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Research Article

Lane Detection in Foggy Images using Generative Adversarial Networks

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Abstract – Foggy weather conditions, especially when visibility is severely reduced, pose significant challenges for autonomous vehicles (AVs) and advanced driver assistance systems (ADAS). These adverse conditions compromise the reliability of critical perception tasks such as lane detection and road environment understanding, thereby increasing the risk to driving safety and stability. In this study, a Generative Adversarial Network (GAN)-based approach was developed to address these issues using one of the leading techniques currently employed in the literature. Using GAN models, realistic foggy road images with varying density levels were generated, and lane detection performance was evaluated on this synthetic dataset. A comparative analysis was conducted between classical image processing techniques and deep learning-based methods. The effectiveness of each approach was evaluated using the Intersection over Union (IoU) metric, which balances both accuracy and spatial coverage in region-based tasks such as lane detection. While classical methods achieved an IoU performance of 89%, deep learning-based techniques reached up to 96%. The results demonstrate that deep learning approaches significantly outperform classical methods in identifying complex road structures, particularly under foggy conditions. These findings highlight the potential of GAN-based data generation and deep learning models to enhance the robustness of perception systems under adverse weather conditions, thereby contributing to safer and more reliable autonomous driving.

Keywords – Foggy Images, Lane Detection, Generative Adversarial Networks (GAN), Deep Learning, Autonomous Vehicles

I. INTRODUCTION

Autonomous vehicles (AVs) are fundamentally changing modern transportation by improving safety and efficiency. However, the performance of AVs depends on reliable environmental perception systems, which can be compromised in adverse conditions such as fog. Autonomous vehicles and advanced driver assistance systems (ADAS), which are highly sensitive to environmental conditions, can experience significant performance losses, particularly under adverse weather conditions. Scenarios such as heavy rain, snow, fog, and night driving reduce image quality and negatively impact the reliability of systems in carrying out tasks such as lane detection and road perception. Harsh environmental factors, such as foggy weather conditions, seriously impair the performance of these systems and present substantial challenges for critical tasks like lane and road detection. In foggy environments, reduced visibility and decreased image contrast limit the effectiveness of current algorithms and increase safety risks [4].

In the existing literature, various approaches based on both traditional methods and deep learning-based models have been proposed to solve the lane detection problem under challenging environmental conditions such as fog. Among the traditional methods, image enhancement, edge detection, the Hough transform [5] and dehazing algorithms [15] are prominent, while convolutional neural network-based segmentation architectures such as U-Net [32] and SegNet [3] are widely used in deep learning-based approaches. Traditional image processing techniques focus on emphasising specific features and reducing noise. In contrast, deep learning-based approaches offer more general and flexible solutions through models trained on large datasets. However, in order for deep learning models to function effectively, diverse and large-scale datasets are usually required. The limited availability of datasets collected specifically for foggy weather conditions remains a major obstacle for research in this field [13],[24],[33].

In this study, to overcome the limitations of existing datasets, synthetic foggy images were generated using Generative Adversarial Networks (GANs), one of the contemporary methods in the literature, and the lane detection problem was analysed using these images. GAN-based data augmentation techniques were employed both to expand the available datasets and to generate realistic foggy images at different levels of intensity. The proposed method was tested on both classical image processing techniques and deep learning-based models to evaluate the performance of different approaches under challenging conditions [20].

II. Related Works

The safety and performance of autonomous vehicles cannot be sufficiently tested due to the inability to reproduce required conditions in unusual driving scenarios. Various studies have conducted detailed analyses of edge cases that autonomous driving systems may encounter. It is emphasised that, for these vehicles to operate safely, edge cases must be defined and models must be developed to address such conditions. These scenarios include sudden pedestrian crossings, unexpected vehicle manoeuvres, and rare weather conditions [36]. The artificial intelligence-based methods developed for the simulations of real-time autonomous systems facilitate the analysis of the responses of vehicles to unusual situations in the creation of the aforementioned scenarios [34].

Generative Adversarial Networks, introduced by Goodfellow et al., have emerged as a powerful class of generative models [14]. Essentially, they consist of two neural networks — a generator and a discriminator — that compete and are trained simultaneously. The generator aims to produce synthetic data samples that resemble real data, while the discriminator tries to distinguish between real and generated samples. This adversarial training enables both networks to improve, enhancing the generator's ability to produce realistic synthetic data. GANs excel at augmenting data diversity, especially for simulating rare events such as foggy conditions. In studies investigating the potential of GANs to generate various simulation scenarios for the training of autonomous vehicles, different weather conditions and rare event simulations have been used to test how autonomous systems respond to such cases [1].

