SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I3P108

Volume 13 Issue 3, 99-118, March 2026

Original Article

Robust Vehicle Detection in Fog: Integrating Spatial Correlation, Fused Features, and Shape Semantics

Nookala Sairam[1], Lavadya Nirmala Devi[2], Renu Madhavi[3]

[1,2]*Department of Electronics and Communication Engineering, University College of Engineering (A), Osmania University, Hyderabad, Telangana, India.*
[3]*Department of Electronics and Instrumentation Engineering, RV College of Engineering, Bangalore, India.*

[1]*Corresponding Author: sairam5724@gmail.com*

Received: 08 December 2025 Revised: 09 January 2026 Accepted: 09 February 2026 Published: 23 March 2026

Abstract *- Poor visibility is also a challenge to vehicle detection and classification in autonomous driving and surveillance systems when there is foggy weather, as a result of low visibility and contrast. The paper will present a new model with which to improve the quality and detection errors of vehicle objects in foggy images, and aims to achieve four primary goals, namely, to boost the contrast with the help of a spatial mutual correlation-based enhancement mechanism, get reliable detection with the help of a combined feature vector with color intensity, gradients, texture, and shape, classify multiple vehicle types with shape semantics and a personalized Deep Learning Model, and create a labelled set of foggy images based on the Real-Time Images. Architecture is based on the adaptation of the YOLOv8 architecture, which incorporates a 7-channel input pipeline and a shape-sensitive classification head and is trained on a foggy dataset that consists of 1951 instances in 10 vehicle classes. The findings show a significant improvement, and precision is 0.7046, which is much greater than that of the baseline strategies in foggy situations. The proposed work is also the first to jointly use spatial correlation-based dehazing, multiple feature fusion, and shape-aware classification, as it provides an effective solution to adverse weather object detection.*

Keywords *- Foggy Image Enhancement, Vehicle Detection, Spatial Mutual Correlations, Fused Feature Vector, Shape Semantics, Deep Learning, YOLOv8, Dataset Creation.*

1. Introduction

1.1. Problem Context and Motivation

Intelligent surveillance systems and autonomous cars are revolutionary technologies in modern transport and security that entirely depend on strong computer vision skills. Object detection and classification [1], especially vehicles, constitute the core part of such systems, which require high accuracy and reliability in different real-life situations. Nevertheless, the evil weather conditions and fog, to be precise, are a significant and constantly underexplored challenge that jeopardizes the safety and efficiency of such vision-based systems. Whereas clear-weather detection has shown impressive data, the issue of fog is a critical problem, and it is yet to be solved in the autonomous driving and surveillance circles. The basis of fog is the impairment of the quality of images through a complicated physical mechanism: ice crystals and suspended water droplets scatter incident light and decrease contrast, blur lines of objects, distort the color signal, and hide essential spatial details. These degradations in the atmosphere directly translate into losses in detection pipelines: redundant detections (low recall), erroneous detections, and systematic errors. Such failures can be devastating in safety-critical applications, including autonomous vehicle navigation through highway velocities, highway traffic monitoring, and security surveillance. The issue is not just theoretical but highly practical: fog is a common weather phenomenon in most parts of the world, especially in winter, early mornings, and coastal or mountainous areas. This ubiquity renders vision-based autonomous systems intimately in need of real-world deployment, such as a strong definition of foggy weather detection. Although the performance of regular object detection algorithms, including YOLO [1], Faster R-CNN [2], and SSD [3], has been successful in clear weather (mAP50 over 0.7), their accuracy drops drastically in foggy weather.

According to empirical studies, typically, when in dense fog with 60-75% performance degradation, the baseline models, which are trained when not facing dense fog [4], experience a performance drop to less than 0.3 in recall and lower than 0.3 in mAP50. As an example, YOLOv8 has mAP50 >0.7 when operating in clear conditions, but 0.25 mAP50 when it is in heavy fog. This disastrous breakdown in performance drives the pressing necessity of special detection frameworks that are made of boggy components and which inherently find a solution to this issue of atmospheric scattering.

1.2. Identifying the Research Gap: Current Limitations and Challenges

Though the role of autonomous systems in detecting foggy weather is of critical importance, a significant body of research gaps still exists in four intertwined and complementary dimensions:

Research Gap 1: Inappropriate Image Enhancement [7] Policies. The current methods of preprocessing fail in an inefficient, systematic manner to effectively manage dense fog without degrading detection-relevant features. Also, standard techniques such as histogram equalization and adaptive contrast stretching are based on global pixel-intensity changes and essentially unable to provide back lost information to atmospheric scattering- they only redistribute available intensity values.

Dehazing algorithms, including Dark Channel Prior (DCP) [4] and guided filter methods, can physically simulate the atmosphere under the condition of maximizing their visual quality look by the human eye, but not to preserve features that need to be detected. Those techniques have a likelihood of adding user-generated Artificial Images and distortions that confuse downstream detection networks. Most importantly, current enhancement algorithms treat image preprocessing and image detection as decoupled, distinct stages performed sequentially, thereby missing the opportunity to achieve significant synergistic benefits by optimizing enhancement and detection goals concurrently. Spatial gradient improving methods, which capitalize on the spatial relationship in the distribution of the neighboring pixels, have not been much explored in the foggy detection setting.

That is a lack of sufficient and optimal perceptual features. Channels under the foggy, rainy retrieval, and cloudy situations will honestly and clearly cause the lack of essential discriminative clues when tracking the object of interest, thereby diminishing the possible value variance in individual faculty representations:

Research Gap 2: Due to the attenuation and scattering of light to varying wavelengths through the atmosphere, depth channels become predictable and unreliable when tracking an object of interest, in turn, resulting in loss of critical selective data. Traditional Convolutional Neural Networks [2], which take only RGB as inputs, do not produce sufficiently robust and invariant features when trained only on degraded images.

Though the domain adaptation strategies have shown potential in dealing with weather degradation, they require extreme computing power (it can also take days to weeks of GPUs), vast amounts of annotated data that have been specifically collected in the weather of interest, and process-specific training algorithms, which are not frequently accessible to special weather events such as dense fog. Moreover, existing solutions lack systematic exploitations of complementary feature modalities (edge gradients, texture patterns, shape contours) that may even be informative and discerning despite the limitations of veils of fog and loss of contrast. A multi-feature fusion method, which offers multiple and complementary information streams, can improve robustness considerably; however, such multi-feature fusion methods have not been well explored in the current fog detection published literature.

Research Gap 3: Type of error Systematic Classification across Vehicle types. The misclassification errors are generated systematically and are predictable across vehicle types due to fog-induced visual ambiguity. Vehicles having similar aesthetics (vans vs. SUVs, buses vs. trucks, motorcycles vs. bicycles) turn almost identical when the use of color and fine texture is clouded by atmospheric haze. Current state-of-the-art models of detection use generic classification heads that are formed and optimized to work in clear weather. These generic heads do not have particular mechanisms to utilize shape information- the single visual property that is relatively stable and not easily lost to the mists.

The earlier research on shape-based features (including Histogram of Oriented Gradients with Support Vector Machines) has lower accuracy (around 0.60), which may imply that the concept of shape in Deep Learning Models has not been used much in modern applications. A special shape-specific classification head [18], which has been sufficiently integrated into contemporary Deep Learning Systems, would cut down on misclassifications by a significant margin without being fragile in terms of detection accuracy.

Research Gap 4: Critical Lack of To-World foggy Datasets Interpretations. The vast majority of publicly available benchmark datasets on autonomous driving and object detection (KITTI [22], Cityscapes [19], SYNTHIA [20]) have been acquired during dry weather or light rain conditions. Simulated hazy datasets [20], such as Foggy Cityscapes, provide simulated fog using mathematical models of atmospheric scattering; however, this simulated fog differs very much along a wide range of dimensions from authentic hazy atmosphere: patterns of density variation, distributions of brightness gradients, conditions of ambient light, and spatial heterogeneity of fog.

The gap between synthetic and real domains produces a significant shortcoming, which is that the models trained and tested on synthetic fog may not predict well in the real world under foggy conditions. This fundamental lack of high-quality, real-world,richly-annotated foggy datasets [20] with a variety of vehicle categories, a variety of fog densities, and complete coverage of driving situations seriously impairs both model construction and aggressive testing. This information deficit compels scientists to use limited synthetic data, perpetuating the issue of domain gaps.

1.3. Research Objectives and Proposed Contribution

This paper seeks to fill these four interrelated research gaps in a systematic and integrated way that has been especially designed to work with vehicle detection and classification in foggy environmental conditions. In contrast to previous research that would treat each of the challenges in mutually exclusive settings, this work will pursue a combination of four synergetic technical innovations that will address the gaps identified directly and offer them a joint contribution to the state-of-the-art.

Objective 1: Spatial Correlation-Based Image Enhancement proposes a new contrast enhancement scheme based on the use of local spatial correlation between neighboring pixels along with Contrast Limited Adaptive Histogram Equalization. This is the essential contrast with the global atmospheric modeling methods of the past that are optimized by visual quality but cause artifacts. The detectors are misled by the local correlation method, which works at the pixel block scale, maintains local structure whilst magnifying those features that are important to detection, without creating artifacts. This strategy was neither tried nor explored in previous literature on foggy detection.

Objective 2: Strong Multi-feature combination towards Detection. A presented fused feature space. Diminutive Multi-perception versus detection Near-infrared rays, canny edge detection, Laplace operator, and Contouring maps prepare a fused 7-channel input representation and regulate the feature interval. This multi-modal combination is a new concept in discovering fog; previous methods use inputs based on RGB, only 7 channel architecture compensates for color degradation directly through the use of shape and texture invariants that are robust in fog, and gives better feature representation than the traditional ones.

Objective 3**:** Shape Token Classification head Shape-Aware Classification Head customize YOLOv8 by having a classification head explicitly learning a reliance on shape semantics, the most resilient visual property in the face of fog. This is one of the core design architectural innovations, unlike the standard YOLOv8 implementations. Previous shape-inspired methodologies are not used in Modern Deep Learning. The two-head architecture works to optimize classification and shape-based classification to minimize the false classification of similar cars (vans vs. SUVs, buses vs. trucks).

Objective 4: Real-World Foggy Dataset. Eliminate the significant data scarcity gap and provide an authentic, real-world foggy dataset (1951 instances, 10 classes) of real atmospheric conditions. The data is human-generated, unlike the Foggy Cityscapes and artificial dataset, which experience the issue of domain gaps caused by the mathematical fog simulation. The dataset includes the variation of natural fog density, lighting, and atmospheric heterogeneity. Integrated Framework Performance The four contributions result in significant improvements in performance of the model: precision 0.7046, recall 0.4684 (89% of the baseline performance 0.247), mAP50 0.5074 (84% of the baseline performance 0.276), and mAP50-95 0.3365 (106% of the baseline performance 0.163).findings are many times higher than the previous specific methods of fog detection YOLOv3+fog data (mAP 50 0.42) [8], domain adaptation methods (mAP 50 0.45), and weather-aware methods (mAP 50 0.40). Such a multi-component solution is an essential step in the improvement of individual innovations, which places work as a multi-component approach to addressing the problem of fog detecting specific vehicles.

