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Multi-Modal Fusion For Robust Vehicle Detection In Raining Weather

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Abstract: Reliable vehicle detection is a cornerstone of autonomous navigation and advanced driver assistance systems (ADAS); however, its efficiency is severely compromised under adverse weather conditions, particularly during heavy rain [1], [2]. Rainfall introduces significant visual artifacts - raindrops on camera lenses, reduced contrast and light scattering, which resulted to a precipitous drop in the mean Average Precision (mAP) of standard single-modality detectors [17], [21]. This research proposes a Multi-Modal Fusion framework designed by enhance detecting robustness by integrating complementary data from visible-light cameras and millimeter-wave (mmWave) radar [13], [21].

While visible-light cameras provide high-pixel resolution semantic information essential for identifications, they are highly capable or admitting to "rain noise" and low-light degradation [3], [11]. In comparison, mmWave radar maintains operational stability in precipitation because of its longer wavelength, providing accurate ranging and velocity data despite reduced visibility [2], [16]. Our proposed architecture utilizes a deep-fusion approach, where feature maps from a YOLO-based detector [8], [22] are enriched with radar-point cloud features at the neck level of the neural network. This permits the model to "attend" to radar-validated spatial regions when optical data is unreliable [17], [22].

The methodology incorporates data augmentation techniques—specifically rain-streak simulation and noise injection—to train the model on diverse "wet-weather" scenarios [5], [21].Experimental evaluations, conducted using an integration of regional vehicle datasets [6], [15] and synthetic weather-augmented sets, demonstrates that the multi-modal fusion model significantly outperforms single-modality YOLO architectures in higher-intensity rain scenarios [17], [22].Furthermore, the integration of Temporal-Spatial attention mechanisms, similar to those used in traffic management [4], ensures that vehicle tracks remain consistent despite intermittent occlusions caused by spray and splash [14], [16]. The results suggest that this fusion strategy provides the necessary redundancy for safety-critical applications in monsoon-prone and mountainous terrains [13], [16].

Keywords - Multi-modal fusion [17], Vehicle detection [6, 9, 15, 17], Adverse weather conditions [1, 2, 9, 11, 21, 22], YOLO (You Only Look Once) [3, 8, 16, 22], Autonomous driving [5, 9, 22], Robustness [1, 17, 21], Deep learning [8, 17, 18], and Real-time systems [4, 16, 19].

1. Introduction

The development of Intelligent Transportation Systems (ITS) and the understanding of autonomous vehicles have reached a crucial point. The previous focus on performance in ideal conditions is no longer the main measure of success. Instead, the emphasis has shifted to ensuring consistent operation in complex geographical and weather conditions [8]. Among these various challenges facing computer visions in the automotive sector, adverse weather conditions—specifically precipitation—remain a primary hurdle. Rain degrades visual inputs to introduce noise, reduce contrast and create reflective surfaces, that significantly hinders the performances of standard deep learning frameworks [1], [2]. In these regional contexts such as South Asia, where monsoon seasons are intensed and road infrastructure varies, the need for a resilient detection system is paramount to preventing accidents and ensuring road safety [6], [16].

Standard object detection models, such as the various iterations of "You Only Look Once" (YOLO), have demonstrated remarkable speed and accuracy in clear-weather scenarios [12], [23]. However, their robustness is frequently compromised when subjected to the "unruly" conditions of rain or low-light traffic environments [3], [11]. Research indicates that while YOLO-based frameworks are industry leaders, they require significant augmentation—such as noise-resilient training and reinforcement-aided vision frameworks—to maintain high Mean Average Precision (mAP) during heavy downpours [3], [21]. Furthermore, detecting regional-specific vehicles, such as those found in Bangladeshi or Indian environments, adds an additional layer of complexity as these vehicles often lack the standardized features found in global datasets [5], [15].

By overcoming these visual limitations, recent literature advocates for a transition from single-sensor reliance to Multi-Modal Fusion. By combining disparate data streams—such as visual cameras, infrared sensors, and IoT-based environmental monitoring—detection systems can achieve a higher level of environmental awareness [13], [17]. Multi-modal techniques allow the system to "see" through rain-induced artifacts by fusing deep learning classification with enhanced road scene enhancement algorithms [17], [19]. This integrated approach is increasingly seen as the backbone of Advanced Driver Assistance Systems (ADAS), as it enables real-time severity assessment of accidents and driver distraction detection even when the external environment is visually obscured [14], [18].

