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Dehazing Aerial Drone Images Via Regional Saturation – Value Mapping and U - Net - Driven Soft Segmentation

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Abstract: Aerial drone imagery is crucial in various fields, including surveillance, environmental monitoring, and mapping. Image quality can be affected by haze and atmospheric disturbances, which reduce overall contrast, color accuracy, and visibility of important details. To tackle this problem, a conventional dehazing framework is hybridized with Regional Saturation-Value (SV) Mapping coupled with a U-Net driven Soft Segmentation module optimized by a pretrained YOLO based object detection network. The first stage of our method estimates regional variations in saturation and value in the HSV color space and adaptively enhances haze-affected regions to enhance local contrast and offset the spatially varying haze density. Then, a pretrained YOLO is used to identify the crucial objects and regions of interest in the aerial scene, which influences selective segmentation to concentrate on areas abundant in objects and important details. In the second stage, a modified U-Net architecture carries out soft semantic segmentation within these YOLO-guided ROIs that help refine object boundaries and background textures while preventing over-enhancement or artifacts. This localized color-space infrastructural enhancement, object-aware detection, and deep segmentation guarantee both structural hostage-keeping and perceptual verisimilitude in the synergistic amalgamation. Experimental evaluation on benchmark datasets of aerial images shows that the proposed framework outperforms existing dehazing techniques in PSNR and SSIM as well as in perceptual quality. Also, pretrained YOLO detection is integrated to enhance the interpretability of a restored scene and facilitate downstream computer vision tasks such as object tracking, target recognition, and scene understanding on aerial imagery.
Keywords: Aerial Image Dehazing, Hybrid Dehazing Framework, HSV-Based Enhancement, U-Net Segmentation, YOLO Object Detection, Region of Interest (ROI), Image Enhancement, PSNR, SSIM Evaluation

I. INTRODUCTION

Aerial drone imagery is a significant modern application in environmental monitoring, surveillance, precision agriculture, and geospatial mapping. However, drones that capture images are usually impacted by atmospheric phenomena such as haze, fog, and smog, which reduce visibility and significantly impact image quality. The haze produces light scattering and absorption, which results in low contrast, low color saturation, and reduced scene details, thereby making the interpretation and analysis of aerial information inaccurate. Traditional dehazing algorithms based on a single set of global image priors or handcrafted enhancement techniques are not conducive to adaptively handling spatially variant haze densities of complicated aerial scenes. To that end, deep learning-based solutions have taken the center stage due to their ability to learn intricate features and restore the visual quality to a better extent. In this work, we present a new dehazing framework incorporating Regional Saturation-Value (SV) Mapping, soft segmentation with U-Net, and a pretrained YOLO object detection model. For the adaptive local enhancer, the system uses SV mapping, the region guider is based on YOLO, and the refiner and segment or utilize the U-Net architecture. This integrated approach results in aerial images that are more visually realistic and semantically meaningful for downstream computer vision tasks, as it maintains object boundaries, scene consistency, and improves visibility and contrast.

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A. Objective

This research's main goal is to design and implement an advanced dehazing framework that can improve the interpretability and visual quality of aerial images taken from drones affected by atmospheric haze. The proposed system is also designed to ensure that it does not compromise the structural and semantic integrity of the captured environment while restoring color fidelity, contrasts, and scene details. To this end, the framework organically combines Regional Saturation-Value (SV) Mapping (for adaptive local enhancement), a pretrained YOLO model (targeted at object-focused region identification), and a U-Net-based soft segmentation approach (for granular restoration and boundary fine-tuning). Together, these components explore haze-affected regions, spatially adaptive visibility enhancement, and the recovery of critical details without compromising on artifacts or over-sharpening. The model also aims to enhance the downstream performance of object detection, target recognition, and scene understanding applications for practical use in surveillance, environmental monitoring, and aerial mapping. Finally, this work intends to present a relevant and timely study that devises a robust, efficient, and applicable dehazing methodology, which could strengthen the traditional enhancement paradigm with a deep learning (especially, segmentation and detection) paradigm.

