IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 10 June 2024, accepted 16 June 2024, date of publication 26 June 2024, date of current version 5 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3419029

RESEARCH ARTICLE

Improving Autonomous Vehicles Maneuverability and Collision Avoidance in Adverse Weather Conditions Using Generative Adversarial Networks

LEILA HAJ MEFTAH[1], ASMA CHERIF[2,3], AND RAFIK BRAHAM[1]

[1]PRINCE Research Laboratory, ISITCom H-Sousse, Sousse University, Sousse 4011, Tunisia
[2]IT Department, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia
[3]Center of Excellence in Smart Environment Research, King Abdulaziz University, Jeddah 21589, Saudi Arabia

Corresponding author: Leila Haj Meftah (leila.hajmeftah@isitc.u-sousse.tn)

This work was supported in part by the Institutional Fund Projects under Grant FPIP:1340-612-1443; and in part by the Ministry of Education and Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, Saudi Arabia.

ABSTRACT In recent years, there has been a significant increase in the development of autonomous vehicles. One critical task for ensuring their safety and dependability, is obstacle avoidance in challenging weather conditions. However, no studies have explored the use of data augmentation to generate training data for Deep learning (DL) models aimed at navigating obstacles in extreme weather conditions. This study makes a substantial contribution to the field of autonomous vehicle obstacle avoidance by introducing an innovative approach that utilizes a Generative Adversarial Network (GAN) model for data augmentation, with the objective of enhancing the accuracy of DL models. The use of a GAN model to generate a training dataset and integrate images depicting challenging weather conditions has been pivotal in enhancing the accuracy of the DL models. The extensive training dataset, consisting of 64,336 images, was created using three cameras installed in VSim-AV, an autonomous vehicle simulator, thereby ensuring a diverse and comprehensive dataset for training purposes. Three DL models (ResNet50, ResNet101, and VGG16 transfer learning) were trained on this dataset both before and after applying the data augmentation techniques. The performance of the augmented models was evaluated in a real-time environment using the autonomous mode of the VSim-AV simulator. The testing phase resulted in the highest accuracy rate of 97.2% when employing Resnet101 following the implementation of GAN. It was observed that the autonomous car could navigate without any collisions, showcasing a remarkable reaction time of 0.105 seconds, thus affirming the effectiveness of the approach. The comparison between the original and augmented datasets demonstrate the originality and value of this study, showcasing its significant contribution to the advancement of autonomous vehicle obstacle avoidance technology. This paper makes significant advances to the field of autonomous vehicle navigation by exploiting Generative Adversarial Networks (GANs) to improve obstacle avoidance capabilities in severe weather conditions, hence increasing safety and dependability in real-world applications.

INDEX TERMS Autonomous-vehicles, obstacle-avoidance, avoiding collision, VSim-AV, deep learning (DL), generative adversarial network (GAN), severe weather conditions, data augmentation, fine-tuning.

The associate editor coordinating the review of this manuscript and approving it for publication was Shadi Alawneh.

I. INTRODUCTION

The field of autonomous vehicles has seen significant advancements in recent years, with the goal of creating safer and smarter transportation systems [1], [2]. The ability of autonomous vehicles to perceive and navigate their surroundings efficiently is a critical aspect. However, due to a scarcity of diverse and realistic training data, training DL models for obstacle avoidance in autonomous vehicles can be challenging [3], [4].

There are numerous approaches for avoiding obstacles that use DL techniques. However, enhancing reaction time, performance, precision, and error rate remains crucial, especially when considering challenging weather circumstances [5], [6]. To enhance the maneuvering capabilities of obstacle-avoidance systems in adverse weather conditions, extensive research has been conducted focusing on both manned and unmanned ground vehicles [7], [8].

The challenge lies in detecting and avoiding each obstacle. Although existing techniques have made substantial progress, they still encounter several limitations that raise concerns about safety and reliability. One such limitation is the ability to avoid obstacles in severe weather situations with limited time for decision-making and reaction.

To verify the capacity of DL models built to avoid obstacles for autonomous vehicles, the use of simulation is crucial. In fact, it facilitates the examination of a wide variety of edge scenarios, which, despite their rarity in real-world testing, are essential for guaranteeing the durability of obstacle avoidance algorithms [8], [9]. Thus, the use of autonomous vehicle simulators not only accelerates development but also enhances the safety and reliability of obstacle avoidance systems before their deployment in real-world scenarios. Several simulators have been developed to replicate realistic driving conditions. These simulators are essential for algorithm testing and refinement, autonomous system training, and evaluating self-driving car performance. Among the various solutions available, the VSim-AV virtual platform for AV simulation is preferred due to its open-source nature and its capability to incorporate any type of element.

Besides, a high-quality dataset is crucial for training DL models to recognize patterns and make accurate decisions. A large and representative dataset is extremely necessary in the context of autonomous vehicle research to ensure that models can navigate real-world scenarios efficiently. In this context, Generative Adversarial Networks (GAN) are employed. GAN can augment small datasets by generating synthetic data that closely resembles the original dataset's distribution, thereby expanding the training data. This synthesized data helps to mitigate the limitations posed by small datasets, enabling more robust training of DL models and improving their performance on various tasks. None of the previous research investigations have examined the crucial area of utilizing data augmentation techniques specifically designed to incorporate images simulating severe weather for training DL models in obstacle avoidance. This reveals a significant research gap, as such an approach could greatly enhance the robustness and real-world applicability of autonomous systems operating in adverse weather conditions. To fill this gap, we investigate the integration of an augmented dataset using VSim-AV 1. By incorporating GANs into the dataset refinement process, we aim to enhance its diversity and precision, thereby encompassing a broader range of real-world scenarios. This innovative approach has the potential to significantly improve the generalization capabilities of deep learning models for autonomous driving tasks.

Our research endeavors to revolutionize the authenticity and quality of training data, laying the foundation for the development of resilient and efficient autonomous vehicle systems. Our study of GAN as a data-enrichment method focuses on adding more diverse and useful samples to the dataset. These include synthetic training examples that mimic real-world obstacles in different weather conditions, like rain, snow, fog, or low-light situations. Through this methodology, we aim to empower the models to learn more effectively, ultimately driving substantial advancements in autonomous vehicle technology.

The remainder of this paper is organized as follows: Section II reviews the approaches used to assist autonomous vehicles in avoiding obstacles. Section III explains the recommended methodology. Section IV discusses simulation and research results. Section V summarizes the paper's conclusions and suggestions for future work.

II. RELATED WORKS

Autonomous vehicles are poised to revolutionize transportation systems, as their capacity to perceive and respond to their surroundings is pivotal for ensuring safety and efficiency. Deep learning has emerged as a potent tool in this realm, empowering vehicles to dynamically sense and navigate their environments. Several studies have delved into the application of deep learning models in the context of autonomous vehicles. In this section, we will scrutinize pivotal research on the utilization of deep learning in intelligent transportation, with a specific emphasis on its applications in obstacle avoidance and navigation under diverse weather conditions.

To address the prioritization of factors contributing to rear-end crashes and mitigate injury severity, the authors in [10] developed a deep learning model based on a deep residual neural network architecture that incorporates residual shortcuts. This model achieved an accuracy rate of 87%, demonstrating its effectiveness in identifying critical explanatory factors and potentially enhancing traffic safety measures. Moreover, in [11], the authors proposed a deep learning model to address the integrated problems of origin-destination estimation and traffic sensor location. This innovative model achieved an accuracy exceeding 90%, showcasing its potential to significantly enhance the precision and efficiency of traffic management systems. The applications of deep learning in various maneuvers related to autonomous vehicles have yielded promising results. These successes inspire the use of deep learning for obstacle avoidance, particularly under challenging weather conditions. This approach holds significant potential to enhance the reliability and safety of autonomous navigation in diverse environments.