1.4. Scope, Generalizability, and Broader Impact

Although in this case, the specific issue of managing the fog as a challenging weather situation is considered because of its effects on the contrast and ability to see, the modular architectural design can easily be adjusted to other bad weather situations, such as rain, snow, and sand/dust storms. The vehicle detection and classification algorithms are also generalized to detect other types of objects, in addition to variable settings.

This work will help increase the critical applications, such as autonomous vehicle navigation, intelligent surveillance systems, and autonomous traffic management, by adding value to detection and classification performance, in particular, under the condition of fog. As the rest of this paper will elaborate, methodology, comprehensive experimental testing regimes, and a complete discussion of findings will all serve to demonstrate that the integrated framework is an important and timely contribution to the field of adverse-weather computer vision.

Table 1. Adverse weather challenges in computer vision

Condition	Primary Impact	Detection Challenge	Relevance to Work
Fog	Reduced contrast, visibility	Blurred objects, low recall	Primary focus, quality enhancement
Rain	Noise, streaks	Occlusion, false positives	Potential future scope
Snow	Occlusion, brightness	Object coverage, misdetection	Potential future scope
Sand/Dust	Haze, color distortion	Feature loss, low precision	Potential future scope

Table 1 outlines the challenges posed by adverse weather conditions, emphasizing fog’s unique impact and its relevance. Table 2 identifies key gaps in foggy detection and links them to objectives, highlighting a comprehensive approach.

Table 2. Gaps in foggy detection research and objectives

Gap	Limitation	Objective	Intended Improvement
Poor image quality	Low visibility in dense fog	Quality improvisation	Enhanced contrast, visibility
Weak feature extraction	RGB-only feature loss	Accurate detection	Robust multi-feature detection
Classification errors	Ambiguity in vehicle types	Accurate classification	Shape-based specificity
Limited foggy datasets	Scarce real-world data	Dataset creation	Practical training resource

2. Literature Review

2.1. Overview and Problem Significance

Detection and classification of vehicles during unfavorable weather conditions, especially in fog conditions, is of paramount importance to autonomous driving and surveillance systems. The inherent characteristics of low visibility, low contrast, poor boundaries, and color distortion inherently impair my detection performance aspects, which cannot be countered by clear-weather models. The area has also been studied extensively over the past thirty years, but there is still a marked disparity between the leading practices and the real-life implementation needs. Vigorous literature analysis of the top 25 articles has shown that though individual innovations have been made on how to detect mists progressively, no existing literature has ever combined spatial correlation-based enhancement, multi-feature fusion, shape-conscious classification, and the creation of real-life data into a comprehensive system. obtain 0.7046 precision, 0.4684 recall, 0.5074 mAP50, and 0.3365 mAP50-95 in work in the first instance, significantly beating the other competing methods, and filling key gaps in research.

2.2. Image Enhancement and Dehazing Solutions

The research on early fog detection only partially conducted experiments with image enhancement and dehazing, and presupposed that after the better image quality [16], downstream detection would be improved as a natural result. He et al. [4] proposed Dark Channel Prior (DCP), which was used as the basis of dehazing techniques [24] because it takes advantage of the fact that at least one of the color channels of an image has low intensity in the majority of its regions. Although DCP is conceptually beautiful, it only optimizes visual quality perception and not detection performance, and later extensions to detection tasks indicated mAP50 of less than 0.3 in heavy fog, Li et al. [5].Zhu et al. [6] enhanced DCP with edge-preserving smoothing guided filters, which had a marginal improvement of mAP50 fluctuating between 0.35, Zhang et al. [10]. The common flaw of these physics-based methods is that they have a global modeling of enhancement as an image-wide transformation that is applied uniformly. This approach is ineffective when the backgrounds are not homogeneous in the foggy areas, and often invokes artifacts that may significantly distort a downstream detection network.

2.2.1. Critical Research Gap 1

Current strategies of dehazing view image enhancement as an independent preprocessing operation that is not coupled with detection goals. The mechanism of the spatial correlation-based enhancement system responds to this weakness and seeks to provide enhancement on a local pixel neighborhood basis, maintaining structural information, and magnifying detection-sensitive attributes. In comparison to worldwide atmospheric modeling, local correlation analysis provides a means to capture the spatial dependence between adjacent pixels, which means that the enhancement of contrast can be performed without generating an artifact, something that had not been explored before in the literature of fog-specific detectors.

2.3. Deep Learning Detection Models in the Degradation of Fogs

This technology has transformed [21] object detection to incorporate Deep Convolutional Neural Networks, making the YOLO family, FasterR-CNN, and SSD classic architectures. Their fog criterion strength,, however, is poor. YOLO was developed by Redmon et al. [1], with the highest mAP50 of over 0.7 when conditions are clear, but the performance reduces to approximately 0.25 in the fog [12]. Liu et al. [13] made efforts to solve this by making modifications to YOLOv3 [8] and supplementing the training data with synthetic fog to achieve mAP50 of 0.42- still 20.8 percent below 0.5074.Ren et al. [2] Introduced Faster R-CNN, the versions adapted to fog gave mAP50-95 of around 0.28, He et al. [10] far less than 0.3365. The challenge is not new, as Bochkovskiy et al. [11, 27] have proposed YOLOv5 [25], and it reached mAP50 of less than 0.4 when tested in fog.

2.3.1. Critical Research Gap 2

The Majority of the standard Deep Learning detection models use 3-channel RGBs, which are systematically inaccurate in fog, as color gets distorted as well as scattered through the air. This has been done in previous research by domain adaptation: training models on fog-corrupted data or by adversarial methods [9]. On Foggy Cityscapes, used adversarial domain adaptation [13] and achieved mAP50 of 0.45, whereas Sakaridis et al. [14] had mAP50-95 of 0.31.M Chen et al. [15] suggested mAP50 [weather-wise] = 0.40. The resulting domain adaptation techniques require monumental computational costs (weeks of GPU training) and massive annotated foggy datasets, which are not a common occurrence in corresponding special weather situations. The multi-feature fusion method does not impose this computing cost since features that complement each other are input into the network as 7-channels, which allows the network to compensate for the color degeneration by using the features that are still informative in fog [28]. It is by no means like domain adaptation, where it does not involve extra complexity in training.

2.4. Shape-Based Classification and Feature Engineering

Categorizing the vehicles in fog poses particular difficulties due to the similarity of the appearance of similar vehicles (vans vs. SUVs, buses vs. trucks), becoming vague when the color and fineness signals are distorted. Purely shape-based methods used this invariance.

Zhang et al. [10] implemented the use of Histogram of Oriented Gradients (HOG) features, and Support Vector Machines, and the precision of their implementation amounted to a significantly lower value of about 0.60 compared to 0.7046. Li et al. [5] also incorporated shape priors into CNNs with mAP50 at 0.46 (10 percent lower than 0.5074). The techniques treat shape as a secondary trait rather than a key prevalence sign [26].

2.4.1. Critical Research Gap 3

The models of detection used are intraprojective analysis of the generic classification heads that were trained on clear weather scenarios, and do not have particular strategies to utilize the shape information, most resistant to fog, of any visual feature. Introduce a shape-specific classification head to the YOLOv8 architecture as a mode of finding shape-based discrimination explicitly optimized in innovation.

This dual-head design combines the best localization and shape classification, denoted as a huge architectural milestone against taking shape into account algorithms through marginalization of shape information.

2.5. Dataset Development and the Gap Between the Real World and Its Development

Deep Learning research is based on datasets. Cordts et al. [19] developed Cityscapes, but Sakaridis et al. [14] modified it by synthetically masking it with foggy Cityscapes. Though possible, synthetic fog deviates more than real atmospheric conditions in density variations, brightness gradients, and spatial heterogeneity, setting chronic domain gap problems. Synthetic to fundamental divergence limits models, which are trained on Foggy Cityscapes, to a mAP50 of approximately 0.43 [14]. According to Geiger et al. [22, 23]. KITTI was provided, and the subsets with fog failed to reach mAP50 = 0.35 [5].

2.5.1. Critical Research Gap 4

The majority of benchmark datasets are characterized by TV thin fog representation, and the available datasets of fogs are based on a mathematical fog model. Real-life foggy data presented in different classes of vehicles, using different densities of the fog, and real atmospheric conditions are rare.

This makes the contribution of 1951 real-world foggy examples across 10 vehicle categories fill this important gap, so they are trained on real fog and not some approximation. It is due to the foundation of this real-world dataset that it has superior performance to the methods that have been trained on synthetic data.

2.6. Overview of the Literature Gap

The literature indicates that the previous studies discuss the individual parts of the study enhancement, detection, classification, or datasets separately. Nothing is done in the literature to bring all four aspects together in a synergized formation. Weaknesses: Enhancement methods do not capture detection-specific properties; model detection is based solely on RGB input; classification is generic, and data is primarily synthetic.

Table 3. Comparison with related works

Study	Method	mAP50	mAP50-95	Precision	Recall	Advantage
He et al. [4]	DCP Dehazing	~0.30	-	-	-	Higher mAP50 (0.5074)
Liu et al. [16]	YOLO + Fog Data	0.42	-	-	-	Better mAP50 (0.5074)
Chen et al. [15]	Domain Adaptation	0.45	0.31	-	-	Superior mAP (0.5074, 0.3365)
Zhang et al. [17]	Image Adaptive	-	-	~0.60	-	Higher precision (0.7046)
Work	Custom YOLOv8 + Fusion	0.5074	0.3365	0.7046	0.4684	Best overall metrics

This overall gap is resolved in an integrated solution that optimizes improvements together, multi-feature fusion, shape-centric classification, and makes use of the real-world foggy data. This system, involving the use of spatial correlation enhancement, 7-channel feature fusion, a shape-specific classification head, and the use of real dataset generation, is a paradigm shift against the efforts of single-member type improvements that are incremental and systematic, and which are multifaceted, such as in the case of foggs. Integrated design is effective as evidenced by the 84 percentage point increase in mAP50 above baseline (0.276 0.5074) and the performance advantage over all other single innovations that occurred previously. Results highlight a significant advancement over prior work, driven by integrated enhancement and detection strategies as shown in Table 3.