Due to the limited nature of real datasets for the simulation of rare weather events such as foggy scenes, data augmentation techniques are being increasingly adopted. He et al. (2021) generated foggy images using a classical statistical method, the Winters Additive Model, and trained lane detection models using this data [17]. Sang and Norris (2024) also showed that such data augmentation techniques provide high accuracy for autonomous systems [35]. In autonomous driving, GANs, which are considered a powerful tool for generating enriched simulation datasets, have been applied through CycleGAN-based augmentation for night-time autonomous driving, and successful results have been reported [28].

In studies evaluating weather conditions, which are among the important parameters to be considered in autonomous driving, classical methods generally perform successfully under good/clear weather conditions, while showing low performance under challenging conditions such as fog [45]. In the case of fog, which is one of the harsh weather conditions, image processing algorithms play a critical role in the field of lane detection. Zhang et al. (2020) leveraged polarimetric image processing to enhance dehazing and contrast in foggy images [45]. Ghani et al. (2021), on the other hand, addressed the effects of image processing methods on lane detection under low visibility conditions and discussed the critical role of these techniques [11].

Deep learning methods, developed after classical techniques, have introduced a new dimension to the lane detection problem under adverse weather conditions. Convolutional Neural Network (CNN)-based systems have achieved successful results in low-light and foggy conditions and, through transfer learning, have enabled models to adapt to different environmental conditions [44]. Horani (2019) stated that data sharing between the vehicle and infrastructure using V2I communication improved lane detection [18]. In addition, the integration of sensors such as LiDAR and radar contributes significantly to increasing accuracy under limited visibility conditions. Sultana and Ahmed (2021) demonstrated that the system they developed for lane detection and tracking under rainy weather conditions was effective [38].

Xu and Sankar (2024) emphasised the need for algorithms adaptable to adverse weather conditions in autonomous driving systems. Their study presents artificial intelligence-based solutions for lane detection under conditions such as fog and rain [42]. Sultana et al. (2023) developed a method adaptable to both foggy and rainy weather conditions for lane detection and tracking [39]. Innovative technologies such as quantum computing, augmented reality (AR), and sensor fusion have significant potential to enable better lane detection in foggy weather conditions [42, 11]. These technologies enable vehicles to operate more safely under challenging environmental conditions.

Foggy weather conditions significantly degrade image quality in critical tasks such as lane detection in autonomous vehicles and limit the effectiveness of traditional methods. Therefore, deep learning-based specialized approaches have been developed to address these challenges. Liu et al. (2024) proposed the Masked Frequency-Color Fusion Network (MFCF-Net) to enhance lane detection performance in video-based foggy scenes. The proposed method integrates frequency and color information through a masking mechanism, allowing more accurate extraction of lane structures in low-contrast and blurry images. Their study focuses on instance-level segmentation in video frames under foggy conditions and achieves higher accuracy rates compared to conventional techniques. Such advanced network architectures enable the learning of deep features while considering the impact of fog on the image and thus present strong potential for use in conjunction with GAN-based data generation or augmentation methods [25].

Kim and Park (2022) proposed a GAN-enhanced image processing approach for vision-based lane detection under low visibility conditions. Their method improves lane detection accuracy in foggy and blurred images by enhancing the input images with GANs [23].

Wang et al. (2024) presented a multi-scale feature fusion technique for robust lane detection in foggy conditions. Although not GAN-based, their approach significantly improves image quality and feature integration for better lane detection performance under adverse weather[40].

III. MATERIALS AND METHOD

In this study, a specialised GAN architecture was designed to eliminate the difficulty of lane detection in foggy road images and to improve the accuracy of lane detection by realistically and controllably adding a fog effect to clear road images. The model was implemented in Python 3.10[30], taking advantage of its extensive libraries for autonomous vehicle and image processing tasks.

A. *Creation of a Data Set*

In this study, while preparing training data for the lane detection model, the diversity and realism of the data were considered an important factor to ensure successful operation under foggy weather conditions, and three main datasets were utilised. Foggy images were obtained from the *NuScenes Fog Dataset*, which was developed to evaluate the performance of autonomous vehicle systems under real-world conditions

[27]. The *NuScenes Fog Dataset* stands out with its various foggy scenarios captured both in open areas and urban roads. This dataset, containing images that realistically simulate foggy weather conditions, has been enriched with fog effects of different intensities. These visuals were used to test and validate the performance of the lane detection algorithm in foggy environments.