A. OBSTACLE AVOIDANCE

One of the early breakthroughs in the development of DL models for obstacle avoidance in autonomous driving was the introduction of convolutional neural networks (CNNs). CNNs have proven to be highly effective in image classification tasks by automatically learning feature representations directly from raw image inputs [12]. This capability has made them well-suited for interpreting visual data obtained from sensors such as cameras, lidar, and radar. Researchers have explored various approaches to leverage CNNs for obstacle avoidance. For instance, [13] proposed a CNN-based architecture that combines a feature extraction module and a decision module. The feature extraction module captures relevant visual information from input images, while the decision module employs a fully connected layer to predict the steering actions required to avoid obstacles. The model was trained on a large dataset of annotated images captured in diverse driving scenarios and demonstrated robust obstacle avoidance in real-world environments. However, a drawback of this model is its lack of training to navigate obstacles in severe weather conditions.

Another strategy is the use of recurrent neural networks (RNNs) to capture temporal dependencies in sequential sensor data. Indeed, autonomous vehicles often rely on both spatial and temporal information to make accurate decisions regarding obstacle avoidance. By using RNNs, models can take advantage of information from previous time steps to inform their current decision-making process. Li et al. [14] proposed an end-to-end RNN-based model that takes lidar point cloud data as input and outputs steering commands. The model was trained on a dataset collected from an autonomous vehicle platform and achieved impressive results in terms of obstacle avoidance performance. However, there is a need to enhance the model's accuracy and train it to effectively navigate obstacles in adverse weather conditions.

In addition to CNNs and RNNs, other DL architectures have also been explored for obstacle avoidance in autonomous driving. For instance, Arvind and Senthilnath [3] proposed a hybrid architecture that combines reinforcement learning and DL. The model learns to navigate and avoid obstacles through interactions with the environment using reinforcement learning techniques, while a deep CNN is used to learn visual representations for obstacle detection. This hybrid approach combines the strengths of both reinforcement learning and DL to achieve effective obstacle avoidance, but, the accuracy of the model needs to be improved.

In the study by Zaghari et al. [15], a You Only Look Once (YOLO) deep learning model was implemented to navigate and avoid obstacles. This approach demonstrated an accuracy rate of 88.7%, showcasing the efficiency of YOLO in real-time object detection and obstacle avoidance tasks. Building on similar objectives, Pehlivan et al. [16] proposed using the Single Shot MultiBox Detector (SSD) approach. The SSD model achieved a higher accuracy rate of 91.2% in detecting and avoiding obstacles. The SSD's advantage lies in its ability to perform object detection and localization in a single forward pass, making it particularly suitable for applications requiring rapid processing and decision-making. In another study, Das et al. [17] introduced a model based on DeepLab, a deep learning architecture designed for semantic image segmentation. The DeepLab model was employed to detect and avoid collisions, attaining an accuracy rate of 89.8%. The use of atrous convolutions by DeepLab, which enables it to effectively capture multi-scale contextual information, significantly improves its performance in complex environments. Furthermore, Sun et al. [18] presented a novel approach named PointMoSeg for obstacle avoidance. Despite having a slightly lower accuracy rate of 87.4%, PointMoSeg offers unique capabilities in segmenting point clouds for obstacle detection. This method emphasizes the importance of spatial information and 3D segmentation in improving the understanding of the environment for obstacle avoidance tasks.

TABLE 1. Accuracy of DL models for autonomous vehicle obstacle avoidance.

Model	Accuracy (%)
Convolutional Neural Networks (CNNs) [13]	90.5
Faster R-CNN [3]	**92.3**
YOLO (You Only Look Once) [15]	88.7
SSD (Single Shot MultiBox Detector) [16]	91.2
DeepLab [17]	89.8
PointNet [18]	87.4

Numerous solutions have been proposed, e.g., [15], [16], [17], [18] (refer to Table 1) and have shown substantial potential for obstacle avoidance in autonomous driving. However, these models require improvement in terms of accuracy and the ability to handle adverse weather conditions. Indeed, autonomous navigation in bad weather poses additional obstacles due to reduced visibility, slick roadways, and unpredictable environmental factors. Recently, there has been an exploration of DL models to enhance autonomous navigation in severe weather conditions.

B. MANOEUVRABILITY IN ADVERSE WEATHER CONDITIONS

Zhang et al. [19] proposed a novel DL model called RainNet to enhance driving safety in rainy conditions. RainNet utilizes a specially designed neural network architecture and a large-scale synthetic dataset to learn how to eliminate rain streaks from input images. The results demonstrated significant improvements in model performance under rainy conditions, effectively reducing visibility degradation.

Similarly, fog poses another major challenge for autonomous navigation. To address this, Kamangir et al. [20] introduced a model named FOGNet, which leverages an encoder-decoder architecture to estimate the transmission map of foggy images. By reconstructing the clear scene from foggy inputs, FOGNet successfully enhances visibility in foggy conditions and enables more accurate perception for autonomous vehicles.

In the work by Notarangelo et al. [21], a Convolutional Neural Network (CNN) was developed to specifically address the issue of rain removal from images captured by autonomous vehicles. Their approach achieved an accuracy rate of 65%, demonstrating the potential of CNNs in mitigating the adverse effects of rain on visual data. The authors [22] explored the use of CNNs for detecting and mitigating the impact of fog on the perception systems of autonomous vehicles. Their model focuses on enhancing visibility and compensating for the loss of detail caused by foggy conditions. Cao et al. [23] introduced an innovative approach to handle "invisible" obstacles, particularly those obscured by adverse weather conditions like snow and heavy rain. They proposed a hybrid DL model that combines Convolutional and Recurrent Neural Networks (RNNs) to enhance the detection of such obstacles. Messaoud et al. [24] developed a relational deep learning framework aimed at understanding and interpreting complex weather-affected scenes. Zeng et al. [25] proposed an adaptive neural network model designed to dynamically adjust its parameters based on real-time weather conditions. Their model uses a feedback mechanism to continuously monitor and adapt to changes in the environment, maintaining high performance even in rapidly changing weather scenarios.

The DL models discussed in [21], [22], [23], [24], and [25] and shown in 2 take into account adverse weather conditions in autonomous driving. However, as indicated in table 2, there is a need for significant improvement in the accuracy of these models. Indeed, ensuring a high level of accuracy is imperative for safe and effective autonomous driving systems.

TABLE 2. DL models accuracy and precision for obstacle avoidance in adverse weather conditions.

Model	Accuracy (%)	Precision (%)	Considerations
LiDAR-based CNNs [22]	75-80	72-78	Robust, limited field
Camera-based CNNs (rain removal) [21]	65	60	Partial visibility, complex scenes
Multi-sensor Fusion (LiDAR + Camera) [23]	85	83	High accuracy, complex/sync challenges
RNNs for Trajectory Prediction [24]	70	68	Temporal dynamics, accurate detection
Deep Q-Learning (adaptive) [25]	75	74	Adapts to changes, slow training/reward
RainNet [19]	–	76.5	Enhances safety in rain, handles adverse conditions
FOGNet [20]	–	79.2	Effective in fog, robust encoder-decoder architecture

C. DATA AUGMENTATION

Data augmentation plays a crucial role in training object detection models for autonomous vehicles. Indeed, current datasets for autonomous driving are often constrained by limitations in diversity, scale, and quality. To address these challenges, numerous studies have suggested employing data augmentation strategies. These strategies aim to enhance dataset coverage and maximize the utility of existing training data, thereby improving the performance and robustness of deep learning models in autonomous driving applications [26].

