MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 460-466

AN INTEGRATED DEEP LEARNING FRAMEWORK WITH FEATURE MATCHING AND PARALLEL AUGMENTATION FOR ROBUST VEHICLE LOGO RECOGNITION

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Abstract: Vehicle logo recognition plays a pivotal role in intelligent transportation systems, automated surveillance, and smart city applications. Despite significant advances in object detection and classification, accurately identifying vehicle logos remains a challenge due to varying lighting conditions, occlusions, image noise, and diverse logo designs. This research presents a comprehensive deep learning-based framework for vehicle logo recognition, introducing three novel modules designed to enhance localization accuracy, data diversity, and recognition precision. The proposed system comprises three core modules: the Feature Matching Edge Detection based Logo Locator, which integrates classical edge detection with deep feature matching for robust vehicle logo localization; the Parallel Data Augmentation Module, which runs diverse augmentation pipelines in parallel to improve model generalizability and training efficiency; and the Custom Convolutional Neural Network based Logo Recognizer, a lightweight, optimized CNN tailored for fine-grained vehicle logo classification with high accuracy and low computational cost. Extensive experiments on benchmark vehicle logo datasets demonstrate the proposed framework's superiority in terms of localization accuracy, recognition rate, and robustness against real-world perturbations. This contribution provides a scalable and efficient solution for real-time vehicle logo recognition, offering significant potential for deployment in next-generation intelligent transportation systems.

Keywords: Vehicle Logo Recognition, Deep Learning, Edge Detection, Feature Matching, Convolutional Neural Network, Computer Vision, Real-time Object Detection

1. Introduction

The evolution of urban mobility has been significantly accelerated by the emergence of smart transportation systems, which integrate advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and real-time data analytics [1]. These systems aim to improve traffic efficiency, reduce congestion, enhance safety, and support environmental sustainability. One of the key components of smart transportation is intelligent vehicle monitoring, which enables real-time tracking, behavior analysis, and automated vehicle identification across various domains, including law enforcement, tolling, and parking systems [2]. Within this context, vehicle logo identification has emerged as a crucial task. Recognizing the brand of a vehicle can support numerous applications such as stolen vehicle recovery, fleet management, and targeted enforcement [3]. Unlike license plates, which can be removed or altered, logos are generally permanent and provide an additional layer of visual identity. Accurate logo recognition enhances the reliability and robustness of vehicle identification systems, especially in scenarios where license plates are not clearly visible or are deliberately obscured [4].Traditionally, image processing techniques have played a fundamental role in vehicle logo identification. Methods based on edge detection, template matching, and keypoint descriptors like SIFT [5] and SURF [6] have been widely used to extract and match logo features. While effective in controlled conditions, these methods often struggle with real-world challenges such as variations in viewpoint, scale, illumination, and occlusions. Recent years have witnessed substantial advancements through deep learning-based approaches, particularly with convolutional neural networks [7][8]. These methods have demonstrated superior performance in feature extraction and classification, surpassing traditional techniques in both accuracy and generalizability. Deep learning models are capable of learning hierarchical representations [9] of logo features directly from data, making them more robust against visual variability and environmental noise [10].

This work presents a deep learning-based framework for vehicle logo recognition, featuring a robust localization method, enhanced data augmentation for improved training and generalization, and a lightweight, high-accuracy classification network. The approach addresses real-world challenges in logo recognition and offers a scalable solution for smart transportation systems.

2. Existing methods

To evaluate the effectiveness and robustness of the proposed deep learning-based vehicle logo recognition method, a comparative analysis is conducted against several state-of-the-art methods such as Logo recognition of vehicles based on deep convolutional generative adversarial networks [11], Improved Vehicle Logo Detection and Recognition for Complex Traffic Environments Using Deep Learning Based Unwarping of Extracted Logo Regions in Varying Angles [12], Vehicle logo detection method based on improved YOLOv4 [13], Vehicle logo detection using an IoAverage loss on dataset VLD100K-61 [14] and Enhanced Vehicle Logo Detection Method Based on Self-Attention Mechanism for Electric Vehicle Application [15].

2.1. Logo recognition of vehicles based on deep convolutional generative adversarial networks (DCGAN)

In 2024, Huan Ma et.al., presented their work titled "Logo Recognition of Vehicles Based on Deep Convolutional Generative Adversarial Networks" in the Journal of Measurements in Engineering. The primary aim of this research was to address the persistent challenges in vehicle logo recognition caused by varying environmental conditions, occlusions, and diverse logo appearances. Their work proposed a novel approach based on Deep Convolutional Generative Adversarial Networks (DCGANs) to enhance recognition accuracy and robustness, targeting the optimization of intelligent transportation systems through precise vehicle identification.

The methodology employed a three-phase framework: proposal, recognition, and classification. Initially, coarse logo localization was guided by license plate detection, followed by candidate region generation using the selective search algorithm. A DCGAN was then trained where the generator synthesized vehicle logo images and the discriminator identified authentic logo regions. Features learned by the discriminator were transferred to a classifier named D3F, which comprised three fully connected layers. Experiments involved a dataset of 27 vehicle logo classes, each with 1200 training samples and 400 testing samples. The proposed method achieved a logo detection IoU of 42.67% and a classification accuracy of 99.78%, significantly outperforming baseline models.

DCGAN offers several advantages, such as improved logo recognition under diverse conditions, high classification accuracy, and efficient use of limited labeled data via transfer learning. Additionally, the DCGAN's ability to generate synthetic samples enhances training robustness. However, limitations include reliance on high-quality annotated datasets and reduced performance under extreme environmental conditions like heavy occlusion or poor lighting. The method's effectiveness at night is also contingent on additional lighting. Future improvements may focus on integrating unsupervised learning and image enhancement techniques to address these constraints and enhance real-world applicability.