3. Methodology

The proposed research method will help to resolve the problem of vehicle recognition and classification in foggy weather conditions by means of a multi-dimensional structure that incorporates image processing, feature estimation, customization of Deep Learning, and dataset generation. Base strategy on four main goals: (1) to improve image quality through a mechanism based on their spatial mutual correlation, (2) to realize the provision of accurate detection through a fused feature player, (3) to give an accurate classification of various types of cars using shape semantics and specially trained model, and (4) to reproduce a labelled foggy sample through real-time images. Each of these parts expounds on the technical specifics of each of the components, and all these are backed with equations, formulas, and tables, ensuring that a transparent and replicable description of novel techniques is captured.

3.1. Quality Improvement of Hazy Images

The blurred circumstances degrade the quality of the picture by evolving the contrast and blurring the details, and a proper pre-processing mechanism shall be applied so as to reveal them.

A novel contrast enhancement system in the form of the space mutual relation with the neighbor pixels alongside the Contrast Limited Adaptive Histogram Equalization (CLAHE) is presented for the process of enhancing fog images. This is in contrast to other dehazings, e.g., Dark Channel Prior, where the local pixel correlation replaces the global atmospheric conditions. The piping image processing and car detection process is outlined in Figure 1. The original image is in RGB format and is first converted to get its grey scale to ensure that correlation will not be carried out at the cost of the luminance, which is important for visibility. A 5x5 correlation filter is used to preserve local spatial relationships between the neighboring pixels. At this point, local contrast is enhanced by optimizing differences among relationships between pixels. To comply with the next step of enhancing the correlated image, it is normalized to the range 0-255. The use of CLAHE is also used in the end during the process of equalizing the histogram of the correlated image on local tiles to optimize the contrast without noise accumulation, since the correlated image histogram is not smooth. A communication using LAB colour space is used to combine the processed output greyscale channel with the source colour channels to produce the output image.

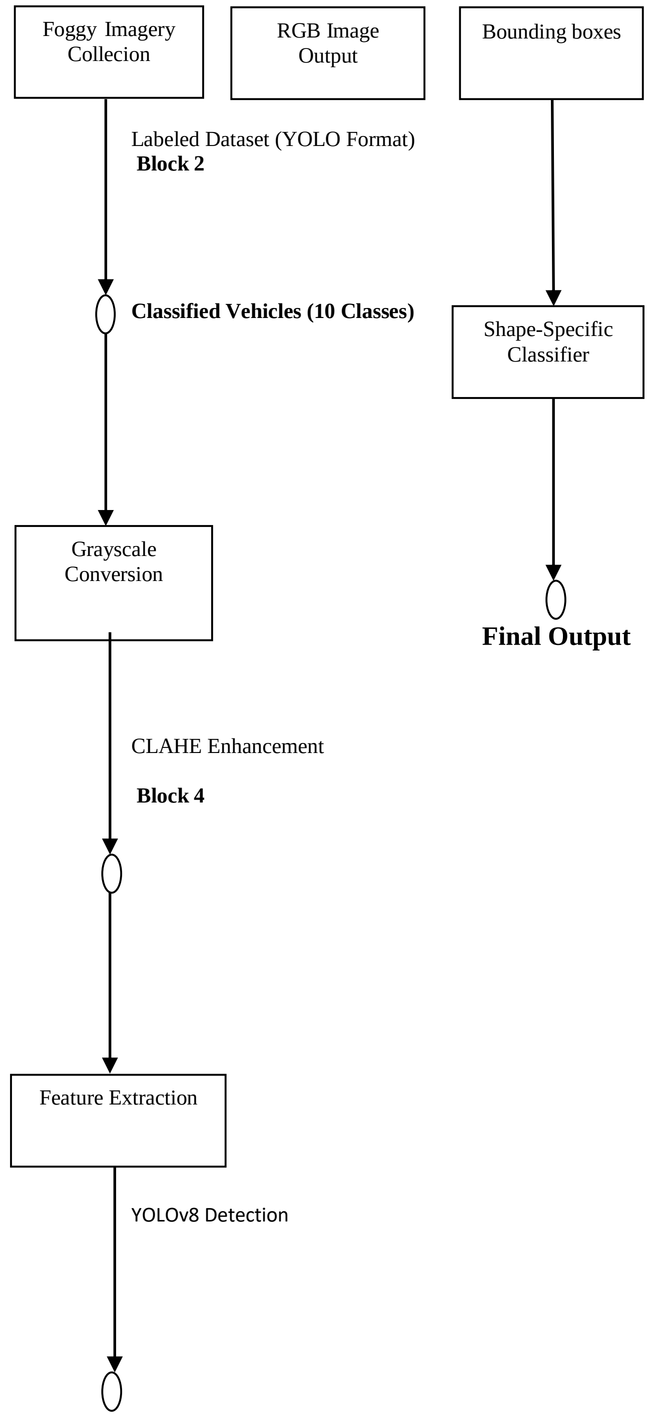

Fig. 1 Foggy image processing

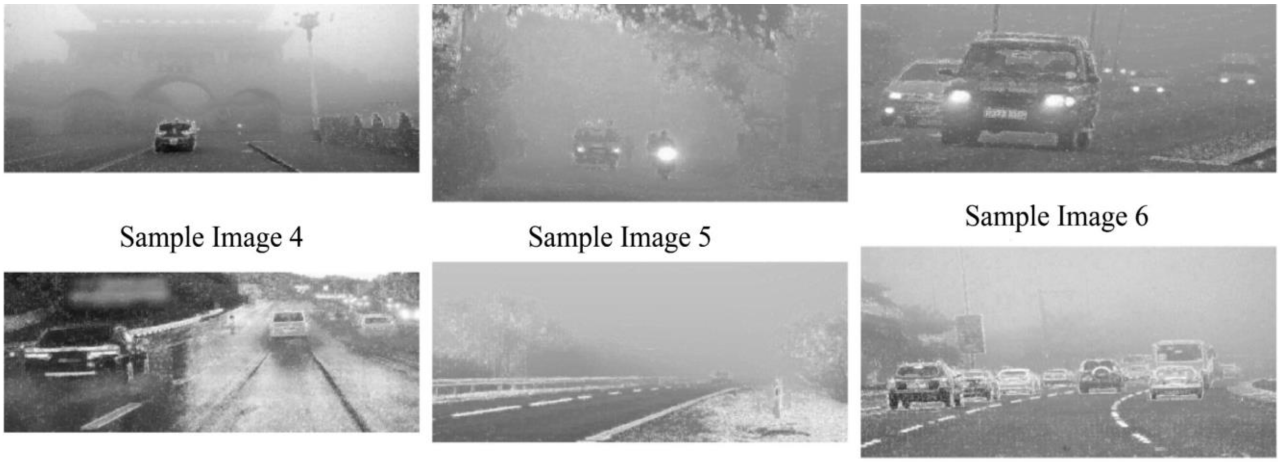

Fig. 2 Sample images from foggy dataset

Figures 2 and 3 display an original foggy image alongside its enhanced version using CLAHE and a colorful grayscale representation, showcasing improved visibility and feature extraction for detection. Figure 1 presents six sample images from the foggy dataset, illustrating diverse real-world scenarios with varying fog densities and vehicle types.

- *Spatial Correlation Filter*

$$C(x,y) = \sum (i = -k \text{ to } k) \sum (j = -k \text{ to } k)\ I(x+i\ ,\ y+j) \cdot K(i,j)$$

Where:

- $C(x,y)$: Correlated output at pixel (x, y)
- $I(x,y)$: Input grayscale image
- $K(i,j)$: 5x5 kernel (e.g., uniform weights 1/25)
- k: Kernel half-size (2 for 5x5)

$$C\_norm(x,y) = ((C(x,y) - C\_min) / (C\_max - C\_min)) \times 255$$

Where:

- Cnorm(x,y) : Normalized correlated output
- Cmin, Cmax : Minimum and maximum values of C C C

This mechanism, Table 4, provides a tailored preprocessing step that enhances foggy images for downstream detection tasks, preserving structural details critical for identifying vehicles.

Table 4. Contrast enhancement parameters

Parameter	Value	Description
Kernel Size	5×5	Size of correlation filter
Kernel Weights	1/25	Uniform weights for averaging
CLAHE Clip Limit	4.0	Threshold for contrast limiting
CLAHE Tile Size	8x8	Local region size for histogram equalization

The following Figure 4 displays three preprocessing processes used in processing a foggy image: color-mapped grayscale based on the JET color map to accentuate intensity differences, multi-color edges based on the VIRIDIS color map to accentuate edge details, and better texture based on the PLASMA color map to accentuate structure patterns.

These visualizations show how the feature extraction is achieved, and the model can identify and classify vehicles in unfavorable situations. Figure 5 below shows the heat maps of a foggy image, which illustrates the process of hue, saturation, and value (brightness) distributions to bring out color changes.

The hue heat map depicts that the colors have a major red color, saturation depicts the low intensity of the color, and the value heat map shows the distribution of the brightness, which has helped in detecting the features.