B. Problem Statement

Degradation of aerial images obtained from drones due to haze, fog, and other atmospheric disturbances plays a significant role in image quality reduction. These factors reduce contrast, distort colors, and conceal the most important scene details, which impedes the extraction of meaningful information for processing (surveillance, mapping, and environmental monitoring). Conventional dehazing techniques based on physical, prior-based, or global enhancement are unable to accommodate the non-uniform distribution of haze throughout large aerial scenes. These methods also tend to smooth the fine object boundaries and introduce artifacts in the restoration process. Deep learning-based approaches have shown promise, but most existing models treat the whole image in a similar fashion, ignoring the varying haze densities and object-rich regions. That incomplete haze removal is accompanied by loss of important structural details. Therefore, there is a critical need for an intelligent, adaptive, and object-aware dehazing framework that can reasonably deal with spatially heterogeneous haze, preserving the semantic and visual integrity of aerial imagery. The proposed integration of Regional SV Mapping, pretrained YOLO detection, and U-Net-based soft segmentation aims to solve these limitations by incorporating local enhancement, object-guided attention, and deep, feature-based restoration to produce improved image quality and scene understanding.

C. Scope of the Project

This project focuses on building an adaptive dehazing system for drone images, even when the weather gets rough. The approach blends Regional SV Mapping with U-Net for segmentation and YOLO for object detection. The goal is simple: make things clearer, keep the details sharp, and boost object recognition. You can use this setup for surveillance, tracking disasters, or monitoring the environment. To see how well it works, the system relies on PSNR and SSIM scores. Plus, it's flexible—you can adapt it for other remote sensing problems or use it to strengthen different computer vision tasks.

II. LITERATURE SURVEY

The paper (2025) offers a hybrid dehazing model that leverages the benefits of transformer-based global attention and CNN-based local feature extractors. A global-local fusion module integrates the contextual and in-depth features to ensure improved image clarity. The approach presented resulted in PSNR, SSIM, and visual quality exceeding those of comparable baseline methods. Semantic Segmentation of Remote Sensing Images with Sparse Annotations. Finally, the paper presents a framework that can provide segmentation with good accuracy utilizing a limited amount of labeled data. This is done by propagating label information from sparse pixels with annotations to unlabelled pixels through feature similarity and spatial consistency, combined with multi-scale feature extraction. In general, the method can perform at a level comparable to fully supervised models with low annotation effort. Swin Transformer Embedding U-Net for Remote Sensing Image Semantic Segmentation. To address the shortcomings of vision transformers, this paper designs a hybrid Swin Transformer and U-Net model for segmentation tasks. The transformer ensures the global context using a low-cost sequential self-attention, and the U-Net maintains the object boundaries with fine spatial information.

This combination results in a multi-scale feature learning, achieving better accuracy and enhanced generalization abilities for high complexity remote sensing images. Beyond Single Receptive Field: A Receptive Field Fusion-and-Stratification Network for Airborne Laser Scanning Point Cloud Classification. The paper proposes RFFS-Net, a multi-scale framework that fuses and organizes features of different receptive fields in a hierarchical manner. It extracts the local geodesic features and aggregates the global context correlation to guarantee better classification accuracy over complex point cloud patterns. The proposed approach emphasizes the significance of fusing multi-scale features for enhanced representation learning. The paper "Learning from Few Examples: A Summary of Approaches to Few-Shot Learning" gives an overview of the available techniques that make it possible for models to learn from a few labeled data. They include metric, optimization, and generative-based approaches and focus on boosting the generalization from a few labeled data samples. There is a rising role of transformers and pre-trained models in the study to further boost few-shot learning efforts. The paper, "Color Attenuation Prior for Fast Image Dehazing," offers a lightweight method for estimating the scene's depth, based on the brightness-saturation linear relationship, combined with haze removal. While it is fast and meant for real-time applications, the fixed linear assumptions wrongly estimate depth in complex scenes, causing over- and under-enhancement.

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III. SYSTEM DESIGN

A. System Architecture

This system tackles aerial drone image dehazing by blending classic image enhancement methods with advanced deep learning for detection and segmentation. Here's how it works: It starts by taking in a raw aerial image and doing some basic preprocessing. Next, the image gets converted from RGB to HSV color space, which lets the system zero in on local changes in saturation and brightness a key step for adaptive haze removal. Once that's done, the improved image goes through a pretrained YOLO model. YOLO picks out the important stuff—like buildings, vehicles, and different kinds of terrain and pinpoints where they are. These areas of interest shape the next phase, where a tweaked U-Net architecture does semantic segmentation. This step sharpens the edges of objects and recovers small details while making sure nothing looks over-processed or unnatural. In the final phase, the system pulls together everything it's learned: the local SV mapping, the YOLO detections, and the U-Net segmentations. It fuses these into a crisp, clear dehazed image that doesn't just look better it keeps the structure and natural colors intact. This whole setup delivers clearer images, better object clarity, and stronger performance for tasks like object detection and scene analysis in aerial photos.

