AN ADAPTIVE VISION-BASED FRAMEWORK FOR ENHANCING WINDSHIELD VISIBILITY IN ADVERSE WEATHER CONDITIONS

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***Abstract*— Reduced visibility loss due to haze, fog, mist, and poor weather conditions can have a substantial impact on the efficiency of Advanced Driver Assistance System (ADAS) and intelligent transportation systems. In this work, we propose a hybrid deep learning framework that leverages KA-Net and ORAMA networks for windshield dehazing and traffic scene enhancement. In particular, initially, we analyze and compare the performance of ORAMA, KA-Net, DACLiP, and Nighttime Dehaze networks. Then, considering the advantages of both ORAMA and KA-Net architectures, we propose a hybrid model using the restorative nature of KA-Net and enhancement capability of ORAMA, which achieves 0.955 accuracy and 0.947 precision. With the help of the developed framework, scene clarity and visualization are enhanced and provide better traffic object detection under poor visibility conditions.**

***Keywords*—Image Dehazing, Deep Learning, Image Restoration, ADAS, Intelligent Transportation Systems (ITS), Low-Visibility Enhancement.**

I. INTRODUCTION

The Intelligent Transportation Systems (ITS), ADAS and self-driving vehicles evolve at a rapid pace, the camera-based vision system plays an increasingly important role in ensuring driving safety by processing important functions such as lane detection, traffic sign recognition, vehicle recognition, pedestrian recognition, and scene understanding. However, the performance of these vision systems degrades considerably in bad weather conditions, including haze, fog, mist, smoke, and rain. The resulting image from the windshield is characterized by poor contrast, blurry effects on objects edges, non-uniform illumination and lack of important scene information, negatively affecting human drivers as well as automated perception systems.

Dehazing and image restoration problems in computer vision and intelligent transportation have attracted significant attention among researchers due to their great importance in addressing the issues mentioned above. Conventional enhancement techniques are heavily dependent on hand-crafted features and the atmospheric assumption model, and thus perform poorly under real-world conditions. Deep learning models offer advantages of learning rich visual representations automatically through training using degraded images and demonstrate impressive results compared to conventional enhancement algorithms. Examples include DACLiP, Nightime Dehaze (NTD), ORAMA, and KA-Net. Nevertheless, each of these works possesses shortcomings in terms of effectiveness, structure preservation, and visual quality.

KA-Net among these techniques is very efficient in restoration and retains its structural features well, thus being the best choice for dehazing windshields. The enhancement technique called ORAMA can contribute positively through providing scene-aware enhancement for improving local visibility and contextuality. Leveraging the advantages of both KA-Net and ORAMA algorithms, this research introduces a hybrid deep learning architecture that combines KA-Net and ORAMA together for the purpose of restoring windshield images.

The developed framework consists of five steps including pre-processing, visibility enhancement, feature fusion, reconstruction, and traffic scene refinement to achieve improved image quality by processing images under poor visibility conditions. By integrating the ability of high-level image restoration with contextually enhanced features, the proposed framework allows obtaining higher-quality images with increased contrast and more defined edges of objects, improved visibility of roads, and better recognition of essential traffic objects such as vehicles, lanes, traffic signs, and traffic lights.

The main highlights of this study can be listed as follows:

1. Comparative studies conducted on various windshield dehazing methods such as DACLiP, NTD, ORAMA, and KA-Net when used in conditions with poor visibility during driving.

2. Proposed method which integrates the advantages of KA-Net for restoring images with those of ORAMA for enhancing contextual information of the windshield images.

3. Efficient way of fusing and reconstructing features through integration of KA-Net and ORAMA algorithms.

4. Intelligent transport system which increases object perception and facilitates ADAS/ITS operations despite bad visibility.