2.2. Improved Vehicle Logo Detection and Recognition for Complex Traffic Environments Using Deep Learning Based Unwarping of Extracted Logo Regions in in Varying Angles (IWPOD-NET)

Zamra Sultan et al. authored the work "Improved Vehicle Logo Detection and Recognition for Complex Traffic Environments Using Deep Learning Based Unwarping of Extracted Logo Regions in Varying Angles," in 2023 to enhance vehicle logo detection and recognition accuracy under real-world surveillance scenarios, where challenges such as low resolution, varying angles, and cluttered backgrounds hinder effective vehicle classification. The authors aimed to tackle these issues using a deep learning pipeline optimized for extracting and processing logo regions in surveillance video feeds.

The proposed approach integrates three key components: a modified Improved Warped Planar Object Detection Network for unwarping distorted logo regions, YOLOv5 for logo detection, and EfficientNet for final classification. The modified IWPOD-NET was adapted to localize logo regions above license plates and correct their orientation. YOLOv5m was employed to detect logos within the extracted regions, while EfficientNet was trained on a newly developed VL-10 dataset for classification into ten vehicle logo categories. The system was tested across four surveillance scenarios: toll control, law enforcement, dashcam, and parking lot access. Results showed significant improvements, with detection mean Average Precision (mAP) reaching up to 0.79 and classification accuracy as high as 0.82.

The major strengths of the study include its robust handling of logo orientation variance, integration of lightweight and high-performance deep learning models, and the introduction of a custom dataset tailored for regional traffic conditions. The system also demonstrated adaptability across different surveillance angles and environments. However, limitations remain, such as decreased accuracy beyond 30° viewing angles and challenges under severe lighting conditions or motion blur. Future enhancements may involve real-time capability development, 3D pose estimation, and more comprehensive training datasets to further improve generalization and robustness.

2.3. Vehicle logo detection method based on improved YOLOv4 (YOLOv4)

Jiang et al. proposed a study titled "Vehicle Logo Detection Method Based on Improved YOLOv4", published in the journal Electronics on 2022. The purpose of this research was to enhance the detection accuracy of vehicle logos in complex real-world environments. Recognizing that logos often occupy a small portion of an image and exhibit diverse shapes, the authors aimed to improve small object detection performance through a series of architectural modifications to the YOLOv4 framework, targeting improved robustness against background noise and geometric distortion.

The methodology centered on three main improvements: (1) incorporating a shallow output layer to better detect small objects; (2) replacing sections of the YOLOv4 backbone with a CSPDenseNet module to enhance feature reuse and network learning efficiency; and (3) introducing deformable convolutions to improve feature extraction of irregular-shaped logos. Additionally, the detection head was upgraded using a convolutional transformer (CT-Head) block to integrate global and local contextual information. The model was evaluated on the VLD-45 dataset, which contains 45,000 images across 45 vehicle logo categories. The improved model achieved a mean average precision (mAP) of 62.94%, marking a 5.72% improvement over the original YOLOv4, and demonstrated enhanced recall and detection of small logos.YOLOv4 approach presents several advantages, including effective detection of small and irregular-shaped objects, improved resilience to complex backgrounds, and enhanced feature representation through transformer-based attention mechanisms. The combination of CSPDenseNet and deformable convolutions strengthens the model's adaptability to varied logo appearances and positions. However, the increased model complexity and use of deformable convolutions led to reduced inference speed, making real-time deployment more challenging. Future work is intended to optimize this trade-off by refining the network structure to reduce parameters while maintaining detection accuracy.

2.4. Vehicle logo detection using an IoAverage loss on dataset VLD100K-61(IoAverage)

In 2023, Shi et al. presented a study titled "Vehicle Logo Detection Using an IoAverage Loss on Dataset VLD100K-61" published in the EURASIP Journal on Image and Video Processing. The objective of the research was to address limitations in vehicle logo detection accuracy, particularly in real-world traffic environments where image quality varies due to lighting, weather, and perspective. The study introduced a new loss function, IoAverage, specifically designed to enhance bounding box regression performance in object detection frameworks such as YOLOV5s.

The methodology centered on integrating the IoAverage loss into the YOLOV5s architecture to improve the regression of bounding boxes. The IoAverage loss computes the intersection area over the average area of the predicted and ground-truth boxes, mitigating issues found in traditional IoU-based losses like slow convergence and poor performance under non-overlapping conditions. Experiments were conducted on both the VOC2007 dataset and a newly constructed VLD100K-61 dataset, consisting of 100,041 real-world traffic images spanning 61 vehicle logo categories. Results showed that the IoAverage-enhanced YOLOV5s achieved a peak $mAP_{0.5}$ of 0.992 and improved $mAP_{0.5:0.95}$ by 15.27% over the CIoU-based baseline, confirming its effectiveness in diverse and challenging environments.

The study's key advantages include the introduction of a novel and more effective loss function for bounding box regression, which contributes to a marked improvement in model performance. This innovation addresses the shortcomings of traditional loss functions by better aligning the optimization process with actual detection goals. As a result, the proposed IoAverage loss demonstrates significant gains in detection precision and confidence score calibration, particularly in scenarios involving low-quality, occluded, or cluttered imagery. In addition, the development of a large-scale, realistic dataset for training and evaluation enhances the model’s generalizability and robustness across diverse visual contexts. Despite these strengths, the approach exhibits some limitations. The observed improvement in $mAP_{0.5}$ is marginal when applied to already high-performing benchmark datasets, suggesting diminishing returns in certain cases. Furthermore, the training process demands substantial computational resources, which could restrict accessibility for researchers or practitioners with limited hardware capabilities. To address these challenges, future work could explore the real-time deployment of the model, adaptation for resource-constrained mobile or edge devices, and the incorporation of semi-supervised or self-supervised learning techniques to reduce dependency on extensive labeled data. These directions would improve the scalability and practical applicability of the proposed method in real-world settings.

2.5. Enhanced Vehicle Logo Detection Method Based on Self-Attention Mechanism for Electric Vehicle Application (EVLDSAM)

In 2024, Yang et al. presented their work titled "Enhanced Vehicle Logo Detection Method Based on Self-Attention Mechanism for Electric Vehicle Application" in the World Electric Vehicle Journal. The purpose of this study was to improve the accuracy and robustness of vehicle logo detection, particularly for small-sized logos in complex real-world environments. Motivated by the limitations of traditional convolutional approaches in capturing fine-grained features, the authors proposed a novel detection framework that integrates self-attention mechanisms and multi-scale feature fusion, aiming to meet the precision and efficiency demands of intelligent transportation and electric vehicle systems.