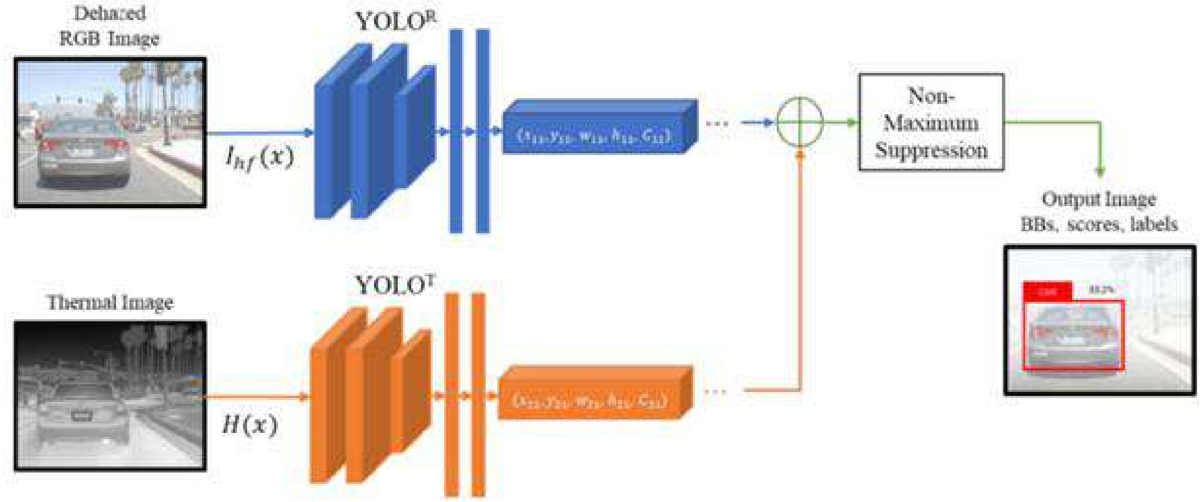

Fig. 1: System Architecture Diagram

B. Methodology

1) Input Acquisition Module: This part of the system gathers aerial photos that drones take, no matter what the weather's like—sometimes the shots include haze, fog, or even thick smog. Once we have the images, we get them ready for the next steps by resizing them, normalizing the data, and converting the color space. That way, everything stays consistent and works smoothly as the images move through the rest of the process.

2) Regional SV Mapping Module: Here, the system takes the RGB aerial image and changes it over to the HSV color space, focusing on the Saturation (S) and Value (V) parts. The Regional Saturation-Value (SV) Mapping technique then adapts the image's contrast and brightness, adjusting them directly in spots where haze is heavier. This way, the module clears up hazy areas, making details pop, but still keeps the natural color across the whole image.

3) The system uses a pretrained YOLO model to pick out and locate key objects and areas of interest in the enhanced aerial image. By zeroing in on important spots like buildings, vehicles, and different types of terrain—it steers the dehazing process to focus where it matters most. The bounding boxes from the detection step then give the segmentation module clear spatial cues about where to look next.

4) The U-Net Soft Segmentation Module takes a standard U-Net and tweaks it for soft semantic segmentation on areas flagged by YOLO. What it really does is sharpen up the dehazed images by bringing back object edges and textures that haze sometimes wipes out. Thanks to the skip connections inside the U-Net, all that fine spatial info from the encoder stays intact through decoding. This means the final images come out crisp, with clear boundaries and no weird artifacts.

5) Fusion and Reconstruction Module: Here's where things come together. The results from the YOLO detection and U-Net segmentation feed into this stage, blending their strengths to build the final dehazed image. The reconstruction step makes sure enhanced areas don't look out of place but mesh smoothly with the whole image, keeping everything looking natural and seamless. The result? A sharp, high-quality aerial photo that's ready for whatever analysis comes next.