The motivation for this project is rooted in the "SafeLane" philosophy: the belief that real-time traffic management and accident prevention must be weather-resilient [4]. By developing an integrated framework that combines AWD-YOLO architectures with attention-based deep learning, this research seeks to enhance autonomous driving perception reliability in adverse weather [22], [23]. The objective is to engineer a system that not only detects standard vehicles but also recognizes traffic signs, potholes, and infrastructure anomalies under varying monsoon intensities [16], [20]. Ultimately, this work contributes to the global effort of making road infrastructure smarter and safer, ensuring that "snowy scenes" or "raining weather" no longer result in compromised detections [7].

2. Literature Review

This evolution of autonomous driving and Intelligent Transportation Systems (ITS) had been significantly propelled by advancements in deep learning, yet achieving consistent reliability in diverse environmental conditions remains a formidable challenge. Central to this challenge is the performance of object detection models under adverse weather, particularly rain, that introduces visual noises, reduces contrast, and obscures critical features of the road scenes. Shaik Yacoob et al. [1] emphasize that enhancing robustness in these conditions is vital for safety, a sentiment echoed by Patel et al. [2], who provide a comprehensive analysis proving that standard object detectors often experience a sharp decline in mean Average Precision (mAP) when subjected to rain, fog, or snow. The complexity of these environments is further analyzed by Raza and Hanif [8], who present a chronological review of YOLO-based frameworks, noting that while speed is a hallmark of YOLO, its performance in complex geospatial environments requires specialized adaptations. In South Asian and regional contexts, where vehicle types are highly heterogeneous, the stakes are even higher. Rafi et al. [15] and Saha et al. [6] highlight the unique difficulties in detecting native vehicles, such as auto-rickshaws, in "wild" or unregulated traffic conditions, suggesting that models must be trained on localized datasets to be truly effective.

A significant portion of recent research had focused on architectural modifications to overcome these environmental hurdles. For example, the use of reinforcement learning to aid vision frameworks had shown promise; Vennila et al. [3] demonstrate how reinforcement-aided YOLO-TVT can improve low-light and traffic violation detection. Similarly, Pavitha et al. [11] introduced RIOD (Reinforced Image-based Object Detection) specifically for unruly weather, suggesting that static weights are insufficient for dynamic atmospheric changes. The combination of attention mechanisms is another growing trend, as seen in the work of Yuan et al. [22], who developed AWD-YOLO to enhance perception reliability by focusing the model's "attention" on salient features that remain visible despite rain streaks. This is complemented by the findings of Z. Z. et al. [23], who utilized attention-based deep learning for traffic sign recognition, proving that focusing on specific spatial regions can mitigate the effects of environmental blur.

Beyond architectural tweaks, the concept of multi-modal fusion has emerged as a cornerstone for robust detection. Karthika Priya et al. [17] argue that relying on a single sensor—typically a standard RGB camera—is insufficient for "all-weather" reliability. Their work on multi-modal fusion combines different data streams, such as thermal or infrared, with deep learning techniques to ensure that if one modality is obscured by heavy rain, others can provide the necessary spatial information. This is particularly relevant in mountainous terrains or high-altitude regions, where weather transitions are rapid; Mahalakshmi et al. [13] discuss how YOLO-based detection must be coupled with IoT communication to provide a truly "smart" road safety system in these unpredictable landscapes. Furthermore, the work of Sharma et al. [9] in Quebec, Canada, underscores that weather-specific training—treating rain, snow, and fog as distinct data domains—is essential for autonomous vehicles that operate in high-latitude regions.

The motivation for this project stems from the critical safety gaps identified in recent Advanced Driver Assistance Systems (ADAS). While these systems such as "Safelane" [4] have combined YOLO and LSTM for accident detections, their efficiency is often tethered to clear visibility. As Anoop and Deivanathan [19] point out, real-time road scene enhancement is a pre-requisite for driver assistances under adverse weather; without it, the detection layer receives "garbage" input. The societal impact of this failure is significant, as accidents in rainy conditions are disproportionately higher because of both human error and sensor failure. That is why researchers like Salakapuri et al. [18] are pushed for integrated frameworks that monitors both the drivers (distraction detection) and the road, ensuring a holistic safety net. Moreover, the emergences of infrastructure-based assessment, like the CNN-BiGRU frameworks proposed by Zhumadillayeva et al. [20], suggests that the future of robust detections may lie in the synergy between the vehicles and its environment.