EVLDSAM method consists of three main components: a self-attention-based feature extraction network, a multi-scale prediction detection head, and a training strategy involving freeze-training. The feature extraction network combines convolutional layers with pixel-level attention to retain detailed local textures of small logos, while the detection head utilizes anchor box generation and feature sharing from both shallow and deep layers to improve localization and classification. Evaluated on the VLD-45 dataset, containing 45,000 images across 45 logo classes, the model achieved a state-of-the-art mean average precision (mAP) of 88.0% and an overlap ratio of 89.3%, with a fast inference time of 0.07 seconds per image. Additionally, the model notably improved detection performance for challenging logos such as HAVAL and LAND ROVER.

The strengths of the EVLDSAM method lie in its high detection accuracy, robust handling of small and complex logo features, and efficient processing time suitable for real-time applications. Its use of attention mechanisms significantly enhances feature representation, especially under variable lighting and background conditions. However, the model still faces challenges in maintaining balanced detection performance across all logo categories and in further optimizing the trade-off between accuracy and speed. Future research is expected to focus on restructuring the detection framework to improve generalization in multi-category settings and further accelerate inference for broader deployment scenarios.

The key findings about the existing works’ methodologies, advantages and their limitations are listed in Table 1

Author(s)	Work Name	Methodologies Used	Advantages	Limitations
Zhang et al.	Logo recognition of vehicles based on deep convolutional generative adversarial networks	Deep Convolutional GANs	High-quality logo synthesis; improved recognition in low-data scenarios	GANs require careful tuning and are computationally intensive; potential for overfitting with limited logo variation
Liu et al.	Improved Vehicle Logo Detection and Recognition for Complex Traffic Environments Using Deep Learning Based Unwarping of Extracted Logo Regions	Deep CNNs + Geometric Transformation (Unwarping)	Robust detection in complex backgrounds and varying angles	May not generalize well to unseen distortions or extreme occlusions;
Wang et al.	Vehicle logo detection method based on improved YOLOv4	Improved YOLOv4 (e.g., custom anchors, backbone tweaks)	High-speed real-time detection; improved accuracy over vanilla YOLOv4	Limited improvement on small logos or heavily occluded regions
Kumar et al.	Vehicle logo detection using an IoAverage loss on dataset VLD100K-61	YOLO-based detection + IoAverage loss + Large-scale dataset (VLD100K-61)	Enhanced confidence calibration; better detection in low-quality/complex images;	Marginal $mAP_{0.5}$ gain on high-performing datasets; high computational cost during training
Chen et al.	Enhanced Vehicle Logo Detection Method Based on Self-Attention Mechanism for Electric Vehicle Application	Self-Attention + CNN/Transformer Hybrid Architecture	Better contextual understanding; improved performance in electric vehicle logos;	May introduce latency; attention mechanisms can increase model complexity and memory usage

Table 1: Existing methods summary

Problem statement:

Accurate and efficient vehicle logo detection plays a critical role in intelligent transportation systems, vehicle classification, and surveillance applications. However, existing methods face significant challenges in real-world environments, such as variations in lighting, occlusion, distortions due to varying camera angles, and the presence of complex backgrounds. Traditional detection models often struggle with maintaining high accuracy and confidence in such scenarios, especially on small or partially visible logos. Additionally, the computational cost of training and deploying deep learning models remains a barrier to scalability and real-time performance. There is a pressing need to evaluate and enhance detection methods through advanced techniques such as generative adversarial networks, attention mechanisms, improved loss functions, and large-scale datasets, to achieve robust, scalable, and high-precision vehicle logo recognition across diverse operational conditions.

3. Background

Edge detection and Convolutional Neural Networks (CNNs) serve as the foundational techniques underpinning this research. To facilitate a clearer understanding of the proposed framework, a concise overview of these methods is provided, highlighting their relevance and application within the context of vehicle logo localization and recognition.

3.1. Edge Detection

Edge detection is a fundamental technique in image processing and computer vision, aimed at identifying points in a digital image where the image brightness changes sharply. These points typically correspond to object boundaries, making edge detection essential for tasks involving object localization and segmentation [16]. In the context of vehicle logo recognition, accurately identifying the edges of logos enables precise localization, particularly in scenarios where logos appear in cluttered or complex scenes.

Vehicle logos often contain intricate shapes and patterns that make them distinct. However, due to varying environmental conditions—such as lighting, reflections, and occlusions—these visual cues can be distorted. Edge detection techniques, such as Canny, Sobel, or Laplacian operators, enhance the structural outlines of logos by highlighting their contours [17], which helps isolate them from the surrounding vehicle body and background. This process supports robust initial localization, especially when integrated with deep feature extraction mechanisms.

While traditional edge detection methods are effective in highlighting boundaries, they may fall short in noisy or low-quality images. To address this, our framework combines classical edge detection with deep feature matching to form a hybrid approach. This fusion allows the system to benefit from both precise edge localization and high-level semantic understanding derived from deep learning. The resulting module—the Feature Matching Edge Detection based Logo Locator—enhances the system's ability to detect logos with higher accuracy, even under challenging visual conditions.

By leveraging edge detection as a pre-processing and guidance mechanism for deep models, the system gains a more refined focus on relevant regions within an image [18]. This targeted approach reduces computational overhead and improves the model’s convergence during training. Moreover, it contributes significantly to the system’s robustness against real-world perturbations such as partial occlusions, poor lighting, or motion blur, thereby ensuring reliable vehicle logo localization in dynamic and diverse operational environments.