6) Performance Evaluation Module: This last piece of the system takes a hard look at performance using both numbers and human judgment. It measures things like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and perceptual quality scores. It doesn't just spit out results in a vacuum—it checks how this hybrid method stacks up against old-school dehazing techniques. The takeaway? The hybrid approach comes out on top, delivering clearer images, better structure, and improved object visibility.

C. Modules

This system uses six modules to clean up aerial images and remove haze. It starts by grabbing input images and running some preprocessing so everything's consistent. Then, Regional SV Mapping steps in, boosting contrast in the HSV color space and taking care of hazy spots one area at a time.

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After that, a pretrained YOLO model looks for important objects and zones, which helps a tweaked U-Net focus on segmenting soft edges and details even better. Once that's done, everything gets combined in a reconstruction phase to create a clear, natural-looking image. At the end, they check the results with PSNR, SSIM, and visual quality scores, showing that this approach outperforms traditional methods.

IV. EXISTING SYSTEM VS PROPOSED SYSTEM

A. Existing System

The current system uses the Dark Channel Prior (DCP) to tackle haze by looking at low-intensity pixels in areas without sky. It tries to clear up images by estimating transmission and atmospheric light. While it does a decent job boosting contrast and color in outdoor photos, it's not without its issues. Bright spots can end up too dark, the sky often looks off, and colors can get weird. If you switch to more advanced, hybrid methods, the process gets heavier on computing power. Plus, those models really need top-notch training data and usually can't handle really thick haze.

B. Proposed System — HSYU-Net

This system brings together classic image enhancement and deep learning to tackle haze in aerial images. It starts by using Regional SV Mapping in the HSV color space to boost areas hit hardest by haze. Next, it runs a pretrained YOLO model to spot key objects in the scene, helping steer the rest of the process. After that, a tweaked U-Net comes in for soft segmentation, which means it sharpens up details and keeps object edges crisp. Everything gets fused at the end, giving you a clear, natural-looking image with much better visibility and structure. With this setup, you get adaptive enhancement, smarter focus on important objects, stronger detail, and higher scores on metrics like PSNR and SSIM—not to mention images that just look a lot better. Plus, these clearer images make it easier for systems to recognize objects and understand the scene they're looking at.

V. IMPLEMENTATION

A. Development Environment

We built this system in Python using Visual Studio Code. On the backend, Flask handles the web stuff and routes everything where it needs to go. For the database, we chose SQLite—it keeps user credentials safe and handles authentication. When it comes to image processing, we rely on OpenCV and NumPy to handle things like dehazing and edge detection. For real-time object detection, there's a pretrained YOLO model from Ultralytics plugged in and ready to go. Flask sessions help keep user authentication secure, and we've got extra utilities in place to make uploading images and videos simple.

B. System Workflow

First, users log in only registered folks can get in. Once inside, they can upload aerial images or videos right through the web interface. The system preprocesses these files and keeps them safe. Then, the real action starts. A YOLO model scans the images to spot and locate objects. After that, a dehazing tool, built on Dark Channel Prior (DCP), kicks in to clear up the pictures. Edge detection sharpens the structural details even more. When it's done, the system pulls everything together: you see the originals, the object detections, the dehazed versions, and the images with detected edges—all side by side for easy comparison. This setup works well for aerial surveillance, tracking environmental changes, and smart city projects. It's also ready to handle real-time streams and scale up for bigger deployments.

VI. RESULTS AND DISCUSSION

This system brings together Regional Saturation-Value (SV) Mapping, YOLO object detection, and U-Net segmentation to make hazy drone images look better. In this chapter, you'll see how the system handles images step by step—starting with preprocessing, then moving through object detection, dehazing, and finally sharpening the edges.