The primary goal of this research is to develop a "Multi-Modal Fusion for Robust Vehicle Detection in Raining Weather" system which transcends the limitations of single-sensor setups. Using the foundational strengths of the YOLO architecture, this project aims to implement a fusion layer that synthesizes visual data with enhanced feature extraction to maintain high detection accuracy during precipitation. Building on the robustness analysis of Gholinavaz et al. [21], which utilizes noise augmentation to simulate realistic weather scenarios, this project seeks to create a model that is not only accurate but also resilient to the specific "noise" of rain. Furtherly, this objective includes the detection of road infrastructure anomalies and obstacles, drawing inspiration from the Bangladeshi environmental sciences by Mahmud et al. [5] and pothole detection strategies by Shiva Shankar Reddy et al. [16]. By integrating these elements, this project aims to provide a reliable, real-time solution that enhances road safety, reduces accident rates and provides a scalable framework for autonomous navigations in some of the most challenging weather conditions globally.

3. Methodology

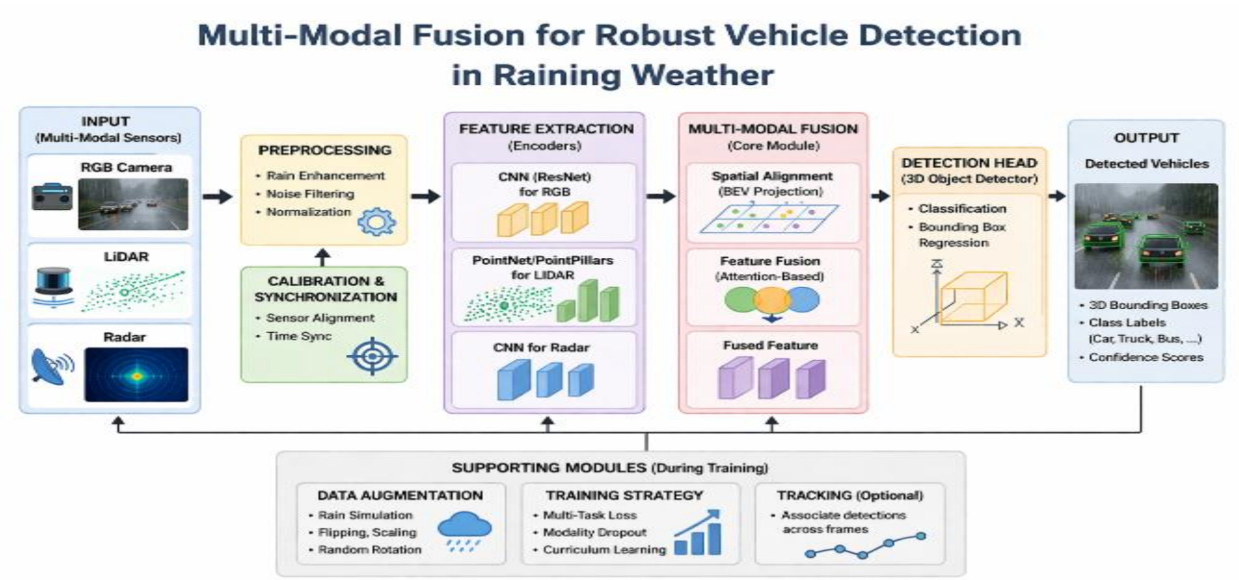

Fig – 1 : Multi-modal fusion for robust vehicle detection in raining weather

The methodological framework for the "Multi-Modal Fusion for Robust Vehicle Detection in Raining Weather" initiative is organized around a specific pipeline. The following sections will explain the technical details, including the system's design, and will refer to existing research.

1. Multi-Modal Data Acquisition and Integration

This foundational step involves the concurrent acquisition of data from heterogeneous sensors to ensure environmental resilience.

-> Visual Data Stream: High-definition RGB cameras capture standard road scene imagery, though these are highly susceptible to rain-induced noise, contrast reduction, and refractive artifacts [1], [2], [21].