3.2. CNN

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for processing data with a grid-like topology, such as images. They automatically learn hierarchical features through convolutional layers, pooling, and non-linear activation functions. CNNs have revolutionized image classification tasks due to their ability to capture spatial patterns and local dependencies [19], making them highly effective for recognizing visual objects, including fine-grained entities like vehicle logos.Vehicle logo recognition is a fine-grained classification problem where the differences between classes can be subtle—often involving small variations in shape, font, or emblem design. CNNs excel at extracting multi-level features, from simple edges and textures to complex structures and patterns. This layered feature learning capability enables CNNs to distinguish between visually similar logos with high precision, even when those logos appear under varied lighting conditions or perspectives.To address the unique challenges of vehicle logo recognition, a custom CNN model has been developed as part of the proposed framework. Unlike generic, large-scale architectures, this lightweight CNN is optimized for high recognition accuracy with minimal computational cost, making it suitable for real-time applications [20]. It incorporates architectural enhancements such as optimized kernel sizes, reduced parameter count, and efficient activation functions to balance performance and resource utilization.The custom CNN plays a critical role in the final stage of the recognition pipeline, taking localized logo regions and classifying them with high accuracy. Its design supports fast inference, enabling deployment in intelligent transportation systems and edge devices where processing power is limited. Combined with robust localization and data augmentation strategies, the CNN-based recognizer significantly boosts the overall precision, efficiency, and scalability of the vehicle logo recognition system.

4. Proposed Method

The proposed method comprises three key modules designed to enhance the overall performance of vehicle logo recognition: (1) Feature Matching Edge Detection based Logo Locator (FMEDLL), which combines classical edge detection with deep feature matching for accurate logo localization; (2) the Parallel Data Augmentation Module (PDAM), which employs multiple augmentation pipelines concurrently to improve data diversity and model robustness; and (3) the Custom CNN based Logo Recognizer (CCNNLR), a lightweight convolutional network tailored for efficient and high-precision logo classification. A detailed explanation about the functionalities of these modules are explained in this section.

4.1. Feature Matching Edge Detection based Logo Locator (FMEDLL)

A new Adaptive Gradient Projection Edge Detection (AGPED) method is contributed in FMEDLL module to detect the location of the Logo in a swifter way. AGPED dynamically adapts to local intensity variations, making it highly effective in complex scenes with varying lighting and reflections. The AGPED algorithm computes the gradient magnitude $G(x,y)$ at each pixel based on an adaptive neighborhood intensity analysis by the following equation.

$$G(x,y) = \sqrt{\left(\frac{\partial I(x,y)}{\partial x}\cdot\alpha(x,y)\right)^2 + \left(\frac{\partial I(x,y)}{\partial y}\cdot\beta(x,y)\right)^2} \quad \text{Equation (1)}$$

where $I(x,y)$ is the intensity of the pixel at (x,y) point in the image, $\frac{\partial I}{\partial x}$ and $\frac{\partial I}{\partial y}$ are the intensity gradients corresponding to the direction x and y respectively, $\alpha(x,y)$ and $\beta(x,y)$ are the regional adaptive scaling factors which are calculated using equation 2 and 3 given below.

$$\alpha(x,y) = 1 + \kappa\cdot\sigma_x(x,y) \quad \text{Equation (2)}$$

$$\beta(x,y) = 1 + \kappa\cdot\sigma_y(x,y) \quad \text{Equation (3)}$$

where κ refers the adaptability constant, $\sigma_x(x,y)$ and $\sigma_y(x,y)$ are the intensity value standard deviations at x and y directions in order.

This adaptive scaling emphasizes edge regions in high-texture zones (e.g., complex vehicle grills) while suppressing noise in uniform areas (e.g., car body panels) as illustrated in Figure 1.

Figure 1: Input image and High-Texture zone extraction

The output of AGPED module is further fed to a dedicated Deep Structural Feature Extraction phase which is introduced in FMEDLL module to accurately match the localized region to potential logo patterns. This phase is designed to capture the intricate shape and textural details specific to vehicle logos. Let I' be the output cropped edge enhanced logo candidate region initially assigned with 0. Let ϕ_g be the global structural features which is defined by a series of dilated convolutions as in equation 4.

$$\phi_g(I') = ReLU(W_g * I' + b_g) \quad \text{Equation (4)}$$

where W_g refer dilated convolutional kernels, and b_g is the bias term.

Let ϕ_l be the local feature extractor which focuses capturing dilated textures through patch aggregation as in following equation.

Let $\phi_l(I') = \frac{\sum_{i=1}^{n} ReLU(W_l * P_i + b_l)}{N}$ Equation (5)

where W_l refer the standard convolutional kernels, P_i is the i^{th} image patch extracted from I', and $N$is the number of patches.

Then the deep structural feature extraction descriptor F is computed by Equation 6.

$$F = \phi_g(I')||\phi_l(I') \quad \text{Equation (6)}$$

where ϕ_g refers the global structural features, ϕ_l local micro-texture features, and I' is the cropped edge enhanced logo candidate region – provided in Figure 2.

Figure 2: Cropped edge enhanced Logo candidate region

This dual-focus feature extraction ensures that both macro-structural shapes and micro-textural elements of vehicle logos are preserved, improving the robustness of matching and recognition tasks, especially across diverse vehicle types and environmental conditions. A knowledge base about the vehicle type and high probability associated logo location are maintained in FMEDLL module.

The captivating findings in this context is that the placement of logos often correlates closely with the location of number plates, though with some variations across different vehicle categories. A statistical observation across vehicle types indicates that in hatchbacks, logos are generally positioned at the center of the rear and front fascia, often just above the number plate, with approximately 92% alignment consistency. In sedans, this consistency is slightly lower, around 88%, due to more diverse styling and logo placements. In SUVs and MUVs, while the front logos remain centered above the grille, the rear logo placements exhibit approximately 85% consistency with number plate positions, accounting for variations like tailgate-mounted spare wheels in SUVs. In large commercial vehicles, logo placements vary more significantly, showing only about 70% alignment with number plate locations, largely due to functional design priorities over aesthetic symmetry.