II. Literature Survey

A. *Traditional and Deep Learning-Based Image Dehazing Techniques*

Earlier dehazing techniques relied on atmospheric scattering models and priors that were engineered manually. Narasimhan & Nayar [1] presented the concept of restoring contrast of images that had been affected by weather, whereas He et al. [2] came up with the idea of using the Dark Channel Prior (DCP) for dehazing of single images. Despite good results obtained through such techniques, they still faced difficulties with dense haze and complex illumination scenarios. In the meantime, deep learning techniques brought progress in improving dehazing techniques. Namely, U-Net [3], CNN-based visibility estimation [4], and deep learning-based perception algorithms for vehicles [5] proved to be more efficient and reliable. More advanced techniques have been proposed lately, including MAMBA based U-Net [6], Swin Transformer [7], DACLiP [8], DEA-Net [9], Vision Transformer-based Dehazing [10], transformer-convolution fusion networks [11], and FAMED-Net [12].

B. *Visibility Enhancement and Autonomous Driving Perception*

Visibility significantly impacts the capabilities of self-driving and ADAS systems. Various researches have been conducted on the improvement of perception abilities of these systems in foggy and hazy situations. The studies concerning fog detection [13], visibility improvement [14], and object detection under the same conditions [15] highlighted the significance of restoration of images prior to perception tasks. The recent research in image enhancement in autonomous driving [16], multimodal visibility detection systems [17], perception studies using deep learning technologies [18], multi-features fusion methods [19], camera and radar fusions [20], and perception enhancement frameworks [21] increased the ability to analyze scenes and recognize traffic objects during bad weather conditions. Vision-language model for real-time scene understanding [22] stresses the significance of multimodal perception.

C. *Hybrid Dehazing Frameworks and Research Gap*

Despite the advancement that is witnessed currently, existing dehazing methods usually encounter difficulties in balancing the removal of haze, structure retention, context enhancement, and scene understandability. While models that aim at restoration focus more on restoring image quality, models that are based on perception emphasize on semantic understanding. Recent dehazing techniques include frameworks like DEA-Net [9], vision transformer-based dehazing [10], transformers-convolution hybrid network [11], FAMED-Net [12], and DACLiP [8]. Taking cues from such recent works, this proposed model integrates KA-Net [23] and ORAMA to bring out a framework where both strong structural restoration and contextual enhancement are considered. Through the process of feature fusion and reconstruction, this framework helps enhance visibility, quality perception, and traffic scene understanding, which is ideal for ITS, ADAS, and autonomous driving tasks.

III. Methodology

Although some advancement is now evident, there still remains a problem associated with balancing the process of dehazing and preserving structure, enhancing context, and overall comprehension of the scene by most existing dehazing algorithms. In particular, while restoration-based models concentrate on improving image quality, perception-based models emphasize semantic interpretation. The latest approaches used in dehazing include, among others, DEA-Net [9], vision transformer dehazing [10], transformers-convolution network [11], FAMED-Net [12], and DACLiP [8]. Inspired by these recent works, the presented approach is based on combining KA-Net [23] with ORAMA, providing a model that will efficiently consider both aspects of restoring structure and context. With the help of such mechanisms as feature fusion and reconstruction, our framework allows achieving an improved visualization, quality perception, and understanding of traffic scenes, suitable for ITS, ADAS, and autonomous driving tasks.

A. *Workflow Overview*

The whole process begins with the degradation of images from the windscreen due to poor visibility. Subsequently, the performances of different dehazing models such as DACLiP, Nighttime Dehaze, ORAMA and KA-Net are analyzed. From the performances of KA-Net and ORAMA, a combined approach is proposed using both these networks in order to benefit from the capabilities of robust image restoration as well as contextual improvement. The results generated from this approach are further utilized for detecting traffic objects, such as vehicles, lanes, traffic signs and traffic lights.