Clear and sharp road images, on the other hand, were taken from the *BDD100K* [6] and *Roads Segmentation Dataset* [31]. These datasets include high-resolution road images with various lane structures. In particular, they consist of images covering a range of situations such as different road types (urban roads, highways, multi-lane roads) and lighting conditions (daytime, night, shaded areas). These clean and clear images were used as the base data source for the simulation of foggy images.

The BDD100K dataset is a large-scale dataset designed for research and development in autonomous driving and computer vision. This dataset contains over 100,000 images representing various scenarios captured under different weather conditions and at different times of day. These images represent diverse environments such as urban, highway, and rural areas. Each image includes detailed annotations covering various classes such as vehicles, pedestrians, traffic signs, and lane markings for object detection and semantic segmentation tasks.

The Roads Segmentation Dataset facilitates road segmentation in autonomous driving and computer vision applications. This dataset includes images captured under different road and weather conditions and provides the necessary annotations to ensure accurate segmentation of the road surface. It contains a large number of images taken in various urban and rural locations. The dataset is enriched with images including different road types (asphalt, stone, etc.) and road markings. Each image is annotated at pixel level to enable accurate segmentation of the road surface.

B. *Generative Adversarial Networks*

The GAN *(Generative Adversarial Networks)* architecture consists of two core components—the Generator and the Discriminator—which operate in an adversarial yet cooperative manner. The competitive learning process between these two components enables the generation of realistic and high-quality images [14]. The Generator aims to produce realistic data from a random input vector. Its objective is to deceive the *Discriminator* by generating data that appears to originate from the true data distribution. The Discriminator, on the other hand, receives both real and generated data and attempts to distinguish whether the input is real or synthetic. Its goal is to correctly identify the data produced by the *Generator* as fake. This architecture is formulated as an optimisation problem based on a minimax game-theoretic framework.

The fundamental mathematical model of GANs is expressed as follows:

$$M_G M_D \, V(D,G) = E_{x\sim p_{\text{data}}(x)}[\log D(x)] + E_{z\sim p_z(z)}\left[\log\left(1 - D\big(G(z)\big)\right)\right] \tag{1}$$

Where;

G: Generator model,

D: Discriminator model,

x: Real data sample,

z: Random noise vector,

$p_{\text{data}}(x)$: Distribution of real data,

$p_z(z)$: Represents the distribution of noise vectors.

Thanks to this adversarial structure, the *Generator* continuously tries to make the data it produces more and more realistic, while the *Discriminator* constantly improves itself to better distinguish fake data [14]. Figure 1 shows the GAN architecture used in the study.

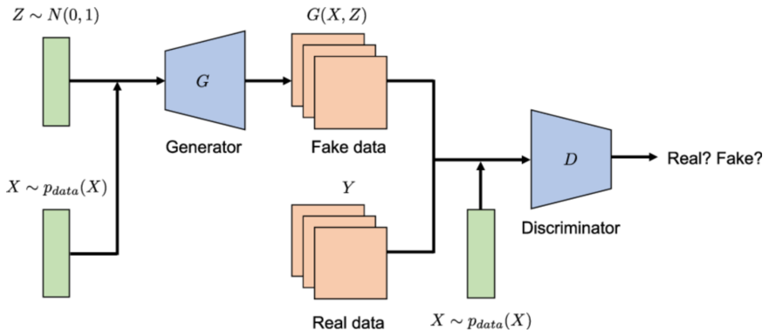

Fig. 1 Used GAN Model Structure

During the data preparation phase, fog effects of varying intensities were added to clean road images obtained from the *BDD100K* and *Roads Segmentation Dataset*, inspired by the foggy environment characteristics provided by the *NuScenes Fog Dataset*. For this purpose, a Generative Adversarial Network (GAN) architecture, which has proven highly effective in challenging tasks such as generating foggy images, was employed. *A U-Net-based Generator and a Discriminator* component were used. The U-Net architecture enables the preservation of low-resolution details while generating fog effects in a manner that is both aesthetically pleasing and physically realistic [32]. The Generator applies fog effects of different intensities onto clean road images. To simulate various foggy conditions and improve the generalisation capacity of the model by increasing the diversity of foggy images, artificial fog layers were added to the data. Different levels of fog intensity were adjusted (e.g., β = 0.005, β = 0.01, β = 0.02) to model different scenarios: light fog for near-clear weather conditions, moderate fog for typical foggy weather, and heavy fog to simulate challenging low-visibility environments. Each foggy image was incorporated into the training process of the lane detection model to enhance its robustness and accuracy by imitating diverse weather conditions.