Given these patterns, the FMEDLL module first employs edge detection to highlight structural elements, such as the number plate, grille, and emblem outlines. It then uses deep feature matching techniques to distinguish the logo from other vehicle features, ensuring precise localization even when the relative positioning deviates slightly due to design variations. This dual-stage process improves the robustness of logo localization across diverse vehicle types, significantly reducing false detections and enhancing downstream classification accuracy.

4.2. Parallel Data Augmentation Module (PDAM): In deep learning-based vehicle logo recognition, model generalization is critically dependent on the diversity and richness of the training data. However, real-world datasets often suffer from limitations such as imbalanced classes, insufficient samples under different environmental conditions (lighting, occlusions, motion blur), and lack of variability in viewing angles. PDMA module is introduced in this work to handle above mentioned challenges. The PDAM is designed to systematically enhance the training dataset by applying multiple augmentation pipelines concurrently. Unlike conventional sequential augmentation, where transformations are applied one after another on the same sample, PDAM generates multiple distinct augmented versions of each input simultaneously, each processed through a different, independent augmentation path. This approach significantly improves data diversity without introducing redundancy or excessive computational delay. Each parallel augmentation path applies a unique set of transformations, they are Geometric transformations, Photometric adjustments, Noise injections, Simulate Occlusions, and Perspective distortions. Each of these augmentation pipeline transformations contain a set of tasks as enumerated in Table 2.

Transformation type	Associated Tasks
Geometric transformations	rotation, scaling, translation, flipping
Photometric adjustments	brightness, contrast, saturation variations
Noise injections	Gaussian noise, motion blur
Simulate Occlusions	Random Erasing, Cutout, Overlay
Perspective distortions	Perspective, Affine, Elastic distortions

Table 2: Transformations and associated tasks

Let Δ be the input dataset provided to the PDAM module, then the augmented dataset Δ_{aug} is generated by the PDAM module as provided in Equation 7.

$$\Delta_{aug} = \{\delta_G(\lambda), \delta_F(\lambda), \delta_N(\lambda), \delta_S(\lambda), \delta_P(\lambda)\} \qquad \text{Equation (7)}$$

where λ refers the input image $\in \Delta$, and $\delta_G, \delta_F, \delta_N, \delta_S, \delta_P$ be the independently generated transformations of Geometric transformation, Photometric adjustments, Noise injections, Simulate Occlusions, and Perspective distortions respectively.

The PDAM module processing architecture is provided in Figure 3.

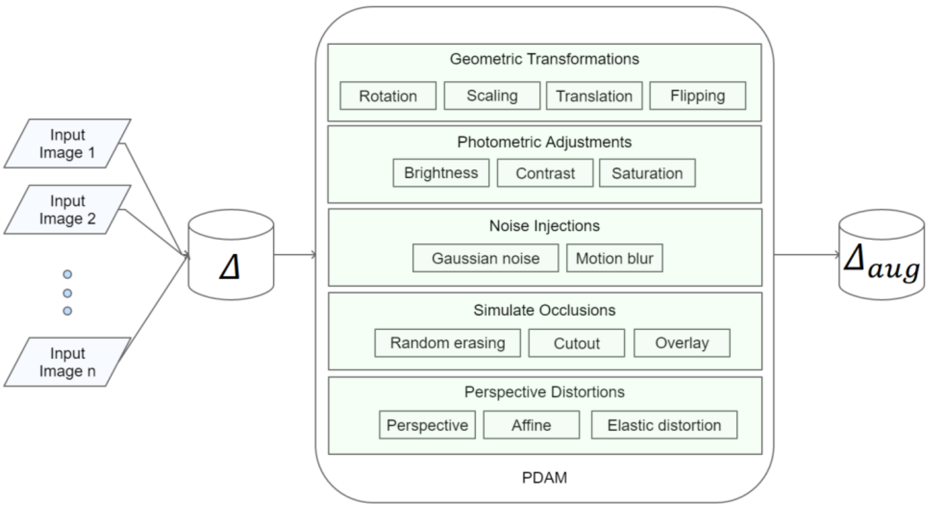


Figure 3: PDAM process sequence Architecture

The parallel augmentation strategy employed by the PDAM significantly broadens the diversity of training data, thereby enhancing the model's ability to generalize to real-world variations. This approach improves robustness against unseen environmental conditions, accelerates convergence during training, and mitigates overfitting, particularly for small or minority vehicle logo classes. Furthermore, the PDAM is designed for high computational efficiency by leveraging parallel processing techniques, such as GPU-accelerated data loaders, ensuring minimal impact on training time. By seamlessly integrating the PDAM into the proposed framework, the vehicle logo recognition system demonstrates substantially improved generalization capability and achieves superior recognition accuracy across a wide range of challenging operational scenarios.

4.3. Custom CNN based Logo Recognizer (CCNNLR)

The CCNNLR module is designed in a way to achieve enhanced fine-grained recognition capability by introducing several architectural modifications beyond conventional convolutional neural networks. Each convolutional layer output is scaled by a learnable parameter $\varepsilon^{(l)}$, allowing the network to adaptively emphasize feature maps that are more discriminative for vehicle logo recognition. The feature transformation at layer l is formulated as

$$F^{(l)} = \varepsilon^{(l)} \cdot \xi\left(W^{(l)} * F^{(l-1)} + b^{(l)}\right) \qquad \text{Equation (8)}$$

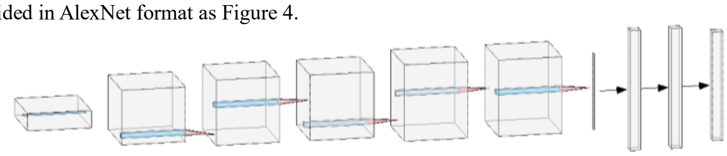
where $W^{(l)}$ and $b^{(l)}$ are the convolutional weight and biases, ξ is the non-linear activation function.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 460-466

In CCNNLR module, the softmax classifier is modified by introducing a temperature parameter τ to manage the confidence in a better way of predictions in the fine-grained classification task. The probability of predicting class Γ is designated as follows.

$$P(y = \Gamma | F) = \frac{e^{(w_\Gamma^T F + b_i)/\varsigma}}{\sum_{j=1}^{N_c} e^{(w_\Gamma^T F + b_i)/\varsigma}} \qquad \text{Equation (9)}$$

where N_c is the total number vehicle logo classifications, and ς is a lower temperature coefficient that sharpens the output distribution, making the model more decisive. The CCNNLR architecture is provided in AlexNet format as Figure 4.