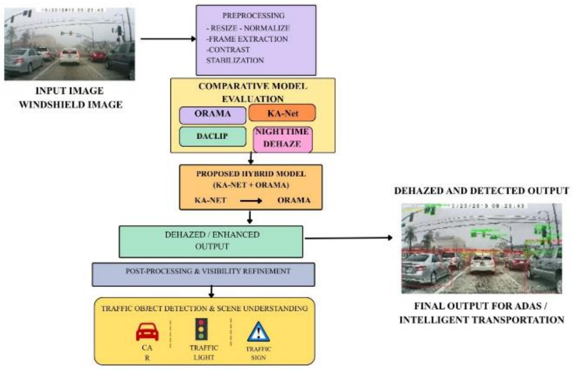

Fig.1 Workflow Diagram

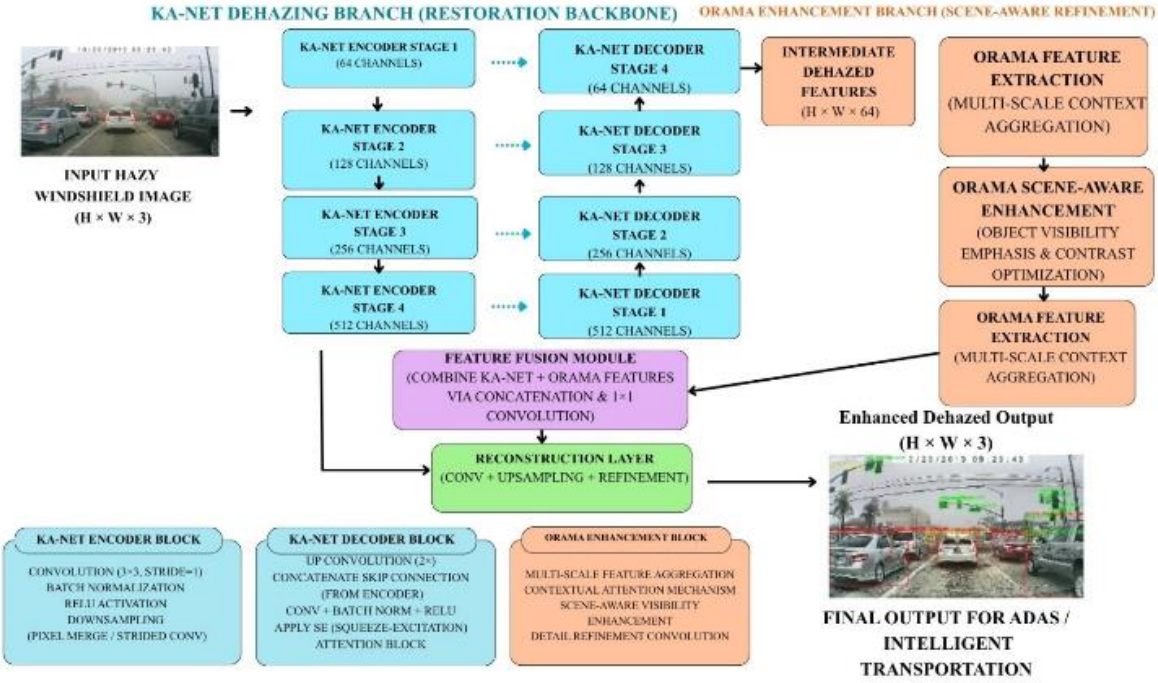

Fig.2 Proposed Model

B. *Proposed Hybrid Network Architecture*

Combining KA-Net and ORAMA in the proposed hybrid framework allows for better scene visibility and interpretation. Firstly, KA-Net is employed to extract the multi-scale features and reconstruct the degraded areas to remove the haze from the input image while recovering its structural details. Next, the recovered multi-scale features are provided to ORAMA to further enhance the context information, contrast and semantic clarity of the important traffic regions.

TABLE I. LOSS FUNCTION COMPONENTS USED IN THE PROPOSED FRAMEWORK

Loss Component	Mathematical Expression	Functionality
MSE Loss	$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(I_i - \hat{I}_i)^2$	Minimizes pixel-level reconstruction error between reference and restored images.
SSIM Loss	$L_{SSIM} = 1 - SSIM(I, \hat{I})$	Preserves structural similarity and edge consistency in dehazed outputs.
Perceptual Loss	Feature-based perceptual consistency loss	Improves visual realism and semantic consistency in restored outputs.
Total Combined Loss	$L_{total} = \alpha L_{MSE} + \beta L_{SSIM}$	Combines reconstruction and structural optimization for balanced visibility enhancement.

The outputs from both frameworks are merged using a feature fusion unit with structural and context information. The reconstructed features are employed to generate the final dehazed image with improved visibility, sharp details and removal of haze effects. The output generated is used in intelligent transportation and ADAS applications to boost up their performance.