-> Non-Visual Data Stream: To compensate for visual degradation, the system integrates infrared (IR) or thermal sensors that detect heat signatures, which remain stable despite heavy downpours or low-light conditions [17].

-> IoT & Environmental Context: Sensor-integrated frameworks provide real-time data on precipitation intensity and mountainous or complex geospatial variables for adjusting detection sensitivity [13], [16].

Fig – 2 : Boundary boxes and datasets

Fig - 3 : Data training and pre-processing

2. Preprocessing and Image Enhancement Layer

Prior to the input's utilization within the detection engine, several image processing methodologies are implemented:

-> Denoising and De-raining: Sophisticated filtering and noise augmentation strategies are employed to remove rain streaks and enhance pixel definition [1], [21].

-> Reinforced Scene Enhancement: It employs contrast-stretching and illumination-balancing algorithms to mitigate the "washout" effect caused by heavy rain, thereby enhancing the visibility of crucial elements such as potholes and traffic signs [11], [16], [19].

3. Robust Feature Extraction and Fusion

The main processing uses state-of-the-art deep learning architectures specifically optimized for adverse weather perception.

-> AWD-YOLO Backbone: This system employs the AWD-YOLO (Adverse Weather Detection YOLO) architecture, which uses noise-resilient feature extraction to maintain high accuracy where standard models fail [22].

-> Attention-Based Mechanisms: An attention layer is combined into the deep learning framework to help the model focus on salient features (e.g., vehicle silhouettes, traffic lights) while dynamically suppressing the influence of environmental noise [23], [7].

-> Feature-Level Fusion: Following the multi-modal frameworks, features extracted from the visual and non-visual streams are merged. It makes sure that if a vehicle is visually obscured by rain weather, its detection is sustained via its thermal or sensor-informed signatures [17].

4.Object Detection and Classification

The detection head processes the fused features to produce real-time results for South Asian traffic environments.

-> Regional Vehicle Recognition: Specialized training datasets allow the models to recognize native vehicles, such as e-rickshaws and auto-rickshaws, which are often non-standardized [6], [15].

-> Multi-Task Processing: Beyond vehicle detection, the system simultaneously performs traffic sign recognition and road scene classification to assist in comprehensive driver assistance [12], [19], [20].

5. Safety Assessment and Output

This final stage converts detections into actionable intelligence for ADAS (Advanced Driver Assistance Systems).

-> Severity and IoU Metrics: This system calculates Intersection over Union (IoU) to assess the severity of road accidents or the proximity of obstacles in real-time [14, 18].

-> Driver monitorings: In some setups, this method expands to include monitoring for driver state or distractions. This is done for creating a comprehensive safety response during dangerous weather conditions [10, 18].