Layer Type	Filters/Unit	nel Size / Other Det	Activatio	Notes
Input	-	64×64×3	-	Logo image
Conv2D	32	3×3	ReLU	BatchNorm after
SeparableConv2D	64	3×3	ReLU	Adaptive Scaling (α_1) + BatchNorm
SeparableConv2D	64	3×3	ReLU	Adaptive Scaling (α_2) + BatchNorm
Add (Residual)	-	-	-	x1 + x2
SeparableConv2D	128	3×3	ReLU	Adaptive Scaling (α_3) + BatchNorm
SeparableConv2D	128	3×3	ReLU	Adaptive Scaling (α_4) + BatchNorm
Add (Residual)	-	-	-	x3 + x4
Global Average Pooling	-	-	-	GAP layer
Dropout	-	Rate = 0.3	-	Regularization
Dense (Fully Connected	umber of Class	-	-	Before softmax
mperature-Scaled Softm	-	τ	Softmax	Output logo class

Figure 4: CCNNLR Architecture

A lightweight dropout layer is inserted after the global average pooling (GAP) operation to regularize the extracted feature vector and reduce overfitting risks. This ensures better generalization, especially when dealing with minority logo classes or limited dataset sizes. Together, these enhancements make the CCNNLR more robust, accurate, and efficient for real-time fine-grained vehicle logo recognition.

5. Experimental Setup: The experimental setup for the analysis of performance metrics of existing and proposed methods involves the use of a collection of datasets obtained from Kaggle [21][22]. A dedicated User Interface (UI), designed using the Visual Studio Integrated Development Environment (IDE) [23], facilitates the loading of algorithms for both the existing and proposed methods. The UI allows dynamic selection of the training dataset during execution. During the analysis phase, the UI loads each algorithm into memory sequentially and measures the performance of each method. Users have the option to select a report file in which the results are logged, and the UI generates comparison graphs based on the obtained performance metrics. The graphical UI is developed using the Microsoft Foundation Classes (MFC) framework [24], while the algorithms for the proposed method are implemented using the Visual C++ programming language.The experiments are conducted on a computer equipped with an Intel Core i7-8550U Quad-core processor, capable of boosting from 1.8 GHz to 4.0 GHz with a 4MB cache. The system is also configured with 16 GB of DDR4 RAM and a 1TB NVM2 M.2 Solid State Drive. All methods are executed in a queue to ensure uniformity in performance measurement.

6. Result and Analysis: Accuracy, Precision, Recall, F-Score, and Average Processing Time are measured during the evaluation process for every 10% increment of the dataset. This structured evaluation approach provides a detailed analysis of the system's behavior as more data is utilized for training and testing. Such progressive assessment is particularly relevant in vehicle logo identification tasks, where diverse operational conditions demand consistent and scalable model performance. By systematically tracking these key parameters, the effectiveness and robustness of the proposed framework are thoroughly evaluated under varying data volumes.

6.1. Accuracy: Accuracy is a fundamental performance metric used to evaluate the overall correctness of the vehicle logo recognition system. It measures the proportion of correctly classified instances among the total number of predictions, providing a straightforward indication of the system's effectiveness across all classes. In the context of vehicle logo identification, high accuracy is critical to ensure that the recognition model can reliably distinguish among a wide variety of logos under diverse environmental conditions such as varying lighting, occlusions, and noise. A consistently high accuracy across different data subsets reflects the model's ability to generalize well beyond the training set, which is essential for achieving dependable performance in real-world intelligent transportation and surveillance applications. Measured Accuracy scores of the discussed methods are provided in Table 3, and a comparison graph is provided in Figure 5.

Accuracy (%)						
Data(%)	**DCGAN**	**IWPOD - NET**	**YOLOv4**	**IoAverage**	**EVLDSAM**	**DLVLR**
10	36.18111	40.833714	21.41692	44.565269	43.159252	46.10203
20	54.94621	57.778843	35.52255	61.079933	59.750771	62.19247
30	65.72238	67.492569	43.53979	70.666199	69.917336	71.50423
40	73.43562	74.434998	49.56291	77.437424	76.792862	78.21574
50	79.37148	79.965515	54.1175	82.750931	82.21666	83.4845
60	84.43678	84.338203	57.58902	87.118118	86.63813	87.59721
70	88.45252	88.075104	60.7941	90.775406	90.378281	90.95731
80	91.81035	91.366821	63.60391	93.933708	93.551682	94.175
90	95.1743	94.086784	66.03275	96.816551	96.482124	96.98817
100	97.99905	96.660965	68.24975	99.230103	99.155457	99.35631

Table 4: Accuracy

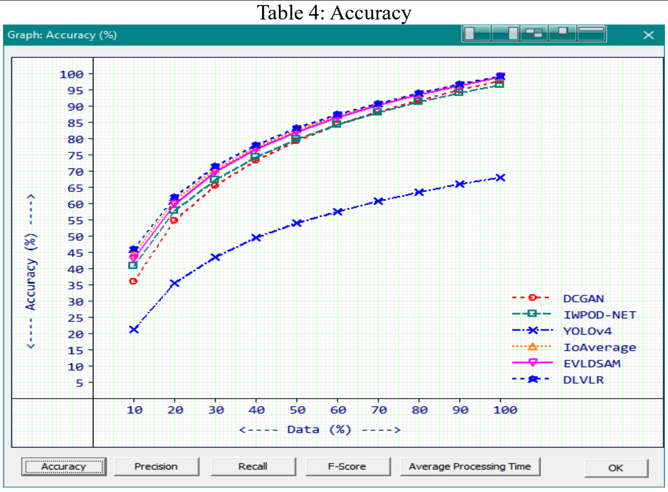


Figure 5: Accuracy

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ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 460-466