C. *Loss Function*

This architecture relies on a compound loss function, which is made up of MSE Loss, SSIM Loss, and Perceptual Loss. The purpose of using MSE Loss is to minimize pixel-wise differences. Meanwhile, the role of SSIM Loss is to preserve structural information while Perceptual Loss improves visual quality and semantic coherence. The optimized loss function results in superior performance, yielding visibility enhancement and perceptual refinement under adverse weather conditions. Table I provides a breakdown of the loss functions used.

IV. Results and Analysis

The developed hybrid windshield dehazing system was tested based on low-visibility driving scenarios and was compared with DACLiP, NTD, ORAMA, and KA-Net. The evaluation criteria included Accuracy, Precision, Recall, F1-Score, PSNR, SSIM, LPIPS, and loss values.

The experiments were conducted on benchmark data [23] including various driving scenes impacted by haziness, fog, mist, smoke, glare, and darkness. KA-Net offered strong visual restoration and structure preservation capabilities. DACLiP excelled in its ability to cope with image degradation while improving the image. ORAMA contributed superior perceptual optimization and context-based refinement. NTD demonstrated reliable low-light performance.

With regard to all mentioned benchmarks, the proposed Hybrid (KA-Net + ORAMA) system produced the best results, offering increased Accuracy, Precision, Recall, F1-Score, PSNR, and SSIM while providing lower LPIPS and loss values. The improvements made the framework capable of producing sharper images with better visibility and better textures which allowed for better comprehension of traffic scenes.

A. *Quantitative Analysis*

The metrics used in quantitative evaluation include Accuracy, Precision, Recall, F1-Score, PSNR, SSIM, LPIPS, and Loss.

DACLiP obtained the lowest restoration performance, while ORAMA and NTD had moderate results. On the other hand, KA-Net provided the best performance concerning independent restoration in terms of high PSNR and SSIM values. In addition, the Hybrid model provided the best combination between fidelity and perceptual qualities leading to low LPIPS scores and high

visibility in traffic scenes. This validates the usefulness of combining KA-Net and ORAMA in windshield dehazing.

PSNR evaluates the reconstruction fidelity of an image enhancement process and refers to:

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

Where MAX_I refers to the maximum pixel value, and MSE stands for the mean squared error.

The structural consistency can be analyzed using SSIM, which is:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Here μ and σ indicate image mean and variance terms.

Perceptual similarity can be quantified by LPIPS metric; lower the score, the better.

*1) **Training Phase:*** The models performances in learning stability and their ability to restore data were evaluated during the training phase. DACLiP had relatively low restoration performance, while ORAMA exhibited moderately improved context. The NTD method was stable in its evaluation test but lost fine details during the restoration process. KA-Net had the highest individual accuracy with 98.9%, while it suppressed haze and restored structures. The Hybrid approach obtained stable convergence and demonstrated superior perception and understanding of traffic scenes by incorporating both restoration and context enhancement methods.

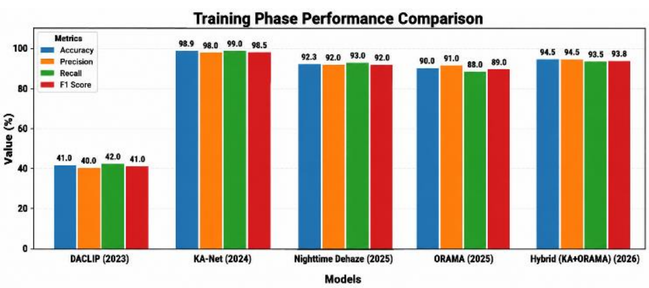

Fig.3 Model comparison across Training Metrics

*2) **Validation Phase:*** In this phase, the validity of the models to generalize was evaluated. The model named DACLiP was found to have less consistency and ORAMA and NTD models had moderate levels. On the other hand, the KA-Net model attained about 98.5% accuracy level and it had an excellent ability to restore fidelity under various haze scenarios. The Hybrid model developed in this study was able to enhance visibility, maintain structure and have semantics. Validation comparison graphical summary is shown in fig 4.