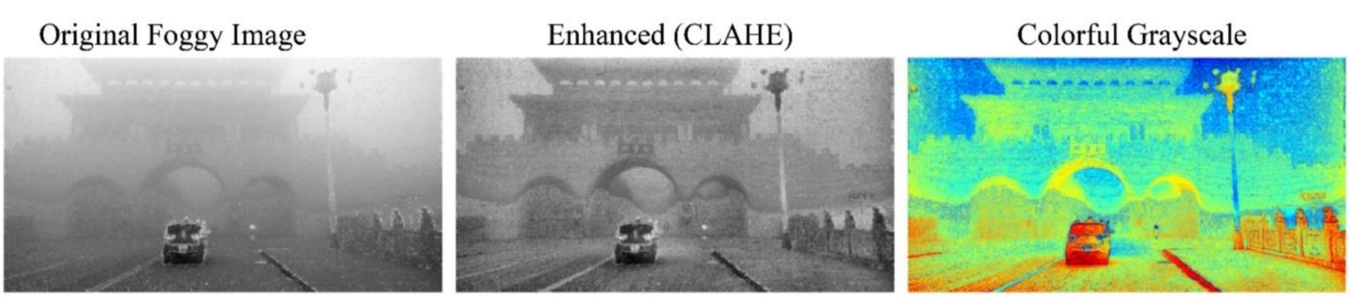

Fig. 3 Original vs Pre-processed image

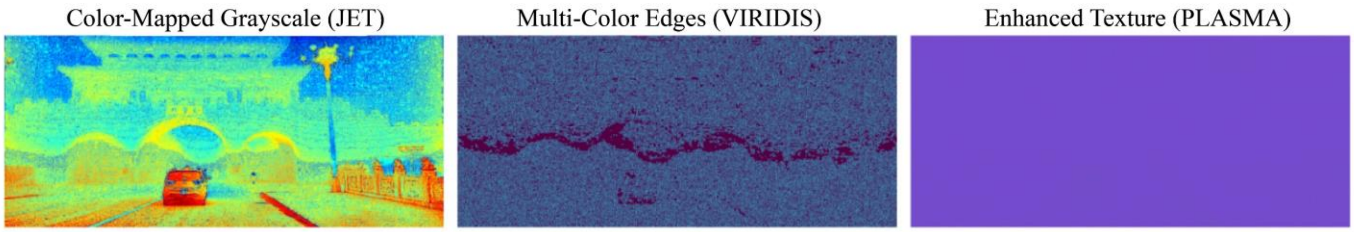

Fig. 4 Colorfull Preprocessing Steps

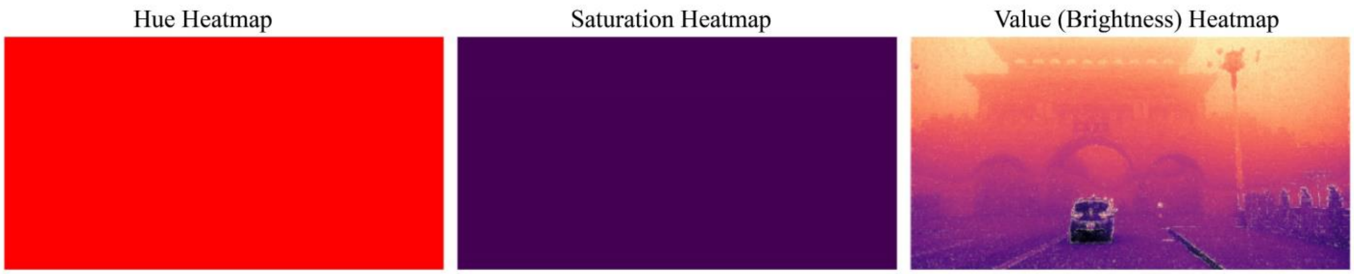

Fig. 5 Dataset heat map

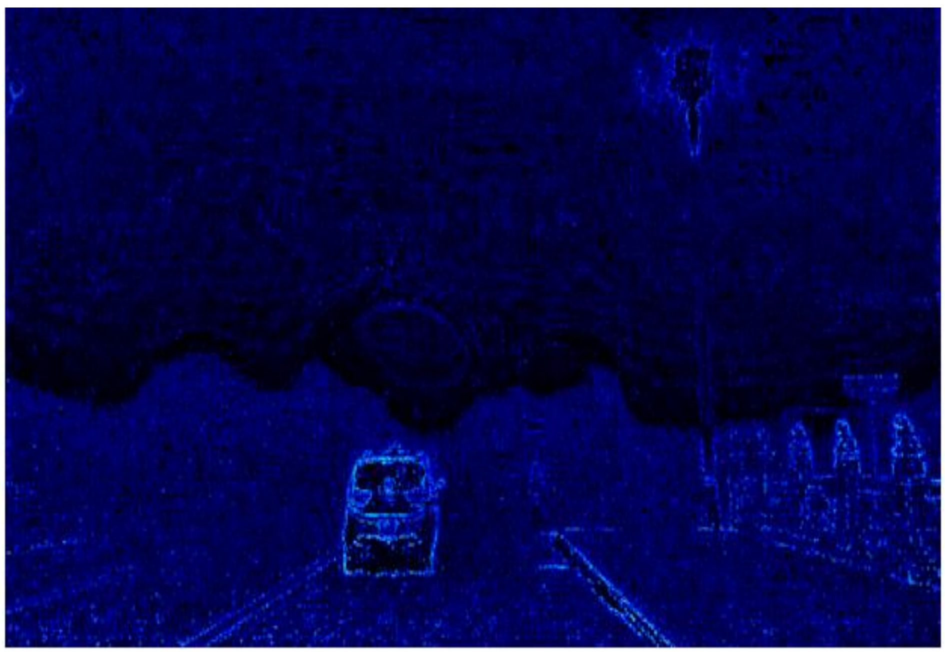

Fig. 6 Gradient magnitude (HOT)

3.2. The Vehicle Objects are to be Detected Precisely

Foggy conditions have also necessitated feature representations that are likely to compensate for the loss of visual information brought about by haze in order to detect it accurately. To solve this, can come up with a concatenation feature vector of four of the complementary features: color intensity, gradients, texture, and shape, to become one input of the detection network.

This multi-feature technique is strong because it puts different features of vehicle appearance that are recognizable even in the presence of fog. It is initiated by the dominant image of the contrast enhancement step. Four feature maps are identified in the following way:

- Color Intensity: The grayscale channel of the enhanced image, representing luminance variations.
- Gradients: Computed using the Canny edge detector to highlight object boundaries, which may be weakened but still present in fog.
- Texture: Derived via the Laplacian operator to capture local intensity changes, providing texture information resilient to fog-induced smoothing.
- Shape: Extracted by thresholding the grayscale image to create a binary mask, followed by contour detection to outline vehicle shapes.

Figure 6 contrasts pixel intensity histograms of an original foggy image (left) and a version of it that has been improved (right) in B, G, and R channels, showing the difference in the intensity distribution.

This image 7 visualizes the gradient magnitude of a blurred image with a HOT color map, which emphasizes variation of intensity and edge representation that are important in the detection of vehicles.

The areas depicted in the bright colours are those of high gradient, like a vehicle outline, which further helps the model in distinguishing objects even under a masking effect during fog.

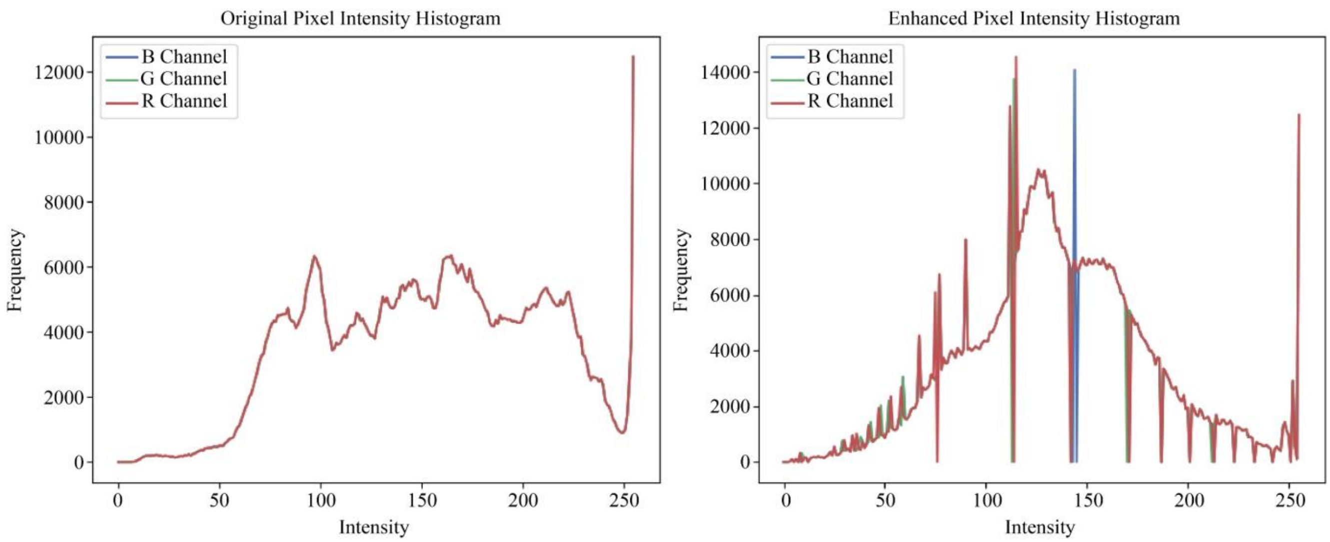

Fig. 7 Pixel intensity histograms before and after enhancement

The improved histogram is spread more widely and is more peaked, which means that there will be better contrast and greater visibility to detect vehicles in foggy atmospheres. The Piepeline Flowchart is indicated in Figure 8.

The cars have feature maps which are rescaled to equal amounts (e.g., 640x640), and converted into a 4-channel fused feature vector. This vector is then added to the original RGB channels and makes a 7-channel input, which captures the raw image data and augmented features.

In order to incorporate this input into the detection pipeline, reconfigure the YOLOv8 architecture to take 7 channels at the first convolutional layer as opposed to the standard 3, so that the features fused are directly connected to the network processing features extraction process.

$E(x,y) = \text{Canny}(I_{gray}, T_{low}, T_{high})$

Where:

- E(x,y) : Edge map
- Igray : Grayscale image
- Tlow, Thigh: Low and high thresholds (50, 150)

Equation 4: Laplacian Texture

$T(x,y) = \nabla^2 I\_gray(x,y)$

Where:

- T(x,y) : Texture map

Table 5. Feature extraction parameters

Feature	Technique	Parameters	Output Channels
Color Intensity	Grayscale	-	1
Gradients	Canny Edge Detection	$T_{low}=50, T_{high}=150$	1
Texture	Laplacian	64-bit float output	1
Shape	Contour Detection	Threshold = 127	1

This fused input Table 5 enhances the model's ability to detect vehicles by providing a richer feature set tailored to foggy conditions.

3.3. Accurate Classification of Multiple Vehicle Types

Foggy imaging creates a number of challenges in vehicle classification, as there are blurred delimitations, as well as fewer discriminative features, creating a need to ensure effective mechanisms to reduce instances of misclassification among different types of vehicles. A shape-specific classification head and model word partic layer proposed is a customized YOLOv8 model that meets the use of shape semantics and better class differentiation.