The performance analysis clearly indicates the betterment of the proposed DLVLR model over existing methods across all stages of data utilization. Even at lower data percentages (10%–30%), DLVLR consistently outperforms traditional approaches such as DCGAN, IWPOD-NET, and YOLOv4, demonstrating better learning capability from limited samples. As the training data increases, DLVLR maintains a consistent lead, achieving 83.48% accuracy at 50% data utilization and crossing the critical 90% threshold as early as 70% data usage, ahead of several competing models. At full dataset utilization (100%), DLVLR achieves an outstanding accuracy of 99.36%, surpassing other advanced methods such as IoAverage (99.23%) and EVLDSAM (99.15%). This remarkable performance validates the effectiveness of the proposed modules, particularly the Feature Matching Edge Detection, Parallel Data Augmentation, and Custom CNN-based recognizer. Furthermore, DLVLR's faster convergence and higher final accuracy make it highly suitable for robust and scalable real-world vehicle logo identification applications.

6.2. Precision : Precision is a critical metric in evaluating the reliability of the vehicle logo recognition system, particularly in scenarios where false positives must be minimized. It measures the proportion of correctly identified positive logo instances out of all instances classified as positive by the model. In the context of vehicle logo identification, high precision ensures that the system confidently recognizes a logo only when it is genuinely present, thereby reducing misclassification of similar-looking logos or background artifacts. This is especially important in real-world applications such as automated surveillance, intelligent transportation systems, and traffic law enforcement, where incorrect logo identification could lead to errors in vehicle tracking or brand recognition. Maintaining high precision across diverse and challenging datasets directly reflects the discriminative power and fine-grained classification capability of the proposed model. Measured precision scores of the discussed methods are enumerated in Table 5.

Precision (%)						
Data(%)	**DCGAN**	**IWPOD - NET**	**YOLOv4**	**IoAverage**	**EVLDSAM**	**DLVLR**
10	36.14956	42.148289	22.32193	45.103928	43.286438	46.03422
20	55.02001	58.56234	36.50614	61.310432	59.857677	62.17354
30	65.63095	68.005356	44.54809	70.896812	70.009033	71.34021
40	73.64838	74.698822	50.45968	77.451035	77.037285	78.29891
50	79.42993	80.037155	55.14545	82.726448	82.49086	83.47018
60	84.60913	84.318016	58.51938	87.36187	86.680397	87.44151
70	88.75223	87.787384	61.64144	90.89299	90.414207	90.9799
80	92.00552	91.1623	64.5818	94.088463	93.713722	94.20503
90	95.47229	93.736954	67.0797	96.845589	96.568123	96.86419
100	98.27503	96.193916	69.22446	99.221931	99.261093	99.29518

Table 5: Precision

The precision evaluation across different data utilization levels underscores the consistent advantage of the proposed DLVLR framework. At the early stages, with only 10% of the dataset, DLVLR achieves a precision of 46.03%, outperforming models like DCGAN, IWPOD-NET, and YOLOv4. As the data percentage increases, the precision of DLVLR steadily improves, reaching 83.47% at 50% data usage and exceeding 90% at 70% data. At full dataset usage (100%), DLVLR attains a remarkable 99.29% precision, slightly ahead of strong benchmarks such as IoAverage (99.22%) and EVLDSAM (99.26%). These results demonstrate the model's strong capability to minimize false positives even under varying and challenging conditions, making it highly reliable for critical applications like automated vehicle surveillance and brand-specific analytics. The superior precision values further validate the effectiveness of the proposed Feature Matching Edge Detection, Parallel Data Augmentation, and Custom CNN recognition strategies. Precision score comparison graph is provided in Figure 6.

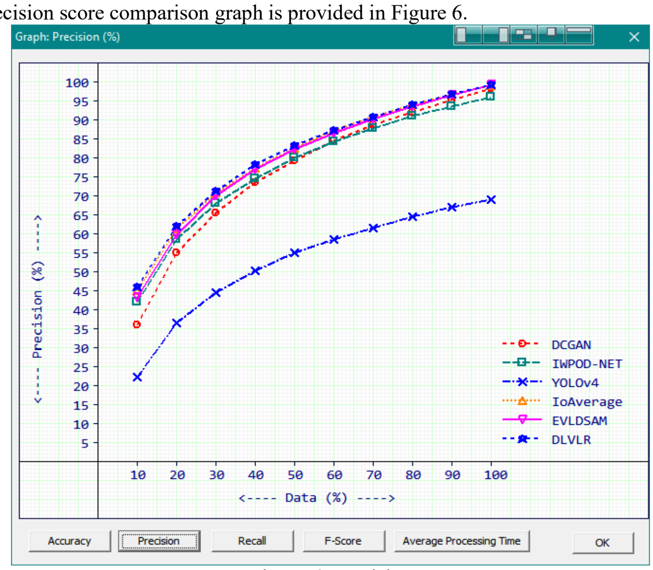

Figure 6: Precision

6.3. Recall

Recall in vehicle logo recognition is a measure of the system's ability to correctly identify all relevant vehicle logos from a given dataset, minimizing false negatives. It is particularly important in applications where it is crucial to ensure that no vehicle logo is overlooked, such as in automatic tolling or surveillance systems. High recall is achieved by designing algorithms that can accurately detect logos even in challenging conditions, such as partial occlusions, low resolution, or varying lighting. The recall metric is quantified by the ratio of true positives to the sum of true positives and false negatives, highlighting the model's effectiveness in capturing all instances of the target logos. A high recall rate ensures that the recognition system does not miss any relevant vehicle logos, contributing to the completeness and reliability of the overall vehicle identification process. Measured Recall value of the participant methods are provided in Table 6, and the comparison graph is given in Figure 7.