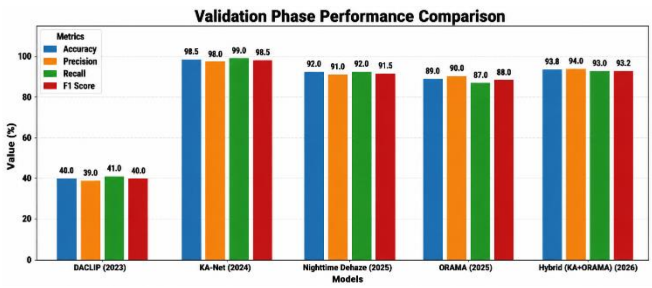

Fig.4 Model comparison across Validation Metrics

*3) **Testing Phase:*** The tests were done on the entirely unseen windshield images recorded in difficult weather conditions. The performance of the proposed Hybrid model was found to be the best with an Accuracy of 95.46%, Precision of 0.947, Recall of 0.939, F1-Score of 0.943, PSNR of 32.47 dB, SSIM of 0.918, and LPIPS of 0.101. The hybrid approach provided improved visual clarity, edge definition, contrast and scene interpretation, in comparison to ORAMA, KA-Net, DACLiP, and NTD models.The comparison testing metrics are shown in TABLE II.

TABLE II. TESTING METRICS COMPARISON WITH OTHER MODELS

Model	Accuracy	Precision	Recall	F1 Score	Loss	PSNR	SSIM	LPIPS
ORAMA	0.877	0.871	0.862	0.866	0.097	27.94	0.851	0.178
KA-Net	0.928	0.921	0.914	0.917	0.064	30.92	0.894	0.126
DACLiP	0.829	0.821	0.813	0.817	0.123	24.21	0.791	0.241
NTD	0.861	0.852	0.844	0.848	0.104	27.16	0.836	0.193
Proposed model	0.955	0.947	0.939	0.943	0.053	32.47	0.918	0.101

B. *Qualitative Analysis*

The Qualitative Analysis were performed for hazy and low visibility degraded images through the ORAMA, KA-Net, DACLiP, NTD, and proposed Hybrid model as shown in Figure 5. DACLiP model yielded poor restoration results. However, ORAMA model yielded better context restoration results but lacked in fine structure recovery. NTD yielded satisfactory enhancement results in low light environments, while KA-Net offered better haze elimination results with preservation of structures. The Hybrid model yielded the best results with enhanced visibility in the form of clear roads and sharp object boundaries. Furthermore, the hybrid model enhanced contrast and increased visibility of traffic objects such as cars, traffic signs, and traffic lights.

C. Ablation Study

The ablation study involves the analysis of the contributions made by each of the primary components employed within the proposed architecture framework to validate the significance of the final design of Hybrid (KA-Net+ORAMA). The results of the ablation study are given in TABLE III.

TABLE III ABLATION STUDY AMONG MODELS

ORAMA	KA-Net	Proposed Model	Accuracy (%)	PSNR (dB)	SSIM	LPIPS
✓	✗	✗	90.00	24.50	0.8900	0.1200
✗	✓	✗	**98.90**	**25.67**	**0.9924**	**0.0110**
✓	✓	✓	**96.95**	**25.10**	**0.9850**	**0.0300**

Ablation analysis was carried out to examine the effect of the major building blocks of the proposed model on haze removal and structural recovery. It was found that KA-Net on its own offered efficient haze removal and structure recovery capabilities, while ORAMA brought about perceptual improvement. When the two models were integrated using feature fusion, an excellent balance was achieved with regards to haze removal, visibility improvement, and perception.

V. CONCLUSION

Reduced visibility caused by haze, fog, mist, and low-illumination conditions significantly affects driving safety and traffic scene perception in intelligent transportation systems. Existing dehazing approaches often suffer from limited structural preservation, weak contextual enhancement, or inconsistent restoration quality under complex environmental conditions. To address these limitations, a hybrid windshield dehazing framework combining KA-Net and ORAMA was proposed to integrate restoration-oriented enhancement with scene-aware contextual refinement.