Several approaches have been suggested to augment datasets for risk identification, pedestrian detection, and driving safety area classification. However, none have considered adverse weather conditions. These studies will serve as benchmarks for evaluating the effectiveness of our proposed methodology. In [27], a more comprehensive data augmentation method is introduced, focusing on pedestrian detection using image descriptions and diffusion models. This method aims to encompass a broader range of scene variations, including diverse conditions and lighting situations. A classifier is designed to select data samples for augmentation. Visual features are then extracted from image captions and transformed into high-level semantic information as textual descriptions corresponding to the samples. This approach enhances the robustness and accuracy of pedestrian detection models. The study by Lee [28] introduces an innovative framework designed to improve the discriminative ability of classifiers in identifying safe driving areas for autonomous vehicles (AVs). This framework utilizes advanced data augmentation algorithms, including generative models such as generative adversarial networks (GANs) and diffusion-based models. By leveraging these cutting-edge techniques, the framework aims to enhance the accuracy and reliability of identifying safe driving zones, thereby contributing to the overall safety and efficiency of AV operations. In [29], a deep learning model is utilized for data augmentation to tackle the issue of identifying risks associated with autonomous buses. The article explores various image data augmentation strategies to mitigate the challenge of uneven sample distribution and evaluates the efficacy of different approaches. We observed that the results obtained from using deep learning models for data augmentation are highly promising. However, no existing work has specifically applied this approach to obstacle avoidance in diverse weather conditions. This insight motivated us to explore the potential of deep learning models in tackling this particular challenge.

III. RESEARCH METHODOLOGY

This study introduces fine-tuned DL models for autonomous vehicle obstacle avoidance, as illustrated in Figure 1. By leveraging GAN for data augmentation and integrating challenging weather conditions, we aim to enhance the performance of the proposed models, which will be

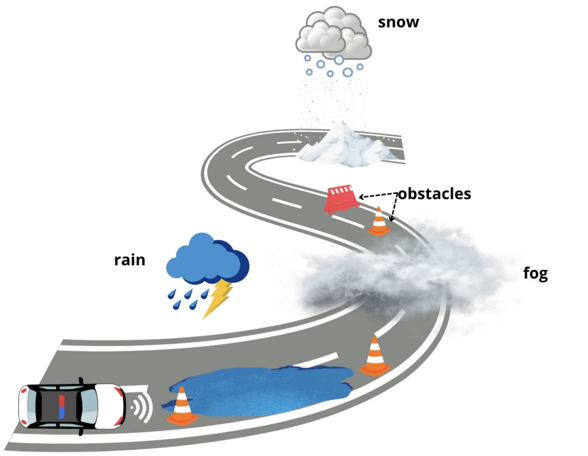


FIGURE 1. Autonomous vehicle obstacle avoidance maneuver in adverse weather conditions.

assessed using the VSim-AV autonomous vehicle simulator. The primary objective of this research is to enhance the performance and accuracy of specific DL models tailored for applications such as identifying and evading obstacles in adverse weather conditions. This section offers a comprehensive explanation of the technique employed in the study, following the steps outlined in Figure 2. Initially, we utilized the Vsim-AV simulator to generate training data by recording the driving experiences of a human driver in avoiding obstacles. Afterward, we conducted data augmentation and preprocessing operations to train a variety of deep learning models. Ultimately, we evaluated the performance of each model in the autonomous simulator mode.

A. TRAINING DATA COLLECTION

The process of collecting training data is a crucial task in DL (DL). It serves as the foundation for all DL models as well as the fuel that drives their learning and development. The quality and quantity of training data directly impact the accuracy and performance of DL models. With more and better data, a model can learn to recognize patterns, make predictions, and perform tasks with greater precision and efficiency. Moreover, a diverse and representative training dataset helps the DL model generalize its knowledge and adapt to new situations. Training a self-driving car only on sunny days would lead to a navigation model that struggles to navigate rainy streets. By including data under various weather conditions and environments, the DL model can learn to handle diverse scenarios. Moreover, images acquisition is crucial for model performance as it allows for accurate and fast obstacle identification to guarantee road safety and efficient traffic management.

Image acquisition for obstacle detection and avoidance systems can be done by several techniques, such as cameras mounted on cars or infrastructure. Monocular cameras are more popular than stereo cameras due to their lower cost and ease of installation. In the present study, we use three strategically cameras placed in the VSim-AV to capture images from diverse perspectives. The driving simulator saves frames from three front-facing cameras, capturing data from the car's perspective, including throttle, speed, and steering angle. Then, the data collected from the cameras is sent to train the model to avoid obstacles.

B. DATA AUGMENTATION

Data augmentation is the process of artificially increasing the training dataset by performing various modifications to the original data, such as rotation, scaling, flipping, cropping, and changes in brightness or contrast. It is critical for improving the performance and durability of DL models when training. This approach has several advantages in the area of DL. For instance, it reduces overfitting by exposing the model to a broader range of samples, preventing it from memorizing the training data and enhancing its ability to generalize to new data. Second, data augmentation helps create a more invariant representation, allowing the model to recognize patterns despite fluctuations in input appearance. Furthermore, this technique encourages the creation of models that are robust to real-world variability and noise. Finally, the proper use of data augmentation allows DL models to reach higher levels of accuracy and performance over a wide range of tasks, making them more versatile and useful in real-world applications [30].

GANs have emerged as an effective technique for training DL models, especially in situations where acquiring diverse and realistic training data is difficult, such as in the case of autonomous vehicles. In this context, GANs serve an important role in creating synthetic training data that may include a variety of environmental circumstances, including bad weather scenarios. Indeed, GANs allow to generate a wide set of images that imitate difficult conditions such as heavy rain, fog, or snow, which is critical for training autonomous vehicles to navigate safely in a real-world environment. Figure 3 shows the architecture of GAN and how it is used in our research. GANs consist of two neural networks: a generator and a discriminator, which are trained adversarially. The generator, denoted as G, creates synthetic data samples from random noise, whereas the discriminator, denoted as D, distinguishes between real and fake samples. Through iterative training, the generator learns to produce samples that closely resemble actual data, while the discriminator enhances its ability to detect fake samples. This adversarial process drives the generator to generate high-quality, realistic data samples. GANs are designed to learn the underlying data distribution from a finite set of high-dimensional training samples. GANs comprise two neural networks: the generator (G) and the discriminator (D), which engage in a zero-sum game with the following value function V(D, G) illustrated in equation 1:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x_{\text{real}} \sim p_{\text{data}}(x_{\text{real}})}[\log D(x_{\text{real}})] + \mathbb{E}_{x_{\text{gen}} \sim p_z(x_{\text{gen}})}[\log(1 - D(G(x_{\text{gen}})))] \tag{1}$$

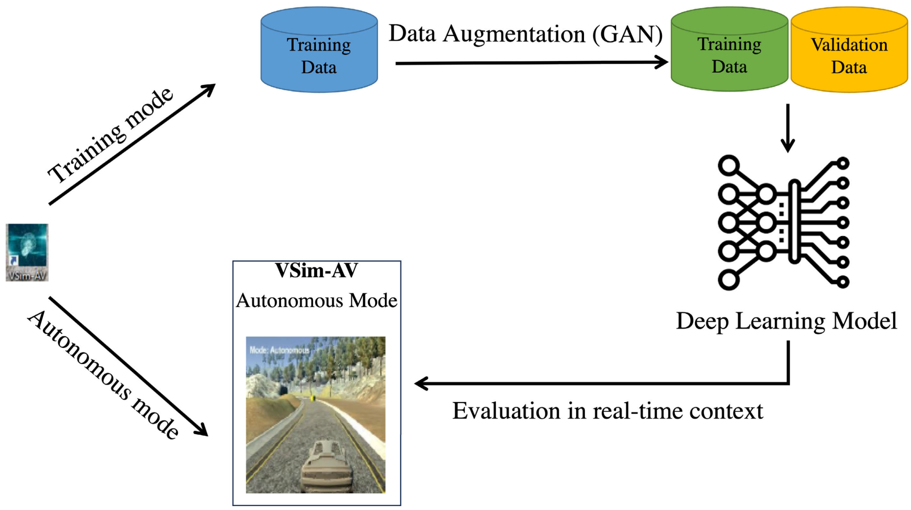


FIGURE 2. Flow chart of the proposed methodology.