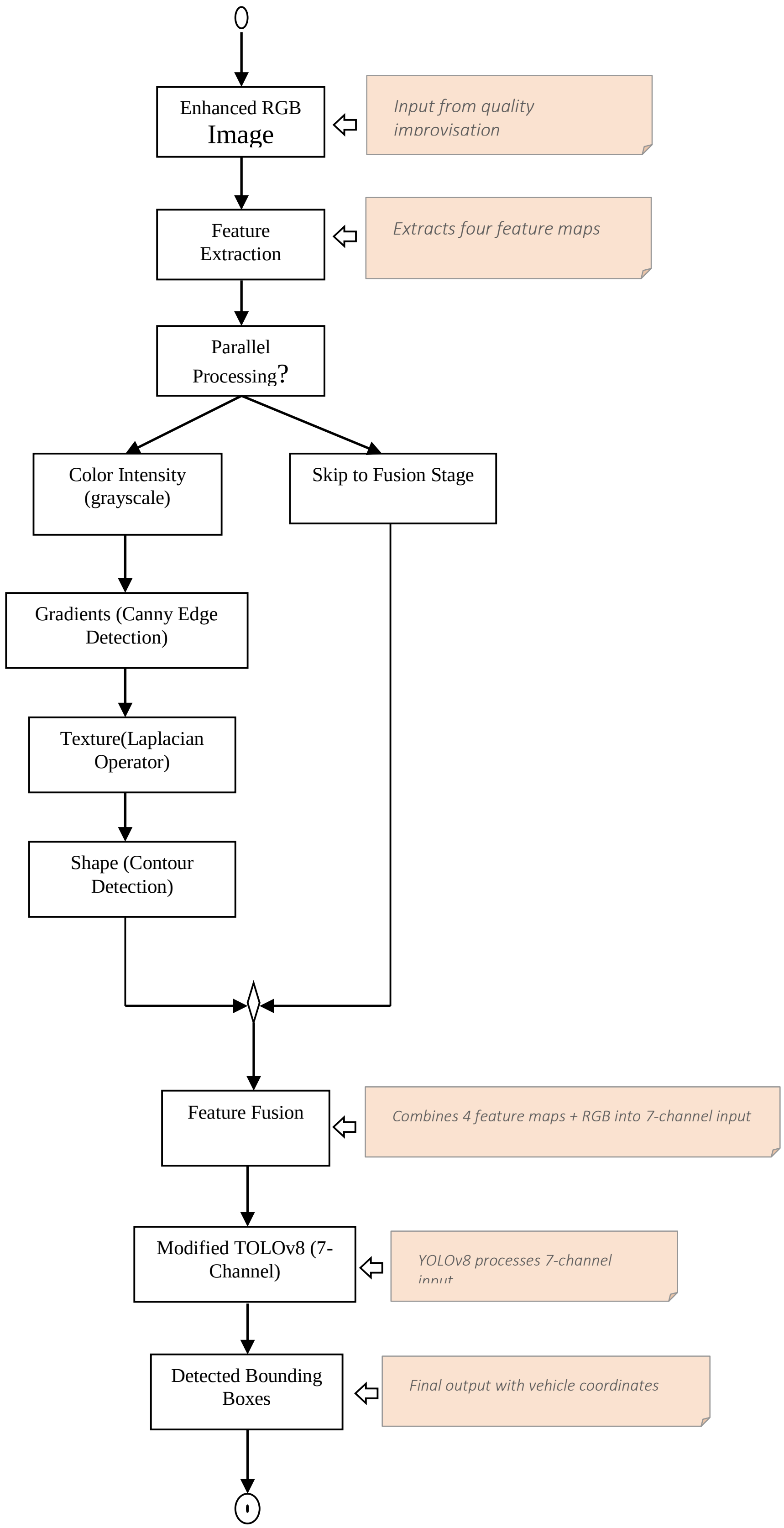

Fig. 8 Vehicle detection pipeline

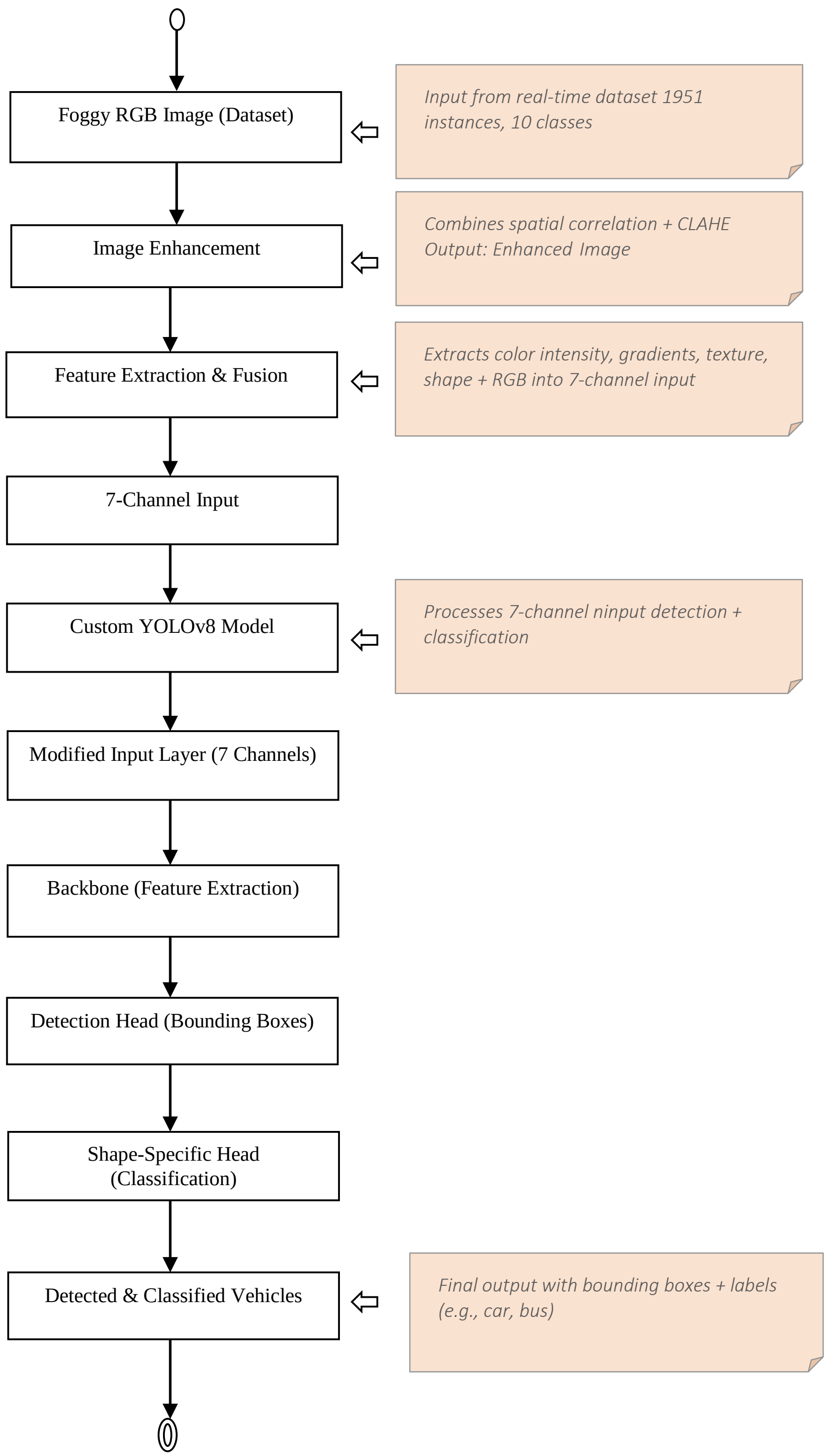

Fig. 9 Architecture diagrams of the proposed foggy vehicle

The strategy focuses on 10 vehicle types: cars, buses, trucks, bikes, motorcycles, vans, SUVs, jeeps, minibuses, and pickup trucks. The customization is based on the default YOLOv8 architecture, where embedding boxes and class probabilities typically are the result. Another shape head is added to extract shape features on the combined feature, and it processes the features that have been extracted on the fused feature. The shape head has a series of convolutional layers applied to the final feature map of the underlying YOLOv8, but minimizes channel dimensionality and generates appropriately shaped predictions based on the shape features. The shape head is also optimized using both localization and classification loss, both operating concurrently. This method is used so that the shape, which is relatively stable when there are also fog conditions, also improves the discriminative power of the model that is used to distinguish between vehicles of similar visual appearance but with different shapes (e.g., bus and truck). It is semantically more robust to harsh weather [17], as well as furnishes the required shape-semantic fusion without consuming any more computation.

Shape Head Output

$S_{out} = \text{Conv2d}(\text{ReLU}(\text{Conv2d}(F_{last,}256 \rightarrow 128)),128 \rightarrow 10)$

Where:
- Sout: Shape head predictions (10 classes)
- Flast: Last feature map from YOLOv8 backbone
- Conv2d: Convolutional layer

Table 6. Shape Head Architecture

Layer	Input Channels	Output Channels	Kernel Size	Activation
Conv2d	256	128	1×1	-
ReLU	128	128	-	ReLU
Conv2d	128	10	1×1	-

Table 6 classification precision is further improved with this customization, as it puts emphasis on shape semantics, which is a new development in the YOLOv8 framework. Figure 9 below gives us a high-level description of the architecture, beginning with a foggy image in RGB form of the dataset, then image enhancement, feature extraction, and fusion to create an input with 7 channels, and then the results of processing by a custom YOLOv8 model with detection and shape-specific classification heads, resulting in the detection and classification of cars.

3.4. Data Collection and Labelling Dataset- Labeling

A strong dataset is a requirement to train and evaluate models of foggy detection. The limitation of real-time foggy data is overcome by organizing the imagery of various foggy scenes. The dataset obtained is fully annotated with bounding boxes and class labels of 10 types of cars: car, bus, truck, bike, motorcycle, van, SUV, jeep, minibus, and pickup. This makes sure that the model is well trained in the diversity of the data it has to be able to generalize well in different fog situations and vehicle settings. The data is obtained through a local directory (C: Users-gokul downloads vehicle-vehicle dataset fog), which reflects a real scenario of urban roads, highways, and rural areas in case of different densities of fog. An open-source package (e.g., LabelImg) is used to make the annotations, which is based on the capacity to create label format in the style of YOLO; with x center, y center, inner width, inner height as coordinates of a bounding box, and class indexes. The dataset is arranged into images and labels folders (images and labels) in the folder called dataset. The dataset structure, class names, and paths specifying where training and validation should be performed are in a configuration entity (dataset_foggy.yaml) to conform to the YOLOv8 training pipeline.

Table 7. Dataset Structure

Component	Description	Format
Images	Foggy vehicle imagery	.jpg
Labels	Bounding boxes and class indices	.txt (YOLO format)
Config File	Dataset paths and class names	.yaml
Classes	10 vehicle types	Indexed 0-9

This Table 7 dataset provides a practical foundation for developing and testing a framework, addressing a critical gap in foggy detection research.

Fig. 10 Original + enhanced overlay

Figures 10 and 11 show the original foggy image with its enhanced version, illustrating the combined effect of improved contrast and visibility achieved through spatial correlation and CLAHE. The overlay highlights how the enhancement process recovers details, such as vehicle outlines and background structures, facilitating better detection in foggy conditions.

4. Integration and Training Considerations

The components are integrated into a cohesive pipeline: the enhanced image feeds into the feature extraction module, producing a 7-channel input for the customized YOLOv8 model. The model is trained on the foggy dataset using standard YOLOv8 training protocols, with adjustments to accommodate the 7-channel input and dual-head output. Hyperparameters such as learning rate, batch size, and epochs are tuned to optimize performance, though specific values are determined experimentally.