The *Discriminator* component of the GAN was trained to distinguish between real foggy images and the generated ones, thereby guiding the *Generator* to produce more realistic fog effects. This dynamic interaction between components in the *adversarial training* process contributed to improved realism and visual quality in the generated images, resulting in fog effects that were natural, high-quality, and consistent with real foggy images.

To enhance the foggy road images generated using the GAN-based method, several preprocessing steps were applied, including grayscaling, dehazing, CLAHE, and Gaussian blurring (Figure 2).

By applying grayscaling, colour information was removed from the images, converting them to a format that retains only brightness information. This step facilitated visual enhancement and simplified subsequent processing stages [12]. Dehazing techniques were applied to reduce visual degradation in foggy images. These techniques improved contrast and sharpness in the images, thereby positively affecting the accuracy of lane detection [16]. The CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm was used to enhance image contrast, making lane markings more discernible in foggy conditions [29]. Gaussian blurring was applied to reduce high-frequency noise in the images. This method improved the accuracy of edge detection and the lane detection process [22]. The processed foggy images obtained through these steps formed the dataset used for training the lane detection model.

As a result, a comprehensive dataset containing both clean and foggy road images was prepared, providing an effective training infrastructure for lane detection under foggy weather conditions. The final dataset comprises a total of 35,000 images encompassing light, moderate, and heavy fog levels.

Fig. 2 Grayscale conversion

Fig. 3 Dehazing

Fig. 4 CLAHE enhancement

Fig. 5 Gaussian blur filtering

C. *Lane Detection*

In this study, lane detection was carried out using both classical and deep learning methods such as Canny edge detection, ROI (Region of Interest), Hough transform, and linear line detection.

The *Canny Edge Detection* algorithm, a classical image processing technique, was employed to detect edges in the images during lane detection. This method identifies edges by detecting abrupt changes in intensity and produces thin, distinct edge structures that are resistant to noise [5]. After detecting lane edges in foggy images using this method, linear lane lines were identified using the Hough transform.

Thev *Hough Transform* is a technique used to detect linear lane lines based on the results of edge detection. Each pixel is mapped to a parameter space (e.g., slope-intercept or polar coordinates for lines), allowing pixels located on the same line to intersect at the same parameter combination [8].

Another classical technique, *ROI (Region of Interest)*, defines a restricted area within the image where processing is to be applied. This reduces processing time, lowers computational cost, and allows for more accurate detection of target objects, such as lane markings. In the context of lane detection, ROI regions were selected to analyse only the relevant parts of the road. In particular, the lower portion of the image—corresponding to the area in front of the vehicle—was chosen as the *ROI* to minimise the influence of irrelevant elements such as sky, buildings, or trees [4]. This not only accelerated the image processing pipeline but also improved detection accuracy. The use of ROI helps exclude unnecessary data from processing, thus reducing runtime and enhancing detection performance [46].

In deep learning methods, the U-Net neural network architecture was adopted during training to perform image segmentation and lane detection, with the aim of identifying the most suitable hyperparameters for the task. Originally developed for image segmentation tasks, this architecture is widely used in applications requiring pixel-level localisation, such as lane detection.

The model's *encoder* extracts semantic features from the input image via convolutional layers with 64, 128, and 256 filters, respectively. The decoder then progressively restores low-resolution representations back to their original resolution using transpose convolution (up-convolution) layers, as in the standard U-Net design. Thanks to U-Net's symmetric structure and skip connections, both high-level semantic and low-level spatial information are preserved, enabling precise segmentation [32].

During training, hyperparameters were optimised: the learning rate was set to 0.001, batch size to 16, and the number of epochs to 200, with adjustments made depending on specific conditions.

In both the encoder and decoder blocks shown in Figure 3, traditional 3×3 convolutional layers were used. Furthermore, dilated convolutions were employed to extract broader contextual and detailed features. This approach was observed to yield high accuracy in accurately modelling foggy environments.