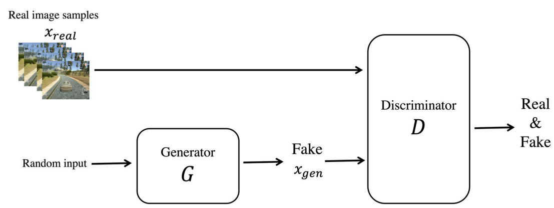


FIGURE 3. The generative adversarial networks (GAN) architecture.

The description of terms in this value function is:

$$\mathbb{E}_{x_{real} \sim p_{\text{data}}(x_{real})}[\log D(x_{real})] \tag{2}$$

This term in equation 2 represents the expectation over all real data points x_{real}. The discriminator D tries to maximize this term by assigning a high probability to real data points being real.

$$\mathbb{E}_{x_{gen} \sim p_z(x_{gen})}[\log(1 - D(G(x_{gen})))] \tag{3}$$

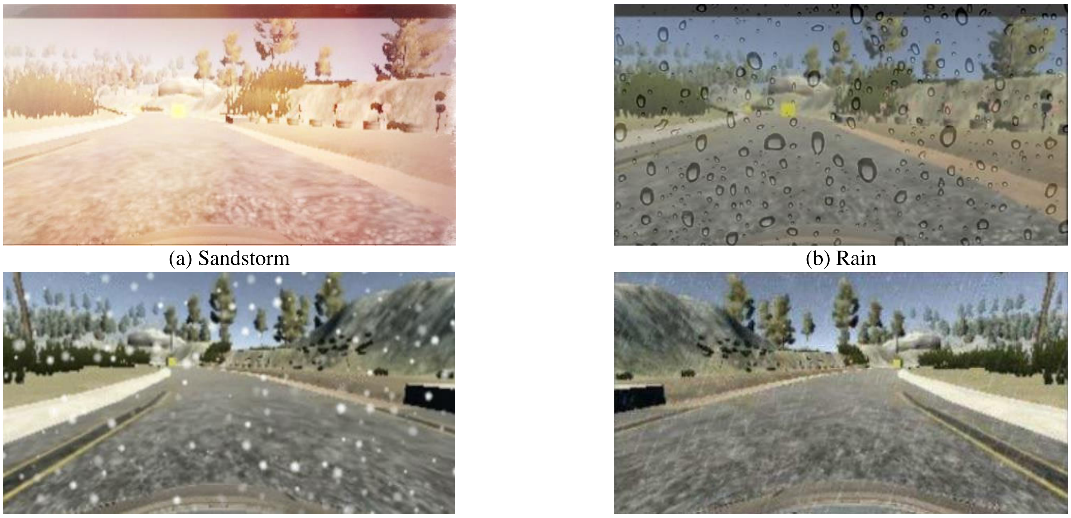
This term in equation 3 represents the expectation over all noise samples x_{gen}. The generator G aims to generate data points $G(x_{gen})$ that are similar to the real data. The discriminator aims to minimize the probability assigned to generated data points being real, thereby improving its ability to distinguish between real and synthetic data. Conversely, the generator seeks to maximize this probability by producing data points that the discriminator incorrectly classifies as real. This adversarial process drives both networks to enhance their performance continuously.

The overall process is illustrated in Algorithm 1. First, we initialize a generator network G and a discriminator network D. In each iteration, real VSim-AV data with clear weather is sampled, and random noise vectors are also sampled. Bad weather masks simulating rain, fog, or snow are generated. These masks are then applied to the real data to create masked versions. The generator takes both the noise and masked data to produce synthetic weather-affected data. The discriminator is trained to distinguish between real and synthetic data. The generator is trained to fool the discriminator and generate realistic bad weather data. The final output is the trained generator G, which can now generate new training data with diverse bad weather conditions.

Algorithm 1 GAN for Bad Weather Data Generation

Setup:
Initialize generator G and discriminator D
Set training iterations T and batch size B
repeat $t = 1$ to T
Sample data:
  Sample real VSim-AV data x_{real} with clear weather (B samples)
  Sample random noise vectors z (B samples)
  Generate bad weather data:
  Generate bad weather masks m_{bad} simulating rain, fog, or snow
  Apply masks to real data: $x_{masked} = m_{bad} \odot x_{real}$
  Generate synthetic weather-affected data: $x_{gen} = G(z, x_{masked})$
Train discriminator D**:**
for $i = 1$ to D steps **do**
    Compute discriminator loss $L_D(x_{real}, x_{gen})$
Update D using gradients of L_D
end for
Improve generator G**:**
for $i = 1$ to G steps **do**
    Compute generator loss $L_G(x_{gen}, D, x_{real})$
    Update G using gradients of L_G
end for
Output: Trained generator G for bad weather data generation

Figure 4 presents various samples of training data, that include meteorological conditions such as fog, snow, rain, and sandstorms.



(a) Sandstorm (b) Rain (c) Snow (d) Fog

FIGURE 4. Samples of generated data under different weather conditions.

C. DL MODELS

This section introduces the DL models utilized in this study, specifically, Resnet 50, Resnet 101, and VGG16 transfer learning models.

1) RESNET50 MODEL

ResNet50 [31], a member of the ResNet family, is a powerful convolutional neural network (CNN) that revolutionized the field of image recognition. It achieved record-breaking accuracy in the 2015 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [32], signifying a significant advancement in the capabilities of computer vision models. ResNet50 addresses the challenge by introducing residual connections, which resolve the problem of vanishing gradients [32]. The skip connections, also known as shortcut connections or residual connections, are a fundamental component of Residual Neural Networks (ResNets). The skip connections traverse these blocks, allowing the network to learn and preserve knowledge at varying levels. These skip connections, as depicted in Figure 5 between blocks of layers, bypass multiple network layers by directly adding earlier layer activations to later layer outputs. This simple yet effective concept enables the network to learn both low-level features and the long-term correlations between them, thereby significantly enhancing performance. Comprising 50 stacked convolutional layers, ResNet50 is organized into four residual blocks (see Figure 5), each containing multiple convolutional layers.

2) RESNET101 MODEL

ResNet-101 [33] has a remarkable 101 convolutional layers stacked like building bricks. These layers are divided into four residual blocks, each with multiple convolutional layers. Information goes through several convolutional layers before ascending residual connections to the next level. ResNet-101 has the following benefits:

- **High Accuracy:** ResNet-101 [34] indeed addresses the vanishing gradient problem effectively, which can occur in very deep neural networks. By introducing skip connections or residual connections, ResNet-101 allows gradients to flow more easily during backpropagation.
- **Deep Networks, Better Learning:** Residual connections enable deeper networks without sacrificing performance [35].
- **Fast and Efficient Training:** By bypassing layers and using residual connections, the network has fewer parameters to learn. This translates into faster training times and less computational power required.