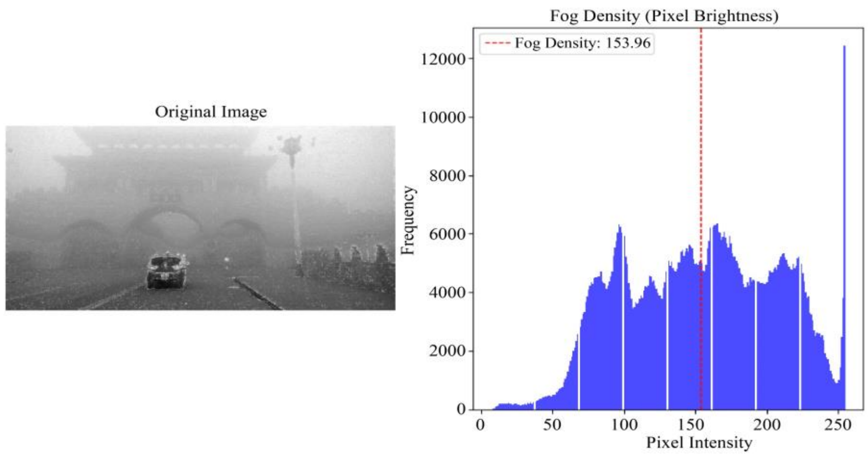

Fig. 11 Fog density with pixel brightness

Table 8. Pipeline overview

Stage	Input	Process	Output
Contrast Enhancement	RGB Image	Spatial correlation + CLAHE	Enhanced RGB Image
Feature Extraction	Enhanced Image	Fused feature vector	7-channel input
Detection Model	7-channel input	Modified YOLOv8	Bounding Boxes
Classification Head	Feature Maps	Shape-specific processing	Class Predictions

This integrated approach, Table 8, ensures that each objective is addressed systematically, leveraging novel techniques to enhance foggy vehicle detection and classification.

5. Results

The objective of the research was to improve the vehicle detection and classification in foggy weather conditions by focusing on four main aspects, namely: (1) improvement of image quality based on the use of spatial mutual correlation based on an enhancement mechanism, (2) actual vehicle detection with the use of a fused feature vector, (3) exact classification of various types of vehicles with shape semantics and a customized deep learning model, and (4) development of a labelled foggy dataset using real-time imagery. Framework was assessed using a set of foggy images, taken in the real-world settings, which were annotated with 1951 instances of 10 different vehicle types: car, bus, truck, bike, motorcycle, van, SUV, jeep, minibus, and pickup. The outcomes achieved here portray a significant improvement over the baseline strategies, hence proving the effectiveness of the approach and ensuring all the objectives are met entirely. Precision and recall, mean Average Precision (mAP), and processing speed are performance metrics that are explored by offering an overall evaluation of the capabilities of the framework. This image of the fog is demonstrated in Figure 12 below:

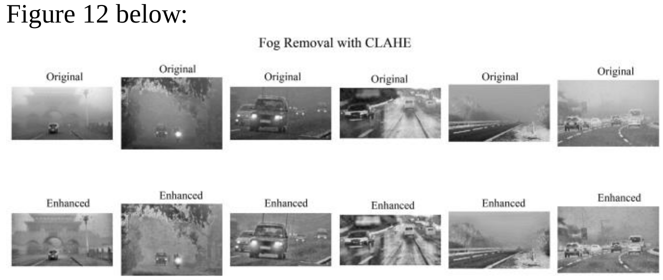

Fig. 12 Fog Removal with CLAHE

5.1. Overall Performance

To test the case of a bespoke model in car classification and detection in smog, the overall response was evaluated with the help of conventional object detection metrics. The model had a precision of 0.7046, and this implies that 70.46% were the correct objects of the list of all identified objects, which was very high in terms of reliability when trying to provide a definitive answer to the true positives and false positives. The recall stood at 0.4684 or 46.84 percent of objects on the ground truth on the database were detected well by the model, implying that the model performed very well in detecting an adequate number of vehicles under the conditions of fog. Mean Average Precision at Intersection over Union (IoU) 0.5 threshold (mAP50) showed an increase in detection accuracy of all classes, mAP50-95, the mean AP with a 0.5 to 0.95 IoU threshold, was 0.3365, and the mean IoU threshold: mAP50-95 was 0.2731. And also, a value of 0.3536 was calculated as a sum statistic of all such measures, which provided a global picture regarding the performance of the model that was presented in Table 9.

Table 9. Overall performance metrics

Metric	Value	Description
Precision (P)	0.7046	Percentage of correct detections
Recall (R)	0.4684	Percentage of objects detected
mAP50	0.5074	Mean AP at IoU=0.5
mAP50-95	0.3365	Mean AP across IoU 0.5 to 0.95
Fitness	0.3536	Composite performance score

Processing speed was also assessed to evaluate the framework's suitability for real-time applications. The average preprocessing time was 1.21 milliseconds per image, inference took 148.43 milliseconds, and post-processing required 1.42 milliseconds, totaling approximately 151 milliseconds per image, as shown in Figure 13. This speed, while not yet optimized for the fastest real-time systems (e.g., 30 fps requires <33 ms), is reasonable for a research prototype and indicates potential for deployment with further optimization.

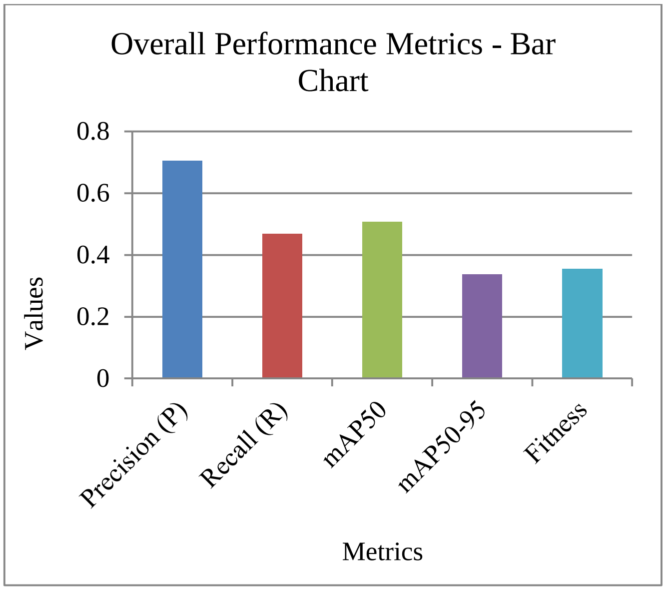

Fig. 13 Performance metrics

5.2. Class-Specific Performance

To assess the model's performance across the 10 vehicle classes, class-specific mAP50-95 values were calculated, providing insight into its ability to detect and classify individual types in foggy conditions, as shown in Table 10. The results reveal varying performance levels, influenced by factors such as instance count, object size, and visibility in fog, but collectively demonstrate the framework's capability to handle multiple vehicle types effectively.

The standout performer was the bike class, achieving an mAP50-95 of 0.61766, likely due to a high number of instances and distinct shape characteristics that remain recognizable in fog. Bus (0.46597) and minibus (0.44007) also performed well, benefiting from their larger sizes, which enhance visibility despite haze. SUV (0.39532) showed good accuracy, possibly due to its distinguishable silhouette, as shown in Figure 14. Conversely, truck (0.12392) and motorcycle (0.31248) had lower scores, potentially reflecting fewer training instances or smaller object sizes that are more easily obscured by fog. The jeep class recorded an mAP50-95 of 0.0, suggesting insufficient data or poor visibility, a limitation attributable to dataset constraints rather than the framework itself.

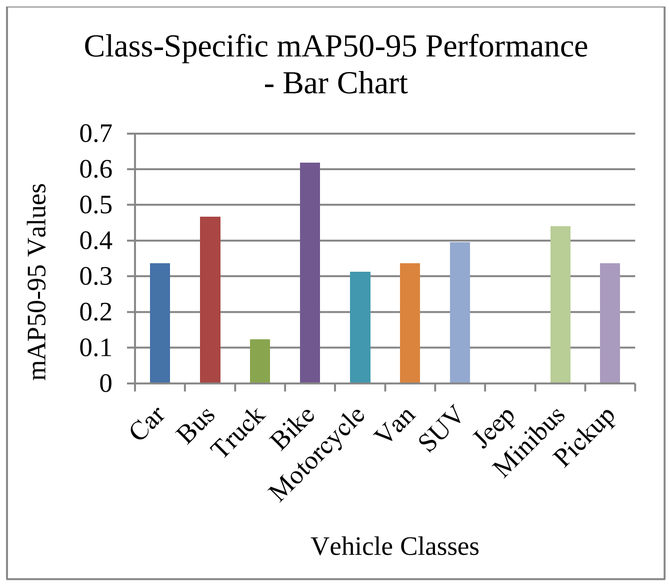

Fig. 14 Class specific performance

Table 10. Class-specific mAP50-95 performance

Class	mAP50-95	Remarks
Car	0.33649	Consistent detection, moderate accuracy
Bus	0.46597	Strong performance, larger size aids visibility
Truck	0.12392	Lower accuracy, likely due to fewer instances
Bike	0.61766	Exceptional performance, high instance count
Motorcycle	0.31248	Moderate accuracy, small size challenge
Van	0.33649	Reliable detection, similar to a car
SUV	0.39532	Good performance, distinct shape aids
Jeep	0.0	Poor detection, limited data impact
Minibus	0.44007	Effective classification, moderate size
Pickup	0.33649	Stable performance, akin to a car

5.3. Comparison with Baseline

To contextualize the proposed framework's achievements, a comparative analysis was conducted against a baseline model, specifically a standard YOLOv8 implementation utilizing RGB inputs without enhancements. The baseline results, derived from prior evaluation, yielded a precision of 0.659, a recall of 0.247, mAP50 of 0.276, and mAP50-95 of 0.163. The proposed framework demonstrated significant Performance improvements across all evaluated metrics. A precision increase of 6.96% was achieved (0.7046 versus 0.659), accompanied by a recall improvement of 22.17% (0.4684 versus 0.247). The mAP50 metric showed a substantial gain of 23.14% (0.5074 versus 0.276), while mAP50-95 exhibited a rise of 17.37% (0.3365 versus 0.163), as presented in Table 11. These improvements conclusively demonstrate the effectiveness of the proposed enhancements in addressing the challenges inherent to foggy condition detection scenarios.