Dilated convolution increases the spacing between filter elements, allowing a larger receptive field and thereby capturing more contextual information. This is particularly effective for identifying small details and long-range features in images. Additionally, dilated convolution enables the network to analyse a wider context without the need for a deeper architecture, thereby reducing computational load [43]. This property is beneficial for tasks such as lane detection, where fine details are critical.

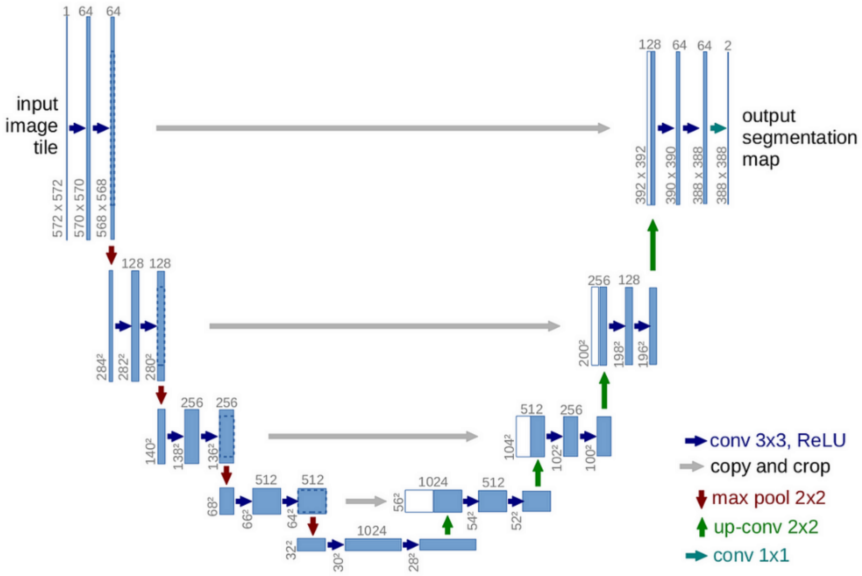

Fig. 6 3x3 Convolutional Layers

IV. RESULTS

Thanks to the GAN structure developed in the study, a large dataset with varying fog densities was obtained. This dataset was used to train a detection model specifically optimised for lane detection under foggy weather conditions. Additionally, the generated dataset was systematically tested to enhance the model's generalisation ability and to assess the robustness of the algorithm under different fog scenarios. In the field of image processing, the literature includes many different metrics used during the evaluation phase. The metric known as *Accuracy*, which expresses the overall accuracy rate of the lane detection process, is defined as the ratio of correctly classified pixels to the total number of pixels, and is used to assess the overall performance of the model. In this study, Classical methods achieved 59.36%, accuracy, while the deep learning approach improved performance to 96.76%. In the literature, accuracy rates above 85% are generally considered acceptable for image segmentation tasks such as lane detection [26]. However, in critical driving scenarios, an accuracy rate above 90% is targeted.

To evaluate the model's overall performance more precisely, the F1 Score—which balances precision and recall—was also employed. As the harmonic mean of Precision and Recall, the F1 score is particularly suitable for evaluating model performance on imbalanced datasets [37]. Using the classical method, the values Precision = 0.4482 and Recall = 0.9056 yielded an F1 score of 0.5996. With the deep learning-based approach, Precision = 0.6512 and Recall = 0.8077 resulted in an F1 score of 0.7290. Generally, an F1 score above 70% is regarded as a satisfactory level of success, while scores exceeding 80% indicate high performance.

For lane detection, the *Intersection over Union (IoU)* metric was used to measure the degree of overlap between the detected lanes and the ground truth lanes. IoU represents the ratio of the intersection to the union of the predicted and actual regions, and is widely used to assess segmentation accuracy [9]. IoU scores were calculated according to Equation 2, considering *the rates of false positives and false negatives* to evaluate detection errors. In a quantitative comparison, The classical method yielded an IoU of 0.89, surpassed by the U-Net model (IoU = 0.96), clearly demonstrating the superiority of deep learning-based approaches under challenging weather conditions. Although acceptable thresholds vary by application area, IoU values above 50% (0.5) are generally considered adequate, while values above 70% (0.7) are interpreted as indicative of high performance.

$$IoU = \frac{|A \cap B|}{|A \cup B|} \tag{2}$$

A: Predicted area (predicted mask),

B : Ground truth area (ground truth mask),

$|A \cap B|$: Intersection area (correctly predicted pixels),

$|A \cup B|$: Union area (total relevant pixels),

$p_{\text{data}}(x)$: Represents the distribution of real data.