Algorithm 2 illustrates the process of training Resnet 101 model with the used dataset after augmentation by GAN.

3) TRANSFER LEARNING USING VGG16

Deep neural network training needs a large amount of computational power. Transfer learning [36] has been investigated to reduce this initiative, and it aids in the employment of neural networks presented by many significant firms with substantial funding. The trained models provided by them can be utilized for academic research projects and companies. The hypothesis is that we applied the concept of learning transfer. Transfer learning is a technique for employing high-quality models that have been trained on huge existing datasets. According to the transfer learning theory, the characteristics learnt are likely to be transmitted to another dataset in the algorithm's lower levels. These lower level attributes will be useful in the present dataset. Indications of transfer learning usage for image recognition, object identification and categorization, and so on. According to current publications, the two articles [37], [38] were illustrated. For the transfer learning strategy to accomplish the required goal, a pre-trained model is applied, i.e. by freezing some levels and training only a few other layers. According to research, models trained on huge datasets

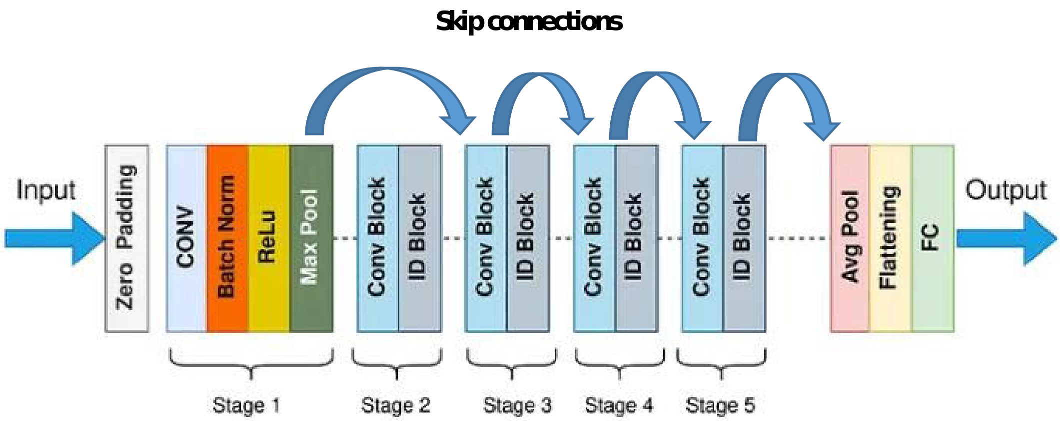


FIGURE 5. **Resnet 50 architecture.**

Algorithm 2 Training ResNet-101 With GAN-Augmented Dataset

Input: Training data X, ResNet-101 model M
Output: Trained ResNet-101 model
Initialize GAN models D and G
Initialize training parameters
Pre-train GAN to generate weather-augmented samples
Pre-train discriminator D on real and generated samples
repeat
for each training iteration **do**
    Sample real images and labels from X
    Sample noise vectors Z
    Generate augmented samples X_{aug} using G and Z
    Train D on X and X_{aug} with labels
    Freeze D, train GAN using G, D, and Z
    Update M using X_{aug}
end for
until convergence or stopping criteria
return Trained ResNet-101 model $M = 0$

such as Imagenet can often perform well for various image identification problems [39]. According to research, starting a model with the weights of a pre-trained model leads to faster convergence than starting the model with random weights [39]. VGG16 has been used to enforce the transfer learning process, and all of the blocks have been frozen from testing with the exception of the final block, which includes a max-pooling layer and three convolution layers.

The process of using transfer learning with VGG16 is illustrated in figure 6.

IV. TESTING RESULTS AND DISCUSSION

The experimental investigation is introduced in this section. It delves into the intricate framework encompassing methodologies, results, and insightful discussions. In the following, we present our experiment comparing the performance of ResNet50 and ResNet101 models, along transfer learning using VGG16, for obstacle avoidance in autonomous vehicles. We explore the impact of dataset augmentation

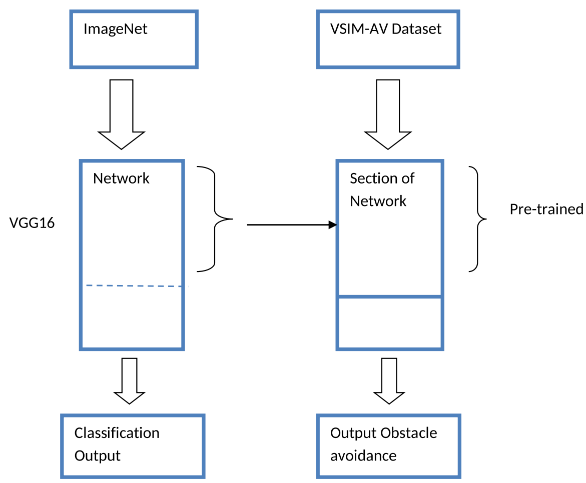


FIGURE 6. **Transfer learning with VGG16 process.**

with Generative Adversarial Networks (GANs) on model accuracy and loss. The evaluation dataset comprises images from real-world driving scenarios. We assess performance metrics, such as accuracy and loss, for each model and dataset combination.

A. EVALUATION METRICS

Several metrics can be utilized in the evaluation phase. These include:

1) ACCURACY

is the proportion of correct predictions to total number of input samples.

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of input samples}} \tag{4}$$

2) MEAN-SQUARE-ERROR(THE LOSS)

We chose the mean-square-loss function for our study (MSE). This loss function is applicable to all regression issues. The MSE imposes severe penalties for significant deviations. This function is straightforward; in a summary, it is the mean of the sum of the squared variances between the actual and

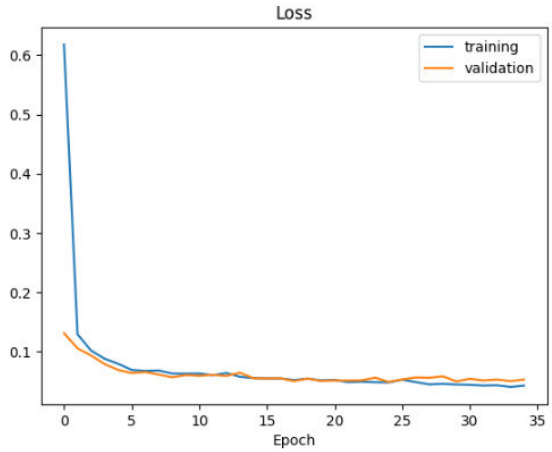


FIGURE 7. Resnet50 loss value curve.