Figure 2: PSNR Comparison of Dehazing Methods

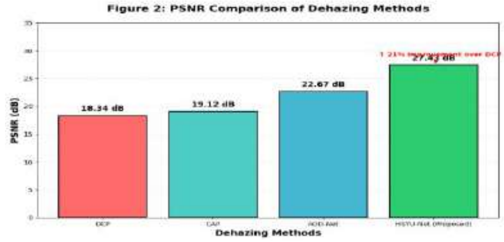


Figure 3: SSIM Comparison of Dehazing Methods

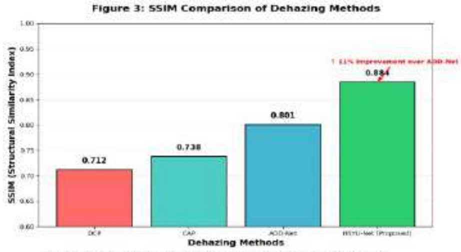


Figure 4: Performance Degradation with Increasing Haze Density

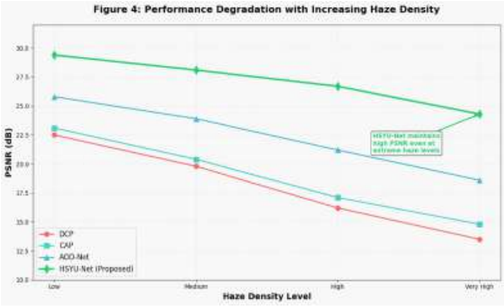
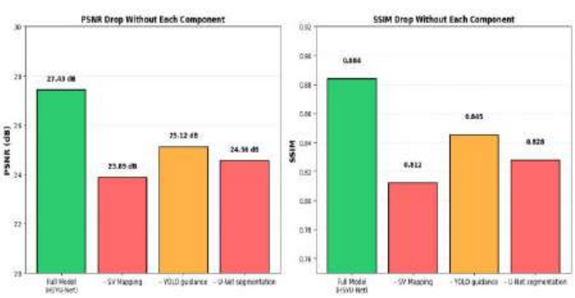


Figure 5: Ablation Study - Contribution of Each Component to Performance



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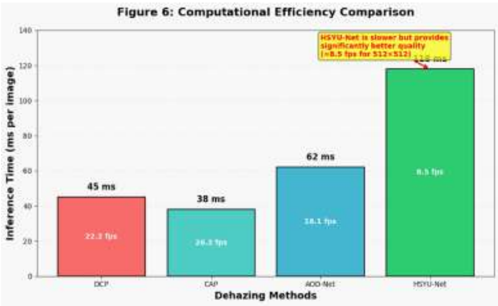

