Phase 1: Literature Review & Feasibility

"Fog-Robust Object Detection on Embedded GPUs Using Hybrid Attention Networks"

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***Abstract*—This paper presents a literature review and feasibility analysis for implementing object detection under hazy and foggy conditions using deep-learning models optimized for embedded hardware, specifically the NVIDIA Jetson Nano (4 GB). The review summarizes research from 2019–2025 on dehazing networks and detection frameworks, emphasizing attention-based optimization, feature fusion, and lightweight model design for real-time embedded deployment.**

***Index Terms*—Haze removal, object detection, YOLOv5, YOLOv7, YOLOX, AOD-Net, TSMD-Net, Jetson Nano, embedded vision.**

I. Introduction

Haze and fog remain major challenges for computer vision systems, as suspended aerosols scatter light and blur scene edges, lowering image contrast and degrading detection accuracy. These effects pose safety and reliability issues for autonomous driving and outdoor surveillance, particularly when processing must occur on resource-limited devices such as the NVIDIA Jetson Nano (4 GB). This work reviews state-of-the-art methods that enhance detection robustness under foggy conditions through joint dehazing, attention-based learning, and lightweight architecture optimization.

II. Literature Review and Feasibility

Recent work on object detection in degraded weather highlights the transition from physical priors to learning-based frameworks capable of combining haze removal and detection in a single pipeline. The following sections summarize major contributions from 2019–2025 that improve detection quality and efficiency while maintaining feasibility for embedded systems.

A. From Physical Priors to Deep Networks

Traditional dehazing relied on the atmospheric-scattering model (ASM), which estimates transmission and airlight to reconstruct clear scenes. The *Dark Channel Prior (DCP)* [7] became foundational but suffered from color distortion and slow computation. Later priors, including the Color-Attenuation Prior and Boundary-Constraint Regularization, improved consistency but still struggled under dense haze.

The advent of deep convolutional networks enabled data-driven learning of haze removal. The *All-in-One Dehazing Network (AOD-Net)* [8] unified illumination and transmission estimation for efficient end-to-end training. Building on this, Li *et al.* [10] combined an improved AOD-Net with YOLOv5s, integrating Hybrid Dilated Convolution (HDC), ShuffleNetv2, GSConv, and CBAM attention. On the RTTS dataset, their system reached 76.8 % mAP with 42 % parameter reduction—demonstrating that optimized designs can run effectively on Jetson Nano after TensorRT conversion.

B. Enhanced Architectures for Foggy Environments

A more integrated approach was proposed by Qiu *et al.* [2], who developed *IDOD-YOLOv7*—a joint dehazing and detection network for foggy and low-light traffic scenes. Their architecture combines an AOD-based restoration module and a Self-Adaptive Image Processing (SAIP) block that learns gamma correction, contrast, and sharpening parameters dynamically. Using the real *FTOD* dataset of 5100 fog/non-fog image pairs, IDOD-YOLOv7 improved YOLOv7 mAP by 7.9 % and achieved 71 FPS on RTX hardware with 46.5 M parameters (94 GFLOPs), confirming modular transferability to embedded GPUs.

Similarly, Raju and Srinivas [9] proposed *TSMD-Net*, a Two-Stage Mixed Dehazing Network that combines contextual encoding with a spatial attention branch linked via Dual Attention Modules (DAM) and Multi-Window Self-Attention (MWSA). On RESIDE-6K and Dense-HAZE datasets, TSMD-Net achieved PSNR = 25.31 dB and SSIM = 0.924, outperforming AOD-Net. Deployed on Jetson Nano, it processed 512×512 images in 1.9 s using 16.3 M parameters, validating embedded feasibility.

C. Recent Advances: YOLOX and Hybrid Attention Strategies

Liu *et al.* [1] introduced a novel *Improved YOLOX* architecture for autonomous-vehicle detection in foggy environments. Their model integrates a dual-branch attention module combining channel and spatial attention to emphasize salient features under reduced visibility. The backbone uses Cross-Stage Partial (CSP) connections with enhanced data augmentation and *Focal Loss* to address class imbalance in fog scenarios. Evaluations on the BDD100K and self-collected fog datasets achieved mAP = 81.2 % (+5.3 % over baseline YOLOX) with 60 FPS on RTX 3060. Despite moderate complexity (70 GFLOPs), pruning and quantization experiments confirmed smooth real-time inference on Jetson Nano 4 GB, making it a promising candidate for embedded deployment in next-phase implementations.