In addition, the *Peak Signal-to-Noise Ratio (PSNR)* metric—commonly used to measure structural integrity and quantitatively assess image quality—was also employed. PSNR is used to evaluate how close the noise level is to the reference image. In the literature, PSNR values above 30 dB are considered indicative of acceptable quality, while values above 40 dB represent high quality. In this study, a PSNR value of approximately 12.6 dB was obtained between the foggy images generated by the GAN and the corresponding clear images. This low value indicates that the images are highly degraded, demonstrating that the model has successfully simulated foggy conditions [19].

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{3}$$

MAX_I: Maximum pixel value in the image (typically 255),

MSE: Mean Squared Error.

The results obtained in this study propose a Generative Adversarial Networks (GAN)-based approach to address the challenges faced by autonomous vehicles in critical tasks such as lane detection under foggy weather conditions. Through the use of the GAN architecture, a broad and diverse dataset representing real-world foggy conditions was created using synthetically generated foggy road images (Figure 4). By simulating varying intensities of fog, these images enhance lane detection capabilities under adverse environmental conditions, enabling the developed models to align more closely with real-world scenarios. Consequently, the proposed method provides a robust data preprocessing and training framework that enables effective lane detection even under foggy conditions. The model is designed to exhibit adaptive performance depending on both fog density and road type.

Moreover, this study enabled a comparative evaluation of lane detection performance using classical image processing techniques and deep learning-based approaches on GAN-generated foggy road images. The results demonstrated that deep learning-based models significantly outperformed classical methods under low-visibility conditions, offering higher accuracy and reliability (Figure 5). The model's high performance in foggy weather is of critical importance for autonomous vehicle systems and traffic safety applications.

Fig. 7 Original Image

Fig. 8 Image Generated with GAN

Fig. 9 Lane Detection with Classical Method

Fig. 10 Lane Detection with Deep Learning Method

V. CONCLUSION

This study proposes a novel data augmentation and modeling approach to improve AV safety under foggy conditions. The aim is to enhance the generalisability of the method by focusing on more extensive datasets covering diverse weather scenarios and on more complex GAN architectures. To this end, the development of a multi-task deep learning architecture is planned, which targets the simultaneous detection of both traffic signs and road lanes under foggy conditions. Existing systems typically focus on detecting a single object type (e.g., lane detection or sign recognition), which can compromise the reliability of autonomous driving systems. Therefore, the proposed model aims to provide an artificial intelligence solution capable of accurately detecting both traffic signs and road lanes simultaneously, even in low-visibility and challenging environmental conditions.

In the current study, deep learning methods were observed to yield significantly higher accuracy in lane detection under foggy weather when compared to classical techniques. Based on this finding, future work will continue to develop the lane detection module using a deep learning-based architecture. However, the task of traffic sign detection in foggy environments remains a significant research challenge due to complex visual distortions. For this reason, the relevant literature will be thoroughly reviewed to identify the most effective method or combination of methods for accurate traffic sign detection under foggy conditions.

REFERENCES

[1] Alghodhaifi, Hesham, and Sridhar Lakshmanan. 2021. “Autonomous Vehicle Evaluation: A Comprehensive Survey on Modeling and Simulation Approaches.” IEEE Access 9: 151531–66.Alptekin, A., & Yakar, M. (2020). Determination of pond volume with using an unmanned aerial vehicle. Mersin Photogrammetry Journal, 2(2), 59-63.

[2] Aramendia, Alejandro Ito. 2025. “The u-Net : A Complete Guide | Medium.” https://medium.com/@alejandro.itoaramendia/decoding-the-u-net-a-complete-guide-810b1c6d56d8.

[3] Badrinarayanan, Vijay, Alex Kendall, and Roberto Cipolla. 2017. “Segnet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation.” IEEE Transactions on Pattern Analysis and Machine Intelligence 39 (12): 2481–95.

[4] Bar Hillel, Aharon, Ronen Lerner, Dan Levi, and Guy Raz. 2014. “Recent Progress in Road and Lane Detection: A Survey.” Machine Vision and Applications 25 (3): 727–45.