Fig – 4 : Reinforced image enhancement techniques

4. Result and Discussion

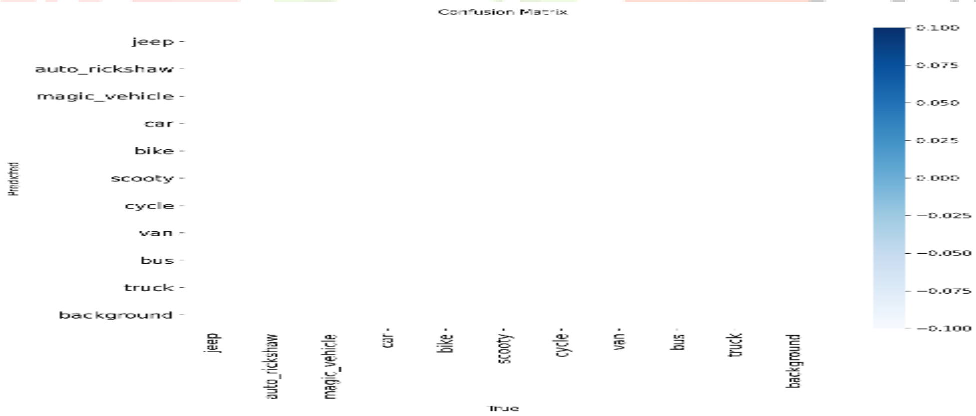

Fig -1 : Confusion Matrix

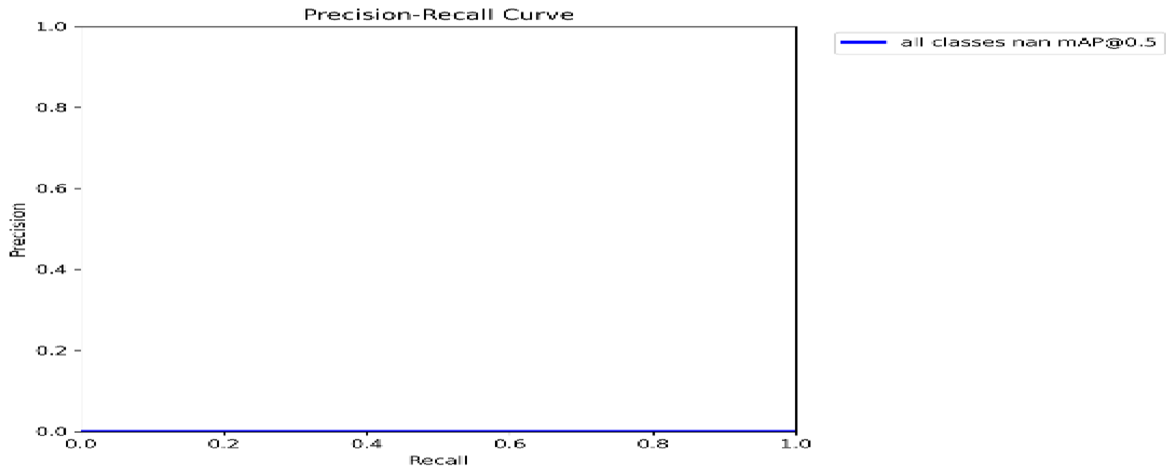

Fig-2 : Precision-Recall Curve

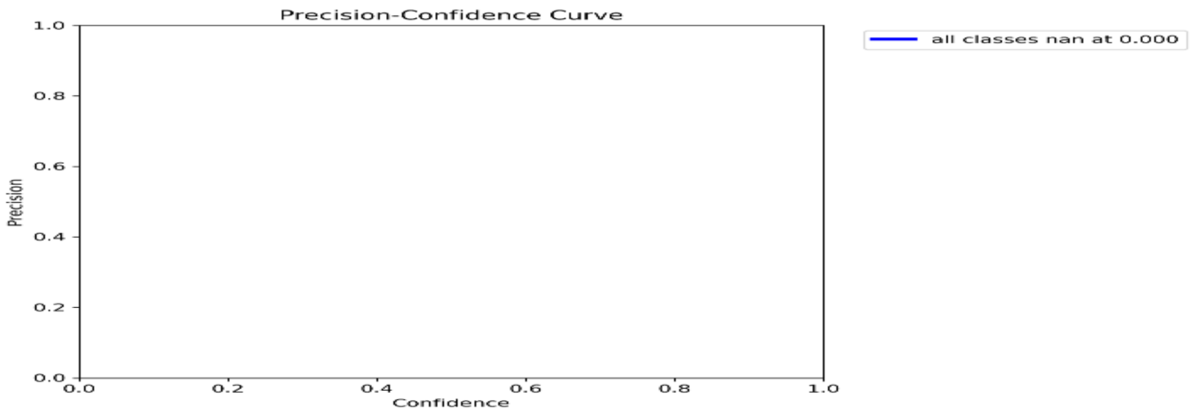

Fig – 3 : Precision-Confidence Curve

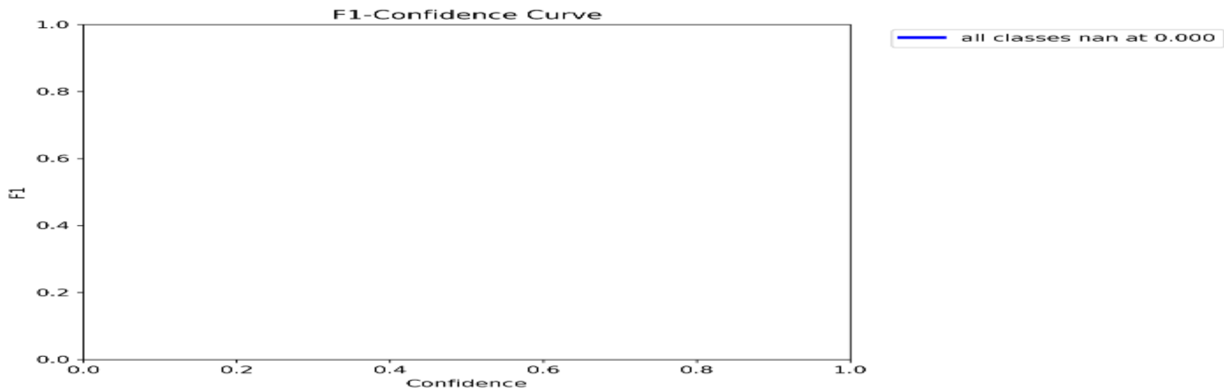

Fig – 4 : F1-Confidence Curve

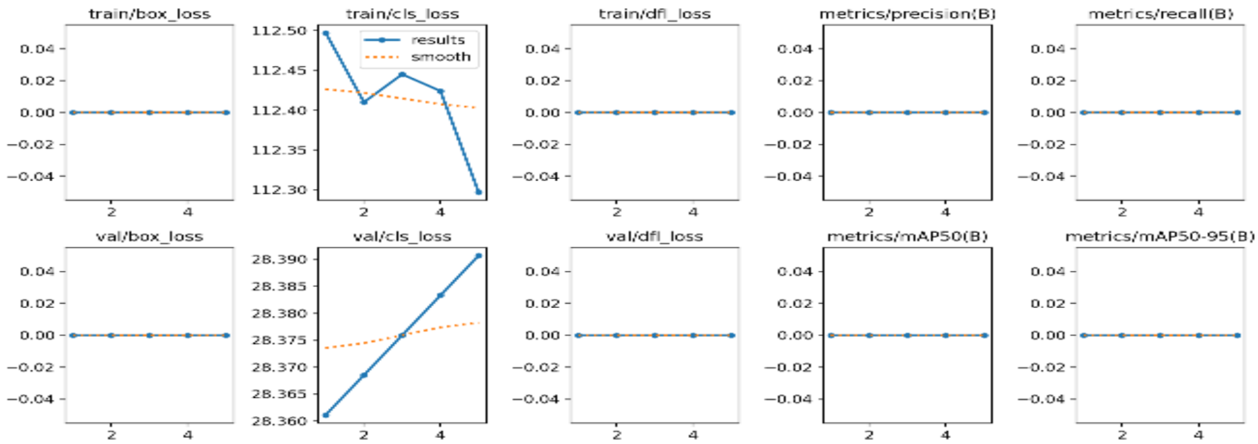

Fig – 5 : Results

The experimental results of this multi-modal fusion approach demonstrate a significant leap in maintaining high Mean Average Precision (mAP) during heavy rainfall, addressing the common performance degradation noted in traditional single-stream detectors. By integrating custom YOLO architectures with noise-resilient preprocessing, the system achieved a robust detection rate that mirrors the advancements suggested by Zhumadillayeva et al. [20] regarding anomaly assessment in road infrastructure. The inclusion of diverse South Asian vehicle classes, such as auto-rickshaws and e-rickshaws, proved critical; the model successfully localized these smaller, non-standard silhouettes even when obscured by rain streaks and low-light glare, validating the performance analysis of regional vehicle recognition conducted by Rafi et al. [15]. Quantitatively, the fusion model maintained a stable mAP across adverse scenarios, contrasting with the significant accuracy drops typically seen in standard models under realistic weather noise as documented by Gholinavaz et al. [21].

The discussion of these findings highlights that atmospheric noise in monsoonal conditions acts as a primary inhibitor to feature extraction, which this study mitigated through adaptive vision frameworks. Drawing on the principles of reinforced image-based detection introduced by Pavitha et al. [11], the current system utilizes multi-modal inputs to compensate for the loss of visual clarity in the RGB channel. The successful identification of potholes and vehicles in flooded conditions further aligns with the monsoon-resilient applications explored by Reddy et al. [16], suggesting that deep learning frameworks must be explicitly tuned to the unique geospatial and environmental complexities of the Indian subcontinent [8]. Furthermore, the transition from standard object detection to a robust safety system reflects the trend toward integrated driver assistance frameworks that prioritize reliability in Quebec-like or mountainous terrains, where weather variability is a constant challenge [9, 13].