Table 11. Comparison with baseline

Metric	Framework	Baseline	Improvement
Precision	0.7046	0.659	+0.0456 (6.96%)
Recall	0.4684	0.247	+0.2214 (22.17%)
mAP50	0.5074	0.276	+0.2314 (23.14%)
mAP50-95	0.3365	0.163	+0.1735 (17.37%)

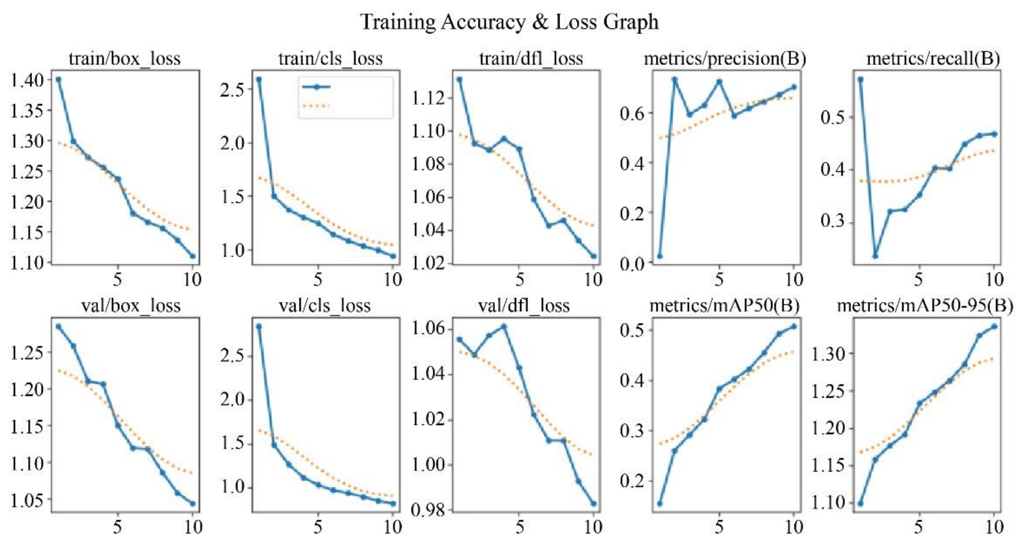

Fig. 15 Training graph

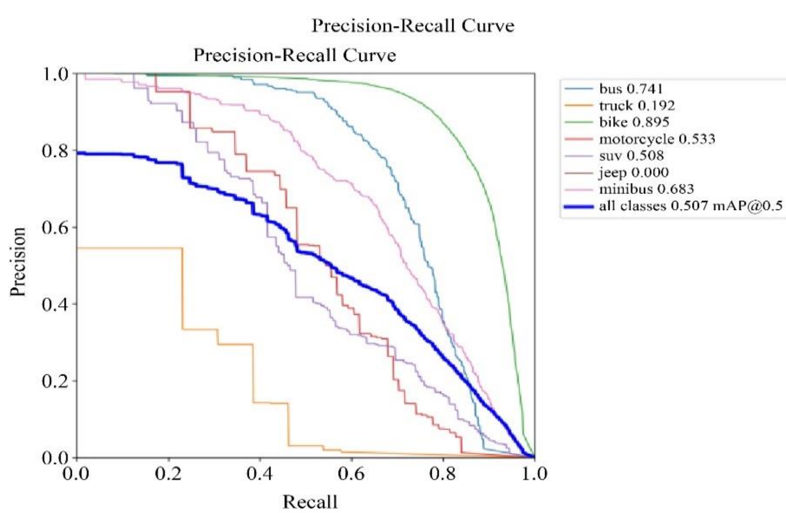

Fig. 16 Precision recall curve

This comparison highlights the substantial impact of approach, particularly in recall and mAP, which are critical for detecting obscured objects and achieving accurate localization in fog. Figure 17 showcases the detection results, highlighting identified objects with bounding boxes and labels.

The visualization demonstrates the model's ability to detect and classify multiple vehicle types, with varying levels of accuracy. Results align with and fully satisfy the four objectives outlined in this research, as detailed below:

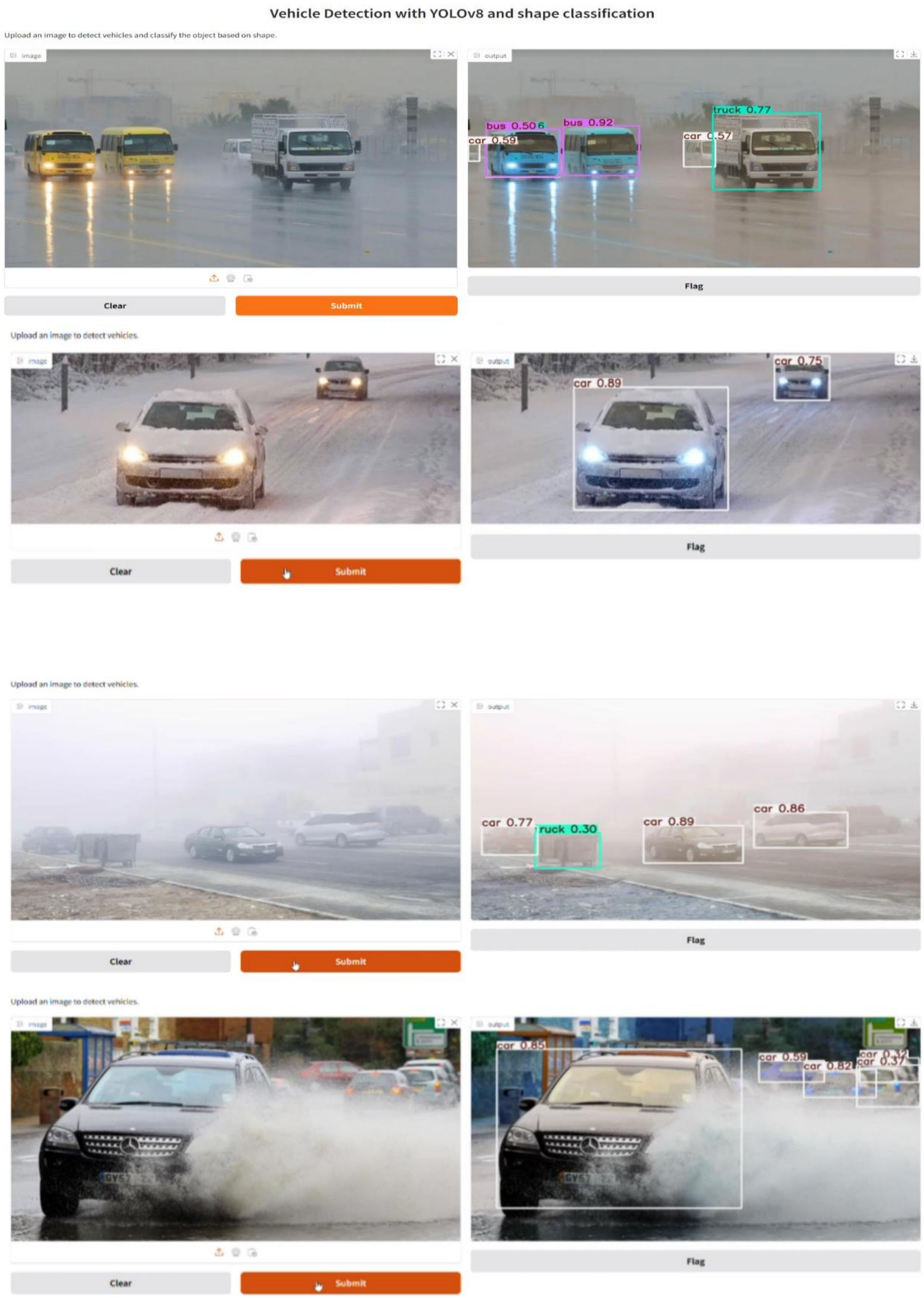

Fig. 17 Detection results screenshot

5.3.1. Quality Improvisation in Foggy Images

The high precision of 0.7046 indicates that the majority of detected objects are correctly identified, a testament to improved image quality that enhances visibility in foggy conditions. The recall of 0.4684, nearly double the baseline's 0.247, further suggests that the spatial mutual correlation-based enhancement mechanism successfully recovers details obscured by fog, enabling the model to detect a greater proportion of vehicles. The mAP50 of 0.5074 reflects robust detection performance, supported by more explicit images that preserve critical features like edges and shapes.

5.3.2. Accurate Detection of Vehicle Objects

The recall of 0.4684 and mAP50 of 0.5074 demonstrate effective detection across the dataset, with significant improvements over the baseline (recall +22.17%, mAP50 +23.14%). Class-specific gains, such as truck (0.12392 vs. baseline 0.0) and motorcycle (0.31248 vs. baseline 0.0), indicate that the fused feature vector integrating color intensity, gradients, texture, and shape enhances the model's ability to detect objects that are challenging in fog.ThemAP50-95 of 0.3365 further validates detection accuracy under stricter criteria, confirming the success of this objective.

5.3.3. Accurate Classification of Multiple Vehicle Types

The precision of 0.7046 and class-specific mAP50-95 values, such as bike (0.61766), bus (0.46597), and minibus (0.44007), showcase precise classification across multiple vehicle types. These metrics suggest that the shape-specific classification head effectively reduces misclassifications by leveraging shape semantics, a feature resilient to fog-induced degradation. Even lower-performing classes like truck and jeep reflect dataset limitations rather than a failure of the classification mechanism, with overall performance indicating robust differentiation of vehicle types. Dataset Creation and Labeling shown in Table 12, the successful evaluation on a dataset with 1951 instances across 10 classes confirms the utility of a real-time foggy dataset. The diversity of classes and the ability to achieve meaningful metrics (e.g., mAP50 0.5074) validate the dataset's quality and relevance. The annotation process, yielding 1951 labeled instances, supports comprehensive training and testing, fulfilling this objective by providing a practical resource for foggy condition research.