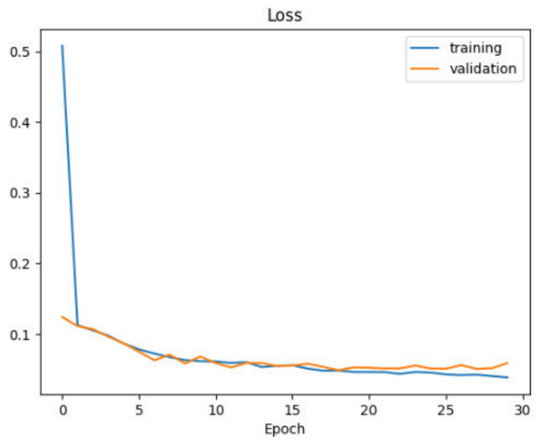


FIGURE 8. Transfer learning with VGG16 loss value curve.

anticipated values, as shown in Equation 4:

$$MES = \frac{1}{n}\sum((y_1 - \hat{y}_1)^2)) \quad (5)$$

RMSE is just the square root of the MSE:

$$RMES = \sqrt{\frac{1}{n}\sum(y_1 - \hat{y}_1)^2} \quad (6)$$

3) LOSS OPTIMIZATION

The study utilized the Adam optimizer (Adaptive Moment Estimation) to optimize the loss. For DL applications, this optimizer is often the preferred choice as it consistently outperforms more general stochastic gradient descent optimization solutions [40]. Initial testing of these models revealed a slowdown in the rate of loss change after only a few epochs. Adam calculates an adaptive learning rate and incorporates learning rate decay in its computation. The learning rate divided by the number of epochs served as the new starting point for the optimizer's decay rate. Throughout the training process, the default parameters of the Keras Adam optimizer yielded satisfactory results. In this study, the Adam optimizer was employed with a lower-than-default learning rate (1e-(3) of 1e-4, which proved to be effective.

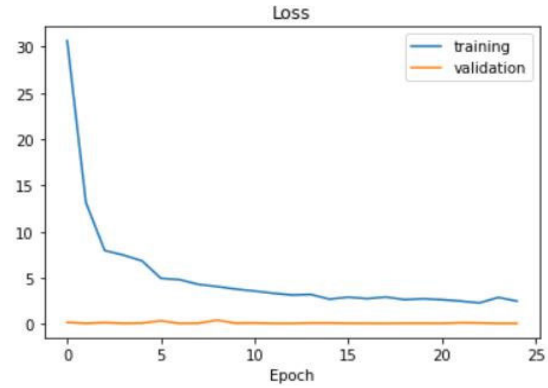


FIGURE 9. Resnet101 model loss value curve.

B. TESTING RESULTS

1) RESNET50 MODEL RESULTS

First, we compare the performance of the ResNet50 model on the original and augmented datasets generated via GAN. The accuracy and loss values for each dataset are presented in Table 3.

We observe that adding GAN-generated samples to the dataset significantly improved the ResNet50 model's accuracy to 95.3%, demonstrating their positive impact on model performance. The loss value of 0.05, as depicted in figure 7, indicates fewer errors compared to the original dataset.

2) TRANSFER LEARNING WITH VGG16 RESULTS

Similarly, we evaluate the performance of transfer learning using the VGG16 model on both the original and GAN-augmented datasets (see Table 3).

Results show the efficiency of using pre-trained weights to appropriately classify obstacles. The low loss value of 0.04 adds to the model's capacity to minimize errors during training. The GAN-augmented dataset resulted in a 2.8% increase in accuracy for the transfer learning strategy utilizing VGG16. The decreased loss value of 0.02 demonstrates improved performance over the original dataset. The figure 8 shows the loss value.

3) RESNET101 MODEL RESULTS

Lastly, we compare the performance of the ResNet101 model on the original and GAN-augmented datasets. Table 3 provides the accuracy and loss values for each dataset.

The ResNet101 model outperformed the ResNet50 and VGG16 transfer learning models, achieving 97.2% accuracy on the original dataset. The lower loss value of 0.02 indicates the model's capacity to reduce errors throughout training. Adding GAN to the dataset improved the model's accuracy by 2.8%, highlighting its potential for improving obstacle recognition and avoidance.

C. SIMULATION PHASE USING VSIM-AV

In order to validate the proposed approach, we utilize the virtual simulation platform VSim AV [41], which resembles

TABLE 3. Testing results.

Model	Dataset	Accuracy	MES (Loss)
Resnet50	Original	90.2%	0.07
	Augmented with GAN	95.3%	0.05
Resnet101	Original	94.4%	0.04
	Augmented with GAN	**97.2%**	**0.02**
VGG16	Original	93%	0.06
	Augmented with GAN	95.8%	0.04

TABLE 4. Comparative study.

Reference	Accuracy
Y.Hu and al, 2020 [13]	95.2%
Y.Quain and al, 2022 [14]	91.2%
Z.liau and al, 2021 [3]	90.8%
S.Chen and al, 2021 [17]	93.6%
L.Wu and al, 2022 [16]	94.7%
Zaghari and al, 2021 [15]	88.7%
Lee and al, 2024 [28]	90.7%
Cheng and al, 2023 [29]	92%
Ours (best result)	**97.2%**

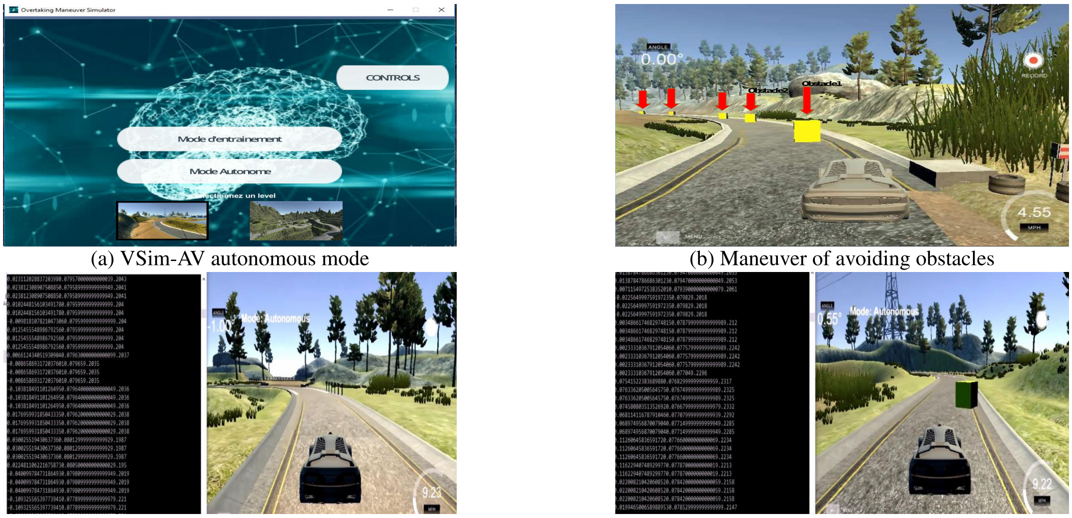
a car racing game and has been set up on two distinct routes. One route was utilized for acquiring training data, while the other was dedicated for testing purposes. The driving simulator captures frames from three front-facing cameras, recording data from the car's viewpoint, along with various driving parameters such as throttle, speed, and steering angle. The camera data is then fed into the model with the expectation that it will learn to navigate obstacles. We modified the road layout, designed a new track, and introduced obstacles to the scenario. Among these obstacles, we selected yellow cubes that are randomly placed along the course, as depicted in Figure 10. Following these modifications, the simulator is prepared to gather data on safe driving behavior. The objective is to collect road navigation data using the car's three cameras and then utilize this data as training data to develop a model for use in the simulator's autonomous mode.

The evaluation phase is conducted in the autonomous mode of the simulator, where it emulates the behavior of a real autonomous vehicle, underscoring the significance of this research and development work. No collision were observed in the designated area. The vehicle handled surprisingly well on the test track, especially since it was its first time there. It quickly adapted to the new environment. Although there were some minor performance variations on the practice track, we consider them acceptable. They illustrate the car's responsiveness to changing surroundings rather than simply following a predetermined path. In fact, these variances underscore the robustness of the model. The vehicle adeptly navigated a few challenging situations, executing precise maneuvers. It's noteworthy that none of these maneuvers were pre-planned, showcasing the model's genuine capacity to handle unexpected challenges posed by diverse weather conditions.

