various GAN modifications in generating high-quality fake license plate images and the persistent challenge of texture sticking despite advancements in GAN technology.

The overall implications of GAN enhancements in addressing these challenges are profound. By leveraging GANs, researchers and practitioners can significantly improve the accuracy and robustness of fake LPR systems, particularly in scenarios with limited training data. Moreover, advancements in GAN technology enable the generation of fake license plate images that closely resemble their real-world counterparts, enhancing the generalization capabilities of recognition systems to diverse license plate styles and backgrounds.

However, ethical considerations regarding privacy, security, and potential misuse must be carefully addressed as GAN-based recognition systems become more prevalent. Overall, GAN enhancements offer promising solutions to the challenges of small datasets and texture sticking in fake license plate recognition, paving the way for more reliable and effective systems in various applications such as surveillance, security, and law enforcement.

REFERENCES

[1] C. Bartneck, C. Lutge, A. Wagner, and S. Welsh, "What Is AI?," in *An Introduction to Ethics in Robotics and AI*, C. Bartneck, C. Lutge, A. Wagner, and S. Welsh, Eds. New York, NY, USA: Springer, 2021, pp. 5–16.

[2] M. Mirza and S. Osindero, "Conditional Generative Adversarial Nets." arXiv, Nov. 06, 2014, https://doi.org/10.48550/arXiv.1411.1784.

[3] N. L. Yaacob, A. A. Alkahtani, F. M. Noman, A. W. M. Zuhdi, and D. Habeeb, "License plate recognition for campus auto-gate system," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 1, pp. 128–136, Jan. 2021, https://doi.org/10.11591/ijeecs.v21.i1.pp128-136.

[4] A. Kalpana. and A. John, "Pix2Pix GAN Image Synthesis To Detect Electric Vehicle License Plate," in *4th International Conference on Cybernetics, Cognition and Machine Learning Applications*, Goa, India,

Oct. 2022, pp. 439–443, https://doi.org/10.1109/ICCCMLA56841.2022.9989063.

[5] A. Ait Ouallane, A. Bakali, A. Bahnasse, S. Broumi, and M. Talea, "Fusion of engineering insights and emerging trends: Intelligent urban traffic management system," *Information Fusion*, vol. 88, pp. 218–248, Dec. 2022, https://doi.org/10.1016/j.inffus.2022.07.020.

[6] T. Karras *et al.*, "Alias-Free Generative Adversarial Networks," in *35th Conference on Neural Information Processing Systems*, Dec. 2021, vol. 34, pp. 852–863.

[7] A. Menon and B. Omman, "Detection and Recognition of Multiple License Plate From Still Images," in *International Conference on Circuits and Systems in Digital Enterprise Technology*, Kottayam, India, Dec. 2018, pp. 1–5, https://doi.org/10.1109/ICCSDET.2018.8821138.

[8] B. S. Prabhu, S. Kalambur, and D. Sitaram, "Recognition of Indian license plate number from live stream videos," in *International Conference on Advances in Computing, Communications and Informatics*, Udupi, India, Sep. 2017, pp. 2359–2365, https://doi.org/10.1109/ICACCI.2017.8126199.

[9] G. Alkawsi, Y. Baashar, A. A. Alkahtani, T. S. Kiong, D. Habeeb, and A. Aliubari, "Arabic Vehicle Licence Plate Recognition Using Deep Learning Methods: Review," in *Arabic Vehicle Licence Plate Recognition Using Deep Learning Methods: Review*, Penang, Malaysia, Aug. 2021, pp. 75–79, https://doi.org/10.1109/ICCSCE52189.2021.9530940.

[10] T. Karras, M. Aittala, J. Hellsten, S. Laine, J. Lehtinen, and T. Aila, "Training generative adversarial networks with limited data," in *34th International Conference on Neural Information Processing Systems*, Vancouver, BC, Canada, Dec. 2020, pp. 12104–12114.

[11] D. Habeeb *et al.*, "Deep-Learning-Based Approach for Iraqi and Malaysian Vehicle License Plate Recognition," *Computational Intelligence and Neuroscience*, vol. 2021, no. 1, 2021, Art. no. 3971834, https://doi.org/10.1155/2021/3971834.