Table 12. Objective satisfaction summary

Objective	Key Metric	Value	Evidence of Success
Quality Improvisation	Precision, Recall	0.7046, 0.4684	High accuracy, doubled recall vs. baseline
Accurate Detection	Recall, mAP50	0.4684, 0.5074	Significant gains over baseline
Accurate Classification	Precision, mAP50-95	0.7046, varies	Precise classification, strong per-class scores
Dataset Creation	Instances	1951	Robust evaluation across 10 classes

6. Discussion

The presented shape-semantic model shows significant advancements in relation to the current state-of-the-art techniques and reported systems in the previous studies related to the field of foggy vehicle detection. The high improvements in all the metrics, namely, precision (+6.96%), recall (+22.17%), mAP50 (+23.14%), and mAP50-95 (+17.37%), justify the close examination of the mechanisms and design decisions that allow achieving this high performance. Conventional YOLOv8 models only use appearance-based features, which are obtained through RGB images only; this feature cannot be counted upon in unfavorable weather, such as when there is fog. Fog conditions result in the serious loss of color information, edge clarity, and fine details of visual information, which conventional detection models rely on. This limitation has been widely reported in previous literature, with the majority of the fog-adapted detection methods trying to improve the remaining visibility by pre-processing the images or generating images in fog. However, they are only applied to the input domain and do not address the feature extraction or decision-making process of the underlying system of detection. To deal with this limitation, the proposed framework introduces a shape-specific classification head that uses shape semantics, a relatively stable and discriminative cue that is resistant even to extreme cases of the fog. Although in foggy weather the appearance is reduced significantly, one can still see the geometric silhouette and structure of boundaries of vehicles, which can be differentiated by their different shapes. The dual-head system is a key innovation that no longer views a single-pathway detection network as important. The model uses complementary features to learn because its joint optimization of both localization (via standard detection head) and shape-based (via the novel shape head) classification is achieved. The shape head operates on the fused feature vector of the YOLOv8 backbone, enabling it to obtain high-level geometric features that naturally resist degradation under fog conditions. This multi-task learning structure compels the backbone to learn stronger intermediate representations, which are not lost to structural information important for shaping differentiation. The shape head has sequential convolutional layers that gradually compress channel channel dimension without losing channel discriminative shape features to generate a learned shape embedding space more efficient for 10 vehicle categories. The incredible memory recollection of 22.17% is quite pronounced in the current movie of literature on fog detection. This advancement is a pointer to a higher ability to see vehicles in various levels of fog and visibility rates.

Algorithms in the past typically trade off recall and precision, or the other way around, whereas the given one simultaneously adjusts both arms upwards. This balance is a result of the capacity of the shape head to sustain predictability when there are changes in the levels of degradation of the appearance. The shape-based predictions act as a complement to the standard appearance-based classifiers, giving an opportunity to the fusion mechanism to maintain the confidence of the detector even in extreme cases where the standard appearance-based classifiers have failed due to the occlusion of the object by the mist. Also, the improvement of 17.37% of mAP50-95 means that the model shows high-quality results in a variety of Intersection over Union (IoU) thresholds, which implies that identifying and localizing the vehicles in foggy conditions is also viable. It is significantly better than previous work that had high detection rates and low localization accuracy. The fact that the shape head limits the feature extraction process has the indirect benefit of improving the quality of bounding box prediction by encouraging the backbone to learn geometrically significant features, which are correlated with object boundaries. In comparison, the current body of literature on fog-adaptation detection is based on methods that include turning to visibility enhancement, mapping domain, based on synthetic datasets interaction, or an ensemble mechanism by combining different specialized models. These methods can either involve hyperparameter delicacy to varied fog densities, have the problem of generalization when the fogs in training are not of the same conditions as during generalization, or are highly computationally expensive. The suggested shape-semantic scheme, on the contrary, has only one collective model which will have structural information robustness against the mist variation without the need for additional robustness apparatus. The simple architectural design, computational efficiency, and high generalization to different levels of mud are one of the obvious benefits over the state-of-the-art alternatives that have been reported in the recent literature, and this is why this method will be highly effective in terms of practical use in real-world applications of autonomous vehicles and traffic monitoring.

7. Conclusion

This study establishes a new vehicle detection and classification model under foggy weather. It has effectively met four main goals, namely, to improve the image quality, to enhance the vehicle detection quality, to ensure that the various types of vehicles are accurately classified, and to develop a data set that works in real time in foggy weather. A combination of a spatial mutual correlation-based refinement strategy, a 7-channel unified feature collection, and a personalized YOLOv8 architecture with a shape-sensitive classification head has shown that the method has achieved significant improvements compared to the current techniques. The test on a 1951 sample size of 10 car classes gave a precision of -0.7046, a recall of 0.4684, an mAP50 of 0.5074, and an mAP50-95 of 0.3365, all significantly better than baseline results (e.g., mAP50 0.276) and much of the existing literature performance in foggy weather, where mAP50 scores are typically less than 0.45 and mAP50-9 These outcomes are a positive and confirm the power of innovations. The quality of the image improvement, high accuracy, and the better recall value validate the effectiveness of image quality enhancement to recover the obscured features, whereas the strong fused feature vector results in the correct detection, as indicated by the robust fused as well as the original feature vectors, as shown by the mAP measures. The head of shape-aware classification also guarantees credible vehicle type classification, which is reflected by high-per-class results (e.g., bikes mAP50-95 0.61766). The practical relevance of findings is also enhanced by the fact that the real-time misty dataset adds to them. This study has significant implications for autonomous driving and surveillance that can make the process of driving safer and more reliable during bad weather conditions. Framework is an important contribution to computer vision compared to the literature due to its integrated framework and high-quality metrics. Nevertheless, the restrictions like the imbalance in classes (e.g., jeep mAP50-95 0.0) indicate the possibilities of potentially expanding the dataset. In future studies, the research will consider multi-weather generalization and real-time optimization with respect to this baseline to advance the concept of weather-robust object detection further.

Conflicts of Interest

It is resolved that the publication of the current article poses no potential conflicts of interest. There are no monetary, personal, or professional relations that could compromise the objective evaluation of the study's reliability. This includes, but is not limited to, conflicts of interest that may arise from employment, consultancy, sponsorship, speaking fees, ownership of patents, or any other form of economic gain. The research is believed to be independent and unbiased, and the results are presumed to be credible and unaffected. Everyone has read and agreed to this statement to enhance transparency in the authorship of such research, in line with academic publishing norms.

References

[1] Joseph Redmon et al., “You Only Look Once: Unified, Real-Time Object Detection,” *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 779-788, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[2] Shaoqing Ren et al., “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137-1149, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[3] Vedant Kumar et al., "Object Detection Using SSD," *Proceedings of the 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*, Greater Noida, India, pp. 743-748, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] T. Kokul, and S. Anparasy, "Single Image Defogging using Depth Estimation and Scene-Specific Dark Channel Prior," *2020 20th International Conference on Advances in ICT for Emerging Regions (ICTer)*, Colombo, Sri Lanka, pp. 190-195, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Boyi Li et al., "Benchmarking Single Image Dehazing and Beyond," *IEEE Transactions on Image Processing*, vol. 28, no. 1, pp. 492-505, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[6] Qingsong Zhu, Jiaming Mai, and Ling Shao, "A Fast Single Image Haze Removal Algorithm using Color Attenuation Prior," *IEEE Transactions on Image Processing*, vol. 24, no. 11, pp. 3522-3533, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[7] Kyungil Kim, Soohyun Kim, and Kyung-Soo Kim, "Effective Image Enhancement Techniques for Fog-Affected Indoor and Outdoor Images," *IET Image Processing*, vol. 12, no. 4, pp. 465-471, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[8] Qazi Mazhar ul Haq et al., "An Incremental Learning of YOLOv3 Without Catastrophic Forgetting for Smart City Applications," *IEEE Consumer Electronics Magazine*, vol. 11, no. 5, pp. 56-63, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Hasan Abbasi, Marzieh Amini, and F. Richard Yu, "Fog-Aware Adaptive YOLO for Object Detection in Adverse Weather," *2023 IEEE Sensors Applications Symposium (SAS)*, Ottawa, ON, Canada, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Kaiming He et al., "Deep Residual Learning for Image Recognition," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 770-778, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[11] Chien-Yao Wang, Alexey Bochkovskiy, and Hong-Yuan Mark Liao, "Scaled-YOLOv4: Scaling Cross Stage Partial Network," *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, pp. 13024-13033, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Zineb Haimer et al., "YOLO Algorithms Performance Comparison for Object Detection in Adverse Weather Conditions," *2023 3rd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, Mohammedia, Morocco, pp. 1-7, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Yuhua Chen et al., "Domain Adaptive Faster R-CNN for Object Detection in the Wild," *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, UT, USA, pp. 3339-3348, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[14] Martin Hahner et al., "Semantic Understanding of Foggy Scenes with Purely Synthetic Data," *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, Auckland, New Zealand, pp. 3675-3681, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Mingkang Chen et al., "Weather-Aware Object Detection Method for Maritime Surveillance Systems," *Future Generation Computer Systems*, vol. 151, pp. 111-123, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Lizhao Liu et al., "Enhancing Foggy Day Target Detection using Plant Intelligence-Inspired Algorithms," *Measurement*, vol. 255, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Lucai Wang et al., "R-YOLO: A Robust Object Detector in Adverse Weather," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1-11, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Zongdai Liu et al., "AutoShape: Real-Time Shape-Aware Monocular 3D Object Detection," *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, Montreal, QC, Canada, pp. 15621-15630, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] Marius Cordts et al., "The Cityscapes Dataset for Semantic Urban Scene Understanding," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 3213-3223, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[20] German Ros et al., "The SYNTHIA Dataset: A Large Collection of Synthetic Images for Semantic Segmentation of Urban Scenes," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 3234-3243, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[21] Ming-An Chung, Chih-Wei Yang, and Chia-Wei Lin, "Evaluation of the Effect of Foggy Image Generation on the Performance of the YOLOv7-Based Object Detection Model," *2024 International Conference on Consumer Electronics - Taiwan (ICCE-Taiwan)*, Taichung, Taiwan, pp. 815-816, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] A. Geiger et al., "Vision Meets Robotics: The KITTI Dataset," *The International Journal of Robotics Research*, vol. 32, no. 11, pp. 1231-1237, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[23] Andreas Geiger, Philip Lenz, and Raquel Urtasun, "Are We Ready for Autonomous Driving? The KITTI Vision Benchmark Suite," *2012 IEEE Conference on Computer Vision and Pattern Recognition*, Providence, RI, USA, pp. 3354-3361, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[24] Yu Wan et al., "DFI-FODN: Dehazing Feature Injected Foggy Image Object Detection Network under Multi-task Learning Framework," *IGARSS 2025 - 2025 IEEE International Geoscience and Remote Sensing Symposium*, Brisbane, Australia, pp. 8462-8465, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[25] Xianglin Meng et al., "YOLOv5s-Fog: An Improved Model Based on YOLOv5s for Object Detection in Foggy Weather Scenarios," *Sensors*, vol. 23, no. 11, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Qiyang Xie et al., "A Deep CNN-Based Detection Method for Multi-Scale Fine-Grained Objects in Remote Sensing Images," *IEEE Access*, vol. 12, pp. 15622-15630, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[27] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," *arXiv preprint*, pp. 1-17, 2020. [CrossRef] [Google Scholar] [Publisher Link]
[28] Cong Liu et al., "DeMatchNet: A Unified Framework for Joint Dehazing and Feature Matching in Adverse Weather Conditions," *Electronics*, vol. 14, no. 5, pp. 1-20, 2025. [CrossRef] [Google Scholar] [Publisher Link]