D. DISCUSSION

This study compared the performance of the ResNet50 and ResNet101 models, as well as transfer learning with the VGG16 model, for obstacle avoidance in self-driving vehicles in adverse weather conditions. Additionally, the study examined the effect of dataset augmentation with GAN on model performance and loss. It delved into the effectiveness of various models and the value of GAN-based dataset augmentation strategies. The proposed approach outperformed previous studies in the autonomous vehicle domain, as illustrated in table 4. This study is significant as it is one of the first to apply GAN-based data augmentation specifically for obstacle avoidance in extreme weather conditions. This approach stands out in the field of autonomous driving, where previous research has primarily concentrated on sensor fusion, classical computer vision techniques, and direct deep learning methods without leveraging advanced data augmentation strategies like GANs. Traditional data augmentation methods, such as rotation, scaling, and flipping, have been used to enhance training datasets. While these techniques are beneficial, they do not provide the same level of diversity and complexity as GAN-generated data. GANs can create highly realistic and varied training samples, significantly improving the robustness and performance of models, particularly for autonomous vehicles navigating unpredictable environments. Earlier studies have often relied on integrating data from multiple sensors (e.g., LiDAR, radar, and cameras) to enhance obstacle detection in adverse weather conditions. Although these sensor fusion methods are effective, they can be hardware-intensive and may not be as cost-efficient as improving software-based image augmentation techniques. GAN-based augmentation offers a software-centric solution that can enhance model performance without the need for expensive and complex hardware setups. However, this study should also recognize potential limitations, such as the computational cost associated with training GANs and the need for substantial computational resources. Additionally, while GANs can generate highly realistic data, the true test of robustness and reliability lies in rigorous real-world deployment and testing beyond simulated environments. Ensuring that models trained with GAN-augmented data perform well in real-world conditions is crucial for the successful application of this technology in autonomous driving.

The study's findings will contribute to enhancing the accuracy of obstacle avoidance systems for self-driving cars. Subsequent research could explore the utilization of different DL architectures, such as DenseNet, InceptionNet, and Transformers, and experiment with diverse data augmentation methodologies to improve performance. Future endeavors will be confronted with the challenge of real-world tests and validation using autonomous cars in real-world environments.



(a) VSim-AV autonomous mode
(b) Maneuver of avoiding obstacles
(c) Simulation of autonomous navigation
(d) Samples of avoiding obstacles in severe weather conditions

FIGURE 10. Virtual simulation platform: VSim-AV.

V. CONCLUSION AND FUTURE WORK

Autonomous vehicles are poised to revolutionize the transportation industry, offering enhanced mobility and safety. The identification and avoidance of obstacles, particularly in adverse weather conditions, are crucial aspects of autonomous driving. DL models play a pivotal role in promptly and accurately recognizing and avoiding obstacles. However, achieving both a swift reaction time and high accuracy remains a key objective. One method to enhance performance is to train a DL model to detect and avoid obstacles in specific settings, such as severe weather conditions (e.g., snow, fog, etc.).

In this study, we evaluated the performance of the ResNet50, transfer learning with VGG16, and ResNet101 models for obstacle avoidance in autonomous vehicles. Additionally, we explored the impact of enriching the dataset with Generative Adversarial Networks (GAN). Our assessments utilized training data from the VSim - AV real-time simulator, demonstrating the models' ability to navigate obstacles in autonomous mode, even in severe weather conditions.

The proposed study is innovative in its advancement of GAN-based data augmentation for obstacle avoidance, particularly in challenging weather conditions. Future research may focus on evaluating the efficacy of the proposed models in intricate driving scenarios, encompassing field tests on various road surfaces, and exploring the integration of alternative deep learning models for enhanced obstacle recognition and decision-making processes.

DATA AVAILABILITY

The authors used data (Colab notebooks and training datasets) saved in this drive link:

https://drive.google.com/drive/folders/1UiAHl7LIhNf2MG6QwQgB3csrC9puCbb7?usp=sharing.

REFERENCES

[1] E. Lowe and L. Guvenc, "Autonomous vehicle emergency obstacle avoidance maneuver framework at highway speeds," *Electronics*, vol. 12, no. 23, p. 4765, Nov. 2023.

[2] C. Ntakolia, S. Moustakidis, and A. Siouras, "Autonomous path planning with obstacle avoidance for smart assistive systems," *Expert Syst. Appl.*, vol. 213, Mar. 2023, Art. no. 119049.

[3] C. S. Arvind and J. Senthilnath, "Autonomous vehicle for obstacle detection and avoidance using reinforcement learning," in *Soft Computing for Problem Solving: SocProS 2018*, vol. 1. Springer, 2020, pp. 55–66.

[4] Y. Huang and Y. Chen, "Autonomous driving with deep learning: A survey of state-of-art technologies," 2020, *arXiv:2006.06091*.

[5] J. Grosset, A. Ndao, A.-J. Fougères, M. Djoko-Kouam, C. Couturier, and J.-M. Bonnin, "A cooperative approach to avoiding obstacles and collisions between autonomous industrial vehicles in a simulation platform," *Integr. Computer-Aided Eng.*, vol. 30, no. 1, pp. 19–40, Nov. 2022.

[6] M. Makhubele, "Convolutional and fully convolutional neural networks for the detection of landmarks in tsetse fly wing images," Ph.D. thesis, Dept. Comput. Sci., Stellenbosch Univ., Stellenbosch, South Africa, 2021.

[7] A. S. Akopov, L. A. Beklaryan, and M. Thakur, "Improvement of maneuverability within a multiagent fuzzy transportation system with the use of parallel biobjective real-coded genetic algorithm," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 12648–12664, Aug. 2022.

[8] W. Yao, W. Dai, J. Xiao, H. Lu, and Z. Zheng, "A simulation system based on ROS and gazebo for RoboCup middle size league," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Dec. 2015, pp. 54–59.

[9] K. Takaya, T. Asai, V. Kroumov, and F. Smarandache, "Simulation environment for mobile robots testing using ROS and gazebo," in *Proc. 20th Int. Conf. Syst. Theory, Control Comput. (ICSTCC)*, Oct. 2016, pp. 96–101.

[10] M. Owais, A. Alshehri, J. Gyani, M. H. Aljarbou, and S. Alsulamy, "Prioritizing rear-end crash explanatory factors for injury severity level using deep learning and global sensitivity analysis," *Exp. Syst. Appl.*, vol. 245, Jul. 2024, Art. no. 123114.

[11] M. Owais, "Deep learning for integrated origin–destination estimation and traffic sensor location problems," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, pp. 1–13, 2024.

[12] Y. Liu, H. Pu, and D.-W. Sun, "Efficient extraction of deep image features using convolutional neural network (CNN) for applications in detecting and analysing complex food matrices," *Trends Food Sci. Technol.*, vol. 113, pp. 193–204, Jul. 2021.

[13] X. Dai, Y. Mao, T. Huang, N. Qin, D. Huang, and Y. Li, "Automatic obstacle avoidance of quadrotor UAV via CNN-based learning," *Neurocomputing*, vol. 402, pp. 346–358, Aug. 2020.