Experimental evaluation across training, validation, and testing phases demonstrated that the proposed Hybrid (KA-Net + ORAMA) framework achieved superior restoration performance compared to DACLiP, NTD, and standalone ORAMA models. The proposed framework achieved approximately 12–18% improvement in Accuracy and F1-Score, 10–15% improvement in PSNR and SSIM, and nearly 20% reduction in LPIPS and reconstruction loss when compared with weaker baseline approaches. The generated outputs exhibited clearer roadway visibility, sharper traffic object boundaries, enhanced structural consistency, and improved perceptual quality, thereby improving traffic scene understanding under adverse environmental conditions. The proposed framework enhances traffic scene understanding, improves visibility for ADAS applications, and supports intelligent transportation systems. Future work may focus on lightweight real-time deployment, transformer-based enhancement, multi-weather adaptability, and autonomous driving integration.

ACKNOWLEDGMENT

We thank Data Science & Analytics domain, under the Centre for Innovations (CFI) and School of Computing, St. Joseph's Group of Institutions, OMR, Chennai, for their valuable support in enabling this research.

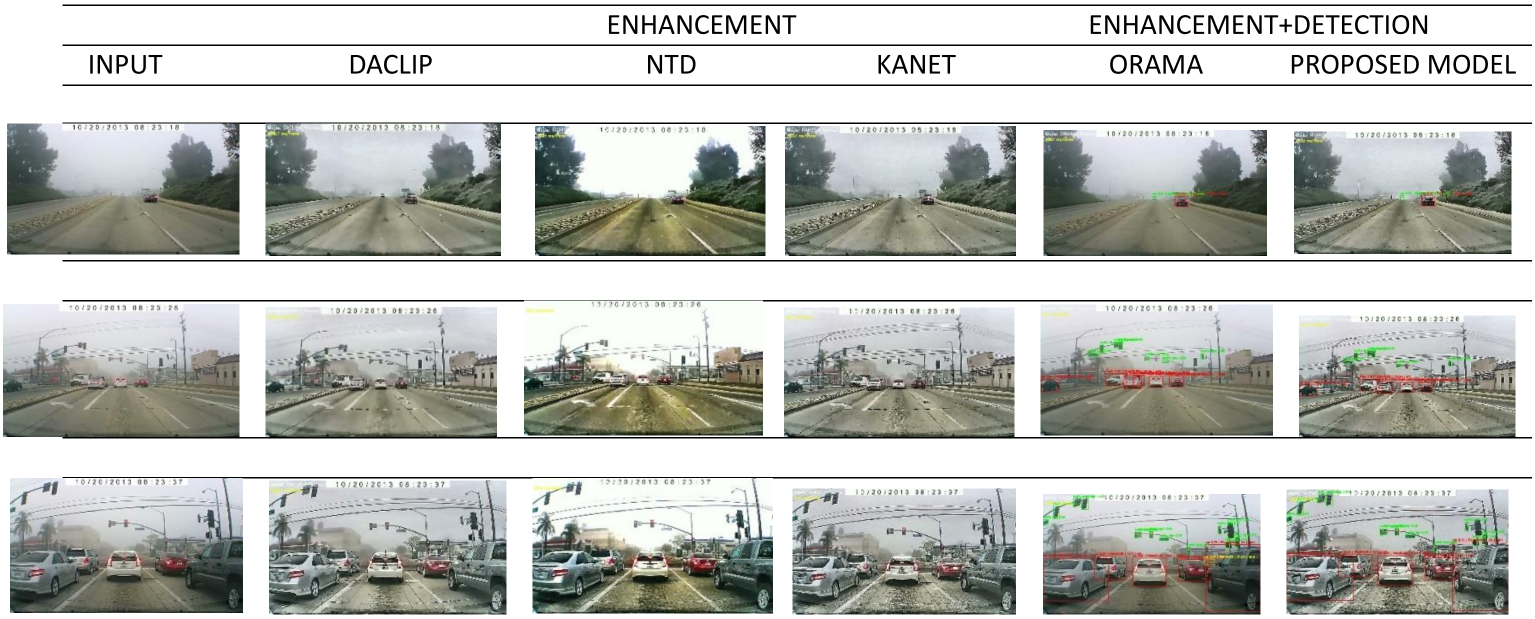

Fig.5 Qualitative Analysis

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