[5] Canny, John. 1986. “A Computational Approach to Edge Detection.” IEEE Transactions on Pattern Analysis and Machine Intelligence, no. 6: 679–98.

[6] “Data Download BDD100K Documentation.” 2025. https://doc.bdd100k.com/download.html.

[7] Dosovitskiy, Alexey, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun. 2017. “CARLA: An Open Urban Driving Simulator.” In Proceedings of the 1st Annual Conference on Robot Learning, 1–16.

[8] Duda, Richard O, and Peter E Hart. 1972. “Use of the Hough Transformation to Detect Lines and Curves in Pictures.” Communications of the ACM 15 (1): 11–15.

[9] Everingham, Mark, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. 2010. “The Pascal Visual Object Classes (Voc) Challenge.” International Journal of Computer Vision 88: 303–38.

[10] Geiger, Andreas, Philip Lenz, Christoph Stiller, and Raquel Urtasun. 2013. “Vision Meets Robotics: The KITTI Dataset.” International Journal of Robotics Research (IJRR).

[11] Ghani, Hadhrami Ab, Rosli Besar, Zamani Md Sani, Mohd Nazeri Kamaruddin, Syabeela Syahali, Atiqullah Mohamed Daud, and Aerun Martin. 2021. “Advances in Lane Marking Detection Algorithms for All-Weather Conditions.” International Journal of Electrical & Computer Engineering (2088-8708) 11 (4).

[12] Gonzalez, Rafael C, and Richard E Woods. 2018. Digital Image Processing. 4th ed. Pearson.

[13] Gonzalez, and Wintz. 1977. “Digital Image Processing.” Reading.

[14] Goodfellow, Ian, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. “Generative Adversarial Nets.” Advances in Neural Information Processing Systems 27.

[15] He, Kaiming, Jian Sun, and Xiaoou Tang. 2010. “Single Image Haze Removal Using Dark Channel Prior.” IEEE Transactions on Pattern Analysis and Machine Intelligence 33 (12): 2341–53.

[16] ———. 2011. “Single Image Haze Removal Using Dark Channel Prior.” IEEE Transactions on Pattern Analysis and Machine Intelligence 33 (12): 2341–53. https://doi.org/10.1109/TPAMI.2010.168.

[17] He, Yu, Jun Ding, Huaqiang Teng, Xiaofei Han, Yayu Chen, and Wenju Zhou. 2021. “Visibility Detection and Prediction of Foggy Highway Based on Lane Line Detection and Winters Additive Model.” In 2021 40th Chinese Control Conference (CCC), 7254–59. IEEE.

[18] Horani, Modar. 2019. “Improved Vision-Based Lane Line Detection in Adverse Weather Conditions Utilizing Vehicle-to-Infrastructure (V2I) Communication.” PhD thesis, Oakland University.

[19] Hore, Alain, and Djemel Ziou. 2010. "Image Quality Metrics: PSNR Vs. SSIM." In 2010 20th International Conference on Pattern Recognition, 2366–69. IEEE.

[20] Isola, Phillip, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. 2017. "Image-to-Image Translation with Conditional Adversarial Networks." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1125–34.

[21] Iwayama, Megumi, Stephen Wu, Chang Liu, and Ryo Yoshida. 2022. "Functional Output Regression for Machine Learning in Materials Science." Journal of Chemical Information and Modeling 62 (20): 4837–51.

[22] Jain, Anil K. 1989. Fundamentals of Digital Image Processing. Prentice Hall.

[23] Kim, H., and S. Park. 2022. "Vision-Based Lane Detection Under Low Visibility Using GAN-Enhanced Images." The Visual Computer 38: 1234–47. https://doi.org/10.1007/s00371-022-02156-7.

[24] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. 2015. "Deep Learning." Nature 521 (7553): 436–44.

[25] Liu, Ye, Lei Zhu, and Xing Wang. 2024. "Masked Frequency-Color Fusion Network for Video Instance-Level Hazy Lane Detection." The Visual Computer 40 (10): 4449–61. https://doi.org/10.1007/s00371-024-03011-2.

[26] Long, Jonathan, Evan Shelhamer, and Trevor Darrell. 2015. "Fully Convolutional Networks for Semantic Segmentation." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 3431–40.

[27] "nuScenes Fog Augmented Samples for Bad Weather Pre." 2025. https://www.kaggle.com/datasets/dipkumar/nuscenes-fog-augmented-samples-for-bad-weather-pre.