[14] H. Li, J. Li, Z. Su, X. Wang, and J. Luo, "Research on active obstacle avoidance control strategy for intelligent vehicle based on active safety collaborative control," *IEEE Access*, vol. 8, pp. 183736–183748, 2020.
[15] N. Zaghari, M. Fathy, S. M. Jameii, and M. Shahverdy, "The improvement in obstacle detection in autonomous vehicles using YOLO non-maximum suppression fuzzy algorithm," *J. Supercomput.*, vol. 77, no. 11, pp. 13421–13446, Nov. 2021.
[16] B. Pehlivan, C. Kahraman, D. Kurtel, M. Nakp, and C. Güzelis, "Real-time implementation of mini autonomous car based on MobileNet–single shot detector," in *Proc. Innov. Intell. Syst. Appl. Conf. (ASYU)*, Oct. 2020, pp. 1–6.
[17] S. Das, A. A. Fime, N. Siddique, and M. M. A. Hashem, "Estimation of road boundary for intelligent vehicles based on DeepLabV3+ architecture," *IEEE Access*, vol. 9, pp. 121060–121075, 2021.
[18] Y. Sun, W. Zuo, H. Huang, P. Cai, and M. Liu, "PointMoSeg: Sparse tensor-based end-to-end moving-obstacle segmentation in 3-D LiDAR point clouds for autonomous driving," *IEEE Robot. Autom. Lett.*, vol. 6, no. 2, pp. 510–517, Apr. 2021.
[19] C. Zhang, H. Wang, J. Zeng, L. Ma, and L. Guan, "Tiny-RainNet: A deep convolutional neural network with bi-directional long short-term memory model for short-term rainfall prediction," *Meteorological Appl.*, vol. 27, no. 5, pp. e195–6, Sep. 2020.
[20] H. Kamangir, W. Collins, P. Tissot, S. A. King, H. T. H. Dinh, N. Durham, and J. Rizzo, "FogNet: A multiscale 3D CNN with double-branch dense block and attention mechanism for fog prediction," *Mach. Learn. Appl.*, vol. 5, Sep. 2021, Art. no. 100038.
[21] N. Notarangelo, K. Hirano, R. Albano, and A. Sole, "Transfer learning with convolutional neural networks for rainfall detection in single images," *Water*, vol. 13, no. 5, p. 588, Feb. 2021.
[22] R. Heinzler, F. Piewak, P. Schindler, and W. Stork, "CNN-based LiDAR point cloud de-noising in adverse weather," *IEEE Robot. Autom. Lett.*, vol. 5, no. 2, pp. 2514–2521, Apr. 2020.
[23] Y. Cao, N. Wang, C. Xiao, D. Yang, J. Fang, R. Yang, Q. A. Chen, M. Liu, and B. Li, "Invisible for both camera and LiDAR: Security of multi-sensor fusion based perception in autonomous driving under physical-world attacks," in *Proc. IEEE Symp. Secur. Privacy (SP)*, May 2021, pp. 176–194.
[24] K. Messaoud, I. Yahiaoui, A. Verroust-Blondet, and F. Nashashibi, "Relational recurrent neural networks for vehicle trajectory prediction," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 1813–1818.
[25] J. Zeng, J. Hu, and Y. Zhang, "Adaptive traffic signal control with deep recurrent Q-learning," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2018, pp. 1215–1220.
[26] M. Shu, Y. Shen, M. C. Lin, and T. Goldstein, "Adversarial differentiable data augmentation for autonomous systems," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2021, pp. 14069–14075.
[27] Y. Wu, Y. Xiang, E. Tong, Y. Ye, Z. Cui, Y. Tian, L. Zhang, J. Liu, Z. Han, and W. Niu, "Improving the robustness of pedestrian detection in autonomous driving with generative data augmentation," *IEEE Netw.*, vol. 38, no. 3, pp. 63–69, May 2024.
[28] D. Lee, "Driving safety area classification for automated vehicles based on data augmentation using generative models," *Sustainability*, vol. 16, no. 11, p. 4337, May 2024.
[29] S. Cheng and J. Wang, "Deep learning method for risk identification of autonomous bus operation considering image data augmentation strategies," *Traffic Injury Prevention*, vol. 24, no. 3, pp. 232–236, Apr. 2023.
[30] A. Hernández-García and P. König, "Further advantages of data augmentation on convolutional neural networks," in *Proc. Artif. Neural Netw. Mach. Learning–ICANN 27th Int. Conf. Artif. Neural Netw.*, Rhodes, Greece. Cham, Switzerland: Springer, 2018, pp. 95–103.
[31] L. H. Meftah and R. Braham, "Deep residual network for autonomous vehicles obstacle avoidance," in *Proc. Int. Conf. Intell. Syst. Des. Appl.* Cham, Switzerland: Springer, 2021, pp. 647–656.
[32] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 770–778.
[33] R. U. Khan, X. Zhang, R. Kumar, and E. O. Aboagye, "Evaluating the performance of ResNet model based on image recognition," in *Proc. Int. Conf. Comput. Artif. Intell.*, Mar. 2018, pp. 86–90.
[34] M. T. Hossain, S. W. Teng, F. Sohel, and G. Lu, "Robust image classification using a low-pass activation function and DCT augmentation," *IEEE Access*, vol. 9, pp. 86460–86474, 2021.
[35] D. Han, J. Kim, and J. Kim, "Deep pyramidal residual networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 6307–6315.
[36] L. H. Meftah and R. Braham, "Transfer learning for autonomous vehicles obstacle avoidance with virtual simulation platform," in *Proc. Int. Conf. Intell. Syst. Des. Appl.* Cham, Switzerland: Springer, 2020, pp. 956–965.
[37] N. S. Punn and S. Agarwal, "Crowd analysis for congestion control early warning system on foot over bridge," in *Proc. 12th Int. Conf. Contemp. Comput. (IC3)*, Aug. 2019, pp. 1–6.
[38] N. S. Punn and S. Agarwal, "Inception U-Net architecture for semantic segmentation to identify nuclei in microscopy cell images," *ACM Trans. Multimedia Comput., Commun., Appl.*, vol. 16, no. 1, pp. 1–15, Feb. 2020.
[39] U. Sumanth, N. S. Punn, S. K. Sonbhadra, and S. Agarwal, "Enhanced behavioral cloning based self-driving car using transfer learning," 2020, *arXiv:2007.05740*.
[40] Z. Zhang, "Improved Adam optimizer for deep neural networks," in *Proc. IEEE/ACM 26th Int. Symp. Quality Service (IWQoS)*, Jun. 2018, pp. 1–2.
[41] L. H. Meftah and R. Braham, "A virtual simulation environment using deep learning for autonomous vehicles obstacle avoidance," in *Proc. IEEE Int. Conf. Intell. Secur. Informat. (ISI)*, Nov. 2020, pp. 1–7.

LEILA HAJ MEFTAH received the M.Sc. and Ph.D. degrees in computer science from Sousse University, Tunisia, in 2012 and 2022, respectively. She is attracted by the application of several scheduling techniques to solve and implement real-life hard problems from different domains. Her research interests include algorithms, simulation, DL, intelligent transport, autonomous vehicles, and artificial intelligence.

ASMA CHERIF received the M.Sc. and Ph.D. degrees in computer science from Lorraine University, France, in 2008 and 2012, respectively. She conducted extensive research with the French Research Laboratory, Inria Nancy Grand Est. Since 2022, she has been leading the IoT Ecosystems Research Team, Center of Excellence in Smart Environment Research (CESER), King Abdulaziz University, Saudi Arabia. She is currently an Associate Professor with the Faculty of Computing and Information Technology, King Abdulaziz University. Her research interests include computational intelligence, distributed systems and communication networks, security, and the Internet of Things.

RAFIK BRAHAM is currently a Professor of computer science with ISITCom, Sousse University, Tunisia, and the Head of the Prince Research Laboratory. His research interests include the intersection of e-learning, neural networks, and computer networks. This suggests a focus on developing and improving educational technologies using artificial intelligence and efficient network structures.