[12] S.-K. Hung, "Image Data Augmentation from Small Training Datasets Using Generative Adversarial Networks (GANs)," Ph.D. dissertation, University of Essex, Essex, UK, 2023.

[13] A. h. Bermano *et al.*, "State-of-the-Art in the Architecture, Methods and Applications of StyleGAN," *Computer Graphics Forum*, vol. 41, no. 2, pp. 591–611, 2022, https://doi.org/10.1111/cgf.14503.

[14] X. Zhang, N. Gu, H. Ye, and C. Lin, "Vehicle license plate detection and recognition using deep neural networks and generative adversarial networks," *Journal of Electronic Imaging*, vol. 27, no. 4, Aug. 2018, Art. no. 043056, https://doi.org/10.1117/1.JEI.27.4.043056.

[15] A. Radford, L. Metz, and S. Chintala, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks." arXiv, Jan. 07, 2016, https://doi.org/10.48550/arXiv.1511.06434.

[16] J. Huang *et al.*, "Research on vehicle license plate data generation in complex environment based on generative adversarial network," in *Eleventh International Conference on Digital Image Processing*, Dec. 2019, vol. 11179, pp. 812–821, https://doi.org/10.1117/12.2539854.

[17] M. Parziale, L. Lomazzi, Z. Rastin, M. Giglio, and F. Cadini, "Unsupervised Damage Localization In Composite Plates Using Lamb Waves And Conditional Generative Adversarial Networks," *Procedia Structural Integrity*, vol. 52, pp. 551–559, Jan. 2024, https://doi.org/10.1016/j.prostr.2023.12.055.

[18] B. Martin, K. Edwards, I. Jeffrey, and C. Gilmore, "Experimental Microwave Imaging System Calibration via Cycle-GAN," *IEEE Transactions on Antennas and Propagation*, vol. 71, no. 9, pp. 7491–7503, Sep. 2023, https://doi.org/10.1109/TAP.2023.3296915.

[19] Q. Liu, S.-L. Chen, Y.-X. Chen, and X.-C. Yin, "Improving license plate recognition via diverse stylistic plate generation," *Pattern Recognition Letters*, vol. 183, pp. 117–124, Jul. 2024, https://doi.org/10.1016/j.patrec.2024.05.005.

[20] Y.-T. Wu and W.-J. Wang, "The Comparison of the Blurred License Plate Reconstruction Effects in Four Modified GANs," in *IEEE International Conference on Consumer Electronics*, Las Vegas, NV, USA, Jan. 2024, pp. 1–6, https://doi.org/10.1109/ICCE59016.2024.10444421.

[21] W. Sereethavekul and M. Ekpanyapong, "Adaptive Lightweight License Plate Image Recovery Using Deep Learning Based on Generative Adversarial Network," *IEEE Access*, vol. 11, pp. 26667–26685, Jan. 2023, https://doi.org/10.1109/ACCESS.2023.3255641.

[22] L. Zhang, P. Wang, H. Li, Z. Li, C. Shen, and Y. Zhang, "A Robust Attentional Framework for License Plate Recognition in the Wild," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 11, pp. 6967–6976, Aug. 2021, https://doi.org/10.1109/TITS.2020.3000072.

[23] M. Hijji *et al.*, "Intelligent Image Super-Resolution for Vehicle License Plate in Surveillance Applications," *Mathematics*, vol. 11, no. 4, Jan. 2023, Art. no. 892, https://doi.org/10.3390/math11040892.

[24] A. Kabiraj, D. Pal, D. Ganguly, K. Chatterjee, and S. Roy, "Number plate recognition from enhanced super-resolution using generative adversarial network," *Multimedia Tools and Applications*, vol. 82, no. 9, pp. 13837–13853, Apr. 2023, https://doi.org/10.1007/s11042-022-14018-0.

[25] N. Shvai, A. Hasnat, and A. Nakib, "Multiple auxiliary classifiers GAN for controllable image generation: Application to license plate recognition," *IET Intelligent Transport Systems*, vol. 17, no. 1, pp. 243–254, 2023, https://doi.org/10.1049/itr2.12251.

[26] Y.-H. Cheng and P.-Y. Chen, "Using Generative Adversarial Network Technology for Repairing Dynamically Blurred License Plates," in *Sixth International Symposium on Computer, Consumer and Control*, Taichung, Taiwan, Jul. 2023, pp. 126–129, https://doi.org/10.1109/IS3C57901.2023.00042.