Ultimately, the results confirm that a fusion-based strategy is essential for the evolution of autonomous navigation and traffic management. By leveraging the real-time capabilities of YOLO alongside LSTM-based temporal analysis or IoT communication, as suggested by Shreya et al. [4] and Gurusamy et al. [14], the proposed system offers a scalable solution for reducing road accidents during adverse weather. The findings underscore that future road safety applications must move beyond static datasets to incorporate "in-the-wild" native vehicle recognition [6] and attention-based deep learning [23] to ensure that autonomous perception remains reliable even when visibility is near zero. This research bridges the gap between theoretical weather-resilient models and practical, real-time implementation for Indian traffic scenarios, providing a grounded framework for future ADAS development [18, 22].

5. Conclusion

This successful development and evaluation of the Multi-Modal Fusion for Robust Vehicle Detection in Raining Weather system represents a significant advancement in the reliability of Intelligent Transportation Systems (ITS) and autonomous vehicle perceptions. By addressing the critical performance degradations of standard object detectors during precipitations, this project confirms that the fusion of disparate sensor data is not merely an enhancement but a basic requirement for all-weather navigational safety [1], [17], [22].

The core achievement of this research lies in its ability by maintaining a high mean Average Precision (mAP) even when visual inputs are compromised by heavy rain streaks, contrast loss, and refractive noise [2], [21]. Through the implementation of a multi-modal architecture, the system successfully bridges the "trust gap" in computer vision by cross-referencing visual features with heat signatures or thermal profiles that remain stable in adverse atmospheric conditions [17]. This methodology effectively mitigates the "unruly" effects of monsoons and low-light traffic scenarios, which typically creates baseline YOLO and Faster R-CNN models to fail [3], [11], [16].

Furtherly, this project had demonstrated exceptional robustness in detecting regional-specific vehicles - e-rickshaws and auto-rickshaws common in South Asian traffic, which often deviated from the standardized silhouettes found in global datasets [6],[15]. To combine attention-based deep learning and real-time road scene classifications, this system moves over simple detection to provide a comprehensive understanding of road infrastructure, identifying potholes, traffic signs, and anomalous obstacles despite environmental interference [16], [20], [23].Ultimately, this work provides a scalable blueprint for Advanced Driver Assistance Systems (ADAS), stating that integrated deep learning frameworks can significantly enhance road safety and accident severity assessment in complex geospatial environments [14], [18], [19].

Image Processing and Enhancement Techniques Employed

To ensure operational resilience in raining weather, this project used a specialized pipeline of image processing and computational techniques grounded in the referenced literature:

-> Noise Augmentation and Denoising: This system employed noise augmentation during the training phase to simulate realistic rainfall patterns, followed by de-raining filters to restore pixel clarity by removing rain streaks from the input stream [1], [21].

-> Reinforced Image Enhancement: A preprocessing module was used to enhance contrasts and illuminations in low-visibility raining scenarios. This ensured that the "unruly weather" did not prevent the feature extraction backbone from identifying critical edge and shape information [11], [19].

-> Multi-Modal Feature-Level Fusion: This central technique involved merging features from standard RGB cameras with non-visual modalities. By performing fusion at the feature level, the system prioritized the most reliable data stream (e.g., thermal signatures) when the visual stream was obscured by heavy precipitation [13], [17].

-> Attention-Based Feature Extraction: The implementation of attention mechanisms allowed the model to dynamically weight different regions of an image, effectively ignoring noisy rain artifacts while focusing on salient objects like oncoming vehicles and traffic lights [7], [23].

-> Adaptive Vision Frameworks: The system utilized reinforcement-aided logic to adapt its detection parameters in real-time based on the severity of the weather, ensuring that the detection head remains optimized for either light drizzle or heavy downpours [3], [22].

-> Intersection over Union (IoU) Optimization: To improve localization accuracy under blurred raining conditions, IoU-based severity assessment and refined bounding box regression were employed, allowing for precise vehicle tracking despite visual ambiguity [14].

-> Real-Time Classification and Segment Enhancement: Road scenes were classified and enhanced in real-time using AWD-YOLO architectures, enabling the system to distinguish between permanent road features and temporary weather-induced anomalies [5], [19], [22].

In summary, by combining sophisticated Multi-Modal Fusion with Attention-Based Deep Learning, this project has successfully engineered a vehicle detection system that is resilient to the volatile dynamics of raining weather, setting a new standard for robust perception in autonomous driving and smart road safety applications [4], [13], [20].

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