D. Lightweight Detection and Dataset Expansion

Meng *et al.* [3] proposed *YOLOv5s-Fog*, which integrates Swin-Transformer attention and Soft-NMS, gaining +5.4 %

mAP on RESIDE/RTTS. Gharatappeh *et al.* [4] presented *FogGuard*, a perceptual-loss distillation framework that improved YOLOv3's haze robustness by 12 %. Feng *et al.* [5] developed *HazyDet*, a 383 k-image dataset with depth-conditioned detection, while Kumar and Chadha [6] reported that excessive dehazing may harm clarity on non-fog scenes—underscoring adaptive pre-processing importance.

E. Feasibility and Key Insights

Across all reviewed studies, three trends emerge:

- **Joint dehazing and detection:** Integration (e.g., IDOD-YOLOv7, AOD-YOLOv5, Improved YOLOX) yields contextual consistency and higher accuracy than sequential pipelines.
- **Attention-guided lightweighting:** Modules like CBAM, MWSA, Swin, and dual-branch attention improve low-contrast recognition under 20 M parameters and 70 GFLOPs—ideal for Jetson Nano.
- **Dataset diversity:** RTTS, FTOD, HazyDet, and BDD100K-Fog provide realistic visibility variations, improving cross-domain generalization.

Liu et al.'s YOLOX, Qiu et al.'s YOLOv7, and Raju & Srinivas's TSMD-Net confirm that quantized FP16/INT8 models can achieve real-time edge inference. For a 10–12 week semester project, replicating Improved YOLOX or IDOD-YOLOv7 on Jetson Nano offers a realistic, measurable goal with academic and practical significance.

REFERENCES

[1] Z. Liu, H. Zhang, and L. Lin, "Vehicle Target Detection of Autonomous Driving Vehicles in Foggy Environments Based on an Improved YOLOX Network," *Sensors*, vol. 25, no. 1, p. 194, 2025.

[2] Y. Qiu, Y. Lu, Y. Wang, and H. Jiang, "IDOD-YOLOv7: Image-Dehazing YOLOv7 for Object Detection in Low-Light Foggy Traffic Environments," *Sensors*, vol. 23, no. 13, p. 1347, 2023.

[3] X. Meng, Y. Liu, L. Fan, and J. Fan, "YOLOv5s-Fog: An Improved Model for Object Detection in Foggy Weather," *Sensors*, vol. 23, no. 11, p. 5321, 2023.

[4] S. Gharatappeh, S. Neshatfar, S. Y. Sekeh, and V. Dhiman, "FogGuard: Guarding YOLO Against Fog Using Perceptual Loss," *arXiv preprint arXiv:2403.08939*, 2024.

[5] C. Feng *et al.*, "HazyDet: Open-Source Benchmark for Drone-View Object Detection in Hazy Scenes," *arXiv preprint arXiv:2409.19833*, 2024.

[6] A. Kumar and A. Chadha, "The Unintended Consequences of Dehazing on Object Detection," *arXiv preprint arXiv:2502.02027*, 2025.

[7] K. He, J. Sun, and X. Tang, "Single Image Haze Removal Using Dark Channel Prior," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2341–2353, 2010.

[8] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng, "AOD-Net: All-in-One Dehazing Network," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, 2017.

[9] N. Raju and K. Srinivas, "TSMD-Net: Two-Stage Mixed Dehazing Network," *Digital Signal Process.*, vol. 155, 104710, 2024.

[10] A. Li, G. Xu, W. Yue, C. Xu, C. Gong, and J. Cao, "Object Detection in Hazy Environments Based on an All-in-One Dehazing Network and the YOLOv5 Algorithm," *Electronics*, vol. 13, no. 1862, 2024.

MANDATORY DECLARATION

ChatGPT (Deep Research Mode) was used to search, verify, and summarize research papers and to generate the narrative literature review. All links were opened and confirmed by the team. All reviewed papers were added to the GitHub repository under `/docs/references`.