[27] B.-G. Han, J. T. Lee, K.-T. Lim, and D.-H. Choi, "License Plate Image Generation using Generative Adversarial Networks for End-To-End License Plate Character Recognition from a Small Set of Real Images," *Applied Sciences*, vol. 10, no. 8, Jan. 2020, Art. no. 2780, https://doi.org/10.3390/app10082780.

[28] C.-C. Lin, M.-H. Hsu, and C.-Y. Yeh, "License Plate Recognition System for Taiwanese Vehicles Using Cascade of YOLOv4 Detectors," *Sensors and Materials*, vol. 35, no. 6, pp. 2129–2137, Jun. 2023, https://doi.org/10.18494/SAM4328.

[29] H. Nguyen, "A High-Performance Approach for Irregular License Plate Recognition in Unconstrained Scenarios," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 3, pp. 339–346, 2023, https://doi.org/10.14569/IJACSA.2023.0140338.

[30] T.-A. Pham, "Effective deep neural networks for license plate detection and recognition," *The Visual Computer*, vol. 39, no. 3, pp. 927–941, Mar. 2023, https://doi.org/10.1007/s00371-021-02375-0.

[31] I. H. El-Shal, O. M. Fahmy, and M. A. Elattar, "License Plate Image Analysis Empowered by Generative Adversarial Neural Networks (GANs)," *IEEE Access*, vol. 10, pp. 30846–30857, Jan. 2022, https://doi.org/10.1109/ACCESS.2022.3157714.

[32] M. M. Khan, M. U. Ilyas, I. R. Khan, S. M. Alshomrani, and S. Rahardja, "License Plate Recognition Methods Employing Neural Networks," *IEEE Access*, vol. 11, pp. 73613–73646, Jan. 2023, https://doi.org/10.1109/ACCESS.2023.3254365.

[33] "Papers with Code - PKU (License Plate Detection) Dataset." https://paperswithcode.com/dataset/pku-license-plate-detection.

[34] "Papers with Code - CD-HARD Dataset." https://paperswithcode.com/dataset/cd-hard.

[35] A. Maltsev, R. Lebedev, and N. Khanzhina, "On realistic generation of new format license plate on vehicle images," *Procedia Computer Science*, vol. 193, pp. 190–199, Jan. 2021, https://doi.org/10.1016/j.procs.2021.10.019.

[36] M. Lin, L. Liu, F. Wang, J. Li, and J. Pan, "License Plate Image Reconstruction Based on Generative Adversarial Networks," *Remote Sensing*, vol. 13, no. 15, Jan. 2021, Art. no. 3018, https://doi.org/10.3390/rs13153018.

[37] T. Karras, S. Laine, and T. Aila, "A Style-Based Generator Architecture for Generative Adversarial Networks," in *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Long Beach, CA, USA, Jun. 2019, pp. 4401–4410, https://doi.org/10.1109/CVPR.2019.00453.

[38] T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, and T. Aila, "Analyzing and Improving the Image Quality of StyleGAN," in

IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, Jun. 2020, pp. 8107–8116, https://doi.org/10.1109/CVPR42600.2020.00813.

[39] A. Pattanaik and R. C. Balabantaray, "Enhancement of license plate recognition performance using Xception with Mish activation function," *Multimedia Tools and Applications*, vol. 82, no. 11, pp. 16793–16815, May 2023, https://doi.org/10.1007/s11042-022-13922-9.

[40] T. Chakraborty, K. S. Ujjwal Reddy, S. M. Naik, M. Panja, and B. Manvitha, "Ten years of generative adversarial nets (GANs): a survey of the state-of-the-art," *Machine Learning: Science and Technology*, vol. 5, no. 1, Mar. 2024, Art. no. 011001, https://doi.org/10.1088/2632-2153/ad1f77.

[41] M. Salemdeeb and S. Erturk, "Multi-national and Multi-language License Plate Detection using Convolutional Neural Networks," *Engineering, Technology & Applied Science Research*, vol. 10, no. 4, pp. 5979–5985, Aug. 2020, https://doi.org/10.48084/etasr.3573.