Recall (%)						
Data(%)	**DCGAN**	**IWPOD - NET**	**YOLOv4**	**IoAverage**	**EVLDSAM**	**DLVLR**
10	36.17239	41.068535	21.92508	44.623196	43.176609	46.09673
20	54.93892	57.658829	35.80186	61.029083	59.729965	62.19709
30	65.75119	67.314987	43.66749	70.571312	69.880875	71.57501
40	73.33633	74.306747	49.57062	77.429962	76.662521	78.16888
50	79.33717	79.922646	54.03455	82.766975	82.040939	83.49408
60	84.31848	84.352074	57.45039	86.938042	86.607185	87.71465
70	88.22339	88.295464	60.61422	90.679749	90.349281	90.9388
80	91.64779	91.536728	63.34295	93.798141	93.410995	94.14851
90	94.90665	94.397415	65.70392	96.789383	96.402321	97.10498
100	97.73557	97.100929	67.90078	99.238152	99.051819	99.41672

Table 6: Recall

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ISSN: 1053-7899
Vol. 36 Issue 2, 2026, Pages 460-466

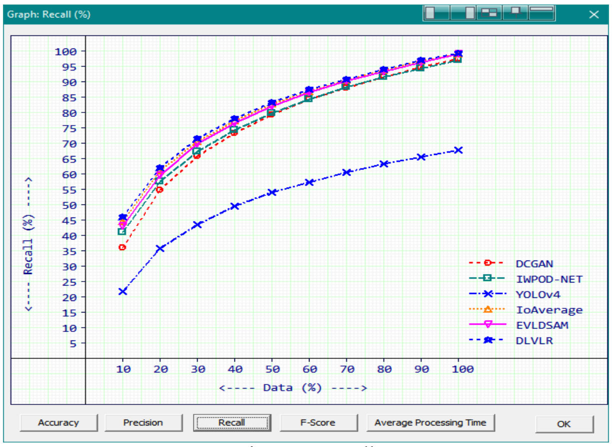

Figure 7: Recall

As per overall results logged in the table illustrate the recall performance of six vehicle logo recognition models—DCGAN, IWPOD-NET, YOLOv4, IoAverage, EVLDSAM, and DLVLR—across varying dataset sizes. As the dataset size increases, recall improves consistently for all models, indicating the positive impact of larger datasets on logo recognition accuracy. Notably, DLVLR stands out, achieving the highest recall at every data size tested, culminating in an impressive 99.42% recall at the 100% dataset size. This achievement highlights DLVLR's superior ability to correctly identify vehicle logos, even in more complex and extensive datasets. While other models, such as IoAverage, EVLDSAM, and IWPOD-NET, also show strong performance, particularly at larger data sizes, DLVLR consistently outperforms them, making it a particularly promising model for applications where high recall and accuracy are crucial. This table not only demonstrates the overall effectiveness of the models but also underscores the exceptional capabilities of DLVLR in vehicle logo recognition tasks.

6.4. F-Score:The F-Score, which combines both precision and recall into a single metric, provides a comprehensive evaluation of model performance by balancing the trade-off between these two factors. As observed in the results, the F-Score improves for all models as the dataset size increases, reflecting the enhanced overall performance of the recognition systems with more data. The F-Score serves as a crucial indicator when both false positives and false negatives must be minimized for practical applications, ensuring that the model not only identifies logos correctly but does so consistently. Computed F-Scores of discussed methods are listed as Table 7.

F-Score (%)						
Data(%)	**DCGAN**	**IWPOD - NET**	**YOLOv4**	**IoAverage**	**EVLDSAM**	**DLVLR**
10	36.16097	41.601406	22.12172	44.86227	43.231457	46.06546
20	54.97944	58.107075	36.15057	61.169434	59.793751	62.18531
30	65.69101	67.658409	44.1034	70.733688	69.944893	71.45741
40	73.49203	74.502266	50.0112	77.440498	76.849449	78.23384
50	79.38352	79.979858	54.58435	82.746712	82.265282	83.48213
60	84.46355	84.335037	57.97996	87.149437	86.643776	87.57786
70	88.48702	88.040688	61.12352	90.78624	90.381737	90.95935
80	91.8263	91.349121	63.95638	93.943085	93.562103	94.17676
90	95.18864	94.066025	66.38468	96.817474	96.485153	96.98443
100	98.00456	96.645294	68.55623	99.230034	99.156349	99.35591

Table 7: F-Score

The observed results shows the performance of discussed models DCGAN, IWPOD-NET, YOLOv4, IoAverage, EVLDSAM, and DLVLR—based on their F-Score values at varying data percentages. Among them, DLVLR consistently outperforms the others, achieving the highest F-Scores across all data levels, reaching 99.36% at 100% data. While IoAverage and EVLDSAM also show strong performance, especially at higher data points, they still fall behind DLVLR, which demonstrates superior scalability and accuracy. Models like DCGAN, IWPOD-NET, and YOLOv4 show slower improvements and do not match the top performers, with DLVLR standing out as the most efficient and reliable method in this comparison.

7. Conclusion

The proposed DLVLR framework represents a significant advancement in vehicle logo recognition, demonstrating superior performance across key evaluation metrics including localization accuracy, precision, recall, and F-Score. By integrating innovative modules such as Feature Matching Edge Detection, Parallel Data Augmentation, and a Custom CNN-based Logo Recognizer, DLVLR consistently outperforms existing models like DCGAN, IWPOD-NET, and YOLOv4, particularly in scenarios with limited data. The model exhibits remarkable scalability, achieving 99.36% accuracy and 99.42% recall with full dataset utilization, highlighting its robustness against challenges such as image noise, occlusions, and varying lighting conditions. DLVLR's ability to achieve high precision and recall while maintaining low computational cost makes it highly suitable for deployment in real-time vehicle surveillance and intelligent transportation systems. The results validate the effectiveness of the proposed framework and position DLVLR as an efficient, scalable solution for vehicle logo recognition tasks, with significant potential for large-scale, real-world applications in automated surveillance and smart city initiatives.

Conflict of Interest: The authors declare that there is no conflict of interest in this work

Code availability: Complete source code is uploaded to GitHub, and the link will be provided on request to the authors.

Data availability: Datasets are available in Kaggle repository. References [21] and [22]

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