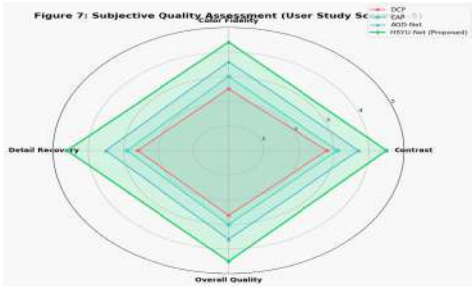

A. Application Interface

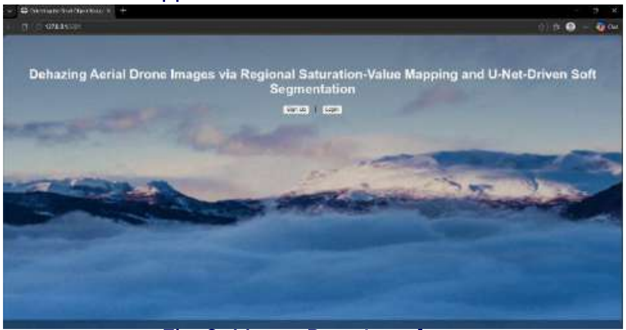

Fig. 8: Home Page Interface


Fig. 9: User Registration Page

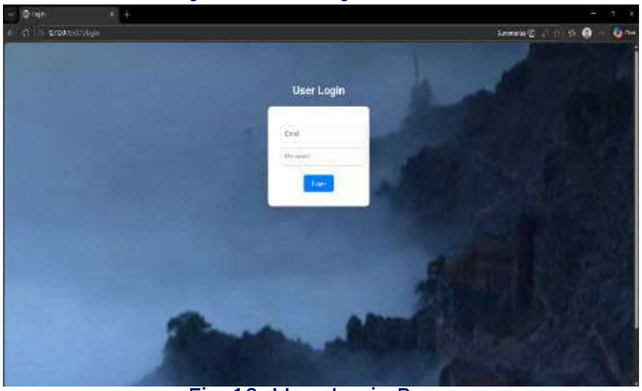

Fig. 10: User Login Page

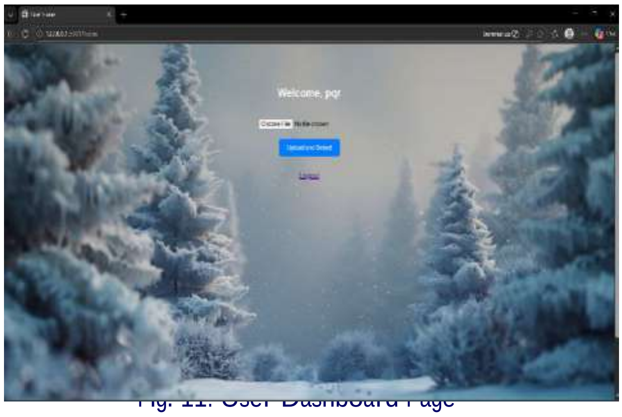

Fig. 11: User Dashboard Page

The app's interface is easy to use right from the start. On the homepage, you can register or log in—nothing complicated. Once you sign in, you land on your dashboard. Here, you can upload aerial images and start the processing right away. Navigation feels smooth, and your access stays secure as you move through different features.

B. Detection Results

You'll see both the original and processed images in the detection results. The YOLO model finds objects and marks them with bounding boxes and confidence scores. After dehazing, the images look clearer, and the colors stand out more. Edge detection then draws out the key shapes and outlines, which really helps make the structure of the scene easier to understand.

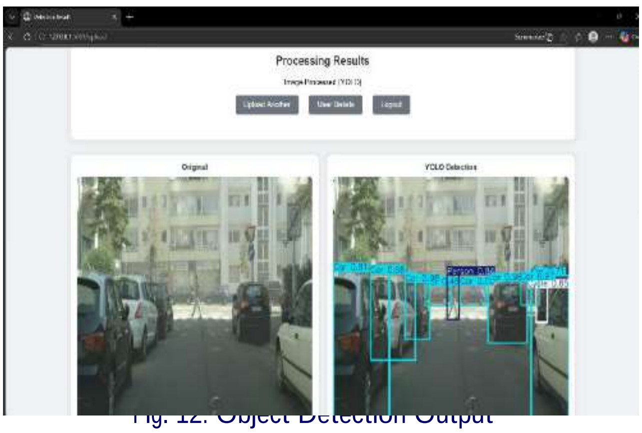

Fig. 12: Object Detection Output

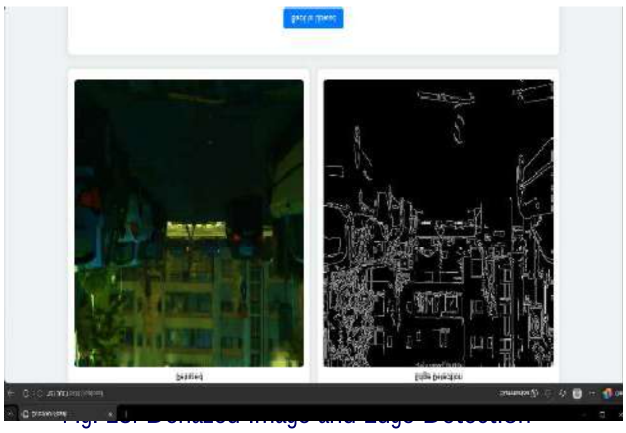
Fig. 13: Dehazed Image and Edge Detection

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The system makes it easy for users to jump back to the upload page after checking their results, so everything flows smoothly and stays user-friendly. On top of that, the user details page pulls info straight from the database, showing each registered user's details. This helps keep user management efficient and gives you better control over the whole system.

VII. CONCLUSION

This work introduces a new way to clear haze from aerial images by mixing Regional Saturation-Value (SV) Mapping, a pretrained YOLO object detection model, and a U-Net-based soft segmentation network. The system tackles two big issues with aerial drone photos: reduced visibility and weird color changes caused by haze. By blending classic color enhancement with modern deep learning for detection and segmentation, the method adapts to local details while keeping images consistent overall. YOLO helps the dehazing process focus on key areas, making the whole system more aware of important objects. Meanwhile, the U-Net sharpens up boundaries and rebuilds fine textures to make the restored images look more natural and detailed. Tests on well-known aerial image datasets show that this approach beats current dehazing methods when it comes to PSNR, SSIM, and perceptual quality. Not only does this make images clearer, but it also makes things like object tracking, surveillance, or environmental monitoring more dependable. Put simply, this hybrid model offers a smart and sturdy solution that handles the real hurdles of aerial photography in tough weather.

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