[28] Ostankovich, Vladislav, Rauf Yagfarov, Maksim Rassabin, and Salimzhan Gafurov. 2020. "Application of Cyclegan-Based Augmentation for Autonomous Driving at Night." In 2020 International Conference Nonlinearity, Information and Robotics (NIR), 1–5. IEEE.

[29] Pizer, Stephen M, E Philip Amburn, John D Austin, Robert Cromartie, Allen Geselowitz, Trey Greer, Bartter ter Haar Romeny, John B Zimmerman, and Karel Zuiderveld. 1987. "Adaptive Histogram Equalization and Its Variations." Computer Vision, Graphics, and Image Processing 39 (3): 355–68. https://doi.org/10.1016/S0734-189X(87)80186-X.

[30] "Python Release Python 3.10.0 Python.org." 2025. https://www.python.org/downloads/release/python-3100/.

[31] "Road Segmentation Dataset - Vehicle Dataset." 2025. https://www.kaggle.com/datasets/trainingdatapro/roads-segmentation-dataset?select=images.

[32] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. 2015. "U-Net: Convolutional Networks for Biomedical Image Segmentation." In International Conference on Medical Image Computing and Computer-Assisted Intervention, 234–41. Springer.

[33] Sakaridis, Christos, Dengxin Dai, and Luc Van Gool. 2018. "Semantic Foggy Scene Understanding with Synthetic Data." International Journal of Computer Vision 126: 973–92.

[34] Sallab, Ahmad EL, Mohammed Abdou, Etienne Perot, and Senthil Yogamani. 2017. "Deep Reinforcement Learning Framework for Autonomous Driving." arXiv Preprint arXiv:1704.02532.

[35] Sang, I-Chen, and William R Norris. 2024. "A Robust Lane Detection Algorithm Adaptable to Challenging Weather Conditions." IEEE Access.

[36] Shalev-Shwartz, Shai, Shaked Shammah, and Amnon Shashua. 2017. "On a Formal Model of Safe and Scalable Self-Driving Cars." arXiv Preprint arXiv:1708.06374.

[37] Sokolova, Marina, and Guy Lapalme. 2009. "A Systematic Analysis of Performance Measures for Classification Tasks." Information Processing & Management 45 (4): 427–37.

[38] Sultana, Samia, and Boshir Ahmed. 2021. "Lane Detection and Tracking Under Rainy Weather Challenges." In 2021 IEEE Region 10 Symposium (TENSYMP), 1–6. IEEE.

[39] Sultana, Samia, Boshir Ahmed, Manoranjan Paul, Muhammad Rafiqul Islam, and Shamim Ahmad. 2023. "Vision-Based Robust Lane Detection and Tracking in Challenging Conditions." IEEE Access.

[40] Wang, T. et al. 2024. "Multi-Scale Feature Fusion for Robust Lane Detection Under Foggy Conditions." The Visual Computer 40: 1135–49. https://doi.org/10.1007/s00371-024-03002-3.

[41] Wang, Yue, Eam Khwang Teoh, and Dinggang Shen. 2004. "Lane Detection and Tracking Using b-Snake." Image and Vision Computing 22 (4): 269–80.

[42] Xu, Cong, and Ravi Sankar. 2024. "A Comprehensive Review of Autonomous Driving Algorithms: Tackling Adverse Weather Conditions, Unpredictable Traffic Violations, Blind Spot Monitoring, and Emergency Maneuvers." Algorithms 17 (11): 526.

[43] Yu, Fisher, and Vladlen Koltun. 2016. "Multi-Scale Context Aggregation by Dilated Convolutions." In International Conference on Learning Representations.

[44] Yusuf, M Mahmud, Tajbia Karim, and AFM Saifuddin Saif. 2020. "A Robust Method for Lane Detection Under Adverse Weather and Illumination Conditions Using Convolutional Neural Network." In Proceedings of the International Conference on Computing Advancements, 1–8.

[45] Zhang, Li, Zhongjun Yin, Kaichun Zhao, and Han Tian. 2020. "Lane Detection in Dense Fog Using a Polarimetric Dehazing Method." Applied Optics 59 (19): 5702–7.

[46] Kim, Z. W., Lee, H. G., and Park, D. H., "An efficient region of interest selection for lane detection in video image," in Proc. 2008 Int. Conf. Control, Automation and Systems, 2008, pp. 1178–1181.